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"COULD BITCOIN BE SEEN AS A VIRTUAL COMMODITY? AN EMPIRICAL ANALYIS"

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Indices

Introduction

Technology has been one of the main economical drivers since the industrial revolution, easing and improving the economic progress through the introduction of new productive factors or innovations that has changed the way in which the economic systems is carried out.

In last decades, the new generation born between 1980 and 2000, called “millennials”, and the most recent one, generation Z, composed by those born in the 21st century, are experiencing a strict bond with technology. These people are always connected, ready to share or read news on social media and looking for the cheapest offer online; their new way of “living technology” is reshaping the economy as a whole.

In the present research, the attention is drawn on how the technology is affecting the financial sector.

When “finance” and “technology” meet, the crasis of the terms generates a new one: “Fintech”, which embraces a wide range of topics, from the companies developing new business models to the adoption of new application solutions.

Among the relevant financial innovations introduced in recent years, I found of particular interest the distributed ledger technology, which is usually associated with the blockchain technology and is at the base of the cryptocurrencies’ development. “Bitcoin” is the expression of its main application since it was the first new currency that gained popularity some years after its release date and it is still the major cryptocurrency in the market. For this reason, the present analysis is focused on studying its price determination, which seems to be still almost unpredictable.

An empirical analysis based on a cost of production model is carried out, trying to answer the following research question: “Could Bitcoin be seen as a virtual commodity?”. The aim of the study is to detect whether the Bitcoin price could be justified by and connected to the profits and costs associated with the mining effort.

Following this purpose, a sample model is constructed, composed by the hardware devices employed in the mining process. After collecting all the technical information required and computing a cost and a profit function for each period, an implied price for the Bitcoin value is derived. The interconnection between this price and the historical one is thereby analyzed adopting a Vector Autoregression (VAR) Model.

In the literature, researchers detect several economical determinants for Bitcoin price. It seems that given the new features of this cryptocurrency, price drivers will change over time. For this reason, several authors analyze various potential factors, which encompass technical aspects (such as the hashrate and output volume), user based growth, Internet components (as Google Trends, Wikipedia queries and Tweets), market supply and demand, financial indexes (like S&P500, Dow Jones, FTSE100, Nikkei25), gold and oil prices, monetary velocity, exchange rate of Bitcoin express in US dollar, euro and yen.

It is not yet clear which are the definitive drivers for Bitcoin price, probably the intuition of their variability over time is credible and many factors should be expressed and studied at the same time to avoid misleading results.

Although this uncertainty, Bitcoin has undoubtedly introduced on the market a new way to think about money transfers and exchanges. The distributed ledger technology could be a disruptive innovation for the financial sector, since it can ease communication without the need of a central authority. Moreover, the spread of private cryptocurrencies, which enter into competition with the public forms of money, could affect the monetary policy and the financial stability pursued by official institutions. For this reasons, central banks all over the word are seeking to understand if it is possible to adopt this technology in their daily operations, with the aim to include it in the financial system and control its implementations, enhancing its benefits and reducing its risks.

In this regard, authorities are investigating the introduction of Central Bank Digital Currency (CBDC) or Cryptocurrencies (CBCC), with the latter being a subcategory of the former. Few possible scenarios seem to be feasible with the future, depending on the results of further studies on this topic, additional developments, social behavior and preferences.

The present work is divided into three sections. In the first one I give a definition of Fintech and list its main innovations by economic functions, highlighting the potential benefits and risks of this new development field. After providing a broad regulatory framework, I focus the attention on cryptocurrency, and in particular on Bitcoin, explaining how the blockchain works.

I develop the research question in the second section, describing the methodology behind the implemented cost of production model, the sources consulted to collect data, the hardware sample composition and the formulas derivations. I present the econometric approach adopted, and discuss the main findings. Then, I expose a literature overview, presenting those papers that investigate other drivers for Bitcoin price formation, developing an alternative approach.

In the third and last part, I consider the framework under which the idea of public digital currency has been developed and give a definition of Central Bank Digital Currency (CBDC) and of Cryptocurrency (CBCC). Four possible scenarios concerning their future applications are introduced, and I finally conclude by providing some examples of countries that want to implement the distributed ledger technology in the future or have already attempted to apply it in their daily operations.

Section 1

In this section I introduce the topic of FinTech, defining which economic functions are affected by these new technological innovations and identifying the main drivers. I proceed in my analysis specifying their potential benefits and risks and giving a broad view of the regulatory frameworks. In the last part I present a cryptocurrency overview and focus the attention on Bitcoin.

1.1 What is FinTech?

A strict definition of FinTech seems to be missing since it embraces different companies and technologies, but a wider one could assert that FinTech includes those companies that are developing new business models, applications, products or process based on new digital technologies applied in finance.

FSB (2017) defines FinTech as "*technology-enabled innovation in financial services that could result in new business models, applications, processes or products with an associated material effect on the provision of financial services*".

OECD (2018) analyses instead various definitions from different sources[1], concluding that none of them is complete since "*FinTech involves not only the application of new digital technologies to financial services but also the development of business models and products which rely on these technologies and more generally on digital platform and processes*".

The services offered by these companies are indeed various: some are providing financial intermediation services (FinTech companies), while others offer ancillary services relating to the financial intermediation activity (TechFin companies). Technology is for FinTech firms an instrument, a productive factor, an input, while for TechFin firms it is the final product, the output. The latter are already familiar with different technologies and innovation; hence they could easily diversify their production by adding some digital and financial services to the products they already offer. They enjoy a situation of privileged competition because they are already known in the market due to their previous non-financial services and thus could take advantage of their customers' information to enlarge their supply of financial services. TechFin firms are the main competitors for FinTech companies[2].

The sure thing is that FinTech, or financial technology, is changing the way in which financial operations are carried out by introducing new ways to save, borrow and invest, without dealing with traditional banks.

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[1] OECD, (2018). *Financial Markets, Insurance and Pensions* pp. 10.
[2] Schena, C., Tanda, A., Arlotta, C., Potenza G., (2018). CONSOB. *Lo sviluppo del FinTech* pp 10-11.

FinTech platforms, firms and startups rose after the global financial crisis in 2008 as a consequence of the loss of trust in the traditional financial sector. In addition, digital natives (or millennials, born between 1980 and 2000) seemed interested in this new approach proposed by FinTech entrepreneurs. Millennials were old enough to be potential customers, who feel much more related to these new, fresh mobile services offered through mobile platforms and apps, rather than bankers. The strength of these new technologies lies in their transparent and easy-to-use interfaces that was seen as an answer to the trust crisis towards banks[3].

We expect the main driving forces behind innovation will come from less developed countries because their lack of infrastructures provides room for new technologies implementation that could not be adopted in the over-banked economies of the West. Whereas FinTech innovations in developed countries involve primarily the online customer experience by trying to simplify all the procedure, startups in developing countries are focused on cell phone users. This because in these geographical areas is easy to possess a smartphone rather than have access to a bank account. Therefore, FinTech in developing countries has the aim to create new infrastructures and improve people inclusion in the real economy, rather to enhance existing services.

1.2 Categories, Innovations and Drivers

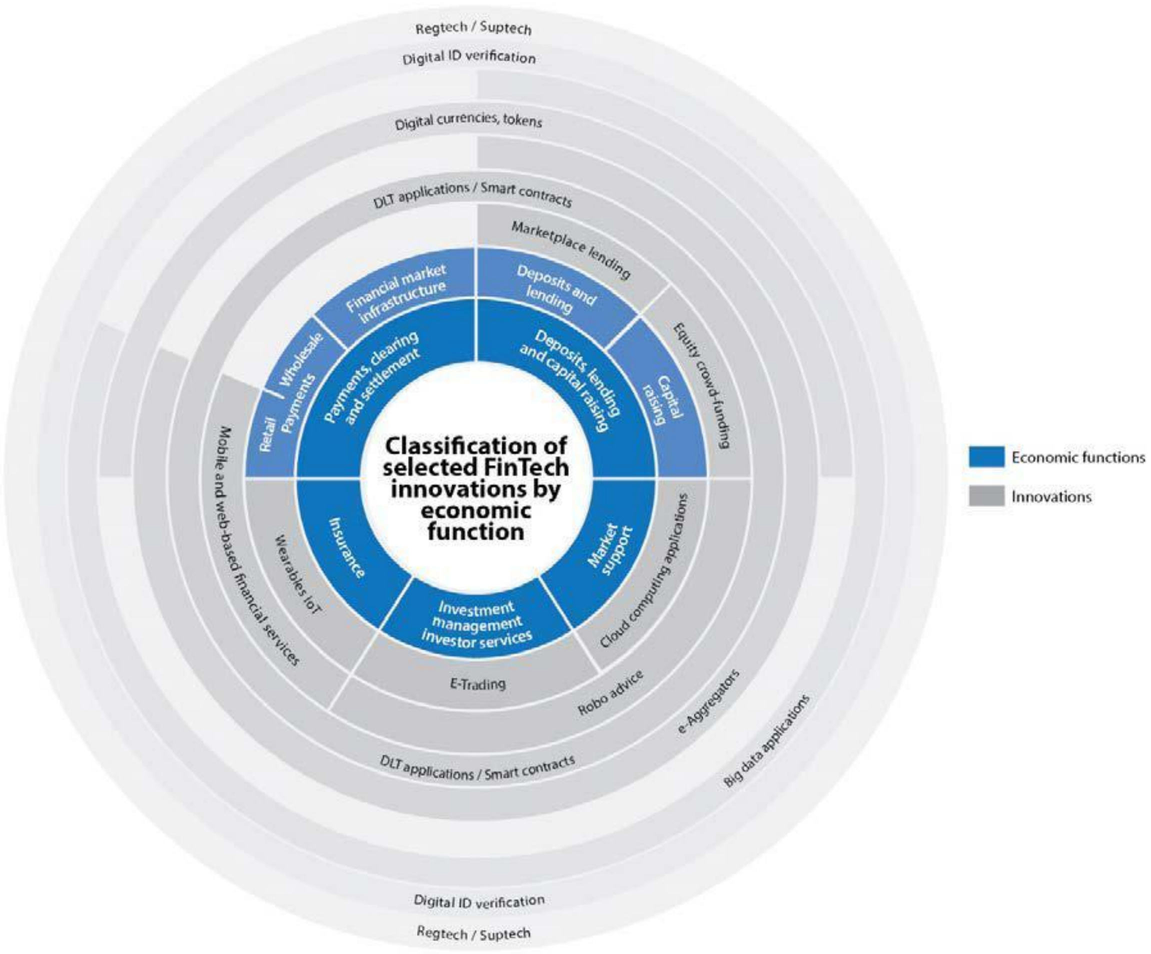
The Financial Stability Board published a report in 2017 describing in depth the FinTech sector and carrying particular attention to the financial stability implication deriving from the adoption of these new technologies.

The authors classify FinTech innovations in five categories, organized by the provided services, which are seen as efforts to reduce some financial frictions such as the information asymmetries, negative externalities, incomplete markets, behavioral distortions, misaligned incentives, and network effects.

Figure 1 shows these five categories: (i) payments, clearing and settlement; (ii) deposits, lending and capital raising; (iii) insurance; (iv) investment management; and (v) market support.

[3] Chishti, S., Barberis, J., (2016). *The FinTech Book.* Menat, R., *Why they are so Excited About FinTech* pp 10.

Figure 1: Stylized classification of selected FinTech innovations by economic function



Source: Financial Stability Board (2017)

The graph defines the economic functions and connects each of them to some specific technology innovations. For example, the “payments, clearing and settlements” function is linked to DLT applications on which digital currencies are based and that required digital ID verification and an adequate regulatory framework.

I want to provide now a brief overview on the main innovations that are being applied in finance by focusing on distributed ledger technologies (DLT) and blockchain, crowdfunding, robo advice, big data applications, internet of things (IoT), cloud computing applications, artificial intelligence and machine learning, digital ID verification and finally RegTech. They are highly interconnected, and, in some cases, their borders tend to blur over time.

- Distributed Ledger Technologies (DLT) and blockchain

Distributed Ledger Technologies (DLT), commonly associated to the blockchain (its popular form), is a decentralized and transparent database technology, distributed across many computers, whose record is available to everyone at any time. It allows to create, transfer and store information. Since it is a peer-to-peer network, DLT incorporates two important features. Firstly, by construction, it does not require the need for intermediaries, such as banks, to keep records for all transactions that took place. Secondly, it is a technical solution to the double-spending problem. The system is trustless, meaning that it does not required verification by third parties, but it is based on consensus among network users and every participant should authenticate and verify each information to avoid that the same transaction happens multiple times. New blocks are added to the chain, or ledger, often through a proof-of-work (PoW)[4] or proof-of-stake (PoS)[5] consensus mechanism.

Each transaction needs to be recorded twice: on the virtual ledger of both the buyer and the seller. The link between them is recorded perpetually on the central blockchain node. Here lies the strength of this new technology: it allows updating the database simultaneously.

Participants provide their identity by using cryptography and digital signature, rather than ID. In this respect, there are two types of blockchains: public chains and permissioned chains based on whether or not they demand some sort of accreditation. The latter does not require mining effort and network participants are entitled only to check the validity of the transactions. This structure is more secure as the risk of cyberattack is reduced. Moreover, since this kind of ledger is available only to community members, it is more appropriate to contain confidential information. This new technology has been applied in many fields, such as: banking sector, payments and money transfer, insurance, cybersecurity and cryptocurrencies.

- Crowdfunding

Platforms that fall into this section help individuals to raise some money from large number of people and are divided into two different categories based on whether they provide a financial return or not: donation-based or reward-based models and equity-based or lending-based platforms.

- Robo advice

The noun “robo advisor” does not always indicate something robotic, nor something that always gives advice. It is more than a journalistic term. Robo advisors are, indeed, automated investment solutions that can automatically rebalance a portfolio using complicated algorithms built on passive investments, investor’s risk preference and diversification strategies. They provide investors with digital tools that allow them to self-asses and shape

[4] PoW protocols are based on two possible algorithms: *SHA-256* hash functions (as the case of Bitcoin) and *scrypt* (as Littlecoin).

[5] PoS protocol differs from the PoW by the method adopted to ensure the safety of a system. PoS is indeed based on the concept of “coin age” while PoW protocol requires users to do some “work”. Tasca, P., (2015). *Digital Currencies: Principles, Trends, Opportunities, and Risks* pp 11.

their investment behavior. Robo advisors, in order to be considered as such, must exhibit at least some of these elements: provide full digital access; perform automated portfolio rebalancing; adopt indexation or passive management; personalize to customers' goals and behavior[6].

- Big Data applications

Big Data derived from the digitalization of daily activities and are composed by data gathered in various forms: texts, numbers, images, video and audio clips generated by communications between devices (e.g. smartphones, PCs). Such data could be used for many scopes, as improve market research or target advertising based on individual's interests and Internet use. This technology is closely related to those of Internet of Things (IoT), cloud computing and artificial intelligence.

- Internet of Things (IoT)

It includes all devices able to capture information regarding physical movements of the customers and, as source of big data, can be used to tailor products, individual willingness to pay and assess risk profiles. Smartwatches are examples of wearable IoT.

- Cloud computing applications

These applications increase the ability of financial institutions to collect and analyze data since they provide a cheap and easy way to process and store them.

- Artificial intelligence and machine learning

Artificial intelligence is commonly used as another world for machine learning and indicates machines programmed to elaborate historical inputs, identify patterns and classify new data. It is important to point out that these machines, despite the name, need a constant human supervision in order to ensure the correct interpretation of data. They are applied in a wide range of scope as recognition, understanding, learning, problem solving, reasoning and decision making[7].

- Digital ID verification

New digital ID verifications rely on biometric technologies able to recognize individuals' physiological or behavioral characteristics useful to verify users' identity. The aim is to increase the security of data transaction involving, in addition to common passwords, other verifications like fingerprint or iris scanning, voice authentication and face recognition.

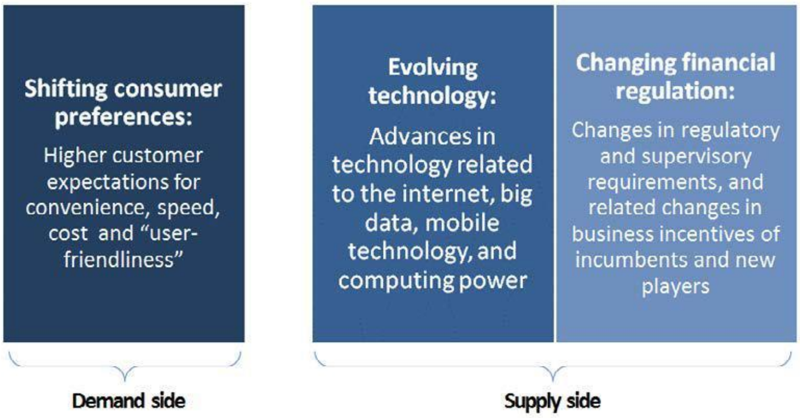
[6] Chishti, S., Barberis, J., (2016). *The FinTech Book*. Sironi, P. *My Robo Advisor was an iPod – Applying the Lessons from Other Sectors to FinTech Disruption* pp 152.
[7] OECD. (2018). *Financial Markets, Insurance and Pensions* pp 13.

- RegTech

RegTech is the latest development of FinTech and is designed to efficiently solve regulatory and compliance requirement by using technologies like machine learning, biometric and application programming interfaces (APIs)[8].

Talking about financial innovations is useful to highlight which are their traditional drivers that affect the demand side or the supply side (Figure 2). The first side entails the shifting in consumer preferences, driven by a higher consumer expectation for more convenient, fast, "user-friendly" and cheaper services. The second side implies expectations on both the evolutions of the provided technologies, such as those related to internet, big data, mobile phone and computer power, and regulatory requirements, which are expected to change with the technological progress.

Figure 2: Drivers of financial innovation



Source: Financial Stability Board (2017)

New services providers could either grow independently as competitors for the traditional ones or could be purchased by banks. By doing so the market could reach different levels of concentration. At this point three aspects of the market structure must be considered: the concentration, the contestability and the composition.

Concentration refers to *"the distribution of market share among competitors offering similar services"*[9]. It could diminish if the competition raises, lowering the market power of intermediaries and hence driving prices down. Technology increases competition in the market by lowering the barriers and the costs to entry for new players. This idea is connected

[8] APIs are particular applications that allow users to have access to data or features of an open system or service and to embed them into new applications. An example is Google Maps that, with its API, gives third party developers the chance to add maps to their own application, such as Uber.

[9] Financial Stability Board. (2017). *Financial Stability Implications from FinTech. Supervisory and Regulatory Issues that Merit Authorities' Attention* pp 11

with the contestability of the market with oligopolistic structure[10], where new entrants could be either innovations technology leaders or firms that obtain access to new technologies. The threat of a higher competition curtails the pricing power of the incumbents. Due to all these aspects, the composition of the service providers in the financial sector could be modified with the consequent result that some new activities fall outside the current regulation, leading to financial stability concerns for the policymakers.

1.3 Benefits and Risks

Besides these new concerns and their related risks, new technology innovations could also enhance the provision of financial services, reducing the existing frictions for the benefit of the entire system. Table 1 presents the main benefits and risks that financial technologies can produce in a system. Risks are divided into subcategories: microfinancial and macrofinancial.

Table 1: FinTech benefits and risks

BENEFITS	**RISKS**	
	MICROFINANCIAL	**MACROFINANCIAL**
Decentralization and diversification Efficiency Transparency Access to, and convenience of, financial services	*financial sources* Maturity mismatch Liquidity mismatch Leverage *operational sources* Governance/process control Cyber risk Third-party reliance Legal/regulatory risk Business risk critical FMIs	Contagion Procyclicality Excess volatility Systemic importance

Source: Author’s elaboration

[10] The lack of barriers represents a threat of potential entry in a market and increases the competition among firms operating in the sector.

1.3.1 Potential Benefits

The main advantages driven by new financial technologies to financial stability are identified by the FSB as: decentralization and diversification, efficiency, transparency and accesso to, or convenience of, financial services.

- Decentralization and diversification in the markets can significantly reduce the effects of financial shocks that occur in the system. If a market is sufficiently decentralized and diversified, a distress situation of an institution can unlikely spread its risk into the market, avoiding affecting similar service providers or the related intermediaries. An example of technology in this respect could be robo-advice that, due to its reasonable fixed costs and characteristics, reduces the barriers to entry allowing smaller firms to operate in the same framework as the biggest one.
- Efficiency, enforced also by the incentives created from contestability, encourages and enhances the development of stable business models, leading benefits to the overall financial system. This could be done for examples with machine learning and AI process that facilitate improvements in decision-making processes in favor of both financial institutions and investors. Robo-advisors could again use algorithms to assess costumers' creditworthiness in a faster and secure way, reducing operational costs for those platforms implementing the technology. Greater efficiency and higher speed while executing transactions could be ensured by distributed ledgers, which contributes to reduce both risks and settlement time required. This has the important effect to curtail the time during which one counterparty is exposed to another. A higher settlement speed leads also to the advantage to unlock collateral and capital for other productive uses.
- Transparency reduces information asymmetries, allowing risks to be properly priced and assessed. It improves the creation of financial instruments with specific features linked to determined financial risks. By doing so, transparency enables market participants to manage risk in a more efficient way. Smart contract has, in this regard, the goal to properly specify those particular risks that users wish to manage[11].
- Access to, or convenience of, financial services foster the financial inclusion of different households and businesses, leading to a diversified exposure to investment risk and supporting a sustainable economic growth. We would expect that the larger is the unbanked population in a region, the greatest is the success of technologies providing access to financial services. The reason is that often in rural regions, where the financial system is

[11] Smart contracts, also called cryptocontracts, are based on blockchain technology. Buyers and sellers write the terms of the agreement in lines of code, planning the self-execution of the contracts if the specified conditions occur. Their subscriptions is transparent, irreversible and traceable.

underdeveloped, the share of cell phone owners is higher than the share of people with access to a bank account. This encourages the diffusion of technologies available from mobile phones, such as digital identity and DLT-based applications, to improve the quality of financial services.

1.3.2 Potential Risks

FinTech innovations, although there are no evidences nowadays, can potentially mine the financial stability through their intrinsic features and characteristics. FSB analyzed these critical aspects by considering microfinancial risks, linked to both financial and operational sources, and macrofinancial risks.

1.3.2.1 Microfinancial Risks

Microfinancial risks gather together two broad categories: financial and operational/non-financial sources, which arise from human errors, management failures or external influences.

Financial sources

- Maturity mismatch arises when the loan period is larger than the related financing period. This entails the necessity to contract new debt, creating rollover risk[12], which if not controlled could result into systemic risk.
- Liquidity mismatch occurs when assets and liabilities are characterized by different liquidity features and the consequent "run risk" forces to promptly liquidate relatively illiquid assets. This procedure causes instability and disrupts markets.
- Leverage, if too high, implies less equity available to cover potential unexpected losses, deriving from different critical sources. This potentially increases the exposure of systemically counterparties to the risk of sudden losses.

Operational or non-financial sources

- Governance/process control, if not adequate, raises the risk of direct disruption while providing financial services. New providers can, indeed, fall outside the regulatory perimeter and be subject to less restrictive regulatory measures. The growth of these entities can endanger the financial system.
- Cyber risks are likely to happen the more different institutions are connected together as a broader use of digital services and technology enlarge the number of entry points cyber hackers might target. Besides that, there is still a chance that financial services evolve in a

[12] Rollover risk is connected to the refinancing of debt and is faced when a debt obligation is going to mature but a country or company needs additional capital. The debt is hence rolled over, or converted, into new debt.

way that, by diversifying the offered services and increasing competition, makes any cyber-attack less systemically significant.

- Third-party reliance is a critical factor since if this third-party, on which different institutions or markets rely, is facing a distress, the counterparties could be likely affected. The more central this third-party is in linking together essential institutions or market, the higher is the chance that a disruption can create systemic risk.
- Legal/regulatory risk is greater when new activities are developing and where regulation does not update or is inadequate and insufficient.
- Business risk of critical financial market infrastructures (FMIs) points at those entities vulnerable to external factors that could affect the balance sheet and, as a consequence, lead to a withdrawal of financial services.

1.3.2.2 Macrofinancial Risks

- Contagion is a common risk in presence of highly interconnected services. A distress in a single financial institution or sector can be transferred to others, leading to a loss of confidence in the overall system. Moreover, a greater automation in trading strategies may cause an unforeseeable form of contagion in the financial market[13].
- Procyclicality risk may be aggravated by market participants' behavior, which steers to larger fluctuations in the system over the short and the long term as well. Examples are the low prices for risk demanded in the financial markets during good times, and the high-risk premia required by investors during bad times.
- Excess volatility could be a characteristic of the financial market when it overreacts to news. The adverse outcomes may create a spiral through the system that leads to solvency or liquidity problems and this effect has a higher chance to occur if business models are homogeneous or exposed to common risks. FinTech innovations can exacerbate the volatility in the system and make it more sensitive to news, by entailing faster operations and transactions and allowing easily changing decision.
- Systemic importance may be another critical factor. If institutions are perceived as being systemically important or too highly interconnected to fail, the risk of moral hazard increases since they can feel confident to be rescued by the public authorities and therefore decide to take excessive risks.

[13] An example is the Flash Crash on May 2010, which involves high frequency traders.

1.4 Regulatory Frameworks

Regulatory frameworks for FinTech innovations are updating frequently due to the features of these new technologies and differ widely between jurisdictions. Discrepancies in regulations depend, firstly, on the size and the structure of the domestic FinTech sector but also on the flexibility and scope of existing frameworks.

Many FinTech activities and business models may be not properly regulated. This could depend on the existing regulatory frameworks, too rigid compared to the flexibility required to go hand in hand with these new services, but could also depend on the fact that even if some entities fall under the regulatory perimeter, they are required to provide only few reports on their activities.

Regulation efforts focus primarily on the areas of payments and capital rising. Many jurisdictions have issued new rules in the fields of mobile payments, non-bank payments and digital currencies in order to ease financial inclusion and guarantee safe new payment services. In 2007 EU has introduced a tailored regulatory framework to rule the market of payment services provided by non-bank entities. The aim was to clarify the legal terms of these services, addressing the related risks of fraud, money laundering and terrorism financing. In 2015 EU has revised its directive on this subject.

Most jurisdictions, with the aim to prevent money laundering and terrorism financing, has imposed further methods for verified clients' identities with know your customer (KYC) identification rules, use of electronic signatures and biometric information. Furthermore, to foster innovation and enhance interactions between FinTech entities, many instruments like sandboxes, accelerators and innovation hubs were developed[14]. These tools are viewed as important sources of information to access risks and incentives of these developing FinTech activities.

[14] See Financial Stability Board. (2017). *Financial Stability Implications from FinTech. Supervisory and Regulatory Issues that Merit Authorities' Attention* pp 28.

1.5 Cryptocurrencies Overview

After the first Bitcoin has been sent in January 2009, a hundred of new cryptocurrencies started being traded in the market, whose common element is to rely on a public ledger (or blockchain technology).

In addition to Bitcoin, in fact, other cryptocurrencies gained popularity, such as: Ethereum (ETH), Dash, Monero (XMR), Ripple (XRP) and Litecoin (LTC)[15].

Ethereum (ETH) was officially launched in 2015 and is a decentralized computing platform characterized by its own programming language.

Dash was introduced in 2014 but significantly increased its market value only in 2017. The peculiarity of this digital coin is that, in contrast with other cryptocurrencies, block rewards are equally shared among community participants and a revenue percentage (equal to 10%) is stored in the "treasury" to fund further improvements, marketing and network operations.

Monero (XMR), launched in 2014, is a system that guarantees anonymous digital cash by hiding the features of the transacted coins. Its market value raised in 2016.

Ripple (XRP) has the unique feature to be based on a "global consensus ledger" rather than on blockchain technology. Its protocol is adopted by large institutions like banks and money service businesses.

Litecoin (LTC) appeared for the first time in 2011 and is characterized by a large supply of 84 million LTC. Its functioning is based on the same of Bitcoin, but some parameters were altered (the mining algorithm is based on Scrypt rather than Bitcoin's SHA-265).

Despite the creation of these new cryptocurrencies, Bitcoin remains the first in terms of usage and for this reason my analysis is focused on it.

1.5.1 Bitcoin

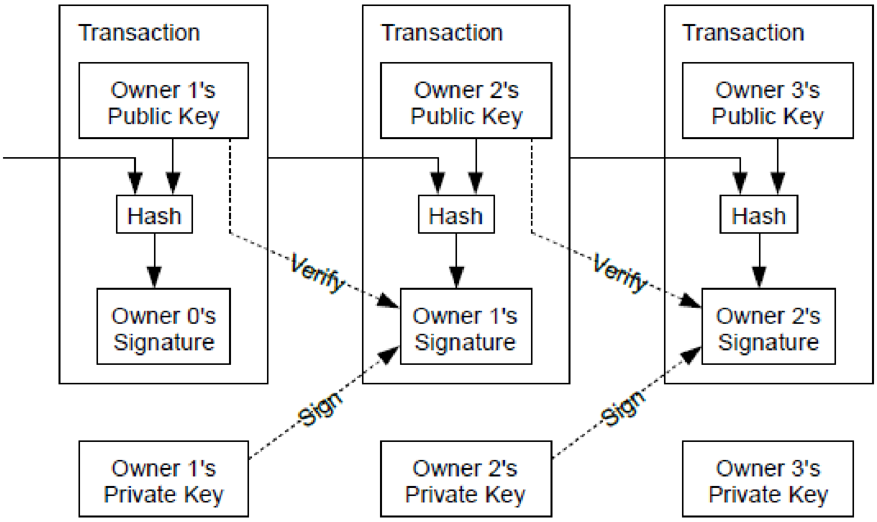
Bitcoin was conceived by a person or a group of people under the pseudonym Satoshi Nakamoto, who in a paper probably released in 2008, presented the main features of this popular currency. It relies on open source software and an open protocol, and thus everyone with some basic computer skills has access to its source code and could start the creation of new digital currencies.

Nakamoto in his paper describes how transactions work giving firstly a definition of electronic coin as a chain of digital signatures. To transfer a coin the owner must digitally sign two elements: a hash from the previous transaction, which is an algorithm that translates and reduces large data into others with a fixed length, and the payee's public key. Both elements

[15] Garrick, H., Rauchs, M., (2017). University of Cambridge. *Global Cryptocurrency Benchmarking Study* pp 15.

are added in this way to the ending part of the coin. The new owner can verify the ownership by checking his new signature (Figure 3).

Figure 3: Transaction Framework



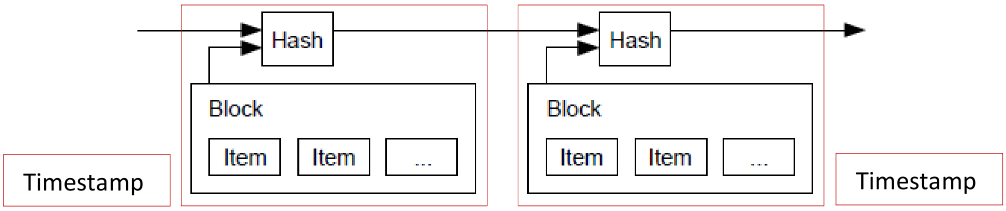
Source: Nakamoto (ndr.)

Bitcoin, as already seen, relies on the blockchain technologies, a peer-to-peer network that avoids banks intermediation and allows solving the double-spending problem. Transactions are publicly announced enabling participants to gain knowledge on them and accept their sequence.

Despite simultaneously updating multiple website containing copies of the blockchain reduces the risk that the same amount would be spent twice, this risk is not completely eliminated in fast transactions, since they are a matter of seconds, but usually required ten or more minutes to be effectively recorded[16].

Nakamoto proposes a system based on a timestamp server (Figure 4), which consists in publishing a hash of a block of items. Each timestamp includes in its hash the previous timestamp and forms a chain. Additional timestamps consolidate the previous ones.

Figure 4: Timestamp Server

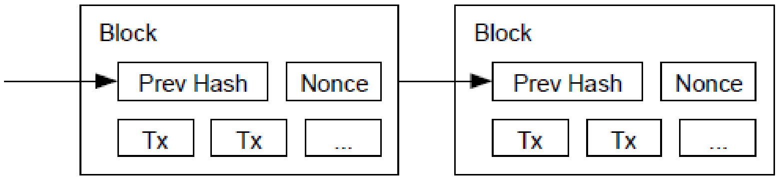


Source: Nakamoto (ndr.)

[16] Dwyer, G., (2015). *The economics of Bitcoin and similar private digital currencies*.

In order to carry out the timestamp server, a proof-of-work system (PoW) is required and implemented by adding a nonce, an arbitrary number, to the block (Figure 5). When the required value to decode this block is found, the hardware effort satisfies this proof and the new block is created and attached to the chain. At this point the block cannot be modified without repeating all the procedure again. Through this process called "mining", which consists basically in finding the solution of a computational problem, new Bitcoins are created.

Figure 5: Proof-of-Work



Source: Nakamoto (ndr.)

If a major of honest participants is exploiting its hardware's computational power to solve these blocks, an honest chain will grow faster. An hacker attack would be possible only if a group of malicious users takes control of the major computational power but in order to achieve this aim they should redo the proof-of-work of a selected block and its subsequent blocks, which requires an incredibly amount of effort since the success possibility decreases as new blocks are added to the chain.

As new hardware are developed and launched on the market, the proof-of-work difficulty, on which the computational problem that miners have to solve is based, increases over time in order to maintain constant the average number of blocks founded within an hour. Moreover, Bitcoin supply is a limit number of 21 million, which is expected to be reached around 2140.

Nakamoto defines in his work the fundamental steps of the network:

1) *"New transactions are broadcast to all nodes.*
2) *Each node collects new transactions into a block.*
3) *Each node works on finding a difficult proof-of-work for its block.*
4) *When a node finds a proof-of-work, it broadcasts the block to all nodes.*
5) *Nodes accept the block only if all transactions in it are valid and not already spent.*
6) *Nodes express their acceptance of the block by working on creating the next block in the chain, using the hash of the accepted block as the previous hash"*[17].

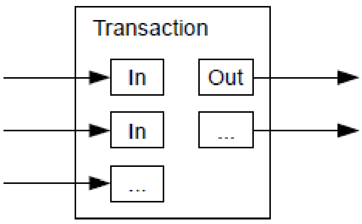
[17] Nakamoto, S., (ndr.). *Bitcoin: A Peer-to-Peer Electronic Cash System* pp. 3.

The longest chain is considered the correct one by nodes but if a couple of them broadcast two different versions of the next block at the same time, these are accepted by different nodes simultaneously. To solve this information conflict, nodes work on the first version received but contemporaneously save the other in order to see how it develops. The next-proof-of-work determines the valid branch, which becomes the extended one. Done that, the other is disregard.

Miners add records to the chain of both the new blocks mined and the recent transactions. To give network users an incentive to register deals, fees are provided but the major payoff is given by Bitcoin mining. In order to increase the probability of success in mining process, specialized hardware are sold and miners can pool together their computers. Incentives are aimed to stimulate nodes to stay honest. In fact, a malicious hacker should find more profitable to act by rules than compromise the validity of the system, even if he gained the major computational power and could act following his own interest.

Transactions are composed by different inputs and outputs in order to be combined and separated if it is required. But since there could be multiple inputs, composed by small amounts of previous submitted transactions, outputs could be at most two: the payment and the change, if any (Figure 6).

Figure 6: Transaction input and output



Source: Nakamoto (ndr.)

Bitcoin holders keep track of their balances by using “wallets”, which do not contain Bitcoins since they are a sort of spreadsheet programs where personal balances are recorded. Since this cryptocurrency relies on blockchain technology, each user has a personal “address” which is a public key used to record personal transactions and track individual balances. As already mentioned, public-key cryptography is connected to both private and public keys that allow encrypting and decrypting massages and checking whether a transaction is valid.

Wallets record the public key (the address) and the private key. If somebody forgets his private key, it cannot be recovered, and Bitcoins are lost since there is no way to transfer the amount owned to anyone else. On the other hand, if a computer hacker obtains a user’s private key, he could send Bitcoins to another address, successfully stealing them. For the victim it would be impossible to recover his losses, even though he knows the thief’s address (the public key). In order to reverse the transaction, the victim must know the thief's private key.

The main advantage of this new digital currency is its low cost of transaction and, contrary on what many people think, anonymity was not one of its main features when this network was designed. An individual could attempt to make his identity less obvious but the evidences available by now do not support the claim that it could be hidden easily, probably it may be impossible. To this purpose fiat physical currencies remain the best option.

Section 2

Starting from my research question "Could Bitcoin be seen as a virtual commodity?", I tried to study the evolution of Bitcoin price by considering a cost of production model introduced by Hayes in his research papers. Adding to his analysis some adjustment proposed by Abbatemarco *et al.* (2018), I recover a series for the hypothetical underling price and study the relationship between this price and the historical one using a Vector Autoregression model. I conclude by presenting the literature on the relevant drivers of Bitcoin price determination.

2.1 Estimation of Bitcoin Price

Adam S. Hayes in this paper "A Cost of Production Model for Bitcoin" (2015) analyses the Bitcoin price formation from a different point of view. As the title of the paper suggests he considers the cryptocurrency as a virtual commodity, starting from the three ways by which an individual could obtain it. Firstly, a person could buy Bitcoins directly in an online marketplace by giving in exchange fiat currencies or other types of cryptocurrencies. Secondly, he can accept them as payment and finally an individual can decide to "mine" Bitcoins, which consists in producing new units, by using computer hardware designed for this purpose. This latter case involves an electrical consumption and a rational agent would not be involved in the mining process if the marginal costs of this operation exceeds its marginal profits. The ratio between these values determines the cost of production price that is the theoretical value underlying the market price, around which it is supposed to gravitate.

The author wrote other two papers based on his intuition, which are "Cryptocurrency Value Formation: An empirical analysis leading to a cost of production model for valuing Bitcoin" (2016) and "Bitcoin price and its marginal cost of production: support for a fundamental value" (2018).

The first one is a cross-sectional empirical analysis that examines 66 different cryptocurrencies in order to identify the main determinants for any cryptocurrency value formation. The results suggest that it is determined by the differences in the relative cost of production on the margin. More precisely, the fundamental drivers according to his view are: the competition level among miners (measured by the computational power); the coin's production rate and the hardness implied in the mining algorithm. The number of units that have been already created (the total money supply) seem not to be a driving factor.

In his last work (2018), Hayes back-tests the pricing model against the historical market price to consolidate the validity of his theory. The findings show how Bitcoin price is significantly described by the cryptocurrency's marginal cost of production and suggest that it does not depends on other exogenous factors. The conclusion is that during period in which price bubbles happen, there will be a convergence between the market price and the model price to solve the discrepancy.

Abbatemarco *et al.* (2018)[18] resume Hayes' studies introducing further elements missed in the previous formulation. The final result confirms Hayes' findings: the marginal cost model provides a good proxy for Bitcoin market price, but the development of a speculative bubble is not ruled out.

Since these studies were published before Bitcoin price raise reached its peak on the 19th December 2017[19], the aim of my thesis is to replicate the analysis considering a larger time frame and verify if, even in this case, the results are unchanged. For this purpose, I replicate the cost of production model to value the Bitcoin price proposed by Hayes[20].

2.1.1 Formulas

The marginal cost function, which estimates the electrical costs of the devices used in the mining process, is presented as (1):

$$COST_{\frac{\$}{day}} = H_{\frac{hash}{s}} * Eff_{\frac{J}{hash}} * CE_{\frac{\$}{kWh}} * 24_{\frac{h}{day}} \qquad (1)$$

Where:

$H_{hash/s}$ is the hashrate (measured by hash/second);

$EFF_{J/hash}$ is the energy efficiency of the devices involved in the process and it is measured by Joule/hash;

$CE_{\$/kWh}$ is the electricity cost computed by US dollar per Kilowatt/hour;

24 is the number of hours in a day;

A marginal profit function, which estimates the reward of the mining activity, is instead depicted as (2):

$$PROFIT_{\frac{BTC}{day}} = BR_{BTC} * \left[\frac{3600_{\frac{s}{h}} * 24_{\frac{h}{day}}}{BTs}\right] \qquad (2)$$

Where:

BR_{BTC} is the block reward that refers to new Bitcoins distributed to miners who successfully solved a block (hence it is measured by BTC) and it is given by a geometric progression (3):

[18] Abbatemarco N., De Rossi L., Salviotti G. (2018). *An econometric model to estimate the value of a cryptocurrency network. The Bitcoin case.*

[19] On the 19th December 2017 Bitcoin price reached its peak and the values was equal to 19.270$.

20 I display in my analysis the formulas introduced by Abbatemarco *et al.* (2018), who, in my opinion, rearranged those proposed by Hayes in a more comprehensible way.

$$BR_{BTC} = BR_1 * \frac{1}{2}^{n-1} \quad (3)$$

n increases by 1 every 210.000 blocks. At the beginning it was $BR_1 = 50$ but during time it halved twice: on the 29th November 2012 and on the 10th July 2016.

3600 is the number of seconds in an hour;

24 is again the number of hours in a day;

BT_s is the block time, which is expressed as the seconds needed to generate a block (around 600 seconds = 10 minutes), and it is computed as (4):

$$BT_s = \frac{D*2^{32}}{H} \quad (4)$$

Where *H* = hashrate and *D* = difficulty. The latter variable specifies how hard is to generate a new block in terms of computational power given a specific hashrate. This is the value that changes frequently to ensure a BT_s close to 10 minutes[21].

In addition to the variables already considered I want to introduce some adjustments proposed by Abbatemarco *et al.* (2018), who thought there were two elements missing in Hayes' formulations.

They add, on the cost side, the one required to maintain and update miners' hardware (MAN, expressed in US dollar) and on the profit side, the fees (FEES) received by miners who place transactions in a block[22].

Maintenance costs are computed as a ratio between the weighted devices price and their weighted lifespan (5), while fees, computed by BTC, are measured as a ratio between the daily total transaction fees and the number of daily transactions[23] (6).

$$MAN_{\$} = \frac{Weighted\ Devices\ Price_{\$}}{Weighted\ Lifespan} \quad (5)$$

$$FEES_{BTC} = \frac{Total\ Transaction\ Fees\ (BTC)}{Daily\ Transaction\ Fees} \quad (6)$$

The new equations become:

$$COST_{\frac{\$}{day}} = H_{\frac{hash}{s}} * Eff_{\frac{J}{hash}} * CE_{\frac{\$}{kWh}} * 24_{\frac{h}{day}} + MAN_{\$} \quad (7)$$

$$PROFIT_{\frac{BTC}{day}} = BR_{BTC} * \left[\frac{3600_{\frac{s}{h}} * 24_{\frac{h}{day}}}{BTs}\right] + FEES_{BTC} \quad (8)$$

[21] Results are shown in the Appendix section, Table A.7. In order to simplify the presentation I display only the values for the last day of each month.

[22] Bitcoin could be obtained through both the mining process and the registration of transactions but, since Bitcoin supply is limited to 21 million, once it will be reached, fees become the only remuneration source in the future.

[23] Fees computation results are displayed in Appendix, Table A.7.

Moreover, due to the equality 1 Joule = 1 Watt*second, the equation (7) could be expressed as follows:

$$COST_{\$/day} = \ H_{hash/s} \ * Eff_{\frac{W*s}{hash}} * CE_{\frac{\$}{kWh}} * 24_{h/day} + MAN_{\$} \tag{9}$$

And by converting Watt in Kilowatt/hour, it can be written as:

$$COST_{\$/day} = \ H_{hash/s} \ * \ \frac{Eff_{\frac{W*s}{hash}}}{1000} * CE_{\frac{\$}{kWh}} * 24_{h/day} + MAN_{\$} \tag{10}$$

$$COST_{\$/day} = \ H_{hash/s} \ * \ Eff_{\frac{kWh*s}{hash}} \ * CE_{\frac{\$}{kWh}} * 24_{h/day} + MAN_{\$} \tag{11}$$

According to the competitive market economic theories, the ratio between the cost and profit functions must lead to the price under equilibrium condition (12):

$$P_{\$/BTC} = \ \frac{COST_{\frac{\$}{day}}}{PROFIT_{\frac{BTC}{day}}} \tag{12}$$

It is important to point out that an historical price below the one predicted by the model would force a miner out of the market, since he is operating in loss, but at the same time, the removal of its devices from the network increases others marginal profits (competition decreases) and at the end the system would return to equilibrium.

On the other hand, an historical price higher than what predicted by the model attracts more miners, thus increases the number of devices operating in the network and this decreases others marginal profits (competition increases). Again, the system would return in balance[24].

[24] Hayes, A., (2015). *A Cost of Production Model for Bitcoin.*

2.1.2 Data

In the following table I present the sources used to collect and compute the required information.

Table 2: Sources

VARIABLES		SOURCES
$P_{hist\ \$}$	Historical price in US dollar	Bitcoinvisuals.com
$H_{hash/s}$	Hashrate	
BR_{BTC}	Block Reward	
D	Difficulty	
BT_s	Block Time	Computed using D and $H_{hash/s}$
$FEES_{BTC}$	Transaction Fees	https://charts.Bitcoin.com/bch/
$CE_{\$/kWh}$	Cost of Energy	Computed using data from: en.Bitcoin.it/wiki/Mining_hardware_comparison
$MAN_{\$}$	Hardware maintaining cost	https://en.Bitcoin.it/wiki/Non-specialized_hardware_comparison
$EFF_{J/hash}$	Hardware energy efficiency	https://archive.org/web/

Source: Author's elaboration

I start my analysis by constructing a hardware sample that evolves during a chosen time window (2010-2018), which is divided in semesters associated with the introduction of a particular device.

Table 3: Hardware sample

TYPE	MODEL	TIME	EFF. (Mhash/J)	PRICE (USD)	LIFESPAN before '17	LIFESPAN after '17
GPU	ATI FirePro M5800	2 s. 2010	1,45	175	2880	1440
GPU	Saphire Radeon 5750 Vapor-X	2 s. 2010	1,35	160	2880	1440
GPU	GTX460	2 s. 2010	1,73	200	2880	1440
GPU	FirePro V5800	1 s. 2011	2,08	469	2880	1440
FPGA	Avnet Spartan-6 LX150T	2 s. 2011	6,25	995	1010	505
FPGA	AMD Radeon 7900	1 s. 2012	10,40	680	1010	505
FPGA	Bitcoin Dominator X5000	2 s. 2012	14,70	750	1010	505

FPGA	X6500	1 s. 2013	23,25	989	1010	505
ASIC	Avalon 1	2 s. 2013	107,00	1.299	540	270
ASIC	Bitman AntMiner S1	1 s. 2014	500,00	1.685	540	270
ASIC	Bitman AntMiner S2	2 s. 2014	900,00	2.259	540	270
ASIC	Bitman AntMiner S3	1 s. 2015	1.300,00	1.350	540	270
ASIC	Bitman AntMiner S4	2 s. 2015	1.429,00	1.400	540	270
ASIC	Bitman AntMiner S5	1 s. 2016	1.957,00	1.350	540	270
ASIC	Bitman AntMiner S5+	2 s. 2016	2.257,00	2.307	540	270
ASIC	Bitman AntMiner S7	1 s. 2017	4.000,00	1.832	540	270
ASIC	Bitman AntMiner S9	2 s. 2017	10.182,00	2.400	540	270
ASIC	Ebit E9++	1 s. 2018	10.500,00	3.880	540	270
ASIC	Ebit E10	2 s. 2018	11.100,00	5.230	540	270

Source: Author's elaboration

Since the first Bitcoin was traded, there has been an evolution of the devices used by miners. The first ones adopted were GPU (Graphical Processing Unit), later FPGA (Field-Programmable Gate Array) but these days only ASIC (Application-Specific Integrated Circuit) are suitable for mining purposes.

For each device model I collect the efficiency, expressed in Mhash/J, and the dollar price at the release day.

Technical data were collected from the Wikipedia pages https://en.Bitcoin.it/wiki/Mining_hardware_comparison and https://en.Bitcoin.it/wiki/Non-specialized_hardware_comparison by using in addition the online archive https://archive.org/web/ , which allows to recover different webpages at the date in which they were modified, enabling the comparison before and after reviews[25].

Since only ASIC devices were created with specifications to mining purpose, there is homogeneity among FPGA and especially among GPU hardware. Due to this fact and considering the difficulty to recover the release prices, I make some simplify assumptions about them based on the information available online. This means that given the same computational power, I suppose prices homogeneity among devices when they were not available for particular models[26].

[25] When it is possible, I double check Wikipedia prices with those on the websites of the companies producing mining hardware and if they are not identical, I choose the latter.
[26] In particular, I approximate the prices of ATI FirePro M5800, Saphire Radeon 5750 Vapor-X, GTX460, FireProV5800, Avnet Spartan-6 LX150T and AMD Radeon 7900.

Given the hardware sample, I construct a weights distribution matrix that represents the evolution of the devices used during each semester of my time window, which are replaced following a substitution rate that increases over time (see Appendix, Table A.1). In fact until 2012, before FPGA took roots, it is equal 0,05; until 2016 I set it equal 0,1 and in the last two years of my analysis it is equal 0,15[27].

All my computations are based on this matrix, indeed I multiplied it by a specific column of the hardware sample table to obtain the biannual Efficiency (J/Hash), Weighted Devices' Prices ($) and Weighted Lifespans (see Table A.2, A.3 and A.4 in the Appendix section).

Regarding this latter matrix, I made further assumptions on the device lifespans by implementing what Abbatemarco *et al.* (2018) supposed in their research paper. I hence set a lifespan equal to 2880 days for GPU, 1010 days for FPGA and 540 days for ASIC but after 2017, due to a supposed market growth phase, I halved these numbers (Table 3).

Even to evaluate the cost of energy I follow the assumptions suggested by the researchers and I divide the world into two parts relative to Europe: Est and West, each one with a fix electricity price equal to 0,04 and 0,175 $/kWh respectively. The weights' evolution of the mining pool is set up in 2010 equal to 0,7 for the West part an 0,3 for the Est part and it changes progressively until reaching in 2018 a 0,2 for the West ad 0,8 for the Est. I obtained a biannual cost of energy evolution measured by $/kWh by multiplying the biannual weights to the electricity costs and summing up the value for the West and the Est (see Appendix, Table A.5).

At this point, to smooth the values across my time window, I take the differences between: $biannualMAN_{\$}$, $biannualEFF_{J/Hash}$ and $biannualCE_{\$/kWh}$ at time *t* and *t-1* and I divide these values by the number of days in each semester, obtaining *DeltaMAN*, *DeltaEFF* and *DeltaCE* (see Appendix, Table A.6). Starting the first day of my analysis with the first value of the biannual matrixes, I compute the final variables as follows:

$$MAN_{\$}(t) = MAN_{\$}(t-1) + DeltaMAN \tag{13}$$

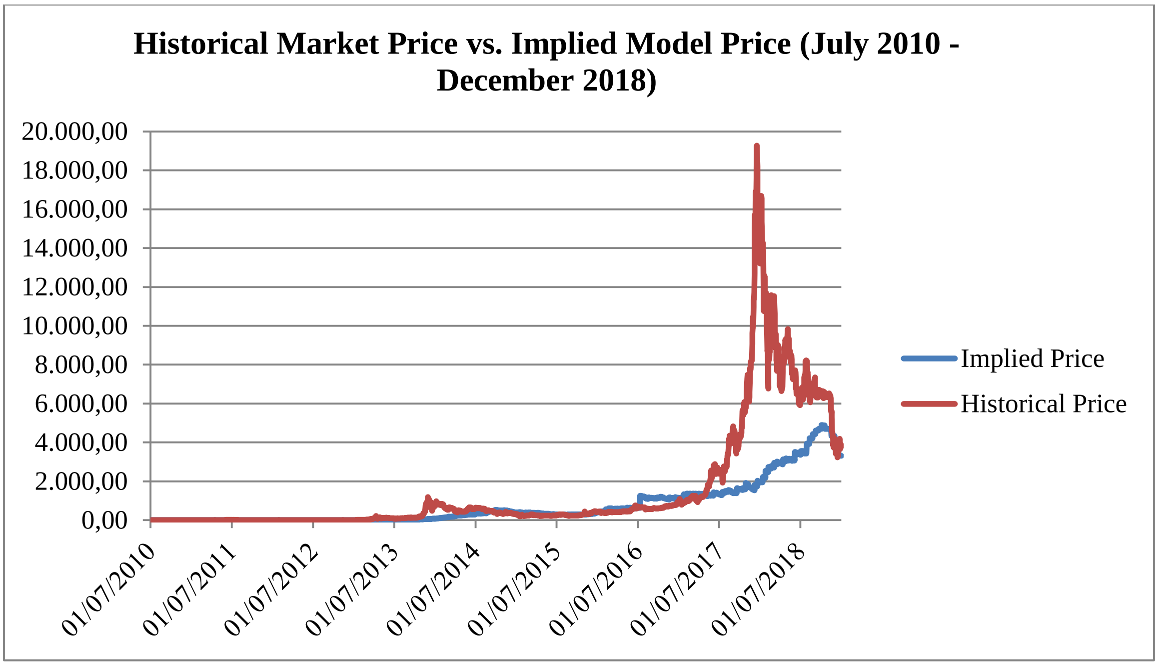
$$EFF_{\frac{J}{hash}}(t) = EFF_{J/hash}(t-1) + DeltaEFF \tag{14}$$

$$CE_{\frac{\$}{kWh}}(t) = CE_{\frac{\$}{kWh}}(t-1) + DeltaCE \tag{15}$$

[27] Despite ASIC have been released for the first time in 2013, they became the main devices used in the mining process only in 2015-2016. In the last two years of my analysis I increase the substitution rate up to 0,15 because the competition among miners has been driven up since more sophisticated hardware are developed with a higher frequency.

By applying the previous formulas[28] I obtain the model price[29] and compare its evolution to the historical one (Figure 7).

Figure 7: Historical Market Price vs. Implied Model Price (July 2010-December 2018)



Source: Author's elaboration

The evolution of the model (or implied) price shows a spike during the second semester of 2016 and this is due to the fact that on the 10th July 2016 the Block Reward helved from 25 to 12,5, leading to a reduction on the profit side and a consequent price increase.

Despite this episode, the historical price seems to fluctuate around the implied until the beginning of 2017, period in which Bitcoin price started raising exponentially reaching its peak with a value equal 19.270$ on the 19th December 2017. It declined during 2018, converging again to the model price.

Another divergence was detected at the end of 2013 but it was of a lower amount and resolved quickly.

[28] Recall:

$$PROFIT_{\frac{BTC}{day}} = BR_{BTC} * \left[\frac{3600_{\frac{s}{h}} * 24_{\frac{h}{day}}}{BTs}\right] + FEES_{BTC} \tag{8}$$

$$COST_{\frac{\$}{day}} = H_{\frac{hash}{s}} * Eff_{\frac{kWh*s}{hash}} * CE_{\frac{\$}{kWh}} * 24_{\frac{h}{day}} + MAN_{\$} \tag{11}$$

$$P_{\$/BTC} = \frac{COST_{\frac{\$}{day}}}{PROFIT_{\frac{BTC}{day}}} \tag{12}$$

[29] In Table A.8 in the Appendix section I display all the variables required to compute the model price and I compare it with the historical price. Since my time window involves 3107 observation days, I decide to simplify the presentation by showing only the results for the last day of each month.

2.2 Econometric Approach

Given the historical and implied price series, I want to make a further step than what Hayes and Abbatemarco *et al.* (2018) did, by including in my analysis time frame even the divergence phase. Therefore, I consider the period from the 9th April 2014 to the 31st December 2018[30].

I start with some unit root tests to verify if the series are stationary in level or need to be integrated (paragraph 2.2.1) and later I identify the proper number of lags to be included in the model (paragraph 2.2.2). I check for the presence of a cointegrating relationship to verify whether I should adopt a Vector Error Correction Model (VECM) or a Vector Autoregression (VAR) model (paragraph 2.2.3). The results suggest that a VAR model is the best suited for my data, hence I display the final result of my analysis (paragraph 2.2.4) and try to improve the outcomes by correcting the heteroscedasticity in my regressions (paragraph 2.2.5).

2.2.1 Unit Root tests

The first step in my analysis is to determine with different unit root tests whether the time series is stationary or not. The presence of a unit root indicates that a process is characterized by time-dependent variance and violates the weak stationarity condition[31].

I test the presence of a unit root with three procedures: the augmented Dickey-Fuller (1979) test, the Phillips-Perron (1988) test and the Zivot-Andrews (1992) test.

Given a time series $\{y_t\}$, both the augmented Dickey-Fuller test and the Phillips-Perron test are based on the general regression (16):

$$\Delta y_t = \alpha + \beta t + \theta y_{t-1} + \delta_1 \Delta y_{t-1} + \cdots + \delta_{p-1} \Delta y_{t-p+1} + \varepsilon_t \tag{16}$$

Where α is the constant, t is the time trend, and p is the order of the autoregressive process[32].

For both tests, the null hypothesis is that the time series contains a unit root, thus it is not stationary (H_0: $\theta = 0$) while the alternative hypothesis asserts stationarity (H_0: $\theta < 0$).

Considering only the augmented Dickey-Fuller test, its basic idea is that if a series $\{y_t\}$ is stationary, then $\{\Delta y_t\}$ can be explained only by the information included in its lagged values (Δy_{t-1} ... Δy_{t-p+1}) and not from those in y_{t-1}.

---

[30] I select this time window also to base the analysis on solid data. As written in paragraph 2.1, due to the difficulty to obtain reliable information on the hardware used in the mining process, I make some simplified assumptions on their features. By choosing this time window I include the hardware sample whose data are more precise.

[31] The condition of weak stationarity asserts that $Var(r_t) = \gamma_o$, which means that the variance of the process is time invariant and equal to a finite constant.

[32] Boffelli, S., Urga, G., (2016). *Financial Econometrics Using Stata.*

For each variable I conduct this test firstly with a constant term and later by including also a trend[33].

The result can be read by looking at the p-value or by comparing the test statistic with its critical value. Therefore, the null hypothesis of unit root can be rejected if the value of the test statistic is higher than the 5% critical value in absolute terms or, equivalently, if the p-value is below 5%. Table 4 presents the main findings of the test.

Table 4: Augmented Dickey-Fuller test

Augmented Dickey-Fuller test

	constant		constant+trend		result
	t-stat	p-value	t-stat	p-value	
lnPrice	-0,606	0,8696	-1,839	0,6856	NO stationary
lnModelPrice	-0,467	0,8982	-1,669	0,7644	NO stationary
ΔlnPrice	-7,694	0,0000	-7,697	0,0000	stationary
ΔlnModelPrice	-8,041	0,0000	-8,038	0,0000	stationary

critical values

constant			constant + trend		
1%	5%	10%	1%	5%	10%
-3,430	-2,860	-2,570	-3,960	-3,410	-3,120

Source: Author's elaboration

The Phillips-Perron test points out that the process generating y_t might have a higher order of autocorrelation than the one admitted in the test equation. This test corrects the issue and it is robust in case of unspecified autocorrelation or heteroscedasticity in the disturbance term of the equation. Table 5 displays the test results.

[33] In order to select the proper number of lags to include in this test I used, only for this part of my analysis, Gretl, which is an open-source statistical software. Its advantage is to apply clearly the Schwert criterion for the maximum lag (p_{max}) estimation, which is given by:

$$p_{max} = integer\ part\ of\ \left[12 * \left(\frac{T}{100}\right)^{1/4}\right]$$

Where T is the number of observations.
The test is conducted firstly with the suggested value of p_{max} but if the absolute value of the t-statistic for testing the significance of the last lagged value is below the threshold 1,6, p_{max} is reduced by one and the analysis is recomputed. The process stops at the first maximum lag that returns a value greater than 1,6. When this value is found, the augmented Dickey-Fuller test is estimates.
Even if Gretl outputs are identical to those presented by Stata, I decide to display the latter since I conduct my entire analysis with this software.

Table 5: Phillips-Perron test

Phillips-Perron test

	constant		constant+trend		result
	t-stat	p-value	t-stat	p-value	
lnPrice	-0,437	0,9037	-1,546	0,8130	NO stationary
lnModelPrice	-0,637	0,8624	-1,805	0,7021	NO stationary
ΔlnPrice	-34,394	0,0000	-34,385	0,0000	stationary
ΔlnModelPrice	-42,972	0,0000	-42,959	0,0000	stationary

critical values

constant			constant + trend		
1%	5%	10%	1%	5%	10%
-3,430	-2,860	-2,570	-3,960	-3,410	-3,120

Source: Author's elaboration

The main difference between these tests is that the latter applies Newey and West (1987) standard errors to take into account serial correlation, while the augmented Dickey-Fuller test introduces additional lags of the first difference.

Since the previous tests do not allow for the possibility of a structural break in the series, Zivot and Andrews propose a way to examine the presence of a unit root including the chance of an unknown date of a break-point in the series. They propose three models to test for the presence of a unit root considering a one-time structural break:

a) permits a one-time change in the intercept of the series:

$$\Delta y_t = \alpha + \beta t + \theta y_{t-1} + \gamma DU_t + \delta_1 \Delta y_{t-1} + \cdots + \delta_{p-1} \Delta y_{t-p+1} + \varepsilon_t \tag{17}$$

b) permits a one-time change in the slope of the trend function:

$$\Delta y_t = \alpha + \beta t + \theta y_{t-1} + \vartheta DT_t + \delta_1 \Delta y_{t-1} + \cdots + \delta_{p-1} \Delta y_{t-p+1} + \varepsilon_t \tag{18}$$

c) combines the previous models:

$$\Delta y_t = \alpha + \beta t + \theta y_{t-1} + \gamma DU_t + \vartheta DT_t + \delta_1 \Delta y_{t-1} + \cdots + \delta_{p-1} \Delta y_{t-p+1} + \varepsilon_t \tag{19}$$

Where DU_t is a dummy variable relates to a mean shift at a given break-date, while DT_t is a trend shift variable.

The null hypothesis, which is the same for all three models, states that the series contains a unit root ($H_0: \theta = 0$), while the alternative hypothesis asserts that the series is a stationary process with a one-time break occurring at an unknown point in time ($H_0: \theta < 0$)[34].

[34] Waheed, M., Alam, T., Ghauri, S. P. (2006). *Structural breaks and unit root: evidence from Pakistani macroeconomic time series.*

Table 6: Zivot-Andrews test

Zitov-Andrews test

	intercept			trend			intercept + trend			result
	t-stat	break	date	t-stat	break	date	t-stat	break	date	
lnPrice	-2,964	1083	26/03/2017	-2,049	261	25/12/2014	-2,562	1196	17/07/2017	NON stationary
lnModelPrice	-3,221	281	14/01/2015	-3,357	408	21/05/2015	-3,914	620	19/12/2015	NON stationary
ΔlnPrice	-34,905	1350	18/12/2017	-34.626	1285	14/10/2017	-34,895	1350	18/12/2017	stationary
ΔlnModelPrice	-42,848	582	11/11/2015	-42,781	1469	16/04/2018	-42,858	582	11/11/2015	stationary

critical values

intercept			trend			intercept + trend		
1%	5%	10%	1%	5%	10%	1%	5%	10%
-5,34	-4,8	-4,58	-4,93	-4,42	-4,11	-5,57	-5,08	-4,82

Source: Author's elaboration

The results in Table 6 confirm what the other tests predict: both series are integrated of order 1.

Since this last test identifies for *ΔlnPrice* the presence of a structural break on the 18th December 2017 and after this date the Bitcoin price reaches its higher value to start declining later, I add to my analysis a dummy variable related to this observation[35]. The graphs of these series are plotted in Figure A.1 of the Appendix section.

2.2.2 Identify the number of lags

To identify the proper lag length to be included in the VAR model I use the "*varsoc*" command in Stata that displays a table of test statistics, which reports for each lag length, the log of the likelihood functions (LL), a likelihood-ratio test statistic with the related degrees of freedom and p-value (LR, df and p) and also four information criteria: Akaike's final prediction error (FPE); Akaike's information criterion (AIC), Hannan and Quinn's information criterion (HQIC) and Schwarz's Bayesian information criterion (SBIC)[36].

The preferred lag length is the one that generates the lowest value of the information statistic considered, which is highlighted by Stata with a *.

Since the output is sensitive to the maximum lag considered I try different option by changing the one included in the command computation[37]. After selecting a maximum lag length equal to 16, the optimal number of lags suggested changes: while the previous results agree recommending 1 lag with each information criteria, now the FPE and AIC diverge and propose 13 lags. To solve this issue I follow Lütkepohl's intuition that "*the SBIC and HQIC*

[35] A dummy variable allows taking into account a broken linear trend in a series.
[36] Every information criteria provide a trade-off between the complexity (e.g. the number of parameters) and the goodness of fit (based on the likelihood function) of a model.
[37] I tried with 4, 8, 12, 16, 20 and 24 lags.

provide consistent estimates of the true lag order, while the FPE and AIC overestimate the lag order with positive probability'[38]. Therefore I select 1 lags to move forward with my analysis.

Table 7: Proper number of lags

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	7160.95				8.0e-07	-8.36581	-8.3611	-8.35308
1	7190.57	59.237	4	0.000	7.7e-07	-8.39575	-8.38633*	-8.37029*
2	7192.42	3.7134	4	0.446	7.8e-07	-8.39325	-8.37911	-8.35506
3	7194.48	4.1059	4	0.392	7.8e-07	-8.39097	-8.37231	-8.34005
4	7195.74	2.5346	4	0.638	7.8e-07	-8.38778	-8.36422	-8.32413
5	7197.81	4.1319	4	0.388	7.8e-07	-8.38552	-8.35725	-8.30914
6	7199.73	3.8486	4	0.427	7.8e-07	-8.38309	-8.35011	-8.29399
7	7201.63	3.8014	4	0.434	7.9e-07	-8.38064	-8.34295	-8.2788
8	7204.56	5.8468	4	0.211	7.9e-07	-8.37938	-8.33698	-8.26482
9	7208.36	7.6003	4	0.107	7.9e-07	-8.37914	-8.33204	-8.25185
10	7212.23	7.7429	4	0.101	7.9e-07	-8.37899	-8.32717	-8.23897
11	7213.48	2.5086	4	0.643	7.9e-07	-8.37578	-8.31925	-8.22304
12	7225.63	24.303	4	0.000	7.8e-07	-8.38531	-8.32407	-8.21983
13	7243.57	35.872*	4	0.000	7.7e-07*	-8.4016*	-8.33565	-8.2234
14	7244.29	1.4495	4	0.836	7.7e-07	-8.39777	-8.32711	-8.20684
15	7246.50	4.4025	4	0.354	7.7e-07	-8.39567	-8.3203	-8.19201
16	7248.86	4.7357	4	0.316	7.8e-07	-8.39376	-8.31368	-8.17737

Source: Author's elaboration

[38] Becketti, S., (2013). *Introduction to Time Series Using Stata*.

2.2.3 Identify the number of cointegrating relationships

A cointegrating relationship is a relationship that describes the long-term link among the levels of a number of the nonstationary variables. Given *K* nonstationary variables, they can have at most *K*-1 cointegrating relationships. Therefore in my analysis, since I have only two nonstationary variables (*lnPrice* and *lnModelPrice*), I could obtain, at most, only one cointegrating relationship.

If series show cointegration, a Vector Autoregression (VAR) Model is no more the best suited one for the analysis but it is better to implement a Vector Error-Correction Model (VECM), which can be written as (20):

$$\Delta y_t = \mu + \delta t + \alpha\beta' y_{t-1} + \sum_{i=1}^{p-1} \Gamma_i \Delta y_{t-i} + \varepsilon_t \qquad (20)$$

Where the deterministic components $\mu + \delta t$ are respectively the linear and the quadratic trend[39] in y_t that can be separated into the proper trends in y_t and those of the cointegrating relationship.

Therefore:

$$\mu \equiv \alpha\nu + \gamma \qquad \text{and} \qquad \delta t = \alpha\rho t + \tau t$$

By substituting in the previous expression, the VECM can be expressed as (21):

$$\Delta y_t = \alpha(\beta' y_{t-1} + \nu + \rho t) + \sum_{i=1}^{p-1} \Gamma_i \Delta y_{t-i} + \gamma + \tau t + \varepsilon_t \qquad (21)$$

Where the first part $\alpha(\beta' y_{t-1} + \nu + \rho t)$ represents the cointegrating equations, while the second $\sum_{i=1}^{p-1} \Gamma_i \Delta y_{t-i} + \gamma + \tau t + \varepsilon_t$ refers to the variables in levels.

This representation allows specifying 5 cases that Stata tests[40]:

1) Unrestricted trend: allows for quadratic trend in the level of y_t (τt appears in the equation) and states that the cointegrating equations are trend stationary, which means they are stationary around time trends;
2) Restricted trend ($\tau = 0$): excludes quadratic trends but includes linear trends (ρt). As in the previous case, it allows the cointegrating equations to be trend stationary;
3) Unrestricted constant ($\tau = 0$, $\rho = 0$): lets linear trends in y_t to present a linear trend (γ) but the cointegrating equations are stationary around a constant means (ν);
4) Restricted constant ($\tau = 0$, $\rho = 0, \gamma = 0$): rules out any trends in the levels of the data but the cointegrating relationships are stationary around a constant mean (ν);

[39] This depends on the fact that in a first-difference equation: a constant term is a linear trend in the level of the variables ($y_t = \kappa + \lambda t \rightarrow \Delta y_t = \lambda$); while a linear trend derives from the quadratic one in the regression in levels ($y_t = \kappa + \lambda t + \omega t^2 \rightarrow \Delta y_t = \lambda + 2\omega t - \omega$).

[40] See Becketti, S., (2013). *Introduction to Time Series Using Stata*.

5) No trend ($\tau = 0$, $\rho = 0, \gamma = 0, \nu = 0$): considers no nonzero means or trends.

Starting from these different specifications, the Johansen test can detect the presence of a cointegrating relationship in the analysis. The null hypothesis states, again, that there are no cointegrating relationships against the alternative that the null is not true. H_0 is rejected if the trace statistic is higher than the 5% critical value.

I run the test with each case specification and the results agree to detect zero cointegrating equations (a maximum rank of zero)[41]. This means that the two time series could be fitted into a Vector Autoregression (VAR) model.

2.2.4 Vector Autoregression (VAR) Model

The Vector Autoregression (VAR) model allows investigating the interaction of several endogenous time series that mutually influence each other. In my analysis I do not only want to detect if Bitcoin price could be determine by the one suggested by the cost of production model but I want also to check if the price has an influence on the model price. This latter relation can occur if, for example, a price increase leads to a higher cost for the mining hardware. In fact, a raise in the price represents also a higher reward if the mining process is successfully conducted, with the risk to push hardware price atop, which in turns could boost the model price up.

To explain how a VAR model is constructed, I present a simple univariate AR(p) model, disregarding any possible exogenous variables, which can be written as[42] (22):

$$y_t = \mu + \phi_1 y_{t-1} + \cdots + \phi_p y_{t-p} + \varepsilon_t \tag{22}$$

Or, in a concise form (23):

$$\phi(L) y_t = \mu + \varepsilon_t \tag{23}$$

where y_t depends on its p prior values, a constant (μ) and a random disturbance (ε_t).

A vector of *n* jointly endogenous variables is express as (24):

$$\mathrm{y}_t = \begin{bmatrix} y_{1,t} \\ y_{2,t} \\ \vdots \\ y_{n,t} \end{bmatrix} \tag{24}$$

[41] Only the unrestricted trend does not display any conclusion from the test but since the other results matched, I consider *rank*=0 the right solution. Results are displayed in Table A.9 in the Appendix section.

[42] Becketti, S., (2013). *Introduction to Time Series Using Stata.*

This n-element vector can be rearranged as a function (25) of n constants, p prior values of Y_t and a vector of n random disturbances, ϵ_t:

$$\mathrm{y}_t = \mu + \Phi_1 \mathrm{y}_{t-1} + \cdots + \Phi_p \mathrm{y}_{t-p} + \epsilon_t \tag{25}$$

Where μ is a vector (26) of the n-constants:

$$\mu = \begin{bmatrix} \mu_1 \\ \mu_2 \\ \vdots \\ \mu_p \end{bmatrix} \tag{26}$$

the matrix of coefficients Φ_i is (27):

$$\Phi_1 = \begin{bmatrix} \phi_{i,11} & \phi_{i,12} & \cdots & \phi_{i,1n} \\ \phi_{i,21} & \phi_{i,22} & \cdots & \phi_{i,2n} \\ \vdots & \vdots & \ddots & \vdots \\ \phi_{i,n1} & \phi_{i,n2} & \cdots & \phi_{i,nn} \end{bmatrix} \tag{27}$$

and ϵ_t consists in (28):

$$\epsilon_t = \begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \vdots \\ \varepsilon_p \end{bmatrix} \tag{28}$$

With $\quad E\epsilon_t = 0 \quad$ and $\quad E\epsilon_t \epsilon'_s = \begin{cases} \Sigma, & t = s \\ 0, & t \neq s \end{cases}$

the elements of ϵ_t can be contemporaneously correlated.

Given these specifications, a pth-order VAR can be presented as[43] (29):

$$\Phi(L)\mathrm{y}_t = \mu + \epsilon_t \tag{29}$$

To clarify this expression, the ith endogenous time series can be extracted from these basic VAR and be represented as (30):

$$\begin{aligned} y_{i,t} = \mu_i &+ \phi_{1,i1} y_{1,t-1} + \cdots + \phi_{1,in} y_{n,t-1} \\ &+ \phi_{2,i1} y_{1,t-2} + \cdots + \phi_{2,in} y_{n,t-2} + \cdots \\ &+ \phi_{p,i1} y_{1,t-p} + \cdots + + \phi_{p,in} y_{n,t-p} + \varepsilon_{i,t} \end{aligned} \tag{30}$$

The result of the Vector Autoregression (VAR) model considering the dummy variable is:

[43] Recall: $\Phi(L) \equiv I - \Phi_1(L) - \cdots - \Phi_p(L)$

Table 8:Regressions of the Vector Autoregression model

VARIABLES	(1) dlnPrice	(2) dlnModelPrice
L.dlnPrice	0.18330223***	0.00799770
	(0.02359822)	(0.02055802)
L.dlnModelPrice	-0.00655017	-0.02899205
	(0.02762476)	(0.02406582)
dummy	-0.00588960***	0.00027999
	(0.00185465)	(0.00161571)
Constant	0.00236755***	0.00149779**
	(0.00086910)	(0.00075713)
Observations	1,726	1,726
R-squared	0.04178812	0.00092579

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Source: Author's elaboration

As expected the dummy is significant in the *dlnPrice* function but not in *dlnModelPrice*.

Looking at the significance of the parameters we can see how *dlnPrice* depends on its lagged value, on the dummy and on the constant term but it seems not to be linked with the lagged value of *dlnModelPrice*. The regression of *dlnModelPrice* appears not to be explained by any variable considered in the model.

I proceed in my analysis by checking the stationarity of the model. The results confirm the model is stable and there is no residual autocorrelation[44].

2.2.5 Heteroscedasticity correction

Given the series' path and the daily frequency of the data, the variables included in the model are probably heteroskedastic. This feature does not compromise the unbiasedness or the consistency of the OLS coefficients but invalidates the usual standard errors.

In time series analysis, heteroscedasticity is usually neglected, as the autocorrelation of the error terms is seen as the main problem due to its ability to invalidate the analysis.

Since is not possible to check and correct heteroscedasticity while performing the VAR model I run each VAR regression separately and check the presence of heteroscedasticity by running the Breusch-Pagan test, whose null hypothesis states that the error variance are all equal (homoscedasticity) against the alternative hypothesis that the error variances change over time (heteroscedasticity).

[44] See Table A.10 Appendix section.

$$H_0: \sigma_1^2 = \sigma_2^2 = \cdots = \sigma^2$$

The null hypothesis is rejected if the probability value of the chi-square statistic (Prob<chi2) is less than 0.05.

Table A.11 in the Appendix section shows the results of the test for both regressions: the null hypothesis is always rejected, implying the presence of heteroscedasticity in the residuals.

I try therefore to correct the issue using heteroscedasticity-robust standard errors, provided by Stata with the command "*robust*". The final results are displayed in Table 9.

Table 9: Regressions with robust standard errors

	(1)	(2)
VARIABLES	dlnPrice	dlnModelPrice
L.dlnPrice	0.18330223***	0.00799770
	(0.04306718)	(0.01592745)
L.dlnModelPrice	-0.00655017	-0.02899205***
	(0.02681078)	(0.00979148)
dummy	-0.00588960***	0.00027999
	(0.00225058)	(0.00142356)
Constant	0.00236755***	0.00149779*
	(0.00078480)	(0.00078942)
Observations	1,726	1,726
R-squared	0.04178812	0.00092579

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Source: Author's elaboration

These new robust standard errors are different from the standard errors estimated with the VAR model, while the coefficients are unchanged. The first difference of *lnPrice* depends even in this case on its lag, but, contrary from the VAR, now the first difference of *lnModelPrice* is not independent from its previous values. This new specification confirms the previous finding that each variable does not depend on the lagged value of the other one. Therefore, it seems that during the time window considered the Bitcoin historical price is not connected with the price derived by Hayes' formulation, and vice versa.

2.2.6 Comment on the results

Looking at Figure 7, it seems that the historical price fluctuated around the model (or implied) price until 2017, year in which Bitcoin price significantly increased. During the lasts months of 2018 the prices seem to converge again, following a common path. In my analysis I focus on the time window in which Bitcoin experienced its higher price volatility and my results suggest that it is disconnected from the one predicted by the model. These findings may depend on the particular features of the new cryptocurrencies, which have not been completely understood jet.

The previous analysis, conducted on different time periods, by Hayes[45] and Abbatemarco *et al.* (2018)[46] assert that Bitcoin price could be justified by the costs and revenues of its blockchain network, leading to an opposite result than mine.

I think the difference is based on the time window analyzed since I make a further step evaluating also the months in which Bitcoin price was pushed atop and did not follow a stable path.

In my opinion there are not enough knowledge on cryptocurrencies to assert that Bitcoin price is (or is not) based on the profit and cost derived by the mining process but these intrinsic characteristics must be considered and check also in further analysis that include other possible Bitcoin price drivers suggested by the literature.

For this reason I present in the following paragraph the literature behind the study of Bitcoin price formation, providing an overview on the main drivers considered by the researchers.

2.3 Literature

Kristoufek (2015)[47] focuses on different sources of price movements by examining their interconnection during time. He considers three different categories: economics, transaction, technical drivers and interest. The results show how Bitcoin's fundamental factors, such as usage, money supply and price level, drive its price over the long term. With regard to the technical drivers, a raising price encourages individuals to become miners but this effect eclipses over time, since always more specialized mining hardware have soured the difficulty up. Evidences show that price is driven by investors' interest but with slightly different effects. During period of explosive prices, interest pushes it atop, while with period of

[45] Hayes, A., (2018). *Bitcoin price and its marginal cost of production: support for a fundamental value.*
[46] Abbatemarco, N., De Rossi, L., Salviotti, G., (2018). *An econometric model to estimate the value of a cryptocurrency network. The Bitcoin case.*
[47] Kristoufek, L., (2015). *What Are the Main Drivers of the Bitcoin Price? Evidence from Wavelet Coherence Analysis.*

declining prices, interest decreases it at even a lower level. He concludes that Bitcoin is a unique asset with properties of both a speculative-financial asset, and a standard one and because of his dynamic nature and volatility, it is obvious to expect that its price drivers will change over time.

The interest element seems to be particularly relevant when analyzing the behavior of Bitcoin price, leading many researchers to study its interconnection with Internet components, such as Google Trends, Wikipedia queries and Tweets.

Kristoufek (2013)[48], for example, tries to understand the relationship between Bitcoin price and two different search queries: Google Trends and Wikipedia. He discovers that a raise in the number of Google researches boost the cryptocurrency price, but this leads to an increase also for the general public interest and this cycle can trigger a bubble. He points out a fundamental difference between the research queries: a price shock yields to an immediate shift in the Google trend, while is connected to a permanent shift in the Wikipedia views. On the other hand, as the results show an immediate price shifts as a consequence of a change in the Google trend, this variation following a Wikipedia queries is not significant. To analyze this latter case, he separates the effect into positive and negative feedbacks. By doing so it is clearly shown how, when prices are going up, the number of researches on Wikipedia increases, while, when prices are decreasing, the public interest, measured as Wikipedia queries, is going even lower. In conclusion, this study finds a bidirectional relationship among Bitcoin price and queries: when the price is above the trend, interest increases souring the price further up. By looking at the opposite case, when the price is below the trend, the interest could push it even deeper. In both cases these behaviors could lead to a bubble behavior.

Even Matta *et al.* (2015)[49] investigate whether information searches and social media activities could predict Bitcoin price comparing its historical price to Google Trends data and volume of tweets. They used a dataset based only on 60 days but in addition to the other papers regarding the topic they implement an automated sentiment analysis technique that allows to automatically identify users' opinions, evaluations, sentiments and attitudes on a particular topic. They use a tool called "SentiStrenght", which is based on a dictionary only made by sentiment words, where each of them is linked to a weight representing a sentiment strength. Its aim is to evaluate the strength of sentiments in short messages that are analyzed separately, and the result is sum up in a single value: a positive, negative or neutral sentiment.

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[48] Kristoufek, L., (2013). *Bitcoin meets Google Trends and Wikipedia: Quantifying the relationship between phenomena of the Internet era.*

[49] Matta, M., Marchesi, M., Lunesu, M., I., (2015). *Bitcoin Spread Prediction Using Social And Web Search Media*.

The study reveals a significant relationship between Bitcoin price and volumes of both, tweets and Google queries.

Ciaian *et al.* (2015)[50] adopt a different approach to identify the factors behind the Bitcoin price formation by studying both the digital and traditional ones. The authors point out the relevance of analyzing these factors simultaneously, otherwise the econometric outputs could be biased. To do so they specify three categories of determinants: market forces of supply and demand; attractiveness indicators (views on Wikipedia and number of new members and posts on a dedicated blog) and global macro-financial development. The results show that the relevant impact on price is driven by the first category and it tends to increase over time. About the second category they assert that the short-run changes on price following the first period after Bitcoin introduction are imputable to investors' interest which is measured by online information search. Its impact eases off during time, having no impact in the long run and may be due to an increased trust among users who become more willing to adopt the digital currency. On the other hand, the results suggest that investor speculations can also affect Bitcoin price leading to a higher volatility that may cause price bubbles. To conclude, the study does not detect any correspondences between Bitcoin price and macroeconomics and financial factors.

Garcia *et al.* (2014)[51] study the evolution of Bitcoin price based on the interplay between different elements: historical price, volume of word-of-mouth communication in on-line social media (information sharing, measured by tweets and posts on Facebook), volume of information search (Google searches and Wikipedia queries) and user base growth. The results identify an interdependence between Bitcoin price and two signals that could form a potential price bubbles: the first concern the word-of-mouth effect, while the other is based on the number of adopters. The first feedback loop is a reinforcement cycle: Bitcoin interest increases leading to a higher search volume and social media activity. This new popularity encourages users to purchase the cryptocurrency driving the price further up. Again, this effect would raise the search volume. The second loop is the user adoption cycle: after acquiring information, new users joint the network, growing the user base. Demand raises but since supply cannot adjust immediately but changes linearly with time, Bitcoin price would sour up.

Kjærland *et al.* (2018)[52] try to identify the factors that have an impact on Bitcoin price formation. They argue that the harshrate, CBOE volatility index (VIX), oil, gold and Bitcoin

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[50] Ciaian, P., Rajcaniova, M., Kancs D.A., (2015). *The Economics of Bitcoin price formation.*

[51] Garcia, D. *et al.* (2014). *The digital traces of bubbles: feedback cycles between socio-economic signals in the Bitcoin economy*.

[52] Kjærland, F. *et al.* (2018). *An Analysis of Bitcoin's Price Dynamics*.

transaction volume do not affect Bitcoin price. The study shows that price depends on the returns on the S&P500, past price performance, optimism and Google searches.

Bouoiyour J. and Selmi R. (2015)[53] examine the links between Bitcoin price and its potential drivers by considering: investors' attractiveness (measured by Google search queries); exchange-trade ratio; monetary velocity; estimated output volume; hashrate; gold price; and Shanghai market index. The latter value is due to the fact that Shanghai market is seen as the biggest player in Bitcoin economic, which could also drive its volatility. The evaluation period is the one from 5th December 2010 to 14th July 2014 and it is investigated through the adoption of an ARDL Bounds Testing method and a VEC Grander causality test. The results highlight the speculative nature of this cryptocurrency stating that there are poor chances that it becomes internationally recognized.

An important study on Bitcoin drivers that does not consider the online queries is the one conducted by Van Wijk (2013)[54]. He investigates, indeed, the closing value: of the exchange rate of the Bitcoin express in US dollar, of the Dow Jones Index, of the FTSE100 Index and of the Nikkei225 Index[55]. In addition he takes into account the exchange rates between the U.S dollar and both the Euro and the Yen, and adds three measurements variables concerning the oil prices: the Brent oil price, the West Texas Intermediate (WTI) oil price and the UBS Bloomberg Constant Maturity Commodity Index (CMCI) of Oil. The time window analyzed spans from the 19th July 2010 until 13th June 2013 and the author implements an Error Correction model. The results show that in the long run, the price of Bitcoin is affected by the value of the Dow Jones, the euro-dollar exchange rate and the WTI oil price. Moreover, Dow Jones Index has a significant effect even in the short run. Van Wijk concludes his work pointing out that the influencing values are related to the US economy and suggests taking care of their path while investigating Bitcoin price.

[53] Bouoiyour, J., Selmi, R., (2015). *What Does Bitcoin Look Like?*
[54] Van Wijk, D., (2013). *What can be expected from the Bitcoin?*
[55] These last three variables are aimed to be seen as a good proxy of, respectively, the economy in US, Europe and Japan.

Section 3

Despite the high volatility characterizing Bitcoin, the interest that this new form of money has drawn to itself leads the financial institutions to contemplate new forms of payment and to a renewal of the banking sector. In the last years has caught on the hypothesis about the possibility that central banks issue their own digital currencies (in the form of cryptocurrencies or not). After a brief overview of the development framework, I present how these new forms of money guaranteed by central banks may look like and their possible future applications. I conclude by addressing some examples of states trying to deal with this new topic.

3.1 Sovereign Digital Currency Development Framework

Nowadays, sovereign fiat moneys (cash and reserves) issued by central banks, and which are their tools to influence the money creation through bank deposits, are competing with privately issued cryptocurrencies (such as Bitcoin) but in the future they may also enter into competition with sovereign, digital currencies issued by other central banks.

In the event that private cryptocurrencies become widely used, central banks' capability to control the monetary power would be harmed, but a proper design of new digital cash guaranteed by banks could enlarge their influence on the money supply. The introduction of central bank digital currency (CBDC) has the potential to shake the structure of the financial system. In fact, just to make an example, if costumers decide to switch their savings from bank accounts to new form of digital monies, the banks' ability to provide cash in a traditional way would be affected[56].

Private cryptocurrencies have not yet become money in the strict sense since they cannot fulfill the three basic requirements: be used as a means of payment, unit of account and store of value. These functions can be satisfied only if they become universally accepted and are perceived as stable with a predictable value.

Moreover, cash, as an established payment instrument, exhibits a lower risk of fraud compare private cryptocurrencies, which lack legal frameworks and are often subject to security breaches at wallet providers. Therefore CBDCs, in order to meet cash's safety level, must be issued by reliable authorities.

Central bank digital currencies (CBDC) may take the advantage to be adopted in a fast way since states and regulation could support them by forcing transactions denominated in these

[56] Mai, H., (2018). Deutsch Bank. *Why would we use crypto euros? Central bank-issued digital cash – a user perspective.*

currencies, for example by demanding tax payments in crypto-euros. This can facilitate the creation of a captive consumer base.

If regulation, on the other hand, does not force the adoption of a CBDC, individuals can autonomously decide among payments systems, therefore CBDCs must satisfy many requirements in terms of price, safety and convenience to become the preferable one,

With regard to price, this new crypto-euro must ensure the absence (or a paltry amount) of additional fees for both, the consumers, who should be allowed to pay with CBDCs without additional charges, and the merchants, who should not bear additional costs for accepting this new instrument of payment.

3.2 Central Bank Digital Currency (CBDC) and Cryptocurrency (CBCC)

Before trying to provide an exhaustive definition for central bank digital currency (CBDC) and central bank cryptocurrency (CBCC), it is important to pinpoint how it is spreading out the tendency of make these terms synonymous. This is not correct since "cryptocurrency" concerns those currencies based on crypto-technology (as distributed ledger technology), while "digital currency" consists in the superset, which includes cryptocurrencies as well as other types of digital exchanges based on other technologies[57].

In the following I present both definitions but, despite the differences, I will use the broad term of CBDC to present the possible future developments in section 3.3.

3.2.1 Design Features

A commonly agreed definition for the term "central bank digital currency" (CBDC) has not been reached yet since it embraces a broad range of different designs and policy choices. In fact, it gathers together many topics as computer science, banking, payments systems, monetary policy, financial stability and cryptography.

Meaning *et al.* (2018)[58] provide a general definition by identify central bank digital currency as "*an electronic, fiat liability, of a central bank that can be used to settle payments or as a store of value".*

Within this wide description, many sub-characteristics and parameters could be identified based on particular features, such as: access, interest, trade, underlying technology, availability, anonymity and limits or caps.

[57] Blakstad, S., Allen, R., (2018). *FinTech Revolution: Universal Inclusion in the New Financial Ecosystem*.
[58] Meaning, J., *et al.* (2018). *Broadening narrow money: monetary policy with a central bank digital currency.*

- Access

CBDCs can be either universally accessible, meaning that everyone can held this type of currency to pursue any object, or restrictively accessible by allowing only some individuals or economic agents to adopt it for finite purposes. Bjerg (2017)[59] distinguishes between "retail CBDC", available only to households and non-financial business, and "wholesale CBDC" used by firms which are not allowed having access to central bank reserves[60].

- Interest

A CBDC may or not bear an interest. An interest-bearing CBDC can pay positive, zero or negative interest in order to pursue different objectives. For examples it could stabilize inflation and output or regulate the demand of CBDCs. A non-interest-bearing CBDC is usually named "e-cash" since it is similar to central bank notes.

- Trade

Many researchers argue whether a CBDC might or not be trade at par with other central bank liabilities. Typically, different types of central bank liabilities are mutually exchanged 1:1, which means that a unit of central bank notes can be exchange with one unit of reserves. Someone could argue that this convention must be modified, but according to Meaning *et al.* (2018) this would confuse the economic agents on whether currency is the proper unit of account in the economy. Moreover, prices of gods and services might be expressed with both values, leading to a raise in the administrative costs.

- Underlying technology

CBDCs could differ by the underlying technology adopted. They could be account-based or token-based currencies[61]. An account-based CBDC involves a transaction of a claim between accounts and the way in which this operation is carry out is similar to the one between commercial bank depositors, with the exception that accounts in this case are hold with the central bank. As shown in Figure 8, user A should log into his account at the central bank and request to transfer some fundus to user's B account, which is also at the central bank. A central ledger is updating to ensure and verify the settlements. Each transaction is completed immediately after the payer's account ownership, the funds availability and the payee's account authenticity are checked. A token-based currency, on the contrary, entails a

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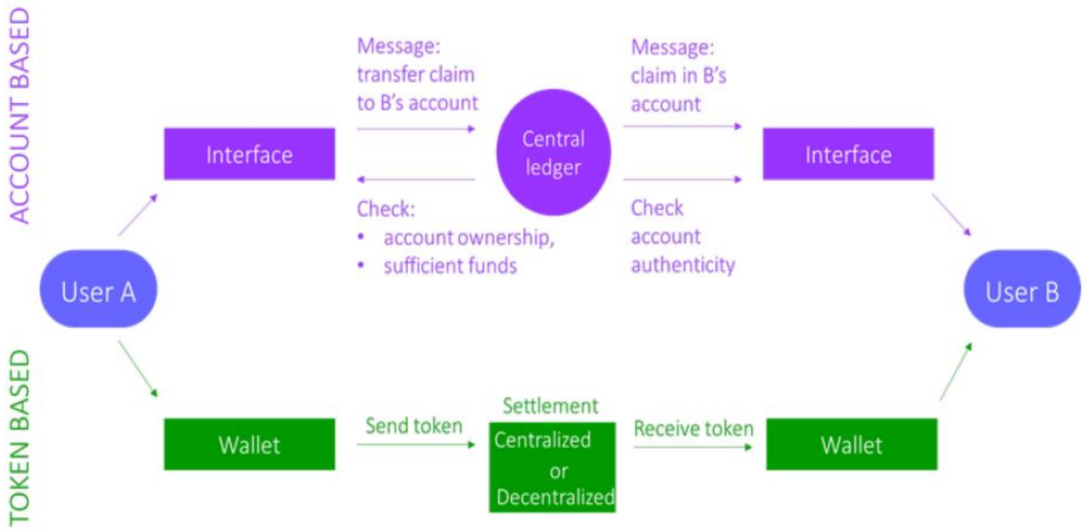
[59] Bjerg, O., (2017). *Designing New Money – The Policy Trilemma of Central Bank Digital Currency.*

[60] Bech, M., Garratt, R., (2017). *Central bank cryptocurrencies.*
Some researchers argue whether a CBDC that is not universally accessible, can be considered as a currency in the strict sense. To solve this issue, the European Central Bank prefers to use the general noun "digital base money".

[61] Mancini-Griffoli, T., *et al.* (2018). *Casting Light on Central Bank Digital Currency.*
The term "cryptocurrency" embraces a wide range of elements that can be pulled together in two sub-categories: tokens and crypto coins (like Bitcoin). The difference between them is slight, since the latter are based on their own blockchain, while the former are built on top of an existing blockchain. For more details see: https://coincentral.com/crypto-coin-vs-token-cryptocurrency/

transaction of a token between wallets, which requires an external verification on both the token and the settlement. As a consequence, this confirmation restricts the anonymity of the transaction in a way that depends on the features of the technology adopted. This verification can be based either on a centralized settlement or on a decentralized settlement through the use of a distributed ledger technology.

Figure 8: Account-based or token-based currencies



Source: Mancini-Griffoli, T., *et al.* (2018).

- Availability

CBDCs could potentially by designed to be available permanently 24 hours a day, 7 days a week.

- Anonymity

CBDCs, similarly to private cryptocurrencies, can ensure different degrees of anonymity. As I said in the first section, Bitcoin is a pseudo-anonymous currency since there are a private and a public key to confirm the identity of each network participant. CBDC's anonymity feature can be calibrate in the development phase by the central bank and should be balanced taking into account the society's needs, preferences and concerns relating to money laundering, privacy and financing of terrorism.

- Limits or caps

By imposing different limits or caps on both, the uses or the amount of holdings, central bank can control for potentially undesirable implications linked to CBDCs' adoption. For example, a cap on the wholesale payments can make them less attractive than retail payments.

This approach, however, prevents a 1:1 convertibility of CBDC and it is linked to the trade characteristic already mentioned[62].

The feature that generates the greater uncertainty is whether or not the CBDC is a cryptocurrency. This new form of money could be both based on a cryptographic technique (CBCC)[63] or on a more established and mature technology. The latter case it is not a cryptocurrency but it is still a form of central bank digital currency.

Different combinations of the parameters just presented could design various CBDC schemes, which vary by their underlying aim. In section 3.3 I will present four possible settings.

3.2.2 Taxonomy of Money

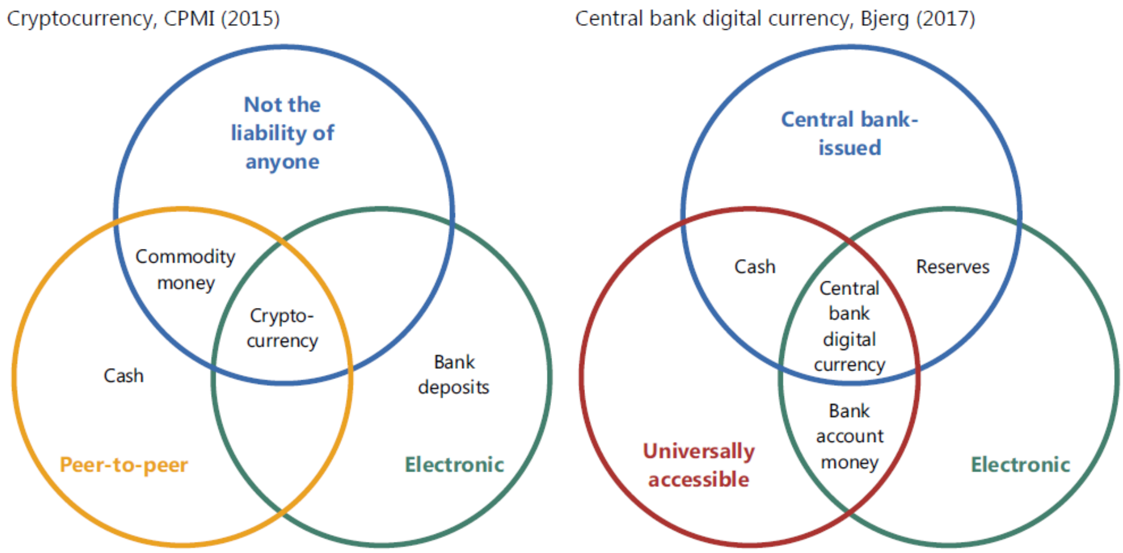
Bech and Garratt (2017) provide a taxonomy of money rearranging the contents of two different papers, one published by the Committee on Payments and Market Infrastructures (2015), and the other written by Bjerg (2017).

The first one tries to define a new class of cryptocurrencies arose through the event of Bitcoin and other altcoins. The report pinpoints three key features of this new form of money: cryptocurrencies are, indeed, electronic; are not the liability of anyone; and have the feature to be peer-to-peer exchangeable. Some of these characteristics belong also to other forms of money (Figure 9, left side). Cash, for example, has the peculiarity to be only a peer-to-peer form of money, while commercial bank deposits consist in a liability for the bank that issues them and are currently transferred between banks or central banks in an electronic form. Commodity monies, like gold coins, are exchanged in a peer-to-peer way but they do not have neither the liability not the electronic feature.

This classification proposed by the Committee on Payments and Market Infrastructures (2015) has the flaw to neglect the characteristic of money accessibility, which is, however, included by Bjerg's (2017) categorization. The author, whose aim is to provide a definition of central bank digital currency, considers again three factors: universal accessibility, electronic and central bank-issued features (Figure 9, right side).

[62] Bank for International Settlements, (2018). *Central bank digital currencies*.
[63] In this case they are central bank cryptocurrencies (CBCCs) but in the literature they are commonly referred as CBDCs.

Figure 9: Two taxonomies of new forms of currency



Source: Bech, M., Garratt, R., (2017).

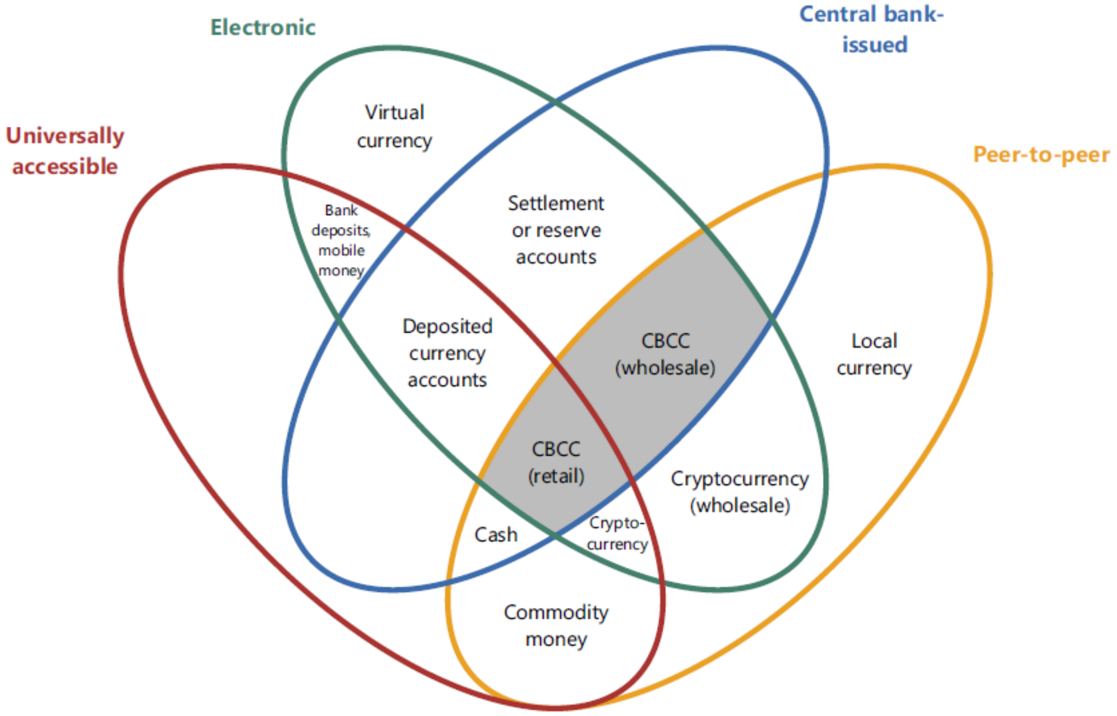
By merging together these two classifications, Bech and Garratt (2017) propose a new taxonomy of money, which relies on four fundamental characteristics: issuer (bank or other); form (electronic or physical); accessibility (universal or limited) and transfer mechanism (centralized or decentralized, i.e. peer-to-peer). In accordance to this classification, central bank cryptocurrencies (CBCCs) are defined as *"an electronic form of central bank money that can be exchanged in a decentralized manner known as peer-to-peer, meaning that transactions occur directly between the payer and the payee without the need for a central intermediary"*[64]. The absence of an intermediary is the key features of this new form of money that discern it from other existing forms of central bank exchanges. Furthermore, the authors incorporate Bjerg's distinction between retail and wholesale CBDC and conceive the terms "retail CBCC" and "wholesale CBCC".

These two forms of CBCCs offer some advantages compared to the classical forms of central bank money. For the consumer-facing kind, indeed, a peer-to-peer element can provide anonymity features similar to those of cash. On the wholesale side, this new form of digital settlement could improve efficiency by reducing the settlement costs. Even if some central banks have tested these wholesale CBCCs, only few have announced to be ready to use this technology[65].

[64] Bech, M., Garratt, R., (2017). *Central bank cryptocurrencies.*
[65] See section 3.4 Global Responses.

Figure 10 offers a graphical representation of the taxonomy through what is called "the money flower".

Figure 10: The money flower: a taxonomy of money



Source: Bech, M., Garratt, R., (2017).

The authors provide also some examples for each of these categories by specifying whether the mentioned projects are still in operation; a suggestion about a future adoption; in experimentation or they are abandoned plans[66].

[66] For more details, see: Bech, M., Garratt, R., (2017). *Central bank cryptocurrencies.*

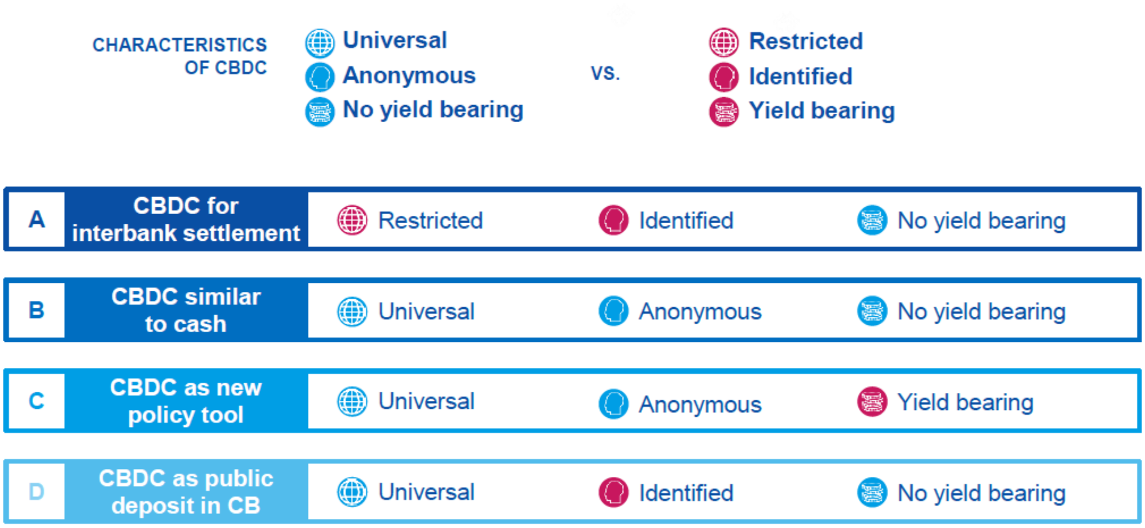
3.3 Possible Future Applications

Cash as mean of payment fulfills four requirements: universality, anonymity, peer-to-peer exchangeability and unit of account. Before the appearance of the distributed ledger technology in 2008, preserving all these attributes in a digitalized form of cash was not an option. DLT offers a smart way to preserve these features and provides a new way of thinking about money as central banks are now searching for new ways to implement CBDC schemes that conserve only some of the keys properties of physical cash[67].

Gouveia *et al.* (2017)[68] present four possible development scenarios of CBDC, ordered from the less to the more disruptive (Figure 11):

A. *"CBDC for interbank settlement: a scheme that rejects universality and anonymity of cash;*
B. *CBDC similar to cash: a scheme that retains all four key attributes of cash;*
C. *CBDC as a new policy tool: a scheme that includes the possibility of bearing interest rates (even negative rates, thus eroding the historical zero-bound to financial repression);*
D. *CBDC as a deposit in the CB: a scheme that rejects anonymity in favor of transparency."*

Figure 11: Four possible development scenarios of CBDC



Source: Gouveia, O., C., *et al.* (2017).

[67] An unsolved aspect is the risk of operational failure of the DLT. As already said in the first section, distributed ledger technology is harder to corrupt but it could happen if a malicious participant, or a group of them, hold the control of the major part of the computational power involves in the system. Therefore, the security of a CBDC which relies on a DLT must be tested on a large scale to ensure safe transactions, before being implemented in the market.

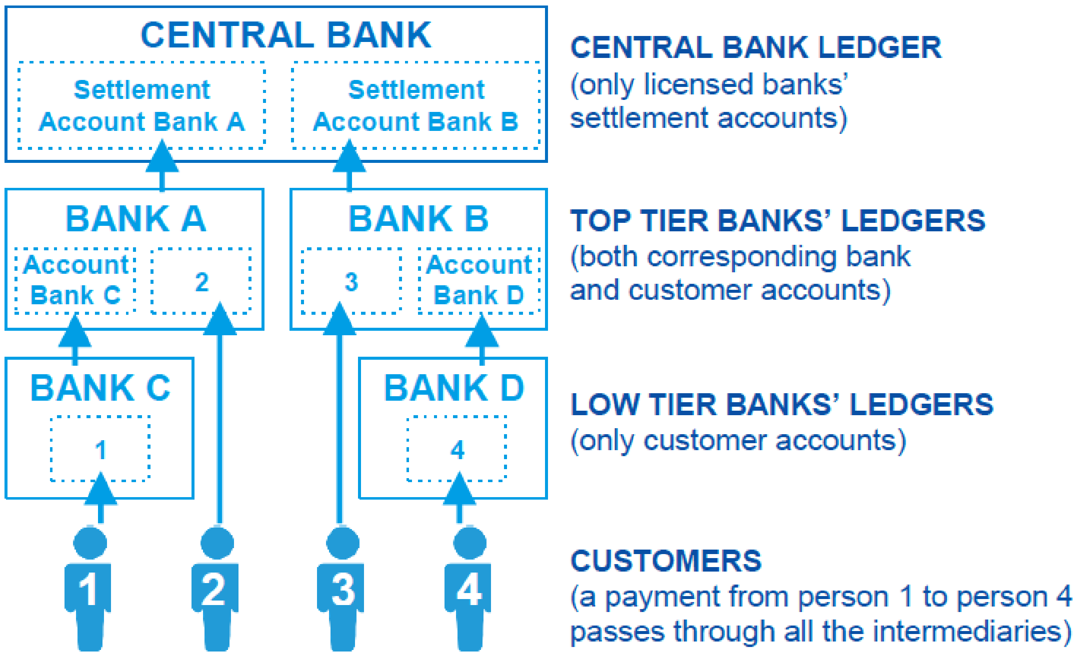
[68] Gouveia, O. C., *et al.* (2017). *Central Bank Digital Currencies: assessing implementation possibilities and impacts.*

3.3.1 Scenario A: CBDC for interbank settlement

In this scenario CBDCs are available only to a limited number of players: Tier1 banks, which are authorized to be engaged in settlement directly with central banks; and those smaller banks or non-bank institutions that handle high volume of transactions but are not allowed to contract with central banks.

In this framework the distributed ledger technology is applied to the intra-bank payments mechanism but CBDCs would not be anonymous: the nodes and the wallets would be known. It competes with the current settlement system, where banks, to obtain financing, open settlement accounts with Tier1 banks, which are the only one eligible to negotiate with central banks. The top-tier banks not only play the role of intermediaries with other banks but also manage their own customers' accounts. Moreover, by construction, the current settlement system has the disadvantage to be extremely costly since it requires a continuous control in order to avoid double spending which can lead to sudden default (Figure 12).

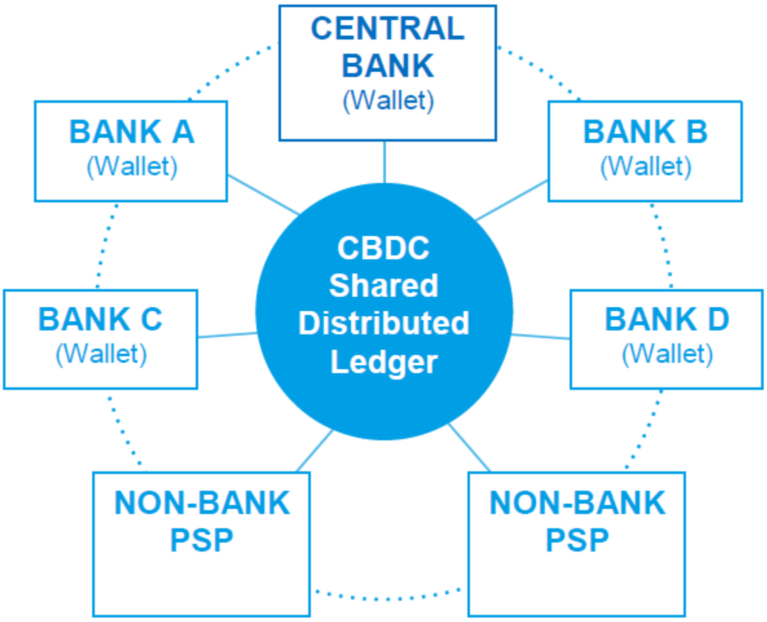
Figure 12: Current Settlement System



Source: Gouveia, O., C., *et al.* (2017).

In the scenario with a CBDC-based settlement system, the distributed ledger technology would replace the centralized ledger and the CBDC wallets would substitute the settlement accounts. This framework would be less costly and would facilitate instant settlements since the central bank becomes another node in the network and each transaction could be validated by all players. Even the non-bank institutions or other players could participate to the network, thus allowing direct setting transfers with the central bank and avoiding the intermediation of Tier1 banks (Figure 13).

Figure 13: CBDC for Interbank Settlement



Source: Gouveia, O., C., *et al.* (2017).

This implementation of CBDC is the more probable since it could represent an intermediate step for testing how this new form of money can work.

3.3.2 Scenario B: CBDC similar to cash

CBDC in this framework has the same characteristic of cash: it is universality acceptable, anonymous, peer-to-peer exchangeable and consists in a unit of account. Banks remain money creators with reserves at the CB and CBDCs are exchanged at parity 1:1 with cash.

Since the value of CBDC is pegged to that of cash, their performance would be equivalent, but this does not rule out their possibility to be subject to exchange rate instability. The usage of CBDCs would increase in those areas where people are familiar with online transactions, but it could not replace cash where people are less confident with technology or the internet connection is poor.

In comparison with bank deposits, CBDCs would be riskier since their anonymity restricts the authorities' ability to act as guarantors: since they are untraceable, once the password or the wallets are forgotten, none can help customers to recover them.

Agents would probably be less prone to use CBDC for illicit purposes, since they could fear that their anonymity can be reveal by authorities at a certain point in time.

3.3.3 Scenario C: CBDC as new policy tool

In this case, CBDCs are designed to be universality acceptable, anonymous and peer-to-peer exchangeable and, most important, an interest-bearing currency. This last feature is possible through the technology on which the new form of currency is based: by changing the face value of the whole stock of CBDCs, they would hold an interest. The new flexibility acquired by the currency allows authorities to apply positive (equivalent to a raise in CBDC's face value) or even negative (equivalent to a reduction of CBDC's face value) interest rates. The first case permits an automatic expansion of the monetary base, while the second disentangles monetary policy to the zero-lower bound limit and gives the chance to quickly react to recession threats.

The new flexibility acquired does not always match with political-social desirability. The new ability of CB to modify CBDC's face value could be seen as an expropriation and raises legitimacy issues about its power to implement fiscal policies. Moreover, since CBDC would not be constant, its role of unit of account is called into question[69].

The new form of money can be compared to cash, bank deposits and other private/foreign currencies. A scenario where this kind of CBDC would coexist with cash is hard to imagine since if rates applied to the new currency are negative, people would switch them in favor of physical cash. On the other hand, if the applied rates are positive, people substitute cash with CBDCs. Scenario C seems, thus, possible to exist only if cash is abolished.

Compare to bank deposits, CBDC has the advantage to be exchanged without intermediaries but it has the disadvantage to lack in its store of value function. For this reason bank deposits would continuous to attract those agents, who are looking for a form of money with this specific financial characteristic. The yield spread between these two options would determine their mutual demands.

The demand of CBDC respect for other types of private/foreign currencies may depend mostly on the perceived stability of former compare to the latters.

3.3.4 Scenario D: CBDC as public deposit in central bank

In this latter scenario, CBDC is universality acceptable, peer-to-peer exchangeable, not interest bearing and, most important, not anonymous. In addition to the fact that this kind of money is identified, CBDCs are also kept in a public deposit and these features make this design, for the end users' point of view, the safer compared to the previous described scenarios but it is perceived as less desirable than cash for a minority of people, who concern

[69] Leaving aside period of high inflation, domestic currencies have always served as prices reference. The interest-bearing characteristic of this new form of money would compromise this property.

about the central authorities' ability to monitor their transactions. This new form of money is also a better possibility to store personal savings compared to central bank deposits, since the risk of keeping them at the CB is lower than having a deposit in a commercial bank. Some agents, on the other hand, would in any case prefer to store their savings in bank deposits as they guarantee higher remuneration and services. CBs, in fact, would lack of incentives and skills to offer customers' oriented financial services and thus they would not be involved in this business.

Risk-loving clients, searching for higher returns and willing to bare higher risks, would turn to commercial banks, which start resembling their competitors: investment banks and mutual funds.

Compared to previous scenario, as already mentioned, CBDC will be a better store of value but its ability to be used as a medium of exchange depends on common belief about safety and anonymity and how society values them.

Storing saving as CBDC deposits in CBs is for end users the same to keep deposits in a narrow-bank, *"i.e. a financial institution that is compelled by authorities to maintain the public's resources under custody in a liquid and safe form, such as in government bonds, rather than leveraging on them in order to create credit"*[70]. It is highly probable that a narrow-banking system would emerge with the introduction of such CBDC scheme.

3.3.5 Advantages and Disadvantages

In this section I briefly sum up the main advantages and disadvantages for each scenario previously described.

Table 10: Advantages and Disadvantages for each scenario

ADVANTAGES	DISADVANTAGES
Scenario A: CBDC for interbank settlement	
▪ Lower costs to manage and control the system; ▪ Full availability (24 hours a day, every day); ▪ The decentralized system is more resilient to cyber-attacks since there are many points that need to be corrupted;	▪ High initial cost of implementation; ▪ Some players loose a source of revenue: - Tier1 banks lose privilege and part of their payment business; - banks' revenues are reduced since non-bank institutions are allowed to compete in the market and thus their

[70] Gouveia, O. C., *et al.* (2017). *Central Bank Digital Currencies: assessing implementation possibilities and impacts.*

▪ The systemic risk could be managed in a better way since the information about the capital flows are transparent and collected in real-time; ▪ CBDCs compete with private digital currencies in order to keep control of the settlement system; ▪ Competition in the business increases due to, both, the integration of non-bank fintechs into the financial system and the cost efficiency in the settlement process; ▪ As competition increases, transaction fees are reduced and thus the costs associated with payments; ▪ Since each player has access to the CB settlement system, competition among them shifts to offer additional services; ▪ Banks maintain their competitive advantage on non-banks in the credit business; ▪ End-customers benefit from cheaper and faster money transfer.	market share increased; However, all things considered, banks' benefits would exceed their costs and revenues losses.
Scenario B: CBDC similar to cash	
▪ Users benefit from a digital representation of cash that, compare to current non-government digital currencies (such as bitcoin): - is free of volatility, price instability, lack of liquidity that characterized private currencies (like bitcoin); - maintains some of their advantages, by allowing cheaper and faster money transections; ▪ This framework: - promotes financial inclusion;	▪ Threats of losing anonymity (due to policy decisions or hacking attempts); ▪ The system undergoes continuous costs to be updated and maintain an adequate security level avoiding hacking attempts; ▪ Users could overcome some "access barriers", such suboptimal infrastructures and technological illiteracy; ▪ Monetary authorities have to finance and implement a new infrastructure that demands new equipment and skills; ▪ Banks' payment system would end since

- allows CBs to compete with other digital currencies and thus limits monetary authorities' lack of control; ▪ Banking regulation might be simplified, because: - the sector would be less concentrated; - banking activity could turn out to be less prone to systemic disruption; ▪ CBDCs facilitate new business opportunities for banks: they could, for example, be entailed to manage and protect the keys for wallets; ▪ For both users and monetary authorities, benefits would overcome costs;	the intermediation for payment transactions becomes redundant; ▪ Banks might suffer for the substitution of bank deposits with CBDC, thus harming their credit formation ability; ▪ Since the deposits' volume decreases and their volatility raises (as there are more alternative to store value), asset and liability management would become more difficult for banks; ▪ Costs would exceed benefits for banks;
Scenario C: CBDC new policy tool	
▪ The framework: - allows the implementation of stronger and more flexible responses in case of recession; - eases a faster path to digitalization; ▪ Banking regulation might be simplified, because: - the sector would be less concentrated; - banking activity could turn out to be less prone to systemic disruption; ▪ CBDCs facilitate new business opportunities for banks: they could, for example, be entailed to manage and protect the wallets' keys;	▪ Threats of losing anonymity (due to policy decisions or hacking attempts); ▪ The likely elimination of cash would raise the costs for end users derived from internal disruption of power shortage; ▪ Authorities incur high costs in order to guarantee universal access to CBDC; ▪ Possibility to apply negative rates raises questions about the authorities' legitimacy to adopt these policy measures; ▪ Since CBDC competes with bank deposits, the volatility of the latter may raise;
Scenario D: CBDC as public deposit in central bank	
▪ Policy makers gain high surveillance powers with the ability to: - prevent illicit activities; - reduce tax evasion; ▪ Reduction of the bank-related risk since a	▪ Large surveillance power raises question about the state of legitimacy to control people's transactions since CB monitor would diminish individuals' decision room;

significant part of deposits would be kept in CB and thus are implicitly guaranteed; ▪ Higher efficiency of the system; ▪ This scenario allows: - CBs to compete with other digital currencies; - cheaper and faster money transfer; ▪ Deposits reduction in commercial banks are larger: - the poorer is the coverage of deposit protection; - the lower is the remuneration of bank deposits; - the worst the services provided by banks; ▪ It is a safer option to store users' savings; ▪ Users would benefit from the increasing competition among banks, central banks and fintechs;	▪ A decreasing in banks' deposits leads to a reduction of credit that is particularly harmful in emerging economies which have not yet benefited from a high bancarization level; ▪ There would be large implementation costs for policy makers; ▪ Banks' funding would be less stable; ▪ Increasing competition with fintechs, would harm banks' profit; ▪ Probably the overall costs of this scheme would exceed its benefits.

Source: Author's elaboration

3.4 Global Responses

Many countries are looking at CBDCs with increasing interest and are trying to understand whether their applications will become reality in the near future. Following what Blakstad and Allen (2018)[71] analyze, I present below a summary of the main implementation attempts.

China, as first example, intends in the following years to issue its own CBDC, the blockchain-based digital Renminbi, becoming the first major country to promote this new form of money. Since Bitcoin has been released, the country has shown an attitude towards blockchain technology, investigating in its possible applications at national level. In January 2017, China's central bank tested a digital note exchange platform that allows commercial banks to exchange notes and in July of the same year, the Central Bank Digital Currency Research Institution initiated to operate separately from People's Bank of China (PBOC). The Chinese CBDC will be probably firstly limited only to intra-banks operations with the goal to be adopted in the future by end users in daily digital transactions[72].

The United Kingdom has started in the early 2015 to explore the possibility to implement a sterling-linked digital currency based on blockchain technology but the Bank of England does not make any promises about the forthcoming development of a crypto-pound, despite it does not neglect this possibility.

Singapore launched a project in 2016, called "Project Urbin" to explore the opportunities offered by this new technology, in particular clarifying the benefits and the implications for security payments. The aim was to implement efficient and simple-to-use alternatives payment system. The project consisted in two phases and the first one, related to the development of a prototype solution for domestic inter-bank payments, was successfully accomplished in March 2017. Later, in October 2017, the Monetary Authority of Singapore (MAS) declared also the second phase concluded and to have successfully implemented three different models for decentralized inter-bank payments. Finally, it announced the will to conduct spin-off projects, investigating new methods of cross-border payments using CBDCs. However, in January 2018, the managing director of the MAS, Ravi Menon, expressed some doubts about the applicability of CBDCs[73].

Canada is another country that has attempted to clarify the implication of blockchain applications by developing a wholesale CBDC, called CADcoin. It has been tested among different fintech firms and Canadian banks, but it has not been released yet. In November 2017, the Bank of Canada listed the benefits and the risks of these new applications in a paper

[71] Blakstad, S., Allen, R., (2018). *FinTech Revolution: Universal Inclusion in the New Financial Ecosystem.*
[72] Wan, D., (2019). *Digital Renminbi: A Fiat Coin to make M0 Great Again.* Coindesk.
[73] O'Neal, S., (2018). *State-Issued Digital Currencies: The Countries Which Adopted, Rejected or Researched the Concept.* Cointelegraph.

titled “Central Bank Digital Currency: Motivations and Implications”, and it reached the conclusion that central banks should move gradually since CBDCs are still a complex and uncertain topic.

Dubai affirmed in September 2017 the intention to launch its own digital currency called “emCash”. This currency, available by smartphones, is planned to satisfy Dubai’s citizens’ needs by ensuring faster processing and delivery time, while reducing complexity and costs. However, since a specific release date was not announced, probably the project is on its early stages.

Sweden is also leading a project to become a completely cashless country. The Risksbank of Sweden has implemented an eKorona project, whose results are expected to be published in late 2019, with the object to develop a system enabling CBDCs to be supplied to the general public. An estimated launch date has not been announced yet, since the authority wants to be careful and verified all the technological implications before made it available to the general public[74].

Russia has a CryptoRouble project under way, which in addition to be “traceable encryption”[75] will probably have the features to be centrally controlled, taxed and regulated. Apparently, Putin and the government see these new CBDCs as a way to circumvent wester sanctions. Moreover, after issuing CryptoRouble they are supposed to be overtaken also by other countries members of the Eurasian Economic Community. The Russian Communications Ministry hypothesized that a 13% tax rate will be charged if this new form of money is converted back to Roubles, implying that the digital currency can be exchange also outside its monitored area.

Ecuador, even its small dimension, was one of the first countries to create its digital currency in 2014, called “the Sistema de Dinero Electrónico”. The reasons behind its introduction were to support the Ecuadorian dollar-based monetary system[76] and reduce both the poverty level and the expanses for changing deteriorating old notes. In 2015, the currency, stored in digital wallets, became to be accepted as payment for public transport, invoicing system and country’s tax but it was not so common among consumers’ payments or widely accepted by country’s banks. Despite the ban of Bitcoin and other cryptocurrencies to ease the diffusion of the new digital money, the CBDC failed. On 26 March 2018 the system was completely deactivated, and all the accounts were closed. The reasons seem to be the inability

[74] News Desk, (2019). *China vs Sweden: who will be the first to launch their own cryptocurrency and what will it mean for the crypto world?*
[75] It seems that the government will hold the keys.
[76] In September 2000, Ecuador started in fact to accept US dollars as legal tender.

of the new money to attract users, combined with their lack of trust in the local central banks and institutions. People were thus reluctant to accept other currencies rather than US dollars.

Japan in 2017 entrusted a Fintech department with the task to offer guidance to banks seeking new business opportunities. Furthermore, the Bank of Japan participated with the European Central Bank to a research project on distributed ledger technologies and in September 2017 they agreed that the blockchain was not evolved enough to be applied in the payment system. Despite this conclusion, the Bank of Japan is planning to release a digital currency during the Olympics in 2020, named “JCoin”. This new form of money will allow payments via smartphones using QR codes and will be convertible at pair with yen.

Estonia announced in December 2017 that it was working on three different models of a new digital currency, the “Estcoin”. The initiative was strongly criticized by the European Central Bank since a member state cannot introduce and adopt its own currency. Despite the manager director of Estonia’s e-residency programme, Kaspar Korjus, replied that Estcoin would not enter into competition with euro[77], the program was shut down and only the other two approaches have been carried out: the “community Estcoin” to reward who voluntarily helps in the enhancing of the system, and the “identity Estcoin” related to the recognition of persons’ digital identities.

Senegal introduced in the market its digital currency based on the blockchain technology, the eCFA. This new form of money was created through a collaboration program between the local bank Banque Régionale de Marchés (BRM) and eCurrency Mint Limited (an Ireland-based startup), and has the properties to be pegged to the country’s currency, the CFA franc, be stored in e-wallets and be compatible with other digital currencies of the African area. BRM and eCurrency Mint claimed, indeed, in a joint statement that *“The eCFA is a high-security digital instrument that can be held in all mobile money and e-money wallets. It will secure universal liquidity, enable interoperability and provide transparency to the entire digital ecosystem in West African Economic and Monetary Union”*[78].

Venezuela with his President Nicolas Maduro announced in November 2017 that the collapsed economic situation would be rescued by the introduction of a digital currency, the Petro or Pedromoneda, backed by country’s oil, gold and mineral reserves. The goals of this launching were to gain control of the monetary sovereignty, ease financial transaction and overcome the financial “blockade”, sanctions erected by the US president Donald Trump’s

[77] Estcoin would not compete with the euro, since it would be pegged to the official currency and available only to Estonia’s digital residents.
[78] O’Neal, S., (2018). *State-Issued Digital Currencies: The Countries Which Adopted, Rejected or Researched the Concept.*

administration that impacted negatively on the local economy[79]. On 20 February 2018, the Pedro was launched as the first digital currency adopted by a state but so far it does not achieve the desired results[80].

Although it seems that also the authorities of India, Iran and Bangladesh are working on the releases of their own national cryptocurrencies, the US Federal Reserves is not looking forward to implement a crypto-backed Dollar because the common belief is that *"the key characteristic of cryptocurrencies are a red flag for central banks"*[81].

Switzerland shares the same idea since, in June 2018, Thomas Moser, the board direction of the Swiss National Bank (SNK), declared that both the blockchain technology and the cryptocurrencies are not established enough to be applied in the creation of CBDCs.

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[79] O'Neal, S., (2018). *State-Issued Digital Currencies: The Countries Which Adopted, Rejected or Researched the Concept.*
[80] For more details, see: Brown, A., (2019). *Venezuela's Failed Cryptocurrency Is the Future of Money.*
[81] De Silva, M., (2018). *The Fed wants no part of a national cryptocurrency.*

Conclusion

The findings of my analysis show how, in the considered time frame, the Bitcoin historical price is not connected with the price derived from the model, and vice versa.

This result is different from the one obtained by Hayes and Abbatemarco *et al.* (2018), who conclude that the Bitcoin price could be explained by the cost of production model.

The reason behind these opposite outcomes could be the considered time window. In fact, the present analysis includes also those months where Bitcoin price sours up, reaching a peak of 19.270$ on the 19th December 2017, without following a stable path. This has a relevant impact on my results even if the historical price started declining in 2018, converging again to the model one.

Looking at the overall time frame, it seems that the increasing value of the historical price from the beginning of 2017 to the end of 2018 is a unique episode that required some months to solve.

Taking into accounts all these considerations, it is now possible to find a response to the research question: “Could Bitcoin be seen as a virtual commodity?”. The answer is: no, or better not only. As Abbatemarco *et al.* (2018) highlight, this approach does not rule out the possibility of a bubble development and, given the actual time frame, this is the reason why it would be more precise to explain Bitcoin price not only with the one implied by the model, but also with other explanatory variables that the literature seems to identify as meaningful.

Therefore, to avoid misleading results, Bitcoin intrinsic characteristics must thus be considered and checked by adding to the profit and cost functions also these suggested parameters that range from technical aspects and Internet components to financial indexes, commodity prices and exchange rate.

This could open new horizons for research, which, despite the traditional drivers, should consider also new factors such as Google Trends, Wikipedia queries and Tweets. These elements are related to the Internet component and appear to be particularly relevant given the social and digital Bitcoin’s nature.

Moreover, Kristoufek’s (2013) intuition, which considers Bitcoin as an unique asset that presents properties of both a speculative financial asset and a standard one, whose price drivers will change over time considering its dynamic nature and volatility, seems to be confirmed.

For sure, the cryptocurrencies introduction, with their distributed ledger technology, had a massive impact in the economy, leading financial institutions to foresee new way of carrying out the economic system. It seems actually possible that an increasing number of central banks would issue their own digital currencies in the years ahead and, moreover, among the four possible presented scenarios, it appears reasonable what Gouveia *et al.* (2017) suggest: Central Bank Digital Currency (CBDC) must firstly be adopted for interbank settlement. This scenario has, in fact, the advantage to consist as an intermediate step for testing how this new form of money can work.

It is important to point out that the success of a CBDC adoption depends, not only on technical issues, but also on individual preferences, social behavior and beliefs. This increases the complexity of their nature, which required further analysis and prudence.

As shown in paragraph 3.4, some countries already tried to adopt various forms of CBDC, but the results are uncertain, since a deep understanding of the topic is required to achieve a suitable implementation. Most central banks are therefore proceeding with caution, trying to find a proper way to balance associated risks and profits.

In conclusion, private and public digital currencies consist in a challenging field of study, whose inherent potential has not been fully understood yet, but probably has the ability to reshape the economic and the financial system in the future.

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Appendix

Table A.1: Weights Distribution

Weights Distribution																
2 s. 2010	1 s. 2011	2 s. 2011	1 s. 2012	2 s. 2012	1 s. 2013	2 s. 2013	1 s. 2014	2 s. 2014	1 s. 2015	2 s. 2015	1 s. 2016	2 s. 2016	1 s. 2017	2 s. 2017	1 s. 2018	2 s. 2018
0,33	0,1833	0,2083	0,2333	0,1750	0	0	0	0	0	0	0	0	0	0	0	0
0,33	0,38	0,20833	0,23333	0,17500	0,13750	0	0	0	0	0	0	0	0	0	0	0
0,33	0,38	0,43	0,233333	0,175	0,1375	0,113	0	0	0	0	0	0	0	0	0	0
0	0,05	0,1	0,15	0,175	0,1375	0,1125	0,1	0	0	0	0	0	0	0	0	0
0	0	0,05	0,1	0,15	0,1375	0,1125	0,1	0,1	0	0	0	0	0	0	0	0
0	0	0	0,05	0,1	0,2	0,1125	0,1	0,1	0,1	0	0	0	0	0	0	0
0	0	0	0	0,05	0,15	0,25	0,1	0,1	0,1	0,1	0	0	0	0	0	0
0	0	0	0	0	0,1	0,2	0,3	0,1	0,1	0,1	0,1	0	0	0	0	0
0	0	0	0	0	0	0,1	0,2	0,3	0,1	0,1	0,1	0,1	0	0	0	0
0	0	0	0	0	0	0	0,1	0,2	0,3	0,1	0,1	0,1	0,0625	0	0	0
0	0	0	0	0	0	0	0	0,1	0,2	0,3	0,1	0,1	0,0625	0,0375	0	0
0	0	0	0	0	0	0	0	0	0,1	0,2	0,3	0,1	0,0625	0,0375	0,025	0
0	0	0	0	0	0	0	0	0	0	0,1	0,2	0,3	0,0625	0,0375	0,025	0,025
0	0	0	0	0	0	0	0	0	0	0	0,1	0,2	0,35	0,0375	0,025	0,025
0	0	0	0	0	0	0	0	0	0	0	0	0,1	0,25	0,4	0,025	0,025
0	0	0	0	0	0	0	0	0	0	0	0	0	0,15	0,3	0,45	0,025
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0,15	0,3	0,45
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0,15	0,3
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0,15
1,00	1,00	1,00	1,00	1,00	1,00	1,00	1,00	1,00	1,00	1,00	1,00	1,00	1,00	1,00	1,00	1,00

Source: Author's elaboration

Table A.2: Biannual Efficiency

biannual Efficiency (Mhash/J)																
2 s. 2010	1 s. 2011	2 s. 2011	1 s. 2012	2 s. 2012	1 s. 2013	2 s. 2013	1 s. 2014	2 s. 2014	1 s. 2015	2 s. 2015	1 s. 2016	2 s. 2016	1 s. 2017	2 s. 2017	1 s. 2018	2 s. 2018
0,483	0,266	0,302	0,338	0,254	0	0	0	0	0	0	0	0	0	0	0	0
0,450	0,518	0,281	0,315	0,236	0,186	0	0	0	0	0	0	0	0	0	0	0
0,577	0,663	0,750	0,404	0,303	0,238	0,195	0	0	0	0	0	0	0	0	0	0
0	0,104	0,208	0,312	0,364	0,286	0,234	0,208	0	0	0	0	0	0	0	0	0
0	0	0,313	0,625	0,938	0,859	0,703	0,625	0,625	0	0	0	0	0	0	0	0
0	0	0	0,520	1,040	2,080	1,170	1,040	1,040	1,040	0	0	0	0	0	0	0
0	0	0	0	0,735	2,205	3,675	1,470	1,470	1,470	1,470	0	0	0	0	0	0
0	0	0	0	0	2,325	4,650	6,975	2,325	2,325	2,325	2,325	0	0	0	0	0
0	0	0	0	0	0	10,700	21,400	32,100	10,700	10,700	10,700	10,700	0	0	0	0
0	0	0	0	0	0	0	50	100,000	150,000	50,000	50,000	50,000	31,250	0	0	0
0	0	0	0	0	0	0	0	90,000	180,000	270,000	90,000	90,000	56,250	33,750	0	0
0	0	0	0	0	0	0	0	0	130,000	260,000	390,000	130,000	81,250	48,750	32,500	0
0	0	0	0	0	0	0	0	0	0	142,900	285,800	428,700	89,313	53,588	35,725	35,725
0	0	0	0	0	0	0	0	0	0	0	195,700	391,400	684,950	73,388	48,925	48,925
0	0	0	0	0	0	0	0	0	0	0	0	225,700	564,250	902,800	56,425	56,425
0	0	0	0	0	0	0	0	0	0	0	0	0	600,000	1.200,000	1.800,000	100,000
0	0	0	0	0	0	0	0	0	0	0	0	0	0	1.527,300	3.054,600	4.581,900
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1.575,000	3.150,000
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1.665,000
1,510	1,551	1,854	2,514	3,869	8,179	21,327	81,718	227,560	475,535	737,395	1.024,525	1.326,500	2.107,263	3.839,575	6.603,175	9.637,975
biannual Efficiency (Hash/J)																
1510000	1550500	1853500	2514000	3869250	8178875	2,1E+07	8,2E+07	2,3E+08	4,8E+08	7,4E+08	1,025E+09	1,33E+09	2,11E+09	3,84E+09	6,6E+09	9,64E+09
biannualEFF(J/Hash)																
6,6E-07	6,4E-07	5,4E-07	4E-07	2,6E-07	1,2E-07	4,7E-08	1,2E-08	4,4E-09	2,1E-09	1,4E-09	9,761E-10	7,54E-10	4,75E-10	2,6E-10	1,51E-10	1,04E-10

Source: Author’s elaboration

Table A.3: Weighted Devices' Price (Average Prices)

Weighted Devices' Price (Average Prices)																
2 s. 2010	1 s. 2011	2 s. 2011	1 s. 2012	2 s. 2012	1 s. 2013	2 s. 2013	1 s. 2014	2 s. 2014	1 s. 2015	2 s. 2015	1 s. 2016	2 s. 2016	1 s. 2017	2 s. 2017	1 s. 2018	2 s. 2018
58,333	32,083	36,458	40,833	30,625	0	0	0	0	0	0	0	0	0	0	0	0
53,333	61,333	33,333	37,333	28,000	22,000	0	0	0	0	0	0	0	0	0	0	0
66,667	76,667	86,667	46,667	35,000	27,500	22,500	0	0	0	0	0	0	0	0	0	0
0	23,450	46,900	70,350	82,075	64,488	52,763	46,900	0	0	0	0	0	0	0	0	0
0	0	49,750	99,500	149,250	136,813	111,938	99,500	99,500	0	0	0	0	0	0	0	0
0	0	0	34,000	68,000	136,000	76,500	68,000	68,000	68,000	0	0	0	0	0	0	0
0	0	0	0	37,500	112,500	187,500	75,000	75,000	75,000	75,000	0	0	0	0	0	0
0	0	0	0	0	98,900	197,800	296,700	98,900	98,900	98,900	98,900	0	0	0	0	0
0	0	0	0	0	0	129,900	259,800	389,700	129,900	129,900	129,900	129,900	0	0	0	0
0	0	0	0	0	0	0	168,500	337,000	505,500	168,500	168,500	168,500	105,313	0	0	0
0	0	0	0	0	0	0	0	225,900	451,800	677,700	225,900	225,900	141,188	84,713	0	0
0	0	0	0	0	0	0	0	0	135,000	270,000	405,000	135,000	84,375	50,625	33,750	0
0	0	0	0	0	0	0	0	0	0	140,000	280,000	420,000	87,500	52,500	35,000	35,000
0	0	0	0	0	0	0	0	0	0	0	135,000	270,000	472,500	50,625	33,750	33,750
0	0	0	0	0	0	0	0	0	0	0	0	230,700	576,750	922,800	57,675	57,675
0	0	0	0	0	0	0	0	0	0	0	0	0	274,800	549,600	824,400	45,800
0	0	0	0	0	0	0	0	0	0	0	0	0	0	360,000	720,000	1.080,000
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	582,000	1.164,000
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	784,500
178,333	193,533	253,108	328,683	430,450	598,200	778,900	1.014,400	1.294,000	1.464,100	1.560,000	1.443,200	1.580,000	1.742,425	2.070,863	2.286,575	3.200,725

Source: Author's elaboration

Table A.4: Weighted Lifespans

Weighted Lifespans																
2 s. 2010	1 s. 2011	2 s. 2011	1 s. 2012	2 s. 2012	1 s. 2013	2 s. 2013	1 s. 2014	2 s. 2014	1 s. 2015	2 s. 2015	1 s. 2016	2 s. 2016	1 s. 2017	2 s. 2017	1 s. 2018	2 s. 2018
960	528	600	672	504	0	0	0	0	0	0	0	0	0	0	0	0
960	1.104	600	672	504	396	0	0	0	0	0	0	0	0	0	0	0
960	1.104	1.248	672	504	396	324	0	0	0	0	0	0	0	0	0	0
0	144	288	432	504	396	324	288	0	0	0	0	0	0	0	0	0
0	0	50,5	101	151,5	138,88	113,63	101	101	0	0	0	0	0	0	0	0
0	0	0	50,5	101	202	113,63	101	101	101	0	0	0	0	0	0	0
0	0	0	0	50,5	151,5	252,5	101	101	101	101	0	0	0	0	0	0
0	0	0	0	0	101	202	303	101	101	101	101	0	0	0	0	0
0	0	0	0	0	0	54	108	162	54	54	54	54	0	0	0	0
0	0	0	0	0	0	0	54	108	162	54	54	54	16,88	0	0	0
0	0	0	0	0	0	0	0	54	108	162	54	54	16,88	10,13	0	0
0	0	0	0	0	0	0	0	0	54	108	162	54	16,88	10,13	6,75	0
0	0	0	0	0	0	0	0	0	0	54	108	162	16,88	10,13	6,75	6,75
0	0	0	0	0	0	0	0	0	0	0	54	108	94,5	10,13	6,75	6,75
0	0	0	0	0	0	0	0	0	0	0	0	54	67,5	108	6,75	6,75
0	0	0	0	0	0	0	0	0	0	0	0	0	40,5	81	121,5	6,75
0	0	0	0	0	0	0	0	0	0	0	0	0	0	40,5	81	121,5
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	40,5	81
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	40,5
2.880	2.880	2.787	2.600	2.319	1.781	1.384	1.056	728	681	634	587	540	270	270	270	270

Source: Author's elaboration

Table A.5: Biannual Electricity Cost

Semester	Year	Wwest	West	CEwest	CEest	biannualCE($/kWh)
2	2010	0,7	0,3	12,25	1,2	0,1345
1	2011	0,66875	0,33125	11,70313	1,325	0,13028125
2	2011	0,6375	0,3625	11,15625	1,45	0,1260625
1	2012	0,60625	0,39375	10,60938	1,575	0,12184375
2	2012	0,575	0,425	10,0625	1,7	0,117625
1	2013	0,54375	0,45625	9,515625	1,825	0,11340625
2	2013	0,5125	0,4875	8,96875	1,95	0,1091875
1	2014	0,48125	0,51875	8,421875	2,075	0,10496875
2	2014	0,45	0,55	7,875	2,2	0,10075
1	2015	0,41875	0,58125	7,328125	2,325	0,09653125
2	2015	0,3875	0,6125	6,78125	2,45	0,0923125
1	2016	0,35625	0,64375	6,234375	2,575	0,08809375
2	2016	0,325	0,675	5,6875	2,7	0,083875
1	2017	0,29375	0,70625	5,140625	2,825	0,07965625
2	2017	0,2625	0,7375	4,59375	2,95	0,0754375
1	2018	0,23125	0,76875	4,046875	3,075	0,07121875
2	2018	0,2	0,8	3,5	3,2	0,067

Source: Author’s elaboration

Table A.6: Deltas

2 s. 2010	1 s. 2011	2 s. 2011	1 s. 2012	2 s. 2012	1 s. 2013	2 s. 2013	1 s. 2014	2 s. 2014	1 s. 2015	2 s. 2015	1 s. 2016	2 s. 2016	1 s. 2017	2 s. 2017	1 s. 2018	2 s. 2018
Number of days																
184	181	184	182	184	181	184	181	184	181	184	182	184	181	184	181	184
Weighted Lifespans																
2880	2880	2786,5	2599,5	2319	1781,375	1383,75	1056	728	681	634	587	540	270	270	270	270
Weighted Devices' Price (Average Prices)																
178,333	193,5333333	253,1083333	328,6833333	430,45	598,2	778,9	1014,4	1294	1464,1	1560	1443,2	1580	1742,425	2070,8625	2286,575	3200,725
biannual Maintenance Cost biannualMAN($)																
0,06192	0,067199074	0,090833782	0,126440982	0,185618801	0,335808013	0,562890696	0,960606061	1,777472527	2,149926579	2,460567823	2,458603066	2,925925926	6,453425926	7,669861111	8,468796296	11,85454
Delta MAN																
2,9E-05	0,000130578	0,000193517	0,000325153	0,000816246	0,0012546	0,002161497	0,004513074	0,002024207	0,00171625	-1,0678E-05	0,002567708	0,019171196	0,006720636	0,004342039	0,01870575	0,000791
biannual Efficiency biannualEFF(J/Hash)																
6,6E-07	6,44953E-07	5,3952E-07	3,97772E-07	2,58448E-07	1,22266E-07	4,68895E-08	1,22372E-08	4,39445E-09	2,10289E-09	1,35613E-09	9,76062E-10	7,53864E-10	4,74549E-10	2,60445E-10	1,51442E-10	1,04E-10
Delta EFF																
-9,4E-11	-5,8251E-10	-7,7037E-10	-7,65519E-10	-7,4012E-10	-4,1645E-10	-1,8833E-10	-4,333E-11	-1,2454E-11	-4,1258E-12	-2,0656E-12	-1,22087E-12	-1,518E-12	-1,1829E-12	-5,9241E-13	-2,6346E-13	-4,1E-15
biannual Electricity Cost biannualCE($/kWh)																
0,1345	0,13028125	0,1260625	0,12184375	0,117625	0,11340625	0,1091875	0,10496875	0,10075	0,09653125	0,0923125	0,08809375	0,083875	0,07965625	0,0754375	0,07121875	0,067
Delta CE																
-2,3E-05	-2,3308E-05	-2,2928E-05	-2,31799E-05	-2,2928E-05	-2,3308E-05	-2,2928E-05	-2,3308E-05	-2,2928E-05	-2,3308E-05	-2,2928E-05	-2,31799E-05	-2,2928E-05	-2,3308E-05	-2,2928E-05	-2,3308E-05	-5,4E-06

Source: Author's elaboration

Table A.7: Block Time and Fees

DateTime	Hashrate	Difficulty	BT (s)	TOT Transaction Fees	Daily Transaction	Fees (BTC)
31/07/2010	2.464.398.497,64	244,213	425,6158	0,3	323	0,0009288
31/08/2010	5.701.927.397,06	623,387	469,5652	0,35	324	0,0010802
30/09/2010	9.570.510.422,87	1318,67	591,7808	0,0	976	0,0000000
31/10/2010	27.510.703.301,01	3091,737	482,6816	0,0	426	0,0000000
30/11/2010	68.953.790.963,51	6866,899	427,7228	0,03	456	6,58E-05
31/12/2010	116.641.878.937,44	14484,162	533,3333	0,0806039	565	0,0001427
31/01/2011	186.021.037.099,02	22012,381	508,2353	2,8210879	2.768	0,0010192
28/02/2011	414.505.489.254,17	55589,518	576	1,09	2.302	0,0004735
31/03/2011	689.209.762.451,73	68977,785	429,8507	4,0509	1.693	0,0023927
30/04/2011	1.030.377.325.650,24	109670,13	457,1429	7,7478269	3.632	0,0021332
31/05/2011	3.242.678.281.859,52	434877,05	576	18,242688	5.303	0,0034401
30/06/2011	13.094.963.916.948,80	1379192,3	452,356	20,008027	9.937	0,0020135
31/07/2011	14.709.605.099.479,30	1690895,8	493,7143	5,4575083	6.100	0,0008947
31/08/2011	13.697.915.570.338,70	1777774,5	557,4194	9,8799633	7.683	0,001286
30/09/2011	10.245.226.789.593,50	1689334,4	708,1967	3,3034121	5.388	0,0006131
31/10/2011	7.836.998.604.789,39	1203461,9	659,542	3,0873172	4.738	0,0006516
30/11/2011	8.783.602.827.814,50	1090715,7	533,3333	5,0343659	6.550	0,0007686
31/12/2011	8.706.721.615.131,83	1159929,5	572,1854	3,2551359	5.034	0,0006466
31/01/2012	9.751.129.414.143,54	1307728,4	576	28,379139	6.053	0,0046884
29/02/2012	12.246.527.873.312,90	1376302,3	482,6816	3,4994847	6.633	0,0005276
31/03/2012	13.745.590.058.278,80	1626553,5	508,2353	4,2526487	6.786	0,0006267
30/04/2012	13.423.639.484.651,40	1508589,7	482,6816	3,9405077	7.840	0,0005026
31/05/2012	10.914.801.619.952,20	1591075	626,087	19,028216	25.517	0,0007457
30/06/2012	11.329.307.771.943,70	1726566,6	654,5455	11,976852	23.222	0,0005158
31/07/2012	13.161.650.967.537,90	2036671,1	664,6154	20,1915	34.444	0,0005862
31/08/2012	16.985.500.288.894,50	2440642,6	617,1429	29,398627	34.045	0,0008635
30/09/2012	22.637.974.308.662,00	2864140,5	543,3962	13,885991	22.483	0,0006176
31/10/2012	23.653.504.403.772,50	3304356,4	600	23,812173	31.096	0,0007658
30/11/2012	21.368.636.454.168,60	3438909	691,2	28,942177	36.545	0,000792
31/12/2012	23.402.729.261.443,20	2979636,6	546,8354	33,267007	43.029	0,0007731
31/01/2013	28.482.674.089.138,00	2968775,3	447,6684	34,459397	41.090	0,0008386
28/02/2013	30.490.785.796.451,20	3651011,6	514,2857	57,564022	61.163	0,0009412
31/03/2013	56.251.874.756.664,30	6695826,3	511,2426	65,680689	60.832	0,0010797
30/04/2013	74.633.390.176.076,10	10076293	579,8658	45,746519	52.096	0,0008781
31/05/2013	105.726.140.279.199,00	12153412	493,7143	47,145952	56.516	0,0008342
30/06/2013	162.269.499.322.755,00	21335329	564,7059	24,446447	36.217	0,000675
31/07/2013	295.220.469.662.408,00	31256961	454,7368	38,709962	43.808	0,0008836
31/08/2013	728.865.067.652.167,00	65750060	387,4439	43,046084	61.944	0,0006949
30/09/2013	1.205.848.335.384.680,00	148819200	530,0613	25,451135	40.430	0,0006295
31/10/2013	4.100.400.017.728.000,00	390928788	409,4787	30,082821	49.095	0,0006127
30/11/2013	6.189.120.342.010.940,00	707408283	490,9091	25,947939	89.811	0,0002889
31/12/2013	10.801.537.922.461.200,00	1,181E+09	469,5652	11,692365	55.125	0,0002121
31/01/2014	20.066.445.524.103.800,00	2,194E+09	469,5652	13,333394	61.116	0,0002182
28/02/2014	28.158.518.665.937.100,00	3,13E+09	477,3481	14,685962	72.528	0,0002025

31/03/2014	44.800.630.179.722.400,00	5,007E+09	480	10,599807	54.971	0,0001928
30/04/2014	54.488.395.027.708.900,00	8,001E+09	630,6569	12,514559	64.708	0,0001934
31/05/2014	76.404.230.086.637.500,00	1,046E+10	587,7551	11,798537	65.979	0,0001788
30/06/2014	110.358.632.936.101.000,00	1,682E+10	654,5455	8,9302009	50.331	0,0001774
31/07/2014	143.434.608.511.561.000,00	1,874E+10	561,039	10,744746	65.667	0,0001636
31/08/2014	222.841.095.649.388.000,00	2,384E+10	459,5745	9,1553722	61.386	0,0001491
30/09/2014	263.623.410.749.534.000,00	3,466E+10	564,7059	12,353139	79.295	0,0001558
31/10/2014	336.304.905.509.895.000,00	3,599E+10	459,5745	13,717535	91.785	0,0001495
30/11/2014	320.532.059.789.074.000,00	4,03E+10	540	11,206979	80.187	0,0001398
31/12/2014	307.081.470.445.705.000,00	4,064E+10	568,4211	12,529827	83.173	0,0001506
31/01/2015	340.579.824.489.384.000,00	4,127E+10	520,4819	10,997977	79.874	0,0001377
28/02/2015	329.538.396.656.713.000,00	4,668E+10	608,4507	14,651859	103.737	0,0001412
31/03/2015	348.351.298.391.091.000,00	4,672E+10	576	15,038765	104.273	0,0001442
30/04/2015	317.142.355.890.591.000,00	4,761E+10	644,7761	16,907277	117.681	0,0001437
31/05/2015	359.082.535.929.914.000,00	4,881E+10	583,7838	16,07206	122.358	0,0001314
30/06/2015	356.089.184.959.351.000,00	4,94E+10	595,8621	18,812457	124.919	0,0001506
31/07/2015	392.414.063.077.807.000,00	5,228E+10	572,1854	34,198081	124.672	0,0002743
31/08/2015	423.446.540.478.744.000,00	5,426E+10	550,3185	19,542684	96.926	0,0002016
30/09/2015	436.537.293.643.837.000,00	5,934E+10	583,7838	27,498236	141.393	0,0001945
31/10/2015	454.915.351.205.089.000,00	6,225E+10	587,7551	31,187957	163.874	0,0001903
30/11/2015	585.641.183.501.102.000,00	7,272E+10	533,3333	22,430798	130.631	0,0001717
31/12/2015	733.276.604.663.887.000,00	1,04E+11	608,4507	31,016518	177.568	0,0001747
31/01/2016	1.080.007.040.825.580.000,00	1,20E+11	477,3481	39,032167	195.293	0,0001999
29/02/2016	1.080.919.494.946.580.000,00	1,63E+11	649,6241	45,836465	239.889	0,0001911
31/03/2016	1.020.134.644.775.590.000,00	1,65E+11	696,7742	45,017414	198.641	0,0002266
30/04/2016	1.296.655.181.852.460.000,00	1,79E+11	591,7808	49,381213	258.674	0,0001909
31/05/2016	1.258.297.790.411.960.000,00	1,99E+11	680,315	56,152944	206.139	0,0002724
30/06/2016	1.561.795.948.283.090.000,00	2,09E+11	576	61,677799	225.270	0,0002738
31/07/2016	1.634.366.548.269.600.000,00	2,13E+11	561,039	66,493384	199.563	0,0003332
31/08/2016	1.470.493.987.208.500.000,00	2,21E+11	644,7761	66,729189	248.782	0,0002682
30/09/2016	1.702.788.621.491.550.000,00	2,41E+11	608,4507	67,666403	241.285	0,0002804
31/10/2016	1.853.292.419.260.720.000,00	2,54E+11	587,7551	61,661948	205.888	0,0002995
30/11/2016	1.989.192.739.728.200.000,00	2,82E+11	608,4507	101,056	289.509	0,0003491
31/12/2016	2.337.271.653.891.100.000,00	3,18E+11	583,7838	99,824641	285.649	0,0003495
31/01/2017	2.832.474.910.223.240.000,00	3,93E+11	595,8621	138,07004	252.964	0,0005458
28/02/2017	3.352.427.031.868.180.000,00	4,41E+11	564,7059	198,13844	283.344	0,0006993
31/03/2017	3.352.999.966.358.030.000,00	5,00E+11	640	206,53209	286.240	0,0007215
30/04/2017	3.918.071.610.127.890.000,00	5,22E+11	572,1854	254,1149	342.452	0,000742
31/05/2017	4.858.244.024.949.570.000,00	5,96E+11	526,8293	589,40149	348.282	0,0016923
30/06/2017	5.448.313.580.843.890.000,00	7,12E+11	561,039	345,33975	232.242	0,001487
31/07/2017	6.200.470.684.210.650.000,00	8,60E+11	595,8621	144,59399	194.083	0,000745
31/08/2017	7.196.655.779.676.010.000,00	8,88E+11	530,0613	391,62567	275.899	0,0014195
30/09/2017	7.569.349.388.439.090.000,00	1,10E+12	626,087	115,05341	256.088	0,0004493
31/10/2017	9.966.505.886.699.330.000,00	1,45E+12	626,087	258,96021	316.229	0,0008189
30/11/2017	11.182.287.318.862.000.000,00	1,35E+12	517,3653	290,66332	399.046	0,0007284
31/12/2017	15.177.350.249.534.300.000,00	1,87E+12	530,0613	764,87176	338.192	0,0022616
31/01/2018	15.139.761.911.894.200.000,00	2,60E+12	738,4615	162,67806	239.721	0,0006786
28/02/2018	23.172.168.746.403.100.000,00	3,01E+12	557,4194	49,929181	215.529	0,0002317

31/03/2018	22.031.861.231.379.800.000,00	3,46E+12	675	25,665438	184.109	0,0001394
30/04/2018	30.990.335.301.692.100.000,00	4,02E+12	557,4194	35,451689	183.970	0,0001927
31/05/2018	36.396.936.182.652.700.000,00	4,31E+12	508,2353	22,629538	205.065	0,0001104
30/06/2018	35.588.942.295.590.800.000,00	5,08E+12	612,766	26,962117	194.781	0,0001384
31/07/2018	43.474.975.975.433.800.000,00	5,95E+12	587,7551	24,510049	231.194	0,000106
31/08/2018	51.833.889.753.678.900.000,00	6,73E+12	557,4194	23,998609	233.840	0,0001026
30/09/2018	57.956.171.195.079.300.000,00	7,15E+12	530,0613	19,399876	222.999	8,70E-05
31/10/2018	58.201.028.613.416.300.000,00	7,18E+12	530,0613	19,021598	287.918	6,61E-05
30/11/2018	33.404.486.801.782.100.000,00	6,65E+12	855,4455	44,471941	245.476	0,0001812
31/12/2018	39.345.457.366.303.000.000,00	5,11E+12	557,4194	13,277209	259.993	5,11E-05

Source: Author’s elaboration

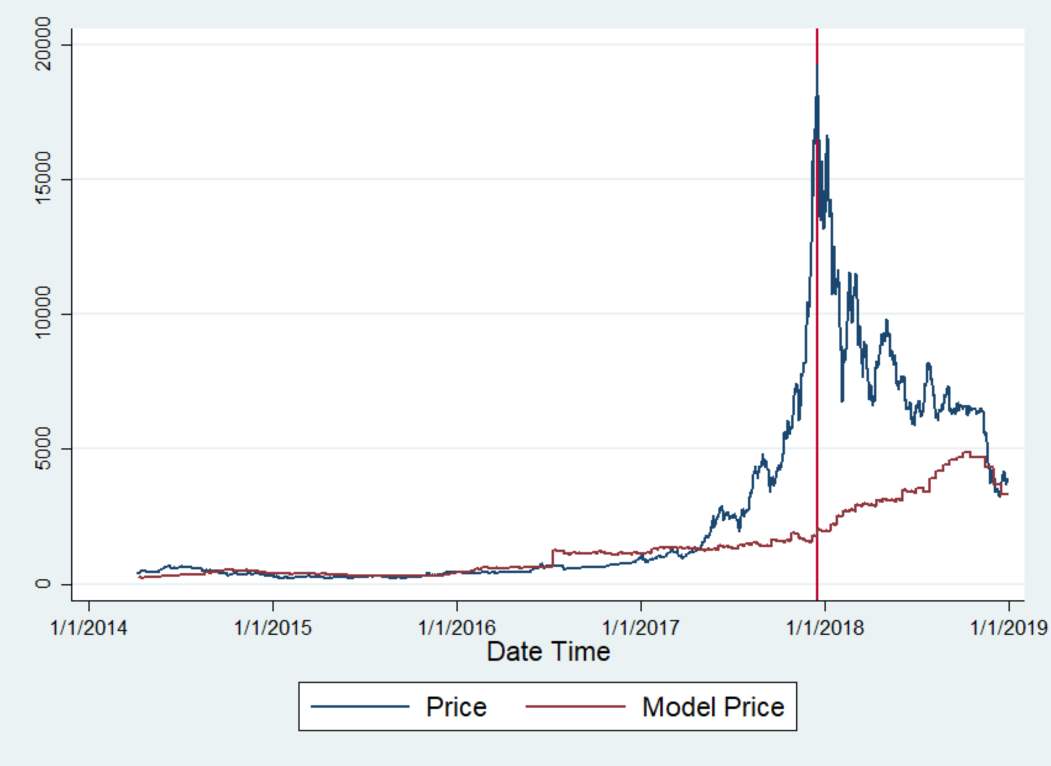
Table A.8: Model Price and Historical Price

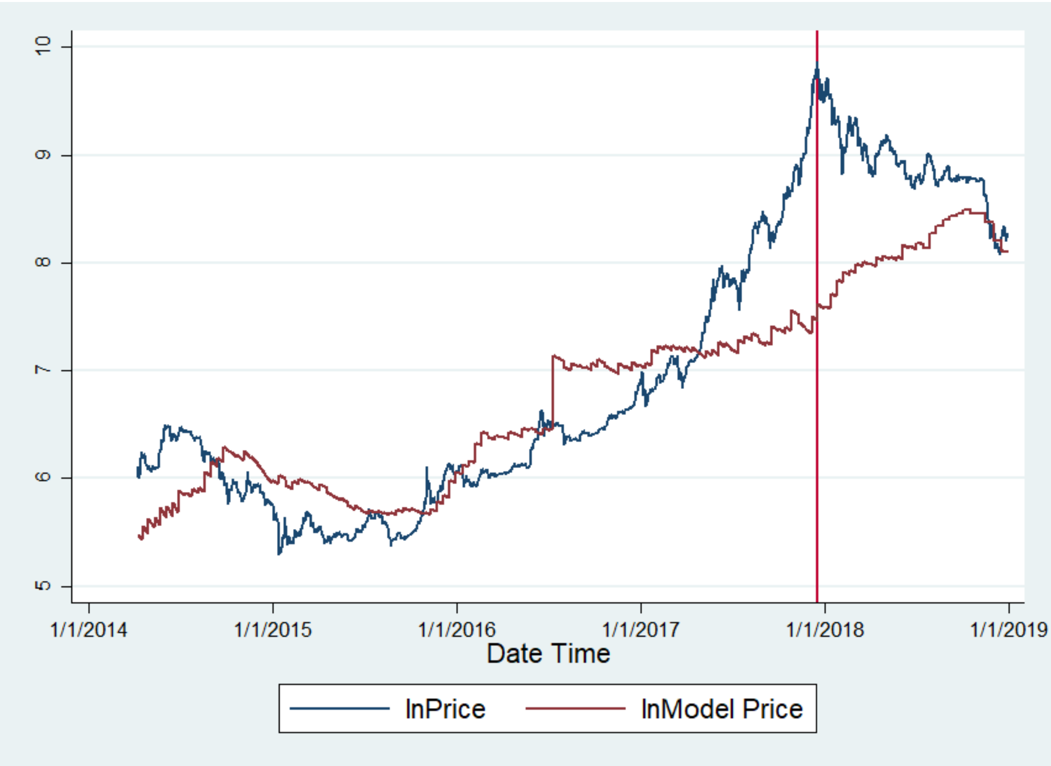
Date Time	Historical Hashrate (H/s)	EFF (J/hash)	CE ($/kWh)	MAN ($)	BR (BTC)	BTs	Fees (BTC)	COST	PROFIT	Model Price	Historical Price
31/07/2010	2.464.398.497,64	6,59E-07	0,13381216	0,06278	50	425,6158	0,00092879	5,28	10.150,00	0	0,06
31/08/2010	5.701.927.397,06	6,57E-07	0,13310139	0,06367	50	469,5652	0,00108025	12,02	9.200,00	0	0,06
30/09/2010	9.570.510.422,87	6,54E-07	0,13241355	0,06453	50	591,7808	0,00000000	19,95	7.300,00	0	0,06
31/10/2010	27.510.703.301,01	6,51E-07	0,13170279	0,06542	50	482,6816	0,00000000	56,66	8.950,00	0,01	0,19
30/11/2010	68.953.790.963,51	6,48E-07	0,13101495	0,06628	50	427,7228	6,58E-05	140,55	10.100,00	0,01	0,21
31/12/2010	116.641.878.937,44	6,45E-07	0,13030418	0,06717	50	533,3333	0,00014266	235,36	8.100,00	0,03	0,29
31/01/2011	186.021.037.099,02	6,27E-07	0,12958201	0,07112	50	508,2353	0,00101918	363,08	8.500,00	0,04	0,51
28/02/2011	414.505.489.254,17	6,11E-07	0,12892939	0,07477	50	576	0,0004735	783,96	7.500,00	0,1	0,88
31/03/2011	689.209.762.451,73	5,93E-07	0,12820684	0,07882	50	429,8507	0,00239274	1.257,87	10.050,00	0,13	0,79
30/04/2011	1.030.377.325.650,24	5,76E-07	0,1275076	0,08274	50	457,1429	0,00213321	1.815,14	9.450,00	0,19	3,29
31/05/2011	3.242.678.281.859,52	5,58E-07	0,12678505	0,08679	50	576	0,00344007	5.501,68	7.500,00	0,73	8,88
30/06/2011	13.094.963.916.948,80	5,40E-07	0,12608581	0,0907	50	452,356	0,00201349	21.402,26	9.550,00	2,24	16,51
31/07/2011	14.709.605.099.479,30	5,16E-07	0,12537466	0,09664	50	493,7143	0,00089467	22.856,91	8.750,00	2,61	13,52
31/08/2011	13.697.915.570.338,70	4,93E-07	0,12466389	0,10264	50	557,4194	0,00128595	20.185,48	7.750,00	2,6	8,35
30/09/2011	10.245.226.789.593,50	4,69E-07	0,12397605	0,10844	50	708,1967	0,00061311	14.309,76	6.100,00	2,35	5,01
31/10/2011	7.836.998.604.789,39	4,46E-07	0,12326529	0,11444	50	659,542	0,00065161	10.329,72	6.550,00	1,58	3,19
30/11/2011	8.783.602.827.814,50	4,22E-07	0,12257745	0,12025	50	533,3333	0,00076861	10.915,61	8.100,00	1,35	2,91
31/12/2011	8.706.721.615.131,83	3,99E-07	0,12186668	0,12625	50	572,1854	0,00064663	10.149,19	7.550,00	1,34	4,6
31/01/2012	9.751.129.414.143,54	3,75E-07	0,12114835	0,1362	50	576	0,00468844	10.626,66	7.500,00	1,42	5,53
29/02/2012	12.246.527.873.312,90	3,53E-07	0,12047613	0,14563	50	482,6816	0,00052759	12.485,93	8.950,00	1,4	4,82
31/03/2012	13.745.590.058.278,80	3,29E-07	0,11975756	0,1557	50	508,2353	0,00062668	12.993,16	8.500,00	1,53	4,88
30/04/2012	13.423.639.484.651,40	3,06E-07	0,11906216	0,16546	50	482,6816	0,00050262	11.734,25	8.950,00	1,31	4,94
31/05/2012	10.914.801.619.952,20	2,82E-07	0,11834358	0,17554	50	626,087	0,00074571	8.747,93	6.900,00	1,27	5,15
30/06/2012	11.329.307.771.943,70	2,59E-07	0,11764818	0,18529	50	654,5455	0,00051576	8.292,15	6.600,00	1,26	6,64
31/07/2012	13.161.650.967.537,90	2,36E-07	0,11693716	0,21011	50	664,6154	0,00058621	8.726,62	6.500,00	1,34	9,24
31/08/2012	16.985.500.288.894,50	2,13E-07	0,11622639	0,23541	50	617,1429	0,00086352	10.106,41	7.000,00	1,44	10,19
30/09/2012	22.637.974.308.662,00	1,91E-07	0,11553855	0,2599	50	543,3962	0,00061762	11.996,08	7.950,00	1,51	12,35
31/10/2012	23.653.504.403.772,50	1,68E-07	0,11482779	0,2852	50	600	0,00076576	10.961,53	7.200,00	1,52	10,99
30/11/2012	21.368.636.454.168,60	1,46E-07	0,11413995	0,30969	25	691,2	0,00079196	8.543,69	3.125,00	2,73	12,51
31/12/2012	23.402.729.261.443,20	1,23E-07	0,11342918	0,33499	25	546,8354	0,00077313	7.836,98	3.950,00	1,98	13,44
31/01/2013	28.482.674.089.138,00	1,10E-07	0,11270701	0,37345	25	447,6684	0,00083863	8.457,79	4.825,00	1,75	20,53
28/02/2013	30.490.785.796.451,20	9,81E-08	0,11205439	0,40857	25	514,2857	0,00094116	8.045,52	4.200,00	1,92	32,67
31/03/2013	56.251.874.756.664,30	8,52E-08	0,11133184	0,44747	25	511,2426	0,00107971	12.806,64	4.225,00	3,03	92,59
30/04/2013	74.633.390.176.076,10	7,27E-08	0,1106326	0,48511	25	579,8658	0,00087812	14.408,91	3.725,00	3,87	138,98
31/05/2013	105.726.140.279.199,00	5,98E-08	0,10991005	0,524	25	493,7143	0,00083421	16.677,88	4.375,00	3,81	127,95
30/06/2013	162.269.499.322.755,00	4,73E-08	0,10921081	0,56164	25	564,7059	0,000675	20.120,62	3.825,00	5,26	94,26
31/07/2013	295.220.469.662.408,00	4,12E-08	0,10849966	0,62774	25	454,7368	0,00088363	31.703,67	4.750,00	6,67	104,48
31/08/2013	728.865.067.652.167,00	3,54E-08	0,10778889	0,69474	25	387,4439	0,00069492	66.751,11	5.575,00	11,97	136,3
30/09/2013	1.205.848.335.384.680,00	2,98E-08	0,10710105	0,75959	25	530,0613	0,00062951	92.217,33	4.075,00	22,63	133,44
31/10/2013	4.100.400.017.728.000,00	2,39E-08	0,10639029	0,82659	25	409,4787	0,00061275	250.371,13	5.275,00	47,46	205,74
30/11/2013	6.189.120.342.010.940,00	1,83E-08	0,10570245	0,89144	25	490,9091	0,00028892	286.757,64	4.400,00	65,17	1.103,89
31/12/2013	10.801.537.922.461.200,00	1,24E-08	0,10499168	0,95844	25	469,5652	0,00021211	338.195,63	4.600,00	73,52	749,09
31/01/2014	20.066.445.524.103.800,00	1,09E-08	0,10426951	1,096	25	469,5652	0,00021817	549.224,69	4.600,00	119,4	827,63
28/02/2014	28.158.518.665.937.100,00	9,72E-09	0,10361689	1,22236	25	477,3481	0,00020249	680.925,85	4.525,00	150,48	552,85
31/03/2014	44.800.630.179.722.400,00	8,38E-09	0,10289434	1,36227	25	480	0,00019283	927.201,32	4.500,00	206,04	458,66
30/04/2014	54.488.395.027.708.900,00	7,08E-09	0,1021951	1,49766	25	630,6569	0,0001934	946.314,38	3.425,00	276,3	445,96
31/05/2014	76.404.230.086.637.500,00	5,74E-09	0,10147255	1,63757	25	587,7551	0,00017882	1.067.613,98	3.675,00	290,51	616,81
30/06/2014	110.358.632.936.101.000,00	4,44E-09	0,10077331	1,77296	25	654,5455	0,00017743	1.184.483,61	3.300,00	358,93	621,19
31/07/2014	143.434.608.511.561.000,00	4,02E-09	0,10006216	1,8382	25	561,039	0,00016363	1.385.002,64	3.850,00	359,74	573,09
31/08/2014	222.841.095.649.388.000,00	3,63E-09	0,09935139	1,90095	25	459,5745	0,00014914	1.931.323,58	4.700,00	410,92	489,75
30/09/2014	263.623.410.749.534.000,00	3,26E-09	0,09866355	1,96168	25	564,7059	0,00015579	2.035.727,82	3.825,00	532,22	381,08
31/10/2014	336.304.905.509.895.000,00	2,88E-09	0,09795279	2,02443	25	459,5745	0,00014945	2.273.037,82	4.700,00	483,63	342,38
30/11/2014	320.532.059.789.074.000,00	2,50E-09	0,09726495	2,08515	25	540	0,00013976	1.871.660,48	4.000,00	467,92	378,9
31/12/2014	307.081.470.445.705.000,00	2,12E-09	0,09655418	2,1479	25	568,4211	0,00015065	1.505.284,24	3.800,00	396,13	315,19
31/01/2015	340.579.824.489.384.000,00	1,98E-09	0,09583201	2,20141	25	520,4819	0,00013769	1.550.292,53	4.150,00	373,56	228,53
28/02/2015	329.538.396.656.713.000,00	1,86E-09	0,09517939	2,24947	25	608,4507	0,00014124	1.402.856,28	3.550,00	395,17	253,52
31/03/2015	348.351.298.391.091.000,00	1,74E-09	0,09445684	2,30267	25	576	0,00014423	1.370.683,33	3.750,00	365,52	246,73
30/04/2015	317.142.355.890.591.000,00	1,61E-09	0,0937576	2,35416	25	644,7761	0,00014367	1.150.317,17	3.350,00	343,38	232,83
31/05/2015	359.082.535.929.914.000,00	1,48E-09	0,09303505	2,40736	25	583,7838	0,00013135	1.189.855,46	3.700,00	321,58	233,76
30/06/2015	356.089.184.959.351.000,00	1,36E-09	0,09233581	2,45885	25	595,8621	0,0001506	1.073.396,69	3.625,00	296,11	263,29

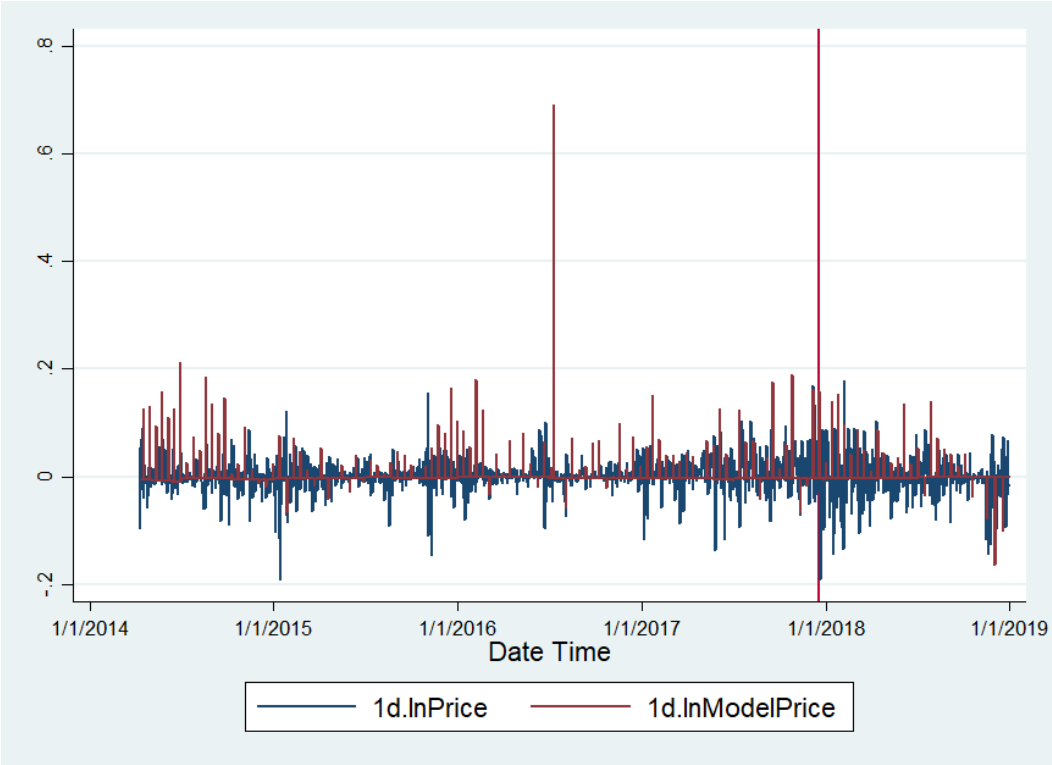
31/07/2015	392.414.063.077.807.000,00	1,29E-09	0,09162466	2,46025	25	572,1854	0,0002743	1.116.751,62	3.775,00	295,83	286,98
31/08/2015	423.446.540.478.744.000,00	1,23E-09	0,09091389	2,45992	25	550,3185	0,00020163	1.136.555,49	3.925,00	289,57	229,97
30/09/2015	436.537.293.643.837.000,00	1,17E-09	0,09022605	2,4596	25	583,7838	0,00019448	1.104.250,41	3.700,00	298,45	238,73
31/10/2015	454.915.351.205.089.000,00	1,10E-09	0,08951529	2,45927	25	587,7551	0,00019032	1.079.093,30	3.675,00	293,63	323,74
30/11/2015	585.641.183.501.102.000,00	1,04E-09	0,08882745	2,45894	25	533,3333	0,00017171	1.301.143,68	4.050,00	321,27	376,91
31/12/2015	733.276.604.663.887.000,00	9,78E-10	0,08811668	2,45861	25	608,4507	0,00017467	1.516.817,82	3.550,00	427,27	427,23
31/01/2016	1.080.007.040.825.580.000,00	9,39E-10	0,08739835	2,53563	25	477,3481	0,00019987	2.128.181,98	4.525,00	470,32	380,6
29/02/2016	1.080.919.494.946.580.000,00	9,04E-10	0,08672613	2,6101	25	649,6241	0,00019107	2.033.940,78	3.325,00	611,71	437,64
31/03/2016	1.020.134.644.775.590.000,00	8,66E-10	0,08600756	2,6897	25	696,7742	0,00022663	1.823.962,81	3.100,00	588,38	419,06
30/04/2016	1.296.655.181.852.460.000,00	8,30E-10	0,08531216	2,76673	25	591,7808	0,0001909	2.202.387,48	3.650,00	603,39	454,91
31/05/2016	1.258.297.790.411.960.000,00	7,92E-10	0,08459358	2,84633	25	680,315	0,0002724	2.022.549,30	3.175,00	637,02	536,74
30/06/2016	1.561.795.948.283.090.000,00	7,55E-10	0,08389818	2,92336	25	576	0,0002738	2.374.565,31	3.750,00	633,22	656,19
31/07/2016	1.634.366.548.269.600.000,00	7,08E-10	0,08318716	3,50106	12,5	561,039	0,0003332	2.311.261,70	1.925,00	1.200,66	637,11
31/08/2016	1.470.493.987.208.500.000,00	6,61E-10	0,08247639	4,09537	12,5	644,7761	0,00026822	1.924.777,31	1.675,00	1.149,12	575,59
30/09/2016	1.702.788.621.491.550.000,00	6,16E-10	0,08178855	4,6705	12,5	608,4507	0,00028044	2.058.030,90	1.775,00	1.159,45	607,31
31/10/2016	1.853.292.419.260.720.000,00	5,69E-10	0,08107779	5,26481	12,5	587,7551	0,00029949	2.050.763,15	1.837,50	1.116,06	703,38
30/11/2016	1.989.192.739.728.200.000,00	5,23E-10	0,08038995	5,83995	12,5	608,4507	0,00034906	2.007.692,39	1.775,00	1.131,09	743,19
31/12/2016	2.337.271.653.891.100.000,00	4,76E-10	0,07967918	6,43425	12,5	583,7838	0,00034947	2.127.820,45	1.850,00	1.150,17	960,06
31/01/2017	2.832.474.910.223.240.000,00	4,39E-10	0,07895701	6,65505	12,5	595,8621	0,00054581	2.356.652,68	1.812,50	1.300,22	944,21
28/02/2017	3.352.427.031.868.180.000,00	4,06E-10	0,07830439	6,84322	12,5	564,7059	0,00069929	2.557.532,97	1.912,50	1.337,27	1.179,77
31/03/2017	3.352.999.966.358.030.000,00	3,69E-10	0,07758184	7,05156	12,5	640	0,00072154	2.305.431,71	1.687,50	1.366,18	1.045,03
30/04/2017	3.918.071.610.127.890.000,00	3,34E-10	0,0768826	7,25318	12,5	572,1854	0,00074205	2.413.124,23	1.887,50	1.278,48	1.331,06
31/05/2017	4.858.244.024.949.570.000,00	2,97E-10	0,07616005	7,46152	12,5	526,8293	0,00169231	2.638.419,76	2.050,00	1.287,03	2.253,65
30/06/2017	5.448.313.580.843.890.000,00	2,62E-10	0,07546081	7,66314	12,5	561,039	0,00148698	2.581.552,37	1.925,00	1.341,07	2.519,27
31/07/2017	6.200.470.684.210.650.000,00	2,43E-10	0,07474966	7,80012	12,5	595,8621	0,00074501	2.699.406,28	1.812,50	1.489,33	2.787,33
31/08/2017	7.196.655.779.676.010.000,00	2,24E-10	0,07403889	7,93473	12,5	530,0613	0,00141945	2.868.460,96	2.037,50	1.407,83	4.689,86
30/09/2017	7.569.349.388.439.090.000,00	2,07E-10	0,07335105	8,06499	12,5	626,087	0,00044927	2.752.160,90	1.725,00	1.595,46	4.286,64
31/10/2017	9.966.505.886.699.330.000,00	1,88E-10	0,07264029	8,19959	12,5	626,087	0,0008189	3.269.542,29	1.725,00	1.895,39	6.248,49
30/11/2017	11.182.287.318.862.000.000,00	1,70E-10	0,07195245	8,32985	12,5	517,3653	0,0007284	3.290.459,48	2.087,50	1.576,27	9.947,53
31/12/2017	15.177.350.249.534.300.000,00	1,52E-10	0,07124168	8,46445	12,5	530,0613	0,00226165	3.945.345,24	2.037,50	1.936,36	13.205,27
31/01/2018	15.139.761.911.894.200.000,00	1,44E-10	0,07051951	9,02997	12,5	738,4615	0,00067861	3.677.978,07	1.462,50	2.514,86	10.044,73
28/02/2018	23.172.168.746.403.100.000,00	1,36E-10	0,06986689	9,55373	12,5	557,4194	0,00023166	5.290.600,85	1.937,50	2.730,63	10.684,50
31/03/2018	22.031.861.231.379.800.000,00	1,28E-10	0,06914434	10,13361	12,5	675	0,0001394	4.679.625,97	1.600,00	2.924,77	7.076,98
30/04/2018	30.990.335.301.692.100.000,00	1,20E-10	0,0684451	10,69478	12,5	557,4194	0,0001927	6.113.500,47	1.937,50	3.155,35	9.275,36
31/05/2018	36.396.936.182.652.700.000,00	1,12E-10	0,06772255	11,27466	12,5	508,2353	0,00011035	6.621.116,56	2.125,00	3.115,82	7.554,11
30/06/2018	35.588.942.295.590.800.000,00	1,04E-10	0,06702331	11,83583	12,5	612,766	0,00013842	5.954.819,71	1.762,50	3.378,62	6.387,05
31/07/2018	43.474.975.975.433.800.000,00	1,04E-10	0,06683696	11,87825	12,5	587,7551	0,00010602	7.227.128,45	1.837,50	3.933,13	7.981,32
31/08/2018	51.833.889.753.678.900.000,00	1,04E-10	0,06666848	11,90276	12,5	557,4194	0,00010263	8.584.395,67	1.937,50	4.430,66	6.977,97
30/09/2018	57.956.171.195.079.300.000,00	1,03E-10	0,06650544	11,92648	12,5	530,0613	8,70E-05	9.563.447,82	2.037,50	4.693,72	6.599,64
31/10/2018	58.201.028.613.416.300.000,00	1,03E-10	0,06633696	11,95099	12,5	530,0613	6,61E-05	9.567.716,85	2.037,50	4.695,81	6.328,46
30/11/2018	33.404.486.801.782.100.000,00	1,03E-10	0,06617391	11,9747	12,5	855,4455	0,00018117	5.471.359,20	1.262,50	4.333,75	4.045,47
31/12/2018	39.345.457.366.303.000.000,00	1,03E-10	0,06600544	11,99921	12,5	557,4194	5,11E-05	6.420.086,82	1.937,50	3.313,59	3.806,18

Source: Author’s elaboration

Figure A.1: Time series







Source: Author's elaboration

Table A.9: Johansen tests for cointegration

1) Unrestricted trend

Johansen tests for cointegration

Trend: trend Number of obs = 1726
Sample: 3 - 1728 Lags = 2

maximum rank	parms	LL	eigenvalue	trace statistic	5% critical value
0	8	7241.364	.	18.6318	18.17
1	11	7248.394	0.00811	4.5719	3.74
2	12	7250.6799	0.00265		

maximum rank	parms	LL	eigenvalue	max statistic	5% critical value
0	8	7241.364	.	14.0599	16.87
1	11	7248.394	0.00811	4.5719	3.74
2	12	7250.6799	0.00265		

2) Restricted trend

Johansen tests for cointegration

Trend: rtrend Number of obs = 1726
Sample: 3 - 1728 Lags = 2

maximum rank	parms	LL	eigenvalue	trace statistic	5% critical value
0	6	7241.3364	.	18.6871*	25.32
1	10	7248.3669	0.00811	4.6261	12.25
2	12	7250.6799	0.00268		

maximum rank	parms	LL	eigenvalue	max statistic	5% critical value
0	6	7241.3364	.	14.0610	18.96
1	10	7248.3669	0.00811	4.6261	12.52
2	12	7250.6799	0.00268		

3) Unrestricted constant

Johansen tests for cointegration

Trend: constant Number of obs = 1726
Sample: 3 - 1728 Lags = 2

maximum rank	parms	LL	eigenvalue	trace statistic	5% critical value
0	6	7241.3364	.	10.4132*	15.41
1	9	7246.3748	0.00582	0.3364	3.76
2	10	7246.543	0.00019		

maximum rank	parms	LL	eigenvalue	max statistic	5% critical value
0	6	7241.3364	.	10.0768	14.07
1	9	7246.3748	0.00582	0.3364	3.76
2	10	7246.543	0.00019		

4) Restricted constant

Johansen tests for cointegration

Trend: rconstant — Number of obs = 1726
Sample: 3 - 1728 — Lags = 2

maximum rank	parms	LL	eigenvalue	trace statistic	5% critical value
0	4	7237.7238	.	17.6383*	19.96
1	8	7245.9474	0.00948	1.1912	9.42
2	10	7246.543	0.00069		

maximum rank	parms	LL	eigenvalue	max statistic	5% critical value
0	4	7237.7238	.	16.4471	15.67
1	8	7245.9474	0.00948	1.1912	9.24
2	10	7246.543	0.00069		

5) No trend

Johansen tests for cointegration

Trend: none — Number of obs = 1726
Sample: 3 - 1728 — Lags = 2

maximum rank	parms	LL	eigenvalue	trace statistic	5% critical value
0	4	7237.7238	.	12.3538*	12.53
1	7	7243.325	0.00647	1.1515	3.84
2	8	7243.9007	0.00067		

maximum rank	parms	LL	eigenvalue	max statistic	5% critical value
0	4	7237.7238	.	11.2023	11.44
1	7	7243.325	0.00647	1.1515	3.84
2	8	7243.9007	0.00067		

Source: Author's elaboration

Table A.10: Stability and Autocorrelation test

1) Stability test

Eigenvalue stability condition

Eigenvalue	Modulus
.1830552	.183055
-.028745	.028745

All the eigenvalues lie inside the unit circle.
VAR satisfies stability condition.

2) Autocorrelation test

Lagrange-multiplier test

lag	chi2	df	Prob > chi2
1	4.3358	4	0.36247
2	4.2015	4	0.37942

H0: no autocorrelation at lag order

Source: Author's elaboration

Table A.11: Breusch-Pagan test

1) Breusch-Pagan test *dlnPrice*

```
Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
         Ho: Constant variance
         Variables: fitted values of dlnPrice

         chi2(1)      =    160.31
         Prob > chi2  =    0.0000
```

2) Breusch-Pagan test *dlnModelPrice*

```
Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
         Ho: Constant variance
         Variables: fitted values of dlnModelPrice

         chi2(1)      =     22.37
         Prob > chi2  =    0.0000
```

Source: Author's elaboration