THE INNOVATIVE ASPECTS OF BITCOIN, MARKET MICROSTRUCTURE AND RETURNS VOLATILITY: AN APPROACH USING MGARCH

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ABSTRACT

This study seeks to analyze conceptual, innovative, marketing and quantitative aspects of Bitcoin (BTC) and how these are reflected in the volatility of its return. After describing basic concepts of digital currencies and BTC, an electronic currency created in 2009, we contextualize BTC as a financial innovation. Regarding market-oriented and structural aspects, we investigated the existence of similarities between BTC's credit and debit market and the traditional structure of the payment card market, known as the Two-Sided Market (2SM). The BTC's perfect adequacy for the 2SM structure was established, but only with respect to the debit-card market. BTC returns for the period from September 2011 to June 2015 were then used as a sample, and returns for the period from March 2013 to June 2015 were used as a subsample. Based on these data, the DCC MGARCH model was estimated, making it possible to obtain the parameters and quasi-correlations of volatilities among variables. The Standard and Poor's 500 index (SPX-500), the price of gold and China's main stock index (SSEC) were considered by virtue of previous exercises conducted by Pavel, D'Artis and Miroslava (2014) and Stråle and Tjernström (2014). The results showed the existence of persistent volatility, possibly indicating that BTC returns had two different phases: (1) a period of "euphoria" followed by (2) a period of "convergence" to the fundamentals that determine these returns.

Keywords: Bitcoin. Innovation. 2SM. Volatility. DCC MGARCH.

RESUMO

A presente pesquisa buscou analisar aspectos conceituais, inovativos, mercadológicos e quantitativos do Bitcoin (BTC) e como os mesmos se traduziram na volatilidade dos seus retornos. Após expostos conceitos basilares sobre as moedas digitais e o BTC, moeda eletrônica criada em 2009, buscou-se contextualizá-la como inovação financeira. Quanto aos aspectos mercadológicos e estruturais, foi investigada a existência de semelhanças entre o mercado de crédito e débito do Bitcoin e a estrutura tradicional do mercado de cartões, conhecida por Mercado de Dois Lados (M2L). Verificou-se a perfeita adequação do BTC à estrutura M2L, mas apenas no mercado de cartões de débito. Mais adiante, foram usadas como amostra os retornos do BTC do período de Setembro de 2011 a Junho de 2015 e, como subamostra, a janela temporal a partir de Março de 2013 a Junho de 2015. A partir desse conjunto de informações, estimou-se o modelo DCC MGARCH, que possibilitou a obtenção dos parâmetros e das quasicorrelações das volatilidades entre as variáveis. Foram consideradas o índice *Standard and Poor's 500* (SPX-500), a cotação do ouro e o principal índice da bolsa da China (SSEC), em virtude de exercícios anteriores realizados por Pavel, D'Artis e Miroslava (2014) e Stråle e Tjernström (2014). Os resultados apontaram existência de volatilidade persistente e que mostra, possivelmente, que os retornos da moeda tiveram duas fases: primeiramente um momento de 'euforia' e depois de 'convergência' aos fundamentos que determinam os mesmos.

Palavras-Chave: Bitcoin. Inovação. M2L. Volatilidade. DCC MGARCH.

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1 INTRODUCTION

A stable price system is essential to the fulfillment of contracts, to issue securities (private or public) and even to the existence and functioning of the financial market. In this regard, the tasks of regulating the financial system, issuing a currency and maintaining its purchasing power are traditionally assigned to the State. Therefore, monetary policies affect social wellbeing by changing a currency's fiduciary power.

That notwithstanding, globalization has not only enabled the opening of new markets but also strengthened trade ties and created zones of influence. New products and markets are emerging at great speed. More interconnected markets can render the environment more sensitive to fluctuations. It can be argued that financial crises have increased the capacity for contagion; commercial interdependence among countries is worrisome. Accordingly, there are calls for greater regulation of these markets, including the creation of laws and government agencies to instill discipline in the financial system.

Governmental actions can compromise a currency's desirability. Participation in conflicts, import-substitution policies, fixed exchange-rate regimes, economic rescue plans and seigniorage are examples of strategies that involve—at least momentarily, and regardless of success—some degree of currency depreciation to affect the price system.

Mediums of exchange reflect the level of social and technological organization. For example, bartering was the main form of peaceful acquisition of goods and services, but this social dynamic was gradually transformed by socioeconomic, cultural and technological events and processes so that with the passage of time, the use of currencies has dominated other forms of trading and become the norm. Credit and debit cards represent a new technical advancement, providing ease of use, security and the ability to change consumer behavior. The proliferation of digital payment methods (i.e., eWallets) such as Paypal, Google Wallet and MoneyGram has further facilitated e-commerce transactions.

Digital currencies represent an electronic medium of exchange with all of the functions and features of traditional currencies, except that they are not physically tangible. Characteristics such as homogeneity, divisibility, portability and ease of handling and transport are even more evident in digital currencies than in physical currency.

Bitcoin (BTC) is the digital currency with the highest liquidity and daily trading volume on the financial markets. In addition, because it was the first digital currency, there are more observations of its series of quoted prices; moreover, the movements of its series reflect not only quantitative aspects but also social changes. BTC is a non-centralized, encrypted currency[3]. It is not governed by statute and is not legal tender.

Having presented some of the characteristics of the proposed topic, this study aims to analyze some of the microeconomic and macroeconomic factors that have led to volatility in BTC returns that have two phases of behavior. To this end, BTC is contextualized according to financial innovation concepts and an attempt is made to analyze BTC from a microeconomic perspective using the theoretical structure of two-sided markets (2SM) to identify similarities to and differences from traditional credit and debit systems. Next, based on Pavel, D'Artis and Miroslava (2014) and Stråle and Tjernström (2014), dynamic conditional correlation multivariate generalized autoregressive conditional heteroskedasticity (DCC MGARCH) models were used to estimate the parameters of the volatilities and their quasi-correlations between variables. The Standard and Poor's 500 index (SPX-500), the price of gold and China's main stock index (SSEC) were considered for this purpose.

This article is organized as follows. Following this brief introduction, section 2 presents theoretical concepts related to both innovation and financial innovation. Section 3 presents the characteristics of BTC. Section 4 sets out the theoretical framework of the two-sided market and notes similarities and differences between the payment card market and BTC. Section 5 presents the methods.

[3]Cryptography is the study of the principles and techniques by which information can be transformed from its original form to another unreadable form so that it can be understood by only the addressee (holder of the "secret key"), thus making it difficult for an unauthorized party to read. Therefore, only the message recipient can easily read the information.

Sample planning and treatment is described in the sixth section. The results obtained are presented in section 7, and section 8 contains the conclusions.

2 INNOVATION ECONOMICS

Innovation economics seeks to identify the causes, dynamics and effects of innovation processes because they transform primary structures, restructuring industries and markets. This section provides a brief review of innovation economics and aims to apply the literature originally conceived for production structures to BTC and other decentralized digital currencies.

2.1 Financial Innovations

According to Jensen et al. apud Oliveira and Torkomian (2009), there are two types of knowledge: *encoded knowledge* and so-called *tacit knowledge*. The first is relatively easy to transmit, whereas the second depends on learning. These concepts are quite common in evolutionary innovation models. Application of these concepts facilitates understanding of the process of market creation in the form of conglomerates.

As a result of the centralization of capital, large financial centers emerge that are geographically clumped together. This conformity depends not only on historical economic and social factors but also on existing externalities in the financial sector. These characteristics promote the maintenance of a production structure in the formation of agglomerates. It can be said that production clusters are knowledge-sharing spaces, emphasizing learning as a localized process that occurs through social interaction and embeddedness, strengthening innovation networks and practices (IPIRANGA, 2006 apud OLIVEIRA; TORKOMIAN 2009, p.4).

The main themes analyzed from the perspective of financial innovation are shared risk and its economic implications, information asymmetry, transaction costs and the role of regulatory restrictions. It is frequently argued that financial markets are excessively affected by intermediaries at the expense of savers and entrepreneurs. The role of intermediaries completes markets by attracting agents and, if economies of scale are found, by lowering costs. Radical financial innovation facilitates the extension of risk management beyond its previous limits, including new risk classes, modifying assumptions regarding financial insurance, hedging strategies and diversification.

The same diffusion process brought about by innovation in other sectors is also observed in financial innovation processes. Schiller (2007, p. 306) argues that financial innovation processes are continuous and tend toward diffusion. The author points to the role of information technology, the understanding of behavior, and psychology applied to finance as determinants of diffusion.

It is understood that full risk sharing, as conceived by Kenneth Arrow, in which there is a market for each price, for each risk and for each natural state, is difficult to measure. Thus, problems such as information asymmetry and its manifestations in the form of *adverse selection* and *moral hazard* associated with risk management involve transaction costs that can be reduced. Wonglimpiyarat (2011) obtains results suggesting that financial innovations affect economic performance by promoting business activities. This is an important sector of the innovation system that can be seen as linking financing and innovation.

The emergence of digital currencies, for example, represents the possibility of disconnecting the financial system from political objectives. It allows users autonomy because they can avoid currencies that have high potential to lose value. Network externalities are also relevant to the increased adoption of user-encrypted currencies because they constitute a special type of externality in which the degree of utility gained by an individual depends on the number of users of the same good. When an individual's willingness to pay exceeds the costs, the market expands and given that at least two equilibria are possible in markets that have network externalities, there is a tendency for the market to reach an equilibrium with a large number of agents.

In markets with network externality characteristics, producers may initially cause disturbances with deals, price discrimination and other strategies to attract users to the network. In the case of digital currencies, at least three factors may determine the network's ability to be attractive: reliability, the possibility of profit, and the maintenance of an entrant rate until the formation of critical mass, which is given by a of volume users that when achieved, makes the network attractive to non-participants because of that network's very existence.

In addition to BTC, there is an increasing number of other digital currencies. Each such currency emphasizes certain aspects that its creators understand to be the most desirable. Among the most popular include the following:

- *Litecoin* - Although this currency closely resembles BTC, its issuance is constrained to 84 million monetary units, and the difficulty of mining represents something close to a quarter, which allows the use of simpler equipment. The initial appeal of this currency was the relative ease of mining. It is important to note that the mining algorithm of Litecoin is different from that of BTC.
- *Dogecoin* – This currency has unlimited issuance with the clear objective of avoiding becoming a currency with deflationary tendencies and facilitating the eventual formation of a credit market.
- *PPcoin* – This currency offers a nondeterministic money supply and has advantages related to its security module. The return on every mined block depends on mining difficulty, with a new block issued every ten minutes;
- *Dash* (previously known as *Darkcoin*) – This currency aims to make transactions anonymous by increasing tracing difficulty through fictitious transactions.

The initial issuance of BTC at a symbolic value of $ 0.01 was seen as indicating a profound respect for the market, granting users full power to attribute value through the power of supply and demand. It can also be seen as a promotional pricing strategy because the two understandings are not mutually exclusive. The strategies of initial promotional prices, dissemination strategies and maintenance of a network growth rate are often adopted by companies operating in markets with network externalities, such as the software market.

When considering the initial issuance price and the lower initial difficulty of mining, one can observe strategies that are similar to those adopted by companies that depend on the formation of a network for greater penetration of their products. As a "product" of potential future value, an increasing number of users, attracted by the possibility of gain, form the initial network. Following publication in the media and maintenance of the network's growth rate, the currency appreciates and these movements are fed back until the formation of critical mass, which leads to market consolidation. In addition, the technology of protocols on which digital currencies applied to financial markets are based can cause numerous marginal innovations, enabling more secure, agile and customized products and gradually transforming the current structure.

3 BITCOIN

3.1 Characteristics

Developed by Satoshi Nakamoto (2008), possibly a pseudonym used by programmers, BTC was deployed on January 3, 2009 and is the most popular encrypted digital currency in the world. According to Nakamoto (2008), use of the P2P[4] network enables operations without the strict need for third parties, transactions are recorded chronologically and information remains available.

The P2P architecture is the same as that used in file-exchange services such as the former *Kazaa* and current *Torrents*. P2P networks allow data transmission without the need for a central server and have the capacity to be self-organizing and fault-tolerant. BTCs are validated using algorithms. A *hash* function can map variable-length data and return fixed-length data. According to Paar and Pelzl (2009), *hash* is a widely used concept. It is a unique data identifier and must necessarily have a one-way function: because the *hash* is the data-entry product, it is impossible to obtain original data from it.

Each BTC user has two "keys": one public and one private. The public key identifies the user on

[4] P2P-type networks are popularly known to facilitate the exchange of files using *torrents*. In this system, each machine works simultaneously as a server and user.

the network and uses a digital signature algorithm called ECDSA. Each user can have as many public keys as desired. For every transaction, the users involved must provide their respective public keys, which can be checked by any network user.

BTC issuance is limited to 21 million and the issue rate is decreasing over time. Taylor (2013) indicates that 58.8% of the total were issued by 2013 and by 2032, that percentage will be 99%. To date, as the chart below shows, approximately 14,357,900.00 BTCs have been mined. System transparency is a factor that makes BTC popular. At any time, it is possible to verify the amounts traded; however, it is not possible to access the direct identification of those involved in the transactions.

Another characteristic of BTC is *irreversibility*, i.e., the negotiator assumes all of the risk to a much greater degree than in a traditional monetary transaction. Records of transfers are permanently kept and according to Taylor (2013), these records could compromise anonymity, even for users who use multiple accounts, because a thorough analysis could reveal the same operator with a relative degree of certainty.

This possibility of checking transaction records made available by some traders to provide credibility to the market could also jeopardize the secrecy of BTC users. However, there are services that aim to make such evidence less clear. These use transmission instruments that are conditional upon future return, but involve a considerable number of accounts, thereby acting as a virtual scrambler.

BTC is widely used as a financial asset capable of generating speculative returns; however, they can also be useful as a tool to make foreign exchange transactions less costly (PAVEL, D'ARTIS and MIROSLAVA, 2014). Despite its popularity, several commercial networks are reluctant to use BTC because most governments prohibit the free movement of other currencies. Russia and China have already indicated that they intend to ban the use of digital currency. Singapore, Taiwan and the USA have expressed concern about illegal activities and defense of the national currency. In addition, the USA, Japan, Germany and Finland have created instruments to institute taxation.

May (1994) describes both governmental efforts to limit their populations' access to encryption tools and the adverse effects that these efforts have caused, for example, in France, the Philippines and the USA. The study’s conclusions highlight the possibility of tax evasion because BTC can significantly compromise the ability of governments to collect taxes. According to Pavel, D'Artis and Miroslava (2014), BTC may be used as a safeguard in a turbulent market, as observed in the financial crisis of 2008, in which the adopted policy flooded the market with liquidity and exposed the adverse effects of an expansionist policy, among them, inflationary acceleration.

3.2 Eletronic Currency characteristics

Electronic currency may come to represent a role similar to gold because its issue rate is not only known in advance but is also less than that of traditional currencies. In this case, the value of an electronic currency against other currencies, most likely even in non-turbulent times, depends on agents accepting that type of currency. There are three ways to acquire BTCs. At the beginning of its issue, the most common way to acquire was the *mining* process. At that time, there was not yet an established market. Nakamoto (2009) explains the term as analogous to gold mining activity. In the case of BTC, effort is represented by greater computational difficulty and electrical energy expenses.

BTC is mined in blocks. The first block mined was called the *Genesis block* and generated fifty BTCs. It should be noted that each hash consists of 64 characters and that each block mined informs the next block's hash. The success of mining generates a record in the blockchain, which is a file that records all transactions made in BTC. Each BTC found by a *miner* must be validated by other users in a systematic and algorithmic fashion.

The popularization of the currency, the increased number of miners and the increased computational power required have made mining less lucrative. In practice, users work in groups called *pools*, sharing the gains among group members based on their individual efforts. Indeed, explorers with little computational power are compelled to work in groups to obtain any return. The higher the processing power of a group of miners, the greater the likelihood of success. The degree of difficulty is regulated independently so that it is possible to maintain a relatively constant decreasing issue rate.

The temporal dynamic creates a future with constantly decreasing issue rates, further complicating mining activity for new entrants. It is possible that by 2032 there may be fewer and more efficient miners, given the greater required computational power and higher hardware costs. In this sense, Taylor (2013) states that two factors are crucial: the first is access to energy and the second is having hardware that is paid off while the returns are high.

In the event of hoarding by miners, end users can develop a relative aversion to the currency. Even considering the extreme divisibility of BTC, users are subject to purely speculative currency attacks. However, there are two reasons that it is unlikely that such processes would be established: (1) it is impractical to coordinate many miners; and (2) miners do not have a matching entry point. Thus, the optimal price between miners differs considerably, even if they are a part of the same pool.

Depending on the entry point of the investment and operating costs, which are individual, if a large number of miners decide to take profits, the prices might never sink below than the cost of mining because at the moment that the market price is equal to the cost of mining, the miners who have not yet reached the point of exit would acquire BTC on the market and keep the machinery mining.

The mining process enables the miner both to be rewarded and to validate transactions. When a buyer of goods or services makes a payment order with BTC, the transaction is not carried out instantly. The buyer's digital wallet has a series of BTCs or fractions that were previously generated through computational effort. The goal of mining is to generate new blocks and these are generated after the "resolution" of a hash function.

Monetary transfers are made through a hash, which carries information from previous transactions and the public key of the recipient of the amount. When a miner deciphers the code and the code is validated by the network, the block is recorded in the blockchain and only after this process do the recipient, trader and miner receive the amount due. Because the block contains past information and the recipient's public key, all network nodes can be sure that the amount that the buyer wishes to pay still belongs to him. This eliminates the possibility of double spending.

The second way to obtain BTC involves free exchange between users. In general, this type of transaction incurs no monetary cost; as Taylor (2013) states, it is symbolic, ranging from 0.0005 BTC to 1 *Satoshi,* which is equivalent to 0.00000001 BTC. Each network node has a copy of the blockchain and because the public key used "assigns" a hash to each transaction, it is possible to compare the trader's public key, eliminating the possibility of double spending. In other words, if the trader no longer owns the traded BTCs, the stored history acknowledges this difference.

Verification of possession on the issuer's part and acceptance of the transfer by the recipient are stored in the blockchain and become available and updated information for each network node. It should be emphasized that the transaction will be stored in a new block, so mining activity is necessary because the transactions do not occur instantly. This modality involves BTC end users, traders and consumers of goods and finished products. For values to be transmitted, the user needs to use his private key.

Although this form of acquisition is the least expensive, it is also the riskiest. Those acting as buyers of a particular good or service have nobody to turn to if an agreement is breached. In reality, this is a determining factor for the currency's penetration capacity because for such a risk to be taken, the value of the good or service purchased would need to be relatively low. Otherwise, some form of guarantee is required.

This form of direct purchase of digital currencies makes it possible to render financial assistance to criminal causes and organizations. The possibility of those responsible being identified and punished are minimal if appropriate identification-protection strategies are used. Terrorist groups, paramilitaries, cartels interested in tax evasion, and even tacit agreements can be made explicit and undetected by traditional audit tools.

In contrast, humanitarian aid, donations to medical research and donations to those combating the excesses of governments that restrict individual freedoms can be considerably mitigated through the use of decentralized currencies. Nevertheless, it is important to note that when a big company decides to adopt BTC, the currency begins to enjoy a credibility that is solidified over the time of its presence on the market, making direct negotiation considerably safer.

The third way to obtain BTC, and currently the most reported in the media, is the trading of intermediated currency. In this case, the user obtains the currency directly from various BTC "exchanges" or "banks." Meiklejohn et al. (2013) note that at the beginning of 2012, the percentage of transactions of less than the monetary unit abruptly doubled and those relating to less than one-tenth of the unit tripled. Not only has the trading of fractional amounts become more popular, but an increase in the velocity of the currency has also been observed[5] and quantified; moreover, it is not an approximation. According to the above authors, only a portion estimated at four million of the available BTCs is traded frequently, but at a high exchange rate.

The spread of BTC is not uniform and many traders avoid adopting it because there are no clearly defined rules and there are issues relating to tax and the high volatility of the currency price. Keeping the currency over a long period can mean significant gains or losses to someone who transacts respecting the parity observed with his or her local currency at the time of purchase. In other words, the *carrying cost* increases, as mentioned previously. Despite users' desire for BTC and other digital currencies to be legalized and regulated, this initiative is at odds with the fundamental ideal of non-regulation and the assumption of all risks on the part of users.

Digital currencies provide growth opportunities for new niche markets known as *long-tail markets*. In these types of markets, the production of certain goods and services sometimes becomes uneconomical because of difficulties in reaching a geographically dispersed consumer market. In addition to other e-commerce tools, digital currencies may make such activities profitable by making exchange processes less bureaucratic and costly. This enables the trading of low-cost goods because there are practically no fees.

The World Economic Forum report (2015, p.102-108) presents three possible scenarios for the future role of financial institutions in response to continuous changes in the preferences of international financial system agents. In the first scenario, a market deconcentration movement is considered with the emergence of new agents and more flexible, intuitive and personalized financial products. In this scenario, current agents evolve and specialize, customizing their products to the greatest extent possible. Risks associated with this scenario include the possibility that the system will become hostage to technology developers, compromising the capacity for customer loyalty and creating uncertainty about regulatory aspects.

The second scenario presented depicts the possibility that the traditional banks shift focus to act as platforms for connecting niche products. In this case, there would also be a lower degree of loyalty and moreover, further specialization should occur, reducing the possibility of cross-subsidies. Critical points include the difficulty of selection because of greater atomicity, the difficulty of assigning responsibility for service failures or fraud, information-asymmetry problems and decreased customer loyalty.

Finally, in the third scenario, financial institutions would increase the points of contact with customers through technology, emulating the human relationship and aiming at retention and loyalty. The goal is to overcome needs with the provision of non-financial services without a significant increase in costs. It is thus possible that non-centralized and unregulated digital currencies will soon be regarded as a radical innovation, with disruptive innovation characteristics. In this case, incremental innovations may emerge, reshaping traditional forms of commerce, taxation and legislation.

All four types of innovation—commercial, organizational, technological and institutional—might occur to a greater or lesser degree depending on the degree of use of decentralized currencies. Institutional innovation is linked to the legally considered means of acting. In this sense, it is essential

[5] Currency velocity is defined as the number of times that currency stock circulates between agents in a given time. The usual formula to estimate currency velocity considers production as a proxy for the number of transactions. However, the use of digital currencies, particularly BTC, means that the actual number of transactions is known, because each exchange is recorded.

that all aspects of a society's legal framework and regulatory institutions, including economic aspects, are indeed both effective and able to provide legal certainty to agents of various market types.

If BTC becomes an asset that is widely accepted as a currency, but the laws do not follow its evolution from the point of view of the legal framework applied to correct economic incentives, it will become largely worthless. Reference is made in this case to the entertainment industry's practices related to copyrights in some countries. Albuquerque and Callado (2015) recognize and provide examples showing that BTC regulation is weak, but despite regulatory issues, on May 19, 2015, the New York Stock Exchange (NYSE) created an official conversion rate between BTC and the US Dollar. This shows that the traditional financial market already accepts the digital currency market as a reality.

4 TWO-SIDED MARKET (2SM)

This section defines and characterizes the theory known as the Two-Sided Market (2SM). Despite the wide range of possible configurations, we will compare the structure of the electronic payment-card industry with the developing structure of the BTC market. Key similarities and differences that impede the BTC market's full conformity with the 2SM structure will be identified.

4.1 General Characteristics of the Two-Sided Market

Models that describe the 2SM have two characteristics: the existence of two distinct groups of participants and the presence of positive network externalities. This structure is based on a platform that allows contact and interaction between two types of user and that must be able to allow the groups to conduct the greatest possible number of transactions. The platform should be structured to promote the perception of the benefit of use on the part of end users.

Rochet and Tirole (2006) state that the 2SM is characterized not only by the existence of a platform that connects two end users but also by the fact that the total volume of transactions primarily depends on the price structure, i.e., how the price is divided between end users. According to Freitas (2007), in the 2SM, the pricing structure and definition of who will assume the majority of the platform costs must be "designed" in such a way that encourages participation by the two sides of the market. It follows that the price paid by a particular participant to use the platform is not necessarily related to the cost of entering the system.

Evans and Schmalensee (2005) cite some markets whose nature and characteristics result in their organization as 2SM, including dating agencies, night clubs, brokers, advertising agencies, newspapers and magazines, computer operating systems, video games, shopping centers and payment cards. According to the authors, this type of structure has three key features: differentiated prices, business design models and the existence of specific rules and regulations.

According to Evans (2003), final prices are charged to end users, consumers and traders to achieve demand balance. It is important both to maintain users and to attract new entrants from both sets of users to the network. The key element of this market, therefore, is balancing the demands of end users. The demand price elasticities for each group play a fundamental role in determining the respective prices charged to each of them. The price tends to be reduced on the more elastic side to facilitate users' entry into this side of the network. In general, the side with lower elasticity tends to bear the majority of the industry's costs.

Business design is crucial in the analysis of the 2SM not only because of the presence of network externalities and demand price elasticities but also because of the need to integrate the two market sides. The existence of specific rules and regulations imposed by the platform is necessary because of the need to construct parameters that promote positive externalities and limit negative ones to produce benefits for end users (BANCO CENTRAL DO BRASIL; SECRETARIA DE ACOMPANHAMENTO ECONÔMICO; SECRETARIA DE DIREITO ECONÔMICO, 2010).

The pricing structure should promote incentives for at least one side without resulting in a very severe punishment to the other, thereby discouraging its participation. This price-fixing process in two-sided markets reflects not only the industry participants' cost structure but also the surplus generated for one of the groups when the market incorporates one user more than another (ROCHET and TIROLE, 2002; 2003). This means that in the pricing structure of a 2SM, if all other conditions remain constant the group that obtained the largest surplus *subsidizes* the other group. The side that bears the costs is called the profit center and the side that benefits is called the loss center.

4.2 Characteristics of the Card Market

In the analysis of the 2SM pricing structure, two characteristics should be observed. The first is the sum of prices coming from the two-sided structure and the second is the distribution of these prices among end users on either side. The prices on each side of the market depend not only on their marginal cost but also on the demand price elasticity of each side of the market, on the value that the entry of an agent on one side generates for participants on the other side (network externality), and on the degree of inter-platform and intra-platform competition (BANCO CENTRAL DO BRASIL; SECRETARIA DE ACOMPANHAMENTO ECONÔMICO; SECRETARIA DE DIREITO ECONÔMICO, 2010).

Fagundes, Ferrés and Saito (2009)[6] explain that externalities of use arise with increases in revenues because of diffusion of the tool. The internalization of positive externalities for trade and consumers can increase the volume of transactions and consequently increase revenues if the burden of use is primarily borne by the agent with less elasticity.

In the traditional case of this type of market structure, the attempt to make the market more competitive based on regulations supported by technical studies that are strongly based on microeconomic theory and that consider price convergence at a level close to the respective marginal costs could eliminate the characteristic of network externality and produce effects of greater magnitude than the surplus generated by the regulatory body. For example, a higher level of competition can only result in lower profitability for the owner. However, the literature[7] suggests that stimuli for competition can promote benefits when a single user has access to multiple cards indiscriminately accepted by merchants.

It could be argued that regardless of the different elasticities among end users, the cost could be passed on (either in whole or in part) from traders to consumers. In other words, by presenting different costs for different types of payments, traders can differentiate and pass on those costs to customers; however, preclusion clauses are imposed on trade groups that would make it difficult to differentiate prices. However, the inability to differentiate prices could cause cross-subsidy, punishing users who choose the less expensive form of payment.

The card market is frequently structured in the form of a platform containing three or four parts. In the three-part platform, the accreditor is also the card issuer. In the four-part platform, these agents are not the same.

Briefly, the market works as follows: the scheme owner (card brand) defines the business rules; the issuers are usually banks that maintain direct contact with cardholders and define credit limits, fees and charges, invoice due dates, benefits programs, etc.; the accreditor then provides a bridge between commercial establishments and the scheme owner by contract; the consumer is the cardholder; the seller is the agent who accepts the card as a means of payment; and the final prices are shared among end users, consumers and sellers to balance the demands of both sides.

5 METHODOLOGICAL PROCEDURES

This section presents the technical procedures involved in this study’s empirical strategy. The GARCH (generalized autoregressive conditional heteroskedasticity) family models will be described briefly to help understand BTC's volatility. As mentioned above, this study was based on the contributions of Pavel, D'Artis and Miroslava (2014) and Stråle and Tjernström (2014). In the former case, vector auto-regressive (VAR) models were estimated with variables that are also used in this study. In the latter study, the authors estimated a GARCH model to show that demand, volume traded, the Mt

[6] Although the authors' focus was on the credit card market, similar reasoning applies to the object of this study, BTCs.
[7] See Evans (2002), Frascaroli (2010) and Rochet and Tirole (2003) for more on this issue.

Gox bankruptcy and the Cyprus crisis, which resulted in capital controls in mid-March 2013, were determinants of BTC price volatility.

Here, estimations of the DCC MGARCH family models aimed to estimate the parameters of changes in volatilities and their quasi-correlations between variables. The SPX-500, the price of gold and China's main stock index (SSEC) were considered for this purpose. Volatility is a characteristic often present in financial asset series quantified by the standard deviation (or variance) of results. Used as an asset risk measure, volatility can be measured by the intensity of variations in the historical process analyzed, which can behave unpredictably based on many factors, including institutional factors, legal factors, macroeconomic factors, or aspects more closely linked to the formation of the market in which the asset in question, in this case, BTC, is negotiated.

To capture the presence of volatility in financial series, it is necessary to use models whose estimators are adapted for historical processes of a heteroskedastic nature. These models consider the variance (volatility) of a return at a given point in time as dependent on past information and therefore consider it as the historical process of a random variable that follows a stochastic process. Engle's seminal work (1982) introduced the possibility of estimating autoregressive conditional heteroskedastic models (ARCH).

5.1 GARCH Multivariate Model (MGARCH)

Engle (1982), to estimate the variance of US inflation, shows that linear models are limited and unable to explain some features. He therefore shows that it is possible to capture the volatility of autocorrelations. The generalized autoregressive conditional heteroskedasticity (GARCH) model, formulated by Bollerslev (1986), is a generalization of the ARCH model. It allows the use of only two parameters to simultaneously capture the mean and variance of the time series of an ARMA process. A GARCH (r, s) model, in which parameter r represents the order of the ARCH component and s the order of the GARCH component. Following the seminal work of Engle (1982), some extensions of the ARCH model were developed, including GARCH, EGARCH and TARCH.

The basic idea stems from the understanding of the existence of heteroskedasticity conditional on the immediate past observation, in other words, that the present return depends on the past return. MGARCH allows the estimation of generalized autoregressive parameters considering conditional heteroskedasticity. Because they are dynamic, MGARCH models allow the mean and conditional covariance to be obtained. This model would be too flexible and it would not be feasible to estimate all parameters. For this reason, a wide variety of GARCH multivariate models enable parameters to be obtained in a more parsimonious manner.

In general, four parameterization methods are used alternatively: the Diagonal VECH model (DVECH), the constant conditional correlation model (CCC), the dynamic conditional correlation model (DCC) and the time-varying conditional correlation model (VCC). Bollerslev, Engle and Woodridge (1988), Bollerslev, Engle and Nelson (1994) and Bauwens, Laurent, and Rombouts (2006) describe general aspects of MGARCH modeling. A definition that allows comparison between alternative models is given by the following equation:

$$y_t = Cx_t + \epsilon_t \tag{1}$$

$$\epsilon_t = H_t^{1/2} v_t \tag{2}$$

where y_t is a dependent variable vector of the order m x 1; C is a parameter matrix of order m x k; x_t is a vector of independent variables that may contain lags of y_t; $H_t^{1/2}$ is the Cholesky factor of the conditional time-varying covariance matrix H_t; and v_t, which is a vector of order m x 1 is with zero mean and i.i.d., with variance equals to unit.

In the general model, H_t is a matrix of univariate GARCHs. For example, a general MGARCH with an autoregressive term of conditional heteroskedasticity (ARCH) and a GARCH term is given by the following equation:

$$vech(H_t) = s + Avech(\epsilon_{t-1}\epsilon'_{t-1} + Bvech(H_{t-1}) \tag{3}$$

where the vech(.) function captures elements above or below the main diagonal; s is a parameter vector and A and B are parameter matrices. Because this model uses the vech function to extract and model unique elements of H_t, it became known as the VECH model. H_t must therefore be positively defined. Equation (3) can be used to show that the parameters in s, A and B are not unique; thus, for H_t to be positively defined other restrictions should be incorporated into s, A and B. The models that the literature proposes vary with respect to the degree of flexibility and parsimony of the specifications imposed on H_t.

5.1.1 MGARCH Diagonal vech (DVECH)

Bollerslev, Engle, and Wooldridge (1988) require A and B to be diagonals. Although more parsimonious than the general case, the model is only advantageous when estimating a small number of temporal processes because the number of parameters increases quadratically. Despite the large number of parameters, the diagonal structure implies that each conditional variance and covariance depends on their own past values, not on other variances and covariances. Formally, in DVECH (1,1) each element of H_t is given as follows:

$$\mathrm{h}_{ij,t} = s_{ij} + a_{ij}\epsilon_{i,(t-1)}\epsilon_{j,(t-1)} + b_{ij}h_{ij,(t-1)} \tag{4}$$

The process requires H_t to be defined as positive in each t, which imposes severe restrictions.

5.1.2 MGARCH Conditional Correlation Models (CC)

In these models, a non-linear combination of GARCH univariate models is used to represent conditional variances. The conditional correlation matrix is defined positively, motivated by the building structure that facilitates the estimation of parameters. In MGARCH conditional correlation models (CC), H_t is decomposed in a conditional correlation matrix R_t and a diagonal matrix of conditional variances D_t:

$$H_t = D_t^{1/2} R_t D_t^{1/2} \tag{5}$$

where each conditional variance follows a univariate GARCH process and the parameterizations of R_t vary according to the specific model. According to (5) we have

$$\mathrm{h}_{ij,t} = \rho_{ij,t} + \sigma_{i,t}\sigma_{j,t} \tag{6}$$

where $\sigma_{i,t}$ is modeled by a univariate GARCH process. The equation highlights that conditional correlation models incorporate non-linear combinations of GARCH univariate models to represent conditional variances and that the parameters in the model $\rho_{ij,t}$ describe the joint dynamics of errors observed in equations i and j. Comparing (4) and (5), it is clear that in conditional correlation models, the number of parameters increases more slowly.

Bollerslev (1990) proposes a conditional correlation model with a time-invariant correlation matrix. For this reason, the model is known as the MGARCH constant conditional correlation model (CCC). By restricting R_t to be constant, the number of parameters reduces and simplifies the estimation; however, this fact can significantly restrict the accuracy of estimation and compromise the analysis.

5.1.3 Dynamic Conditional Correlation Models (DCC)

Engle (2002) introduced a dynamic conditional correlation model (DCC) wherein R_t follows a GARCH (1,1) process. As described by Engle (2009), the parameters of R_t are not standardized to be correlations and are called quasi-correlations. To maintain parsimony, all conditional quasi-correlations are constrained to follow the same dynamics. This model is significantly more flexible than the CCC and does not introduce a much larger number of parameters for the number of series. Because of this advantage, DCC MGARCH modeling was used for this study.

This model uses weighted non-linear combinations of time-variant univariate GARCHs. The diagonal elements of H_t are modeled using univariate estimates (GARCH) and the remaining elements are modeled by nonlinear functions based on the terms resulting from the diagonal. In a DCC MGARCH we have

(12)

where the terms $h_{ii,t}$ and $h_{jj,t}$ follow the GARCH process and $\rho_{ij,t}$ follows the dynamic process as outlined in Engle (2002). The DCC MGARCH can be written as follows:

$$y_t = Cx_t + \epsilon_t \tag{7}$$

$$\epsilon_t = H_t^{1/2} v_t \tag{8}$$

$$H_t = D_t^{1/2} R_t D_t^{1/2} \tag{9}$$

$$R_t = diag(Q_t)^{-1/2} Q_t diag(Q_t)^{-1/2} \tag{10}$$

$$Q_t = (1 - \lambda_1 - \lambda_2)R + \lambda_1 \tilde{\epsilon}_{t-1} \widetilde{\epsilon'}_{t-1} + \lambda_2 Q_{t-1} \tag{11}$$

where the only term still unexpressed is D_t, then we have that y_t is a dependent variable vector of the order *m* x *1*; C is a parameter matrix of the order m x k; x_t is an independent variable vector that may contain lags of y_t; $H_t^{1/2}$ is the Cholesky factor of the time-variant conditional covariance matrix H_t; v_t is a vector of the order m x 1, which is a vector of zero mean and i.i.d., with variance equals to unit; and D_t is a diagonal conditional variance matrix.

$$D_t = \begin{bmatrix} \sigma_{1,t}^2 & 0 & \cdots & 0 \\ 0 & \sigma_{2,t}^2 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \sigma_{m,t}^2 \end{bmatrix}$$

where each $\sigma_{i,t}^2$ evolves according to a univariate GARCH given as follows:

$$\sigma_{i,t}^2 = s + \sum_{j=1}^{p_i} \alpha_j \epsilon_{i,t-j}^2 + \sum_{j=1}^{q_i} \beta_j \sigma_{i,t-j}^2 \tag{12}$$

or when the constant term is included:

$$\sigma_{i,t}^2 = \exp(\gamma_i z_{i,t}) + \sum_{j=1}^{p_i} \alpha_j \epsilon_{i,t-j}^2 + \sum_{j=1}^{q_i} \beta_j \sigma_{i,t-j}^2 \tag{13}$$

where γ_i is a 1 x p parameter vector, z_i is a p x 1 vector of independent variables including a constant term, α_j are ARCH parameters and β_j are GARCH parameters. The conditional quasi-correlation matrix will be:

$$R_t = \begin{bmatrix} 1 & \rho_{12,t} & \cdots & \rho_{1m,t} \\ \rho_{12,t} & 1 & \cdots & \rho_{2m,t} \\ \vdots & \vdots & \ddots & \vdots \\ \rho_{1m,t} & \rho_{2m,t} & \cdots & 1 \end{bmatrix}$$

where $\tilde{\epsilon}_{t-1}$ is a *m* x *1* vector of standardized residuals, $D_t^{-1/2} \tilde{\epsilon}_t$; and λ_1 and λ_2 are parameters that govern the quasi-correlation dynamics. In addition, λ_1 and λ_2 are non-negative and meet condition $0 \leq \lambda_1 + \lambda_2 < 1$. When Q_t is stationary, matrix R is the weighted average of the covariance matrix of the standardized residuals $\tilde{\epsilon}_t$, denoted by $\bar{R}$ and the unconditional average of Q_t and denoted by $\overline{Q}_t$. Because $Q_t \neq R_t$, as demonstrated by Engle (2009), R does not represent either the correlation matrix or the unconditional average of Q_t; for this reason, the parameters in R are called quasi-correlations.

6 SAMPLE PLANNING AND TREATMENT

All of the data used in the study were obtained from the site *br.investing.com.* A sample of 1,362 observations was used and the period from September 13, 2011, to June 23, 2015, was considered. In addition, to test the robustness of the estimates, a subsample was built, which considered only the data from March 10, 2013, and on, with 1,192 observations. The latter is explained by events and trends that impacted the historical series of BTC prices, as discussed in the text.

One of the technical instruments justifying the need to analyze the samples separately was MS-VAR modeling, which indicated the convergence of the historical series of variables considering two regimes, with regime 1 showing an expected duration of 75% of the time period and regime 2 having an expected duration of 25%. This model was used to define the time window for determining the subsample, i.e., in addition to visual and historical evidence, the MS-VAR of the two regimes was estimated. Furthermore, the ARCH and GARCH effects, as demonstrated by Stråle and Tjernström (2014), were evident.

For analytical purposes at the microeconomic level, the 2SM theory was used to explain one of the possible phenomena associated with this phase, and a second phase of "convergence" to the fundamentals that determine the prices of the currency. The last one persists until the end of the series, where peaks of the same magnitude are no longer observed.

At level, the series presents undesirable characteristics; an abyssal range is observed between the maximum value of US $1,132.01 and the minimum value of $ 2.24. By visually comparing the sample returns to the subsample returns, the differences in magnitude are clear. Series denoted in the form of returns enable the mitigation of persistent trend effects; however, visual analysis suggests periods of high volatility that possibly affect variance over time. According to this analysis, GARCH family models are suitable to attempt to quantify conditional variance effects.

In this study, the hypothesis of normality was rejected for all variables in all samples. In addition, excess kurtosis indicates leptokurtic series that are common in financial time series, thus strengthening the argument for the use of models capable of measuring volatilities and studying how they are correlated. In addition to the BTC price, the SPX-500, the price of gold and China's main stock index (SSEC) were used. In all cases, the series showed both skewness and kurtosis. Descriptive statistics of the sample and subsample of variables used are shown in Table 1:

Table 1 - Descriptive statistics of the sample* and subsample**

Variables	Mean	Median	Maximum	Minimum	Standard Deviation	Skewness	Kurtosis
*BTC**	0.001256	0.000389	0.450252	-0.409647	0.0293	1.245677	89.84125
*BTC***	0.000483	0.000211	0.066043	-0.130503	0.011374	-1.639805	30.0825
*XAU**	-0.0000439	-0.00000638	0.006592	-0.013292	0.001278	-1.129933	15.68017
*XAU***	-0.0000488	-0.0000198	0.006592	-0.013292	0.001313	-1.356306	19.10513
*SSEC**	0.0000565	0.000021	0.00575	-0.007908	0.001198	-0.348153	9.388075
*SSEC***	0.000106	0.000103	0.00575	-0.007908	0.001223	-0.762647	10.46889
*SPX-500**	0.0000597	0.0000322	0.005984	-0.007674	0.000924	-0.43433	11.42462
*SPX-500***	0.0000503	0.0000413	0.00312	-0.003425	0.000747	-0.186709	5.734772

Source: The authors' work based on selected data.

7 RESULTS

This section presents all of the statistical procedures for the estimates of volatility measures according to the models presented in section 5. The series is sensitive to extreme values, but these observations should not be suppressed because the size of the oscillation and the existence of wide gaps characterize the BTC returns series. As described above, a visual analysis of the BTC series revealed that it showed a tendency to appreciate in times of economic and political crisis.

Moreover, attacks on financial institutions result in the opposite tendency. Despite the impossibility of predicting economic cycles deterministically, an analysis of macroeconomic fundamentals can provide BTC speculators with information that they can use to change strategy. Crises seem to act as an expansion factor of both the BTC market and digital currencies in general. In terms of technical analysis of the data, it is reported that the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests indicated stationarity of the returns series, as shown in Table 2. It therefore follows that like the other variables, BTC returns are stationary and therefore do not depend on time.

Table 2 - Unit Root Tests

Unit Root Tests (Sample)			Unit Root Tests (Subsample)		
Variables	**ADF**	**PP**	**Variables**	**ADF**	**PP**
BTC	-8.301624*	-41.44987*	*BTC*	-28.14421*	-28.16805*
XAU	-32.75358*	-32.82711*	*XAU*	-29.23710*	-29.24580*
SSEC	-36.55772*	-37.03559*	*SSEC*	-23.68373*	-23.76906*
SPX-500	-37.20030*	-37.20349*	*SPX-500*	-28.87981*	-28.87969*

Source: The authors' work based on selected data. Note: *The null hypothesis is rejected at 1%.

The choice of best model by degree of fit was based on the Akaike Information Criterion (AIC) and the Schwartz Bayesian Criterion (SBC). According to Tsay (2005), the smaller the AIC and SBC, the better the model fit to the data series. Using the parsimony criterion, the ARMA model (0,2) offered the best fit and had the expected characteristics of non-correlated returns and severe correlation of the squares of returns, which justifies estimation by models capable of capturing conditional volatility effects.

Table 3 - Best fit ARMA model

Model	Schwarz criterion	Akaike Criterion
BTC AR(0) MA(2) Sample	-4.31091	-4.318593
BTC AR(0) MA(2) Subsample	-6.108152	-6.101125

Source: The authors' work based on selected data.

The third step in building the ARCH model was to attempt to fit the ARMA model using the *sample* to verify the serial correlation of the series. It should be noted that the data have a long memory; thus, the ARCH test only captured volatility from the second residual lag onwards. Table 4 shows the test results:

Table 4 - F Statistic - ARMA (0,2)

Test: ARCH - ARMA Model (0,2)			
F Statistic - Sample	8.098550	Prob. F (4.1348)	0
Obs* R^2	31.75133	Prob. Chi-square (4)	0
F Statistic - Subsample	52.71409	Prob. F (4.819)	0
Obs* R^2	168.7086	Prob. Chi-square (4)	0

Source: The authors' work based on selected data. *The series shows volatility

Among the estimated models, the best fit model for the *sample,* with 1357 observations, was the GARCH (1,1) according to the Schwartz criterion. The model completely corrected residual autocorrelation and when the ARCH test was repeated, a lack of conditional volatility was found. The resulting estimated model is given by

$$h_t = (3{,}46)10^{-6} + (0{,}220539)X_{t-1}^2 + (0{,}800577)h_{t-1} \quad (8)$$

Tables 5 and 6 summarize the results of the model and its F statistic, respectively:

Table 5 - Results of GARCH Model (1,1)

Variable	Coefficients	Standard Error	Z statistic	P Value
Intercept	0.000114636	0.00029024	0.39497012	0.69286494
MA (2)	0.055499339	0.027560405	2.013734487	0.044037417
		Variance equation		
Intercept	3.46E-06	2.17e-07	15.93489162	3.63E-57
Residuals (-1)²	0.220539029	0.012605408	17.49558823	1.55E-68
GARCH (-1)	0.800576674	0.008196231	97.67619844	0
R^2	-0.037313333			
R^2 adjusted	-0.038078878			
SQR	1.207575369		*Akaike criterion*	-6.039195489
DW statistic	2.103768306		*Schwarz criterion*	-6.019987561

Source: The authors' work based on selected data.

Table 6 - F statistic – GARCH (1,1)

Test: ARCH GARCH Model (1,1)			
F statistic	0.004481	Prob, F(1.1354)	0.9466
Obs* R^2	0.004488	Prob, Chi-square (4)	0.9466

Source: The authors' work based on selected data.

Thereafter, autocorrelation tests of the returns residuals and squared returns residuals—i.e., the *Q* statistic—were performed to dispel doubts about the robustness of the results. Table 7 shows the test results:

Table 7 - Autocorrelation test for residuals and the square of residuals—*Q* Statistic

Autocorrelation	Partial autocorrelation	*t*	AC	PAC	Q-Stat	Prob*
| |	| |	1	0.047759972	0.047759972	3.102185399	
| |	| |	3	0.032210437	0.034184226	4.973127558	0.083195354
...	...	...	...	...	...	...
|* |[1]	|* |	7	0.097656629	0.093272095	22.84401255	0.000850442
| |	| |	1	0.001819164	0.001819164	0.004500734	0.946512036
| |	| |	2	0.006343791	0.006340502	0.059272623	0.970798538
|* |[2]	|* |	3	-0.023150262	-0.023174272	0.789221532	0.852043326

Source: The authors' work based on selected data. [1]Residuals. [2] Square of residuals.

The relevant analysis rests on the variance equation coefficients, which were all significant at the 1% level. With $\alpha_1 = 0.220539$ and $\beta_1 = 0.800577$ it is clear that both immediate shock and persistence are quite representative, but there is a preponderance of persistence.

Estimations similar to the previous ones were made for the 1,192 *subsample* observations and as expected, the model with best fit for volatility diverged. The ARMA model (0,2) also resulted in both a better fit according to the Schwarz criterion and the best fit for volatility for a GARCH model (1,1), i.e., an identical structure to that observed previously. However, the resulting coefficients are essentially different. The adjusted model is given as follows:

$$h_t = (6{,}74)10^{-6} + (0.240146)X_{t-1}^2 + (0.698707)h_{t-1} \quad (9)$$

Tables 8 and 9 summarize the results of the model and its F statistic, respectively:

Table 8 - Results of GARCH Model (1,1)

Variable	Coefficients	Standard error	Z statistic	P Value
Intercept	-0.000348	0.000286	-1.214364	0.2246
MA (2)	-0.010033	0.041015	-0.244615	0.8068
Variance equation				
Intercept	6.74E-06	6.30E-07	10.71209	0.0000
Residuals (-1)²	0.240146	0.024194	9.926044	0.0000
GARCH (-1)	0.698707	0.021892	31.91609	0.0000
R^2	-0.04835			
R^2 adjusted	-0.006051			
SQR	0.107511		*Akaike criterion*	-6.805601
DW statistic	1.948503		*Schwarz criterion*	-6.794671

Source: The authors' work based on selected data.

Table 9 - F statistic – GARCH (1,1)

Test: ARCH GARCH Model (1,1)			
F statistic	0.333927	Prob. F(1.825)	0.5635
Obs* R^2	0.334602	Prob. Chi-square (4)	0.5630

Source: The authors' work based on selected data.

As in the case of estimations for the *sample*, autocorrelation tests of returns residuals and squares of returns residuals—i.e., the *Q* statistic—were performed with data from the *subsample* to dispel doubts about the robustness of the results. Table 10 shows the results of this test:

Table 10 - Autocorrelation tests of residuals* and residuals^2** – *Q statistic*

Autocorrelation	Partial autocorrelation	t	AC	PAC	Q-Stat	Prob*
| |*	| |	1	0.063624561	0.063624561	3.363973072	0.024955675
| |	| |	2	0.037853145	0.033942462	4.556126953	0.032801171
| |	| |	3	0.027915075	0.023551218	5.205257526	0.074078587
...	...	...	...	...	...	...
|* |	|* |	6	0.11480386	0.108584665	18.26474391	0.002632269
|* |**	|* |	1	0.02011261	0.02011261	0.336155164	0.562056987

Source: The authors' work based on selected data.

In addition, the conditional variance model GARCH (1,1) eliminated the serial correlation observed in the ARMA modeling (0,2) and the ARCH test indicates the absence of the effect after proper estimation. When comparing this result with the previous estimation, it can be seen that the constant term has almost doubled, which may indicate the perception of a market that is not incipient. The parameter β_1, however, lost relative importance, indicating that volatility persistence had declined. The term α_1 essentially did not change.

As described among the objectives of this study, the DCC MGARCH model (1,1) was estimated. Estimates using the *sample* indicated a series of volatile behaviors with an almost perfect degree of volatility persistence. Table 11 shows the results of the model best fit for the *sample*, and the model tests are shown in Tables 12 and 13:

Table 11 - MGARCH (1,1) model results

Parameter	Value	Standard error	*t*	*t*-prob.
ρ_{21}	0.074760	0.075238	0.9936	0.3206
ρ_{31}	0.002272	0.047111	0.04823	0.9615
ρ_{41}	0.016071	0.056024	0.2869	0.7743
ρ_{32}	-0.001535	0.070378	-0.02181	0.9826
ρ_{42}	0.068042	0.059743	1.139	0.2550
ρ_{43}	0.080281	0.065381	1.228	0.2197
□	0.004629	0.0024437	1.894	0.0584
□	0.989691	0.0083055	119.2	0.0000
Akaike	-38.659429		Shibata	-38.660821
Schwarz	-38.522963		Hannan-Quinn	-38.608006

Source: The authors' work based on selected data.

Table 12 - Normality tests for the MGARCH model (1,1)

	Statistic	Value	t-Test	*p*-Value
BTC	Skewness	-1.2121	17.105	1.3533e-065
	Excess kurtosis	11.351	80.163	0.00000
	Jarque-Bera	6691.2	-	0.00000
XAU	Skewness	0.20592	2.9061	0.0036594
	Excess kurtosis	4.0215	28.401	1.9845e-177
	Jarque-Bera	811.66	-	5.6319e-177
SSEC	Skewness	-0.38843	5.4818	4.2112e-008
	Excess kurtosis	3.6039	25.451	6.8162e-143
	Jarque-Bera	675.05	-	2.6045e-147
SPX500	Skewness	-0.57573	8.1251	4.4700e-016
	Excess kurtosis	5.6941	40.213	0.00000
	Jarque-Bera	1676.2	-	0.00000

Source: The authors' work based on selected data.

Table 13 - Autocorrelation tests of residuals* and residuals^2** – Q statistic

TC	(Q5) = 0.952249	[0.9663245]	SSEC	(Q5) = 2.31352	[0.8042793]
	(Q10) = 8.09680	[0.6193817]		(Q10) = 6.61360	[0.7613499]
	(Q50) = 58.2710	[0.1973003]		(Q20) = 13.3655	[0.8611587]
BTC^2	(Q5) = 1.34048	[0.9307118]	SSEC^2	(Q50) = 39.4433	[0.8583046]
	(Q10) = 4.41971	[0.9264334]		(Q5) = 17.1297	[0.0042603]
	(Q50) = 30.0825	[0.9884888]		(Q10) = 45.6557	[0.0000017]
XAU	(Q 5) = 10.1627	[0.0707548]	SPX500	(Q 5) = 3.51488	[0.6211372]
	(Q 10) = 19.6281	[0.0329728]		(Q 10) = 9.58548	[0.4775813]
	(Q 50) = 48.5299	[0.5325121]		(Q 50) = 37.5876	[0.9021283]
XAU^2	(Q 5) = 10.3517	[0.0658617]	SPX500^2	(Q 5) = 14.2121	[0.0143168]
	(Q 10) = 25.1507	[0.0050671]		(Q 10) = 17.8319	[0.0578655]
	(Q 50) = 102.662	[0.0000168]		(Q 50) = 72.4295	[0.0207066]

Source: The authors' work based on selected data.

According to analysis of the table 11 parameters using data from the *sample*, the degree of interdependence between the volatilities of the BTC returns series and the other variables was low. These results are in line with previous empirical studies such as Pavel, D'Artis and Miroslava (2014) and Stråle and Tjernström (2014). Their results did not indicate significant conditional variance coefficients for any of the variables considered.

The characteristics that hinder good model fit are revealed in the normality and serial autocorrelation tests shown in tables 12 and 13. For the latter, the null hypothesis that there is no serial correlation cannot be rejected because the probabilities Q < Chi squared for all lags are high. Using the same specifications as before, a model was estimated for the *subsample* with 663 observations. Table 14 presents the best fit result:

Table 14 – Results of MGARCH (1,1) model

Parameter	Value	Standard error	*t*	*t*-prob.
ρ_{21}	-0.021574	0.045540	-0.4737	0.6358
ρ_{31}	0.062535	0.039347	1.589	0.1125
ρ_{41}	-0.074188	0.047476	-1.563	0.1186
ρ_{32}	-0.005211	0.052837	-0.09863	0.9215
ρ_{42}	-0.064615	0.054152	-1.193	0.2332
ρ_{43}	-0.008687	0.051871	-0.1675	0.8671
α	0.020865	0.024322	0.8579	0.3913
β	0.664926	0.27447	2.423	0.0157

Source: The authors' work based on selected data.
Observations: 663 Variables: 1-BTC; 2-XAU; 3-SSEC; 4-SPX500.

In this study, it was decided not to include binary variables in the model estimations as because would be impossible to keep them when estimating the multivariate models. To obtain a date limit for determining the subsample beyond the visual and historical evidence, the MS-VAR model of the two regimes was estimated. Furthermore, the ARCH and GARCH effects, as demonstrated by Stråle and Tjernström (2014), were obvious.

Some other changes in relation to the previous results should be highlighted. The variable α, which indicates the effect of the impact of volatility at the time the shock occurs, was no longer significant in the multivariate results. However, the SSEC variable became significant at 11.25% and the same occurred with the SPX-500 variable at 11.86%. Although above the 10% threshold, this convergence seems to indicate that the BTC markets are transforming and gradually becoming more interdependent by observing the estimated parameters. Tables 15 and 16 show the normality and autocorrelation tests, respectively:

Table 15 - Normality tests MGARCH model (1,1)

	Statistic	Value	t-Test	*p*-Value
BTC	Skewness	-1.1073	11.666	1.8963e-031
	Excess kurtosis	8.6850	45.819	0.00000
	Jarque-Bera	2219.2	-	0.00000
XAU	Skewness	-0.49425	5.2073	1.9163e-007
	Excess kurtosis	5.6201	29.650	3.3973e-193
	Jarque-Bera	899.55	-	4.6204e-196
SSEC	Skewness	-0.086449	0.91080	0.36240
	Excess kurtosis	3.1366	16.548	1.6633e-061
	Jarque-Bera	272.61	-	6.3640e-060
SPX500	Skewness	-0.25520	2.6887	0.0071723
	Excess kurtosis	2.7393	14.451	2.4555e-047
	Jarque-Bera	214.48	-	2.6658e-047

Source: The authors' work based on selected data.

Table 16 – Autocorrelation tests of residuals* and residuals^2** – Q statistic

BTC	(Q5) = 4.18133	[0.5236152]	SSEC	(Q 5) = 6.80759	[0.2353482]
	(Q10) = 12.7910	[0.2355925]		(Q10) = 18.1040	[0.0532340]
	(Q50) = 68.3933	[0.0429550]		(Q50) = 52.0189	[0.3952199]
BTC^2	(Q5) = 0.616186	[0.9872502]	$SSEC^2$	(Q5) = 9.04407	[0.1073194]
	(Q10) = 1.95980	[0.9966391]		(Q10) = 27.9164	[0.0018617]
	(Q50) = 31.8304	[0.9788777]		(Q50) = 111.270	[0.0000015]
XAU	(Q5) = 1.45537	[0.9181620]	SPX500	(Q5) = 2.16674	[0.8256249]
	(Q10) = 3.47511	[0.9679367]		(Q10) = 3.75388	[0.9577674]
	(Q50) = 40.8745	[0.8178095]		(Q50) = 60.1708	[0.1536360]
XAU^2	(Q5) = 12.4954	[0.0285950]	$SPX500^2$	(Q5) = 11.0774	[0.0498660]
	(Q10) = 14.3132	[0.1591778]		(Q10) = 33.9054	[0.0001916]
	(Q50) = 47.4270	[0.5772369]		(Q50) = 168.501	[0.0000000]

Source: The authors' work based on selected data.

In summary, gold does not show statistical significance in any of the multivariate models estimated. Thus, these results possibly capture the inertial aspect of the "euphoria" phase. It should be recalled that at the beginning of the sample period, the currency was not used mainly as a medium of exchange because of the factors presented in relation to adaptation of BTC in relation to 2SM. It is therefore possible that most agents demanded BTC for the purposes of speculation, and perceived all negative returns as a buying opportunity, not as a reversal of trend in prices.

In addition, note that because of the many robustness exercises needed to achieve the models presented here, the profile of the BTC returns series renders hedging strategies virtually impossible for those who use it to invest, which increases the carrying cost for those who transact with the currency. In general, as discussed, it is possible that the series is dominated by shocks arising from expectations, whether because of rumors about prohibition or regulation or hacker attacks on active financial institutions.

The results obtained in the estimation of the DCC MGARCH model, although not significant, represent some progress because of the methodology used. It should be noted that Pavel, D'artis and Miroslava (2014) attempt to identify the BTC price formation process by VAR modeling and similarly, the parameters obtained by those authors are not significant.

This multivariate analysis could indicate volatility as a BTC price formation component. Although the persistence of autocorrelation might have affected the estimated parameters of the multivariate model for the *sample* and *subsample*, one can see that the pressure of a sudden increase in demand caused by political and economic crises and the observed effects of hacker attacks on the BTC exchanges seem to affect the estimated volatilities. Nonetheless, the results of the multivariate analysis for the most recent observations indicate convergence to significant parameters that seem to reflect the financial system's adherence to BTC. The perfect adaptation to the 2SM structure of debit cards may indeed be only one of many possible effects of this convergence.

8 CONCLUSIONS

To achieve the overall objective, the institutional and operational aspects of BTC were analyzed. The study revealed that the emergence of BTC coincided with a period of intense effects of the global crisis originating in the US. This historical and social context might have been decisive in BTC achieving popularity. In other words, it can be said that crises seem to act as an expansion factor of the BTC market and digital currencies in general.

The study revealed the existence of antagonisms limiting BTC's operation. It was found that the most restrictive laws are found in places in which the national currency has weak desirability and BTC is thus characterized as radical innovation because it does not conform to the structures observed before its emergence. When considering the conceptual typifications of disruptive innovation, BTC has potential characteristics of the *low disruption* and *new market* types, but its impact on the economic environment is fundamentally dependent on it being perceived as a currency. BTC and other non-centralized issue currencies are apparently being absorbed by the financial system more intensely not as a currency, but as a financial asset.

The wide range of digital currencies available promotes competition, and the population might or might not choose a dominant type. The adoption of BTC by financial institutions, despite its potential for creative destruction, contrasts with the low number of traders willing to accept it. Perhaps financial institutions are not overly rigid in adapting their services. Digital currencies could represent opportunities for net gains when relativized with possible losses by enabling the supply of new products and the acquisition of new customers who did not previously participate in the market. Legal instabilities, carrying cost attributable to fluctuating prices and irreversibility represent possible factors that limit the spread of BTC.

Understanding that non-regulated digital currencies are indeed financial assets mitigates the potential threat to national legal tender currencies. The more restrictive laws therefore tend to be stricter for financial managers and traders. The comparison of BTC with the payment card market based on the 2SM structure showed that the use of BTC for obtaining credit has no similarity to the traditional model. However, when considering the debit system, the structure was adequate. This result indicates that BTC is considered an asset when incorporated into the financial system. In this sense, the processes of BTC price formation and the volatility associated with it were estimated using models that considered conditional heteroskedasticity. Each was estimated for the sample and subsample, as described above. The estimation of quasi-correlations between volatilities made it possible to obtain dynamic conditional volatility parameters of the DCC MGARCH (1,1) model. Analysis of the results shows that with the passage of time, the market has absorbed the BTC innovation.

Although attacks on financial institutions that transact BTCs are also elements that significantly affect price volatility, they adversely affect price. Because of the relationship between peaks in the price of BTC and epicenters of political and economic crises, it is suggested that future studies aiming to measure the volatility of BTC prices should incorporate variables into a multivariate approach capable of indicating the imminence of crises. Despite the impossibility of predicting economic cycles deterministically, analysis of macroeconomic fundamentals can provide BTC speculators with information useful for changing their strategies.

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