UNIVERSIDADE FEDERAL DE UBERLÂNDIA

PROGRAMA DE PÓS GRADUAÇÂO EM ECONOMIA

TATIANA SILVEIRA CAMACHO

FINANCIAL AND PAYMENT INNOVATIONS: CRYPTOASSETS, INSTANT PAYMENTS AND CENTRAL BANK DIGITAL CURRENCIES.

UBERLÂNDIA
2022

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Thesis presented to the Post Graduate Program in Economics (PPGE), Universidade Federal de Uberlândia (UFU), as a partial requirement for obtaining a Doctor degree in Economics.

Concentration Area: Applied Economics

Advisor: Prof. Dr. Guilherme Jonas Costa da Silva (UFU)

Co-advisor: Prof. Dr. Jefferson Donizeti Pereira Bertolai (FEARP - USP).

UBERLÂNDIA
2022

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C172
2022

Camacho, Tatiana Silveira, 1984-
Financial and payment innovations: cryptoassets, instant payments and central bank digital currencies. [recurso eletrônico] : I / Tatiana Silveira Camacho. - 2022.

Orientador: Guilherme Jonas Costa da Silva.
Coorientador: Jefferson Donizeti Pereira Bertolai.
Tese (Doutorado) - Universidade Federal de Uberlândia, Pós-graduação em Economia.
Modo de acesso: Internet.
Disponível em: http://doi.org/10.14393/ufu.te.2022.393
Inclui bibliografia.
Inclui ilustrações.

1. Economia. I. Silva, Guilherme Jonas Costa da,1976-, (Orient.). II. Bertolai, Jefferson Donizeti Pereira , 1983-, (Coorient.). III. Universidade Federal de Uberlândia. Pós-graduação em Economia. IV. Título.

CDU: 330

Bibliotecários responsáveis pela estrutura de acordo com o AACR2:
Gizele Cristine Nunes do Couto - CRB6/2091
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Programa de Pós-Graduação em:	Economia				
Defesa de:	Tese de Doutorado, Nº 82, PPGE				
Data:	29 de agosto de 2022	Hora de início:	14:00	Hora de encerramento:	17:05
Matrícula do Discente:	11813ECO007				
Nome do Discente:	Tatiana Silveira Camacho				
Título do Trabalho:	Financial and Payment Innovations: Cryptoassets, Instant Payments and Central Bank Digital Currencies				
Área de concentração:	Desenvolvimento Econômico				
Linha de pesquisa:	Economia Aplicada				
Projeto de Pesquisa de vinculação:	Fragilidade Financeira, Crescimento e Desenvolvimento Econômico				

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Documento assinado eletronicamente por **Fernando Antônio de Barros Júnior**, **Usuário Externo**, em 30/08/2022, às 15:12, conforme horário oficial de Brasília, com fundamento no art. 6º, § 1º, do Decreto nº 8.539, de 8 de outubro de 2015.

Documento assinado eletronicamente por **Hugo Carcanholo Iasco Pereira**, **Usuário Externo**, em 30/08/2022, às 15:44, conforme horário oficial de Brasília, com fundamento no art. 6º, § 1º, do Decreto nº 8.539, de 8 de outubro de 2015.

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Referência: Processo nº 23117.061665/2022-00 SEI nº 3858421

TATIANA SILVEIRA CAMACHO

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Concentration Area: Applied Economics

Uberlândia, August 29, 2022

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I dedicate this thesis to my family and friends, for their unconditional support and affection.

(In memorian) Irene Maia Machado

ACKNOWLEDGEMENTS

I would first like to thank my family for giving me unconditional love and acceptance during this hard journey. To my father José Roberto Camacho, my mother Stelamaris Machado da Silveira Camacho. My sister Gabriela Silveira Camacho, my brother-in-law Luiz Eduardo Moreira Guedes, and my beautiful niece who arrived in our family during this time to bring even more joy and tenderness in my life, Anahí Guedes Camacho. My heart goes to my extended family (uncles, aunts, cousins) and those that have paved the way before me so I can be here today. My loving grandparents (*in memorian*): José Gomes Camacho, Maria Pillar Rodrigues Camacho, Irene Maia Machado e Edgar Machado da Silveira.

To my Professor and Advisor Guilherme Jonas Costa da Silva, my thanks for the encouragement, dedication and trust placed in me. I extend the same gratitude to my Co-advisor Prof. Dr Jefferson Donizete Pereira Bertolai, who helped me with great patience in the development of the theme. The examination board Prof. Dr. Fernando Antônio de Barros Jr., Prof. Dr. Hugo Carcanholo Iasco Pereira, Prof. Dr. Julio Fernando Costa Santos and Prof. Dr. Flávio Vilela Vieira who kindly accepted the invitation.

I thank all my friends and colleagues who have helped me during all these years, especially the 2017 and 2018 Post Graduate entrants. In a timely manner, I will not be able to mention them all, electing two in the recognition of others that have assited me through the way: Kelmaistes Wanderson Rodrigues Correa do Amaral and Daisy Caroline Nascimento Pereira, with their support and friendship.

I thank the Post Graduate Program in Economics (PPGE) at Universidade Federal de Uberlândia (UFU), and all the professors for their teachings. Instituto de Economia e Relações Internacionais (IERI) where I graduated nearly 15 years ago and now postulating a title as a Philosophical Doctor. CAPES (Coordenação de Aperfeiçoamento de Pessoal de Nível Superior) for the scholarship granted during my PhD. Finally yet importantly, invaluable life lessons of resilience that I have learned, especially through the COVID-19 pandemic and the concomitant development of this thesis.

“I cannot teach anybody anything. I can only make them think”
— *Socrates*

RESUMO

Uma grande variedade de modos de transação digitais suplantaram a moeda tradicional mudando a natureza do dinheiro ao longo destes últimos 30 anos. O objetivo principal do trabalho é apontar como algumas inovações foram transformadoras para o fluxo internacional de recursos a partir da crise de 2008: criptomoedas, tecnologias de pagamentos instantâneos e moedas digitais dos bancos centrais. Antes de entrar na análise feita em cada paper, na introdução é realizado um breve panorama teórico de diferentes linhas do pensamento econômico sobre a natureza do Bitcoin. O primeiro artigo aborda a mudança no ecossistema Bitcoin com a crescente presença de *players* institucionais. Com dados diários da Glassnode Studio, a metodologia *wavelet coherence* foi aplicada em três intervalos de tempo distintos (halvings do BTC) decompondo preço (em USD) e transações. As estimativas mostraram correlações mais fortes em frequências mais baixas, indicando o movimento de investidores instutucionais. Co-movimentos em frequencias mais altas são creditadas a pequenos e médios investidores via decomposição da contagem de transações. Para compreender como os grandes investidores se apresentam no mercado cripto, foi utilizado modelos Autoregressivos de Defasagens Distribuídas e Modelos Autorregressivos Não-Lineares de defasagens distribuídas. Variáveis internas e externas a Blockchain demonstraram mudanças excessivas de preço e volume do retorno real do BTC. Cálculos de assimetria apontaram para uma maior presença destes *players*, por meio da quantidade de transações realizadas nas *exchanges* e sua presença no mercado de ativos norte-americano. A novidade proposta no terceiro artigo é através de metodologia de séries de tempo extrair lições da recente experiência indiana com a *Unified Payments Interface* para o Pix brasileiro. Variáveis macro, substitutos para pagamentos e medida de popularidade relativa de aplicativos bancários foram escolhidas para entender os volumes de UPI. Substitutos ao volume de pagamentos instantâneos (UPI) revelaram uma natureza complementar, enquanto o grau de sofisticação do sistema financeiro tem efeitos de curto e longo prazo. Choques assimétricos de curto prazo produziriam impactos negativos maiores nas transações via UPI. No último artigo, as Moedas Digitais do Banco Central (CBDCs) foram estudadas a partir da perspectiva dos mercados emergentes. Indices de uso de moeda física (Khianarong & Humphrey, 2019) foram calculadas com dados anuais do BIS, aplicando um algoritmo de previsão com a melhor estimativa econtrada. As tendências decrescentes do uso do dinheiro no Brasil e na Índia corroboram que as moedas digitais emitidas pelos bancos centrais poderiam se tornar um instrumento de pagamento alternativo. A conclusão geral da tese é que os investidores institucionais começaram a beneficiar-se da dinâmica do halving no Bitcoin, para gerar lucros especulativos em um ambiente de liquidez internacional. Este conjunto de fatores modificou não apenas o volume negociado de BTC, mas também o seu preço, transformando a relação da criptomoeda com o mercado de ativos tradicional. A preocupação dos Bancos Centrais, nesta nova era inovadora é a de que pagamentos podem migrar para grandes plataformas privadas, mercados de moeda digitais não regulamentadas tais como stablecoins internacionais. Com a sua institucionalidade sendo crescentemente contestada, à luz de riscos quanto a soberania monetária de países emergentes, os bancos centrais passaram a propor novos intrumentos como pagamentos instantâneos e CBDCs.

Palavras-chave: bitcoin; investidores institucionais; bancos centrais; pagamentos instantâneos e CBDCs.

ABSTRACT

A wide variety of digital transaction modes has supplanted traditional currency and changed the nature of money over the past 30 years. The main objective of this study is to point out how some financial innovations have been transformative for the international flow of resources since the 2008 crisis: cryptocurrencies, instant payment technologies and central bank digital currencies. Before entering the analysis made in each paper, the introduction provides a brief theoretical overview of different lines of economic thought on the nature of Bitcoin. The first article addresses the change in the Bitcoin ecosystem with the growing presence of institutional players. With daily data from Glassnode Studio, the wavelet coherence methodology was applied in three different time intervals (BTC halvings) decomposing price (in USD) and transactions. Showing stronger correlation at lower frequencies, estimates indicate institutional investor's market movement. Co-movement at higher frequencies are credited to small and medium investors via transaction count decomposition. To understand how large investors present themselves in the crypto market, Autoregressive Distributed Lag models and Non-Linear Autoregressive Distributed Lag Models were used in the second paper. Both internal and external Blockchain variables demonstrate excessive changes in price and volume of actual BTC return. Asymmetry calculations pointed to a greater presence of these players, through the number of transactions carried out on exchanges and in the North American asset market. The novelty proposed in the third article is, through time series methodology, extract lessons from the recent Indian experience with the Unified Payments Interface for the Brazilian Pix. Macro variables, payment substitutes and measure of relative popularity of banking applications were chosen to understand UPI volumes. Substitutes for the volume of instant payments (UPI) revealed a complementary nature, while the degree of sophistication of the financial system had both short-term and long-term effects. Short-term asymmetric shocks would produce greater negative impacts on UPI transactions. In the last article, Central Bank Digital Currencies (CBDCs) were studied from the perspective of emerging markets. Physical currency usage indices (Khianarong & Humphrey, 2019) were calculated with annual data from the BIS, applying a forecasting algorithm with the best estimate found. The decreasing trends in the use of money in Brazil and India corroborate that digital currencies issued by central banks could become an alternative payment instrument. The general conclusion of the thesis is that institutional investors have started to benefit from the halving dynamics in Bitcoin, to generate speculative profits in an environment of international liquidity. This set of factors changed not only the volume of BTC traded, but also its price, transforming the cryptocurrency's relationship with the traditional asset market. The concern of Central Banks in this new innovative era is that payments may migrate to large private platforms, unregulated digital currency markets such as international stablecoins. With their institutionality being increasingly contested, in light of risks regarding monetary sovereignty of emerging countries, central banks began to propose new instruments such as instant payments and CBDCs.

Key words: bitcoin; institutional investors; central banks; instant payment; CBDCs.

SUMMARY

1. INTRODUCTION

Technology and the internet has become pervasive in all devices, taking over almost all aspects of our economy (i.e. banking, retail, entertainment). With the development of information and data transmission in the last 30 years, the increasingly complex intertwining of the economy with information flows in the global dimension is noticeable. Driven mainly by capital appreciation through global competitive processes, produces clear reflections on the economic development of nations.

Digitalization has affected many countries around the world with declining demand for paper money, as consumers use credit, debit cards, mobile phones, and online payment methods. Today there is a vast array, a nascent ecosystem of different payment modes, with options for the consumer and merchant. Advances in electronic payment systems and media technology, have replaced traditional currency transactions in more advanced economies.

Over time, the range of assets with money attributes has increased, greatly changing the nature of money and the role of Central Banks over the last decade. Credit money (a creation of the fractional reserve system) is purely virtual, as it is merely a record of the accounting relationship between creditor and debtor (Dwyer, 2015). Money held electronically in an electronic storing medium (through cards or hard drives), is therefore no different from electronic storage of value between economic agents. That being said, the monetary authority has but a very indirect control over a relevant portion of the money supply, which is now provided by private banks and financial firms in the form of loans or speculative activities.

Different variations in respective to liquidity can present themselves, and even pass as "money" but are in fact payment modes or financial assets. This theses aims to apprehend today's main innovations that are seen to be "disruptive" of the "payment" market: cryptoassets, instant payment technology, and central bank digital currencies (CBDCs). These innovations come in the context of globalization and fast track real-time transactions, changing, the vision of what payments and settlement systems are, affecting daily transactions of individuals and economic agents.

Conscious that technology is constantly evolving, an essential part of capitalism, where new forms of profit and valuation are constantly created, it is not possible to completely rule out that hundreds of cryptos now circulating (direct decedents of Bitcoin) might develop into other forms. In other words, there is no intention in making predictions or prophecies, but simply outline these new forms of social-economic manifestation in our society. As Fama, Fumagalli & Lucarelli (2019, p. 175) explain: "*The intention is to avoid possible confusion with the dominant narrative, but also to remark the fact that sociotechnical innovations introduced by bitcoin have concretely opened the possibility of deeply rethinking money* "…or not?

Mostly fuelled by libertarian theories about the "denationalization of money", joined with anti-state anarchist ideas, only a few people noticed the launch of Bitcoin in early 2009. Satoshi Nakamoto (Bitcoins' idealizer) intended to facilitate value transfer between members of the World Wide Web (WWW), using decentralized ledger technology (DLT). Concurrently, due to their idiosyncratic characteristics cryptocurrencies (or cryptoassets) are radically different from electronic money.

Through competing nodes that have a financial incentive to validate transactions in the Bitcoin network, exchanges carried out on the blockchain are theoretically, faster and less bureaucratic (Fama et al, 2019). The blockchain works like a public accounting record, with total disclosure to all participants. It registers user's credits in the system, connecting all previous transfers, into blocks of information. Before information is chained to the blockchain, reaching consensus among participating nodes within the Bitcoin network is essential. Verification depends on a "proof of work" (PoW) algorithm, in which competing nodes have a financial incentive (receiving Bitcoins) to validate transactions, allowing high levels of trust between users, eliminating the need for a network "guardian" (MAURER ET AL, 2013; RASKIN; YERMACK, 2016; FAMA ET AL, 2019).

Created and introduced into a "debt-free economy", making it similar to fiat money issued by the state[1], it manifests as an independent currency with focus on decentralized governance and record keeping. Bitcoin would be a new currency backed by the reliability of cryptography, reducing the central bank to a set of equations. Supporters insist that privacy, value and trust are "embedded" in network protocols (MAURER ET AL, 2013).

[1] When commercial banks issue new credit, it is usually a debt owed by the customer to the bank. As the customer's debt is typically charged at a higher rate than the banks debt to the customer, there is an inherent tendency in this system for the total amount of debt to grow faster than the total money supply (BJERG, 2016).

Different theoretical views support bitcoins nature as money or as a financial asset. Following Kocherlakota & Wallace (1998), Kocherlakota (1998), Luther & Olson (2013) argument that like money bitcoin is memory. Another line of researchers tends to call cryptocurrencies a synthetic commodity money as it does not fit into existing money types like commodity money or fiat money. They resemble fiat money, as they do not hold any nonmonetary value, and on the other hand, they are scarce like commodity money (Selgin, 2015).

Bjerg (2016) takes a different philosophical approach, assuming as a premise that the very ontological basis of money is inherently indefinable. Money has no real essence; therefore, its nature has and will always be a controversial issue. This does not mean that there is no money in the real world, but that money has no transhistorical essence that would lead to atheoretical general definition.

In discussing the nature of money in economics, three general theories about the origin and constitution of money are emphasized: the theory of commodity money, the chartalist theory, the theory of money as credit. As each of these theories capture a dimension of the functioning of money, none of them alone would be able to provide a coherent and conclusive account of the nature of money. They constitute ideal types to uncover the ontological constitution of bitcoin as money (BJERG, 2016).

According to Dequech (2013), money is a convention[2] in itself closely related to organizations. In line with Fama et al (2019) that identifies money as an institution that binds individual actors into social relations of interdependence and conflict. Institutions, central political powers represent a guarantee of the value of money, essential to prevent abuses and misconducts, fostering the ability of money to fulfill its social function.

Based on Keynes' definition on the essential properties of money[3], there are three main attributes of currency: *medium of exchange, unit of account, store of value*. It can be inferred

[2] Therefore, there are two properties that can characterize the use of money as a convention: 1) third party compliance and 2) arbitrariness. These characteristics bring relevant points to the public acceptance of currency. Compliance is linked to the "public's estimate" in relation to currency, and within arbitrariness, one can generally accept that anything could be money, provided it was accepted by everyone and as such satisfied the essential properties of money (DEQUECH, 2013).

[3] Money has an insignificant elasticity of production in the private sector; low elasticity of substitution (this property is directly related to the capacity of money being a unit of account); and the essential property is low or negligible carrying costs in terms of money custody (the use of money as a store of value certainly depends on this characteristic) (DEQUECH, 2013).

that bitcoin (and cryptos in general) reasonably meets the first criterion, whereas a number of online traders, seem willing to accept it as a form of payment. As for the unit of account, daily volatility would require that prices are constantly remarked, minimizing its potential as a unit of account. Fluctuations would have direct and indirect costs in calculating back and forth between currencies, with detrimental effects on people's savings and the economy as a whole (YERMACK, 2013; BJERG, 2016; CARVALHO, 2017; BAUR; DIMPLF, 2018).

Moreover, as a store of value, bitcoin faces major challenges due to hacker attacks and other security-related issues. It cannot be deposited in a bank, and because it is kept in a virtual wallet, it is susceptible to virtual predators, making it an expensive store of value. Transaction fees have become high[4], which makes bitcoin unsuitable for small retail payments. However, there are financial intemediares and exchanges that accept deposits issuing credit and debit cards denominated in cryptoassets, some operate in Brazil[5] (ARAGÃO, 2019; YERMACK, 2013).

Bitcoins volatility, compared to other financial instruments (such as commodities and derivatives), demonstrate high variance. Stability in its external and internal value is essential if a currency where to be a reliable store of value. The concept of a "crypto asset" brings bitcoin closer to that of an intangible asset, which most users invest their money to speculate, priced in dollars, highly volatile, with strong appreciation[6]. With a demand side driven by expected profits (of holding the asset, selling it with a profit) and with a fixed supply function that evolves according to an algorithm, volatility becomes one of the main market features of cryptos, with prices rising and falling in a course of a single day.

Currently remaining as a niche market dominated by young male investors (Auer & Tercero-Lucas, 2021) Bitcoin (BTC) price is largely affected by its attractiveness as a profit opportunity: an increase or decrease in media attention may influence potential investors positively or negatively depending on the type of information that dominates internet platforms (Guizani; Nafiti, 2019).

Keynes' liquidity preference theory can offer a theoretical base to analyse cryptoassets.

[4] Average time confirmation for a transaction is also remarkedly high, compared to other digital payment systems, and with some transactions that can remain unverified for a long time (FAMA ET AL, 2019).
[5] Xapo, Alter, Opey and Atarpay, were the first in the Brazillian market, according to the author's knowledge.
[6] Despite knowing the underlying difference in nomenclature, cryptocurrency will be used interchangeably for crypto asset, algorithmic asset, and digital currency.

Different degrees of liquidity must be offset by pecuniary returns that define the rate of return[7] obtained by ownership of different assets. The interest rate of each asset is a measure of its expected total return, measured not only in terms of income entitlement, but also in terms of capital gains that can be obtained from its sale. Thus, each asset will offer an individual interest rate and investors will choose those that offer the highest possible rate of return. Competition among wealth holders to obtain the best assets available will determine prices of these assets, signalling which are scarce and which are in excess supply (CARVALHO ET AL, 2012).

A desirable attribute of a liquid financial market is to have a substantial number of market participants who hold continuously differing expectations about the future. Market stability would require a continuous spectrum of both bull and bear expectations simultaneously (Davidson, 2002). Expectations cannot be described as either rational or ex ante correct. In a world of instant communication, any event can set off rapid changes in subjective evaluation of the market value of one's portfolio. If enough agents have the same expectations, driven by speculation of other market players' sentiments this can result in herd like behaviour, becoming self-reinforcing and self-justifying, creating future outcomes.

In the occasion of an abrupt change of sentiments, there could be a rapid swing in prices. The bandwagon effect, cited by Davidson (p. 194, 2002), occurs when market consensus takes a turn, due to a severe change in financial asset pricing. These circumstances requires a market maker with sufficient resources to assure price stability, preventing volatility. This institution or organization must be seen as credible toward market participants, in its efforts to implement a buffer stock policy. On the other hand, in the pervasiveness of such market maker, the only speculators that would exist would be a small group of disagreeing speculators, whose actions will not affect market movements.

Before entering per-se as to the main topics of the four papers here presented, it was important to qualify the debate in terms of theories that support different visions of how bitcoin is seen (as money or a financial asset), and the chosen approach to understand bitcoin. The

[7] The assets interest rate is calculated using the values assumed by four different attributes: 1) Expected rate of earnings for the possession or use of the asset; 2) Carrying costs incurred in maintaining the asset in its original state; 3) Liquidity premium, which measures the ease of trading an asset in the event of a desire to change the composition of the portfolio, as some assets are more easily tradable than others, giving its owner an important return in the form of flexibility in the face of unexpected changes in the economy; 4) Expected rate of appreciation of the asset at the end of a period (CARVALHO ET AL. 2012).

formulated theoretical background gives not only substance to this thesis scope, but justification towards the chosen theme. Connexion between each paper will be understood while clarifying their underlying objectives, towards why these subjects are important.

In paper 1, the focus is to address the growing presences of big market players in the Bitcoin ecosystem. As institutions started entering the crypto market, leaving imprints on transaction flows and price cycles. Wavelet coherence methodology was applied in order to decompose price and transactions in scale and frequency. Estimations through daily data (from January 2011 to December 2021) taken from Glassnode Studio, was organized in three distinct phases (in line with the three Bitcoin Halvings).

Estimations showed that flows were altered by the arrival of leveraged investors with stronger correlation between these two variables at lower frequencies. Halvings do affect price and quantity co-movements in the BTC market, confirming the presence of market makers that accumulate positions expecting valuation. More accurate estimates of market movements were provided from wavelet analysis of transaction count. Higher frequencies during the last two periods are attributed to small and medium sized investors.

The second paper highlights the same underlying assumption, that excessive price and volume changes in the BTC market corroborates our "big player" hypothesis. The Wyckoff method, makes a direct connection to the professionally traded market that bitcoin has turned into. Large institutional investors, who professionally manipulate the market, create major imbalances.

Asset pricing literature has largely documented that bitcoin displays uncorrelated price behaviour to traditional assets, macroeconomic and financial indicators. Applying the Autoregressive Distributed Lag Model (ARDL) and the Non-Linear Autoregressive Distributed Lag Model (NARDL), Bitcoins real return is captured over the last 10 years. Internal (Bitcoin transaction count) and external variables (One Year Treasury Constant Maturity Rate, S&P500, Google Trends), were used to explain how institutional investors have been present in crypto trading. Short-term and long-term spill overs from risk-free bond markets and the stock market were inferred. Our proposed novelty are through nonlinear asymmetric relationships, towards transaction count and S&P500.

An interesting point made by Fama *et al* (2019) and De Vries (2021) is that although bitcoin is a decentralized currency, many aspects of its ecosystem are not. Multiple parties do have a significant influence on bitcoin and its surrounding ecosystem. A small group of developers manages the corresponding bitcoin repository. This community controls the codex of the mining algorithm organizing it according to a certain degree of trust. Potential updates are discussed via bitcoin improvement proposals (BIPS), as there is no automatic updates, network participants decide which code they run on their node.

A few players control a relevant portion of all bitcoins in circulation, having therefore the power of rapidly increasing and decreasing its value. Exchanges, managers of fiduciary funds, or influencers with a huge number of followers, can easily tip investment sentiment, leading to market power abuse. Considering that, a small number of privately owned mining pools do control the majority of computational power in the Bitcoin network, they are able to create new points of control, from within the blockchain infrastructure. Supply chain of specialized mining devices is also concentrated among a few companies, contesting the supposed "decentralized" ethos.

Presently, unregulated middleman are an essential part of the bitcoin ecosystem. These exchanges function normally like banks, where customers buy and sell bitcoins, buy maintaining their balances in both currencies, without direct access to the cryptocurrency[8] itself (Gandal et al., 2018). Unfortunately, these intermediaries open a door for illegal activities[9] and hacker attacks. Exchanges and end-user wallets that interact with bitcoin operate on centralized servers, meaning that all information is stored in one location, making them "sitting ducks" to criminals (Mavadiya, 2017).

There are also implications for the formal financial sector. Institutions should assess whether they are indirectly enabling money laundering through cryptocurrencies. Flow of funds originating from cryptos should be taken into account by compliance professionals, through blockchain techniques to verify risk. This risk is particularly critical for financial providers that offer banking services to cryptocurrency businesses (FANUSIE; ROBINSON, 2018).

Since the Bitcoin ecosystem is currently "self-policing", as it becomes more integrated

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[8] Despite knowing the underlying difference in nomenclature, cryptocurrency will be used interchangeably for crypto asset, algorithmic asset, and digital currency.

[9] The importance of Silk Road to the bitcoin economy cannot be downplayed. According to Fernholz (2013), with the seizure and closure of the site in 2013, a revenue of approximately 9.5 million bitcoins were estimated to have been collected by the site since 2011.

into the international financial circuit, policy-makers my need to take a more active oversight role. Institutions like banks, particularly central banks and higher rank institutions like the Bank for International Settlements (BIS) have a track history of infusing innovation, always looking to diffuse international policies and practices that assist countries to reliably manage payment mechanisms.

Progressive digitalization of money and diminishing cash use have put retail financial innovations (cryptocurrencies, global stablecoins and private payment providers) on the radar of central banks around the world. Instant communication via-email and social media have become the template towards payments, especially novel digital services stemming from big tech companies. The Brazilian Central Bank (BCB) was fast to provide an alternative to wider digital financial inclusion, creating an Instant Payment System (SPI) on top of the Real Time Gross Settlement Systems (RTGS) implemented in the 2000s. In November 2020, Pix went into operation, enabling fast payments through registered digital keys.

In order to apprehend the prime factors associated to instant payment mechanisms, the Indian Unified Payments Interface (UPI) was used as a study case. Although empirical studies on payment systems are specific to each jurisdiction, stemming from unique social and cultural attributes, statistic correlation to Brazilian and Indian financial deepening (M1/GDP) and payment system characteristics can support main findings from the third paper. Through time series methodology and an Indian dataset, (April 2016 to November 2020) inferences bring to the debate relevance towards financial innovation as an instrument for economic development.

Macro-level variables (financial sophistication, economic growth, payment substitutes and measure of relative popularity of banking apps) were chosen to understand UPI volumes. During adoption, these payment mechanisms increase exponentially while the ratio that measures popularity of banking apps had a direct effect on UPI flows. Credit and debit cards as alternatives to fast payments had a complementary character to these instruments, while financial sophistication has short-term and long-term effects. Short-term asymmetric shocks were confirmed from credit card transactions and financial deepening to volume of instant payments.

With decision-making complexities and network externalities, payment systems are frequently viewed as public good, driving central banks to propel new enhancements through their resources, influence and knowledge. Bitcoin by itself may not have been the most important motive as to why central banks took digitalization so seriously. A part in this new fintech wave are social media companies and private payment service providers (PsP), promoting new services to a vast array of clientele benefitting on scale advantages.

To privately address payment markets is to increase profit margins (sometimes at the detriment of public welfare) pressuring monetary authorities to rethink their settlement infrastructures. If payments are continuously redirected into private systems this may have consequences towards central banks ability to foster monetary policy. Central Bank Digital Currencies (CBDCs) have been gaining traction as subsidiary alternative to fast payments, especially in emerging market economies (EMEs).

Central Bank Digital Currencies (CBDCs) are by definition a digitally issued fiat currency, a liability on the central banks balance sheet. The main motives as to why developing economies are interested in implementing this second (or first-layer) of publicly promoted deployment can be summarized in: financial inclusion, support access to payments, promoting efficiency, resilience, combating illicit transactions, cyber risks, bank disintermediation, financial stability, cross-border payments and last but not least, monetary sovereignty (Soderberg et al, 2022).

Brazil and India with their fast payments systems in place have already developed systems that could breach problems related to financial inclusion, but not so much as to safeguarding domestic payments. This fast track environment leads authorities to have a nuanced vision towards the future monetary system. The architecture of the Brazilian central bank digital currency as a smart payment platform is an example of this need to foster an environment for companies to innovate using new functionalities, such as programmable money. Even though digital money should be designed as to remain trustworthy, protecting costumers' interest, requiring prudence and expert foresight, governments need to maintain legitimacy "future proofing" the payment system.

The last article supports our arguments towards Brazilian and Indian central bank-led transformations, towards decreasing currency use and generational preferences. Four measures of cash-share (Khiaonarong; Humphrey, 2019) were estimated using BIS annual data (2012-2020). The best calculus was used for a linear regression prediction exercise through MathCad, in order to visualize future trends (2021-2026) in physical currency usage.

Central Bank Digital Currencies (CBDCs) could in fact become an interesting and reliable payment mechanism, for many jurisdictions leaning towards decreasing cash in circulation. For financial inclusion considerations, their greater applicability would be in countries which alternatives are not already popular.

In Brazil and India instant payment systems laid ground for more fundamental transformations that are yet to come, creating an environment that can presently aid the informal sector. To further address, financial inclusion is to look at infrastructural policies that can guide developing countries into this new technological environment that will require specific capabilities from future generations. Investments in education, increasing digital literacy, internet access, minimizing broadband gaps to regions that are poorly assisted are some of them.

PAPER 1. BITCOIN HALVINGS AND INSTITUTIONAL INVESTORS: A WAVELET ANALYSIS

Resumo: O objetivo deste artigo consiste em analisar através da metodologia *Wavelet* a dinâmica do preço do Bitcoin (BTC), sob a ótica dos Halvings. O Halving constitui um atributo técnico importante e pouco estudado na literatura acadêmica, da formação do preço e valorização do ativo. Argumentamos que por ser altamente especulativo e volátil, sua demanda baseia-se muito mais nas percepções dos agentes sobre tal inovação financeira, em especial, as instituições que começaram a atuar de forma mais efetiva no mercado, provocando alterações nos fluxos de transações e nos ciclos de preços. Para avaliar as causas e consequências dos três halvings e como eles alteraram a dinâmica de movimentações no mercado BTC, emprega-se a metodologia *Wavelet*. Foram extraidos da Glassnode Studio dados diários de Janeiro de 2011 a Dezembro de 2021 do preço do bitcoin e das transações realizadas na plataforma. Organizando estes dados em três fases distintas, a decomposição em escala e frequência através da sincronia de sinais, apontam que os fluxos foram alterados pela chegada de novos investidores. Houve um aumento de captalização de mercado com correlações mais fortes entre preços e transações, a frequências mais baixas (horizonte temporal mais longo).Estimativas mais precisas foram encontradas na decomposição da variável transações realizadas, demonstrando que os movimentos mais fortes aconteceram em frequências mais altas (horizonte temporal curto) nas últimas fases, por meio de pequenos e médios investidores.

Abstract: The objective of this article is to analyse, through wavelet methodology, Bitcoin (BTC) price dynamics carried out on the blockchain platform, from the Halvings perspective. Halving constitutes an important technical attribute, rarely studied in academic literature of BTC price formation and asset valuation. As a highly speculative, volatile asset, its demand is based much more on the perceptions of agents about such financial innovation. Especially “institutions that began leaving a bigger footprint in the market, causing changes in transaction flows and price cycles. To assess the causes and consequences of the three halvings and how they changed dynamics in the BTC market, Wavelet methodology was carried out with daily data (from January 2011 to December 2021), taken from Glassnode Studio on Bitcoin price and transaction count. Organizing the data into three distinct phases, decomposition in scale and frequency through signal synchronicity, indicate that flows were altered by the arrival of new investors. There was an increase in market capitalization with stronger correlations between prices and transactions at lower frequencies (longer time horizon). Accurate estimates were found decomposing transaction count in wavelets, demonstrating that the strongest movements took place at higher frequencies (short time horizon) in the last phases, through small and medium sized investors**.**

2. INTRODUCTION

"Cryptocurrencies", particularly Bitcoin (BTC), have attracted considerable attention through media, academic research, economic, political circles, gaining increasing notoriety. Institutional investors, hedge funds and private equity firms, started to invest heavily in Bitcoin in the last few years (Iyer, 2022). With global economic uncertainty consequences of the COVID-19 pandemic and the Ukraine war[10], coupled with the quantitative easing policy promoted by the US Federal Reserve (FED) and the Bank of England (BOE) (Kang et al, 2019)[11], companies are trying to protect their holdings from expected inflationary effects and profitability losses.

Under certain specific circumstances, Bitcoin has proved to be an investment vehicle, an alternative diversifier, and a hedge[12] against or with other assets: Baek & Elbeck, (2015); Bouoiyour, Selmi & Tiwari (2015), Bouoiyour & Selmi (2015), Briére *et al*. (2015), Cheah & Fry (2015); Dyhrberg (2016); Bouri *et al* (2016); Blau, (2017); Bouri *et al*, (2017); Demir *et al*, (2018); Dyhrberg *et al* (2018); Jareño *et al*, (2020) Kang *et al* (2019) ; Bhuiyan *et al* (2021).

Speculation, trading algorithms (Gray & Breton, 2021), can efficiently capitalize on potential arbitrage opportunities between different exchanges (Kristoufek, 2015; Tut, 2022), while market dynamics in the form of dramatic volatility swings and bubbles, have followed largely bitcoins lead. As is today heightened economic and regulatory environment tends to drive instability, wavering investor confidence, triggering frequent sellofs, increasing market

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[10] Referencing current events Tut (2022) arguments that Bitcoin can provide a channel for transferring large amount of funds across international borders, without any third party involvement. With increased Bitcoin price and returns during the immediate onset of the Russian-Ukraine war, Bitcoin to some extent could have served as a safe asset during periods of political uncertainty.

[11] According to Robert Skidelsky quantitative easing can be seen as an example of state-created financial instability. Increasing money through QE gives a big temporary boost to housing and financial securities, greatly benefiting asset holders. The professor references Keynes's, argument in the *Treatise of Money,* that during an economic downturn, money is not necessarily hoarded, but it flows from "industrial" to "financial" circulation. And when in financial circulation, it is used for "*holding and exchanging titles to wealth, including stock exchange and money market transactions*". Depression is marked by the transfer of money from industrial to financial circulation, from investment to speculation (SKIDELSKY, 2021).

[12] If an asset is negatively correlated with another asset, putting them together decreases portfolio risk significantly. Bouri *et al* (2016, p. 2) to better qualify terminology, differentiates between a diversifier, a hedge, and a safe haven: "*A diversifier is an asset that has a weak positive correlation with another asset on average. A weak (strong) hedge is an asset that is uncorrelated (negatively correlated) with another asset on average. A weak (strong) safe haven is an asset that is uncorrelated (negatively correlated) with another asset on average during times of stress*".

hype (OMANE-ADJEPONG ET AL, 2019).

Knowing that Bitcoin price dynamics are closely linked to the halving phenomenon, market flow may have been altered by the arrival of big players[13], and that the last BTC price cycle may have behaved differently then other previous ones. Halving is deterministically given by the Bitcoin algorithm, nonetheless, price and transaction volumes in exchanges are a manifestation of how agents value (or undervalue) a specific crypto asset. Identifying periods with stronger measures of cross-correlation between these two variables provides a timeframe in which market players are most active, distinguishing between short and long-term relationships.

Wavelet methodology targets periodic phenomena in time series in the presence of potential frequency changes across the time domain (Rösch; Schmidbauer, 2018). A useful technique for analysing financial relations. Its ability to work with non-stationary data is particularly advantageous, as most econometric methodology assumes stationarity, which may or may not be apparent in economic data (Crowley; 2007). Specifically in this study, continuous wavelet power analysis, wavelet coherence and phase difference are used to access correlations, capturing market dynamics through time and across scales of Bitcoin price series (in USD) and the number of transactions in BTC.

Hypothesis construction is based on the following questions: 1) Did the last BTC price cycle behave differently than the other cycles? 2) Is it possible to observe through co-movements between BTC price and transaction count how institutions are active in the BTC market, through frequency and scale decomposition? 3) Does transaction count give a better measure of market activity? Study rationale is that the main crypto environment (Bitcoin) has changed with the arrival of agents empowered with high financial leverage capable of leaving specific trails when analysing price vis-à-vis their impacts on transactions over different time frequencies. This shift points to different dynamics that could influence not only low to middle-income speculators, but also market reaction and volatility.

Providing information on the direction of co-movements, as well as potential causal relationships between Bitcoin price in USD and transactions, wavelet findings appoint to escalating market price of the crypto-asset with short-term intensified movements from small

[13] Here we define big players or institutions as a company that owns a large sum of Bitcoins.

retail investors, added to long-term movements from large speculators. Access to crypto investment through specialized exchanges, increased market capitalization, pushing to a long-term trend (lower frequency) in price/transaction correlation. Wavelet powers of transaction count gives additional substance to our hypothesis, marking higher frequency in the very short-term.

The paper is divided as follows. The first section is a review of the academic literature, that has three subsections: an introduction to the original article by pseudonymous Satoshi Nakamoto (2008), followed by a theoretical approach on the halving phenomenon, closing with an academic review on wavelet methodology. The second section provides a more detailed explanation, specifically continuous wavelet, wavelet coherence, and phase difference. Dataset, interpretation specifics and results are the third and last part of the article ending with conclusions.

3. REVIEW OF THE ACADEMIC LITERATURE

3.1 Orginal Article by Nakamoto (2008)

A large portion of commerce on the Internet has come to rely almost exclusively on financial institutions serving as intermediaries to process electronic payments. While the traditional payment system works for the majority of transactions, according to Nakamoto (2008) there is an inherent weakness[14]. The centralized trust-based model increases transaction costs, as payments become bloated and expensive to the payer and payee. As financial institutions cannot avoid mediating disputes, this puts additional pressure on the system, through third-party discretion (MAVADIYA, 2017).

Nakamoto's decentralized peer-to-peer (P2P) model, computes time stamped transactions by miners with a consensus algorithm shared by nodes. When transactions are performed in the Bitcoin blockchain platform, miners group these transactions into blocks in the order in which they are received by the system. Through mathematical calculations ("proof-

[14] A detailed explanation on Nakamoto's (2008) paper is in the Appendix.

of-work"), using hash-power (electricity) miners find the solution that links the actual block to the previous block of transactions. Each block is algorithmically linked to the previous one through a "*hash*"[15].

The main incentive in sharing the solution with the network is in receiving as a reward a predefined quantity of bitcoin. The "miner" receives 6.25 BTCs for each block of transactions discovered, a payment for having granted its computational power and enabling transactions carried out in BTCs. They can also be rewarded by receiving transaction fees[16] . Users offer fees so their transactions are prioritized by miners in the formation of their candidate blocks, increasing the chances of transactions being made more quickly.

Other nodes in the network express their acceptance of the new block by starting to work on the next block using the hash of the validated one (Maurer et al, 2013; De Vries et al, 2021).Once proof-of-work has been done and CPU energy expended, the block cannot be changed. The longest chain in the network will always represent majority, as it has most computational power invested in it.

Bitcoin blockchain transactions can be summarized as follows: "miners" solve specific math problems, earning newly minted cryptos and non-mandatory transaction fees, by providing network services, verifying and collecting newly broadcasted transactions. Payments are recorded in a public "ledger" (blockchain), which contains blocks of verified transactions to track the ownership of each BTC. This decentralized registry monitors property and transfers of each crypto after it is mined (BJERG, 2016; CIAIAN, 2016; HAYES, 2017; YERMACK, 2013).

Every four years miners' remuneration is reduced by half, which leads to a perceived increase in Bitcoin market value, with important implications for institutional investors seeking profitability and crypto miners that depend on BTC revenue. The halving event will be technically discussed, in the next section.

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[15] *A hash function is a computational method that can map an indeterminate size of data into a fixed size of data (...) A cryptographic hash function uses one-way mathematical functions that are easy to calculate to generate a hash value from the input, but very difficult to reproduce the input by performing calculations on the generated hash"* (EDGAR, MANZ;2017, p.56). Common hash functions are SHA-1, SHA-2, and SHA-3. The SHA-2 family of hash functions includes bitcoins SHA-265, an approved algorithm, by the US National Institute of Standards and Technology (NIST) (NIST; 2022a).

[16] "*If the output value of a transaction is less than its input value, the difference is a transaction fee that is added to the incentive value of the block containing the transaction"* (Nakamoto, 2008, p.4).

3.2 Theoretical Review on Halving

Despite its importance as an important technical element to the Bitcoin network, halvings are not thoroughly studied in academic literature. Economic studies dedicated to Bitcoin are generally driven towards market power, supply, demand, production cost, and public interest through mass media (Meynkhard, 2019).

As previously seen, the creation of new bitcoins is not only predictable, but also automatically set to the system code. With limited production, supply would decrease over time and *ceteris paribus,* the price of these assets would increase[17]. One of the main purposes of Bitcoin is to avoid currency devaluation. Since theoretically, no government or central authority could manipulate its supply-side, circulation cannot be influenced by monetary policy (there is limited issuance).Increasing/decreasing mining complexity is aonter important principle that regulates BTC[18].

Graph 1 shows the number of Bitcoins in circulation from January 2009 to October 2021. With data collected from Glassnode Studio, Bitcoin supply is above 18 million, with only 3 to 2.5 million left to be mined. Graphing BTC emission over time has become a way of conveying the deterministic nature of the crypto economy: the rounded curve, which approaches 21 million but does not ever reach it. According to Nakamoto (2008), the constant addition of a predetermined amount of new coins would be analogous to the extraction of gold[19]. This is not just rhetoric, *digital metalism;* an expression coined by Maurer *et al* (2013) captures how Bitcoin evokes its self-conception, as a form of commodity money.

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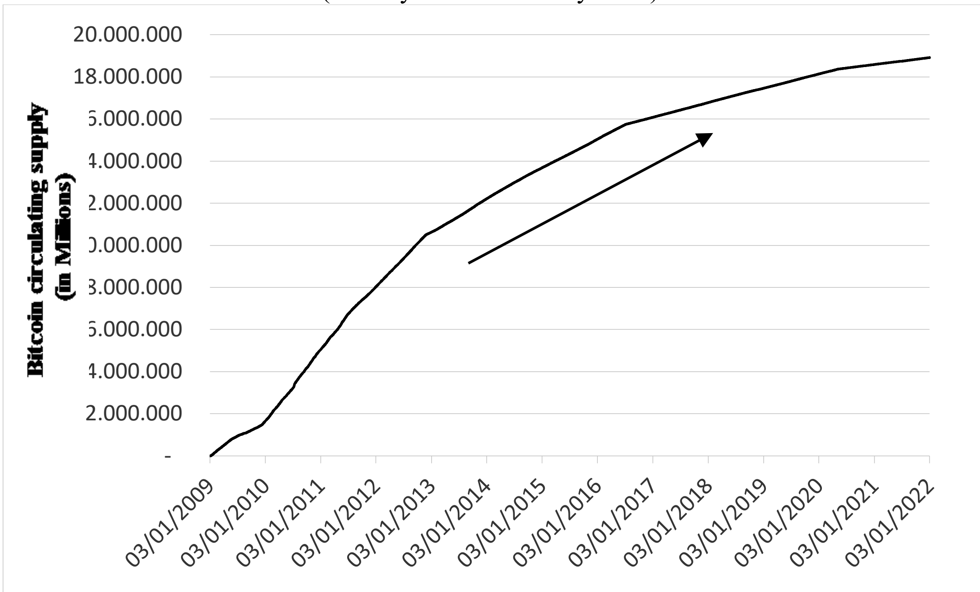
[17] Although some enthusiasts have suggested a connection between the algorithmic growth rate of Bitcoin and Milton Friedman's monetary orthodoxy, the crypto asset protocol does not aim at an optimal rate of money growth. Seignorage is estimated to asymptotically decrease to zero by 2140 when the last Bitcoin is scheduled to be released and the final total will be fixed at 21 million units (BOUOIYOUR; SELMI, 2015; CARVALHO et al; 2017).

[18] There are three basic market principles to Bitcoin: 1) limited issuance, 2) mining difficulty (complexity), and 3) the halving event (Meynkhard, 2019) I will attain myself to better qualify limited Bitcoin issuance, and the halving phenomenon in this paper.

[19] "*The steady addition of a constant amount of new coins is analogous to gold miners expending resources to add gold to circulation. In our case, it is CPU time and electricity that is expended*" (Nakamoto, 2008, p.4).

Graph 1 - Number of Bitcoins in circulation (2009-2021), in Millions (daily data) (January 2009 to January 2022).



Note: Author's elaboration. Source: Glassnode Studio (2021).

Following the completion of new blocks on the blockchain, the frequency with which they are generated is constant: six blocks per hour. Each BTC block is limited to 1MB size and cannot handle more than eight transactions per second (Tut, 2022). The amount of coins mined by the network is reduced in a geometric progression: every 210 thousand Bitcoins mined; there will be a 50% reduction of BTC reward, corresponding to a four-year cycle. A clear timetable for Bitcoin emission can be created (Table 1).

When Bitcoin was launched, the award for the transaction block was 50 BTC. In one hour, the network produced a turnover of 300 BTC or 7200 BTC per day. Three halving events have happened since bitcoins inception, which was in 2012, 2016, and 2020 (Graphs (2a), (2b), and (2c). The end of 2012 marked a decline in emissions from 50 to 25 BTC for each newfound block. Which consequently generated 150 BTC per hour, 3600 BTC per day, and 1.312.500, 00 BTC per year. Market price was at approximately $12 when halving happened; a year later BTC price reached a maximum of $1.150, amounting to a rise of 9600% (Graph 2a).

Table 1 - Bitcoin emission

Year	Block remuneration	The amount of mined Bitcoins	Percentage (%) of the number of Bitcoins emitted	The amount of mined Bitcoins by cumulative totals
2009	50	10.500.000,00	50,00%	10.500.000,00
2012	25,0	5.250.000,00	25,00%	15.750.000,00
2016	12,50	2.625.000,00	12,50%	18.375.000,00
2020	6,250	1.312.500,00	6,25%	19.687.500,00
2024	3,125	656.250,00	3,13%	20.343.750,00
2028	1,5625	328.125,00	1,56%	20.671.875,00
2032	0,78125	164.062,50	0,7813%	20.835.937,50
2036	0,39063	82.031,25	0,3906%	20.917.968,75
2040	0,195313	41.015,63	0,195313%	20.958.984,38
2044	0,097656	20.507,81	0,097656%	20.979.492,19
2048	0,0488281	10.253,91	0,04882813%	20.989.746,09
2052	0,0244141	5.126,95	0,02441406%	20.994.873,05
2056	0,01220703	2.563,48	0,0122070313%	20.997.436,52
2060	0,00610352	1.281,74	0,0061035156%	20.998.718,26
2064	0,003051758	640,87	0,0030517578%	20.999.359,13
2068	0,001525879	320,43	0,0015258789%	20.999.679,57
2072	0,0007629395	160,22	0,0007629395%	20.999.839,78
2076	0,0003814697	80,11	0,0003814697%	20.999.919,89
2080	0,0001907349	40,05	0,0001907349%	20.999.959,95
…	…	…	…	…
2140	0,0000000058	0,001222360	0,0000000058%	21.000.000,00

Source: Adapted from Meynkhard, 2019, p.8

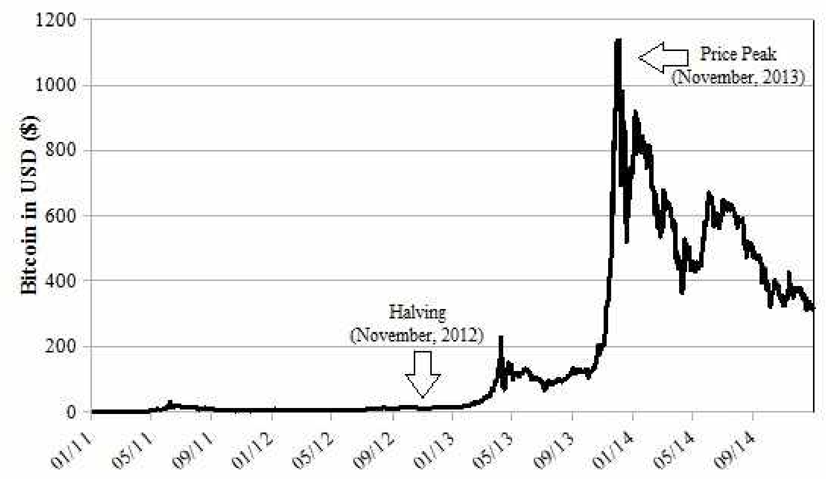
The second halving event occurred in July 2016, releasing 2.625.000, 00 BTC in circulation, which is 12.5% of the maximum issuance of Bitcoin (Table 1). At the time of halving BTC price was $670 for a unit of BTC, after nearly a year and a half in December 2017, Bitcoin price reached $19.500, a new all-time high in its price, resulting in a 2910% increase in BTC market value (Graph 2b).The last halving event occurred in May 2020 and block reward went down from 12.5 to 6.25 BTCs per block. Bitcoin price was at $ 8.599, at the time of the halving event. To date there were two highs, one in May 2021 when BTC price reached $58.218, and the other towards the end of 2021, consolidating $65.342 (Graph 2c), a new high for BTC (697%). The next halving will happen when miners reach a total amount of 20.343.750 mined Bitcoins, and it is scheduled to happen between February/June 2024.

Therefore halving can significantly affect Bitcoin market value, in addition to influencing overall miners' earnings (Meynkhard, 2019; El Mahdy, 2021). Hypothetically, Bitcoin network participants who used to mine 100 BTC per month, and then sold them to offset their production costs, began to produce two times fewer coins after halving, leading to a decrease in the supply of "new" BTCs. With the same level of demand and twice-decreased supply, there is a market reaction increasing asset price. By the year 2140, Bitcoin circulating supply would peak (Graph 1), with a total of 21 million crypto units, and emission would stop. After that, the miners' computer power will be used to allocate transactions, receiving commission or fees paid by members of the system when making payments in BTCs (MEYNKHARD, 2019).

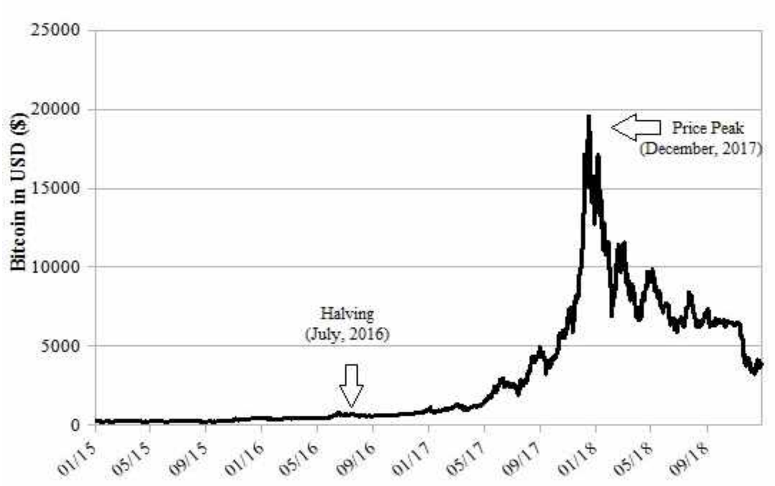
During COVID-19 Bitcoin holders witnessed the highest peak in prices since its inception: Bitcoin trading price, which started around $0.0008 in July 2010, has reached over $60,000 in October 2021. Escalating BTC prices are traditionally attributed to supply and demand fundamentals, estimated output volumes, the role of global financial development, equity market indices, exchange transactions and long-term price behaviour (Ciaian *et al*, 2016; Bouoiyour & Selmi, 2015, Bouoiyour *et al*, 2016a, Kristoufek, 2015, Iyer, 2022). Additionally a large number of companies and institutional investors that started to view Bitcoin not only as an interesting investment asset but also as "*the future of money*" makes its perceived value real. This spurs speculation on whether price surges are a bubble or a reaffirmation that it is becoming a more popular "*store of value*".

Graph 2 - First, second and third Halving Events (Bitcoin price in USD). Daily Data taken from Glassnode Studio (from January 2011 to December 2021).

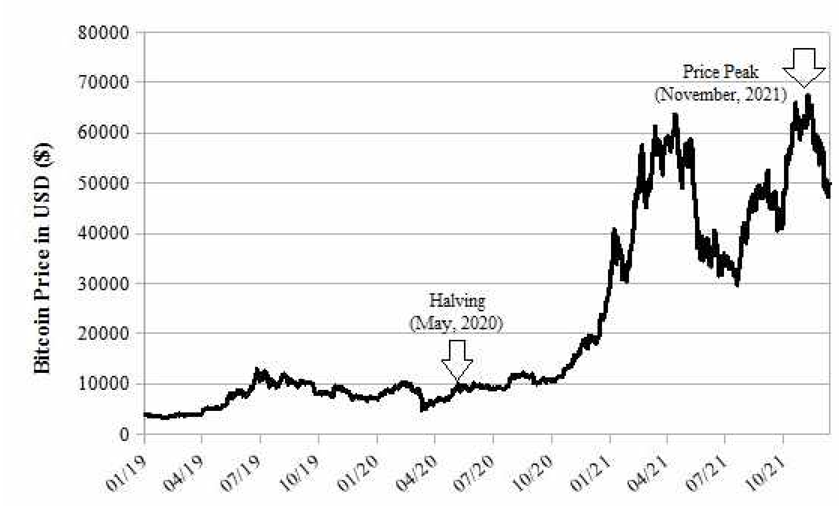
(2a)



(2b)



(2c)



Bitcoin market is globally integrated by a diverse group of holders, which are increasingly looking at its artificial scarcity. Albeit long-term trends in BTC markets, current and prospective traders should bear in mind that prices are mainly driven by the most recent BTC halving, the current global economic environment, with asset bubbles and short-term trader expectations, making Bitcoin a highly volatile[20] and speculative investment. The next section aims to provide an overview of the empirical academic literature driving attention to the applicability of wavelet analysis, specifically wavelet coherence and phase difference, in the crypto market context.

3.3 Methodological Literature Review

Wavelet coherence, which monitors temporal relationships over the short, medium, and long run, has been widely used in the financial literature. Crypto focused wavelet literature has identified co-movement between Bitcoin and its fundamental attributes (Krisotufek, 2015; Phillips & Gorse; 2018) global uncertainty (Bouri *et al*; 2017), hedging capabilities, informational inefficiencies (Kang *et al*, 2019; Omane-Adjepong *et al*; 2019 Qiao *et al*; 2020, Bhuiyan *et al*, 2021), and regional markets (Lim & Masih; 2017).

One of the first to analyze bitcoins (BTC) main drivers with wavelet coherence analysis was Kristoufek (2015). Economic attributes, transactions, and technical[21] features, were the possible drivers examined for BTC price. According to the author, if Bitcoin is used for trade, it appreciates on the long run, boosting demand for the crypto asset, and motivating users to become miners. However, this effect vanishes over time as specialized mining hardware

[20] Interesting enough, in their quarterly report Coinbase explicitly claims an extensive number of risk factors involved in their trading activities, reaffirming the highly erratic nature of this market: "*there is no assurance that any supported crypto asset will maintain its value or that there will be meaningful levels of trading activities. In the event that the price of crypto assets or the demand for crypto assets decline, our business, operating results, and financial condition would be adversely affected"*(COINBASE QUARTERLY REPORT, 2021a. p.57)

[21] Kristoufek (2015) used the following variables: 1) Bitcoin price index, 2) blockchain information (total Bitcoins in circulation, number of transactions, estimated output volume, trade volume vs transaction volume ratio, hash rate, difficulty), 3) exchange rates (exchange volumes as a sum of four of the most important exchanges at the time, accounting for 90% of all USD exchange transactions), 4) search engines (Google Trends and Wikipedia views), 5) Financial Stress Index (FSI) provided by the Federal Reserve of Cleveland, and 6) Gold price for a troy ounce.

components drive hash rates and difficulty even higher.

Revisiting and extending Kristoufek's (2015) study, Phillips & Gorse (2018), used wavelet coherence, and generalized supremum augmented Dickey-Fuller (GSDAF) bubble test to address online usage factors and market regime. This combination of methods was applied to determine whether relationships strengthen during market bubbles[22]. Social media variables from Reddit, Google search volumes, and Wikipedia page views were analysed for four different cryptocurrencies (Bitcoin, Ethereum, Litecoin, and Monero).

Bouri *et al* (2017) using wavelet-based quantile-in-quantile regressions, examines whether Bitcoin can hedge global uncertainty. Unlike Kristoufek (2015) that did not identify safe-haven properties on Bitcoin, authors reveal that BTC reacts positively to uncertainty at higher quantiles and shorter frequency movements of Bitcoin returns. Daily data of Bitcoin price and VIX[23] (implied volatility index) covering the period from 17th March 2011 to 7th October 2016, was used in estimation. Standard OLS, two different quantile-based approaches, and wavelet-filtered data were the chosen methods to the analysis. Results showed that for short-term frequencies, Bitcoin does hedge against risk when the market is in a bull regime (upper quantiles) but not in a bear regime, where BTC returns are negatively impacted by uncertainty[24].

To identify the relationship between Bitcoin and different asset classes, Bhuiyan *et al* (2021) employs a wavelet approach to analyse BTC and several representative asset classes, including gold, the U.S. dollar index, oil, the Dow Jones commodity index, the S&P 100 global index, and the EMTX 7-10Y bond. Studying daily prices from July 2014 to November 2019, through wavelet covariance and wavelet correlation a neutral dependence was shown in most circumstances, with a notable exception to gold prices, indicating a strong bidirectional relationship. This outcome implies that the Bitcoin market is relatively isolated from the global

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[22] Short-term intervals of co-movement are caused by sector-wide news or cross-market contagion. In the medium-term relationships with online factors strengthen during price bubbles, associated with increased social media activity Long-term relationships are strengthened given that successful cryptocurrencies are likely to have a growing, active community of supporters and investors (PHILLIPS; GORSE, 2018).

[23] Global uncertainty was measured by the common component of the VIXs of 14 developed and developing equity markets (BOURI ET AL, 2017).

[24] By decomposing Bitcoin returns into its various investment horizons, and accommodating estimation methods that incorporate information from quantiles, for both BTC returns and global uncertainty, Bouri *et al* (2017), show that BTC can serve as a hedge against uncertainty at the extreme ends of the market but at shorter time horizons.

financial system; nonetheless, BTC shared important features with gold.

Kang *et al* (2019) are also interested in diversification properties of gold futures vis-à-vis Bitcoin prices[25]. Research aimed to reveal whether the bubble patterns in gold future prices could be used to hedge against overall market and sector downside risk in the Bitcoin market and vice-versa. There was evidence of volatility persistence, causality, and phase differences between Bitcoin and gold futures. Contagion increased during the European sovereign debt crises (2010-2013). Also indicating relatively high co-movement across the 8-16 weeks frequency band between Bitcoin and gold future prices for the 2012-2015 period.

Using wavelet coherence analysis Qiao *et al* (2020) analyse relationships across returns, volatility, and risk under a time-frequency domain. Among representative cryptocurrencies[26], hedging effects are considered in different investment horizons. Results indicate that time and scale, are important determinants in the co-movement between returns, whether in correlation or phase difference. Bitcoin has a closer relationship with newly issued cryptos because they are not stable enough to withstand external influences. However, under different investment periods, risk reduction is possible, with positive correlations between Bitcoin and other cryptocurrencies.

With a multivariate GARCH DCC (MGARCH-DCC) and wavelet tools[27], Lim & Masih (2017), conducts an exploratory study on whether Bitcoin can be used as a portfolio optimization strategy, for Islamic fund managers. Collecting daily closing prices from January 1st, 2013 to January 2nd, 2017, and a holding period of 8-16 days, correlations are negative for all indices[28] indicating that investors should look into Bitcoin as a short-to-medium term

[25] Conditional correlations (DCCs) with the GARCH specification model and wavelet coherence method to weekly data from 26th July 2010 to 25th October 2017 were the chosen methods. Variables were sourced from the Coindesk Price Index while gold futures were drawn from the Thomson Reuters dataset. Continuously compounded weekly returns were calculated by the difference between prices in logarithms (KANG ET AL, 2019).

[26] Dataset was obtained from coingecko.com and consists of daily samples of cryptocurrencies that accounted for 86% of market capitalization, from April 21, 2014, to October 12, 2019. Which includes Bitcoin (BTC), Ethereum (ETH), Ripple (XRP), Bitcoin Cash (BCH), Litecoin (LTC), EOS (EOS), TRON (TRX), Cardano (ADA), Stellar (XLM), Monero (XMR), ChainLink (LINK) Dash (DASH), and Ethereum Classic (ETC) (QIAO ET AL, 2020).

[27] Namely, wavelet coherency to capture correlation, continuous wavelet transforms (CWT), and maximum overlap discrete wavelet transform (MODWT).

[28] Lim & Masih (2017) uses the following price indexes: FTSE Bursa Malaysia Emas Shariah, DJ Islamic Europe, DJ Islamic World Developed, DJ Islamic World Emerging Markets. All of them were taken from the Thomson-Reuters DataStream dataset. The bitcoin price index was from Coindesk. Returns from all 5 indices are calculated as differences of the logarithmic daily closing prices of indexes.

investment diversifier.

Omane-Adjepong et al (2019) employing ARFIMA-FIGARCH class models under the Gaussian and T Student's distributions with a modified log-periodogram method, explores the persistence of the eight largest cryptocurrency markets, using daily data from August 2015, to March 2018[29]. Market (in) efficiencies are examined using derived and filtered conditional market returns across short, medium, and long run trading horizons through Maximal Overlap Discrete Wavelet (MODWT). Authors uncover that informational efficiency and volatility persistence are highly sensitive to time-scale, and regime shift[30].

For empirical purposes, it would be more effective to have a transform that would also carry out an adaptive basis. The Empirical Mode Decomposition (EMD) for daily time-series related to Bitcoin price index (BPI), from December 2010 to June 2015 performed by Bouoiyour *et al* (2016a), explains the time-frequency evolution of multi-component signals, showing that Bitcoin seems largely explained by long run factors. Although Bitcoin does behave as a bubble (high frequency component) prone to speculative attacks, long-term fundamentals (low frequency component) are likely to be major contributors of BTC price variation. Thereby, investigations about price dynamics should be highly aware of the identified data properties. Since our main objective is to recognize patterns of price dynamics vis-à-vis their impacts on transactions over the short and the long-term, motivation behind the next section is to comprehend wavelet methodology, and the underlying data generating process.

[29] Daily data on the eight largest cryptocurrencies, by market capitalization: Bitcoin (BTC), Ethereum (ETH), Ripple (XRP), Litecoin (LTC) Stellar (XLM), Monero (XMR), Dash (DASH), NEM (XEM), are used for the study. With a reliable data span of at least two years of market operation, and 992 market realizations (OMANE-ADJEPONG ET AL; 2019).

[30] Traders will have greater opportunities in reaping excess benefits from the market in the short to medium-term, gains that are much more likely to disappear on the long run (OMANE-ADJEPONG ET AL; 2019).

4. METHODOLOGY, DATASET AND RESULTS

4.1 Methodology

Given the highly complex nature of the crypto market, methodological problems arise when one wants to assess how BTC prices evolves through time (Bouoiyour et al, 2016a). Resulting from the Heisenberg uncertainty principle[31], wavelet[32] analysis has its origins in the signal processing literature. Dealing with both stationary and non-stationary data, acting locally in both frequency and time, decomposing fluctuations, wavelets provide a convenient and efficient way of representing complex variables[33]. By allowing different time scales, it provides a fruitful understanding of dynamic economic relationships (CROWLEY, 2007; RAMSEY; 2014).

A rectified version of the wavelet power will be used in which time and scale will correspond to the series variance, with a proportional factor of $\frac{1}{s}$. In order to infer about frequency contents and synchronicity of two time-series, the cross-wavelet transform will provide the appropriate mathematical framework:

$$W_{xy}(u,s) = \frac{1}{s} W_x(u,s) W_y * (u,s) \; (1)$$

Where $W_x(u,s)$and $W_y(u,s)$are continuos wavelet transforms of series *x(t)* and *y(t)*.

The wavelet power spectrum is understood econometrically as the local variance of the time series, while the cross-wavelet power of two time series portrays the local covariance. Usually used as a measure of co-movement between two series, the cross wavelet power uncovers regions of common high power in the time-frequency space[34]. Nevertheless, it has

[31] The Heisenberg uncertainty principle, states that the more certainty that is attached to the measurement of one dimension (frequency, for example), the less certainty can be attached to the other dimension (here the time location).

[32] Wavelets are "*small waves, that begin at a finite point in time and die out at a later point in time*" Crowley (2007, p. 208).

[33] A detailed explanation on the methodology is provided in the Appendix.

[34] The cross-wavelet transform of two-time series *x(t)* and *y(t)* with respective wavelet transforms decomposes the Fourier co-and quadrature-spectra in the time-frequency (or time-scale) domain (RÖSCH; SCHMIDBAUER; 2018, p.6).

limitations: the unit of measurement may not be ready for interpretation concerning the degree of association between the two series (Aguiar-Conraria *et al*, 2014; Kristoufek, 2015). Wavelet coherency remediates this problem as it measures the cross-correlation of two time series as a function of frequency. Coherency is analogue to classical correlation, requiring smoothing of both cross-wavelet spectrum and normalizing the individual power spectra:

$$Coherence = \frac{|sWave\ .xy|^2}{sPower.x \cdot sPower.y} \quad (2)$$

Or

$$R_{xy}^2(u,s) = \frac{\left|S\left(\frac{1}{s}W_{xy}(u,s)\right)\right|^2}{S\left(\frac{1}{s}|W_x(u,s)|^2\right)S\left(\frac{1}{s}|W_y(u,s)|^2\right)} \quad (3)$$

"S" is the smoothing operator. There is no agreement in academic literature about the direction and the amount of smoothing (scale or time), to obtain an appropriate measure of coherence without loss of information. Its importance lies on the fact that without smoothing, coherency would have modulus equal to one at all scales[35]. Wavelet coherence Equation (3) can be understood as the ratio of the cross-wavelet power to the product of the individual wavelet power, comparable to the squared coefficient of correlation. In other words, it is the correlation coefficient around each moment in time and for each frequency, ranging between 0 and 1.

Due to the use of the squared coherence, plus the complexity of wavelets the direction of the relationship between variables is lost (Kristoufek, 2015; Phillips; Gorse, 2018). Phase difference is introduced, separating real and imaginary parts of the wavelet, providing both local amplitude and instantaneous phase information of the periodic process.

Wavelet coherence[36] provides a timeframe in which market agents are most active, through BTC price movements and transactions. Allowing disaggregation of the assumed relationship between BTC price (in USD) and transactions, it is possible to recognize patterns of price dynamics vis-à-vis their impacts on transactions over different frequencies. Phase

[35]The R Package used in our study WaveletComp provides three directional options and a variety of filtering windows over time and scale, but with tuneable width to choose from (RÖSCH; SCHMIDBAUER; 2018).
[36] Constructed based on Torrence; Compo (1998); Aguiar-Conraria; Soares (2011); Aguiar-Conraria *et al* (2014); Ramsey (2014); Rösch; Schmidbauer (2018).

difference approach furnishes information on the direction of the co-movements, as well as potential causal relationships between transactions and Bitcoin price. Variables, dataset and wavelet analysis specificities will be detailed in the next segment, to better encompass results that are presented in section (3.3).

4.2 Dataset

Placing both time and frequency, as relevant measures to comprehend driving forces behind Bitcoin (BTC) price action, wavelet coherence not only identifies correlation but also offers evolution in time and across scales between variables. It can shed more light on the co-movement between prices and transactions, in comparison to conventional analysis (KANG ET AL, 2019).

Two variables were chosen to evaluate with detail the consequences of the three halvings, that have already taken place in the Bitcoin network: 1) Bitcoin closing price in US Dollars, estimated in natural logarithm, and 2) the total amount of transactions in BTC converted to natural logarithm through EViews 10. As explained by Phillips and Gorse (2018), raw financial price time series can be multi-modal, as they are likely to locate around psychological supports and resistances. Converting them into logs produces unimodal distributions that are nearer to the normal distribution.

Daily data was taken from Glassnode.com[37,38,] from January 1st, 2011, to December 11th 2021, and simulations were applied through WaveletComp 1.1 R package)[39]. Time frame was divided into three phases:

[37] Glassnode is a blockchain data and intelligence provider that generates on-chain metrics tools for institutional and retail crypto investors through Glassnode Studio web site and API, as well as market analyses and commentary through Glassnode Insights. According to the "About Glassnode site", conventional valuation metrics from traditional finance are deemed insufficient for analyzing crypto markets, and on-chain metrics are more trustworthy measures of relevant economic activity in crypto networks (ACHESON; 2021; GLASSNODE; 2021).

[38] Even though transactions in the blockchain are subject to economically spurious Bitcoin exchanges, as emphasized by Makarov and Shoar (2021), correlation between BTC price and BTC transaction count are expected to not only maintain but provide relevant clues to market behavior. Glassnode.com defines transaction count as the total amount of transactions, in which "*only successful transactions are counted*". In other words, the volume that was effectively traded, and can directly affect BTC price. Knowing that many economically relevant transactions are linked to price action and speculation.

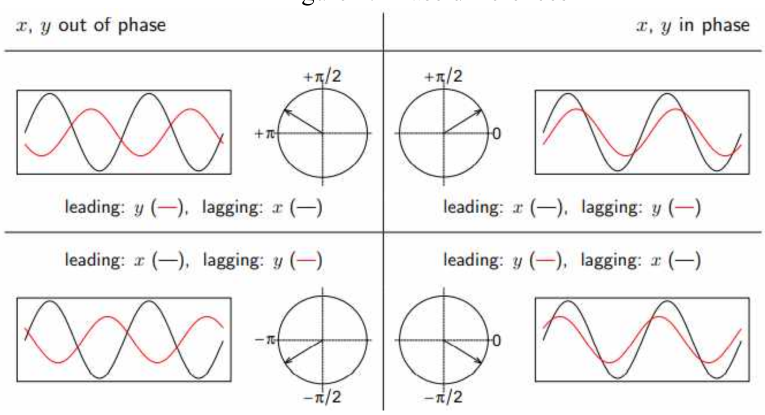
[39] The appendix provides additional information on the R script used for estimation.

1) The first phase: from January 1st, 2011 to December the 31st, 2014, in which the first *halving* occurred in November 2012 (block reward *halved* to 25 BTC).
2) The second phase: From January 1st, 2015 to December 31st, 2018, compatible with the second halving, that occurred in July 2016 (block reward halved to 12.5 BTC).
3) The third and last phase January 1st, 2019 to December 11th, 2021, comprises data available at the time of writing to capture the third halving that occurred in May 2020 (block reward halved to 6.25 BTC).

Before entering into data analysis per se, it is important to clarify, some interpretation specifics. Wavelet coherence shows regions where time series covariate, in time and space, given by frequency. The vertical axis shows frequency, with a smaller time scale (in days), while the x-coordinate, the horizontal axis, shows time in years. Warmer colours (yellow, orange, and red) represent regions in which the two-time series are highly correlated, while cooler colours (green, light blue and blue) show a lower relationship between them.

The arrow on the coherence wavelet plot represents the direction of relevance, as well as the lead-lag relationship. It is the synchronization in terms of instantaneous or local phase advance of the periodic component of (x_t) to the correspondent component of (y_t), or the phase difference of x over y. Figure 1 illustrates the range of possible phase differences (displayed as arrows) and their interpretation, while Table 2 elucidates comprehension of our variables in the wavelet context.

Figure 1. Phase differences



Source: Rösch; Schmidbauer (2018), p.7

Arrows that point to the right (left) show that variables are in phase (out of phase), with a positive (negative) correlation, respectively. When two series are in phase, this indicates that they move in the same direction, and when they are out of phase, they move in the opposite direction. If they are pointing to the right/up or left/ down indicate that the first variable (log of Bitcoin) is the one that is leading, and the second variable (log of transaction count) is one lagging. If the arrow points to the right/ down and left/up, the second variable (log of transaction count) leads, and the first (log of Bitcoin) lags.

Table 2 - Wavelet analysis, arrow interpretation
Variables: Bitcoin (BTC) price and Number of transactions in Bitcoin (BTC).

Arrow Direction	Variable Interpretation	Arrow Direction	Variable Interpretation
→	Positive correlation (phase) without lag, of BTC price in log (lnbtc), and number of transactions in BTC in log (lntranscount).	↗ =	Positive correlation between the leading variable BTC price (lnbtc) and the lagging variable number of transactions in BTC (lntranscount).
←	Negative correlation (anti-phase) without lag, of BTC price in log (lnbtc), and the number of transactions in BTC in log (lntranscount).	↘ =	Positive correlation between the number of transactions in BTC (lntranscount) and BTC price with a lag.
↑	Lag of BTC price in log (lnbtc), and the number of transactions in BTC in log (lntranscount). But with no apparent correlation.	↙ =	Negative correlation between the leading variable BTC price (lnbtc) , and the lagging variable (lntranscount).
↓	Lag of the number of transactions in BTC in log (lntranscount), to BTC price in log (lnbtc). However, it is not possible to infer correlation.	↖ =	Negative correlation between the leading variable number of transactions in BTC (lntranscount) and the lagging BTC price (lnbtc).

Source: Author's elaboration based on Rösch & Schmidbauer (2018).

Kristoufek (2015) underlines that interpretation of phase difference is partially dependent on specific expectations that rests upon de variables being analysed. A leading relationship in-phase can easily be a lagging one in anti-phase. High-power areas, between white contour lines indicate joint periodicity and significance, for which the null hypothesis of a white-noise process is rejected at the default significance level of 10%. The white shaded area shows the cone-of-influence (COI). In wavelet analysis, it is standard to use a COI to represent areas subject to border distortions. As with other types of transforms, the continuous wavelet transform (CWT) applied to a finite length time series, suffers from edge effects, because values of the transform at the beginning and at the end of the time series are incorrectly computed. They involve missing values of the series which are artificially prescribed, consequently, this area of the time-frequency plane should be interpreted carefully (AGUIAR-CONRARIA; SOARES, 2011).

Results of the wavelet coherence tests for the log of bitcoin and log of transaction count will be presented in the following subsection. Besides correlation and phase difference, short, medium, and long-term effects will be defined: the short-term refers to the 2-4 and 4-8 period bands, the medium-term refers to the 8-16 and 16-32 daily bands, and the long-term are the 32–64, 64–128, 128–256 frequencies. Wavelets for transaction count will also illustrate our main argument, in view of the three phases identified above. Analysing transaction count individually and in correlation to BTC price, will show statistically relevant periods of co-movement while identifying underlying dynamics.

4.3 Results

4.3.1 Wavelet Coherence: BTC in USD and Transaction Count

Wavelet coherence output for the first phase (from January 1st, 2011 to December 31st 2014) is displayed below (Figure 2a). Observing closely 2011 (horizontal axis), Bitcoin price and transaction count roughly displayed the same overall trend, at the 64 to the 128 frequency. Arrows point to the northeast, showing that variables are in phase and Bitcoin price leads the relationship, while transaction count lags. Sharp price increases started in May, and consolidated in June (June 9th, 2011), when Bitcoin reached its high.

With BTCs starting to peak, agents that are more familiar with the inner workings of the system become interested. This sharp price increase led to a downtrend that made Bitcoin vary between $15 and $2.19. Marking a very volatile second semester ending 2011 at $4.72. Transactions also dropped, but not at the same rate. There is a more heated spectrum, during the 128 and 256 period following the time trend that year (fire sales due to price slumps).

In 2012, phase difference is pronounced between the short to medium term. Agents buy bitcoins in a timid movement as relationships changes and arrows start pointing up and the number of transactions starts lagging behind towards the halving event in November 2012. Both variables alternate in leading and lagging relationships but are always in phase. The yellow line that traverses all years, at the 128-day mark (four-month frequency) shows that there is an increasingly stronger correlation on the long run between price and quantity cycles throughout time.

Entering 2013, Bitcoin started witnessing an upward trend in prices. Wavelet coherence shows relevant statistical significance between price and number of transactions between the 16 and 128-day frequency, compatible with the sharp price growth that started in April 2013. At the end of the year, BTC reached fice times that value, in the all-time high in November.

Although Bitcoin USD prices declined in 2014 (started the year at $753.40 ending it at $320.00), it is possible to trace a linear growth trend, in the number of transactions time-series. At lower frequencies (128, 256, 365 days) there are warmer colours (yellow and orange), emphasizing *hodling*[40] characteristics of crypto investors in a bear-market.

Taking a comprehensive look over this four-year cycle (2011-2014), at higher frequencies (short to medium term) there is a stronger correlation between transactions and Bitcoin price action. Whereas at the 64-128 days lower frequencies (long-term) there is a weaker (but growing) relationship between price and quantity. The only exception is at the end of 2013, accounting for the halving event.

Phase two (from January 1st, 2015 to December 31st, 2018) Figure 2(b) shows warmer colours (yellow and orange) above the 128 period. A stronger correlation between these variables at increasingly lower frequencies (long-term), a tendency that came from the last cycle, can be attributed to crypto-exchanges.

These institutions are around since the beginning of Bitcoin yet these virtual platforms,

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[40] The term was originally typed as HODL, misspelled from the English word "hold" in a post in the Bitcointalk forum. In December 2013, there was a huge fall on Bitcoin price, and an investor GameKyuubi posted on the forum "I AM HODLING". After rambling on his poor trader skills, he concluded that the best course was "to hold". A clear investment strategy that become a byword approach to crypto investment (FRANKENFIELD & MANSA, 2021)

gain bigger importance during the second phase[41,42]. Bitcoin prices ranged between $172.20 (in January 14th, 2015) to $463.12 (in December 17th, 2015). Wavelet coherence levels at the 128 to the 256 frequency (vertical axis), show that there is a positive correlation (they are in phase) but without lag. Throughout 2016, there is very little statistical significance between transaction count and BTC price. Only at the 16-32 frequency, in the middle of 2016. Halving occurred at the beginning of July 2016, and a month before prices went up ($767.45, June 19th, 2016) fuelled by market optimism. Both variables are in phase and BTC price leads the relationship, while transactions are lagging.

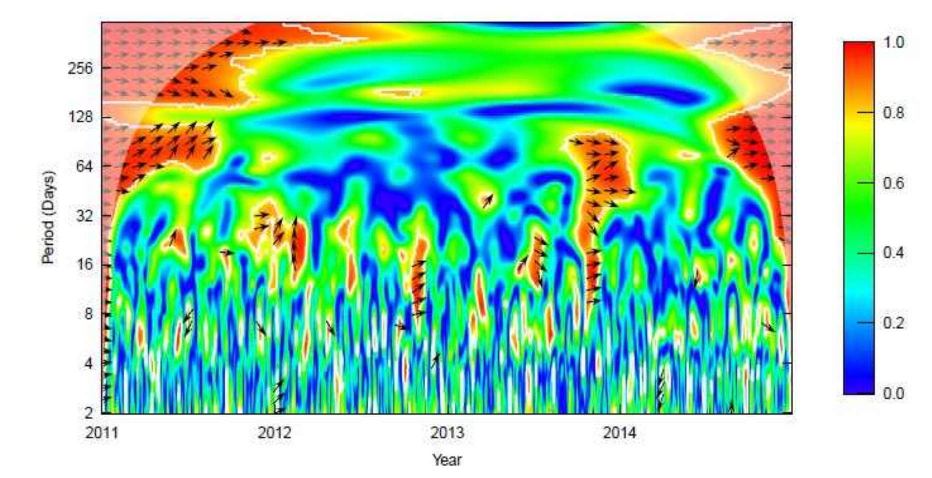
Price decreases marked the second semester, climbing again at the end of the year ($967.74 at December 31st, 2016). Nevertheless, the actual all-time high came in December 2017, where it reached $19,179.66. It started 2017 at $ 995.93 and saw a slow and continuous upward climb until September. A steeper hill marked the last months of the year reaching the top in December. Wavelet coherence levels showed high correlation (red and orange colors) at the 64/256 daily frequency. Both variables are positively correlated (in-phase), with transaction count leading the relationship while BTC price lags. Political and policy events, including US presidential elections combined with the impact of Bitcoin halving, increased market volatility in 2017 (QIAO ET AL, 2020).

[41] The oldest crypto exchanges or institutionalized space where cryptos could be exchanged for other currencies, cryptos or services, that are of my knowledge are Mt Gox (2010), Bitstamp (2011), Kraken (2011), and the Silk Road (2011). Launched in July (2010) Mt. Gox was one of the first world's leading exchanges, filing bankruptcy in 2014, due to 850,000 missing (stolen) bitcoins. The Silk Road anonymous marketplace was founded in 2011 by Ross Ulbricht, in the Deep Web. Financial transactions linked to illegal and criminal activities, lead to its shut down in 2013 by US FBI officials.

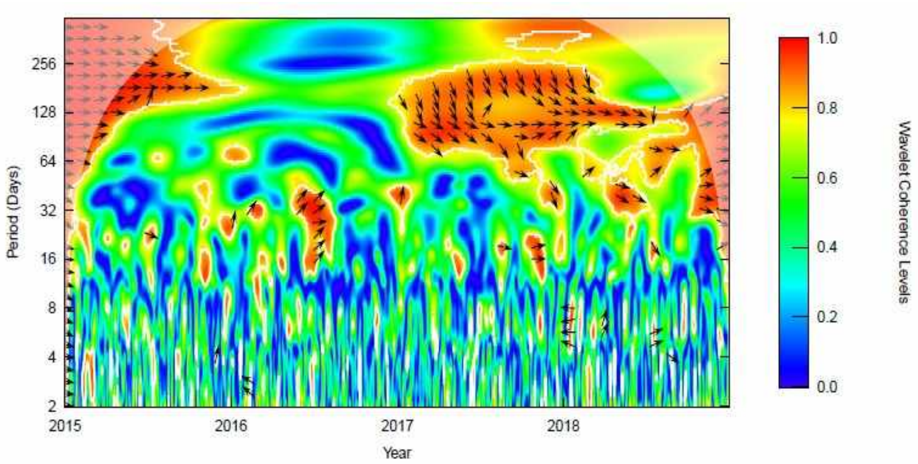
[42] The biggest crypto exchanges in existence today, ordered chronologically by foundation: Bitstamp (2011), Kraken (2011), Local Bitcoin (2012), Coinbase (2012), Coincheck (2012), Bitfinex (2012), Houbi (2013), Bitflyer (2014), Gemini (2014), KuCoin (2013), but was officially launched as an exchange in 2017. Crypto.com (2016), Binance (2017), Gate.io (2017), Bybit (2018), FTX (2019).

Figure 2 - Wavelet coherence: first, second and third phase (from January 1st, 2011 to December 11th, 2021)
Variables: Log of BTC in USD and Transaction Count

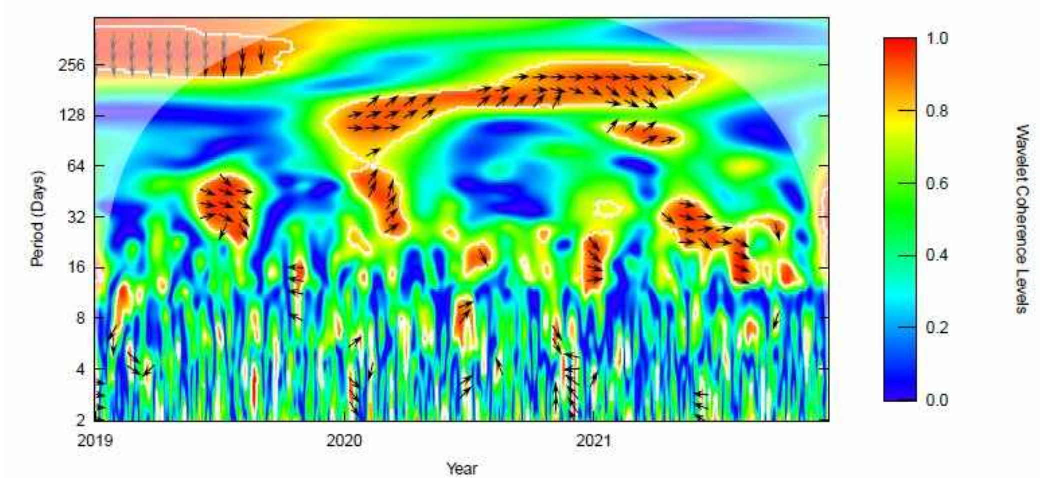
(2a)



(2b)



(2c)



These related trends continue in 2018, with high BTC prices and number of transactions, during January. Coherence levels are heated between the 32/128 frequency at the begning of 2018, with both variables in-phase (continuing 2017 trend). Transactions move precipitously leading phase difference as Bitcoin price declines at a slower pace. Looking at the four-year cycle (2015/2018), although still correlated, BTC price starts lagging number of transactions. The all-time high of the second halving was much more anticipated by investors, which started building positions in BTC at the 64-day frequency and transactions were more volatile leading to price changes. This is an important indication that more exchanges are providing access to investors, generating more market movement.

Wavelet coherence of the third and last phase (January 1st, 2019 to December 11th, 2021), starts depicting warmer colours at the 32 frequency, with positive correlation and Bitcoin price lagging. Prices peaked in July ($12,560.62) and stayed between the $10,070.39 mark until September to then go on a downward slope. Positive correlations turn to a clear BTC price leadership in 2020, the year of the first wave of COVID-19 and the third halving. Shutdowns, and the inevitable economic downturn, due to social distancing increased uncertainty, and accelerated fears about the global economy, making investors turn to cryptos as a risky investment option.

Closely observant of price movements market players took advantage of the slump that Bitcoin suffered at the beginning of the year, seizing the opportunity to build up positions in expectation of the halving in May. Phase difference can be seen from the 32 frequency beyond. The arrows start directing a clear leadership of BTC price, which turns into a distinctive positive correlation (64/128 frequency) to then alternate leadership between BTC price and transactions.

Prices started at $ 6.985,65 in January, and arrived at a new high in December 2020, reaching $ 28.988,64. A favourable year for Bitcoin investors was 2021 price remained above 29.783,00. Two price peaks were reached that year April 2021 ($63.603,70) and November 2021 (67.589,00).

It is important to keep in mind, that just showing diverging relationships between different frequencies do not answer the important question of what is effectively driving these periodic movements. Over the last 10 years, considering both the number of transactions and price, the first, second, and third phases are marked with in phase relationships. If seen in days, 128/256 frequencies which are long-term horizons for short-term investors, are most relevant in the second and third phases. The long-term is expected to play an important role considering the relationship between Bitcoin price and its supply (Bouoiyour et al, 2016a). Since asset supply is known in advance, price dynamics can be easily included in BTC expectations of users and investors (Kristoufek, 2015).

The all-time high after the first halving in November (2012), was exactly a year later November (2013), where BTC price reached $1,134.39. After the second halving in July (2016), a year and a half later, bitcoins price reached $ 19.179,00 in December (2017). After the third halving in May (2020), BTC maximum price was in November (2021) which surpassed the 65K mark. Prediction theories (like the Stock-To-Flow Model) expect that BTC will surpass the 100k mark, until 2024.

Stock-To-Flow Model[43]treats Bitcoin as being comparable to commodities (like gold, silver, and platinum). Due to their relative scarcity and retaining value over long periods, they are known as "stores of values". Bitcoin requires a lot of electricity and computing effort to augment supply, and Stock-to-Flow ratios (SF) are used to evaluate the current stock of commodities, against the flow of new production (SF = stock/ flow). A higher ratio indicates that the commodity is increasingly scarce, and therefore more valuable. Theory suggests that it is possible to project where prices may go, a calculation based on the Bitcoin mining schedule, and the projection that BTC will have a low-price elasticity supply. Halving events become important for BTC prices and the stock-to-flow ratio (SF) as they cause supply growth rate to be stepped (PLANB, 2019)[44].

Alternating leading and lagging relationships (phase difference) between BTC price and the number of transactions depends on the “halving moment”, overall political environment, systemic downturns, which reinforces how speculative markets are moved by anticipation, expectations, and self-fulfilling prophecies. Prediction or expectations coming true simply because agents believe and anticipate that it will happen, such that the person's behaviour will align to fulfil that belief, or in which consequences must conform to the initial belief.

To define self-fulfilling prophecy Merton (1948) quotes W.I. Thomas "*If men define situations as real, they are real in their consequences”* (Merton; 1948, p. 193). The underlying explanation is that agents respond not only to the objective features of a situation but also, to the meaning that this situation has for them. Once they have assigned meaning, their behaviour and consequences are determined by that particular interpretation: "*public definitions of a situation (prophecies or predictions) become an integral part of the situation and thus affect subsequent developments*” (Merton; 1948, p. 195).

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[43] https://www.lookintoBitcoin.com/charts/

[44] Another directive of the model is the indication of a power law, in which every halving, the stock-to flow-ratio (SF) doubles, and market value increases 10x, a constant factor. Bitcoin crashes (or Bubbles) also look very similar, with 80% dips but at very different log scales: $10 (2011), $1000 (2014), $10,000 (2018) (PLANB, 2019).

The most interesting self-fulfilling prophecies are those that involve more complex social processes such as financial markets and investment bubbles. If investors believe that, an investment generates large returns they will invest. Here enters the *"greater fool theory",* which is the idea that during a market bubble, one can make money by buying overvalued assets and selling them with a profit later, because there will always be someone who is willing to pay a higher price (BOGAN,2020?).

As more agents invest, the asset becomes more valuable, possibly enabling price manipulation and Ponzi schemes that provides initial investors with generous promised returns. This process eventually becomes unsustainable, ending with financial failure. Nevertheless, Bitcoin Ponzi schemes are not the point here (although abundant in unregulated, and relatively new investment types like cryptocurrencies), self-fulfilling prophecies show how economic agents can be "*caught in a web of their own making*" (Biggs; 2013, p.766).

Bitcoin in itself is algorithmically determined, but agents are the ones that allocate value to the asset. If speculators share conventions, common beliefs, proxies, and crypto market prognostication, prophecies will come to pass reinforcing demand for the asset. All in all, scarcity is not enough to create price value, there needs to be demand (Prasad, 2021), even if it is a speculative one.

MicroStrategy a publicly traded mobile software company, bought $425 million in Bitcoin in August and September 2020. As of December 2021, it held 124.391 BTC in reserve, equivalent to over $5.8 billion in Bitcoins. CEO of Microstrategy Michael Saylor, when opting for Bitcoin over gold as a reserve asset, stated that "*returns in gold didn´t look nearly as compelling as Bitcoin: if you are looking for a non-fiat derivatives store of value in an inflationary environment, that's logical that you should settle upon Bitcoin as digital gold*." (GRAVES; PHILLIPS, 2021; MORRIS, 2021).

Tesla's 42.902 bitcoins are currently worth $2.04 billion (at the time of writing). Bitcoin purchase reflects the company's investment policy aimed at diversifying its cash on hand and maximizing returns. Its SEC filing states *"we may invest a portion of such cash in certain alternative reserve assets including digital assets, gold bullion, gold exchange-traded funds, and other assets as specified in the future."* (GRAVES; PHILLIPS, 2021).

Blockchain technology that underlies bitcoins functioning is an important factor that may boost investors' confidence and demand, as a valuable tool for many practical "real-life" applications[45]. Another example is the association of member companies and private initiatives

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[45] Smart-contract-based tokens, decentralized finance (DeFi), protection of intellectual property rights,

that created one of the biggest cryptocurrencies in valuation, only behind Bitcoin[46]. Enterprise Ethereum Alliance launched in February 2017, is a blockchain-based decentralized software platform, that enables smart contracts and allows users to create and deploy their distributed applications[47,48] . As Bitcoin market value goes up, transactions will oscillate, at both lower and higher frequencies, as demonstrated in the next section.

4.3.2 Wavelet Power: Transaction Count

Figures 3a, 3b, and 3c are the wavelet power spectrum of the traded amount (transaction count) in log. Disaggregation shows how transactions move according to the environment. Given that the original time-series is a function of only one variable, the continuous wavelet (CWT) will plot it separately into time and frequency. Series correlation is illustrated in a two-dimensional diagram that helps identify and interpret patterns or hidden information. Thus, wavelets: "*provide an alternative representation of variability and relationship structure of certain stochastic processes on a scale-by-scale basis* (BHUIYAN ET AL; 2021, p.4)

Observing specifically the four-year cycle, looking at diagram (3a), in 2012 red colouring spans all frequencies at the middle of the year, in preparation of the halving event in November. The same phenomenon occurs with stronger intensity in the second semester of 2015 (3b), also in anticipation of the halving event in July 2016. At the beginning of 2018, there are also warmer colouring traversing all frequencies, however this time as a consequence of the December 2017 price peak. Statistical significance, with warmer colours between the 128/256 frequency are apparent at the first phase (2011-2014) and second phase (2015-2018).This trend softens in the third phase (2019-2021).

Overall higher frequencies (4/64 daily frequencies) are gaining relevance in comparison

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authenticating the ownership of digital arts, marketing and supply management (collect sales, industry trends, marketing and product information data during each point of the supply chain) are some of the expected industry uses. Therfore Blockchain usability goes beyond the creation of Bitcoins, providing solutions for both individuals and businesses (El Mahdy, 2021; Tut, 2022).

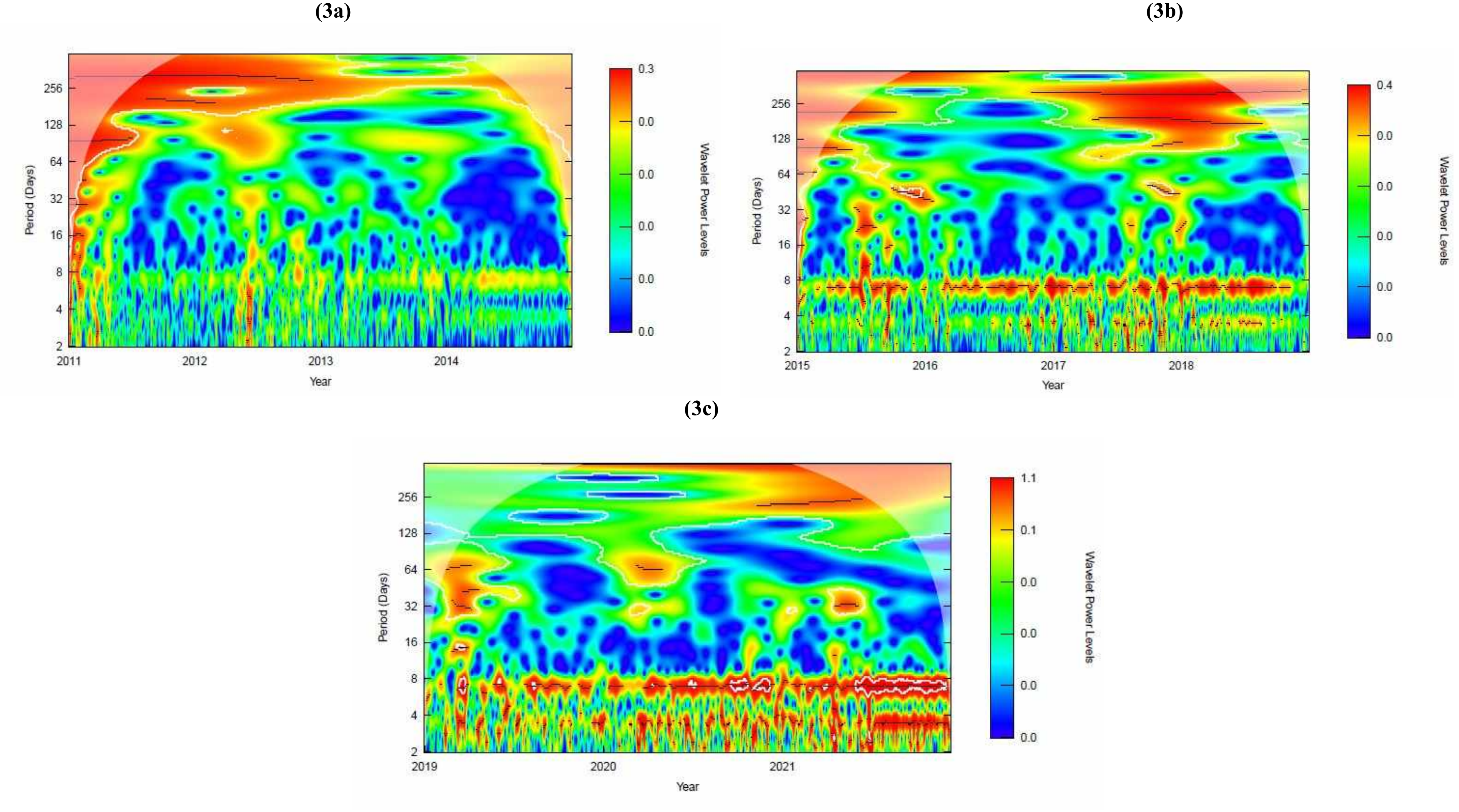
[46] The Founding members of Enterprise Ethereum Alliance (EEA) include Accenture, Banco Santander, BlockApps, BNY Mellon, CME Group, ConsenSys, IC3, Intel, J.P.Morgan, Microsoft, and Nuco. The Members of the EEA represent varied businesses from every region of the world, including technology, banking, government, healthcare, energy, pharmaceuticals, marketing, and insurance (FRANKENFIELD; 2021).

[47] https://entethalliance.org/

[48] Crypto researcher Loi Luu in 2017 explained that through Ethereum, one could easily build an app to facilitate cross-border money remittances at a cost of a fraction of the current charges, which could ultimately benefit senders and receivers. Micropayments and insurance are other possible areas enabled by Ethereum and blockchain technology, allowing people to make very small payments (a fraction of a cent), and to claim insurance without worries that the service provider will not honor their promise (MAVADIYA, 2017).

to lower time frequencies (128/256 daily frequencies). The short-term becomes more prominent in the last four years. At the 32/64 frequency, statistical relevance is accounted for due to rising prices in the first semester of 2019, with a growing expectation due to the halving event, in May 2020. Co-movement, in 2021 (256 frequency) is market anticipation to price records.

Figure 3 - Wavelet: first, second and third phase (from January 1st, 2011 to December 11th, 2021)
Variables: Log of Transaction Count



Observing 2011 at the higher 8-day frequency, a yellow line traverses all four years (2011-2014). This yellow line in the second phase (2015-2018), becomes pronounced gaining red colouring, with a new tendency showing at the 4-day frequency. By the last phase (2019-2021), there are two clear red lines at the 4/8 frequency.

The red line grows stronger through the years at higher frequencies and tendency increases with the incoming of new types of short-term investors. Frequency and scale change, altering co-movement between transactions and price. These clear lines demonstrates trading regularities at the beginning of each month. Dividends, paychecks, bitcoin ETFs, and bitcoins tax compliance are some explanations.

To obain bitcoin exposure, exchange-traded funds (ETF) enters long positions in the near-term (one-month). Since futures contract are a legal agreement to buy or sell a particular asset at a predetermined price at a specific time in the future and Bitcoin cost of carry tends to be positive, future prices are generally above spot prices with an upward-sloping curve (long-term futures contract are more expensive than short-term ones).

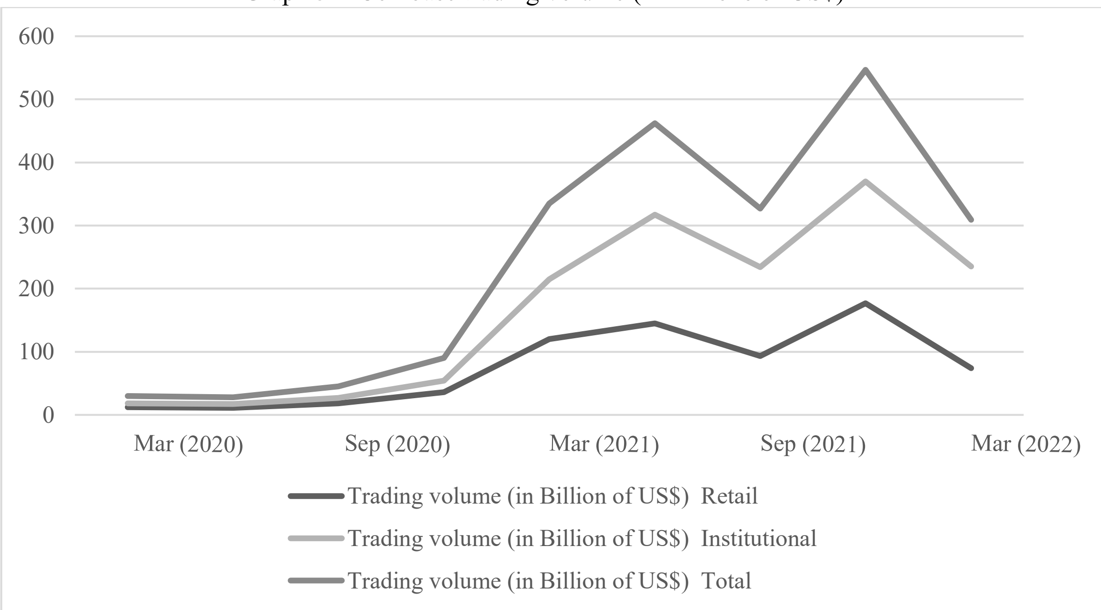
Which would likely affect prices in two ways: 1) flow rebalancing: when an ETF buys future contracts in response to inflows pushing prices up, or pushing prices down in case of outflows; and 2) calendar rebalancing: as ETFs gradually sell future contracts before expiration, prices will fall, and if ETFs buys longer-dated futures contracts, prices increase (Todorov, 2021, p.12).

Increase in the number of Bitcoin ETFs reflects growing interest in Bitcoin as an investable asset. Particularly: "*high frequency trading funds and long-short equity funds using cash-and-carry strategies had have an average return of at least 10% by buying Bitcoin and selling CME futures*" (Tut, 2022, p.11). Using sophisticated trading strategies (as tail-risk hedging and factor based investing) and leveraging in early stages of exchanges, institutional investors are able to reduce risk exposure.

Through crypto-market "inefficiencies" hedge funds, can take advantage of mispricing, reducing profit-making opportunities for retail traders. Price manipulation with pump and dump strategies in the crypto-space also suggests that individuals should be highly aware about their level of portfolio exposure.

Thus, investment funds have evolved into a source of crypto exposure. Even though dedicated crypto funds remain a small fraction of the market, flow into funds have grown quickly since 2020. Additionaly, rising share of trading volume from institutional investors (hedge funds and asset managers) are becoming an important source of revenue for exchanges (Graph 3). Taken from Coinbase's quarterly report, trading volume is the total of US equivalent value of matched trades between buyer and seller using the company's platform (during the period of measurement). Bitcoin price and crypto asset volatility affects directly trading volume, which has consequeces towards transaction revenue. In periods of high Bitcoin price and crypto volatility, Coinbase experiences equally bigger levels of trading volume (COINBASE; 2022).

Graph 3 - Coinbase trading volume (in Billions of US$)[49]



Source: Coinbase quarterly and annual reports (2020-2022). Author's calculations.

Other services provided by exchanges like margin financing are likely to gain importance. As important counterparties in this market, expectations towards their creditworthiness would likely require stronger liquidity positions and loss absorbing capacity (AUER ET AL, 2022).

For taxing purposes, Bitcoin and cryptos in general are basically seen as properties[50,51].

[49] Source: https://investor.coinbase.com/financials/quarterly-results/default.aspx

[50] In March 2014, the United States Internal Revenue Service (IRS) announced that it would treat Bitcoin and other cryptos as properties. The adjusted basis is calculated upon acquisition determined by the fair market value of cash, goods or services exchanged for digital currencies. Short-term capital gains have higher taxes than those who hold Bitcoin for more than a year, liable only for long-term capital gain tax (WISEMAN, 2016; HAMPTON, 2016; ROONEY; 2018, GOLDMAN & LEWELLEN, 2021).

[51] In some countries like Canada consider cryptocurrecies as commodities and are taxed as either business income or as capital gains (50%). Moreover, if they are used in the exchange for goods and services then they are treated as barter transactions. Hungary taxes any crypto income at 15% once it has been converted to fiat currency regardless the source(s). In Brazil in 2014, the Receita Federal (the Brazilian IRS) announced that the government does not see bitcoin as a currency, and that 15% of tax would be applied to all crypto asset holders whenever total sales exceed R$35,000 per month (BITCOIN REGULATION, 2018; TUT, 2022).

As such every time Bitcoin is bought or sold, it results in a taxable transaction, with record keeping and reporting requirements to the taxpayer, no matter how small the gain. When accumulating more taxable events in cryptos, investors harvest crypto losses by selling a losing position to offset their total tax liability. According to Ankier (2020, p.899) “straddles” are a “*systemic vulnerability for cryptocurrency holders that enter into transactions with the sole purpose of generating artificial taxable losses to offset against income*.” Since the market is very volatile, investors can quickly re-establish their derivative position later buying back into the coin of their choice at average price, with a more favourable tax rate. The opposite manoeuvre, which is gain tax harvesting, favoured by high net worth investors, also contributes to selling pressures around crypto (HOLLERITH, 2021).

Nonetheless, more must be seen in financial reporting and discounted dividend models, as firms may use investment in cryptocurrencies, to cover up their poor financial performance. Over 2020, Tesla has faced scrutiny from critics in regards it being overvalued, with a massive growth in stock price, which did not reflect the company’s intrinsic value. Rather the result of investments that alludes to the risk of speculative bubbles.

The early 2021 investment that Tesla made in Bitcoin (1.5 billion) when the price was skyrocketing produced a profit ranging from $0.29 to $0.98 billion, in a very short period. Contemporaneously, MicroStrategy's (2020/2021) push for Bitcoin comes as the company reports growing financial losses. Companies can make it or break it from trading cryptocurrencies, as BTC price can go any other way. Government oversight needs to be emphasized in order to minimize risks to consumers and investors limiting negative spill overs to traditional financial markets (WHITCOMB, 2020; EL MAHDY; 2021, PRASAD, 2022).

Accordingly, institutions are interested in Bitcoin due to a number of factors. Arbitrage opportunities that exist due to price differentials between crypto-linked assets in traditional finance and on-chain products are one of them. Yield in an environment of lower returns on traditional assets, portfolio diversification stratagies, alternative store of value, and a long-duration asset, with potential price appreciation should be considered. Moreover, indirect investments in Bitcoin and in the cryptocurrency space could be done via venture capitals that explores new technological capabilities through Blockchain technology (TUT, 2022; AUER ET AL, 2022).

4. CONCLUSIONS

Most crypto-focused wavelet literature concentrate on bitcoins fundamental attributes, global uncertainty, hedging capabilities, informational inefficiencies, regional markets. Our study uses a well-known methodology in a novel way: to specifically adress, how halvings affect price and quantity relations in the Bitcoin (BTC) market.

Using daily data from, January 1st, 2011 to December 11th 2021, Bitcoin price in USD and transaction count were decomposed in a scale-by-scale basis (different frequency bands) using wavelet coherency methodology. Cycles and transient dynamics between the two time-series, revealed a growing presence of institutions that articulate market entries and exists, which influence overall market sentiment (at lower frequencies, higher timescales).

Through speculation, co-movements between BTC transactions and prices are in line with upcoming halving events. Big operators, in recent years, started accumulating positions in BTC expecting valuation. With limited supply, Bitcoin is by definition a scarce asset, which could be considered a venture tool for portfolio considerations.

Wavelet coherence analysis, of the first phase shows strong correlations at the 8/64 daily frequency (short-term) to then convert to a stronger correlation at the 64/256 daily frequency (long-term), in the last two cycles. Since supply is curtailed, the long-term plays an important part, as dynamics are included in price expectations.

However, prediction models (like the Stock-to-Flow model, in which basic hypothesis is that scarcity drives value) can create its own measure of self-fulfilling prophecies. In market psychology, conventions could eventually feed into these theories, as market bubbles run on the greater fool theory (Bogan, 2020?): any price, no matter how high, can be justified since another buyer is willing to pay an even higher price. *“Bitcoin is worth exactly as much as users are willing to pay for it”* (Wiseman, 2016, p.424). This notion, amplifies the volatility problem as rogue entities could manipulate crypto market pricing (ANKIER, 2020).

In the third and last phase, BTC price and transactions are gaining bigger correlation in the medium to long-term. There is a change in dynamics, with increasing investor access through crypto-exchanges (a trend that started in the second phase), with more Big Players"in the game", plus economic uncertainty prevailing, due to the COVID-19 pandemic. Skyrocketing prices highly incentivised BTC *hodling,* with some companies exposing themselves, pumping up their financial performance.

Transaction count was also calculated through wavelet power dynamics in daily frequency and timescale.The same trend appears, with statistical significance, between the

128/256 frequency at the first (2011-2014) and second phase (2015-2018). In the last cycle (2019-2021) there is a clear strong co-movement between the 2-8 daily frequency. Regularities that accompany transactions (ETFs), with a large array of companies and exchanges specialized in crypto trade and futures.

Answering the questions posed in the introduction, it is possible to infer that although technical attributes of the halving dynamics cannot change due to its algorithmic nature, comparing the last two BTC price cycles, a change in market dynamics is observable. As a main contribution to the debate, confirming that co-movements between BTC price and transaction count do provide a measure of how instiutions are active in the market, flows have been altered by the arrival of these market makers with stronger correlations at lower frequencies (64-256 daily frequencies) between price and quantity through wavelet coherence. Increasing access of investors through crypto exchanges in the second phase and market entries in the last phase motivated by global economic crises/pandemic, increased market capitalization, which pushed price/transaction correlation.

Transaction count does give a more precise estimate of market activity, showing a stronger co-movement at higher frequencies (2-8 daily frequencies), through retail trading activity. Future researches in Bitcoin price should address its correlation to more ample measures such as global liquidity. Given bitcoins recent bear market and global monetary tightening; empirical tests should be performed to understand if prices (even though they move around much more than other assets due) do have a floor compared to the post-halving market price. Moreover, if halvings could substantiate the fundamental aspect that its mean average is increasing looking at the long run.

PAPER 2. BITCOIN, CORPORATE FINANCE AND THE COMPOSITE OPERATOR: A LINEAR AND NONLINEAR APPROACH.

Resumo: O mercado de Bitcoin (BTC) sofreu uma mudança gradativa nos últimos anos. Nos primeiros períodos de sua existência era um ativo totalmente desvinculado de outros ativos tradicionais. Mas recentemente vem mostrando uma correlação crescente com indícies importantes do mercado financeiro. Com dados retirados do Glassnode Studio (de Agosto de 2011 a Agosto de 2021) utilizando o modelo Autoregressivo de Defasagens Distribuidas (ARDL) e o modelo Autoregressivo Não-Linear de Defasagens Distribuidas (NARDL) capturamos os componentes de longo e de curto prazo entre o retorno real do Bitcoin, variáveis internas ao mercado (Transaction Count) e variáveis externas (One Year Treasury Constant Maturity Rate, S&P500 e o Google Trends). Ao contrário do que a literatura acadêmica afirmava há um crescente transbordamento de curto e longo prazo dos mercados de títulos livres de risco e do mercado de ações para o mercado de criptomoedas. O objetivo e a principal contribuição do artigo por meio de estimativas não-lineares, cálculos de assimetria e o método de Wyckoff, é apontar para a participação de investidores instutionais, através da quantidade de transações realizadas dentro das exchanges (Transaction Count) e o mercado de ativos norte-americano (S&P500) afetando o retorno real do ativo. Mudanças excessivas de preço e volume no mercado BTC corroboram a nossa hipótese.

Abstract: The Bitcoin (BTC) market has undergone a gradual change in recent years. During the first periods of its existence, it was uncorrelated from other traditional assets, but recently it has shown an increasing correlation with important indicators of the financial market. With data taken from Glassnode Studio (from August 2011 to August 2021) using the Autoregressive Distributed Lag (ARDL) model and the Non-Linear Autoregressive Distributed Lag (NARDL) model, long and short-term components were captured between Bitcoin real return, internal market variables (Transaction Count) and external variables (One Year Treasury Constant Maturity Rate, S&P500 and Google Trends). Contrary to what the academic literature claims, there is an increasing short-term and long-term spillover from the risk-free bond markets and the stock market to the cryptocurrency market. The objective and the main contribution of the article through non-linear estimates, asymmetry calculations and the Wyckoff method, is to point to the participation of institutional investors, through the amount of transactions carried out within exchanges (Transaction Count) and the US market (S&P500) affecting the asset's real return. Excessive price and volume changes in the BTC market corroborates our hypothesis.

1. INTRODUCTION

Even though crypto markets are still not as big as traditional financial money markets (1 trillion in market capitalization in January 2021), are still under development and critical observation, it has caught the attention of investors, and institutions, becoming an important theme in terms of public policy (El Mahdy, 2021; Bhuiyan *et al*, 2021).

However, something extra can be said about companies and intermediares concerning the Bitcoin ecosystem. Previously dominated by crypto enthusiasts, the last couple of years witnessed the entry of big market players, institutional investors that are constantly looking for novelty assets, a store of value to not only safeguard their revenue from depreciation, but increasing profits through speculative investments. Hedge funds, private equity firms, started to invest in Bitcoin and crypto currencies, not only pushing prices even higher (Mavadiya, 2017), but transforming it into a high-profile market. With a bigger return/risk ratio, it became extremely attractive to holders, investors, and risk managers[52], as well as a threat to financial market stability (EL MAHDY, 2021).

Relatively isolated from the global financial system in the pre-pandemic era and not yet subject to the influence of business cycle patterns derived from monetary policy and central bank control, Bitcoin could, **in very specific conditions**, become a diversifier (Bouri *et al*, 2016). It could be a hedge[53] against or with other assets (DYHRBERG, 2015; DYHRBERG, 2016; BRIÉRE ET AL., 2015; BOURI ET AL., 2017, KANG ET AL., 2019; BHUIYAN ET AL., 2021)

The motivation of this paper is through time series analysis explain how institutional players have been increasingly active in Bitcoin crypto trading. Underlying long, short run and asymmetries between bitcoins real return (in USD) internal variable (Bitcoin transaction count) and external variables (One Year Treasury Constant Maturity Rate, S&P500 and Google Trends) were estimated with monthly data (August 2011 to August 2021). Employing Autoregressive Distributed Lag model (ARDL), proposed by Pesaran *et al.* (2001)[54] and

[52] Long-term relationships are typically critical for holders (or “hodlers” in the crypto lingo), as well as for portfolio managers. Hedgers seek the highest correlated asset market in the short-to-medium term, while short run volatility is of interest to speculators (QIAO ET AL, 2020).

[53] If an asset is negatively correlated with another asset, putting them together decreases portfolio risk significantly. Bouri *et al* (2016, p. 2) to better qualify terminology, differentiates between a diversifier, a hedge, and a safe haven: "*A diversifier is an asset that has a weak positive correlation with another asset on average. A weak (strong) hedge is an asset that is uncorrelated (negatively correlated) with another asset on average. A weak (strong) safe haven is an asset that is uncorrelated (negatively correlated) with another asset on average during times of stress*”.

[54] As an ARDL model estimates the dynamic relationship between a dependent variable and explanatory variables, it is possible to transform the model into a long-term representation, showing the long-term response of the

Nonlinear Autoregressive Distributed Lag Models (NARDL) introduced by Shin *et al* (2014), increasing interconnectedness was captured between US equity markets to bitcoins returns, in line with Iyer (2022).

An extent academic literature attests to the fact that Bitcoin exhibits an autonomous price behavior, totally unattached to other traditional assets, macroeconomic and financial development coefficients (Briére *et al.*, 2015; Baur *et al.*, 2017, Guizani & Nafiti, 2019) Nevertheless, this has gradually changed to an environment that has been progressively affected by asset market spill overs. US monetary policy influences investors' risk perception and those of US companies, which causes impacts in international financial markets and consequently Bitcoin. Our contribution rests upon the long, short run and asymmetry estimations, which showed that the volume exchanged (transaction count), the S&P500 and the one-year treasury constant maturity rate (1 YTCMR), are relevant in determining BTC real returns.

The econometric ARDL linear analysis is the basis in which our hypothesis are constructed and nonlinearities are tested: does an increase in the S&P500 index has a stronger impact on Bitcoin real returns than a decrease? What about exchange volume (transaction count) and market sentiment? Translating bitcoins inconstant nature Wyckoff's theory of climatic price and volume movements, substantiate not only speculative markets, but also Bitcoin price movements. They become indicators of hidden intentions (the composite operator), in which trend direction is an integral part of profiting. Intended innovation are through asymmetries in real returns considering the S&P500 and Transaction Count.

This paper is divided in five main parts. In the first section a brief contextualization of the Bitcoin market and institutional investors are made, to then in the second part treat the empirical literature on the subject. Dataset and model specifications in the third section. In part four diagnostic, ARDL and NARDL estimations are performed with long and short run results, finalizing our econometric approach with the long run Wald asymmetry tests. Section five concludes our study summarizing main results.

dependent variable, considering a change to the independent variable. Pesaran & Shin (2001) also note that unlike other methods of estimating cointegration relationships, the ARDL representation does not require symmetry in the lag dimension; each variable can have a different number of lagged terms.

2. BITCOIN AS A CRYPTOASSET: FROM ORIGIN TO THE INSTITUTIONAL INVESTOR'S ENTRY

Bitcoin (BTC) was born out of the 2008, US banking/real estate crises. This assumption becomes evident when analysing the text encoded in the first block of Bitcoins created, a direct reference to the front page of the New York Times of January 3rd, 2009: "*Chancellor on Brink of Second Bailout for Banks*". The headline is a direct comment on the fragility of the global banking system and an implicit critique on how governments reacted to the housing bubble. Fiat money issued by central banks has been a frequent answer to fiscal, financial and governmental problems. Sataoshi's peer-to-peer (P2P) "currency" (Nakamoto, 2009) would be a solution to mediate transactions between members of the World Wide Web using decentralized ledger technology (DLT) (BORNHOLDT & SNEPPEN, 2014; GANDAL; HALABURDA, 2014; MAURER ET AL., 2013).

Cryptocurrencies can be acquired in three ways: i) trade (through the exchange of goods and services for Bitcoins); ii) direct purchase of cryptos through currency; and iii) reward for participating in "mining", the activity by which users update the blockchain. Many agents have been dedicating themselves to mining this asset over the past ten years, becoming highly expensive and monopolized activity. Bitcoins circulate and are transferred to users in an open computer network that anyone with an internet connection can join. Cryptos are stored in a specific software, colloquially called digital wallets (NARAYAN ET AL, 2016).

Subject to trade and portfolio gains, the concept of a "crypto asset" brings Bitcoin (BTC) closer to that of an intangible speculative instrument, in which users invest their money, priced in dollars, with strong appreciation. Price is largely affected by its attractiveness as a financial opportunity. An increase or decrease in media attention, may influence potential investors depending on the type of information that dominates news platforms (GUIZANI, NAFITI; 2019).

Investor's sentiment becomes a crucial variable in a market that is dominated by speculators. Earlier on Kristoufek (2013) quantified the relationship between Google Trends, Wikipedia and Bitcoin. Strong causal bidirectional relationship was found: not only do search queries influence prices but prices also influence queries. Shen *et al* (2019) also examines the link between investor attention, Bitcoin returns, trading volume and realized volatility employing the number of tweets from Twitter. Authors found that the volume of tweets are significant drivers of realized volatility (RV) and trading volume, supported by vector autoregressive (VAR) model, linear and nonlinear Granger casualty tests.

Baur & Dimplf (2018) applied Granger causality tests, and found that in Bitcoin markets realized volatility is found to Granger cause volume, but not the other way around. Beliefs and sentiments induce excess volatility and higher volumes providing support for the hypothesis of sentiment driven trading. Information about Bitcoin per se is very fickle, and as new facts arrive, it is incorporated in prices, changing traded volume. With prices rising and falling in a course of a single day, each trader might attach different expectations to Bitcoin, rooted in individual considerations, which differs substantially among investors.

A contradictory and persistent behaviour among crypto traders is the phenomenon of *hodling*: "*to buy a crypto and hold onto it for a prolonged time without any selling or trading activity*" (Frankenfield & Mansa, 2021). The most interesting part of this phenomenon is that owing to the poor liquidity characteristics of Bitcoin and cryptos in general, *hodlers* typically wash their hands on volatility and prognostication, counteracting two destructive tendencies of novice investors in these markets which is: the fear of missing out (FOMO) leading to buying high, or even the fear, uncertainty and doubt (FUD) which can lead to selling low (also occasionally referred to as SODling). Avoiding short-term trading, amateur investors, who are positioned in cryptos in the past will likely remain invested in the future[55].

Analysing variables that may factor in price and demand, in the short and long-term are essential for economic comprehension of cryptocurrencies, specifically Bitcoin. Even if it is not currently acting as a safe haven asset or hedge, it could perhaps act like it in the medium to long-term. Correlation between macro variables and prices of digital assets, could be "created", making Bitcoin a legitimate refuge asset[56].

The debate about the definition of what financial assets are, their properties and how they are analyzed by investors, whether "bulls" or "bears", is traditional in economic theory. In Keynes' (1886-1946) analysis, it is not so much how we perceive these assets, but how we think that others perceive them, and from this view formulate an expectation of what will happen. Individual opinion does not prevail, but rather what the majority think is about to happen, which would ultimately determine a self-fulfilling prophecy regarding the pricing of these assets.

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[55] "*Owning a cryptocurrency increases the probability, on average, of owning a cryptocurrency in one's portfolio the following year by more than 50%*" (Auer; Tercero - Lucas, 2021, p.4).

[56] Recently, there was a simultaneous surge in gold, oil and Bitcoin due to the death of Iranian General Qasem Soleimani (January 3rd 2020). Analysts said the impact on the crypto market was not yet clear at the time, as one party claimed that the rise in bitcoins value may have been a coincidence, while another party claimed that digital "currency" is becoming a new type of refuge for speculators. There are still those who claim that heightened geopolitical risk has resulted in the rise of both Bitcoin and gold, but for different reasons. American writer, entrepreneur and financial commentator Peter Schiff commented on his social network that while "*gold is being bought by investors as a safe haven, Bitcoin is being bought by speculators who are betting investors will buy it as a safe haven*" (MONEYTIMES,2020).

Needless to say, there is still resistance and skepticism about the idea of a crypto asset. Its price instability in the specialized international market, small market scope (compared to other assets), added to the need for advances in cybersecurity and international regulation are relevant steps if there is to be a safer use of cryptos. Volatility, uncertainty, and risk are inherent aspects of digital assets that, on the one hand, make them highly profitable and, on the other, susceptible to large drops in their price. As a "commodity" on the open market, Bitcoin has been vulnerable to speculation, resulting in violent swings in the exchange rate with the dollar (MAURER ET AL., 2013; BOUOIYOUR ET AL., 2015).

Investment strategy has evolved, and in spite of the increasing number of addresses that own BTCs, in an atomized market of buyers and sellers, there are big players that have a significant amount of the crypto assets. Data publicly available doesn´t clearly discriminate between companies and independent investors, since on-chain data is cryptographically protected, and a big part of crypto assets are maintained in offline wallets.

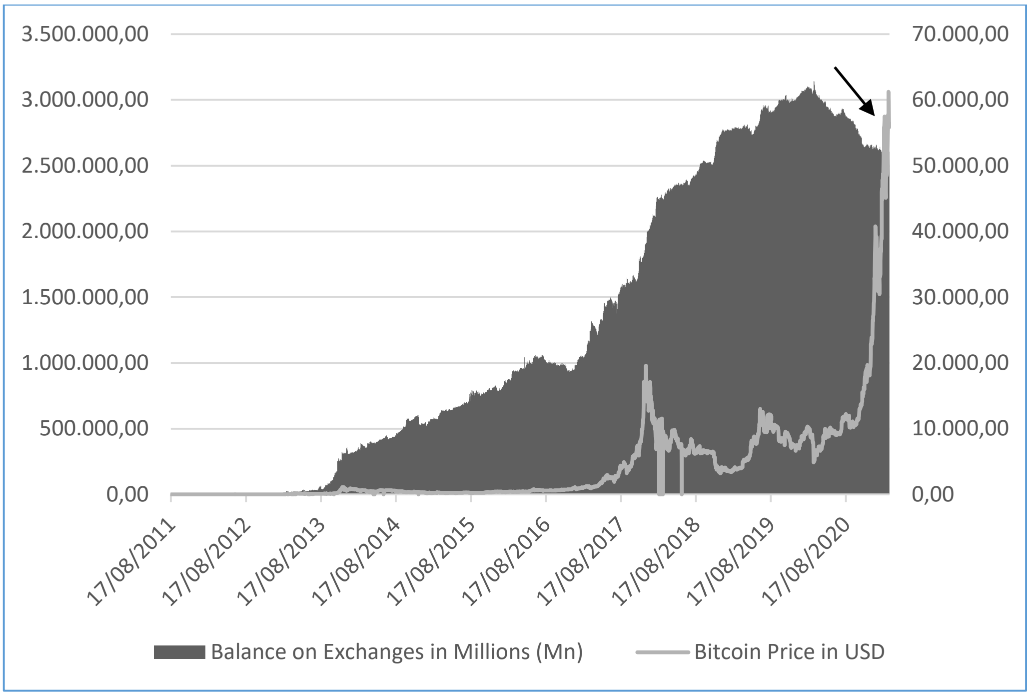
Big players which buy large volumes of BTCs do not leave their crypto assets in exchanges. They buy them and then move them offline (in cold wallets) keeping them safe under private keys. On the other hand (Auer et al, 2022) arguments that institutional investors are likely to invest via fianancial intermediares, rather holding crypto assets directly. Due to operational complexity and safety issues outsourcing these activities is far more cost efficient.

All in all, exchanges play an important role as key nodes in the crypto environment[57]. Trading activities are highly concentrated in a few exchanges. The largest exchange by market share (Coinbase) accounts for one third of BTC holdings, while Bitcoins held in custody has risen threefold over the past five years (AUER ET AL, 2022).

Observing daily data of balance on exchanges from August 2011 to October 2020 (Graph 4) there is an overall increasing tendency on how much coins are held in exchanges in the first six to seven years of bitcoins existence. Zooming in the last two years of the data, January 2019 to March 2021 balance on exchanges reaches its peak between February/March (2020) with 3 million BTCs, to then enter a downward trend. This demonstrates that a big part of investors was looking at the long run market appreciation, *hodling* their coins. As balance on exchanges goes down, Bitcoin prices go even higher.

[57] Underscoring the decentralization illusion, these agents have emerged offering services in the same manner as in commercial banking and securities trading, without the same supervisory oversight. These custodians largely grew benefitted from light regulation, with many headquarted in offshore financial centers. Additionaly they are not required to submit detailed data to regulators (AUER ET AL, 2022).

Graph 4 - Balance on Exchanges (daily data) - August 2011 to March 2021



Note. Author's elaboration. Source: Glassnode Studio (2022).

Market trend typically starts to turn around when institutional investors move their bitcoins to exchange addresses showing that they are interested in negotiating. Gray and Breton (2020) tested the hypothesis that the crypto market followed the same cycles and methods of price manipulation, as proposed by Wyckoff (1984), with indications of big players in the form of climatic or excessive price and volume changes[58].

Wyckoff proposed that any professionally traded market moved in what he termed "price cycles", and that these cycles could be predictably and reliably navigated to produce consistent profit. Imbalances in supply and demand could be identified analysing price action, volume and timespan: "*For a while news may influence opinion and sentiment, it is only the orders that are executed on the floor of the exchange that actually influence prices* (Wyckoff, p.18, 1984). These major imbalances and large movements, are created primarily by large, institutional investors, whom he termed the "Composite Operator" (Big Players or Institutions), who professionally manipulate the market:

> *"Just as a scenario writer endeavors to mystify his audience, so pools and manipulators strive to confuse and influence the public into thinking a stock is moving*

[58] The authors automated Wyckoff's strategies, to be able to recognize climatic price and volume events, with support and resistance levels closing trades with a profit. Quoting their words: *"to take advantage of the repeatability and immutability of algorithmic operations which remove the human element of distraction or emotional miscalculation from the equation"* (GRAY; BRETON, p.2, 2020).

> *in a certain direction when the ultimate purpose is to have it move the other way (Wyckoff, p.42, 1984).”*

According to Wyckoff’s theory, price moves due to an effort represented by trading volume. When price action[59]and trading volume represent the same sentiment, the current trend has a greater chance of continuing. However, if volume does not support price action, it will create divergence, leading to a stop or change in direction. Climatic price and volume movements are not only typical, but also indicators of institutions intentions and in which trend direction is an integral part of profiting. Climatic events do not happen in a vacuum, they are usually enclosed by support and resistance levels, that if ignored would negate the short-term benefit of using them as trading signals (BYBIT LEARN, 2021; GRAY; BRETON, 2020).

Timing is one of the most important elements of Wyckoff’s cycle. The method includes looking at how big players execute the bull and bear market. The market moves from markup to markdown and the perfect buying and selling position is valid only when the timing is right. The two main price cycles illustrated by Wyckoff are the “distribution phase” and “accumulation phase”. The ultimate target is to enter a sell position when the distribution schematic is over (markdown) and open a buy position once the accumulation schematic is over (markup) (BYBIT LEARN, 2021).

Bitcoin prices have been particularly prone to these movements in the last 2 years (Figure 4). Observing specifically 2021 during its first months the crypto market cycled through a distribution phase (January 2021 to May 2021).

[59] Price action is a process used to anticipate the price movement of any trading instrument by observing its price (BYBIT LEARN, 2021).

Figure 4 - Candlestick Chart in Bitcoin Price (January 2021 to May 2021)
And Wykcoff's Distribution Phase[60,61]

Source: Candlecharts.com (2021);Binance (2021)

In the beginning of the distribution phase, big players will mark up the price far beyond the previous range as demand will exceed the supply through a bullish pressure. Institutions will sell the previously accumulated shares at higher prices spreading over a narrow range of prices to the masses of retail traders that are now enticed to jump into the market, by the large rise in asset prices. The last stage of a distribution marks the beginning of a downtrend, with a break in the support region, caused by the strong dominance of supply over demand. Larger players will liquidate their positions, which will take the price even lower.

The accumulation schematic has similar phases to the distribution phase but with many of the same events happening in the opposite direction (Figure 5). During the accumulation phase (May to October 2021) market makers will amass large amounts of shares in stocks (or

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[60]CANDLECHARTS.COM. Steve Nielson's Candelcharts.com. Candlestick training the Right Way.Bitcoin/U.S.Dollar (BITSTAMP). Website. Retrieved from: https://candlecharts.com/candlestick-chart-look-up/. Access date: 21 Out.2021

[61] BINANCE. Binance Blog. The Wyckoff Approach to Crypto Futures (10.06.2021). Retrieved from: https://www.binance.com/en/blog/421499824684902176/a-wyckoff-approach-to-crypto-futures. Access date: 21 Out.2021.

crypto assets), spreading their buys over time within a narrow range of prices. Large players build positions and eliminate retail traders from the market by creating hopes of a further drop in prices. Once smaller players are confident about the price drop, institutions will aim to move higher after filling their positions. The composite operator ensures that there is little supply in the market, misleading investors to give up their buy positions. It is a final attempt to buy assets at a cheaper price before the uptrend starts (BYBIT LEARN, 2021; GRAY; BRETON, 2020).

Figure 5 - Candlestick Chart in Bitcoin Price (May 2021 to October 2022)
And Wykcoff's Accumulation Phase[62,63]

Source: Candlecharts.com (2021);Binance (2021)

Volume is a fundamental variable in support and resistance analysis. On chain activity (active addresses, new on-chain entities, transaction count and transfer volumes) are useful tools to tracking bitcoin demand. An accelerated growth rate is likely to support price recovery.

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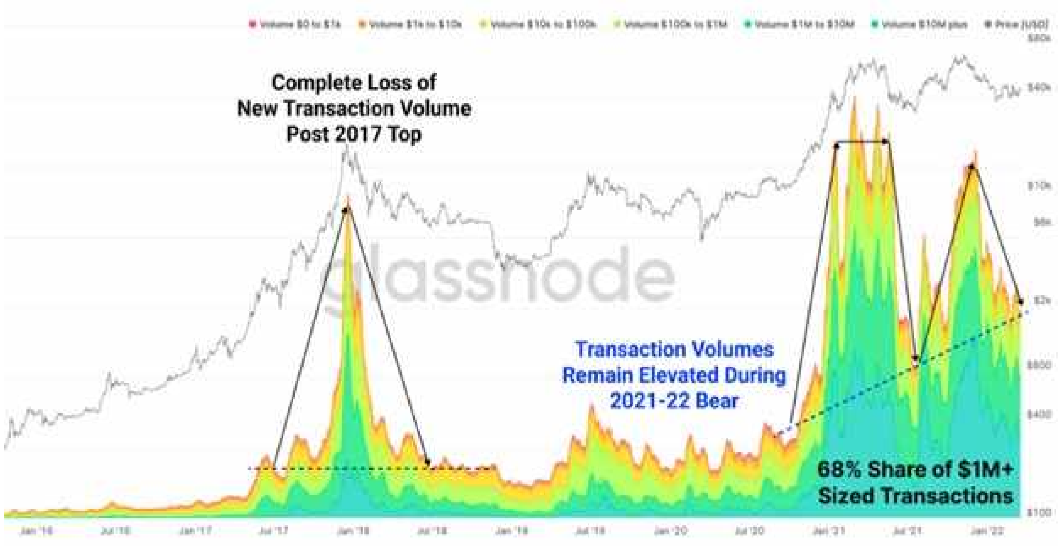
[62]CANDLECHARTS.COM. Steve Nielson's Candelcharts.com. Candlestick training the Right Way.Bitcoin/U.S.Dollar (BITSTAMP). Website. Retrieved from: https://candlecharts.com/candlestick-chart-look-up/. Access date: 21 Out.2021

[63] BINANCE. Binance Blog. The Wyckoff Approach to Crypto Futures (10.06.2021). Retrieved from: https://www.binance.com/en/blog/421499824684902176/a-wyckoff-approach-to-crypto-futures. Access date: 21 Out.2021.

Conversely, these metrics collapse during early bear markets, with a deterioration of network utilization as a sign of demand exhaustion. Transaction count are typically the economic weight of these network users, and transaction volume represents the sheer size of these transactions.

According to a 2022 Glassnode report[64] the 2017 bull market, pushed prices to the all-time high of 20k, followed by a drastic fall with the "loss" of new transaction volume (Figure 6). Throughout 2018 - 2019, large size transactions (bigger than 1 million in value) represented between 10% and 30% of total transaction volume. In the 2021 -2022, bear market, large size transactions represent a sustained 65% to 70% dominance.

Figure 6 - Bitcoin Total Transfer Volume Breakdown by Size (Entity-Adjusted) and Bitcoin Price from 2015 to 2022



Source: Glassnode.com (2022)

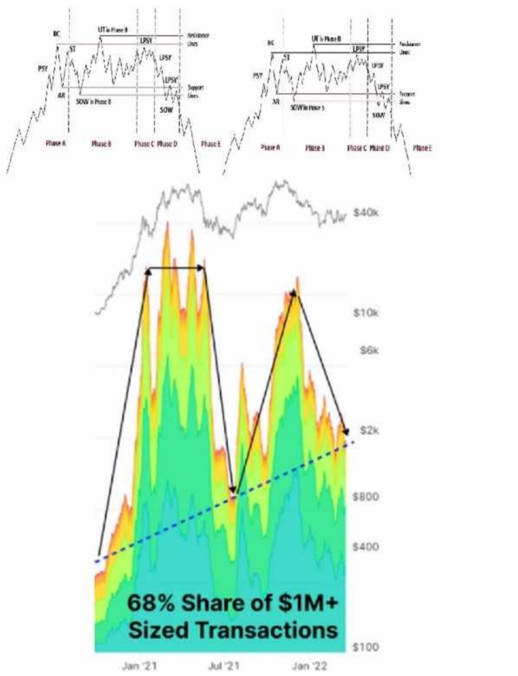
With million sized transactions increasing market weight, there is a clear tendency in which institutions are consolidating their positions. The upward trend line in figure 6 clearly identifies the predominance of different types of entities operating in this market.

Juxtaposing Wyckoff's distribution cycle to transaction volumes and Bitcoin price (Figure 7), behaviour is compatible to the composite operator. Wyckoff's theory proposes to analyse markets through the eyes of institutional investors considering what their ultimate goals are, and how current market behaviour will indeed reflect their interest. By carefully scrutinizing trades it is possible to observe hidden intentions that were executed through each

[64]GLASSNODE.COM.High Volatilty is on the Horizon. 21.Mar.2022. Retrieved from: https://insights.glassnode.com/the-week-onchain-week-12-2022/ . Access date: 24.Mar. 2022.

market cycle. Favouring our argument that accumulation and distribution cycles (recent market movements) can be traced back to institutions that have entered the BTC market. A broad assertion made by the Glassnode report is that long-term holders own coins before the market high and short-term holders own coins purchased during or after the market top. In line with Wyckoff's price cycles: composition and investment strategy has evolved with a progressively professionally traded market.

Figure 7- Bitcoin Total Transfer Volume Breakdown by Size (Entity-Adjusted) and Bitcoin Price from 2021 to 2022 and Wyckoff's Distirbution Cycle.



Source: Glassnode.com (2022) Binance (2021).

Although created to generate confidence in digital transactions, and still widely unregulated it is believed that the best way to understand bitcoin pricing today is not considering it as a means of exchange, but as a speculative investment, being part of a portfolio, together with bonds, currencies, and other commodities (Maurer et al., 2013; Bouoiyour et al., 2015). To paint a bigger picture towards bitcoin as a financial asset, and to better understand variables that are directly related to speculative pricing, the next section is dedicated to review empirical academic literature on the subject.

3. EMPIRICAL LITERATURE REVIEW ON BITCOIN

While most assets exhibit at least some fluctuations of their price and can thus be labelled risky, Bitcoin comparatively appears to be highly speculative. Academic literature provides evidence that Bitcoin traditionally exhibited a relatively independent price behavior from other traditional assets: such as stocks, bonds, and commodities. Empirical studies involving crypto assets and Bitcoin can be divided into issues related to: *1) Price stability and volatility of the crypto market*: Elbahrawy *et al.* (2017); Baur & Dimpfl (2018); Sovbetov (2018); *2) Usage of crypto assets as an investment or speculative tool:* Baek & Elbeck, (2015); Bouoiyour, Selmi & Tiwari (2015), Bouoiyour & Selmi (2015), Briére *et al.* (2015), Cheah & Fry (2015); Dyhrberg (2016); Bouri *et al* (2016); Blau, (2017); Bouri *et al*. (2017); Demir *et al.* (2018); Dyhrberg *et al* (2018); Jareño *et al.* (2020); *3) Internal determinants of crypto price:* Ciaian et al, (2016); Guizani & Nafiti (2019) *4) Exchange price of cryptos:* Gandal & Halaburda (2014); Li & Wang, (2017); Özdemir *et al* (2018).

One of the first economic studies carried out in the theme emphasized the characteristics of Bitcoin as a "non-currency", due to the absence of an intrinsic value and its weaknesses in terms of liquidity. Although intangible and "mined" through computational work (not human or mechanical), Bitcoin does have an intrinsic price. Ciaian *et al.* (2016) studied the formation of Bitcoin prices considering the traditional determinants of asset pricing. The authors analysed market forces (supply and demand) and specific characteristics of the digital "currency", such as the attractiveness of Bitcoin for investors and the development of the global macro-financial environment.

Guizani & Nafiti (2019) suggests that the number of addresses, attractiveness indicator, and mining difficulty have significant impacts on BTC price. Applying time series data from 19/12/2011 to 06/08/2018, using Autoregressive Distributed Lag Model (ARDL), and the Granger Causality test in the sense of Toda and Yamamoto (1995), demand has a significant impact on the short-term BTC price as well as the long-term. Nonetheless, transaction volume, stock, the EUR/USD exchange rate, macroeconomic and financial development coefficients do not determine BTC price in the short as well as on the long run.

Price instability is one of the main criticisms towards BTC. Baur & Dimpfl (2018) using realized volatility conducts a detailed analysis of Bitcoin market volatility[65]. High information

[65] Using data from six different markets, covering exchange rates with the US dollar, the Chinese renminbi and the Euro, the authors conclude that Bitcoin markets exhibit excess volatility (the observed volatility is up to 30 times higher than foreign exchange markets) (BAUR & DIMPLF, 2018).

variability (dispersion of beliefs regarding bitcoins fundamental value) and the absence of market regulation might ultimately be reasons for the existence of volatility spikes.

Through selected economic variables, Baek & Elbeck (2015)[66] report strong evidence that bitcoins volatility is mostly internally (buyer and seller) driven, leading to the conclusion that the market is highly speculative. Blau (2017) also using volatility to account for stylized facts about Bitcoin price dynamics concludes that speculative trading is not directly associated with Bitcoin volatility. Nevertheless, BTC returns and trading activity directly influences volatility[67].

To cover the role of Bitcoin as an investment tool. Bouoiyour, Selmi & Tiwari (2015) seek to address the following issue: Bitcoin income is a long-term promise or a "speculative bubble"? Confirming their expectations, they found that BTC price has a higher exchange ratio in the short and medium term and that investor attractiveness will affect price on the long run.

Elsewhere, Bouoiyour & Selmi (2015) via ARDL and the Granger VEC causality test examine the short and long-term links between Bitcoin price and factors that drive it: including investor attractiveness, the volume of crypto asset exchanged, Bitcoin circulation speed, estimated bid volume, hash rate, gold price, and the Chinese stock market. In the short-term, investor attractiveness, exchange rate, estimated supply volume, and the Shanghai index are positively correlated with Bitcoin price. Hash rate explains the dynamics of this new virtual reality on the long run, but speculation, estimated supply/production volume, and the Chinese stock market index become statistically insignificant.

Following Baek & Elbeck (2015), Fama, Fumagalli & Lucarelli (2019) conduct regressions to find out whether monetary policies carried out by the Federal Reserve System (Fed) and the European Central Bank (ECB) have the potential to influence Bitcoin volatility. The authors analyse monthly variation in the Bitcoin market price using fundamental variables of the USA and the European Monetary Union (EMU) from August 2010 to November 2018.

They show that the spread between daily high and low prices, as an internal factor of the BTC market is statistically significant. The S&P500 is also positively correlated with the

66 Limiting their study to volatility (risk) and return, Bitcoin market risk is compared to the stock market, fundamental economic variables that affect Bitcoin market returns. Bitcoin data was downloaded from Bitcoin Charts as daily prices ($US) from July 2010 to February 2014. Fundamental economic data was retrieved from the Federal Reserve Bank of St. Louis. These variables include the consumer price index, industrial production, real personal consumption expenditures index, 10-year Treasury note, euro exchange and the national average unemployment rate (BAEK; ELBECK, 2015).

67 Obtaining price and volume data from Bitcoin Charts (from July 17th, 2010, to June 1st to 2014) and also gathering historical exchange-rate data for 51 other currencies during the same time period from Bloomberg, time-series models was used to measure the dynamic relation between volume, prices, and volatility (GARCH (1,1) model). Univariate correlation and multivariate tests were also used (BLAU; 2017).

monthly change in Bitcoin (BTC) value, suggesting that, in certain circumstances, investors do consider crypto as an alternative financial asset when the S&P500 index increases. On the other hand, the Federal Fund Rate and the Euribor are not statistically significant, which shows that dominant monetary policy instruments seem completely irrelevant in the explanation of BTC volatility[68].

Regarding its possible hedge characteristics, Briére *et al*. (2015) examine Bitcoin investment from the point of view of the American investor with a diversified portfolio. Using weekly data from 2010 to 2013, results showed that its correlation with other assets was remarkably low, yet coverage tests confirmed that investing in Bitcoin offers significant diversification benefits. That is, including even a small proportion of Bitcoins can dramatically improve the risk-return trade-off of well-diversified portfolios. Cheah & Fry (2015) also carry out econometric modelling of Bitcoin prices. Confirming that, like many asset classes, Bitcoin exhibits speculative bubbles and empirical evidence that shows that the fundamental price of Bitcoin is zero.

These inquiries are in line with Dyhrberg (2016) which details Bitcoin interaction with other assets. Study motivation was to explore bitcoins hedging capabilities and therefore provide a detailed view of its functions given a portfolio and risk management analysis. Using ARCH and GARCH models, the author proves that Bitcoin has a place as an investiment tool and can be used as a hedge. As Bitcoin can be traded continuously, it has specific advantages over existing financial assets.

Bouri *et al.* (2016) further investigate the potential role of Bitcoin as a safe haven. Using dynamic conditional correlation (DCC) model, against various asset prices (stock indices, bonds, oil, gold, the general commodity index, and the US dollar index) with daily and weekly analysis there is evidence that Bitcoin is an effective diversifier for most of the cases.

A word of caution is warranted from the authors. First, Bitcoin investments are far less liquid than conventional assets and Bitcoin diversification abilities are not constant over time (due to the sample period and high price volatility). Even though individual investor's accessibility improved a lot with the growing emergence of funds, ETFs, and financial derivatives, these products could increase instability and potentially harm investors (Auer &

[68] All variables chosen are considered as external Bitcoin market factors, except for the monthly change in the spread between daily high and low Bitcoin prices (suggested as an internal Bitcoin market factor). Bitcoin data was downloaded from www.Bitcoincharts.com at daily prices (US$) from July 2010 to November 2018, which was then computed in monthly historical series. Data for the US economy, included the monthly change in the euro/dollar exchange rate, from the Federal Reserve Bank of Saint Louis, for the Eurozone data was collected from the Eurostat. The Federal Fund Target Rate, Euribor, Standard & Poors 550 index, and Euro Stoxx index from www.investing.com.

Tercero-Lucas, 2021).

In a later study, Bouri *et al.* (2017)[69] examine if Bitcoin can hedge global uncertainty measured by the first principal component of the volatility index of the American Stock Market (VIXs)[70] of 14 developed and developing equity markets. Employing quantile regressions, authors reveal that Bitcoin does act as a hedge against uncertainty at shorter investment horizons.

Also uncovering hedging characteristics of Bitcoin Demir *et al.* (2018) using the Bayesian Graphical Structural Vector Autoregressive technique (BGSVAR model), the Ordinary Least Squares (OLS) as well as the Quantile-on-Quantile (QQ) regression estimations, concludes that Economic Policy Uncertainty (EPU) index has predictive power over Bitcoin returns. Their results are in line with Bouri et al (2017) in which the relationship between uncertainty and Bitcoin returns are mainly negative, but Bitcoin can be used for portfolio diversification during times of bear-market.

Jareño *et al.* (2020) also uses VIX and some other risk factors such as the US stock market returns, interest rates, crude oil prices, and the Saint Louis Financial Stress Index (STLFSI) to analyse Bitcoin sensitivity returns to changes in gold prices. The study applies the quantile regression approach and the NARDL model for the 2010-2018 period. Estimations found that the most relevant risk factor is the VIX index followed by changes in the STLFSI stress index with a positive connectedness between Bitcoin and gold price returns.

Li & Wang (2017) conduct an empirical study using Vector Error Correction Models (VECM) and Autoregressive Distributed Lag Models (ARDL), aimed at determining the Bitcoin exchange rate against the dollar[71]. The authors bring to the discussion literature on technology and monetary economics recognizing that crypto assets are both a technological artifact and an economic instrument. Analysis suggests that mining and public recognition play

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[69] Bouri *et al* (2017) main purpose is to determine whether the relationship between global uncertainty and Bitcoin returns is positive at various frequencies, conditional on the state of the Bitcoin market whether it is bear or bull, and whether world uncertainty is high or low. Daily data is used to covering the period from 17th March 2011 to 7th October 2016, with global uncertainty being measure by the common component of the VIXs of 14 developed and developing equity markets. Using standard OLS and two different quantile-based approaches (standard quantile and quantile-on-quantile regressions) applied to wavelet filtered data to capture movements of Bitcoin returns ad various investment horizons.

[70] "*VIX is a key market risk indicator that reflects market sentiment and investor expectation. It is used by market participants in their risk management strategy, in which higher values of VIX indicate more market uncertainty and vice-versa*" (Bouri *et al*, 2017, p.88).

[71] The main variables used were: Bitcoin/USD exchange rate, US GDP, US Federal Funds Rate, US inflation rate, total amount of Bitcoins in circulation (Bitcoin supply), total value of Bitcoin-supported transactions (Bitcoin transaction value), number of Bitcoin-supported transactions (Bitcoin transaction volume), total value of traded Bitcoins in the exchange (trading volume), variance of Bitcoin exchange rate (volatility),Google trends index on the term "Bitcoin", number of tweets mentioning the term "Bitcoin" (Tweets) and Bitcoin mining difficulty.

an important role in determining the Bitcoin exchange rate. Moreover, there would be a gradual "evolution" of Bitcoin towards a mature state, which resembles other monetary assets, aligning with economic "fundamentals".

Through a three-year data set (2015-2017) composed of three distinct groups: fiat money (US dollar, Chinese Yuan, and Euro), commodities (Iron, Gold, and Cotton), and cryptocurrencies (Bitcoin, Ripple, Ethereum, and Litecoin), Özdemir et al (2018), applied covariance and correlation tests to changes in daily closing prices. As covariance values are positive, with a stronger correlation to fiat money as to commodities, the authors assume that this is the reason why cryptocurrencies are structurally determined as currency rather than a commodity. However, cryptocurrencies are not "structurally" determined as currency, but that this strong correlation is an intrinsic necessity to "pair" themselves to existing exchange rates to assure market liquidity in line with Dyhrberg *et al.* (2018)[72], Auer & Tercero- Lucas (2021)[73]. This further enhances the hypothesis that cryptos are mainly used for investment purposes.

To account for important market features Sovbetov (2018) builds a "Crypto 50" index, considering the total traded volume and volatility of these "currencies". The index is composed of the top 50 crypto assets according to their proportional contribution to market capitalization (their respective weights)[74]. With some cryptos displaying an exponential price trend and others disappearing Elbahrawy *et al.* (2017) arguments that several market properties have been stable for years. Considering Bitcoin history, the authors study the behaviour of 1,469 virtual assets introduced between April 2013 and May 2017[75]. From an ecological perspective, the neutral evolution model can reproduce a key number of empirical observations, shedding light on the properties of the crypto market and establishing a first formal link between ecological modelling and the study of this growing parallel global system.

Network effects[76] directly affect competition in the cryptomarket. A virtual "currency"

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[72] Examining the investment component of Bitcoin by exploring its trading dynamics and market microstructure on three US cryptocurrency exchanges using high frequency intraday data, Dyhrberg et al (2018) finds that the highest trading activity and volatility and the lowest spreads coincide with US market trading hours, suggesting that most trades are done by retail investors.

[73] Employing the Survey of Consumer Payment Choice (SCPC), a representative micro-level data set (provided by the Federal Reserve Bank of Atlanta), covering the 2014-2019 period, and using linear and logit models disprove the hypothesis that cryptocurrencies are sought as an alternative to fiat currencies or regulated finance in the US.

[74] Conducting a study that examines the price of crypto assets both in the long and in the short-term (the ARDL empirical technique), between 2010-2018, using weekly data, of five leading digital currencies at the time (Bitcoin, Ethereum, Litecoin, Dash and Monero), the stock market (SP500 index), gold price and macroeconomic indicators, the author found evidence for a significant role of the attractiveness of crypto assets in determining their prices on the long run (SOBETOV; 2018).

[75] These include the number of assets that are active in the market, market share and asset turnover (ELBAHRAWY ET AL; 2017).

[76] When the value of a product or service increases with the number of users.

is most useful when more people adopt it (exchange becomes more liquid with more buyers and sellers). In this type of market, we could expect a convergence towards a dominant asset, as it attracts more holders and creates a bigger "market share". As Bitcoin price and volatility rise there are prevailing substitution effects that increases demand for other cryptos[77] (GANDAL; HALABURDA, 2014)

Financial innovations are difficult to price and assets linked to them are likely to exhibit characteristics similar to speculative bubbles. Returns can be linked to novelty, with levels that may (or may not) be reached in subsequent periods. If they are considered to be an investment or a speculative vehicle largely depends on the investor's appetite for risk. Thus, past Bitcoin returns should be used with care when evaluating expected future returns. Its exchange rate against the US dollar can be valued by its internal factors (factors that are dictated by the Bitcoin platform and technology data) and by its external factors (market, global asset, and informational data).

Based on the academic literature reviewed, bitcoins exchange rate against the US dollar can be valued by its internal factors (factors that are dictated by the Bitcoin platform and technology data) and by its external factors (market, global asset, and informational data). On-chain data (transaction count), market data (One Year Treasury Constant Maturity Rate and S&P500) and market sentiment data (Google Trends) were chosen to understand how BTC real returns are impacted in the long and the short run. Nonlinearities are considered, corroborating the main hypothesis on how the BTC market has changed in the last few years by the presence of institutions. In the next section methodology, dataset, model specifications and results will be presented.

[77] Nguyen *et al*. (2019) specifically raises the question of whether the introduction of new altcoins will affect Bitcoin price, and if speculators view altcoins as substitutes to Bitcoin for risk diversification purposes. Estimations point out that BTC is vulnerable to potential competition form the introduction of new altcoins. Using daily data from 28/04/2013 to 15/08/2018 (1936 observations), and accounting for 62 of the largest altcoins in terms of market capitalisation in the cryptocurrency market, through an Autoregressive Distributed Lag Model, Nguyen et al (2019) found that the introduction of a new altcoin has a significant and negative impact on Bitcoin return. Roughly a new altcoin reduces Bitcoin return by 0.7%. These results suggest that investors may partly substitute Bitcoin and invest in new altcoins to diversify their cryptocurrency risk instead of holding only Bitcoin.

4. METHODOLOGY, DATASET, MODEL SPECIFICATIONS

As previously seen, existing academic literature focuses on several determinants of BTC price formation: market forces (supply and demand), BTC attractiveness (market sentiment), technological factors (hashing power and difficulty in mining) and the macroeconomic/financial development environment (Guizani; Nafiti, 2019). A brief survey of the literature was important to define the empirical approach that will be traced in this paper. Our main interest is to capture BTC real returns over the last 10 years taking into consideration market growth and new institutional players. As discussed earlier, BTC prices are subject to factors that substantially differ from those that affect conventional assets. In this sense, three different groups of dependent and independent variables were comprised to define empirical models for Bitcoin:

1. Global asset data: 1) Bitcoin (BTC) price in American Dollars USD (monthly): the asset's closing price in USD. From August 2011 to August 2021, retrieved from Glassnode.com.
2. Bitcoin on-chain data: 1) Bitcoin (BTC) transaction count (monthly): The total amount of transactions, in which only successful transactions were counted, taken also from Glassnode.com.
3. US Market data: 1) USA One Year Treasury Constant Maturity Rate, in percent (monthly) and not seasonally adjusted. All historical data from the Federal Reserve Bank of Saint Louis (FRED) dataset; 2) Data from the S&P500 taken from Yahoo Finance (^GSPC: S&P 500). Monthly closing data, historical prices (USD), not seasonally adjusted.
4. Market Sentiment Data: 1) Google Search Data (monthly), random non-real time data, from Google Trends in discrete value index.

A question may rest on why using proxies that are from the American economy, since BTC is an international asset. Empirical papers have incorporated variables from the Chinese market and the Euro market in the intuition of uncovering different aspects of price formation. However, from a global monetary policy point of view, the US American dollar is not only the main exchange rate to Bitcoin, but it is its primary market, from which major speculative impacts on the Bitcoin system come from[78].

Auer *et al.* (2022) states that the Chinese Renimbi accounted for the vast majority of BTC transactions during the first half of the past decade. With Chinese authorithies cracking down on crypto activity (transaction prohibition in 2017 and mining banning in 2021), Renminbi transactions fell substantially. The US dollar took over the majority of cross-country BTC transactions since 2018.

To capture dynamics on the US economy, stock market and different demands on speculative commodities Baek & Elbeck (2015) use the 10-year Treasury note rate and the S&P 500 index. Sovbetov (2018) uses the S&P 500 index and gold prices. Bouoiyour & Selmi (2015); Bouri *et al*. (2016), Jareño *et al.* (2020), and Nguyen *et al*. (2019) also elect gold prices as a proxy, but the latter considers the US treasury rate as well. Due to their importance the one-year treasury constant maturity rate and the S&P500 index were incorporated in our econometric models. Constant maturity yields are typically used as a pricing reference for debt security issued by corporations and institutions. Average yields of Treasury securities are frequently adjusted, modifying the term structure of interest rates in an index known as the one-year constant maturity rate. Equity indices reflect financial development in the global economy (stock market indices, exchange rates, oil price, gold price), and could directly affect BTC demand.

Google Trend queries and Wikipedia reads (Nguyen et al, 2019) have recently proven to be good measures of interest and source for sentiment analysis considering financial applications. Li & Wang (2017) postulate that daily Google search data serves as a indicator for market movements. Research intensity and search frequency of terms related to the asset or even the term "Bitcoin" focuses on theme recognition, driven by information retrieval, indicating express intention to learn about the crypto (Kristoufek, 2013).

In spite of that, for Shen *et al.* (2019) well-informed investors, will not be using the Google search engine but instead tweeting about it, commenting, making predictions of future prices or just giving an opinion. They argue that the volume of Bitcoin tweets is a stronger measure of investor attention. Accompanying Li & Wang (2017) and Kristoufek (2013), Google Trends was selected as the best proxy available for market sentiment analysis. Google Trends provides access to an unfiltered sample of actual search requests made to Google. It normalizes

[78] Guizani & Nafiti (2019) found a positive correlation with de Dow Jones index and a negative one with the Nikkei 225, which shows that BTC has a more positive correlation with the US economy than with the Japanese one.

search data to make comparisons between terms easier[79].

As for variables directly pertaining the BTC system Hayes (2015) argues that the cost of Bitcoin production via mining represents a lower bound for price. Ciaian *et al*. (2016) shows that supply and demand affect BTC especially the total number of unique transactions per day. Transaction count was deemed relevant as to capture short and long run estimation to BTC real return. Data range is from August 2011 until August 2021) containing121 observations. Descriptive statistics are reported in Table 3.

Table 3 - Descriptive Statistics of the analysed variables (August 2011 to August 2021)

Unit	Variable	Mean	Median	Maximum	Minimum	St. Dev
Price in US dollars	Bitcoin Market Price (BTC)	6.194,03	731,95	58.954,50	2,94	11.524, 57
In percent	1 Year Treasury Constant Maturity Rate (1 YTCMR)	0,74	0,23	2,70	0,05	0,83
In closing US historical prices	S&P500 (SP500)	2.357,03	2.168,27	4.522,68	1.131,42	766,31
In millions (MM)	Transaction Count (TRANSCOUNT)	5.497.106,00	6.323.546,00	11.500.776,00	164.875,00	3.510.231,00
In index	Google Trends (TRENDS)	12,12	6,00	100,00	0,00	16,48

Note: Author´s elaboration. Data computed through software EViews 10. Not seasonally adjusted. Data Source: Glassnode.com, Federal Reserve Bank of Saint Louis (FRED), Yahoo Finance, Google (2021).

Google Trends as a discrete index number presents a wide range: its minimum value at zero (0) reporting very few searches in the platform and a maximum of 100 characterizing peaking interest in this asset, specifically in December 2017. Also showing discrepancy between high and low values is BTC market price in dollars with a minimum of $2,94 (November 2011) to a maximum of $58.954,50 (March 2021) and a standard deviation of $11.524,57.

The one-year treasury constant maturity rate shows significant growth from 2015 to 2018 and then it drops to historical levels in 2019. In the second trimester of 2020 it decreases close to its median value (0,23). The S&P500 (in closing prices) shows constant growth throughout the years reaching maximum value in August 2021 $4.522,68. Bitcoin transaction

[79] Search results are normalized to the time and location of a query, by the following process: 1) each data point is divided by the total searches of geography and time range, representing relative popularity; 2) resulting numbers are then scaled on a range of 0 to 100 based on a proportion to all searches on all topics. Nevertheless, different regions that show the same search interest for a term don´t always have the same total search volume (ROGERS, 2016).

count shows overall BTC market growth through our time series. With a significant fall in February 2018, it peaked again in May 2019.

To understand Bitcoin real returns, Autoregressive Distributed Lag Models (ARDL) proposed Pesaran & Shin (1998), Pesaran *et al.* (2001) and the extended Non-Linear Autoregressive Distributed Lag Model (NARDL) developed by Shin *et al*. (2014) were the chosen methods used to estimate long-term relations, dynamic interactions and asymmetries between returns and the chosen explanatory variables. Econometric, cointegrating relationships and model specifications will be theoretically discussed in the next section.

4.1 Autoregressive Distributed Lag Model (ARDL) and Nonlinear Autoregressive Distributed Lag Models (NARDL).

As in Guizani & Nafiti (2019), Sovbetov (2018), Li & Wang (2017) and Bouoiyour & Selmi (2015) the ARDL empirical technique was implemented to examine if the chosen variables affect BTC returns. Autoregressive Distributed Lag Models (ARDL) are ordinary least square (OLS) estimations that tests the existence of a dynamic relationship considering both dependent and independent variables that are related not only contemporaneously but across historical (lagged) values. These econometric procedures have gained popularity as a method for examining long and short-term relationships that are estimated simultaneously, removing problems associated with omitted variables and autocorrelation.

With considerable advantages over non-stationary tests, it yields consistent estimates irrespective of whether variables are I(0), I(1) or mutually cointegrated. A single equation approach that is known to be unbiased, efficient, suitable for smaller sample sizes and does not require symmetry in lag dimension. To choose sufficiently large lags to mitigate residual correlation problems and over-parameterization, a delicate balance is required (Pesaran; Shin, 1998). Model selection procedures are available to determine lag length criteria, among them: Akaike, Shwarz and Hanna-Quinn. Alternatively, the adjusted R^2 from the least square regression could be applied (PESARAN & SHIN; 1998; PESARAN ET AL., 2001; NARAYAN; 2004).

To test for the existence of a level relationship between the dependent variable and a set of regressors, the F-bounds test is used in the ARDL and NARDL framework. In a generalized Dickey-Fuller type regression, two sets of asymptotic critical values for I(0) and I(1) bounds are estimated. These sets provide a band covering of all possible classifications of the regressors into: I(0), I(1) or mutually cointegrated. So, if the computed F-statistic is higher than the upper bound I(1), or lower than the lower bound I(0), inference can be drawn that variables are or aren´t cointegrated (respectively). If the F-statistic falls inside these bounds estimation is inconclusive and knowledge of the order of integration of the underlying variables is required before conclusions can be drawn (PESARAN ET AL., 2001).

Once the cointegrating relationship is confirmed the long-term coefficients can be estimated as well as the ECM (Error Correction Model) that provides adjustment speed to the long-term equilibrium. The ARDL method is capable of retrieving short and long-term properties of the estimated model, in which adjustment speed can be faster or slower, depending on regression characteristics. Equilibrium adjustment speed (the ECM coefficient) must be negative, statistically significant and smaller than one in module (-1). The general ARDL model is as follows:

$$\Delta y_t = \alpha_0 + \alpha_{1t}\Gamma + \delta_1 y_{t-1} + \delta_2 x_{t-1} + \sum_{i=0}^{n} \varphi_{1i}\Delta y_{t-i} + \sum_{i=0}^{m} \varphi_{2i}\Delta x_{t-i} + \varepsilon_t \quad (4)$$

Wherein Δ is first difference operator; α_o the constant; $\alpha_{1t}\Gamma$ the trend; $\delta_i, i = 1{,}2$ are the long run parameters; $\varphi_{i,}i = 1{,}2$ are the short run parameters; and ε_t is the error term that must be a white noise. A residual term which is supposed to be: serially independent, homoscedastic and normally distributed (*i.i.d*). Observing equation (1) above, the dependent variable is represented as the past values of itself, the past values of the explanatory variable, and the past differenced values of itself and of the independent variable. The ability to host sufficient lags, enables best capturing of the data generating process mechanism (MENEGAKI, 2019).

Choosing to extend the ARDL approach popularized by Pesaran & Shin (1998) and Pesaran *et al.* (2001), Shin *et al.* (2014) developed a flexible parametric framework, in which short and long run asymmetries are introduced via positive and negative partial sum decompositions of the explanatory variables. The NARDL functional form is:

$$\Delta y_t = \alpha_0 + \alpha_{1t}\Gamma + \rho y_{t-1} + \delta_1^{+} x_{1t-1}^{+} + \delta_1^{-} x_{1t-1}^{-} + \delta_2^{+} x_{2t-1}^{+} + \delta_2^{-} x_{2t-1}^{-} + \; + \sum_{i=0}^{p-1} \lambda_i \Delta y_{t-i}$$
$$+ \sum_{i=0}^{q} \varphi_{1i}^{-} \Delta x_{1t-i}^{-} + \sum_{i=0}^{r} \varphi_{1i}^{+} \Delta x_{1t-i}^{+} + \sum_{i=0}^{s} \varphi_{2i}^{-} \Delta x_{2t-i}^{-} + \sum_{i=0}^{p} \varphi_{2i}^{+} \Delta x_{2t-i}^{+} + \varepsilon_t \quad (5)$$

As in equation (1) Δ is first difference operator; α_o the constant; $\alpha_{1t}\Gamma$ the trend; $\delta_i, i = 1{,}2$ are the long run parameters; $\varphi_{i,} i = 1{,}2$ are the short run parameters; and ε_t is the error term that must be a white noise (*i.i.d*). "*The equation has two distinctive parts comprising the short run and the long run, where x_t^{+} and x_t^{-} are partial sums of positive (+) and negative (-) changes in x_{1t} and x_{2t}*" (Shin et al, 2014; p.8).

Measuring separate responses to positive and negative shocks of the regressors on the dependent variable, the nonlinear autoregressive distributed lag model (NARDL) shows the same advantages as the ARDL framework: it exhibits small sample properties, and it is appropriate regardless of the stationarity of the variables. It yields estimates of both short and long run coefficients, it is free of residual correlation (it is not prone to omitted lag bias) and solves multicollinearity through the choice of the appropriate lag length of variables (JAREÑO ET AL., 2020).

Summarizing NARDL procedures: 1) the dynamic error correction representation associated with the asymmetric long run cointegrating regression is derived (the nonlinear ARDL) ; 2) following Pesaran & Shin (1998), Pesaran *et al.* (2001) the bounds testing procedure is employed, for the existence of a stable long run relationship which is valid irrespective of whether the underlying regressors are I(0), I(1) or mutually cointegrated; 3) Asymmetry tests are performed to statistically prove nonlinearities between the dependent and explanatory variables. Thus, the bounds test proposed by Shin et al (2014) examines the presence of cointegration while hosting asymmetries.

4.2 ARDL and NARDL Model Specification

As a proxy for the US equity market, Baek & Elbeck (2015), Sovbetov (2018), Fama *et al.* (2019) refer to the S&P500. It is the main index comprising the large-cap 500 constituent companies, weighted by float-adjusted market capitalization. One of Fama *et al.* (2019), main findings is that the S&P500 is statistically significant and positively correlated with the monthly change in BTC value suggesting that in certain circumstances BTC is an alternative financial asset when the S&P500 index increases[80].

The same reasoning would be applied to the one-year treasury constant maturity rate (1 YTCMR). This index is used to set interest rates, published by the Federal Reserve Board, and determined by the U.S Treasury from the daily average yield curve of a range of treasury securities. Although, dominant policy instruments seem completely irrelevant in the explanation of Bitcoin price. Transaction count as a proxy for volume and marginal interest on the asset, and Google Trends, capturing market sentiment through searches, are expected to have a direct positive effect on BTC real returns:

Model 1 (ARDL): $BTC = \beta_0 + \beta_1 1YTCMR + \beta_2 SP500 + \beta_3 TRANSCOUNT + \beta_4 TRENDS + \varepsilon_t$ (6)

Nonetheless, the common assumption that a cointegrating relationship may be represented as a linear combination of the underlying stationary variables maybe excessively restrictive and insufficient to permit strong inference and reliable forecasts. In general, long run cointegrating relationships will also be subject to nonlinearities. With an explicit intention to estimate asymmetries, NARDL basically captures when positive and negative variations of the explanatory (X) variable do not have the same impact on the dependent variable (Y).

Decomposing the reactions of Y to negative and positive changes in X, it is possible to infer asymmetric relationships between variables. Considering the ARDL model estimated and a linear relationship between variables[81]: Does an increase in the S&P500 index has a stronger impact on real BTC returns than a decrease in the index? Or does an increase on transaction count has a stronger impact on returns than its decrease? What can we affirm towards market sentiment (Google Trends)?

Four NARDL versions of the ARDL model were developed (Table 4), concentrating efforts towards two variables, transaction count and S&P500. To advance in our analysis, unit root tests of the variables were taken, and important diagnostic tests were made to confirm the

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[80] Considered as an important alternative investment to BTC, Gold prices in US dollars (World Gold Council) was also used as a proxy. But due to considerable correlation between gold prices and BTC price rate, the analysis was limited to the S&P500 index.

[81] Symmetric relationship is not the same as a positive relationship between the variables. Symmetry is when the degree of impact of X on Y is the same when X increases and when X decreases. Which is not the same as a positive or negative relationship, identifying the direction of the relationship: if the variables X and Y increase or decrease together.

robustness of our models. We first start with ARDL estimations and results to then analyse NARDL calculations and asymmetry tests.

4.3 Diagnostic tests and estimations

To identify the order of integration of each variable, the Dicky-Fuller (DF), the Augmented Dickey-Fuller (ADF), Philips-Perron (PP), Kwiatkowski-Philips-Schmidt-Shin (KPSS) Tests were performed to show the non-existence of I(2) variables corroborating ARDL modelling[82]. Schwarz Information Criterion (SIC) was used for lag selection (and stationary was considered when at least three of these tests indicated the same result), all variables where considered to be I(1).

After accounting for seasonality[83] and applying unit root tests (Appendix), BTC market price in American dollars was transformed in natural logarithm and first differenced (DLNBTC) to calculate real-returns. The only variables that weren´t estimated in natural logarithm was the US government's one-year treasury constant maturity rate (1YTCMR) and the Google Trends index (TRENDS). Coefficients are expected to have a: negative (1 YTCMR), positive (LNSP500), positive (LNTRANSCOUNT), positive (TRENDS) effect.

Due to abnormal market movement during the COVID-19 pandemic, a dummy variable was applied for the years 2020 and 2021. The number of observations was 121 (August 2011 to August 2021). The model selection criterion was Akaike; trend specification was kept at restricted constant and no trend; also performing the HAC covariance matrix (Newey-West) with degrees of freedom adjustment for robust estimations. Maximum lag selected for the dependent and for the explanatory variables were kept at three (3).

Description of the estimated models are available in Table 4. Google Trends was also decomposed into positive and negative shocks for NARDL estimations; however, no statistical significance was found. Proceeding with ARDL diagnostic tests, the Cumulative Sum (CUSUM) and the Cumulative Sum of Squares (CUSUM Squared) recursive residual test (Graph 5), proposed by Brown, Durbin, and Evans (1975) to detect departures from constancy

[82] The ADF, DF-GLS and PP tests, T- statistic is applied, and its null hypothesis is that the time series has a unit root. The KPSS test uses the Lagrange Multiplier (LM) statistic, and its null is that the time series of the analysed variable is stationary.

[83] Variables were seasonally adjusted with two different methods: the census-13 EViews 10 using x-11 and TRAMO/SEATS tools.

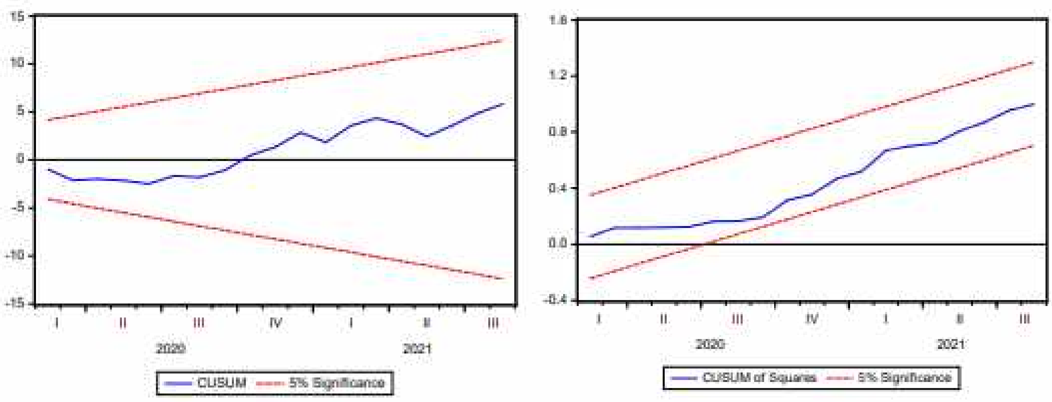
of regression relationships over time, observed that the ARDL model is dynamically stable falling in between the 5% critical lines in both tests.

Table 4 - Estimated ARDL and NARDL models (August 2011 to August 2021)

Dependent Variable	Model	Positive and Negative Shocks	Dependent Variables	Model Selected
DLN*BTC	ARDL	_	1YTCMR, LNSP500, LN*TRANSCOUNT, TRENDS.	(1,0,1,1,3)*
DLN*BTC	NARDL 1	LN*TRANSCOUNT + LN*TRANSCOUNT-	1YTCMR, LNSP500, LN*TRANSCOUNT +, LN*TRANSCOUNT-, TRENDS.	(1,0,1,0,1,3)*
DLN*BTC	NARDL 2	LN*SP500 +, LN*SP500 -	1YTCMR, LN*SP500 +, LN*SP500 -, LN*TRANSCOUNT, TRENDS.	(1,0,1,2,1,3)*
DLN*BTC	NARDL 3	LN*SP500 +, LN*SP500 - ,LN*TRANSCOUNT + , LN*TRANSCOUNT-	1YTCMR, LNSP500 +, LN*SP500 - ,LN*TRANSCOUNT+, LN*TRANSCOUNT-, TRENDS.	(1,1,1,0,0,1,3)*
DLN*BTC	NARDL 4	LN*TRANSCOUNT +, LN*TRANSCOUNT-, TRENDS +, TRENDS -.	1YTCMR, LNSP500 ,LN*TRANSCOUNT+, LN*TRANSCOUNT-, TRENDS +, TRENDS -.	(1,0,1,0,1,0,3)*

Note. ARDL and NARDL model with maximum of three (3) lags. Model choice based on Akaike Information Criteria. DLN*BTC: Bitcoin price in dollars, in natural logarithm and first differenced. LN*: natural logarithm transformation. * Case 2: Restricted constant and no trend. Author's elaboration. Data output from EViews 10.

Graph 5. CUSUM and CUSUM SQ Test. ARDL



Note: Author's elaboration (EViews 10).

For robust inference other tests were also performed (Table 5). Failing to reject the null that there is no autocorrelation in the Lagrange Multiplier (LM) Test, the model is free from serial correlation. The Breusch-Pagan-Godfrey and the White[84] heteroskedasticity tests, were also estimated failing to reject the null of no heteroskedasticity (residuals are homoscedastic). Functional form is also well defined, failing to reject the null hypothesis of correct model specification according to the Ramsey Reset-Test[85].

Tabel 5 - Diagnostic Tests. ARDL model: dependent variable DLNBTC (August/2011 - August/2021)

ARDL Model (1,0,1,1,3) *	
Tests	Statistics
Serial Correlation LM Test [Prob]	F (3,103) = 0,36 [0,77]
Heteroskedasticity Breusch-Pagan-Godfrey [Prob]	F (11,106) = 0,67 [0,76] R^2(11) = 7,68 [0,74]
Heteroskedasticity White Test [Prob]	F (11,106) = 0,32 [0,97] R^2(11) = 3,89 [0,97]
Ramsey - Reset Test [Prob]	F (1,105) = 0,22 [0,63]
Cointegration Test	
F- Bounds Test	Critical values (1%)
17,9	3,60 - 4,78

Note. ARDL model with maximum of three (3) lags. Model choice based on Akaike Information Criteria. H_0 for Autocorrelation LM Test = no autocorrelation.H_0 for Heteroskedasticity BG Test = no heteroskedasticity. *Case 2: restricted constant and no trend. Source: Author's elaboration (EViews 10).

With stability and diagnostic tests done the ARDL bounds testing methodology (Pesaran et al, 2001) can be applied, to confirm that variables have a long run relationship. The joint significance of the model's long-term parameters, are checked thorough an F-test, under the null of no cointegration[86]. Over the I(1) critical value variables do have a long run cointegrating relationship.

The ARDL long run cointegrating equation is depicted in Table 6. These variables compose the levels equation, calculated by dividing the negative of dependent variable by the independent variable coefficient. Observing the T-statistic and the p-value (< 0,05) a 1% increase in the S&P500 (LNSP500) will negatively affect the Bitcoin real returns in 0,64%. As short-term investors become increasing skeptical towards price volatility in BTC market, they are inclined to sell-out and take their investments to global equity markets. On the long run

[84] The standard White test was adopted. EViews 10 default is to include White's terms in the regression, but due to the insufficient number of observations, the test was estimated without the crossed terms (the number of observations and the square of the residual of the original variables).

[85] The Jarque-Bera normality test indicated a non-normal distribution of errors, which is expected to be corrected adding a bigger number of observations in the future.

[86] Cointegration occurs when two or more variables, do not drift too far apart on the long run. Granger (1981, 1986) and Engle and Granger (1987), noted that a linear combination of I(1) series may be stationary or I(0), which could be interpreted as a cointegrating equation and a long run equilibrium relationship among these variables.

companies will return to the S&P500 were risk is lower and institutional investors will take advantage of short run market appreciation.

Transaction count (LNTRANSCOUNT) shows that a 1% increase in BTC transactions, can have a positive impact of 0,11% on BTC returns. This finding accompanies not only literature but part of logic behind bitcoin constant price increase. If market negotiation increases, this feeds into the fear of missing out (FOMO) of most speculators, which could consequently induce more transactions, negotiation, rising prices and returns. Although this logic is applied to small investors, big players have the incentive to manipulate price, and take advantage of these fears (Wyckoff).

Table 6 - ARDL long run coefficients (levels equation) (August/2011 - August/2021).

Model: ARDL (1,0,1,1,3) *		
Dependent Variable: BTC real returns (DLNBTC)		
Variable	Coefficient	T-Statistic [Prob]
1 YTCMR	0,0286	(0,6822) [0,496]
LNSP500	**-0,6432**	**(-2,135) [0,035]****
LNTRANSCOUNT	**0,1117**	**(2,3052) [0,023]****
TRENDS	0,0001	(0,9334) [0,352]
C	**3,2335**	**(1,9787) [0,050]*****

Note. ARDL model with maximum of three (3) lags. Model choice based on Akaike Information Criteria. *Case 2: restricted constant and no trend. ** Statistically significant at the 5% value. *** Statistically significant at the 10% value. Source: Author's elaboration (EViews 10).

The one-year treasury constant maturity rate (1 YTCMR), represents the one-year equivalent of the most recently auctioned treasury securities, reflecting conditions in the American economy, which can be mostly detached from speculative market movements (not statistically significant). Concurrently, market sentiment captured by Google Trends (TRENDS) does not show any long run significance, but it does have a short run impact, as will be seen shortly.

Table 7 shows the short run estimations of the ARDL model, through the error correction regression. The most relevant variables are the SP&500 (1 lag), transaction count (1 lag), and google trends (3 lags). These variables are significant at 5% level (p-value), with positive signs. A 1% increase in the S&P500 index in the short run will increase in 1,27% returns. A positive short run impact shows euphoria from equity markets, towards high speculative gains from the crypto market. And as on the long run, in the short run transaction count will have a positive impact on BTC, but with a higher coefficient. A 1% increase in the number of transactions in exchanges, will impact real BTC yields in 0,55%. Google Trends, as a market sentiment proxy (although with a low coefficient), does indeed affect BTC, with a high p-value.

The Error Correction Mechanism (ECM) that portrays short-term deviations from the long run was (-0,95), a negative and statistically significant adjustment coefficient at the 1% level. Therefore, given a shock today 95% of the deviations from the long run trajectory of BTC real returns will be corrected in the next month. What is important to notice is that both S&P500 and transaction count have significant short-term coefficients, and the ECM is relatively high corroborating the fast pace of the crypto market.

Table 7 - Short run ARDL model (Error Correction Regression): dependent variable DLNBTC (August/2011 - August/2021)

Model: ARDL (1,0,1,1,3)*		
Dependent Variable: BTC real returns (DLNBTC)		
Variables	Coefficient	T-Statistic [Prob]
D(LNSP500)	**1,2706**	**2,0401 [0,043]****
D(LNTRANSCOUNT)	**0,5559**	**3,0782 [0,002]****
D(TRENDS)	**0,0078**	**2,8627 [0,005]****
D(TRENDS (-1))	-0,0037	(-1,379) [0,170]
D(TRENDS (-2))	**0,0062**	**2,2885 [0,024]****
DUMMY	**0,2152**	**3,5100 [0,000]****
ECM	**-0,95**	**(-10,606) [0,000]****

Note. ARDL model with maximum of three (3) lags. Model choice based on Akaike Information Criteria. *Case 2: restricted constant and no trend. ** Statistically significant at the 5% value. Source: Author's elaboration (EViews 10).

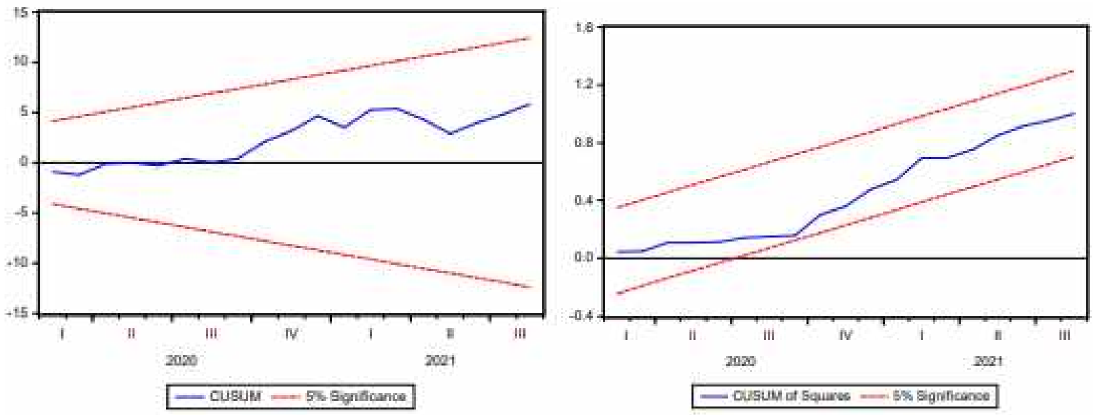
As bigger institutional investors enter the market with high leverage, the BTC market will undergo relevant changes, including price corrections. In price slumps, there is an increase in sell-out and herd behaviour that will transfer BTCs from small investors to big institutions. Transaction count shows these movements (buying and selling), accounting for a strong and direct correlation to BTC yields. The long and short run importance of the S&P500 shows that there is an increasing spill over between the BTC market and traditional asset markets. Previous evidence that Bitcoin exhibited a relatively independent price behaviour from other traditional assets, today can no longer be categorically affirmed. Institutional investors will tend to negotiate (buy) at lower prices and "hold" on to their Bitcoins in the intention of profiting on the long run, with historical price increases.

Positive and negative series of the relevant explanatory variables are decomposed, to study potential relationships with the dependent variable. Diagnostic, cointegration and stability tests are crucial before NARDL estimation (Table 8). Cumulative Sum (CUSUM) and the Cumulative Sum of Squares (CUSUM Squared) recursive residual test, proposed by Brown, Durbin, and Evans (1975), attested coefficient stability (Graphs 6, 7, 8 and 9). The cumulative sum lines and the cumulative sum of squares of the four NARDL models did not traverse outside the area between the 5% critical lines.

Accounting for autocorrelation and heteroscedasticity, diagnostic tests where run (Table 8). All four models do not reject the null of the LM Test (H0: no serial correlation), the White and Breusch-Pagan-Godfrey Heteroskedasticity Test (H0: residuals are homoscedastic), in other words our residuals are not serially correlated nor heteroskedastic. It is important to remember that the Akaike information criteria was used to identify optimal lag length, and HAC (Newey-West) coefficient covariance matrix, was used to perform robust estimates.

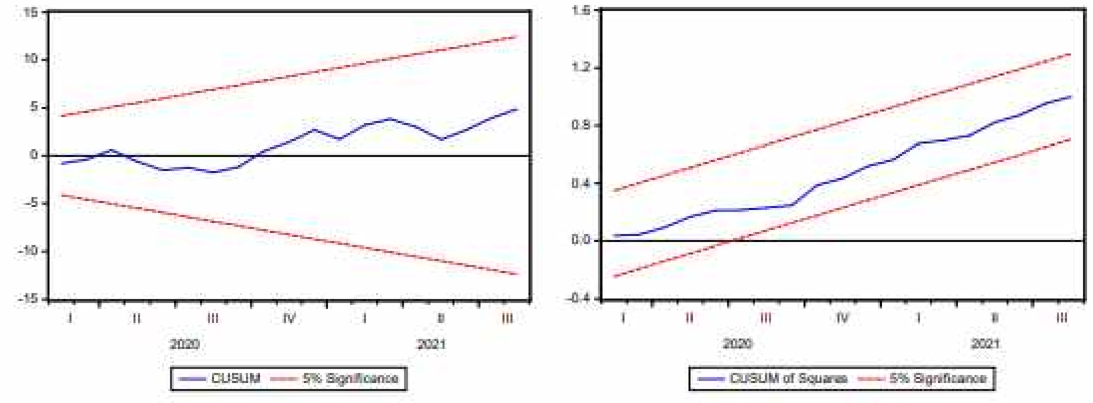
To properly identify that there is cointegration between the dependent and the explanatory variables of each model, the F – Bounds was performed. The tests are displayed in Table 9. The F-statistic is greater than the upper critical value in all models, rejecting the null hypothesis at 1% significance that there is no cointegration between variables. This confirms a long-term relationship between the dependent variable and the respective explanatory variables.

Graph 6 - CUSUM and CUSUM SQ Test. NARDL (1,0,1,0,1,3) Model 1.



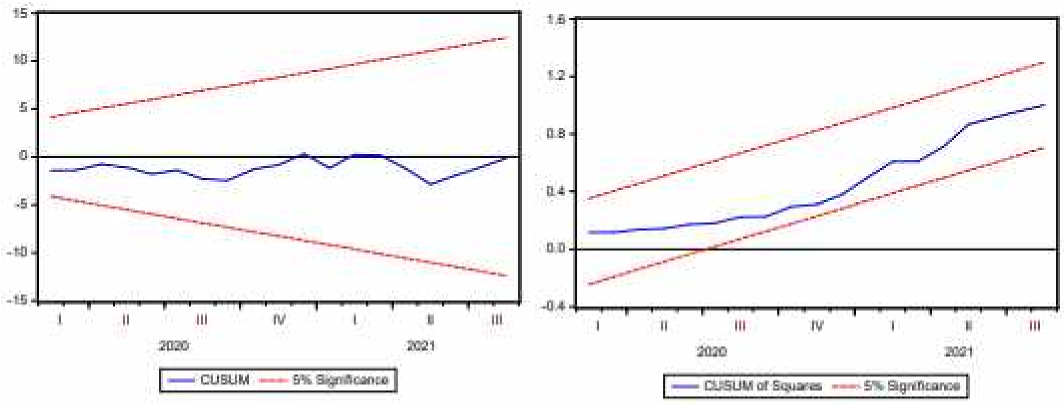
Note: Author’s elaboration (EViews 10).

Graph 7- CUSUM and CUSUM SQ Test. NARDL (1,0,1,2,1,3) Model 2.



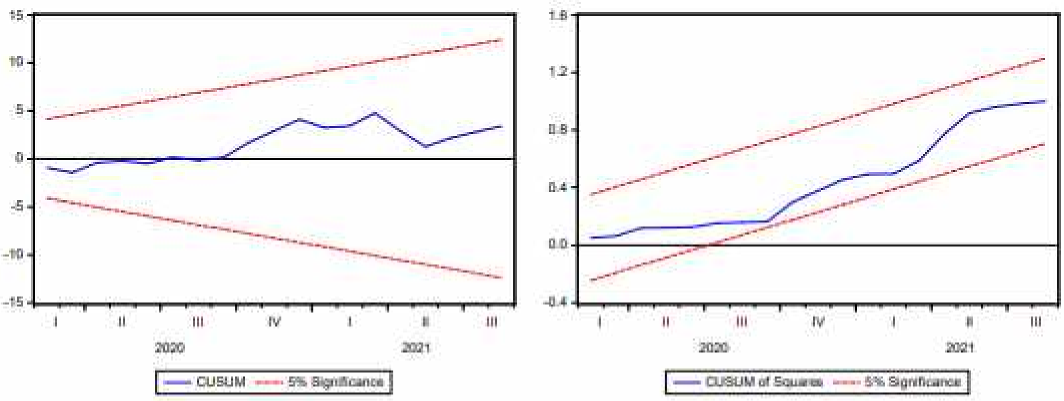
Note: Author’s elaboration (EViews 10).

Graph 8 - CUSUM and CUSUM SQ Test. NARDL (1,1,1,0,0,1,3) Model 3.



Note: Author’s elaboration (EViews 10).

Graph 9 - CUSUM and CUSUM SQ Test. NARDL (1,0,1,0,1,0,3) Model 4.



Note: Author’s elaboration (EViews 10).

Table 8 - NARDL models: dependent variable DLNBTC (August/2011 - August/2021)

Model	Selected Lags	LM Test [Prob]	Breusch-Pagan-Godfrey [Prob]	White Test [Prob]	Ramsey Reset Test [Prob]
1	(1,0,1,0,1,3)	F(3,102) 0,39 [0,75]	F(12,105) 0,57 [0,86]	F(12,105) 0,36 [0,97]	F(4,101) 1,16 [0,33]
2	(1,0,1,2,1,3)	F(3,100) 0,91 [0,43]	F(14,103) 0,51 [0,91]	F(14,103) 0,21 [0,99]	F(4,99) 1,59 [0,18]
3	(1,1,1,0,0,1,3)	F(3,100) 0,47 [0,70]	F(14,103) 0,52 [0,91]	F(14,103) 0,23 [0,99]	F(4,99) 0,157 [0,95]
4	(1,0,1,0,1,0,3)	F(3,100) 0,35 [0,78]	F(13,103) 0,56 [0,88]	F(13,103) 0,41 [0,96]	F(4,99) 0,58 [0,67]

Note. NARDL models with the maximum of three (3) lags. Choice of model based on Akaike Information Criteria. H_0 for Autocorrelation LM Test = no autocorrelation.H_0 for Heteroskedasticity BG Test = no heteroskedasticity.H_0 for White Test = no heteroskedasticity. Source: Author's elaboration from EViews 10.

Table 9 - Cointegration Tests. NARDL models: dependent variable DLNBTC (August/2011 - August/2021)

Model: NARDL				
Dependent Variable: DLNBTC				
Model and Variable Decomposition	Model 1 TRANSCOUNT	Model 2 S&P500	Model 3 S&P500; TRANSCOUNT	Model 4 TRENDS; TRANSCOUNT
F - Bounds Test	17,29	16,05	15,46	14,65
Critical Values*	3,35 - 4,58	3,35 - 4,58	3,17 - 4,48	3,17 - 4,48

Note. *Pesaran et al. (2001): with restricted constant and no trend, at the 1% significance level. Author's elaboration. EViews 10.

In Table 10, the four NARDL long run level estimations are presented, only significant variables will be analysed (p-value <0.05). Model 1, contains transaction count's decomposition in positive and negative impacts on BTC real returns. They will have a positive causal effect: A 1% increase in transaction count, though a positive shock, will increase returns in 0,15%, and a 1% decrease in transaction count, through a negative shock will decrease BTC real yields 0,52%.

This brings us to the conclusion that a reduction in transactions through the Bitcoin system will have a bigger negative impact on returns. Like most speculative markets, fuelled by fleeting sentiments, transaction upsurge will attract interest and investors to the crypto market, pumping BTC real returns. Howbeit if prices are below trend, they will plunge even deeper. Price descents are stronger due to herd instinct, which leads novice investors in selling low, a primal response to fear, uncertainty, and doubt (FUD).

The one-year-treasury constant maturity rate (1 YTCMR) has an immediate positive and significant impact: a 1% increase in the 1 YTCMR, there will be a 0,12% increase in BTC yields. This finding hints us to a long run spill over between risk-free securities (a proxy for pricing debt securities) to the crypto market, in the sense that investors will use parts of their resources in these markets to bet on even bigger gains in Bitcoin.

Model 2 presents long run effects between equity markets and BTCs. Positive changes in the SP500 index will have an inverse effect on BTC yields, decreasing returns in 1,0%. A negative shock will increase BTC real returns in 1,21%. In a market hype, agents will tend to shift investments transferring their assets from BTC to stocks, dampening real returns. Otherwise, a downturn in the stock market, will have cascading positive effects to BTC. Transaction count also stands as a significant variable in Model 2, increasing Bitcoin price rate in 0,14%. Market optimism tends to spill over to BTC price, through an increased exchanged volume.

Accounting for decompositions of both the S&P500 and Transaction Count (Model 03) estimations show that positive and negative changes of S&P500 are not statistically significant. But similar to Model 1, the 1-year treasury constant maturity rate (1YTCMR) increases DLNBTC in 0,10% on the long run. Positive and negative changes of transaction count remain positive and statistically significant. A 1% increase in transaction count, though a positive shock, will increase BTC real returns in 0,12%, and a 1% decrease in transaction count, through a negative shock will decrease returns in 0,63%. In an upper trend market, investors will take their holdings and invest part of them in BTCs. While, crypto market oscillations will tempt emotional reactions from these investors, as price slumps become a stronger fear factor than price rises, which will affect real returns.

Considering positive and negative shocks of transaction count and google trends, Model 04 follows roughly previous estimations. A positive change on transaction count, increases BTC real return in 0,18%, and a negative impact will decrease BTC yields in 0,59%. Decompositions from Google Trends to BTC real returns accounts for a small but significant effect. Positive Google Trend impacts have bigger effects than negative ones. The 1-year treasury (1 YTCMR) constant maturity rate has yet again importance: a 1% increase on the 1 YTCMR, will concurrently increase DLNBTC in 0,11%.

Overall, on the long run, there is a significant impact of the 1-year treasury constant maturity rate on Bitcoin real returns. This finding shows that risk free security markets have a positive effect on the crypto market, where investors will seek bigger gains. When accounting for positive and negative shocks of the number of transactions, a decrease will have a bigger negative impact on Bitcoin prices (Models 01, 03 and 04). Volume of negotiations through exchanges will directly impact the crypto asset, whereas equity markets (represented by the

S&P500) will have an inverse relationship with BTC real returns.

If Bitcoin effectively settles at a higher price level as speculators predict, there is a possibility in the long-term that big players will return to the S&P500 where there is less uncertainty regarding the valuation of their equity. In these terms, Bitcoin can establish itself as a niche market in portfolio investing alongside other traditional assets.

Market sentiment (Google Trends) has a small, but significant positive impact on BTC real returns. Our econometric analysis advances and brings forth important findings, in verifying statistical significance in variables that were deemed not important when explaining Bitcoin price oscillations: like the one-year treasury constant maturity rate (1YTCMR) that is now gaining importance, due to increasing market participation of institutional investors.

Table 10 - NARDL models. Long run coefficients (levels equation). Dependent Variable: BTC real returns (DLNBTC) (August/2011 - August/2021)

	Model 01		Model 02		Model 03		Model 04	
	NARDL (1,0,1,0,1,3)**		NARDL (1,0,1,2,1,3)**		NARDL (1,1,1,0,0,1,3)**		NARDL (1,0,1,0,1,0,3)**	
Variables	Coefficient	T-Statistic [Prob]	Coefficient	T-Statistic [Prob]	Coefficient	T-Statistic [Prob]	Coefficient	T-Statistic [Prob]
1 YTCMR	**0,127**	**2,283 [0,024]**	0,045	1,327 [0,187]	**0,101**	**2,078 [0,040]**	**0,1134**	**2,289 [0,024]**
LNSP500	0,159	0,500 [0,617]					0,0766	0,241 [0,809]
LNSP500 POS			**-1,006**	**-2,712 [0,007]**	0,283	0,941 [0,347]		
LNSP500 NEG			**-1,210**	**-2,191 [0,030]**	-0,340	-0,760 [0,448]		
LNTRANSCOUNT			**0,1438**	**2,889 [0,004]**				
LNTRANSCOUNT POS	**0,152**	**3,266 [0,001]**			**0,128**	**3,096 [0,002]**	**0,1842**	**2,533 [0,012]**
LNTRANSCOUNT NEG	**0,527**	**2,983 [0,003]**			**0,636**	**3,067 [0,002]**	**0,5988**	**2,465 [0,015]**
TRENDS	0,002	1,384 [0,169]	0,002	1,381 [0,170]	0,002	1,276 [0,204]		
TRENDS POS							**0,0034**	**2,301 [0,023]**
TRENDS NEG							**0,0026**	**1,669 [0,098]**
C	-1,05	-0,461 [0,645]	-1,731	**-2,806 [0,006]**	0,069	1,096 [0,275]	-0,4565	-0,201 [0,841]

Note. NARDL models with maximum of three (3) lags. Model choice based on Akaike Information Criteria. case 1: no constant and no trend, **case 2: restricted constant and no trend, ***case 3: unrestricted constant and no trend, ****case 4: unrestricted constant and no trend; *****case 5: unrestricted constant and unrestricted trend. Source: Author's elaboration (EViews 10).

Short-term estimations of the NARDL models are presented in Table 11. NARDL (1,0,1,0,1,3), model 01 with positive and negative variations of transaction count, show that S&P500, Transaction Count and Google Trends are significant. With a 1% increase in the S&P500, there will be a 1,56% increase in BTC real returns. Concerning transaction count if there is a negative shock with a 1% decrease in the variable, there will be a 1,52% decrease in BTC real returns. This shows how the quantity of transactions occurring inside exchanges, are relevant to detect relative optimism or pessimism towards Bitcoin. If agents are less willing to buy BTCs in the short-term, this is a signal of disinterest, which makes prices fall.

Google trends displays relevance two periods previously, with a very low coefficient, with both a positive and negative impact on returns. These oscillations, demonstrate a loss of interest (or increased interest) on behalf of market agents after a short period. Search intensity indicates the expressed intention to learn about Bitcoin, however, information about the asset *per se* is very inconstant. It is hard to separate interest due positive and negative events: if market sentiment is being driven by a price increase or a strong fall in prices (KRISTOUFEK; 2015).

The speed of adjustment to long-term equilibrium is a negative and statistically significant coefficient at the 1% level, but not smaller than 1 in module. Adopting a confidence interval of 0,05, given a shock today, 100% of the deviations from the long run trajectory of the BTC real returns will be completely corrected in the next month.

NARDL (1,0,1,2,1,3), model 02 comprises positive and negative variations of S&P500. The variables: S&P500, transaction count and Google Trends index show statistical significance (p-value < 0,05). A 1% decrease in the S&P500, will decrease BTC real returns in 2,77, a month previously to the shock, while an increase in transaction count will increase BTC yields.

Google trends index has a significant impact in the current period: with a 0,007 increase in returns. Public recognition reflects market demand for Bitcoin, and an increase in the demand for the asset can lead to appreciation in the short-term. But just like model 01, lags of market sentiment displays econometric relevance at the 10% level, with low coefficients and positive and negative impacts on BTC yields. The ECM found in Model 2, was (-1,0) a negative and statistically significant adjustment coefficient at the 1% level, where 100% of the deviations from the long run trajectory of the BTC real returns will be corrected in the next month.

Including both positive and negative variations of S&P500 and transaction count, NARDL (1,1,1,0,0,1,3) model 03, shows that the one-year treasury constant maturity (1 YTCMR) rate and a positive shock of the S&P500 are important in explaining BTC price. A 1% increase in the one-year treasury constant maturity rate (1 YTCMR), has a positive and significant impact on BTC real returns in 0,41%. Speculators are constantly trying to reap bigger gains, a movement that is translated through the S&P500 index: a positive shock (in 1%) will increase BTC real returns in 1,97%.

Models 1 and 2 show similarities to model 3. A decrease in transaction count will decrease BTC real returns in accounting for disinterest in negotiating the asset. Nevertheless, market sentiment will have a positive impact on the current period and statistically significant lags of Google Trends at the 10% level corroborate results from models 01 and 02. Portraying short-term deviations from the long run, the Error Correction Mechanism (ECM) of model 3 is negative and statistically significant at the 1% level, but not smaller than one in module. With positive and negative shocks on the explanatory variables (S&P500 and transaction count), 100% percent of the deviations from the long run trajectory of the BTC real returns will be corrected in the next month.

The last estimation NARDL (1,0,1,0,1,0,3), model 04, in which positive a negative shocks of transaction count and Google Trends index where estimated, S&P500 showed (again) a positive impact on BTC real returns in 1,45%. Transaction count also showed a direct relationship to BTC yields. These results are closely related to model 1, in which complementary aspects of the stock market and crypto market where emphasized, along with the importance of how number of transactions is a good proxy for BTC speculative market conditions, as it accounts for negotiated volume inside exchanges.

In model 04, Google Trends index was unpacked to understand better it´s positive and negative variations. With a 1% negative impact in Google Trends index, decreases BTC real returns in 0,008%. One month previously, there would have been an increase in BTC real returns, with a bigger econometric significance (p-vaule <0,05), and two months before that, there would have been another decrease in yields (significance inferior to the 10% p-value).

Confirming that there is in fact a relationship between returns and proxies for public recognition, there are however some caveats. Its variability is probably due to market sentiment volatility, with lag effects to shocks and difficulty in separating public interest through positive and negative media coverage that would increase or decrease prices. As in model 03, model 04 ECM is also (-1,04) negative and statistically significant at the 1% level, but not smaller than one in module. Given positive and negative shocks today on the explanatory variables (Transaction Count and Google Trends), 100% percent of the deviations from the long run trajectory of the BTC real returns will be corrected in the next month. Dummy variables in all four models show statistical significance, demonstrating the importance in accounting for the COVID-19 pandemic during the 2020/2021 period.

Market expectations, like confidence or distrust, are commonly observed through the number of transactions that occur inside crypto exchanges. Demand indifference makes prices fall, typifying that Bitcoin returns are more prone to negative impacts than positive ones. One of our contributions rests on the performed estimations, which showed that the volume exchanged (transaction count), the S&P500 and the one-year treasury constant maturity rate, are relevant in determining BTC real returns in the short-run, contrary to previous literature on the subject.

Institutions and market makers will tend to look not only to traditional asset classes but also Bitcoin as an alternative. Our analysis is coherent to Iyer (2022) that formally assessed the interconnectedness between crypto and equity markets. Using an econometric approach proposed by Diebold-Yilmaz (2012, 2014) and a vector autoregression (VAR) to analyse the system-wide as well as pair-wise spill overs across different asset classes[87].

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[87] The model was estimated using daily data for Bitcoin and Tether prices, plus US equity indices (S&P500, Russel 2000) over the period January, 2017 to November, 2021, excluding non-trading days. Crypto and equity prices are considered endogenous variables and includes oil prices and the 10-year US Treasury bill (T-bill) as exogenous variables to control for potential variations in commodity prices and financial conditions. Estimating for asset returns and price volatility, two approaches were followed: first the model was estimated for pre-pandemic (Jan 2017 – Dec 2019), and post-pandemic (Jan 2020 – December 2021); and second a rolling-window estimation was done for the entire sample to compute spill overs during normal times versus market stress periods (IYER, 2022).

Table 11 - NARDL models. Short run estimations (Error Correction Regression): Dependent Variable: BTC real returns (DLNBTC) (August/2011 - August/2021)

	Model 01		Model 02		Model 03		Model 04	
	NARDL (1,0,1,0,1,3)**		NARDL (1,0,1,2,1,3)**		NARDL (1,1,1,0,0,1,3)**		NARDL (1,0,1,0,1,0,3)**	
Variable	Coefficient	T-Statistic [Prob]	Coefficient	T-Statistic [Prob]	Coefficient	T-Statistic [Prob]	Coefficient	T-Statistic [Prob]
D (1 YTCMR)					**0,411**	**2,285 [0,024]**		
D(LNSP500)	**1,569**	**2,594 [0,010]**					**1,454**	**2,377 [0,019]**
D(LNSP500) POS			1,254	1,259 [0,210]	**1,976**	**2,334 [0,021]**		
D(LNSP500) NEG			1,327	1,228 [0,222]				
D(LNSP500) NEG (-1)			**2,775**	**2,209 [0,029]**				
D(LNTRANSCOUNT)			**0,601**	**3,310 [0,001]**				
D(LNTRANSCOUNT) NEG	**1,520**	**4,385 [0,000]**			**1,614**	**4,545 [0,000]**	**1,658**	**4,194 [0,000]**
D (TRENDS)	**0,006**	**2,445 [0,061]**	**0,007**	**2,865 [0,005]**	**0,006**	**2,496 [0,014]**		
D(TRENDS) (-1)	**-0,005**	**-2,238 [0,027]**	**-0,004**	**-1,759 [0,081]**	**-0,005**	**-2,099 [0,038]**		
D(TRENDS) (-2)	**0,006**	**2,220 [0,028]**	**0,005**	**1,906 [0,059]**	**0,005**	**1,975 [0,050]**		
D (TRENDS) NEG							**0,008**	**1,809 [0,073]**
D(TRENDS) NEG (-1)							**-0,012**	**-2,484 [0,014]**
D(TRENDS) NEG (-2)							**0,007**	**1,688 [0,094]**
DUMMY	**0,432**	**6,4607 [0,000]**	**0,261**	**3,793 [0,000]**	**0,176**	**2,782 [0,006]**	**0,405**	**5,943 [0,000]**
ECM (CointEq (-1))	-1,03	(-11,311) [0,000]	-1,00	(-10,904) [0,000]	-1,04	(-11,495) [0,000]	-1,04	(-11,188) [0,000]

Note. NARDL model with maximum of three (3) lags. Model choice based on Akaike Information Criteria. case 1: no constant and no trend, **case 2: restricted constant and no trend, ***case 3: unrestricted constant and no trend, ****case 4: unrestricted constant and no trend; *****case 5: unrestricted constant and unrestricted trend. Source: Author's elaboration (EViews 10).

Findings suggest that the interconnectedness between crypto and equity markets has increased notably over the 2017-2021 period. Correlation between Bitcoin price volatility and S&P500 index volatility has increased more than four-fold, while bitcoins contribution to the S&P500 volatility variation was estimated to have increased by 16 percentage points post-pandemic. The patterns are similar for returns, with increased spill overs in the reverse direction from equity to crypto asset markets. Growing acceptance of crypto-related initiatives propelled investiments by retail and institutional investors, which is the main cause of significant market integration.

4.4 Asymmetry Analysis

According to Shin et al (2014) correctly specifying the nature of a long run relationship is critical to avoid drawing incorrect inferences or even making incorrect policy decisions. That is if a long run relationship exists, identified by the bounds test, we proceed to test if the difference in the asymmetric coefficients are statistically significant through the Wald Test. It is important to clarify that the NARDL model not only distinguishes between the long and short run , it admits three general forms of asymmetry: "*1) long run or reaction asymmetry, associated with $\varphi^{+} \neq \varphi^{-}$; 2) impact asymmetry, associated with the inequality of the coefficients on the contemporaneous first differences Δx_t^{+} and Δx_t^{-}; 3) adjustment asymmetry, captured by patterns of adjustment from initial equilibrium to a new equilibrium following an economic perturbation (dynamic multipliers)*" (Shin et al; 2014, p. 17).

We will limit our analysis to the first form of long run (reaction asymmetry). A test that identifies differences in positive and negative decompositions of the estimated long run coefficients:

$$H_0: \frac{-\varphi^{+}}{\rho} = \frac{-\varphi^{-}}{\rho}$$

$$H_A: \frac{-\varphi^{+}}{\rho} \neq \frac{-\varphi^{-}}{\rho}$$

The null hypothesis H_0 states that the two impacts are the same (symmetrical) and there is no long run asymmetry. The alternative hypothesis H_A, confirms the existence of long run asymmetry between coefficients. Rejecting H_0 and accepting the alternative, means that there is long run asymmetry, and the magnitude of the change in Y when X increases (decreases) is not the same as when X decreases (increases). Observing the four NARDL models estimated in the last section, BTC real returns (DLNBTC) would theoretically be asymmetrically affected by positive and negative shocks of transaction count (Model 01), and the S&P500 (Model 02) on the long run.

In Model 01, both positive and negative changes on transaction count have a long run positive impact on BTC real returns (an increase in transaction count through a positive shock will increase BTC real returns). Model 02, with positive and negative changes on S&P500 have a long run negative impact on BTC real returns (an increase in the S&P500 through a positive shock will decrease BTC real returns). Nevertheless, are the two impacts of the same magnitude (symmetric) or are they different (asymmetric)? Shin et al (2014, p. 14) states that the null hypothesis of a symmetric long run relationship can be tested using the Wald statistic that follows an asymptotic χ^2 distribution (p-value of the χ^2 statistic < 0,05 or < 0,10). Using the stepwise regression, with the unidirectional selection method (forward), and a stopping criterion at the 0.05 p-value on the long run coefficients, asymmetries were tested on these models.

Model 01 NARDL (1,0,1,0,1,3), with 3 lags and positive and negative shocks of transaction count, showed some indication of asymmetries but, coefficients weren't sufficient to perform the long run Wald Test. Examining Model 02, NARDL (1,0,1,2,1,3) with positive and negative shocks of S&P500, the long run Wald Test was performed, and the Chi-square (χ^2) statistic confirmed a long run asymmetry between the S&P500 and the BTC real returns at a 10% p-value. In sight of these results, the lag lengths on both NARDL models where increased to six (6). Stability, diagnostic, cointegration test, as well as, long run and short run results of these two models, are exposed in the Appendix.

Table 12 presents the long run asymmetry Wald Tests on NARDLs model 01 (3 and 6 lags) and model 02 (3 and 6 lags)[88]. And as observed, it is possible to reject the null hypothesis (p-value < 0.05), and accept the alternative that there is long run asymmetry between BTC real returns and transaction count, analysing Model 01 NARDL (1,0,0,5,6,3) with 6 lags. In other words, the magnitude of change in DLNBTC when transaction count decreases are bigger than when it increases[89].

[88] NARDL models 03 and 04 of Table 11 were tested for assymetries but did not show statistical significance.

[89] Model 01 NARDL (1,0,0,5,6,3) (6 lags): A 1% increase in transaction count through a positive shock, will increase BTC price rate in 0,21%, and a 1% decrease in transaction count through a negative shock will decrease BTC price rate in 0,82% (Appendix).

Table 12 - Asymmetric Wald Test Models 01 and 02 (with 3 and 6 lags). Dependent Variable: BTC real returns (DLNBTC) (August/2011 - August/2021)

	Positive and Negative Shocks	Model	Lags	Wald Test [Prob]
Model 01	LNTRANSCOUNT + LNTRANSCOUNT-	NARDL (1,0,1,0,1,3)**	3 Lags	-
Model 01	LNTRANSCOUNT + LNTRANSCOUNT-	NARDL (1,0,0,5,6,3)**	6 Lags	χ^2 (1) 18,767[0,000]
Model 02	LNSP500 +, LNSP500 -	NARDL (1,0,1,2,1,3)**	3 Lags	χ^2 (1) 3,183 [0,074]
Model 02	LNSP500 +, LNSP500 -	NARDL (1,0,1,4,6,2)**	6 Lags	χ^2 (1) 7,820 [0,005]

Note. NARDL model with maximum of three (3) lags. Model choice based on Akaike Information Criteria. case 1: no constant and no trend, **case 2: restricted constant and no trend, ***case 3: unrestricted constant and no trend, ****case 4: unrestricted constant and no trend; *****case 5: unrestricted constant and unrestricted trend. Source: author's elaboration (EViews 10).

The same rationale is applied to Model 02 NARDL (1,0,1,4,6,2) with 6 lags, in which the null hypothesis is rejected (p-value < 0.05), and the alternative is accepted, confirming that the magnitude of change in Bitcoin real returns (DLNBTC) when the S&P500 increases is not the same as when it decreases, in fact the degree of a negative impact is bigger than the degree of a positive one, confirming the nonlinear relationship[90]. These nonlinear asymmetric relationships, in which the magnitude of change in Bitcoin real return is bigger when transaction count decreases (with a decrease in BTC return) and when the S&P500 decreases (with an increase in BTC returns), demonstrates excessive price and volume changes in the BTC market, which corroborates our big player hypothesis.

90 Model 02 NARDL (1,0,1,4,6,2) (6 lags): A 1% increase in the S&P500, through a positive shock, will decrease BTC price rate in 1,43%, and a negative shock (decrease) will increase BTC price rate in 1,92% (Appendix).

5 CONCLUSIONS

Market dynamics typically show that Bitcoin is a speculative asset by nature, with a niche market: traders in this market are typically men, with higher educational attainment, mostly young and digital natives that tend to hold their investments for longer periods (*hodling*) (Auer & Tercero-Lucas, 2021). Investor's sentiment (given by Google Trends, Wikipedia, and Twitter) becomes crucial variables in understanding Bitcoin price swings, being good proxies for interest on the asset (Kristoufek, 2013; Kristoufek,2015; Li & Wang, 2017; Shen *et al.*,2019; Phillips & Gorse, 2018; Nguyen *et al.*, 2019). Information about Bitcoin *per se* is very volatile, as new information arrives; it is incorporated to prices changing traded volume.

The value that each trader attaches to Bitcoin might therefore be rooted in individual considerations, and two concurrent tendencies: the fear of buying high and selling low. However, market has changed in the last few years and investment strategy has evolved. Bitcoins supply is determined by its total stock in circulation while demand is represented by its use in exchanges. Price will generally decrease with the quantity of bitcoins in circulation (the higher the amount of cryptos flowing into the system, the lower its price level). Since production is limited, prices are likely to be bullish. Growing market recognition will further enhance price movemnts (GUIZANI; NAFITI, 2019).

The reviewed empirical literature on Bitcoin (BTC) comprises internal (Transaction Count) and external variables (Google Trends, One Year Treasury Constant Maturity Rate and the S&P500) that are important to determine its price. The ARDL estimation showed that if BTC negotiation increases and more transactions flowing through the platform, prices will go up, with rising real returns. Conditions in the real economy (1 YTCMR) and market sentiment (Google Trends) are mostly detached from bitcoins speculative market movements on the long run.

In the short run (NARDL models) there is a positive relationship between S&P500 and BTC returns. While prices are high and above trend, there is market interest that pushes prices even higher, if prices are below trend, they will go even lower. The one-year treasury constant maturity (1 YTCMR) also maintains statistical relevance (NARDL Model 03), where 1% increase, has a positive and significant impact on BTC real returns in 0,41%.

The quantity of transactions occurring inside exchanges shows relative optimism or pessimism: if agents are less willing to transact, prices will fall. Since market sentiment (Google Trends) can be elusive, it might have positive or negative effects in BTC price, reflecting

FOMO and FUD of inexperienced speculators. Kristoufek (2013) arguments that a crucial disadvantage of measuring interest using search queries such as Google Trends is the fact that it is hard to separate sentiment due positive or negative events concerning BTC. There is a difference in searching for information during a price surge and after a price fall.

Nonetheless, returns can be inversely impacted by an increasing S&P500 index in the long-term: a indication that institutions will return when there is less uncertainty regarding the valuation of their capital. In these terms, Bitcoin has the potential of becoming another asset in a wide range of established instruments. With big players on the field after a highly speculative asset, BTC logic has effectively been subsumed to financial markets (FAMA ET AL., 2019).

Through asymmetry tests, the degree of a negative impact is bigger than of a positive one, considering the S&P500 and Transaction Count, this translates bitcoins inconstant nature (through its real returns), and another way to demonstrate excessive price and volume changes in BTC pricing. Putting together analyzes made in paper 1 through wavelet coherence methodlogy with the ARDL/NARDL estimation in paper 2, it is possible to make a formal link to the presence of institutions in this growing parallel market.

PAPER 3. INSTANT PAYMENTS AND BRAZILIAN PIX: LESSONS FROM THE INDIAN EXPERIENCE IN THE 2010'S.

Resumo: Os sistemas de pagamento são um componente essencial da infraestrutura financeira e necessários para qualquer economia de mercado que dependa da liquidação diária de milhões de transações. A globalização e a internet mudaram rapidamente a forma como os agentes interagem com seus investimentos e recursos, principalmente com o uso generalizado de celulares e aplicativos. Os pagamentos instantâneos fazem parte desse ecossistema em crescimento, promovendo acesso rápido e fácil a fundos. A pandemia do COVID-19 acelerou a descontinuidade nos pagamentos em dinheiro em mercados desenvolvidos e em desenvolvimento em todo o mundo. Esse ambiente impulsionou o Banco Central do Brasil (BCB) a assumir a implantação do Sistema de Pagamentos Instantâneos (SPI) e do Pix. Por meio dos Modelos Autoregressivos de Defasagens Distribuídas (ARDL) e dos Modelos Autoregressivos de Defasagens Distribuídas Não Lineares (NARDL, este artigo tem como objetivo tirar lições para o Pix brasileiro da recente experiência indiana com a Unified Payments Interface (UPI), considerando a correlação e as características do sistema de pagamento. A infraestrutura de pagamentos rápidos se desenvolveram onde há dois fatores importantes alinhados: opções limitadas de alternativas de pagamento e alta penetração de telefones celulares. Os resultados empíricos trazem para o centro do debate a importância da inovação financeira, da adoção do mobile banking e da internet para o desenvolvimento econômico. No curto prazo, o uso de pagamentos instantâneos aumenta exponencialmente durante a adoção. As transações via aplicativos de mobile banking e base de assinatura wireless (MB/WLESS) tiveram influência direta nos fluxos de UPI. Os substitutos para pagamentos instantâneos, como cartões de crédito e débito, têm caráter complementar a esses instrumentos, no longo prazo, pois aumentam o fluxo monetário na economia. O grau de sofisticação do sistema financeiro (M1/PIB) tem efeitos de curto e longo prazo. Além disso, confirmou-se a hipótese de que há efeitos não lineares. Choques assimétricos negativos especificamente de curto prazo nas transações com cartão de crédito e aprofundamento financeiro (M1/PIB) produziram maiores impactos nos sistemas de pagamentos instantâneos.

Abstract: Payment systems are an essential component of the financial infrastructure, and necessary for any market economy that depends on the daily settlement of millions of transactions. Globalization and the internet have changed rapidly the way agents interact with their investments and resources, especially with the widespread use of mobile phones and apps. Instant payments are part of this growing ecosystem, promoting quick and easy access to funds. The COVID-19 pandemic accelerated discontinuity in cash payments in developed and developing markets all over the world. This environment propelled the Brazilian Central Bank (BCB) to take on the implementation of the Instant Payment System (SPI) and Pix. Through Autoregressive Distributed Lag Models (ARDL) and the Nonlinear Autoregressive Distributed Lag Models (NARDL) this paper aims to draw lessons for the Brazilian Pix from the recent Indian experience with Unified Payments Interface (UPI), considering correlation and payment system characteristics. Fast payments have developed rapidly where there are two important factors aligned: limited options of payment alternatives, and high penetration of mobile phones. Empirical results bring to the centre of the debate the importance of financial innovation, the adoption of mobile banking and the internet for economic development. In the short run, instant payments usage increase exponentially during adoption. Transactions via mobile banking applications and wireless subscription base (MB/WLESS) had a direct influence on UPI flows.

Substitutes for instant payments, such as credit and debit cards, have a complementary character to these instruments. The degree of sophistication of the financial system (M1/GDP) has short-term and long-term effects on instant payments. Furthermore, the hypothesis that there are non-linear effects was confirmed. Specifically short-term negative asymmetric shocks of credit card transactions and financial deepening (M1/GDP) produced greater impacts on instant payment systems.

1. INTRODUCTION

Buying and selling have never been easier. Using social media accounts agents perform transactions in a global market where retailers and entrepreneurs, present their products in a platform directed to niche customers. There is presently a corresponding drive towards immediate payments, real-time gross settlement systems and automated clearinghouses within countries, across regions that are bundling clearing and transaction settlement. Customized financial solutions in payments, loans and investments are possible using customer data through application programming interface (API). A stream of innovations that lead to new emerging technologies, unseen and unimplemented capabilities that propel service transformation, higher functionality and new revenue strategies (Gomber et al., 2017). It is known that financial deepening goes hand in hand with economic development, in which fast payments can easily be put in this category.

Decentralized finance, digital assets and the COVID-19 pandemic accelerated discontinuity in cash payments in developed and developing markets all over the world. This environment has required more assertive strategic actions by policymakers, propelling the Brazilian Central Bank (BCB) to take on the implementation of the Instant Payment System (SPI). Being the biggest economy in Latin America and in comparison to its counterparts in other areas of the world, Brazil needed to enhance payments technology. Pix was made public in November 2020, with a promise in reducing cash transactions, providing the informal economy with financial inclusion through internet infrastructure. Paper motivation is directed to fast payment mechanisms and testing hypotheses towards their underlying explanatory variables. On a macro-level, financial sophistication, economic growth, payment substitutes, and a measure of the relative popularity of banking apps are used to better understand these dynamics.

The Indian Unified Payments Interface (UPI) implemented in 2016, was identified and used as a broader study case for the Brazilian Pix. Using time-series methodology, specifically Autoregressive Distributed Lag Models (ARDL) and Nonlinear Autoregressive Distributed Lag Models with an Indian dataset (April 2016 to November 2020) important inferences are made. Empirical studies on payment systems are typically country-specific, which makes a comparison difficult. But, due to statistic correlation, territory dimensions and both being BRICS countries, some important parallels can be made between Brazil and India, towards impacts on instant payments.

This article directly contributes to the growing literature in payment innovations. A novel analysis, in which few studies are presented from a macro perspective. A time series empirical application, that emphasizes short, long run and asymmetries towards practical policy lessons for both countries. Preliminary results show that financial sophistication has important effects on instant payment mechanisms (and vice-versa). Other payment options such as credit and debit cards, will have a complementary nature and mobile banking volume will enhance fast deployments. Through mobile banking transactions and telephone wireless subscription base, there is a measure of relative popularity of banking apps, a case for policies towards a nationwide internet telecommunication infrastructure.

This study is divided into four main parts, including this introduction. In the next section, the Brazilian Payment Systems will be defined and briefly debated, encompassing the Instant Payment System (SPI) and Pix. Unified Payment Interface (UPI) the Indian study case is analysed in the following item making important inferences to substantiate our econometric approach. The last section starts with an empirical review on payment systems and dataset. Since we are applying two complementary empirical methodologies (ARDL and NARDL), they are first briefly presented to then introduce long, short-run and nonlinear estimation results. Finishing the article with main conclusions.

2. INSTANT PAYMENTS, CENTRAL BANKS AND PIX

According to the Bank for International Settlements (BIS), "*a payment system is a set of instruments, procedures, and rules for the transfer of funds between or among participants and the entity operating the arrangement*" (BIS; IOSCO, 2012, p.8). Brazilian law (Lei nº 10.214 de 27 de Março de 2001, Art. 2º)[91] defines the Payment System (SPB) as: *"entities, systems, and procedures related to the transfer of funds and other financial assets, or the processing, clearing, and settlement of payments in any form"*. The Brazilian Association of Financial and Capital Market Entities (ANBIMA) has a broader definition stating that the Brazilian Payment System (SPB) is a "*set of entities, systems, and mechanisms related to the processing and settlement of funds, transactions with foreign currency or with financial assets and securities* (ANBIMA, 2020, p.24).

[91] Provisional Measure nº 2.115-16, of February 23rd, 2001, which was converted into Law nº 10.214 of 2001.

Payment Systems are based on an agreed-upon operational infrastructure, with participants and the operator of the arrangement (Bech; Hancock, 2020). They are usually divided into **large-value payment systems (LVPS)** which handle high-priority payments; and **small value payment systems (SVPS)** that deals with a large volume of low-value payments like cheques, credit transfers, direct debits, card-based systems, internet banking, at a low cost reliably and securely. **Retail payments** are typically between end customers such as households and firms (person-to-person, person-to-business, business-to-business), with many forms of payment instruments, run by both private and public sector providers (BRITO, 2002; PINTO, 2004; KAHN; ROBERDS, 2009; CARVALHO, 2011; BIS; IOSCO, 2012; BECH ET AL., 2017; LUBIS ET AL., 2019, BECH; HANCOCK, 2020).

The *front end* is where these payments usually initiate (like a bank account) including the channel used to process the payment (a mobile application) and the payment instrument (credit transfer). *Back-end* arrangements comprise clearing and settlement of payment instruments. Settlement can be done one at a time and in real-time, *Real-time Gross Settlement Systems* (RTGS), provided that the payer's service provider has enough funds. Otherwise, the payment is rejected or queued. The alternative is the *Deferred Net Settlement* (DNS) a clearing system that operates on a net basis, where settlement take place after a specified period. There are also hybrid systems that combine characteristics of RTGS and DNS (BECH; HANCOCK, 2020).

In an environment where consumers are progressively used to instant communication, payments have evolved to offer the same experience in commercial transactions. Fast payments[92] can be defined by two key features: speed and continuous service availability. According to the BIS report: "*fast payment" is defined as a payment in which message transmission and availability of "final" funds to the payee occur in real-time or near-real-time as near as a 24-hour and seven-day (24/7) basis as possible"* (BIS; 2016, p.6). Final funds are received such that the payee has unconditional and irrevocable access to them, providing strong certainty of payment to the payee (BIS, 2016)[93].

Traditional payment messages are not cleared or settled until the subsequent business day. Payment orders are collected in batches, which introduces delays. On top of that, these

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[92] The terms used for fast payments may vary, although the underlying meaning could still be the same. Other common terms are "instant", "immediate", "real-time" or "faster payments" (BIS, 2016).

[93] An interesting point made by Giraldo-Mora *et al.* (2020) is that a real-time payment only needs to provide the perception of an instant payment, in the foreground, with no regard to the actual process in the background. Considering these technical and organizational conceptualizations of real-time, the authors define instant payments a little differently: *as a traceable and predictable payment instrument in which funds are made available to end consumers just in time for the payment context* (GIRALDO-MORA et al, 2020, p.3).

procedures are often limited to certain days or business hours. So, the payee typically does not receive funds until inter-PSP settlement occurs, which could be a day or more after payment initiation (BIS, 2016).

Immediate payment system implementation requires interaction and collective decision-making. Therefore, a common challenge in many countries is to overcome potential conflicting issues between different stakeholders, Bech et al (2017). Benefits to consumers from new payment methods often depend on seamlessly coordinating across large networks needed for fast payment system success, requiring either a large degree of control by one firm or a great deal of cooperation among rivals[94].

The involvement of authorities is one of the seven key drivers identified by Hartmann *et al.* (2019) in implementing instant payments infrastructure[95]. Although external factors may influence supply-side actors (private payment providers) to offer instant payment services, customers demand to use such services (adoption decisions by the end-user) and strong network effects (number of initial users, coverage, reach) are fundamental to promote a new payment technology[96].

How features and pricing of fast payments compare with alternative methods (such as cash, credit, debit cards, cheques, traditional credit transfers) will also indicate different use cases, as clients start placing value on speed, convenience and service availability. Costumer demographic characteristics (age, education, income, payment habits), acceptance by merchants, internet, mobile device accessibility are also important to factor in while analysing diffusion of novel instruments.

Creation of complementary innovations, including mobile payment services, vastly broaden the potential of instant payments, since it imports the benefits of traditional banking instruments to compete in retail payments. Context-specific instruments enables more granular services, however, structuring and sharing of data promote their integration, which largely depends on sector-wide cooperation. PSPs may need to incur not only in individual costs to update their internal systems but investments that will establish data consistent inter-PSP systems to provide fast payments (BIS, 2016; GIRALDO MORA ET AL, 2020)

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[94] BERGER, A *et al*. A framework for analysing efficiency, risks, costs, and innovations in the payments system. Journal of Money, Credit and Banking**,** v. 28, n. 4, p. 696-732, 1996.

[95] The seven key drivers are: 1) Involvement of authorities in instant payments; 2) Structure of the market for payment services; 3) End user access to telecommunications and payment infrastructures; 4) consumer's characteristics; 5) payment preferences and habits; 6) transfer speed; 7) fee levels (Hartmann *et al.,* 2019).

[96] To achieve high coverage of potential users depends on numerous factors such as: 1) the decision of individual PSPs regarding the participation in one or more fast payment systems or schemes; 2) the access criteria imposed on PSPs by a fast payment system; 3) the percentage of the population that have payment accounts at PSPs and that choose to adopt the service; and 4) ease with which different system interoperate (BIS; 2016, p. 11).

Each potential provider will likely consider its private expected return based on its perception of costs, benefits and investment in a cooperative effort. Individual PSPs in a particular market may also try to set their system as the standard, leading to a diversity of incompatible networks and, to a lower outcome from the end-user perspective. Development of payment innovations that require investment in shared payment infrastructure, at the level of the individual firm, tends to be slow and socially suboptimal (BIS, 2016; HARTMANN ET AL; 2019).

Thus, featuring network externalities, with decision-making complexities and viewed as a public good, it may be a long time before a new payment technology is adopted in the absence of a strong external incentive. Central banks play an important role not only in ensuring cooperation between the different actors, establishing common standards, but sometimes taking on an operational role, fostering greater efficiency and system resilience (BECH ET AL, 2017).

Central Bank motivations are quite different from profit considerations driving the private sector (Blix et al, 2003; Bech, Hobijn, 2006). Using their influence, knowledge, analytical capabilities with authorities and industry stakeholders, central banks contribute by adopting a long-term perspective with positive externalities. A consistent strategy to promote an efficient outcome about these deployments in accordance with its mandate[97].

The Brazilian Central Bank (BCB) has actively taken a catalyst, oversight, and operational role, with a high degree of involvement in Pix's development, considered as a strategic public policy objective. Broad coverage, interoperable systems, network effects, and potential long-term positive externalities that are difficult to measure presently, are very strong arguments to understand why the Brazilian Central Bank (BCB) engaged in such enterprise. Conveying user-centric modernization of Brazilian retail payments, other arguments favouring Pix's implementation will be discussed alongside its technical attributes.

Market sophistication, the expansion of trade involving multiple currencies, financial segments with instant communication have significantly impacted payment systems[98] through

[97] In general terms, three approaches can be identified, pertaining instant payment implementations and the central bank's catalyst role: 1) Low degree of involvement: central banks that have not actively promoted fast payments in their catalyst role for change; 2) Moderate degree of involvement: while not pursuing a specific strategic policy to develop a fast payment system; central banks have a mandate to secure and facilitate the operation of these systems, with an open dialogue to market participants, providing resources and guidance when necessary; 3) High degree involvement: some central banks consider the implementation of fast payments as a strategic policy objective in the field of retail payments, to modernize a country's payment infrastructure: to bring it on par with that of other economies, contribute to payment innovations, improve the general speed of payments, facilitate financial inclusion and faster remittances (BIS, 2016, p.58).

[98] Progressive liberalization and innovation in financial instruments, also increases risks in payment systems due to 1) instant communication and capital volatility, 2) interconnection of the international financial system and 3) new financing agents, which are beyond the control of central banks (BIASSOTO, BRESSADA; 2004, p.7).

financial globalization and the rise of the internet in the 1990s. Bearing in mind the institutional mission of the Brazilian Central Bank (BCB) to maintain the economy's financial soundness, continuous improvement of the payment system, and the currency's purchasing power, in June 1999 the board of the Brazilian Central Bank approved the restructuring of the Brazilian Payment System (SPB). Changes established by the BCB between 1999/ 2002, were so intense that market agents (including the central bank itself) called it the "New Brazilian Payment System" declaring implicitly a rupture between the old and the new (BRITO, 2002; PINTO, 2004; FIGUEIREDO & ARTES; 2008; CARVALHO, 2011).

Technological progress and reform were aimed at increasing the speed of processing transactions, redirecting the focus to risk management: implementing a large-value transfer system with Real-Time Gross Settlement (RTGS) the "*Brazilian Central Bank will exclusively operate through real-time gross settlement systems*" (Resolution nº 2.882 of August 30, 2001, Art. 9º); with changes in the operational regime of reserve accounts. The main features of the new SPB were the feasibility of interbank settlements and real-time control of reserves. This was achieved through the implementation of the so-called *Reserve Transfer System* (STR)[99] that went into operation on April 22, 2002, established by circular nº 3.100/2002[100].

With a rise in the use of direct debits, credit, debit cards and a decrease in checks (for large sums) the new system changed payment instrument profile, imposing a clear tendency to a strong expansion of electronic payment mechanisms (TRICHES & BERTOLDI, 2006).

The Brazilian Payment System (SPB) is currently characterized by a solid and comprehensive legal groundwork, with mandatory use of central counterparties for the settlement of obligations, with certainty as well as irrevocability based on risk management mechanisms. Related activities within the scope of the National Financial System (SFN) and the Brazilian Payment System (SPB) have been followed by the BCB, in a coordinated and multidisciplinary manner[101]. Technological evolution is central to the agenda in developing structural issues such as inclusion and competition.

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[99] There are three types of accounts in the Reserve Transfer System (STR): 1) Reserve accounts, mandatory to commercial banks, multiple banks with a commercial portfolio, savings banks, and investment banks; 2) settlement accounts, mandatory to chambers that operate clearing and settlement systems considered systemically important; and 3) the National Treasury account (PINTO, 2004, p.25).

[100] Direct access to the STR is made through the National Financial System Network (RSFN), a private network that supports the traffic of messages between participants. As of April 22, 2010, access to STR was made through an application developed by the Central Bank, called STR - Web (BRITO, 2002; PINTO, 2004; CARVALHO, 2011).

[101] Through its Agenda BC#, the BCB, comprises guidelines and dimensions to be pursued by its policies. The agenda is structured in four main dimensions*: Inclusion, Competitiveness, Transparency* and *Education*. Each of these dimensions is developed through thematic groups (BCB, 2020a).

According to the Brazilian Central Bank (BCB; 2020a, 2021) the Instant Payment System (SPI), is a centralized infrastructure for the settlement of fast payments between different institutions. A unique architecture for Real-Time Gross Settlement (RTGS) via messaging on the Brazilian Central Bank reserve transfer system (STR). Payments are cleared through specific purpose accounts that direct participants in the system maintain with the BCB, called Instant Payment Accounts (CPI). Overdraft is not allowed (BCB, 2020).

The instant payment ecosystem will be formed by: 1) an open arrangement instituted by the BCB (Pix); 2) payment service providers participating in the arrangement (financial and payment institutions); 3) a single platform that will settle transactions (SPI) and 4) the *Directory of Transactional Account Identifiers* (DICT)[102], whose responsibility is to store keys used to identify accounts.

Both the Instant Payment System (SPI) and the DICT will be developed, operated, managed by the BCB and will function 24 hours a day, seven days a week, every day of the year. Transactions will occur in the National Financial System Network (RSFN), the data communication infrastructure that aims to support traffic information within the scope of the National Financial System (SFN), for services authorized by the Brazilian Central Bank, provided in the circular 3.970, of November 28th, 2019[103].

To participate in the SPI, the provider must be: 1) Transactional account provider; 2) Payment initiation service provider; 3) Indirect participant; 4) Direct participant; 5) Governmental entity; 6) Special liquidator[104]. Commercial banks, multiple banks with a commercial portfolio and savings banks must be direct participants, settling transactions in the

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[102] Pix keys are stored in the DICT, and in the process of initiating a Pix, identification of the user's transactional account must be done by consulting the DICT, when dealing with transactions between end users with different participants. But, if the transaction occurs between transactional accounts in the same participant, it is up to the participant, and consulting his internal dataset to identify the receiver.

[103] Its main objective is to support data traffic directly related to critical services, it is able to support traffic of another nature, as long as there is no harm to its main objective (BCB, 2020).

[104] Definitions: 1. Transactional account provider: a financial institution or payment institution that offers a transactional account (deposit account, savings deposit or a prepaid account) to the end user. 2. Payment initiation service provider: institution that will initiate payment at the request of a customer holding a transactional account but doesn't participate in the financial settlement. This form of participation is subject to specific regulations.3. Indirect participant: institution that offers a transactional account to an end user, but that does not own a PI account at the BCB, nor does it have a direct connection with the SPI. Uses the services of a settler in the SPI for the purpose of settling instant payments.4. Direct participant: an institution authorized to operate by the Central Bank that offers a transactional account to an end user and who, for the purposes of settling instant payments, holds a PI account.5. Governmental entity: National Treasury, with the sole purpose of making payments and receiving payments related to its typical activities; 6. Special liquidator: a financial or payment institution authorized to operate by the Central Bank of Brazil whose purpose is to provide settlement services to other participants and that observes the requirements to act as a liquidating participant in the SPI. But it does not meet Pix's requirement for participation and does not send or receive a Pix to its end users (BCB, 2020).

SPI and accessing the DICT directly. Payment institutions without authorization to operate (that are Pix providers) are necessarily indirect participants in the SPI.

Major banks, financial, payment institutions authorized to operate by the BCB, with more than 500 thousand active client accounts (deposit, savings and prepaid payment accounts) had mandatory participation, therefore network effects were guaranteed by the Central Bank (BCB Resolution No. 1, of August 12, 2020).

Pix went into restricted operation (test mode) on November 3rd, 2020, and in full operation on November 16th, 2020. It enables only "push" transactions, with payment orders and fund availability in real-time. Requiring previous registration, the payer will use his keys to link his accounts through the bank's API. Payers can initiate payments in different ways (Article 12, BCB Resolution No. 1): a) using keys or nicknames to identify the transactional account, such as a cell phone number, individual registration number (CPF), legal entity registration number (CNPJ), an e-mail address or a random key created through the banking app; b) through QR Code (static or dynamic)[105,106]. Each recipient will freely choose the type of instant payment initiation he will accept. If none of the options available is acceptable, informing complete data account users can proceed with settlement manually (BCB, 2020).

Correctly identifying the receiver through the DICT, the payer sends an instruction that will eventually reach the payment service provider and the direct participant in the Instant Payment System (SPI). The message will pass through the addressing dataset and the unique Real-Time Gross Settlement infrastructure. The SPI direct participant is warned that his client will receive a credit in his account, after information verification, settling the transaction.

Fast payments can be offered at the discretion of each institution through internet banking, bank branches, correspondents and ATMs. It started with no minimum or maximum value limit for transfers, but due to safety issues in October 2021, the BCB limited evening transfers to R$1000,00 (between eight p.m. to six a.m). Pix participants will be able to set maximum value limits, per paying user, per transaction, by day or by month, based on criteria and regulations to mitigate fraud, money laundering and preventing terrorism.

The Brazilian Central Bank has the two most important roles in Pix: it operates the system and it sets the rulebook (Figure 1). It fully developed the infrastructure, the Real-Time

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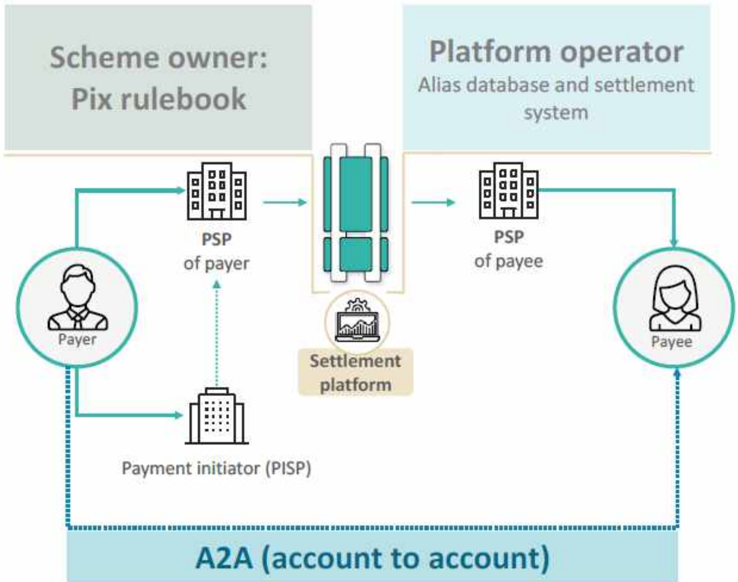
[105] The dynamic QR Code is generated exclusively for each transaction, it allows the insertion of information such as recipient identification, facilitating reconciliation and commercial automation. The static QR Code is used in multiple transactions as it allows the definition of a fixed price, or the entry of an amount defined by the payer. In this sense, it is ideal for small retailers, service providers and individuals (BCB, 2020).

[106] BR Code is the QR Code standard that should be used by payment arrangements that are part of the Brazilian Payment System (SBP) that offer transaction initiation through this mechanism, as provided in circular nº 3.989/2020.

Gross Settlement system (RTGS) and the database that underlies the platform. As the rulebook manager it sets specifications and procedures to which the payment service providers (PsP) should operate. Enforce rules that maintain the platform, such as costs, data use and technical standards. Open APIs (application programming interfaces) are a key part of this system, securely transmitting only the data needed for a particular transaction.

Figure 8 - Pix Ecosystem



Source: Duarte *et al*. (2022, p.3)

With more than 60 million keys registered, in the first week of November 2020, 700 institutions authorized by the Central Bank to offer Pix, it entered the payment market to spearhead the digital revolution in the National Financial System (SFN), propelling inter-bank payments instantly. Designed primarily at improving the experience of payers and payees, the goal was to build a solution that would be easy and quick as making a cash payment, while also making use of the backend architecture (RTGS) already built with the reestablishment of the Brazilian Payment System in the 2000s.

Numerous instant payments use cases around the world could be a parameter to the Brazilian Pix, like CODI in Mexico[107]. Being a BRIC member, the Indian Unified Payment Interface (UPI) was chosen as a study case. Possible asymmetries, with short and long run implications, could eventually substantiate important public policy for the Brazilian payment

[107] ALFONSO, Viviana C. *et al.* Retail payments in Latin America and the Caribbean: present and future. **BIS Quarterly Review**, 2020.

market, briefly presenting the context and technical characteristics of the Unified Payment Interface (UPI) in the next section.

3. THE INDIAN PAYMENT SYSTEMS AND UNIFIED PAYMENT INTERFACE (UPI)

As in March 2016, total currency circulation in India was Rs.16,415 billion which constituted about 12.04% of the GDP. Compared to Brazil (3.93%), there was a clear dependence on cash, on behalf of the Indian population. The 2016-2017 period was a pivotal moment for the payments ecosystem in India[108] where new systems and rapid changes in user behaviour were propelled by Demonetization[109]. Playing an important part in this transition was the National Payment Corporation of India (NPCI) a non-profit owned by the Reserve Bank of India (RBI) and 56 commercial banks. In operation with UPI since 2016, the RBI, intending to bring payment efficiencies to low-value transactions driving the next generation of digital payments (D'Silva *et al.,* 2019), created it as an umbrella organization.

Formally inaugurated by the RBI Governor and launched for public use in August 2016, UPI[110] is an Indian network for real-time payments. An around-the-clock platform that offers a set of Application Programming Interface (API) specifications to facilitate online payments. The objective of NPCI was to create a uniform and affordable payment system, consolidating, integrating disparate systems with varying service levels, into a nationwide platform.

Built over the Immediate Payment Service (IMPS) infrastructure, UPI is used as a switching mechanism to enable digital instant payments between financial institutions. A single mobile application that powers multiple accounts, working as a common layer that orchestrates transactions and settlement across participating banks. Using the existing systems to ensure payment reliability across various channels, it takes advantage of infrastructure investments made so far.

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[108] Through the Pradhan Mantri Jan Dhan Yojana financial inclusion program of the Government of India, allowed simple no-frills bank accounts, to individuals if they could supply their identity details. Up to July 2016 226 million accounts and 183 million cards were provided. By December 2019, almost 380 million bank accounts had been opened under PMJDY (THOMAS; CHATTERJEE, 2017; D'SILVA ET AL, 2019).

[109] Where 86% of the currency notes were worthless overnight.

[110] Abraham (2020) and D'Silva et al (2019), emphasize that UPI was not created in a vacuum and is often referred to as the "cashless layer" of India Stack. India Stack is the shared brand for a suite of applications and their accompanying platforms,that constitute the technological ecosystem around Aadhaar, India's centralised biometric identification system. The link created between the national digital identity system and the national payment system was aimed at creating network effects. They create a powerful "stack" of applications and innovative digital platforms.

With full interoperability, this unified layer offers peer-to-peer immediate payment, an interface designed for account holders to transfer funds, without entering any compelling information, through smartphones with a single identifier (payment identity) which can be either an Aadhaar[111] number, mobile number, a virtual payment address (VPA) or a UPI ID (NPCI, 2015; GOCHHWAL, 2017; NPCI, 2021; RBI,2021).

There are three following key players in the UPI ecosystem:

> *"(...) 1) The payment service providers (PSPs) who provide the interface for the payer and the payee (...) interoperability will ensure that, unlike wallets, the payer and payee can use two different PSPs; 2) Banks that provide the underlying accounts for the payer and payee. In some cases, the bank and the payment service provider will be the same; and 3) the NPCI which will act as the central switch to determine the virtual payments address (VPA) rendering credit and debit transactions through the IMPS platform, settling funds across banks (THOMAS; CHATTERJEE, 2017, p. 193).*

Downloading any UPI app, an encrypted SMS will be sent from the user's smartphone to check the authenticity of the number registered with his bank, binding the device with the mobile number. A unique Virtual Payments Adress (VPA) is created by the user, which can now register its accounts on the app. The issuing institution authenticates the number providing a list of all bank accounts filed against that mobile number. Account details like: username, bank name, account number and IFSC code are stored in the PSP. By entering the last 6 digits of the customer's debit card, the client's bank will be registered with the UPI application (GOCHHWAL, 2017; KAKADE; VESHNE, 2017).

The virtual ID can be shared with a third party to receive payments and customers can use any PSP app he desires to start doing transactions safely. Clients can pay (push payment) and collect (pull payment). To "pull" or collect money the beneficiary enters the virtual address of the payer. The payer gets a notification on his mobile and decides to accept or decline. If he accepts the payment, the payer enters his MPIN (which is encrypted using NPCI public key) to authorize the transaction. If the customer wishes to pay, he undertakes the "push" option (sending money) entering the virtual address of the payee, authorizing the payment with an M-PIN (NPCI, 2016; GOCHHWAL, 2017; THOMAS; CHATTERJEE, 2017).

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[111] India is the only country which was able to register more than one billion (88.6% of its population) on its identification dataset, Aadhaar. The aadhaar system is purely focused on identity, as it collects minimal data or just enough to provide unique identity (name, date of birth, gender, and residential address). Aadhaar was predominantly used for transferring government benefits through the Pradhan Mantri Jan Dhan Yojana (PMJDY) initiative (NPCI, 2015; THOMAS; CHATTERJEE, 2017, D'SILVA, 2019).

Due to UPI's *sui generis* characteristics[112] taking full advantage of mapping payment flow, it has witnessed rapid growth in the last five years. Graph 10 shows the volume of UPI transactions from April 2016 to May 2021. A clear polynomial trend line indicates overall growth. The abrupt decrease in transactions in the first quarter of 2020 reflected the global pandemic. The initiative gained traction as social distancing became a public health issue. Presently 316 banks are operating with UPI (as more banks and financial institutions operate with it, bigger the network effects). In May 2021 the volume flow was roughly 2,539.57 million transactions (NPCI, 2021).

Treating digital payments as a "public good"[113] and an important "infrastructure", design of the Indian Payment System challenges the business case for stand-alone private systems, establishing that central banks can be proactive and partners with the private sector counterparts when it comes to fostering technological innovation in the financial sphere. The same argument could be made to Brazil's Pix. While it is still in its infancy, potential market failure could be a valid reason for why NPCI, and the Brazilian Central Bank (BCB), played an important oversight and operational role in the implementation of these payment rails, sustaining the importance of governmental participation wherever private firms find insufficient market opportunity (ABRAHAM, 2020).

Even though UPI has a negligible value in comparison to other electronic payments, it has changed the landscape for small-scale retail payments in India. With an enormous growth of smartphone users and internet penetration in rural areas, there is increasing potential for acceptance among the Indian population. UPI leverages high teledensity in India to make mobile phones a primary device for consumers and merchants. It cost-effectively facilitates payments without any POS (point of sale) machines and intermediaries like card networks, allowing immediate settlement (GOCHHWAL, 2017).

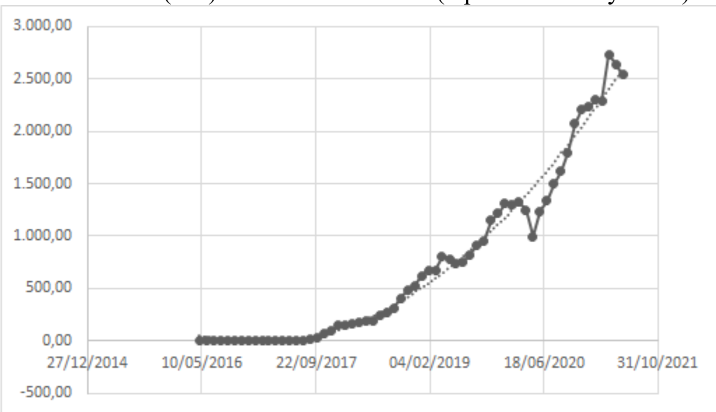
Where payment provision is limited and mobile phone penetration is high, fast payments have developed more rapidly, overcoming barriers to financial inclusion boosting access to the

[112] The key aspects of the Unified Payments Interface are: a) permits payments via mobile app, web; b) payments can be both sender and receiver initiated; c) payments are carried out in a secure manner, aligned with RBI guidelines; d) payments can be done using Aadhaar Number, Virtual Address, Account Number & Indian Financial System Code (IFSC), Mobile Number and MMID (Mobile Money Identifier); e) the payment uses 1-click, 2-factor authentication, biometric authentication and the use of the payer's smartphone for secure credential capture (NPCI, 2016).

[113] *India's approach is built upon four pillars: (i) providing digital financial infrastructure as a public good; (ii) encouraging private innovation by providing open access to this infrastructure; (iii) creating a level playing field through the regulatory framework; and (iv) empowering individuals through a data-sharing framework that requires their consent. India offers important lessons that are equally relevant for both advanced economies and emerging market and developing economies (D'SILVA ET AL, 2019, p.1).*

banking system. Real-time services magnify scalability meaning that they can be applied to hundreds of millions of customers, increasing payment volumes, bringing efficiencies to retail and small-scale transactions, providing cheap payment services to ordinary citizens (D'SILVA ET AL, 2019).

Graph 10 - Volume in million (Mn) of UPI transactions (April/2016-May/2021) – (Indian Dataset)



Source: National Payments Corporation of India (NPCI): https://www.npci.org.in/. Author's elaboration.

Looking at the bigger picture around faster payments, for countries that are in development like Brazil and India, problems like digital literacy, internet infrastructure, access to bank accounts, a mobile number and a smartphone are still questionable. Especially considering economic inequality coupled with rural poor telecommunication coverage.

However, the progressive dematerialization of currency and the financial dimension of digital sovereignty have become a priority for many countries. To better understand this phenomenon, through an economic perspective UPI was chosen as a study case due to specific characteristics: as a member of BRICS, demographic, territory dimensions, instant mobile transfer, 24/7 money transfer, four-year data availability and statistic correlation. Aware of local cultural specificities and the differences between systems, UPI can bring some light to what we can expect aggregately for the Brazilian instant payment system. An empirical review will be done in the following topic, paving our way to the chosen methodology, dataset and model specifications.

4. EMPIRICAL REVIEW ON PAYMENT SYSTEMS AND DATASET

Empirical literature examining the role of electronic payment systems and their dynamics is quite sparse (Bech; Hobijin, 2006; Rooj; Sengupta, 2020). Only picking up speed in the last few years with the increasing importance of these innovations, changing the research focus from traditional money demand theories to modern empirical analyses (REDDY; KUMARASAMY, 2017).

Following a heterodox approach, Raj *et al.* (2020) develops a menu of models through ARIMA, ARCH, ARDL estimations, to find that currency circulation in India has been moderated over the last decade, reflecting innovations in digital payment technology (debit and credit cards). Chaudhari *et al.* (2019); Reddy & Kumarasamy (2017)[114] reached the same conclusion, in which digital volume transactions through payment technology innovations will have a statistically significant inverse relation with India's currency demand on the long run.

Incorporating both the role of inside money and the role of outside money Lubis *et al* (2019) explores the relationship between efficiency of payment system services and financial intermediation. Generalized method of moments (GMM) and vector correction model (VECM) were applied to a data set collected from Indonesia, only to conclude that financial intermediation is inversely affected by currency in circulation. Card-based payment systems have a statistically significant impact (through long run effects with debit cards and short run effects with credit cards) on the reduction of money demand.

Yilmazkuday (2011) investigated the credit channel of the monetary transmission mechanism through credit card usage, in a small economy (Turkey). Through a reduced-form vector autoregression VAR framework[115] both the credit view (through credit cards) and the monetary view (through short-term interest rates) seem to be important during high inflationary episodes for the real side of the economy. Specifically, credit cards have been positively and significantly affected mostly through shocks of output and lagged credit card usage, suggesting its role as a consumption-smoothing tool.

In addition to monetary policy, economic growth is crucial while analysing electronic payments. The Reserve Bank of India report (RBI, 2020a) published a study supporting a statistically significant unidirectional Granger causal relationship from the growth of nominal GDP and private final consumption expenditure to the growth of digital retail transaction value. Using an autoregressive distributed lag model (ARDL) as an additional framework, a long run relationship between digital retail transactions and private final consumption was revealed.

Rooj & Sengupta (2020), through a multivariate bayesian autoregressive vector model (BVAR) uncovered that high-value online transactions and economic growth are closely

[114] While credit cards decrease currency demand due to fewer cash transactions, debit cards increase money requirements increasing its marginal utility (REDDY; KUMURASAMY, 2017).

[115] Sample period (2002-2009).

interlinked, indicating a presence of bidirectional causality between Real-Time Gross Settlement Systems (RTGS) and economic expansion in India. Lee & Yip (2008) argue that the RTGS system is a good performance indicator for the economy: high turnover of the RTGS system is usually associated with a growing economy. Gross Domestic Product (GDP) and employment can boost the transacted volume (with a positive sign), increasing proportionally is the quantity of money publicly held (M1) (M1/GDP)[116].

The Indian Central Bank (RBI) uses currency over GDP (CIC/GDP) as a measure of currency in circulation. However, Gala, Araújo, and Bresser-Pereira (2010) as a measure of the degree of financialization of an economy uses M1/GDP[117], based on Edwards (1995). It is relevant to notice that, statistical correlation between M1/GDP India and M1/GDP for Brazil is above 50% (0.56) between 2010 (Q2) and 2021 (Q3), making it a good proxy for the Brazilian economy[118].

Credit (NT1) and debit cards (NT2) are included as the closest substitute for fast payments, whereas a negative and opposite sign can be expected between them. To enhance econometric procedures, total volume of transactions via mobile banking was divided by telephone wireless subscription base in millions (counting urban and rural telephone subscribers)[119], creating a ratio that describes popularity of banking apps (MB/WLESS). Access to new communication rails, like an increase in mobile phone usage and wireless subscription is expected to directly influence instant payment flows.

Monthly data was collected (April 2016 to November 2020) with 56 observations. To not only capture effects on payment volumes and telecommunications infrastructure, but also technological innovations and currency demand, these factors can be better explained when indicators are taken in volume rather than in value terms (CHAUDHARI ET AL, 2020).

Volume of transactions via UPI was retrieved from the National Payments Corporation

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[116] To calculate a proxy for monthly GDP, the strategy was to find the ratio of annual imports (the sum of monthly imports) to India's annual GDP. With the annual percentage, the share of imports to GDP is calculated:

$$Mont\ hlyGDP = \frac{Mont\ hlyImports}{PercentageofImportsbyGDP\,(referenceyear)}$$

[117] An underlying assumption is that there may be endogeneity in relation to M1/GDP (explanatory variable) to the volume of transactions carried out by UPI (dependent variable). To better understand the nature of these variables, a Granger causality test was performed using Eviews 10. Considering six lags and p-value inferior to 0.05. It clearly appoints to a bidirectional movement: UPI Granger causes M1/GDP, and M1/GDP Granger causes UPI. This estimate provides some substance to the notion that UPI does in fact impact the degree of financialization of the Indian economy.

[118] Quarterly data on M1 and Real Gross Domestic Product (GDP) for Brazil and India was taken from the Federal Reserve Bank of Saint Louis (FRED). Correlations were estimated with Eviews 10.

[119] Since mobile banking is considered to be an I(2) variable, mobile banking in first differences was divided by wireless subscription base in millions: $\left(\frac{DMB}{WLESS}\right)$, in order to be estimated in the ARDL framework.

of India (NPCI). RTGS data, volume of transactions via mobile banking (MB), total number of credit card transactions at POS terminals (NT1) and debit card transactions at POS terminals (NT2), from the Reserve Bank of India (RBI). India's M1 was taken from the Federal Reserve Bank of Saint Louis (FRED) and telephone wireless subscription base in millions (WLESS) from the Telecom Regulatory Authority of India (TRAI).

Table 13 presents the descriptive statistics of the analysed variables. Data from payment systems are expressed in Lakh[120] volume in millions of transactions. Out of all three payment system data, mobile banking has the biggest amount of customer transactions, followed by UPI and finally RTGS (although important in value, RTGS has small volumes of customer transactions). The M1/GDP ratio shows stability around 2.55 throughout the sample period, peaking in the first months of 2020. Which is expected, since COVID-19 increased significantly physical currency demand M1 (the most liquid portions of money supply), due to economic uncertainty.

Total number of debit card transactions at the point of sale (POS) terminals (NT2) is much bigger in the Indian economy than the total number of credit card transactions at the point of sale (POS) terminals (NT1). Debit cards in addition to functioning as an alternative medium of payment (compared to cash and instant payments) they are also used as a medium for immediate liquidity, employed to withdraw money from bank accounts. Mobile banking volumes to telephone wireless subscription (MB/WLESS) ratio shows relative stability. A sharp decrease at the beginning of 2020 (second quarter) following a spike, that accounts for an increase in mobile applications usage through social distancing impositions.

[120] Lakh is an Indian unit of measure that is equal to 100.000 Rupees. For example, in India, 150.000 Indian Rupees becomes 1.50 lakh. So, if I have 236.93 Lakh in transactions (October 2019) there are 236.93 * 100,000 = 23.693 million in transactions.

Table 13 - Descriptive statistics of the analysed variables (Indian Dataset) - April 2016 to November 2020 (Not seasonally adjusted)

Unit	Variable	Mean	Median	St. Dev	Minimum	Maximum
Lakh (Mn in vol)	UPI	563,827	279,192	610,261	0,000373	2.210,23
Mn (Transactions)	NT1	134.121.119,04	132.319.906,00	35.652.698,19	72.827.537,00	204.968.027,00
Mn (Transactions)	NT2	318.054.207,91	337.317.940,00	95.431.068,94	118.203.204,00	458.447.093,00
Lakh (Mn in vol)	MB	6.683,45	3.744,38	6.495,49	486,67	22.713,54
Lakh (Mn in vol)	RTGS	106,3612	107,8927	18,5089	53,3488	136,5361
Ratio	M1/GDP	2,549603	2,339114	0,720418	1,449796	5,571920
Ratio	MB/WLESS	0,326498	0,151530	0,681786	-1,49	3,586411

Note: Data computed through software EViews 10. Not seasonally adjusted. *Mn: million; *Mn in vol: million in volume. Data source: National Payments Corporation of India (NPCI), Telecom Authority of India (TRAI), Reserve Bank of India (RBI), and Federal Reserve Bank of Saint Louis (FRED), (2021).

Data was seasonally adjusted with EViews 10, Census-13 tool, using x-11 and TRAMO/SEATS[121]. Two different methods were employed to seasonally adjust, due to better fit in data idiosyncrasies[122]. Given the recent empirical literature on the subject, most of the studies presented are based on an aggregate behaviour a macro framework. Which theoretically substantiates the chosen dataset, methodology and empirical analysis.

Capturing the relevance of digitalization in India through Unified Payments Interface (UPI) considering long, short run and nonlinearities (ARDL and NARDL model), important inferences can be made considering financial sophistication, payment substitutes and relative popularity of banking apps. These estimations with India's experience support lessons for other developing BRICS countries like Brazil, their public policy towards telecommunications and payment infrastructure. Proceeding to empirical analysis, Autoregressive Distributed Lag Models (ARDL) will be briefly explained detailing equation specifications to perform the necessary unit root tests, diagnostic tests for estimation done in the next section.

4.1 ARDL Methodology, model specifications, and results

The Autoregressive Distributed Lag Model (ARDL) as proposed by Pesaran & Shin

[121] X-11 bases seasonal adjustment with automatic ARIMA selection. SEATS bases seasonal adjustment with automatic outlier detection and TRAMO automatic ARIMA.

[122] By seasonally adjusting UPI and Mobile Banking, some variables become negative. This happens when time series are very close to zero, and by seasonally adjusting them, you take away the seasonal effect of that period. So, if the variable is already at a very low level, it becomes negative.

(1998), Pesaran *et al* (2001) is an Ordinary Least Squares (OLS) time series model, a cointegration analysis that is known to be unbiased and efficient. Its main intuition is to test for relationships between variables in level, considering not only the dependent and independent variables that are related contemporaneously, but across historical (lagged) values. Therefore, long run and short run components are estimated simultaneously, removing problems associated with omitted variables and autocorrelation.

Being a single equation approach, it has advantages over other time series analysis, such as Vector Autoregression (VAR) and Error Corrected Vector Autoregression (VEC) models. Suitable for smaller sample sizes, they are an improvement over non-stationary cointegration tests since they can be used regardless of whether variables are I(1), I(0), or mutually integrated. Models are selected with the most appropriate lags for each variable through criterion choices, such as Akaike (AIC), Schwarz (SC), or Hannan-Quinn (HQ). The ARDL model is estimated in the form of error correction vectors (ARDL-ECM), as illustrated in equation (1), below:

$$\Delta y_t = \alpha_0 + \alpha_{1t}\Gamma + \delta_1 y_{t-1} + \delta_2 x_{t-1} + \sum_{i=0}^{m} \varphi_{1i}\Delta y_{t-i} + \sum_{i=0}^{n} \varphi_{2i}\Delta x_{t-i} + \varepsilon_t \quad (7)$$

Wherein Δ is first difference operator; α_o the constant; $\alpha_{1t}\Gamma$ the trend; $\delta_i, i = 1{,}2$ are the long run parameters; $\varphi_{i,} i = 1{,}2$ are the short run parameters; and ε_t is the error term that must be a white noise. A residual term which is supposed to be: serially independent, homoscedastic and normally distributed (*i.i.d*).

After OLS estimations, the bounds testing approach (F-Statistics) developed by Pesaran & Shin (2001), are used to verify joint significance of long-term parameters. Two sets of asymptotic critical values (limits) for I(0) bounds and I(1) bounds are estimated[123].With the null that there is no cointegration $H_0 = \beta_1 = \beta_2 = \beta_3 = 0$, and the alternative $H_1 \neq \beta_1 \neq \beta_2 \neq \beta_3 \neq 0$, if the null hypothesis is rejected, there will be strong statistical evidence that variables have long-term relationship between them.

[123] These sets provide a band covering of all possible classifications of the regressors into: I(0), I(1) or mutually co-integrated. If the computed Wald or F-statistic falls below the lower critical value bounds, a conclusive inference can be drawn, that there is no cointegrating relationship. If the empirical analysis shows that the estimated F is higher than the upper bound, it is possible to infer a cointegrating relationship between dependent variable and regressors. If the value of the Wald or F-statistic falls inside these bounds, inference is inconclusive and knowledge of the order of integration of the underlying variables is required before inferences can be made.

Confirming the existence of cointegrating vectors among variables of interest, the long-term and short-term coefficients of the models are estimated, as well as the speed of adjustment to the long run equilibrium. Equilibrium adjustment speed (ECM coefficient) must be negative, statistically significant and smaller than one in module. Auxiliary econometric procedures will be necessary in addition to ARDL estimations for robust inference:

- Traditional unit root tests to diagnose stationarity such as the Dickey-Fuller (DF), the Augmented Dickey-Fuller (ADF), Phillips-Perron (PP), and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) tests. It is not necessary that the variables be stationary, but that at least one of them must be non-stationary.
- Evaluation of serial correlation using the LM (Lagrange Multiplier) test.
- Heteroscedasticity analysis through the Breusch-Godfrey (BPG) test and White test.
- Functional form and model specification with the Ramsey-Reset Test.
- Parameter stability analysis through the Cumulative Sum of Residuals (CUSUM) and Cumulative Sum of Residuals squared (CUSUMSQ) tests, according to Brown *et al* (1975). Structural breaks can be observed if the cumulative sum and the cumulative sum squared line traverses the area between the 5% critical values.

Estimated models and choice of explanatory variables are carried out under the groundwork of the reviewed empirical literature. A macro-framework with reduced form equations was devised to better comprehend, the nature of instant payments, with direct applicability to the Indian UPI. Financial innovation in payment systems plays a supportive role. A straight analogy is that payment systems are the "plumbing" of the economy (Kahn; Roberds, 2009). If plumbing is well planned and installed, consequently there will be a continuous flow of water. Instant Payments enhances economic activity (water flow), reaching the most pervasive item today, which are smartphones. Hence, transaction volume of instant payments directly depends on internet infrastructure, access to smartphones (wireless telephone subscription) and mobile banking apps.
In this sense:

- Volume of transactions via mobile banking by telephone wireless subscription base in millions (MB/WLESS) ratio, would be positively correlated to Unified Payments Interface (UPI). Growing mobile banking usage (MB) could motivate the adoption and use of instant payment transactions.

- Total number of credit card transactions at point-of-sale (POS) terminals (NT1), and total number of debit card transactions at point-of-sale (POS) terminals (NT2), provide a convenient form of making payments for goods and services being interpreted as direct substitutes for instant payment systems.
- As a measure of financial sophistication M1/GDP ratio could directly impact fast payments, while, Real-Time Gross Settlement System (RTGS), would be an approximate variable of total payments made in the economy. With large values flowing through its system and customer transaction volume inferior to UPI, it is still expected to have a positive marginal effect on fast payments.

Seven models are specified (Table 14), each model is a variation of the previous one, with alternating payment modes and UPI as the dependent variable. Three important groups were separated: variable of interest, control variables and those that need to be controlled considering the research question. The first four equations (MB/WLESS) and (M1/GDP) ratios were kept as explanatory control variables, whereas the last three equations with (MB) and (M1/GDP) were the chosen explanatory control variables. Each equation was calculated using EViews 10, HAC covariance matrix (Newey-West) with degrees of freedom adjustment. Lag choice was done through the Akaike information criterion, with up to six lags.

A notable aspect of using payment indicators is that they exhibit large shifts, reflecting the introduction of new instruments, policy interventions and external shocks to the system. A dummy variable was applied to the year 2020, reflecting the plunge in payments, a significant change in time-series dynamics explained by the COVID-19 global pandemic.

Table 14 - Estimated ARDL models. Dataset from Indian payment systems (April 2016 – November 2020).

Method	Model	Dependent Variable	Independent Variables	Model Selected
ARDL	1	UPI	D(MB)/WLESS, RTGS, M1/GDP	(6,1,6,0)
ARDL	2	UPI	D(MB)/WLESS, NT1, M1/GDP	(4,0,6,2)
ARDL	3	UPI	D(MB)/WLESS, NT2, M1/GDP	(2,6,1,1)
ARDL	4	UPI	D(MB)/WLESS, D(MB), M1/GDP	(2,6,3,0)
ARDL	5	UPI	NT1, D(MB), M1/GDP	(4,6,0,2)
ARDL	6	UPI	NT2, D(MB), M1/GDP	(2,1,6,1)
ARDL	7	UPI	RTGS, D(MB), M1/GDP	(6,6,1,0)

Note. ARDL models with a maximum of six (6) lags. Model choice based on Akaike Information Criteria. Author’s elaboration. Data output from EViews 10.

Accounting for seasonality and applying unit root tests (Appendix), all variables are I(1)[124]. Diagnostic tests were also performed, to attest model stability, absence of autocorrelation, heteroscedasticity and overall econometric consistency (Table 15). The Brown, Durbin & Evans (1975) Cumulative Sum (CUSUM) and Cumulative Sum of Squares (CUSUMSQ) tests showed that all of them were dynamically stable at the 5% level. Autocorrelation was not detected through the Lagrange Multiplier (LM) test. The null hypothesis of no serial correlation in the errors was confirmed. Residuals are also homoscedastic, failing to reject the null of no heteroscedasticity, through the Breusch-Pagan-Godfrey (BPG) and White test. The Ramsey regression equation specification error test (RESET) shows that the functional form of the conditional mean in all seven models are correctly specified.

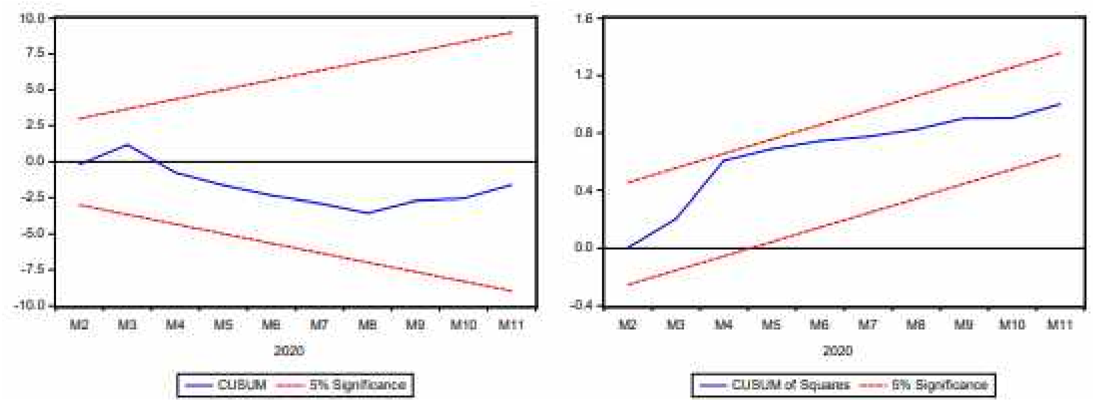
Table 15- Diagnostic test ARDL models: dependent variable UPI (April 2016 – November 2020). Dataset from Indian payment systems

		Diagnostic Tests			
		Autocorrelation	Heteroskedasticity		Functional Form
Model	ARDL	Serial Correlation LM Test [Prob]	Heteroskedasticity BPG Test [Prob]	Heteroskedasticity White Test [Prob]	Ramsey-Reset Test [Prob]
1	(6,1,6,0)**	F(6,26) = 0,64 [0,69]	F(17,32) = 0,53 [0,91]	F(17,32) = 0,27 [0,99]	F(1,31) = 0,33 [0,56]
2	(4,0,6,2)**	F(6,27) = 0,66 [0,68]	F(16,33) = 0,53 [0,90]	F(16,33) = 0,79 [0,68]	F(1,32) = 0,03 [0,85]
3	(2,6,1,1)**	F(6,28) = 0,42 [1,03]	F(14,34) = 0,30 [0,99]	F(14,34) = 0,29 [0,99]	F(1,33) = 0,00 [0,97]
4	(2,6,3,0)**	F(6,27) = 1,56 [0,19]	F(15,33) = 0,71 [0,75]	F(15,33) = 0,63 [0,82]	F(1,32) = 0,18 [0,67]
5	(4,6,0,2)**	F(6,27) = 0,65 [0,68]	F(16,33) = 0,53 [0,91]	F(16,33) = 0,79 [0,68]	F(1,32) = 0,03 [0,85]
6	(2,1,6,1)**	F(6,28) = 1,06 [0,40]	F(14,34) = 0,30 [0,98]	F(14,34) = 0,29 [0,99]	F(1,33) = 0,00 [0,98]
7	(6,6,1,0)**	F(6,26) = 0,65 [0,68]	F(17,32) = 0,53 [0,91]	F(17,32) = 0,27 [0,99]	F(1,31) = 0,35 [0,55]

Note. ARDL model with a maximum of six (6) lags. Model choice based on Akaike Information Criteria. H0 for Autocorrelation LM Test = no autocorrelation. H0 for Heteroskedasticity BG Test = no heteroskedasticity. *case 1: no constant and no trend, **case 2: restricted constant and no trend, ***case 3: unrestricted constant and no trend, ****case 4: unrestricted constant and no trend; *****case 5: unrestricted constant and unrestricted trend. Source: Author's elaboration (EViews 10).

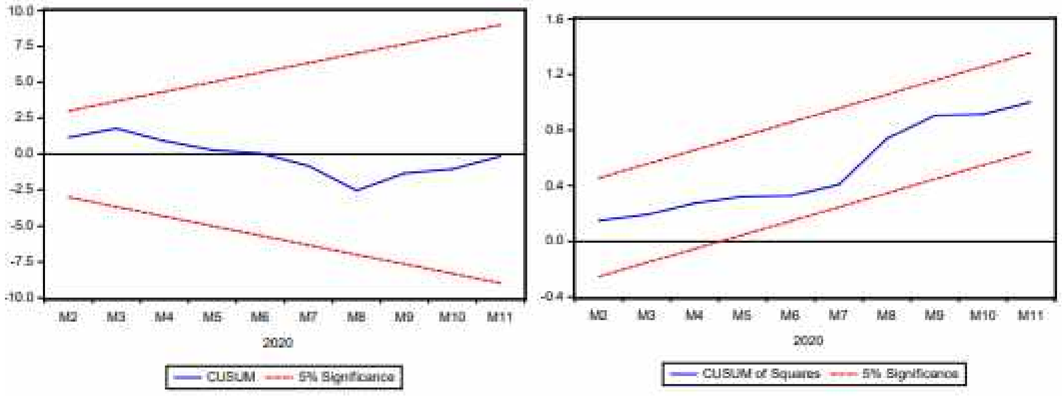
[124] The one that showed idiosyncrasy was mobile banking (MB), that after first difference produced ambiguity between being non-stationary and stationary (two out of two models). Mobile banking was transformed into first difference D(MB) in order to be better fitted through the chosen methods.

Graph 11. CUSUM and CUSUM SQ Test. ARDL Model 01.



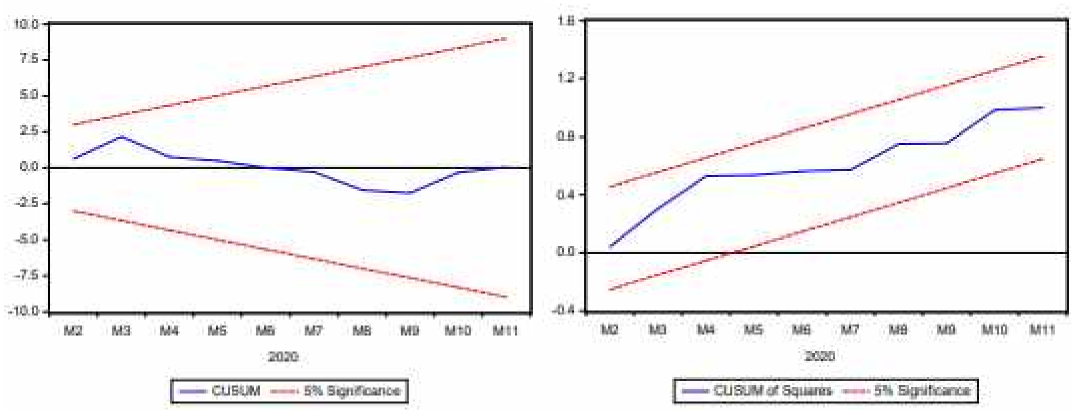
Note: Author’s elaboration (EViews 10).

Graph 12. CUSUM and CUSUM SQ Test. ARDL Model 02



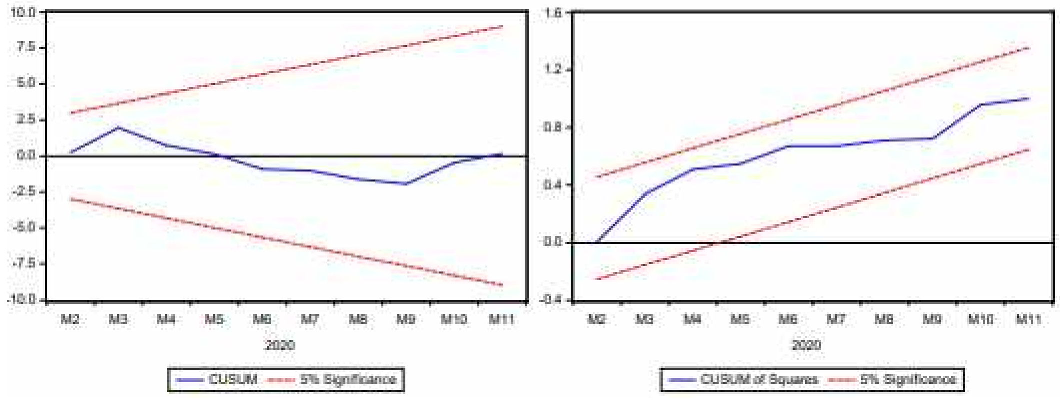
Note: Author’s elaboration (EViews 10).

Graph 13. CUSUM and CUSUM SQ Test. ARDL Model 03.



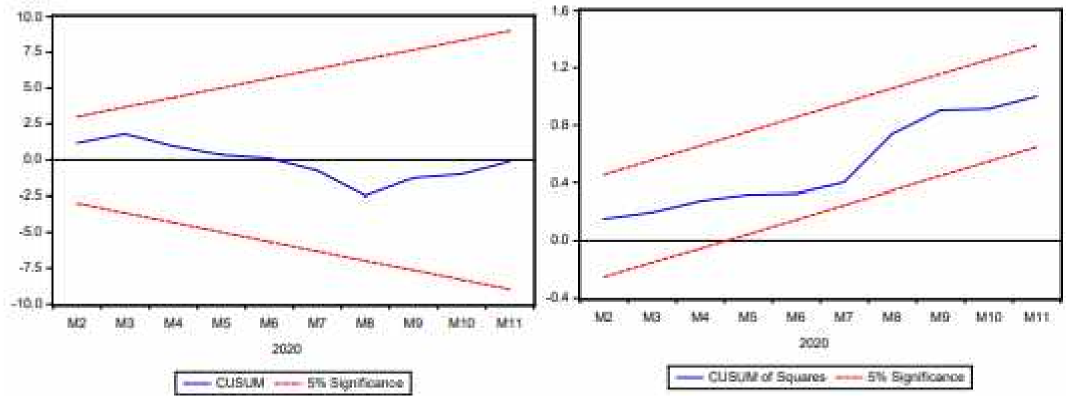
Note: Author’s elaboration (EViews 10).

Graph 14. CUSUM and CUSUM SQ Test. ARDL Model 04.



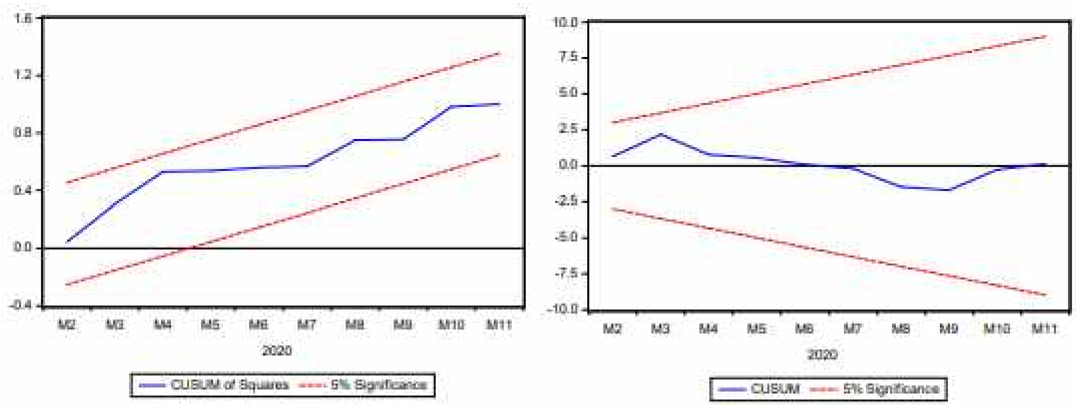
Note: Author’s elaboration (EViews 10).

Graph 15. CUSUM and CUSUM SQ Test. ARDL Model 05.



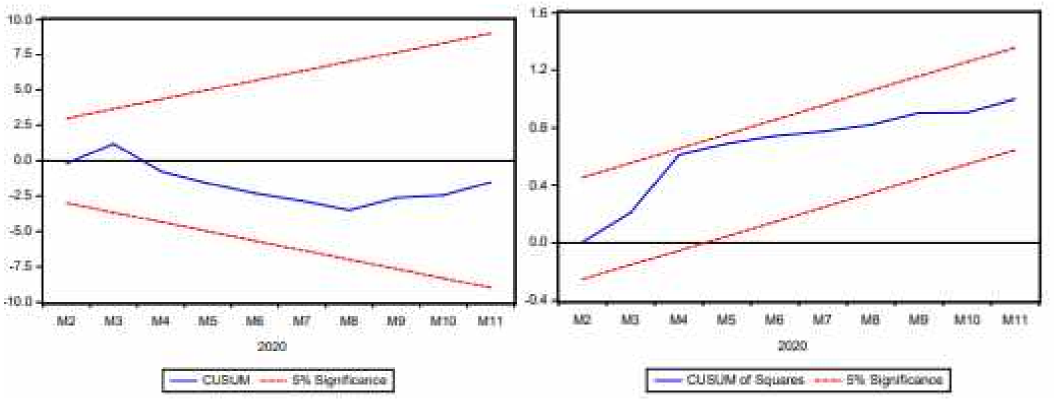
Note: Author’s elaboration (EViews 10).

Graph 16. CUSUM and CUSUM SQ Test. ARDL Model 06



Note: Author’s elaboration(EViews 10).

Graph 17. CUSUM and CUSUM SQ Test. ARDL Model 07.



Note: Author's elaboration (EViews 10).

Diagnostic tests and stability tests done, the next step is to apply the ARDL bounds testing methodology (Pesaran et al, 2001), to confirm long run cointegrating relationships between variables. Narayan & Smyth (2005), point out that with small sample sizes the relevant critical values potentially deviate from the critical values reported in Pesaran *et al* (2001). In an earlier paper, Narayan (2004) calculates F-statistic critical values to their specific sample size[125]. Tabulating critical values for sample sizes ranging from 30 to 80 observations, critical values become 35.5% higher than those reported in Pesaran *et al* (2001) and 17.1% higher than those reported in Pesaran & Pesaran (1997). The ARDL cointegration test considering Narayan's and Pesaran's critical values, are showed in Table 16. As can be seen, the F-statistics of all seven models, fall in the I(1) superior bound at least at the 5% significance level.

[125] The critical value bounds are calculated using stochastic simulations for T=31 (observations) and 40.000 replications for the F-statistic (NARAYAN, 2004).

Table 16 - ARDL Cointegration Test: Bounds Testing Approach, for the seven specified models. Critical values (Narayan, 2004; Pesaran et al, 2001) (April 2016 – November 2020). Dataset from Indian payment systems.

			Critical Values								
			Narayan (2004)				Pesaran et al (2001)				Long run cointegration
Model	ARDL Model	Bounds Test - F	I(0) Bound		I(1) Bound		I(0) Bound		I(1) Bound		
			5%	1%	5%	1%	5%	1%	5%	1%	
1	(6,1,6,0)	11,2	3,04	4,18	4,00	5,32	2,79	3,65	3,67	4,66	Yes
2	(4,0,6,2)	4,26	3,04	4,18	4,00	5,32	2,79	3,65	3,67	4,66	Yes (at the 5% level)
3	(2,6,1,1)	9,65	3,04	4,18	4,00	5,32	2,79	3,65	3,67	4,66	Yes
4	(2,6,3,0)	12,73	3,04	4,18	4,00	5,32	2,79	3,65	3,67	4,66	Yes
5	(4,6,0,2)	4,25	3,04	4,18	4,00	5,32	2,79	3,65	3,67	4,66	Yes (at the 5% level)
6	(2,1,6,1)	9,66	3,04	4,18	4	5,32	2,79	3,65	3,67	4,66	Yes
7	(6,6,1,0)	11,35	3,04	4,18	4,00	5,32	2,79	3,65	3,67	4,66	Yes

Note. Data computed through software EViews 10. Pesaran et al (2001) bounds testing approach, H_0: no long run relationship. Critical values are those from (Narayan, 2004) and Pesaran et al (2001), considering case II: restricted constant and no trend (for 50 observations).

After confirming long run relationships, it is important to advance in coefficient interpretation. **Long run** equations are depicted in Table 17, calculated by dividing the negative of the coefficient of the dependent variable by the independent variable coefficient, to find the levels equation. In all seven models the constant (C), M1/GDP ratio, credit card transactions (NT1), and debit card transactions (NT2) are the most significant variables. Equations 01 and 07 are not statistically significant, therefore they will not be analysed.

Observing the remaining models, some regularities can be ascertained. Equations 02 and 05 are very similar in output. Volume of credit card transactions at POS terminals (NT1) is significant at least at the 10% value, which means that credit card transactions affect positively the volume of UPI transactions. A 1 million increase in credit card transactions will rise UPI in 2.81×10^{-6} and 2.76×10^{-6} in instant payment volumes. At an even higher level of significance is the (M1/GDP) ratio that also affects positively UPI transactions (a 1% increase in the M1/GDP ratio will increase UPI in 8,12% and 8,13%).

The total number of debit card transactions at POS terminals (NT2) is statistically relevant in models 03 and 06, an increase of 1 million debit card transactions will cause a concurrent increase of 2.08×10^{-6} and 1.96×10^{-6} unified instant payments (UPI) transactions. Both credit and debit card transactions show a positive correlation on the long run, to instant payments at the 10% significance level. Ratio (M1/GDP) also affects positively the volume of

UPI transactions: a 1% increase in the M1/GDP ratio will increase UPI transactions by 5,26% and 5,21%.

Model 04 is somehow different from the other models as it is the only one that depicts statistical significance at the 10% level to the total volume of mobile banking transactions. With a 1% increase in mobile banking transactions, there will be a 0,24% increase in instant payment transactions through UPI. This is relatively straightforward, if there is an increase in UPI users more people will turn to mobile banking activities on the long run.

Table 17 - ARDL Long Run Coefficients (levels equation) for the seven specified models (dependent variable UPI),(April 2016 – November 2020). Dataset from Indian payment systems.

Model	1	2	3	4	5	6	7
ARDL Model	(6,1,6,0)	(4,0,6,2)	(2,6,1,1)	(2,6,3,0)	(4,6,0,2)	(2,1,6,1)	(6,6,1,0)
D(MB)/WLESS	3702.69 [0.14]	833.05 [0.15]	2663.50 [0.251]	(-25983.5) [0.100]			
D(MB)				**24.932** **[0.073]***	0.716 [0.152]	2.285091 [0.246]	3.141 [0.129]
NT1		**2.81E-06** **[0.086]***			**2.76E-06** **[0.090]***		
NT2			**2.08E-06** **[0,065]***			**1.96E-06** **[0.080]***	
RTGS	30.70 [0.14]						29.485 [0.134]
M1/GDP	(-154.19) [0.66]	**812.213** **[0,00]***	**526.9347** **[0.020]***	(-51.409) [0.819]	**813.159** **[0.005]***	**521.158** **[0.021]***	(-145.4409) [0.668]
C	**(-2749.39)** **[0.074]***	**(-2182.30)** **[0.00]***	**(-1495.98)** **[0.011]***	126.776 [0.800]	**(-2177.34)** **[0.001]***	**(-1453.154)** **[0.014]***	**(-2651.929)** **[0.066]***

Note: Software used for estimation EViews 10. ARDL models considered are case II: Restricted Constant and No Trend. *Statistically relevant variables at the 5% and 10% levels.

Possible substitution characteristics between UPI, credit and debit cards were emphasized previously. From a macro view and due to the short time frame studied, they are not so much substitutes as they are means that increase instant payment usability and acceptability (complementary). This also occurs with mobile banking in equation 04. Bigger usage of banking apps in India, induces more UPI transactions, with a deeper profusion of digitalization.

Fast payments and mobile banking applications have the same intuition as credit and debit cards: intensifying money transactions and currency circulation domestically. To redirect transfers to the real side of the economy and induce income-generating activities, the Brazilian Central Bank (BCB) implements instant payments, reducing transaction fees to nearly zero. If per capita income and standard living are rising, purchasing power grows incentivizing transactions, deepening sophistication of the national payment system.

If payments are an easy and accessible instrument, transactions will naturally rise. More specifically, through the Granger causality test performed [footnote[27]] the measure of financial development of an economy (in this case India) Granger Causes instant payment transactions, and UPI transactions Granger Causes financial development of an economy, in a bidirectional movement. Electronic payments are impacted by the level of sophistication of the financial system, while digital connectivity becomes an instrument to help overcome insertion of the unbanked (LUBIS ET AL, 2019).

Short-term adjustments via the error correction mechanism (ECM) were also estimated (Table 18). The historical past value of the dependent variable, considering the previous five months, **model 01 (6,1,6,0),** will have a negative coefficient, quite contrary to what is expected from economic inference. Previous rise in payments would induce more growth and use in periods to come (network effects). This goes to show that an increase in instant payments would not rise transactions in the following periods. During system implementation, growth rate of UPI is much higher. As an innovative payment mechanism, it attracts a bigger proportion of users. With diffusion, it continues to grow, but at a lower rate, adoption can in fact decrease, if it is not convenient to a particular type of customer.

RTGS as a proxy for all payments is statistically relevant at the 5th lag, with a positive effect on instant payments (volume-wise). While (MB)/WLESS ratio has an immediate impact of 0.92% on UPI transactions. The error correction mechanism (ECM) is negative with a p-value < 0,01 showing that 3% of deviations from the long-term trajectory will be corrected in the following month.

In **model 02 (4,0,6,2)** previous values of UPI transactions, p-value < 0.05, yield a positive coefficient of 0.33 lakh. Total number of credit card transactions (NT1) has a significant impact at the 5th lag increasing UPI transactions by 1.30×10^{-6} lakh. Ratio of money publicly held to the Gross Domestic Product (M1/GDP), increases UPI transactions immediately in 0.60% after one lag. In the following month, 7% deviations from the long run trajectory will be adjusted in the short run.

Lagged value of UPI transactions will impact its present value in -0.325 in **Model 03 (2,6,1,1).** After 5 lags (MB/WLESS) ratio will negatively impact UPI transactions, and M1/ GDP will also have an immediate negative impact on UPI transactions: a 1% increase in M1/GDP will decrease UPI transactions by -0.5%. The error correction mechanism is negative and statistically significant correcting 6% of the long-term trajectory.

Model 04 (2,6,3,0) is similar to model 03. UPI lagged dependent variable (p-value <

0.05), is negatively correlated to its present value. The ratio of volume of mobile banking transactions versus wireless subscription base (MB/WLESS) will negatively impact UPI transactions, at the 5^{th} lag, decreasing UPI transactions in -0.25%.Volume of transactions through mobile banking also shows a negative and significant coefficient in the short run. The error correction mechanism is also relevant at the 1% level, showing that 9% of deviations from the long-term trajectory will be corrected in the next period.

Fast payments will increase by 0.31 lakh if there was a previous rise in flow two periods previously, **model 05 (4,6,0,2)**. Credit card transactions have a lagged positive relevant impact on UPI transactions. Money publicly held to GDP (M1/GDP) also impact UPI transactions. After one lag a 1% increase in M1/GDP will increase transactions by 0,60%, at a p-value (< 0.05). Like model, 02 deviations from the long run trajectory will be corrected in 7%.

In **Model 06 (2,1,6,1)** the lagged dependent variable, is negatively correlated with a p-value (< 0.05). The total volume of mobile banking (MB) transactions in lakhs also inversly impacts UPI transactions in the short run: an increase in 1 lakh transactions in mobile banking will impact UPI in -0.01 million transactions. M1/GDP ratio will have a significant negative impact on UPI transactions, a very similar result to model 03.

Models 03, 04 and 06 include total number of debit card transactions at POS terminals (NT2), MB/WLESS, M1/GDP ratio, and mobile banking transactions (MB). Debit card transactions are not statistically significant; however, M1/GDP, MB/WLESS and (MB) have relevant p-values producing a negative impact on instant payment transactions. These last variables are relatively constant through the estimated time frame. Nonetheless, interaction with positive increases in these variables could produce a reduction on instant payments.

Lagged past UPI values affect positively and negatively all estimations. Particularly in **model 07 (6,6,1,0)** an increase of 1 lakh transactions five lags beforehand, will decrease UPI transactions presently in -0.34 lakhs. Mobile banking has an immediate positive impact on UPI in 0.08 lakh. RTGS has a p-value (< 0.05), five lags previously increasing instant payments in 3.9 lakh transactions (volume-wise). The ECM produces a 9% correction of the long run deviations in the next month.

Table 18 - ARDL Short Run Dynamics: Error Correction and Significant Variables, for the seven specified models (dependent Variable UPI), (April 2016 – November 2020). Dataset from Indian payment systems.

Model	1	2	3	4	5	6	7
ARDL Model	(6,1,6,0)	(4,0,6,2)	(2,6,1,1)	(2,6,3,0)	(4,6,0,2)	(2,1,6,1)	(6,6,1,0)
D(UPI (-1))			**(-0.325) [0.036]***	**(-0.319) [0.036]***		**(-0.326) [0.035]***	
D(UPI (-2))		**0.313 [0.002]***			**(0.314) [0.002]***		
D(UPI (-5))	**(-0.342) [0.000]***						**(-0.347) [0.000]***
D(MB)/WLESS	**92.55 [0.000]***						
(D(MB)/WLESS (-5))			**(-18.398) [0.022]***	**(-25.568) [0.004]***			
D(D(MB))							**0.080 [0.000]***
D(D(MB) (-2))				**(-1,923) [0.046]***			
D(D(MB) (-5)))						**(-0.016) [0.020]***	
D(NT1 (-5))		**1.30E-06 [0.000]***			**1.29E-06 [0.000]***		
D(RTGS (-5))	**3.878 [0.000]***						**3.901 [0.000]***
D(M1/GDP)			**(-51.607) [0.005]***			**(-51.612) [0.005]***	
D(M1/GDP (-1))		**60.963 [0.031]***			**60.782 [0.032]***		
DUMMY	**52.47 [0.000]***	**65.25 [0.000]***	**22.672 [0.077]***	**82.541 [0.000]***	**65.537 [0.000]***	**23.735 [0.065]***	**54.042 [0.000]***
CointEq (-1)	**(-0.036) [0.000]***	**(-0.074) [0.000]***	**(-0.060) [0.000]***	**(-0.098) [0.000]***	**(-0.074) [0.000]***	**(-0.061) [0.000]***	**(-0.037) [0.000]***
R-squared (R2)	0,903	0,889	0,835	0,853	0,889	0,834	0,903
Durbin - Watson Statistic	2,184	2,01	2,146	2,175	2,013	2,15	2,198

Note: Software used for estimation EViews 10. ARDL models considered are case II: Restricted Constant and No Trend. * Statistically relevant variables at the 5% and 10% levels.

Dummy variables have small p-values ($p < 0.05$) demonstrating how important it is to account for the COVID-19 impact on payment systems. The R-squared (R^2) of all short run models are relatively high, ranging between 0.83 and 0.90. Following Granger & Newbold's (1974) rule of thumb for detecting spurious regressions, Durbin-Watson statistics are presented, maintaining values close to two, confirming econometric procedures.

MB/WLESS growth rate has remained constant in the short run; however, UPI's trend is increasing, when compared to the MB/WLESS ratio and mobile banking (MB). The MB/WLESS ratio can partly explain UPI, but since it reflects volume of mobile banking transactions to mobile telephone subscriptions, it does not constitute a direct relationship, only an approximation for popularity of banking apps (not all mobile users adopt API banking).

Fast payments will capture a portion of clientele in the payments market, just like credit cards and debit cards, becoming a complementary instrument, in the growing list of possibilities. Both credit and debit card transaction volumes show a positive correlation, to instant payments at least at a 10% significance level. These instruments will enhance instant payments usage, which will gradually occupy a bigger portion of the retail payments market. Nonetheless it will not eliminate other payment options altogether.

For the Brazilian use case (Pix), our study confirms a high adoption rate in the first months of implementation, credit and debit card usage is expected to incentivize instant payments, through payer/payee flow mechanisms. Banking apps will induce more Pix transactions, although to confirm if Pix/UPI are effectively reaching the informal economy and the unbanked, a thorough analysis must be taken on, investigating which sectors of society reached higher acceptance rates. An increase in mobile banking transactions to telephone wireless subscription base directly influences instant payment volumes in the short run. Due to the continental dimension of both India and Brazil, telecommunications, infrastructure and internet diffusion polices to remote places must be put in place to reap bigger benefits of such initiatives, promoting a greater impulse for instant payment applications.

A Pricewaterhouse Coopers Study in partnership with Instituto Locomotiva ("*O abismo digital no Brasil*", 2022) showed that there is a lot of work to be done in order to eliminate gaps related to inequality in internet connection in the country, having their roots, in problems associated to access to hardware devices, deficiencies in our educational system and inequality[126]. There are marked differences in internet access between extremes of income classes (100% in class A, compared to 64% in DE). Lack of infrastructure is directly related to the income of a given region: lower the income, worse the signal (problems with quality, distribution, in addition to cost and equipment)[127]. Policymakers must view initiatives towards telecommunications and internet infrastructure seriously.

[126] The PwC/Instituto Locomotiva study was structured based on two quantitative surveys carried out between July and August 2021. One of them, was carried out online, and brings together a national sample of 1,754 internet users, men and women, aged 18 and over. The margin of error is 2.3 percentage points. The other national survey, 2,300 people aged 18 or over were interviewed. Here, the margin of error is 1.9 percentage points. The results were weighted by region according to gender distribution, age group and schooling of Internet users aged 18 or over (PNAD – IBGE) (PwC, Instituto Locomotiva; 2022, p. 31)

[127] São Paulo, for example in lower income districts, show increasing connectivity inequality between low and high income citizens. Problems that are seen in other state capitals in Brazil.

4.2 NARDL methodology, model specifications, and results

A linear econometric analysis doesn´t clarify much of UPI's underlying functioning. Knowing that instant payment mechanisms may be subject to asymmetries, analysis is developed by applying a nonlinear autoregressive distributed lag (NARDL) approach to the estimated ARDL equations. Shin *et al* (2014) advanced NARDL modelling as an extension of the ARDL framework (Pesaran & Shin, 1998; Pesaran et al, 2001) in which short and long run nonlinearities are introduced via positive and negative partial sum decompositions of the explanatory variables. Asymmetry occurs when positive and negative variations of the explanatory variable (X) do not have the same impact (in magnitude) on the dependent variable (Y). Decomposing these shocks, it is possible to verify if relationships are nonlinear.

Long run ARDL levels equation showed that credit card transactions at POS terminals (NT1), debit card transactions at POS terminals (NT2), mobile banking (MB), and M1 ratio to Gross Domestic Product (M1/GDP), have long run impacts on Unified Payments Interface (UPI). Therefore, are there non-linearities that have not surfaced through ARDL estimations? Do they provide important insights into instant payments? Table 19 introduces the four (4) selected NARDL equations and the positive and negative shocks of the explanatory variables. Only mobile banking (MB) and debit card transactions in POS terminals (NT2) are not accounted for because they did not show significant statistical results.

Table 19 - Estimated NARDL models. Dataset from Indian payment systems

Model ARDL	Method	Dependent Variable	Positive and Negative Shocks	Dependent Variables	Model Selected
1	NARDL	UPI	RTGS +, RTGS -	D(MB)/WLESS, RTGS +, RTGS -, M1/GDP	(6,1,6,6,6)
2	NARDL	UPI	NT1 +, NT1 -	D(MB)/WLESS, NT1+, NT1 -, M1/GDP	(6,0,2,6,2)
3	NARDL	UPI	M1/GDP +, M1/GDP -	D(MB)/WLESS, M1/GDP+, M1/GDP-, NT2	(1,5,0,4,4)
4	NARDL	UPI	NT1 +, NT1 -	D(MB), NT1 +, NT1-, M1/GDP	(6,2,6,0,2)

Note. ARDL models with a maximum of six (6) lags. Model choice based on Akaike Information Criteria. Author's elaboration. Data output from EViews 10.

Similarly, to ARDL estimations, a dummy variable was applied to the year 2020. Akaike information criteria was used to identify optimal lag length and HAC (Newey-West) coefficient covariance matrix was applied for robust estimates. Parameter stability and diagnostic tests were also performed to attest autocorrelation, heteroskedasticity, and overall econometric consistency (Table 20).

Table 20 - Diagnostic test NARDL models: dependent variable UPI (April 2016 – November 2020). Dataset from Indian payment systems

		Tests			
		Autocorrelation	Heteroskedasticity		Functional Form
Model ARDL	NARDL	Serial Correlation LM Test [Prob]	Heteroskedasticity Breush-Pagan-Godfrey [Prob]	Heteroskedasticity White Test [Prob]	Ramsey-Reset Test [Prob]
1	(6,1,6,6,6)	F(6,12) = 0,39 [0,87]	F(30,18) = 0,78 [0,73]	F(30,18) =0,77 [0,74]	F(1,17) = 0,41 [0,52]
2	(6,0,2,6,2)	F(6,21) = 0,55 [0,76]	F(21,27) = 0,91 [0,57]	F(21,27) = 1,87 [0,06]	F(1,26) = 0,78 [0,38]
3	(1,5,0,4,4)	F(6,24) = 1,44 [0,23]	F(19,30) = 0,32 [0,99]	F(19,30) = 0,41 [0,97]	F(1,29) = 0,00 [0,97]
4	(6,2,6,0,2)	F(6,21) =0,54 [0,77]	F(21,27) = 0,90 [0,58]	F (21,27) = 1,84 [0,06]	F (1,26) = 0,81 [0,37]

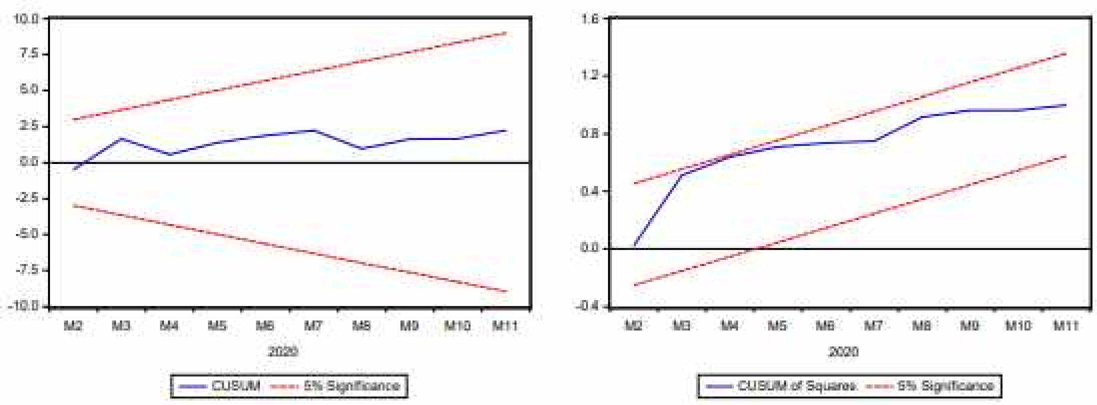
Note. NARDL model with maximum of six (6) lags. Model choice based on Akaike Information Criteria. H0 for Autocorrelation LM Test = no autocorrelation.H0 for Heteroskedasticity BG Test = no heteroskedasticity. *case 1: no constant and no trend, **case 2: restricted constant and no trend, ***case 3: unrestricted constant and no trend, ****case 4: unrestricted constant and no trend; *****case 5: unrestricted constant and unrestricted trend. Source: Author's elaboration (EViews 10).

Results show that at a 5% significance level, it is not possible to reject the null of no serial correlation applying the Lagrange Multiplier (LM) Test (H_0: no serial correlation). Estimates also confirm that residuals are homoscedastic, through the Breusch-Pagan-Godfrey heteroskedasticity test and the White test. As a general test for specification errors the Ramsey RESET test conveys that functional forms of the regressions are well defined, failing to reject the null of correct model specification.

The Cumulative Sum (CUSUM) and the Cumulative Sum of Squares (CUSUM Squared) recursive residual test, proposed by Brown, Durbin, & Evans (1975) was performed to attest coefficient stability. The test detects departures from constancy over an estimated time series. All four models are dynamically stable, statistics do not exceed the 5% significance level.

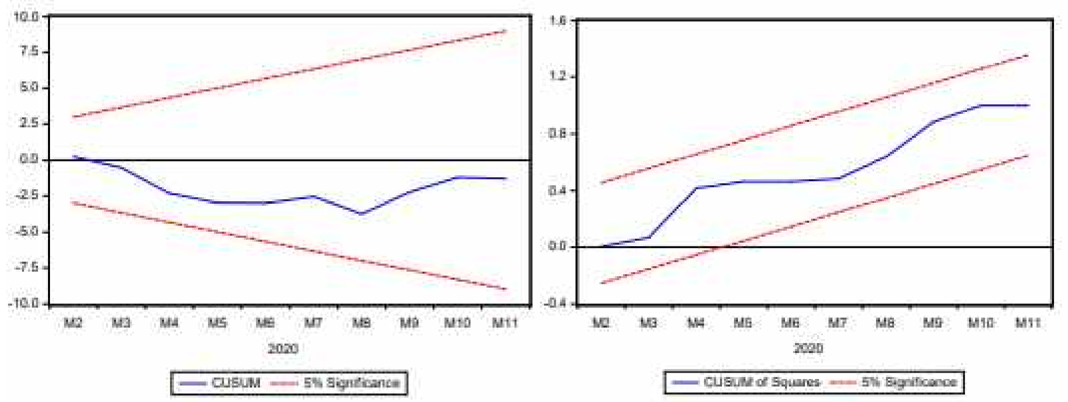
The second step is to identify cointegration between explanatory and dependent variables. The joint significance of all four NARDL models long-term parameters are checked by performing an F-test, under the null of no cointegration. The test provides upper and lower bound statistics. In all models displayed in Table 21, the F-statistic is greater than the upper critical value, rejecting the null hypothesis at 1% (models 01 and 03) and at the 5% statistical significance (models 02 and 04) that there is no cointegration between variables.

Graph 18 - CUSUM and CUSUM SQ Test. NARDL Model 01



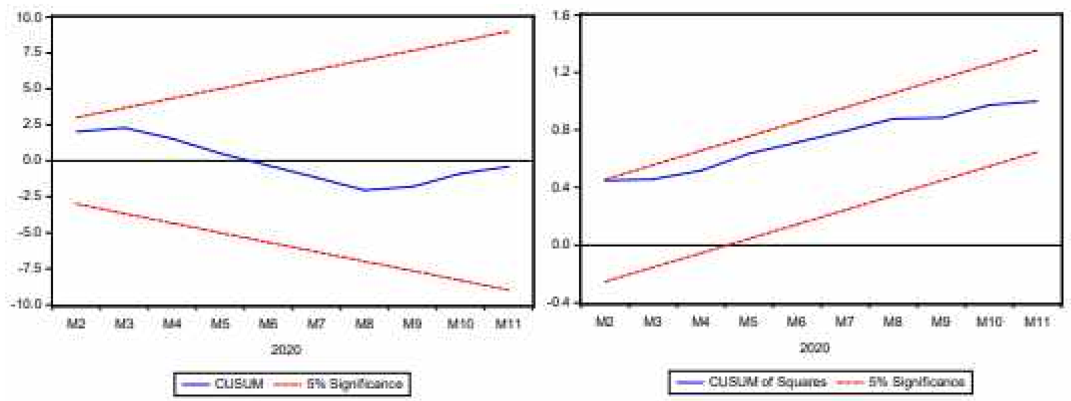
Note: Author’s elaboration (EViews 10).

Graph 19 - CUSUM and CUSUM SQ Test. NARDL Model 02.



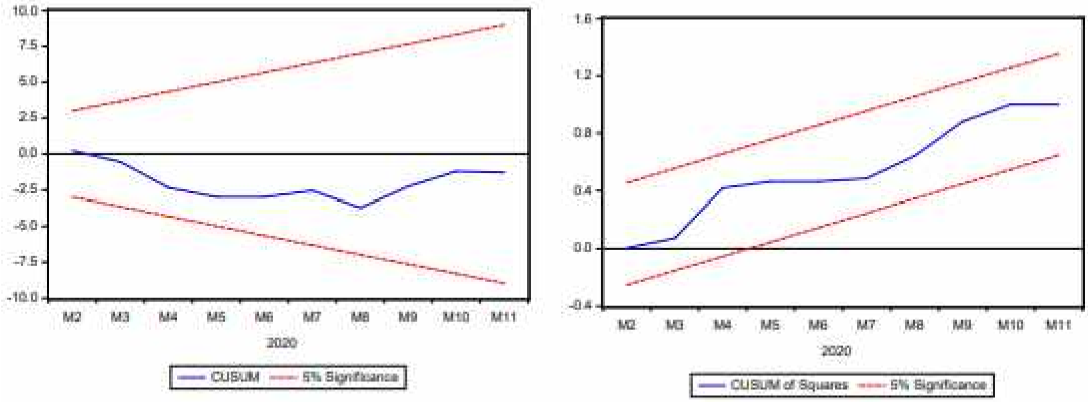
Note: Author’s elaboration (EViews 10).

Graph 20 - CUSUM and CUSUM SQ Test. NARDL Model 03



Note: Author’s elaboration (EViews 10).

Graph 21 - CUSUM and CUSUM SQ Test. NARDL Model 04



Note: Author's elaboration (EViews 10).

Table 21 - NARDL Cointegration Test: Bounds Testing Approach, for the specified models. Critical values (Narayan, 2004; Pesaran et al, 2001) (April 2016 – November 2020). Dataset from Indian payment systems

			Critical Values								
			Sample size 50				Sample size 45				Long run cointegration
Model ARDL	NARDL Model	Bounds Test F-Statistic	I(0) Bound		I(1) Bound		I(0) Bound		I(1) Bound		
			5%	1%	5%	1%	5%	1%	5%	1%	
1	(6,1,6,6,6)*	6,88**	2,82	3,84	3,87	5,15	2,85	3,89	3,90	5,17	Yes
2	(6,0,2,6,2)*	5,07**	2,82	3,84	3,87	5,15	2,85	3,89	3,90	5,17	Yes, at the 5% level
3	(1,5,0,4,4)*	9,20**	2,82	3,84	3,87	5,15	-	-	-	-	Yes
4	(6,2,6,0,2)*	5,05**	2,82	3,84	3,87	5,15	2,85	3,89	3,90	5,17	Yes, at the 5% level

Note: *Included observations in the estimation 49. ** Statistically significant Note. Data computed through software EViews 10. Pesaran et al (2001) bounds testing approach, H_0: no long run relationship. Critical values are those from Narayan (2004) and Pesaran et al (2001), considering case II: restricted constant and no trend.

With the main diagnostic tests done, it is time to advance to the long and short run NARDL estimations. Since econometric analysis is restricted to variables with significant p-values ($p < 0.01$, $p < 0.05$, $p < 0.10$), none of the long run level coefficients of the NARDL estimated models had relevant p-values (results are presented in the chapter's appendix). Consequently, it is not possible to affirm long run non-linearities between the explanatory and dependent variables[128]. However, evidence was found of additive short run asymmetries enabling

[128] Even though two NARDL models presented relevant long run asymmetries through the Wald Test (models 02 and 05).

coefficient analysis and testing (Table 10).

Table 22 displays **short run estimations** of the four NARDL models, coefficients and p-values. Only statistically relevant calculations (<0.01, < 0.05, < 0.10) are presented. In **model 01** UPI's past volumes will have a negative impact, on its present values (one and five periods previously). Two to three months beforehand there is a positive and significant impact on instant payment volumes increasing in 0.37 and 0.47 lakh transactions. Ratio of mobile banking transactions to mobile phone subscriptions (MB)/WLESS and level of sophistication of the financial system M1/GDP increased UPI transactions in 1.01% and 1.11%. Positive and negative decompositions of Real-Time Gross Settlement Systems (RTGS), five months prior, were significant (p-value <0.05). Inferring that instant payments are a positive function of both positive and negative changes in RTGS in the short run (a positive RTGS shock increases UPI transactions, and a negative one decreases them).

In conformity to its trend, **in model 02**, UPIs past transactions will also impact its present volumes positively and negatively. Decomposing credit card transaction volume (NT1) shows that UPI volume is a positive function of both positive and negative changes in credit card transactions. With an increase in credit card transactions, there will be a concurrent increase (in 2.46×10^{-6}) in instant payment volumes. A decrease will reduce UPI volumes (in 5.36×10^{-6} lakh transactions). On the other hand, M1/GDP past value has a 0.95% positive impact on instant payment transactions (p-value < 0.05).

Usage of mobile banking transactions to mobile phone users (MB/WLESS), gains relevance in **model 03**, whereas up until four lags it is possible to affirm statistical significance. Its immediate impact is positive and significant, increasing volume of instant payments in 0.53%, converting then to negative shocks. Not all mobile phone users will be mobile banking or UPI clients, producing an inverse relationship as time passes. Decomposition of the level of sophistication of the Indian financial system (M1/GDP) affects UPI payments immediately in -0.42%. After two lags, the previous increase of currency in circulation would convert into a bigger quantity of deposits, incentivizing the use of instant payments, with a rise in 0.64% in volume of instant payment transactions (p-value < 0.10).

Table 22 - NARDL Short Run Dynamics: Error Correction and Significant Variables, for the four specified models (Indian Dataset).

ARDL Model	1		2		3		5
NARDL	(6,1,6,6,6)	NARDL	(6,0,2,6,2)	NARDL	(1,5,0,4,4)	NARDL	(6,2,6,0,2)
Variables	Coef [Prob]	Variables	Coef [Prob]	Variables	Coef [Prob]	Variables	Coef [Prob]
D(UPI (-1))	(-0.529) [0.002]*	D(UPI (-1))	(-0.254) [0.035]*	D(MB)/WLESS	53.611 [0.000]	D(UPI (-1))	(-0.256) [0.034]*
D(UPI (-2))	0.372 [0.005]*	D(UPI (-2))	0.350 [0.004]*	D(MB)/WLESS (-1)	(-65.291) [0.000]	D(UPI (-2))	0.348 [0.004]*
D(UPI (-3))	0.460 [0.000]*	D(UPI (-4))	(-0.251) [0.080]*	D(MB)/WLESS (-2)	(-71.296) [0.000]*	D(UPI (-4))	(-0.253) [0.079]*
D(UPI (-5))	(-0.308) [0.038]*	D(UPI (-5))	(-0.159) [0.081]*	D(MB)/WLESS (-3)	(-17.957) [0.0928]*	D(UPI (-5))	(-0.160) [0.079]*
D(MB)/WLESS	101.354 [0.000]*	D(NT1 POS)	3.59E-06 [0.001]*	D(MB)/WLESS (-4)	(-39.259) [0.000]*	D(NT1 POS)	3.64E-06 [0.001]*
D(RTGS POS (-5))	5.037 [0.000]*	D(NT1 POS) (-1))	2.46E-06 [0.015]*	D(M1/GDP POS)	(-42.264) [0.044]	D(NT1POS) (-1)	2.48E-06 [0.015]*
D(RTGS NEG (-1))	5.127 [0.000]*	D(NT1 NEG (-1))	5.36E-06 [0.000]*	D(M1/GDP POS (-2))	64.404 [0.092]*	D(NT1 NEG) (-1)	5.33E-06 [0.000]*
D(RTGS NEG (-2))	3.572 [0.043]*	D(NT1 NEG (-3))	2.38E-06 [0.002]*	D(M1/GDP POS (-3))	(-74.420) [0.023]*	D(NT1 NEG) (-3)	(2.36E-06) [0.003]*
D(RTGS NEG (-4))	7.210 [0.000]*	D(NT1 NEG (-4))	2.64E-06 [0.009]*	D(M1/GDP NEG (-1))	112.234 [0.012]*	D(NT1 NEG) (-4)	(2.62E-06) [0.009]*
D(RTGS NEG (-5))	3.960 [0.0127]*	D(NT1 NEG (-5))	1.24E-06 [0.034]*	D(M1/GDP NEG (-2))	(-156.85) [0.000]*	D(NT1 NEG) (-5)	(1.23E-06) [0.036]*
D(M1/GDP (-1))	111.365 [0.000]*	D(M1/GDP (-1))	95.569 [0.001]*	D(M1/GDP NEG (-3))	171.346 [0.000]*	D(M1/GDP (-1))	95.370 [0.002]*
D(M1/GDP (-2))	62.398 [0.0176]*						
D(M1/GDP(-3))	48.430 [0.050]*						
D(M1/GDP (-4))	78.066 [0.002]*						
DUMMY	114.400 [0.000]*	DUMMY	41.485 [0.022]*	DUMMY	32.102 [0.051]*	DUMMY	41.06087 [0.024]*
CointEq (-1)	(-0.039) [0.000]*	CointEq (-1)	(-0.081) [0.000]*	CointEq (-1)	(-0.032) [0.000]*	CointEq (-1)	(-0.083) [0.000]*
R-Squared (R^2)	0.942	R-Squared (R^2)	0.914	R-Squared (R^2)	0.891	R-Squared (R^2)	0.913
Durbin-Watson Statistic	2.406	Durbin-Watson Statistic	2.283	Durbin-Watson Statistic	2.408	Durbin-Watson Statistic	2.281

Note: Software used for estimation EViews 10. ARDL models considered are case II: Restricted Constant and No Trend. * Relevant estimations.

Negative shocks of M1/GDP will also produce diminishing volumes of transactions in 1.12%. With a decreasing M1, after the second period, more people would use their money in the bank to consume, increasing instant payments by 1.56%. Overall, UPI payments suffer a bigger impact through negative shocks than positive shocks. In periods of economic downturns, agents prefer to retain liquidity (paper money or demand deposits) postponing spending due to economic uncertainty (Keynes, 1996), limiting their expenses to autonomous consumption. Currency allows agents to keep options open in face of unpredictable outcomes (precautionary demand).

As seen in models 01 and 02, in **model 04** UPI's past volumes have negative and positive impacts on UPI present value. Similar to model 02, credit card transactions in point-of-sale terminals (NT1) are decomposed in positive and negative variations. Positive shocks to credit card transactions increase the volume of UPI instant payments immediately in 3.64×10^{-6} and in 2.48×10^{-6} after a lag (at a p-value < 0.05).

Negative shocks will also affect UPI transactions, considering the estimated lags in Table 10. Level of development of the financial system (M1/GDP) will increase instant payments in 0.95%. Dummy coefficients are significant in all four models and error correction terms (CointEq), were negative and relevant at the 1% level. In models 01 and 03, 3% of deviations from the long-term trajectory will be corrected in the next month, totalling two years for total conversion. In models 02 and 04, 8% of deviations will be corrected in the next period, with full adjustment occurring in a year.

Estimations confirm that mobile banking volumes are relatively constant over time; however, an immediate positive short run shock, incentivizes instant payment transactions. Directly impacted by the central banks monetary policy towards currency emission, M1/GDP can negatively impact UPI transactions, converting into a positive impact owing to a rise in deposits. Monetary economics are highly prone to downturns in economic activity, in which valleys becomes deeper and steeper than peaks: *"The substitution of a downward for an upward tendency often takes place suddenly and violently, whereas there is, as a rule, no such sharp turning point when an upward is substituted for a downward tendency"* (Shin *et al.*, 2014 *apud* Keynes, 1936, p.314).

These dynamics most clearly show the prevalence of nonlinearities in economics. Three out of four models presented statistically relevant short run asymmetries. Since payment system volumes are closely linked to major economic upturns and downturns, and particularly prone to habits developed by economic agents, correctly capturing short run asymmetries are important to illuminate response differences. Asymmetric Wald tests will confirm short-run relationships.

4.3 Asymmetric relationships

The final procedure is to test if the difference in asymmetric coefficients are statistically significant. Short run non-linearities according to Shin *et al.* (2014, p.17) are considered an: "*impact asymmetry, associated with the inequality of the coefficients on the contemporaneous first differences* Δx_t^+ *and* Δx_t^-*.*" In other words, the short run Wald Test evaluates the equality of the sum of the positive and negative lags of each regressor. The null hypothesis H_0 states that the two impacts are the same (symmetrical) and there is no short run asymmetry. Rejecting H_0 of summative symmetric adjustment and accepting the alternative is evidence of short run asymmetry:

$$H_0\colon \sum_{i=l}^{q} \sigma_i^+ = \sum_{i=l}^{q} \sigma_i^-$$
$$H_A\colon \sum_{i=l}^{q} \sigma_i^+ \neq \sum_{i=l}^{q} \sigma_i^-$$

The Wald statistic follows an asymptotic χ^2 distribution. Using the stepwise regression, with a unidirectional selection method (forward) and a stopping criterion at the 0.05 p-value on short run coefficients, asymmetries were tested (Table 23). Even though there was indication of short run asymmetries between UPI and RTGS, NARDL model 01 (6,1,6,6,6), with 6 lags was unable to provide consistent estimates. Examining model 02 (6,0,2,6,2), with positive and negative shocks of credit card transactions in volume (NT1), the short run Wald test found Chi-square (χ^2) statistic that confirmed asymmetry between NT1 and instant payments (UPI) at a 5% p-value. The NARDL model 04, also arrived at the same results, with a Chi-square (χ^2) estimate that corroborated short run asymmetry between NT1 and UPI (p-value < 0,05). These correlations show that short run negative shocks from credit card transactions (NT1) will produce bigger spill overs to instant payments[129].

[129] Performing the long run asymmetric Wald test on **models 02 and 04**, there are significant nonlinearities in which magnitude of change in instant payments are bigger when credit card volume decreases (becomes negative). Long run positive shocks produce instant payments increase, but a negative shock increases even more the volume of instant payments, indicating possible substitution effects on the long run. Long run or reaction asymmetry is identified through the following Wald test, (which is basically a division of the negative and positive shocks by the dependent variable coefficient).

$$H_0\colon \frac{-\gamma^+}{\rho} = \frac{-\gamma^-}{\rho}$$
$$H_A\colon \frac{-\gamma^+}{\rho} \neq \frac{-\gamma^-}{\rho}$$

The null hypothesis H_0 states that the two impacts are the same (symmetrical) and there is no long run

Table 23 - Short run Asymmetric Wald Test. All four NARDL models (6 lags). Dependent variable Unified Payments Interface (UPI) (Indian Dataset).

	Positive and Negative Shocks	Model	Lags	Wald Test [Prob]
Model 01	RTGS +, RTGS -	NARDL (6,1,6,6,6)	6 lags	-
Model 02	NT1 +, NT1 -	NARDL (6,0,2,6,2)	6 lags	χ^2 (1) 23,130 [0,000]
Model 03	M1/GDP +, M1/GDP -	NARDL (1,5,0,4,4)	6 lags	χ^2 (1) 8,335 [0,003]
Model 04	NT1 +, NT1 -	NARDL (6,2,6,0,2)	6 lags	χ^2 (1) 22,923 [0,000]

Note. NARDL model with a maximum of six (6) lags. Model choice based on Akaike Information Criteria. Case 1: no constant and no trend, **case 2: restricted constant and no trend, ***case 3: unrestricted constant and no trend, ****case 4: unrestricted constant and no trend; *****case 5: unrestricted constant and unrestricted trend. Source: author's elaboration (EViews 10).

Giving further emphasis to level of financial sophistication (Gala, Araújo e Bresser-Pereira, 2010; Edwards, 1995), positive short run impacts of the M1/GDP ratio (model 03) demonstrates how monetary policy and economic growth are important to volume of instant payments. Technological enhancements in payment systems can reach sectors of society that are not completely integrated with the financial system, the partially unbanked. Macroeconomic policies will have a significant short run impact. Negative M1/GDP shocks will produce an immediate response with retraction throughout the economy, counter cycle measures will only produce positive outcomes with a lag. Depending on which direction public policies are taken and economic conditions, there will be excessive volume changes on instant payments.

5. CONCLUSIONS

The world has observed substantial transformations in financial and payment systems with the rise of new private platforms. In the midst of these digital transformations are retail Instant/Fast Payments, which provide speed and continuous service availability, such that the payee has unconditional and irrevocable access to funds.

Central banks have become relevant actors in policy deployment establishing common standards, procedures, even taking on an operational role increasing efficiency and system resilience. Pix and UPI are examples of such user-centric policies, conveying not only financial inclusion but demand-oriented instruments improving the experience of payers, while also

asymmetry. The alternative hypothesis H_A, confirms the existence of long run asymmetry between the coefficients. Rejecting H_0 and accepting the alternative, means that there is long run asymmetry, and the magnitude of the change in Y when X increases (decreases) is not the same as when X decreases (increases).

making use of back-end infrastructures that were already put in place in Brazil (restructuring of the Brazilian Payment System between 1999/2002) and Demonetisation in India.

Progressive digitalization of currency, the financial dimension of digital monetary sovereignty, the COVID-19 global pandemic put forces into motion and Pix was implemented in November 2020. To comprehend the instant payment phenomenon, UPI was chosen as a study case for the Brazilian Pix. The Indian Unified Payments Interface (UPI) is a low-cost layer service created over the backbone of the Immediate Payment Service (IMPS). Using virtual payments address (VPA) a unique UPI ID shields account details while making payments or requesting them

Through short run and long run estimations, the main contribution of this paper, in comparison with the reviewed literature Reddy & Kumarasamy (2017), Chaudhari *et al* (2019), Raj *et al* (2020), Lubis *et al* (2019), Yilmazkuday (2011) Rooj & Sengupta (2020), is identifying underlying instant payments characteristics, through financial sophistication (M1/GDP), economic growth (RTGS), payment substitutes (NT1/ NT2) and a measure of relative popularity of banking apps (MB/WLESS).

UPI empirical models (April 2016/ November 2020) confirm very high adoption rates in the first months of implementation, in which credit and debit card usage is expected to propel instant payments. Taking into account the timeframe studied (April 2016 to November 2020) with 56 observations, they are much more a complementary means that increase faster payments usability and acceptability. Bigger usage of banking apps in India, induces more instant payment transactions and financial deepening (M1/GDP).

Interlinked with economic growth, and considered a proxy for all payments made in the Indian economy (Rooj & Sengupta, 2020; Lee & Yip, 2008) Real Time Gross settlement System (RTGS) is statistically relevant in the short run with positive effects on instant payments (volume wise). Credit card transactions (NT1) have a lag effect, while MB/WLESS and M1/GDP ratios can produce an immediate impact on instant payment transactions. However, negative shocks on instant payments, can also be explained through bigger positive changes in these variables.

Short run non-linear (NARDL) estimations showed that ratio of mobile banking transactions to mobile phone subscriptions (MB/WLESS) and level of development of the financial system (M1/GDP), increased instant payment volumes. If there is increasing mobile banking transactions to mobile phone usage; this causes an immediate impact of 0.95% (models 02 and 04). The proxy for depth and sophistication of the financial system (M1/GDP) (Gala, Araújo e Bresser-Pereira, 2010; Edwards, 1995), has a clear effect on real-time payments. Emphasizing also a bidirectional causality between them.

Decomposing credit card transaction volume (NT1) (models 02 and 04) and M1/GDP, UPI volume responds positively to credit card transactions and inversely to M1/GDP in which impacts will only be felt with a lag. Concluding that instant payments are more affected by short run negative shocks than by positive ones. Highly sensitive to economic conditions, agents shade themselves retaining liquidity, limiting consumption. Credit, debit card and mobile transaction volumes are viewed as means to increase UPI/Pix usability and acceptability through payer/payee flow mechanisms in the short run.

Fast payments have developed more rapidly where there are two important factors aligned: limited options of payment alternatives and high penetration of mobile phones (D'Silva et al, 2019). This may well been created artificially in the Indian case through a forced digitalization during Demonetization period (2016/2017).Nonetheless, for the Brazilian economy, that had a comparatively lower currency dependence that argument is valid.

New technologies and systems could mitigate risks, enabling widely accessible, low-cost digital payments that might broaden financial inclusion. In light of a macro view of payment systems, credit, debit card and mobile transaction play supportive roles on the long run. An increase in relative popularity of banking apps directly impacts instant payment volumes in the short run. Financial sophistication and economic growth are also important in promoting a greater impulse for real-time payment applications.

Reducing transaction fees through instant payments enhances economic activity, assisting the informal sector redirecting transfers to the real side of the economy. If per capita income and standard living are rising, economic logic leads us to the understanding that purchasing power grows incentivizing transactions, deepening development and sophistication of the national payment system.

Academic evidence of the importance of using digital technologies and internet services for economic and social development are abundant (Alves et al, 2018). Domestic context plays into the main challenges for financial inclusion such as adequate digital infrastructure (broadband coverage), affordable electronic devices, digital, financial literacy, assuring population accessibility (Araujo, 2022). Half of all Indians do not own a smartphone capable of downloading an app to transact over a 3G network. Adequate internet connectivity coverage may also be lacking in important and relatively remote areas (EICHENGREEN ET AL, 2022).

Internet access services are also unevenly distributed across the Brazilian territory, with infrastructure gaps in lower-income regions. There is an overall concern that a shift away from cash will disintermediate the elderly, the poor and the technologically disadvantaged. Public policies towards universalizing quality signal, is not only necessary to develop financial sophistication but to promote economic growth: *internet inequality not only reflects the country's socioeconomic disparity but also helps reinforce it* (PwC, Instituto Locomotiva; 2022, p.27). This is a highly important avenue for future studies; internet connectivity in low-income districts might have a relevant impact on information access, reducing inequality, digital and financial inclusion[130].

[130] The World Bank and IPEA have estimated that doubling a country's average connection speed can increase the GDP growth rate by about 0.3 p.p. increasing access to information and reducing inequality (ALVES et al; 2018).

PAPER 4. CENTRAL BANK DIGITAL CURRENCIES (CBDCS) IN EMERGING MARKET ECONOMIES

"festina lente"
Make haste slowly (Subbarao, 2022)

Resumo: Este artigo visa delinear teoricamente as principais ressalvas para a implementação de uma Moeda Digital do Banco Central (CBDC) apresentando-a como uma alternativa institucionalizada para ativos digitais e provedores de serviços de pagamento privados (PsP). Com base em Khiaonarong & Humphrey (2019) levando em consideração estatísticas mais amplas de uso de dinheiro no Brasil e na Índia, retiradas do BIS (2012-2020), direcionamos a discussão para pagamentos sem dinheiro como alternativas concorrentes, no contexto de economias de mercado emergentes. A análise teórica e um exercício de extrapolação baseados nos índices destes autores fundamentam nossas descobertas de que a demanda por alternativas digitais ao dinheiro é baseada na diminuição do seu uso, em uma sociedade cada vez mais conectada virtualmente. As Moedas Digitais do Banco Central (CBDCs) encontrarão seu lugar nesse ecossistema se oferecerem atributos e características que as diferenciam de alternativas atualmente regulamentadas.

Abstract: This article aims to theoretically outline the main caveats for the implementation of a Central Bank Digital Currency (CBDC) presenting it as an institutionalized alternative to digital assets and private payment service providers (PsP). Building on Khiaonarong & Humphrey (2019) taking into account broader cash use statistics in Brazil and India, taken from the BIS (2012-2020), discussion is directed to cashless payments as competing alternatives, in the context of emergent market economies. Theoretical analysis and an extrapolation exercise based on these authors' indices support our findings that demand for digital alternatives to cash is due to decreasing use in a society that is highly digitalized. Central Bank Digital Currencies (CBDCs) will find their place in this ecosystem if they offer attributes and characteristics that differentiate them from currently regulated alternatives.

1. INTRODUCTION

With the ubiquity of electronic devices, high-speed networks, coupled with blockchain innovation popularized through cryptocurrencies, there has been a growing interest not only from the public but from international financial organizations on payment systems. What was deemed esoteric a few years ago, today is a reality in many parts of the world. Private initiatives proliferate, with digital representations of value that can be transferred at the click of a button and in some cases across national borders.

New methods of financial intermediation and their underlying technological breakthroughs take place within a larger story of economic disruption and regulatory reform. New capabilities, business models are results from a series of emerging innovations such as machine learning, blockchains, future quantum computing, driving automation and new functionalities that will change provision of financial services (PAYPAL; 2021).

Payment systems are overseen by central banks, which can take an additional step forward in enhancing and operating these key infrastructures (Duarte et al, 2022). Nonetheless, safety and stability towards payments and finance varies significantly in a highly digitalized society, leading central banks around the world to explore testing projects, in regard to, operational and technological aspects of issuing a central bank digital currency (CBDC) (FED, 2022; ADRIAN & MANCINI-GRIFFOLI, 2021; BCB, 2022).

A Central Bank Digital Currency (CBDC) is defined as a digital liability on the central bank's balance sheet that is widely available to the public[131]. A digital fiat currency that has a full backing of the central bank. In this respect, they are analogous to paper money but different from existing forms of digital commercial bank money available. According to IMF data, CBDCs are being analysed, piloted, or likely to be issued in at least 110 countries. Examples range from the Bahamas' Sand Dollar (already in use) to the People's Bank of China e-CNY pilot project and the Digital Real in Brazil (FED, 2022; ADRIAN & MANCINI-GRIFFOLI, 2021).

The Fed hesitantly is just now analysing the pros and cons of issuing a Digital Dollar, in its recent publication *"The U.S Dollar in the Age of Digital Transformation*". Rogoff (2022a)

[131] That´s the main difference of what we see today with other widespread forms of digital cash like direct deposit, debit and credit cards in which commercial banks will update the client's account balance against its own reserves (RATHBURN, 2022).

clarifies the air towards the Fed's laggard approach. The dollar's international dominance brings the United States insurmountable benefits, with low-interest rates and control over international funding. Privileged access to information on worldwide transactions and advantage over the global financial system's plumbing, allows the US authorities to impose significant financial sanctions[132].

Although the United States government has considerable regulatory and legal power to enforce the adoption of its digital currency, which could conceivably undercut international crypto demand, public acceptance is crucial. Adding to these pressures are the range of technologies and governance issues that could shape a CBDC, leaving very little margin for adoption failure.

With big tech, fintech firms moving into financial services and technology platforms planning to launch their own digital assets (with a suite of services for their billions of clients) substitution of domestic currencies by transnational private digital ones are feasible in a proximate future. When pulling transactions away from the domestic banking network and into private ecosystems, monetary sovereignty and economic stability could be threatened in the medium to long-term, diminishing the central bank's ability to set interest rates, control money supply and manage inflation (SUBBARAO, 2022).

Private technological advances have addressed (or attempted to address) long-lasting problems with the payment system, ushering in push-type central bank innovations. Countries like Brazil and India with a large informal economy, low-income levels and limited financial literacy, Instant/Fast Payments stepped in to address this gap in access to the formal banking system. Launched by the Brazilian Central Bank (BCB) in 2020, 15 months after launch (Febuary 2022), 114 million individuals, nearly 67% of the Brazilian adult population had made or received a Pix transaction[133].

On the other spectrum, cross-border payments currently face several challenges, including slow settlement, high fees and limited accessibility. These types of payments directly affect micro, small, medium-sized enterprises (MSMEs) that participate in cross-border trade making payments to global suppliers. They typically face higher fees, waiting much longer than larger retail customers (Feyen et al., 2021). Reducing these costs could benefit economic growth, enhance commerce, as retailers could receive payments cheaply and instantly from

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[132] The United States currently maintains financial sanctions on more than a dozen countries, hundreds of entities, and thousands of individuals, crypto becomes a natural refuge (ROGOFF, 2022b).

[133] The BCB decided to make Pix transfers free of charge for individuals, and a paying low fee for PSPs (BRL 0.01 per 10 transactions), which coupled with ease of use has increased its reach (nearly 33.2 transactions per capita) a record among peer jurisdictions (DUARTE ET AL, 2022).

foreign customers.

High remittance costs also have a significant impact on households that depend on these transactions. Transferring money back and forth across borders through traditional channels can be prohibitively expensive, especially for developing economies (Adrian & Mancini-Griffoli, 2021; Fed 2022; Wheatly & Klasa, 2021). Dependence on remittances and dollarization may have pushed El Salvador to adopt Bitcoin (BTC) as legal tender. Nevertheless, making Bitcoin (a notoriously volatile asset and not subject to institutional controls) into legal tender was and is showing to be a highly unjustifiable social gamble.

With little support from Salvadorans (seven in 10 Salvadorans don't want Bitcoin as legal tender), while halting negotiations with the International Monetary Fund (IMF), and backlash from the World Bank, fears over the crypto asset's effect on macroeconomic stability, financial system integrity, and the pandemic recession is concrete (Nugent, 2021)[134]. Another growing concern to regulatory bodies is the closer correlation between cryptos and traditional holdings in developing countries (US technology stocks, government bonds, and crude oil), that could raise contagion risks across financial markets (FLOOD,2022; ADRIAN & MANCINI-GRIFFOLI, 2021; ADRIAN, IYER, QURESHI; 2022; IYER, 2022).

Cryptocurrencies payment capabilities are limited to the crypto exchange "*shadow economy*" around the world (off chain transactions) or through the Bitcoin blockchain, enhanced by the second tier[135] of payments (the lightening network). Knowing that its value is still limited compared to traditional money markets, spill overs through payments could come from widely adopted stablecoins like Tether and their need to maintain a value at par with the US dollar. A run on its value is quite possible (or even probable) as exemplified by the Terra Luna incident.

CBDCs could offer a safer centralized alternative, with opportunities to emerging market economies. However, there are no small challenges to be faced by Central Banks in the issuance of CBDCs: bank disintermediation, technology choices and privacy concerns are the most important ones. Albeit, particularly relevant to Brazil and India, is that if instant payments

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[134] These possible consequences are not exclusive to El Salvador. According to the IMF (2021), sharp price swings in cryptos may cause "destabilizing" capital flows, with "immediate" and "acute risks" to emerging markets, as a result if their existing established currencies being replaced by crypto assets, a process that has been called "cryptoisation". Capital flows that are transmitted through new instruments, channels and service providers, an unregulated shadow banking, parallel market, are a challenge for regulator's toolkit and a threat to "*status quo*".

[135] Blockchains are often referred to as "layer 1" networks, ie the base networks that can validate process and finalise transactions on the chain without the need for another network. "Layer 2" solutions build on layer 1 networks, but transactions mostly happen off-chain and are only sporadically reported back to the underlying layer 1 chain (BOISSAY ET AL, 2022, p.2).

have delivered financial inclusion and immediate settlement why adopt a CBDC?

This section provides an overview of this discussion, as specific objectives rest upon putting forward arguments that emphasize design issue considerations and arguments as to why emerging market economies (EMEs) are most susceptible to implement CBDCs. Substantiating Brazilian and Indian central bank-led transformation, four measures of Cash Share to payments are analysed for Brazil and India, through annual BIS (2012-2020) data, based on Khiaonarong & Humphrey (2019). Our best index is used for a small exercise through linear regression prediction (MathCad) in an attempt to estimate possible future trends on how cash shares will behave in the years to come based on previous annual data. Falling currency in circulation is attributed to younger adult's preferences in using less cash, in this new digitalized environment.

Governments need to maintain legitimacy over a system that is being increasingly contested by private digital assets and a new type of shadow market. Digital money should be designed requiring expertise, discretion and public interest. Remaining trustworthy, protecting consumers' wealth, safety and anchored in legal frameworks (Adrian, Iyer, Qureshi, 2022). Inexperienced investors could easily lose their scant savings and notably, those who are excluded from traditional financial services are the ones who cannot afford to take any risks with their money.

This paper is divided in two main parts and four subsections. Sections 2 and 2.1 provide a theoretical overview of the monetary system, substantiating definitions and design attributes of a CBDC. In section 2, we delineate how emerging market economies (EMEs) have stronger motivations to issue a fiat digital currency liability than advanced economies (AEs). To illustrate this argument measures of cash use in Brazil and India are pared with a simple linear prediction model in section 3.1. The last section are final comments and conclusions.

2. THE MONETARY SYSTEM AND WHY ISSUE A DIGITAL CURRENCY?

A monetary system is typically defined as money plus the mechanisms to execute payments. Playing an active role in overseeing the national monetary system, one of the central bank's mandate is to ensure that payment systems function smoothly and that reserves adequately respond to changes in money demand. To keep the unit of account and the means of payment stable, traditional settlement and custody systems are safe, economical, handling high volumes of transactions daily, accommodating growth in payment volumes quickly, efficiently and at low costs (BIS; 2018)[136].

Borio (2019) emphasizes that there has been a strong tendency to abstract from payment mechanisms and assume that they operate smoothly in the background. Money is much more than just a convention it is also a social institution. It needs infrastructure to ensure that it is widely accepted. Transactions, contracts are fulfilled and agents can rely on the systems that are put in place. The high volume of payments in our modern economies highlights how important they really are[137].

Economic uncertainty typically generate fluctuations, induces instability in the value of money (and debt), in terms of goods and services, undermining currency as a means of payment and a store of value. Trust must be embodied through these mechanisms, as they are the social tissue, which maintains the monetary system. To secure both price and financial stability, the central bank relies on its balance sheet to supply the means of payment, to set interest rates and to manage foreign currency reserves (BORIO, 2019).

Given that CDBCs could have potential destabilizing consequences for the financial system why then study the possibility of implementing it? The primal impulse for these changes in policy thinking are global tendencies that have been around for a while: velocity in payments, globalization, big tech and demographic change.

The quest for speedier payments is old (Carstens, 2019). Faster systems for retail payments have emerged, allowing the public to receive funds within seconds, anytime and anywhere. Real-time gross settlement systems (RTGS) have been accelerating payments since the 1980s. On the other hand, globalization has increased demand for international payments, and since most of them still rely on bilateral relationships between commercial banks, this subsidizes noteworthy power to big tech companies. Lael Brainard (2019) was quite blunt in exposing the potential pitfalls of the emergence of a digital global stablecoin, backed by a basket of sovereign currencies, Facebook´s late Libra (Diem) project. Digital payment methods from big tech companies have unprecedented network and scale advantages. Adopted on a global scale and in a very short time, it could quickly establish itself as a new unit of account.

Retail financial and payment innovations (cryptocurrencies, global stablecoins and private payment providers) pushed financiers, market regulators and academics to rethink whether central banks should in fact reinvent national currencies. That said Central Bank Digital Currencies (CBDCs) could serve as a tangible marker of trust in money (Chen et al., 2022)

[136] Scalability is important because despite the large volume of payments being equal to many multiples of the GDP, the expansion of its use does not lead to a proportional increase in costs (BIS, 2018).

[137] Volumes exceed GDP many times over, thousands of times in fact. Largely payments correspond to financial transactions and their sheer volume dwarfs “real” economic activity (BORIO, 2019).

aiding central banks in maintaining their role as issuer of the unit of account and anchor of the monetary system.

Extensive work about CBDCs are being done worldwide (Boar et al, 2020). Central banks in emerging economies are generally more strongly motivated than advanced economies, especially when the CBDC is designed as a complement or substitute for money (ENGERT & FUNG, 2017; KHIANARONG & HUMPHREY, 2019; BOAR ET AL, 2020; KOSSE & MATTEI, 2022; SODERBERG ET AL, 2022; CHEN ET AL, 2022).

Motivations are described depending on country specificities. One of these particularities is demographic change, a strong force behind decreasing cash usage (Khianarong & Humprey, 2019). As younger adults tend to favour non-cash payment methods over cash, this progression will be hard to stop or reverse, as they form a bigger percentage of the labour force. Nonetheless, a more complete assessment of these motivations depends on the nature of a CBDC, its design, generating different trade-offs. Complexity plays into structure implementation, which drives different outcomes. In other words, effects would depend on its attributes, which is difficult to predict, given the extent of the innovation implemented. The next section highlights definition and design characteristics.

2. 1 Definition, design characteristics

There are numerous definitions of what a Central Bank Digital Currency (CBDC) is, including what are their most important characteristics (Meaning et al, 2018). In an attempt to clarify terminology Barrdear & Kumhof (2016, p. 7) state that: "*By CBDC, we refer to a central bank granting universal, electronic, 24x7, national-currency denominated and interest-bearing access to its balance sheet*." According to Meaning *et al.* (2018, p.4), a Central Bank Digital Currency is "*simply an electronic, fiat liability of a central bank that can be used to settle payments or as a store of value".* The FED (2022, p. 13) formulates that: *a CBDC is formally and broadly defined as a type of digital money issued by the central bank denominated in the same way as its currency* .

It is a sovereign currency in an electronic form representing a direct claim on the central bank's balance sheet exchangeable at par with cash (Sankar, 2021). It differs from existing forms of cashless payment instruments available to consumers and businesses (i.e: credit transfers, direct debits, card payments and e-money). Boar *et al* (2020) and Kosse & Mattei (2022) distinguishes two types of CBDCs through their accessibility levels: a wholesale and a retail CBDC. A wholesale digital liability is a restricted-access form of money targeted to financial institutions for interbank payments and securities settlement. The general-purpose variant (retail) is a publicly accessible option for storing value and making payments, similar to “digital money”.

Bech & Garratt (2017) presents a taxonomy within their representation of the “monetary flower”. The analysis focuses on a subset of “currencies” based on cryptographic technology and discusses the central bank's cryptocurrencies (CBCCs) instead of CBDCs. In this study CBDC is interpreted as a digital retail universally accessible currency, a step forward to the traditional monetary system which presents two forms of central bank money: cash (settlement system) and reserves (custody system) (CARSTENS, 2019; MEANING ET AL., 2018, FED, 2022).

With a settled definition of what is a Central Bank Digital Currency (CBDC), design characteristics are the next single most important attribute. To operationalize policy goals CBDCs clearly depend on: 1) Technology; 2) Operating Model; 3) Design Features; 4) Legal Foundations; and 5) Project Implementation. We will restrict ourselves to the first three, considering the underlying objective of this paper. A basic crucial choice is how CBDCs will be issued, circulated, and the roles of the central bank and the private sector.

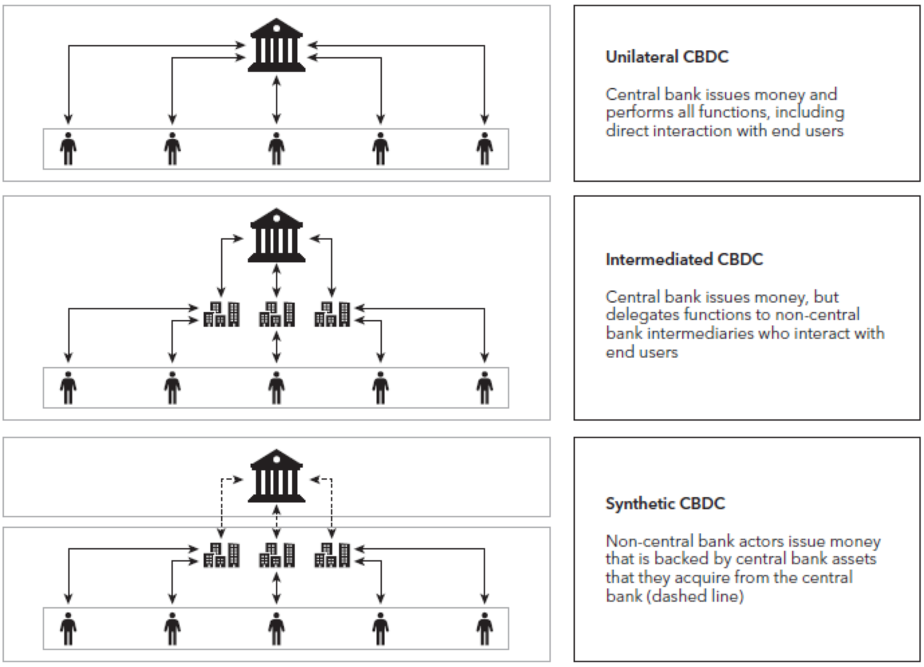
Bordo & Levin (2017) propose that a CBDC could be created from accounts held directly at the central bank, serving as a medium of exchange at virtually no cost[138]. Citizens and companies could open accounts at the monetary authority, instead of depositing their funds at commercial banks, as is today. In other words, it would be a *unilateral CBDC* (a one-tiered model) when the central bank carries out all the functions in the payments system (issuing, distributing and interacting with the end-users), keeping records of transactions and balances (Figure 9).

The *intermediated* CBDC also entails issuance by the central bank, but it includes a role for commercial banks and private sector firms, conducting customer-faced services. In the third and final model, the digital currency is not issued by the central bank but by designated financial institution that backs the issuance by holding CBDCs. This third model will not be a CBDC but rather a special type of stablecoin and it is referred as to a *synthetic CBDC* or *sCBDC* (SODERBERG ET AL., 2022).

[138] For the initial creation of each CBDC account, the identity of the account holder would need to be verified using procedures similar to those followed when obtaining a driver's license, or when opening a commercial account. But from that moment on, transactions could be carried out quickly and the central bank will be able to monitor any unusual activity and implement additional anti-fraud policies if necessary (BORDO; LEVIN, 2017).

Issuing, validation[139] and ledger update are crucial functions that need to be carried out in these systems, and they could be done in either a centralized (CLT) or decentralized form (DLT) across the network[140]. Should CBDCs be tokenized similar to a money-analogous project it could use some form of DLT[141] to verify ownership of each token. The central bank would determine the supply of CBDCs, fixed in nominal terms, having the option to encode, supervise and validate each transaction. Combining encryption with sophisticated self-execution[142] codes and data permissioned systems, the central bank maintains its exclusive right to add or modify entries to the ledger (ENGERT; FUNG, 2017; RASKIN; YERMACK, 2016).

Figure 9 - CBDC Operating Models



Source: Soderberg *et al.* (2022, p.9)

The two main models (DLT and CLT) have relative advantages and disadvantages, and neither architecture fully dominates the other. The Bahamas and the Eastern Caribbean Central

[139] Issuing refers to the possibility that CBDCs will be a liability on the central bank, just like cash. Validation can take place in a distributed ledger technology and it could refer to more traditional processes including checking the user's identity, the authenticity of money and the availability of funds (SODERBERG ET AL., 2022).

[140] In terms of resilience, the key vulnerability of the CLT system is the failure of the central entity, while the DLT system, which is based on the consensus mechanism, is a denial of service attack. On the other hand a DLT may offer more programmable or smart features (CHEN ET AL., 2022).

[141] *In the case of the DLT, at least three alternatives exist: 1) the central bank owns the infrastructure of the entire ledger and updates it (i.e. the Bahamas Sand Dollar); 2) the central bank owns the ledger, but private intermediaries update it; 3) a private intermediary owns part of the ledger and updates that same part of the ledger, conditional on the central bank's approval* (Soderberg *et al*, 2022, p.10).

[142] Some decentralized protocols like Ethereum already allow smart contracts that self-execute payment flows for derivatives (BIS, 2018).

Bank have DLT-based systems, and staff from both central banks cite technology security as valuable for their needs. The Public Bank of China (PBOC) has committed to a "hybrid architecture", with openness to different technologies. This is a part of what the PBOC calls a "*Long-Term Evolution System*", through which new features of technology can continue to be added to the e-CNY even though its core is a centralized ledger (SODERBERG ET AL., 2022).

The practical distinction between a decentralized token based and centralized account based CBDCs depends on the method of verification and its costs. Operational burdens include maintaining system stability and cyber security. A CBDC must be stable, scalable, robust and resilient, recovering from operational disruptions in a timely manner mitigating any associated credit and liquidity risks. Compared to a *unilateral CBDC*, where costs associated with user-facing activities rest squarely on the central bank, a two-tiered system (*intermediated CBDC*) would reduce the operational burden on central banks reducing verification costs[143] (CHEN ET AL., 2022; FEYEN ET AL., 2021).

Hypothetically speaking if deposits are retained in supervised accounts for a period, what would occur with the value of those CBDC funds in the central bank? Should CBDC's nominal value remain constant, be indexed to a general price level (thus preserving its real value) or earn interest like those paid on short-term government bonds? Design difficulties become clear as implementation of a retail fiat digital currency may lead to different consequences for monetary policy, as highlighted by the BIS (2018).

Unlike money, CBDCs can pay interest, securing its value, with a similar rate of return to other "risk-free" assets such as short-term government bonds serving as a potential tool for conducting monetary policy. Barrdear & Kumhof (2016) argue that a CBDC with built-in interest would lead to a huge increase in demand for central bank liabilities and in seigniorage.

In tandem, central banks are also concerned about the possibility of CBDCs disintermediating commercial banks (Chen et al, 2022). Paying interest on central bank deposits (CBDCs) is likely to attract deposits away from commercial banks (Khiaonarong & Humphrey, 2019). Concentration of deposits at the monetary authority would imply the end of fractional reserves[144] "narrowing" the banking system[145] .

[143] New transactions are collected in blocks and must be confirmed before being added permanently to the registry. This involves computational procedures that are highly complex and consume a lot of energy. As the entire property chain must be stored in an encrypted record and a copy of that ledger stored in each node.

[144] For Raskin & Yermack (2016) Fedcoin would represent the revival of the 1933 "Chicago Plan", a widely discussed academic proposal to end fractional reserves and restore public confidence during the Great Depression.

[145] Engert & Fung (2017) and Raskin & Yermack (2016) argument that policy would be easier to implement under a digital currency system. Allowing better response to the economic cycle and interest rate control guaranteeing efficiency in tax collection, anti-money laundering polices, fraud and theft detection. By not being the lender of last

Since bank deposits are a relatively inexpensive stable source of funding for commercial banks, increased competition for deposits could be a big incentive for banks to consider other financing sources. With raising funding costs, private banks would have to reduce credit creation or increase loan rates in direct competition with the central bank in face of a crowding out of private bank deposits (Keister & Sanches, 2018, 2020)[146]. Net cash inflows could decrease, banks may respond by increasing their risk exposure, changing business models over time, affecting financial stability, maturity transformation and banks' internal capacity to generate capital[147].

With CBDCs high in demand, this would lead to an expansion of the central bank's balance sheet, with a risk premium opening up between commercial bank deposits and central bank digital currencies. The monetary authority will need to hold additional assets such as government bonds, loans to commercial banks, international reserves, interfering with liquidity flow. Bank disintermediation is likely to be more abrupt in crises, given that CBDCs would have a safe haven status. This effect could be stronger in emerging market economies (EMEs) with less developed banking sectors (CHEN ET AL., 2022).

Potential destabilizing risks of introducing a CBDC (crowding out, facilitating bank runs…) with monetary policy implications, raises the question about imposing limits on CBDC transactions and balances. Those, which have a point of view, consider that limits on CBDCs fall under two main categories: restrictions on remuneration of CBDCs (they do not pay interest) and quantitive restrictions on holdings and transactions. Restricting convertibility between CBDCs versus bank deposits, limits competitiveness between them[148]. A non-interest

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resort, central banks would not be vulnerable to runs against commercial banks, and they would no longer need to raise deposit funds in the short-term to lend in the long-term. There would be significant changes in moral hazard between banks and monetary authorities.

[146] *By designing its digital currency so that it can be used in a wider range of transactions and/or offers a more attractive interest rate, the central bank can increase the quantity of publicly-provided (i.e., outside) liquidity held by agents. A larger supply of public liquidity, in turn, tends to promote more efficient levels of exchange. However, this outside liquidity may also crowd out inside liquidity in the form of bank deposits and thereby lead to a decrease in bank-financed investment. The optimal design of a digital currency may require striking a balance between these two competing effects* (Keister & Sanches, 2020, p.5)

[147] Garcia *et al*. (2020) examine this possibility by conducting a sensitivity analysis using regulatory data from 2018 and 2019 (before COVID-19), for the six largest Canadian banks. The authors find that the domestic systemically important banks were positioned to absorb potential temporary negative effects on profitability and liquidity associated with the introduction of a CBDC. High return on equity (ROE) and liquidity levels, could lead banks to assimilate the shock under plausible scenarios.

[148] Only the Bahamas, China and Eastern Carribean (ECCU) have a circulating CBDC, and they currently do no pay interest on these holdings. If there is no interest, CBDC can still be attractive as a means of payment, while its use as a store of value (savings instrument) diminishes. There is a potential policy trade-off between limiting competition with bank deposits and ensuring a effective monetary policy transmission mechanism. A possible solution is a CBDC with an interest rate that is consistently lower than the policy rate, imposing fees on transactions above a certain threshold. So far this has not been tried yet (SODERBERG ET AL., 2022).

bearing CBDC is consistent with objectives of providing a cash-like digital means of payment, trading at par with other bank liabilities keeping monetary policy in check [149] (SODERBERG ET AL., 2022; CHEN ET AL., 2022; FEYEN ET AL., 2021).

Regulatory concerns towards market concentration on the hands of the monetary authority could cause problems related to power abuse (Fernandez-Villaverde et al; 2020a)[150]. Nevertheless, private financial intermediation would continue with CBDC implementation (Andolfatto, 2018). As institutional designs, CBDCs will have a different impact on the nature of payments (Priyadarshini & Kar, 2021). Key to developing a socially relevant instrument incorporates the importance of performing market research to understand public needs, collaborating with participating private intermediaries and face-to-face contact with end-users. CBDC adoption will be driven by its usefulness to consumers and merchants, by themselves, they might not do much to increase deposits or encourage credit provision. The next section will provide important insights into why these fiat digital currencies would be important for emerging market economies.

3. CBDCS IN EMERGING MARKET ECONOMIES

Work on CBDCs has gained traction, after the Bahamas launched a live retail CBDC (the Sand Dollar) in 2020, Nigeria followed in 2021 with the issuance of the eNaira. The Eastern Caribbean and China released pilot versions of their respective DCash and e-CNY, with more to come. According to a 2021 BIS survey[151] (Kosse & Mattei, 2022) about 68% of central banks, consider that they are likely to issue a retail CBDC in the short or medium term. A share of 90% of central banks reported to be engaged in some form of CBDC work. Simultaneously, market capitalization of cryptos grew 3.5 times in 2021 to 2.6 trillion. Rapid crypto market

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[149] Meaning *et al* (2018) raises the possibility that the economy could start operating with two currencies simultaneously, at a managed exchange rate (in case of broken parity). Significant questions are raised when which of the two currencies, would be the unit of account of the economy. If both forms of the store of value were to be widely used in the economy, the prices of goods and services would need to be quoted in both, adding significant administrative costs.

[150] In another paper Fernandez-Villaverde *et al* (2020b) analyses implications for price and financial stability when CBDCs allow opening of retail deposits at the central bank, exposing it to demand from its depositors. Such a model emphasizes the role of banks in maturity transformation: banks finance long-term projects with deposits, which can be withdrawn in the short-term to meet liquidity shocks.

[151] In 2021, a record 81 central banks replied to the survey. The jurisdictions of the responding central banks represent close to 76% of the world's population and 94% of global economic output. Twenty-five respondents are in advanced economies (AEs) and 56 are in emerging market and developing economies (EMDEs) (KOSSE & MATTEI, 2022).

evolution and structural vulnerabilities has raised instability concerns, spurring central bank interest in CBDCs: on average six out of 10 central banks said that this growth has accelerated their work on digital fiduciary liabilities, with a special interest towards retail CBDCs.

Benefits of issuing a CBDC should definitely outweigh costs and risks. Being tailored and perfectly aligned to the country's national context, it could offer a range of public benefits. Top motivations for CBDC issuance vary across EMEs, with no single factor dominating (Chen et al, 2022). Policy goals often differ across jurisdictions, reflecting domestic challenges. However the most important ones according to Soderberg *et al* (2022)[152] are: 1) financial inclusion; 2) access to payments; 3) making payments more efficient; 4) resilience in payments; 5) reducing illicit use of money; 6) monetary sovereignty.

CBDCs are a potential tool that could offer a digital form of payment that is cheaper to operate. Just like fast payment mechanisms (the Brazilian Pix and the Indian UPI), they could increase efficiency (as an additional backup) in face of concentration risks in a few private alternatives. By directly and indirectly competing with existing payment forms, CBDCs could create low barriers of entry for firms seeking to offer new services. Providing an open infrastructure that lays down the "rules of the game", creating markets and delivering benefits to consumers (ENGERT & FUNG, 2017; CHEN ET AL, 2022).

The public sector subsidizes the cost of developing certain functions that private initiatives would not find profitable. Retail CBDC projects are carried out primarily with domestic payments in mind, as design features are crucial to increase financial resilience while developing solutions and improving access. Offline availability, compatibility with non-smartphones, e-Know Your Customer procedures (integrated with the national ID scheme like in India), merchant access and low-cost design, could aid users gain contact to new payment forms like CBDCs. Just like in instant payment deployment, an interoperable open system with no or low fees enhances adoption.

Availability of digital infrastructure, mobile phone, internet penetration, level of competition in payment systems and governance arrangements are factors that shape the objectives of CBDC issuance, determining their value added (Feyen et al, 2021, Chen et al

[152] Studying six advanced CBDC projects Soderberg *et al* (2022) shines some light on the frontier of development, studying and discussing their key experiences and lessons. The chosen CBDC projects follow the specified criteria: 1) A CBC that has been already issued (Central Bank of Bahamas (CBOB)); 2) A pilot CBDC that has been or is being tested involving actual households and firms (People's Bank of China (PBOC), the Eastern Caribbean Central Bank (ECCB) and Banco Central de Uruguay (BCDU)); 3) A CBDC project that has been brought onto the country's political agenda and is being analysed by government or parliamentary bodies (Sveriges Riksbank); 4) the central bank has carried out a CBDC project and decided against issuing a CBDC for the time being (Bank of Canada (BOC) . Lessons are typically country specific and need not be applied elsewhere, the sample of countries remain small and country circumstances differ widely.

2022, Kosse & Mattei, 2022). Nonetheless, banking history, currency crises, unsustainable monetary and fiscal policy, coupled with weak growth and high inflation attaints trust in the public sector, making private options more attractive to users in EMEs. This raises significant alarms if higher volumes of transactions start occurring through private payment providers and crypto exchanges.

Ultimately, cryptos, stablecoins and private digital assets could render less effective monetary policy transmission, especially in countries that face political, economic and financial distress. Countries with large cross-border inflows may face difficulties in maintaining international reserves, creating liquidity and redemption shocks, since foreign exchange (FX) markets are shallower in EMEs (SODERBERG ET AL, 2022, CHEN ET AL, 2022, FEYEN ET AL, 2021).

If from a host perspective there is potential that these assets could increase in market share, authorities may lack control over operations that involve residents. When domestically adopted at scale this could inhibit monetary authority effective oversight. Accessing "off-chain" exchanges citizens circumvent authorities, making information virtually inaccessible (FEYEN ET AL, 2021; ROGOFF, 2022b).

These activities occur outside safety net perimeters, which may lead to the build-up of considerable risks. Additionally, authorities in EMEs may have more difficulty in adjusting their surveillance given resource constraints. Emerging market economies will likely act as hosts to entities, which are possibly headquartered elsewhere. Relying on exchange and custody functions from intermediares and cross border wallet providers that elude "host" supervisory reach, calls for additional regulatory framework.

Biggest investors in cryptos may be in advanced market economies; however, uses and harms may have been mainly in EMEs. On the other extreme are countries that are looking to adopt Bitcoin as fiat currency. Knowing that El Salvador is already a fully dollarized country, this sets it apart from other Latin American countries, where the Dollar circulates, in cash, side by side with local currency. However controversial it may be, bearing low accountability towards population's resources, relying in a highly volatile asset as a store of value, a means of payment and a unit of account has led many analysts to question the level of acceptance of this new form of private "money" among Salvadorians (Edwards, 2021). Caution needs to be casted on arbitrary decision making that are potentially harmful for EMEs and especially the most vulnerable.

The alternative hypothesis is to accept that over time physical cash may be replaced by other instruments. As discussed above literature has focused primarily on: benefits of digital cash, why it may be needed and possible consequences. Particularly, Feyen *et al* (2021), addresses the potentialities of digital money (stablecoins and CBDCs), reviewing if motivation for adoption could differ between them. Factors relate to both supply side (the digital money provider) and the demand side (the end user, household or business) (Annex).

As Khiaonarong & Humphrey (2019), we direct our discussion to measures of cash use across Brazil and India, focusing on the demand side of digital cash. Using BIS annual (2012-2020) data we analyse measures of usage, concluding that the two best proxies show a decreasing trend in both countries. After analysing specificities for Brazil and India, policy goals that where treated in this section will gain clearer dimensions towards practical decisions that the Reserve Bank of India (RBI) and the Brazilian Central Bank (BCB) are taking towards implementing a digital fiat liability.

3.1. Measures of Cash Use in Brazil and India

CBDC demand will depend on cost and convenience for users compared to availible substitute payment systems. Without a competitive edge over currently used deployments, cash can continue to decline to such low levels that even the issuance of a digital form does no longer amass benefits to central banks. To measure changes in cash use, it is possible to estimate these indexes on a per person basis, as a ratio to GDP, using household consumption or cash expenditures plus the value of other payment instruments. On these definitions, we follow Khiaonarong & Humpfrey (2019), calculating four ratios in order to find the best (containing most information with the available data) for the Brazilian and Indian economy.

Roughly reflecting cash use in a country is currency in circulation (CIC) to nominal GDP (CIC/GDP). This ratio's main flaw is that the denominator does not exclusively reflect the value of consumption goods bought with cash. The second measurement takes the value of household consumption and subtracts the value of all non-cash payment instruments used domestic payments estimating the residual as cash use: $Resi\,dualHC = HC - (CARD + E - Money)$. Since it is not possible to subtract all non-cash payments, there is an overestimation on cash usage.

Assuming that money withdrawn from ATMs are entirely spent on household items, this value can be related to the value of domestic consumption: $Cash\,HC = ATM/HC$. This comprises our third approach. Per contra, as withdrawals do not include those taken over the counter at banks and cash back at point of sale, the measurement does not concentrate on cash purchases. The denominator lacks more precise estimations to include purchased consumption goods with cash and current direct substitutes (KHIAONARONG, HUMPHREY; 2019).

The fourth and final ratio uses the value of ATM cash withdrawals as a ratio to cash plus the value of the currently most popular payment instrument that substitutes for cash: $Cash\,Share = ATM/(ATM + CARD + E - Money)$. The main difference to the previous measure is that the denominator is smaller, conveying the best proxy according to Khiaonarong & Humphfrey (2019)[153]. Even though our data set is too small, we can try to identify if cash use is falling in Brazil and in India and pose questions as to why this is occurring. The Bank for International Settlements (BIS) was the source for annual data (2012/2020). The following variables were taken from country tables:

1) Total banknotes and coins in circulation (total value in billions of USD); (a proxy for Currency in Circulation)
2) Card and e-money payments (in value in billions of BRL/INR): were used to approximate major cash substitutes used in household final consumption expenditures. Cards include domestically issued cards for local and overseas purchases.
3) Cash withdrawals (with cards) inside the country were analysed in value in BRL/INR billions (a proxy for ATM withdrawals)
4) Final consumption expenditure as a percentage of GDP was taken from World Development indicators, used to estimate participation of household consumption (HC) in nominal GDP for Brazil and India.
5) Nominal GDP in billions of BRL/INR and in billions of USD.

Table 24 shows all four estimations for Brazil and India, from 2012-2020. Both countries ratio of currency in circulation (as total value in USD of banknotes and coins in circulation) to nominal GDP (CIC/GDP), decreases until 2016, to start on a growing direction after 2017. A polynomial time trend forms a mild u-curve that is steeper for India (Appendix). With a sharp decline in GDP in 2016, there was a parallel strong increase in CIC/GDP ratio for Brazil. Inversely demonetization influenced negatively this ratio for India (decline in currency

[153] There is still a problem of insufficient information on the value of other important payment deployments (i.e. instant payments) used to purchase consumption goods, and over the counter bank data of cash usage.

in circulation) marking an interruption in time series.

Residual cash use in terms of household consumption minus value of card and e-money payments shows the same linear growth trend, for Brazil and India indicating increasing cash use (Appendix). The underlying dilemma with this measurement is that it is overestimated, since it does not consider most non-cash payments (only cards and e-money), that go into household consumption. Brazil shows a more gradual curve shaped growth in 2012-2019, compared to the abrupt trend saw in India. Cash use in both countries drops during the last two years.

Table 24 - Cash use estimations for Brazil and India in annual data (2012-2020) based on Khiaonarong & Humphrey (2019).

		CIC (USD)/GDP(USD)	Residual Cash[154] (in billions of value in BRL/INR) = HC - (Card + E-Money)	Cash HC = ATM/HC	Cash Share (in billions value of BRL /INR) = ATM/ ATM+ card+e-money	Percent change of Cash Share
Brazil	2012	0,036931818	3.122,21	0,247063949	0,566746	
	2013	0,034817814	3.443,00	0,249418095	0,556305	-1,84227
	2014	0,033808554	3.774,32	0,248666233	0,548582	-1,38828
	2015	0,031737194	3.957,15	0,259502441	0,550486	0,34704
	2016	0,03946637	4.174,50	0,246913421	0,536665	-2,51061
	2017	0,036821705	4.317,61	0,244680728	0,520412	-3,02856
	2018	0,035490605	4.474,16	0,225876574	0,480590	-7,65212
	2019	0,037273695	4.461,26	0,228029957	0,440111	-8,42277
	2020	0,049134948	4.189,31	0,235908765	0,421326	-4,26823
India	2012	0,115529285	64.768,80	0,254609941	0,894737	
	2013	0,10960334	73.321,44	0,262049565	0,869565	-2,89474
	2014	0,112090064	81.491,30	0,257336133	0,846154	-2,76680
	2015	0,116961789	90.625,98	0,261435243	0,833333	-1,53846
	2016	0,085988651	99.132,13	0,224022438	0,750000	-11,11111
	2017	0,108993902	107.762,42	0,244184979	0,725000	-3,44828
	2018	0,1112722	117.597,30	0,248873852	0,687500	-5,45455
	2019	0,118685121	128.940,26	0,232972045	0,666667	-3,12500
	2020	0,146396396	125.356,67	0,206616473	0,659091	-1,14943

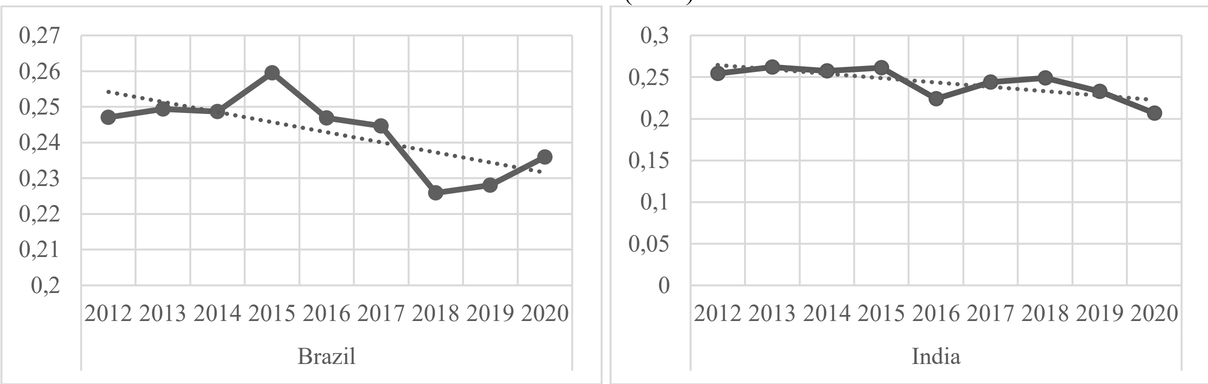
Source: Bank for International Settlement (BIS) and World Bank (2022). Author's calculations.

The last two estimations(Cash HC and Cash Share) are better approximations (Graph 13 and Graph 14) compared to previous ones. Cash to household consumption (Cash HC) comprise a more precise ratio, then CIC/GDP, focusing only on variables that can account for family spending in consumer goods, through cash withdrawn in ATMs. Overall, there is a decreasing linear trend for Brazil and India. Brazil shows stronger peaks (2015) and valleys (2018), and a slight rising trend in 2019/2020. Demonetization in 2016 accounted for the

[154]Household consumption (HC) used to estimate Residual Cash and Cash HC was calculated based on nominal GDP in billions (of BR/INR) and final consumption expenditure (in percentage of GDP).

strongest downward movement in India and the following inertia in decreasing money use.

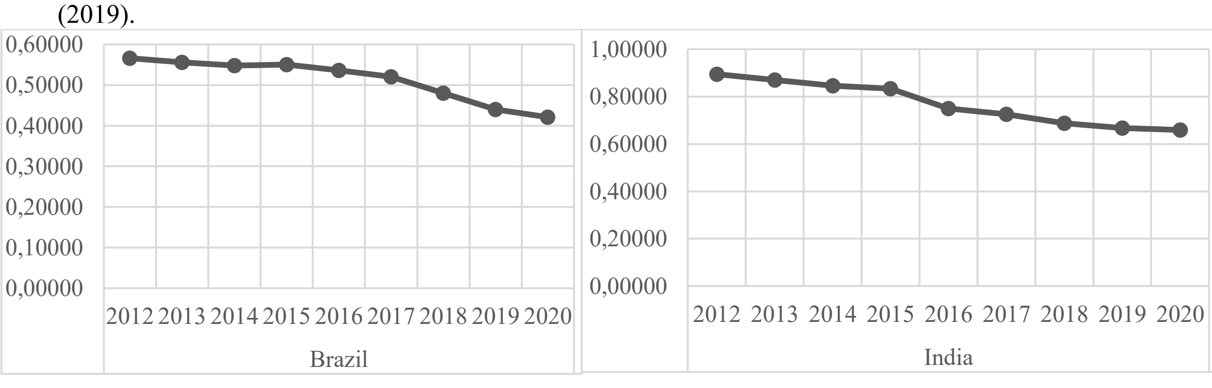
Graph. 22 - Annually Cash HC ratio for Brazil and India (2012-2020) based on Khiaonarong & Humphrey (2019).



Source: Bank of International Settlements (BIS) and World Bank (2022). Author's calculations.

Eight years of data through Cash Share ratio (Graph 14) show slowly decreasing cash use as younger adults favour non-cash payment methods (cards, mobile phones) over cash, while the reverse applies for older adults (Khiaonarong & Humphfrey, 2019). According to a research done by PayPal (2021) "*The Third Wave of Fintech Innovation*"[155], natural demographic change plays into declining cash use as younger consumers report relatively higher usage of electronic payments. The negative percent change of cash share (last column of Table 24) for Brazil and India further corroborates the observed downward direction.

Graph.23 - Annually Cash Share (ratio) for Brazil and India (2012-2020) based on Khiaonarong & Humphrey (2019).



Source: Bank for International Settlements (BIS) and World Bank (2022). Author's calculations.

To improve Cash Share index, a proxy on the value of personal checks would need to

[155] This survey commissioned by PayPal (2021) explores emerging and evolving trends in Fintech. The research study draws upon data collected from a survey of 4,000 individuals from four markets: China, Brazil, the U.S and Germany.

be added to current estimation. Values of large-value corporate checks could overestimate calculations. Multiplication of the average value per bankcard by the number of check transactions is an interesting alternative. Credit and debit transfers are also not considered due to interbank payments used by governments and businesses (KHIAONARONG, HUMPHREY; 2019).

A plot of annual observations of cash use over time would be very similar to a reverse Gompertz S-Curve [156]. Cash use would fall; gather speed, reaching an inflection point to then start a slow downward trend until cash use is very small. As society moves towards the end of physical currency, there is reason to believe that it will remain popular with consumers (Brazilian respondents of the PayPal survey indicated cash usage in 38% of daily situations) at least in the short to medium term. As the digital preference of Millennials (born between 1981 and 1996) establish, cash will be gradually replaced.

A linear prediction algorithm is used to return future expected values of Cash Share measures. Assuming that the data is at equal time intervals, the linear prediction method in Mathcad provides a function, which uses existing data to estimate points lying beyond the existing ones. The function uses Burg's method (Appendix) to calculate autocorrelation coefficients for the last *m* points in *v*, which are then used to predict the value of m+*1*, creating a moving window that is m points wide. Knowing that *v* is a real data vector of equally spaced data samples, m, n are positive integers, $0 < m < length\ (v)\ -1$ (PTC MATHCAD, 2022).

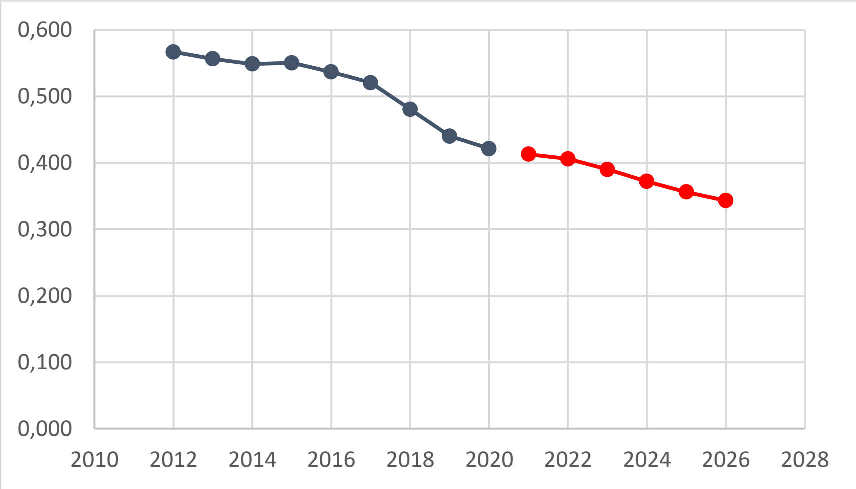
In practice, *m* should be much smaller than *length (v*). As you increase the number of *n* (previous values) larger than *m* (future predicted values), this might produce undesirable results, since extrapolated values are computed based only on past values. The function calculates a weighing factor for each prior value used for predictions. For *m* unknowns, the function needs *m* equations to work with. It builds estimations from the following model:

$$X_k = c_0 \cdot X_{k-3} + c_1 \cdot X_{k-2} + c_2 \cdot X_{k-1} \quad (8)$$

Where *x* is the time-series and *c* is the vector of weighing factors. Useful when data is smooth and oscillatory, linear prediction, $y(predi\ ct) = predi\ ct(y, n, m)$ are typically used for extrapolation hypothesis. For length (v = 9) data points, (m = 6) and (n = 5), Cash Share ratio predictions for Brazil and India are presented in Graph 14 and Graph 15 below.

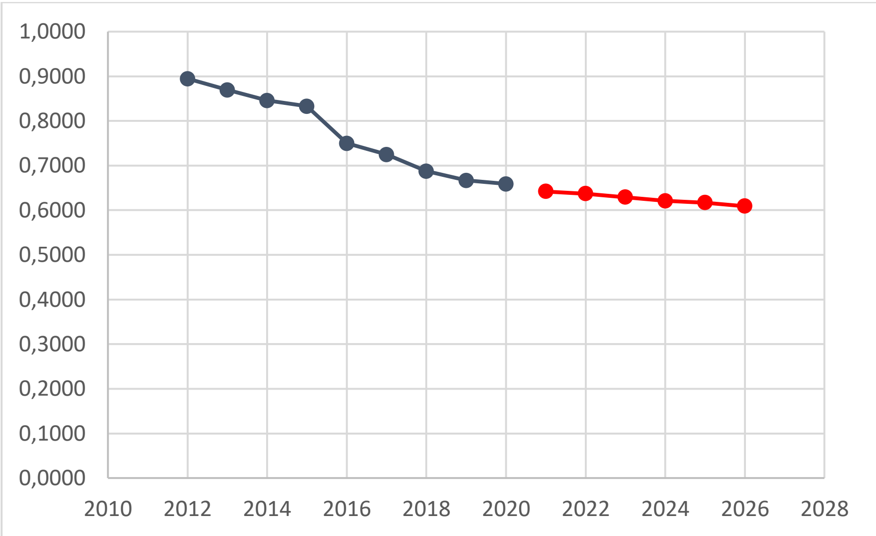
[156] *"Logistic and Gompertz growth or S-curves have been used in a variety of situations to forecast the adoption and dispersion of new technologies in industry and consumption (e.g., the adoption of the telephone and TVs) and can be adapted to forecast the possible future use of cash* (KHIAONARONG; HUMPHREY, 2019, p.16)."

Graph 24 - Annually observed and predicted Cash Share ratio for Brazil (2012 -2026) through Mathcad Predict function.



Source: Author’s calculations

Graph 25- Annually observed and predicted Cash Share ratio for India (2012 -2026) through Mathcad Predict function.



Source: Author’s calculations

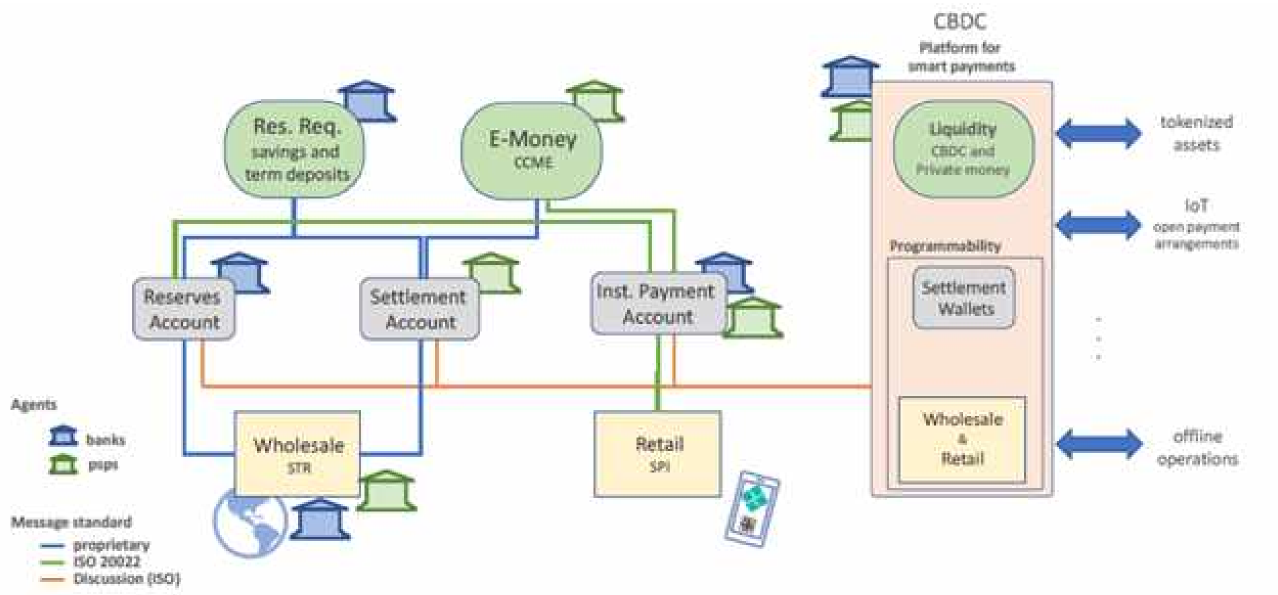
The blue spotted lines are the observed data and the red spotted lines are the predicted values. Highly aware of data limitations (only nine observations), with clear intentions in expanding this data frame, it is still possible to consider the last five years as templates for future observations. In both cases (Brazil and India), a decreasing progression will be hard to stop or reverse for the predicted years (2021-2026).

In light of these results, implementation of a reliable alternative like CBDCs or fast payment instruments may be best before private cash substitutes become so widespread that the viability of domestic alternatives would be in doubt. Adoption speed and market share of new ways in making payments depend on various attributes (user cost, supplier cost and convenience) in competition with characteristics of payment instruments already used for similar transactions: "*the greater convenience of digital cash depends on the method of access*" (Khiaonarong & Humphrey, 2019.p.24).

Credit and debit card payments are very popular but they are also vulnerable to alternative means that have lower cost of acceptance. Recently there is being a surge in transfers that are being made via the internet with digital identification tied to deposit accounts. Deemed cheaper and more convenient than using a card at a terminal, instant payments, like Pix, UPI, Codi (Alfonso et al, 2020) and Target, are one of these new instruments replacing person-to-person payments. Increased convenience, flexibility and safety (PayPal, 2021) alone are unlikely to generate enough demand for digital cash or CBDC in countries where instant payments have already been implemented. If a CBDC is just as good as an instant payment option (with a zero interchange-fee like Brazil), why switch?

The main argument rests on the idea that for the Brazilian Central Bank (BCB) and the Reserve Bank of India (RBI), Pix and UPI were the main mechanisms conducted to broaden financial inclusion. CBDCs would not have that overlapping function. The digital Real is being envisioned as an asset on the commercial bank ledger backed by the central bank. Its infrastructure will be intermediated, decentralized: a *synthetic CBDC* (sCBDC) (Figure 10).

Figure 10 - Brazilian CBDC as a smart payment platform



Source: Araujo (2022, p.34).

Rather a stablecoin or a special type of e-money, a *synthetic CBDC* (sCBDC) replicates and preservers the current two-tier architecture of the monetary and payments system, by allowing private sector entities to issue currency or payment instruments, which represents liabilities on commercial banks, backed one-to-one by central bank reserves (SODERBERG ET AL., 2022; ARAUJO, 2022).

The structure of the Brazilian CBDC will serve not as a currency widely disseminated in the population for daily use, but a **wholesale asset**, as foundation of a smart payment platform. Banks will monetize their deposits, through tokenization[157], issuing stablecoins that will be backed by the Brazilian CBDC. These promote arrangements that would preserve the public-private partnership in providing liquidity to the market (ARAUJO, 2022; MARTINES, 2022).

As envisioned by the Brazilian Central Bank (BCB) it will be a platform for smart contracts, an environment to innovate using technologies such as programmable money, enabiling new functionalities beyond those brought by Pix. As conveyed in the BIS annual economic report (BIS, 2022), the future monetary system will meld new capabilities with a superior representation of central bank money at its core. Technologies available in the cryptoasset ecosystem, opens up space for new business models and products. On top of the traditional division of labour between the central bank and commercial banks, new standards such as application programming interfaces (APIs) augment interoperability and network effects that will allow payment systems to scale and serve the real economy.

Programmability and composability allow individuals to transform their deposits into tokens capable of accessing services provided by this new platform, under the explicit commitment that payment service providers convert them into CBDCs on demand (Figure 10). These are one of the new functions that could be unlocked by wholesale CBDCs, the tokenisation of deposits (M1), represented on permissioned DLT networks. According to the BIS (2022), this could facilitate new forms of exchange, including fractional ownership of securities and real assets, allowing for innovative financial services that extend well beyond payments.

Tokens issued by PSPs and fully backed by reserves at the central bank would inherit all applicable regulation and features from their originating assets, such as reserve requirements,

[157] Decision regarding the use of token-based technology, for the digital Real has not been reached yet. The BCB is still considering other more centralised architectures. The term token is used to simplify our argument.Whatever the platform chosen to issue the digital Real, PsPs will provide private money regulated by the BCB, offering the same technological functionality (ARAUJO, 2022).

constraints on liquidity, portfolio risk and backstops. Rendering stability and parity between these tokens and fiat currency (ARAUJO, 2022).

Traditional commercial bank money in comparison to digital substitutes, poses key challenges in emerging market and developing economies. As they require a bank account, the poor often lack proper documentation to comply with bank due diligence. Maintenance costs on minimum balances on accounts are too onerous considering highly informal economies like Brazil and India. Financial institutions often concentrate market power with higher mark ups, more expensive financial services with limited incentives for innovation. Looking at the structure towards the Brazilian CBDC (Figure 10) it is possible to question if there would be motivation to foster lower fees and better services in a smart payment platform with wholesale assets. If the system will be open enough to challenge rents in a concentrated banking sector (like in Brazil) reducing costs for end users.

The Reserve Bank of India (RBI) is currently working towards a phased implementation strategy, examining use cases, which could be implemented with little or no disruption (Sankar, 2021). On design features of the digital Rupee, not much can be said, other than it will have a hybrid architecture (Auer & Böhme, 2020)[158] like the Brazilian CBDC. To bypass the need to build newer capabilities, central banks prefer to shift responsibilities to commercial banks and authorized intermediaries to continue to onboard users, enforce KYC rules and handling retail payments in a "*Hybrid/Intermediated/Synthetic CBDC"* model.

While it is intended that a CBDC would provide a safer alternative to private virtual currencies, it is still unclear how this will be achieved in India (Priyadarshini & Kar, 2021). Motivations and policy priorities include fostering financial inclusion, responding to dwindling usage of paper currency, the desire to enhance efficiency of banking, to facilitate international payments, heightening fiscal transparency, and to meet public's need for digital currencies (Sankar, 2021). These reasons are shared across the board with Brazil, particularly declining cash usage.

Eichengreen *et al.* (2022) provides a sceptical rationale behind CBDC emission. According to the authors, proponents fail to acknowledge that some of the goals attached to CBDCs, can be advanced at a lower cost and at less risk through alternative means. This point

[158] In this model, a direct claim on the central bank is combined with a private sector messaging layer. The hybrid CBDC would have both advantages and disadvantages compared to the indirect or direct CBDC architectures described in (Auer & Böhme, 2020). As an intermediate solution it might offer better resilience, but at the cost of a more complex infrastructure. On the other hand, it is simpler to operate than the direct CBDC. Knowing that the central bank does not directly interact with retail users, it can concentrate on a limited number of processes, while intermediaries handle other services.

becomes specifically true for India, with its already existing Unified Payments Interface (UPI), and ongoing financial inclusion efforts. Contrary to the latter, Pryadarshini & Kar (2021) considers that it is not a question of if, but when and in what form should a CBDC be introduced in India.

The basic fear of central banks, particularly for Brazil and India is that payments migrate away from UPI and Pix to a private-label stablecoins, to exchanges in unregulated digital currency markets, or single large private payment providers. Cost efficiencies, speed, reach, driven by network effects offered by their large presence in social media could become hard to compete with in the absence of an institutionalized alternative.

In some countries like China[159] and Sweden the use of alternative payment services offered by private entities (e.g. mobile payment system such as Swich, Alipay and WeChat) have become so dominant that they could pose monopoly risks, high entry barriers with non-interoperable services to the costumer and potential misuse of data, with safety and technology risks. Tightening regulation might not be enough to ensure transactions, to protect consumers and mitigate systemic risk to the financial system, in the face of concentrated market power and "too big to fail" characteristics (PRIYADARSHINI; KAR, 2021; EICHENGREEN ET AL, 2022).

There are also macro angles of interest related to EMEs: 1) the likely consequences of CBDC issuance, in terms of ability to conduct monetary policy and 2) what are the possible effects on the domestic economy if major advanced economies (AEs) adopts CBDCs and allows cross-border transactions.

These questions include the effect of payment innovations on prices, exchange rate and seigniorage (Engert & Fung, 2017) especially currency substitution. Edwards (2021) arguments that if convertible currencies (like the USD or Euro) are accessible digitally in an emerging country, transaction costs for using foreign currency as a medium of exchange and/or a store of value would decline. An increase in the degree of currency substitution through global CBDCs and global stable coins (GSCs) would have a negative effect on seigniorage[160] by reducing its base.

In a not too distant future global stablecoins could be accepted more widely. Unregulated and denominated in foreign currencies they could become a threat to domestic

[159] China has seen near universal adoption of digital payments with nearly 94% of mobile transactions supported by Tencent or Alibaba (Priyadarshini & Kar, 2021).

[160] "*Seigniorage is paid on the stock of domestic money relative to GDP*". If there is a reduction costs in using foreign currencies (through currency depreciations and high inflation), this ratio goes down and the amount of seigniorage collected declines (EDWARDS, 2021, p.9).

monetary policy in the absence of a CBDC. Emerging markets will benefit from the implementation of stronger macroprudential regulations and central banks could minimize budgetary effects by issuing digital cash earlier before cash use may fall to minimum levels (KHIAONARONG, HUMPHREY; 2019; SANKAR, 2021; PRYADARSHINI; KAR, 2021; ARAUJO, 2022).

Subbarao's (2022) comment placed in the beginning of this article ***"festina lente"***, clearly explicit the necessary cautiousness and urgency towards the demands placed on EMEs central banks. Instruments, which function both as cash and as financial assets could also have significant international spill overs, if permitted across borders. These premises rest upon the importance of remaining internationally competitive, protecting national interests, ensuring digital and financial security. Justifications are largely outside the domestic context, in which most of the major economies in the world, see the development of a national CBDC and their interoperability as a major drive of international payments. A global system where only sovereign-backed digital currencies will be trusted (SANKAR, 2021; PRYADARSHINI; KAR, 2021; ARAUJO, 2022).

Some emerging market economies (EMEs) also depend on low-value cross-border remittances (Raskin & Yermack, 2016). In 2019, these transfers reached the $551 billion mark exceeding official development assistance by a factor of three (prior to the Pandemic), on the track to overtaking foreign direct investment (FDI) flows. Carefully managed[161] with intergovernmental cooperation, CBDCs could be used in cross-border payments to lower dependency on intermediaries, mitigating potential risks, reducing costs[162], yielding economic gains for families and entrepreneurs.

As in instant payments, domestic context plays into the main challenges for financial inclusion such as adequate digital infrastructure (broadband coverage), affordable electronic devices, digital, financial literacy, assuring population accessibility (Araujo, 2022). Half of all Indians do not own a smartphone capable of downloading a central bank app and digital wallet

[161] A cross-border CBDC would typically address: technical interopprerability, oversight framework, liquidity constraints, negative spill overs on other economies (such as currency substitution). Lack of coordination on technology and messaging standards, plus treatment of data, privacy concerns, tax, payment laws and capital flow management measures are particularly complex (CHEN ET AL., 2022; KOSSE & MATTEI, 2022; SODERBERG ET AL., 2022).

[162] Three CBDC arrangements for cross-border interoperability that incorporate digital IDs or usage limits are gaining traction. In each of these models, users would be able to hold CBDCs from various jurisdictions in their CBDC wallet of their home jurisdiction, subject to some limits. One of these models, the *multi-CBDC Bridge* project is under study by the Public Bank of China (PBOC), in collaboration with the BIS innovation Hub and other central banks (Thailand and the United Arab Emirates). An experimental CBDC using DLT facilitating cross-border payments, laying the ground for an international system (EDWARDS, 2021;SODERBERG ET AL., 2022; CHEN ET AL., 2022).

to transact over a 3G network. Adequate internet connectivity coverage may also be lacking in relevant and relatively remote areas (Eichengreen et al, 2022).

In this case, for many central banks, fiduciary digital liabilities (CBDCs) will not offer significant advantages over fast payment systems in terms of increasing financial inclusion of the unbanked population. Pix and its use during the pandemic helped reach what is probably the limit of that inclusion in Brazil, given the current level of broadband and internet access (Araújo, 2022). Fast payment systems could offer more immediate improvements to constituencies. Tailored to targeted users, broad adoption comes from reducing frictions in payments.

As seen above, CBDCs could be an alternative instrument that can affect the competitive structure of the payment system, supporting new digital technologies (Chen et al, 2022). Even if the RBI has a focus on CBDC design, exploring offline payments functionality, any improvement in financial inclusion would require extra efforts to address base causes of exclusion in both countries.

Functionally the Brazilian CBDC will be very different compared to Pix. Corroborating the hypothesis that, CBDCs (in their traditional definition), as an instrument to enhance financial inclusion will be "*less controversial in countries where cash use is still very important for a wide range of transactions and substitutes for cash are relatively new and not firmly established*" (Khiaonarong, Humphrey; 2019, p. 26). In many OECD countries substitutes (i.e: bank cards, instant payments, mobile phone payments) are already widespread, like in Brazil and India.

4. CONCLUSIONS

Financial markets and payment systems are organizing themselves to not only deal with the flow of information generated by our daily routines, but also taking part in modernising initiatives in a broader process of digital transformation in our society (Araujo, 2022). Globally today, 90% of central banks recently surveyed by the BIS (2022) are doing some form of work on wholesale and retail CBDCs. There are three live retail CBDCs, 28 pilots, including the large-scale pilot by the People's Bank of China, which now counts 261 million users. With a logistic rate of adoption, similar to the earlier experience with real-time gross settlement (RTGS) systems, fast payments are now in operation in over 60 constituencies, and some are already being planned for the years to come like FedNow in 2023 (BECH ET AL, 2017; FED, 2022).

In partnership with member central banks, the BIS Innovation Hub is developing mCBDC platforms for cross border transfers: project Jura (with the central banks of Switzerland and France) Project Dunbar (with Singapore, Malaysia, Australia and South Africa), and mBridge (with Hong Kong SAR, Thailand, China and the United Arab Emirates) (EDWARDS, 2021; SODERBERG ET AL., 2022; CHEN ET AL., 2022, BIS, 2022).

Placing greater emphasis and having bigger concerns than advanced economies (AEs) to financial inclusion, monetary policy, economic stability, cyber risks, bank disintermediation and cross-border payments efficiency, there are clear differences in developing country circumstances. Modernizing and future proofing the payment system, providing cash like digital instruments, in light of reduced currency usage and an increase in private payment services is the most common consideration.

Today, the Brazilian Pix is used by two thirds of the adult population. With about 50 million users making a digital payment for the first time (Duarte et al, 2022), and offered by over 770 private PSPs it already surpassed credit and debit card in transaction volume. As of early 2022, nearly 300 banks participated in the Indian UPI, hosting 70 billion transactions, making it the world's largest real-time payment system (Eichengreen et al, 2022).

This final article shows interesting points towards how a younger population of digital natives, private payment providers and a stronger crypto ecosystem through exchanges, has led to concrete measures from countries like Brazil and India, in order to safeguard their monetary system. Declining cash use puts forward arguments that emphasize architecture, design considerations and motives as to why emerging market economies (EMEs) are those most interested in implementing Fast Payment Systems or Central Bank Digital Currencies (CBDCs).

To delineate demand considerations, as in Khiaonarong & Humphrey (2019), we use the same approximate calculations (four indexes) with data taken from the Bank for International Settlements (BIS), between the years 2012-2020 to conclude that there are two "best" ratios for cash demand in Brazil and India. Out of these, one was selected and used in an extrapolation exercise as to illustrate future decreasing trends (2021-2026) in both countries.

These measures show that without a digital version of fiat currency, it is possible that over time cash will be almost entirely replaced by other more competitive private instruments. As younger adults use more electronic deployments, this necessarily reduces the overall use of paper currency. A CBDC would allow ordinary people and companies to make payments electronically using central bank[163] issued money.

There is no universal design or recipe for CBDCs, nor is it unanimous in its need throughout constituencies in the near term. Cultural aspects and country context play in to open issues like sustainable business models, pushing the boundaries to innovation in payments market. Those that view a case for digital central bank liabilities, argue that a careful design can keep risks to a minimum, ensure a stable financial system while yielding benefits.

Difficulties going forward include making choices in a very new and rapidly evolving field, as well as costs associated with the development process. CBDC pilots and proofs of concept are testing DLT, however experiences suggest that there is no universal case for DLT as the primary engine of CBDC. Additionally jurisdictions have different views on the potential merits of the technology. A new and important trend, spearheaded by the Public Bank of China (PBOC), is a more pragmatic view of technology, which draws upon the strengths of both distributed (DLT) and central ledger-based (CLT) network structures (SODERBERG ET AL., 2022; CHEN ET AL., 2022).

Areas of convergence between central bankers towards CBDCs' main characteristics can be identified. Countries are seeking to strike a balance between preserving key aspects of the traditional financial system, updating their role in the digital era. Exploring the intermediated operational model, central banks maintain a two-tier system where the private sector has a major role to play as a partner to the monetary authority. Limiting competition with bank deposits, there is a preference for a "payment-focused CBDC", one that steers away from "store of value" attributes. Concurrently they do not envision offering remuneration on CBDCs and prefer limits on balances and transaction values that could cause distentermediation and major monetary policy implications (CHEN ET AL., 2022).

These facts can lead us to argument that CBDCs are a viable alternative to these societal transformations, but their feasibility are only possible where digital payment alternatives are not already wide-range, with lacking accessibility. Fast payment systems create a supporting background on the ongoing innovations propelled by central banks to maintain digital monetary sovereignty, a stepping-stone toward financial inclusion in Brazil and India. If CBDC's purpose is financial inclusion (as Pix), they will have an intrinsically different function as that

[163] In modern economies, there are two types of liabilities: banknotes and electronic bank deposits. Anyone can keep and use notes (cash), they are bearer instruments, and the parties involved in the transaction canremain anonymous, so that the transaction is final and irrevocable. Electronic bank deposits are the main means of payment among end users, while Central bank reserves are the means of payment between banks. In this system, trust is generated through Central banks, which maintain reserves through their equityholdings, operating rules, regulations, and supervision of deposit insurance schemes in the commercial banking sector (ENGERT; FUNG, 2017; BIS, 2018).

envisioned by the definition of what it really is. As in the Brazilian case, in accordance with recent central bank reports, a sCBDC (synthetic CBDC) will be the main element of a platform for smart payments, connecting current sources of liquidity to a digital asset ecosystem.

5. FINAL CONSIDERATIONS

In an internet-based hyper-globalized economy, informational boarders have been partially dissolved, and with the emergence of private payment system providers, international flow of funds are being continuously streamed through these channels. In his speech to the European Forum on Currency and Finance, Carstens (2019) highlights that today; almost everyone has access to digital payment methods. Through debit cards, banking API on a smartphone, transactions are made digitally and instantly. These transformations come from innovation continuum since the second wave of Fintech in the 1990's (PayPal, 2021).

The overall aim of this thesis was to address global digital innovations (in a retail perspective) that began to emerge with the 2008/2009 crises, including bitcoin (BTC), fast payment systems and more recently the discussion and testing of Central Bank Digital Currencies (CBDC). Although radically different in nature, functioning, objectives, potential pitfalls and background they are part of this new ecosystem that is rapidly emerging of products and services, promoted by increasing global financialization.

The first two papers contemplate the development of bitcoin and how it translates economically into an asset as it gains status and media recognition. These discussions go against as to the primary purpose of bitcoin in its inception (Nakamoto, 2009) as to create an alternative method of making payments. It would essentially eliminate intermediaries out of the money-flow chain, as well as the need for government bodies to control and regulate financial organizations.

While incredibly volatile, highly energy-intensive, unregulated and extremely prone to illicit flows crypto-assets (specifically Bitoin) is becoming an international asset class (for better or for worse). Search for alternative investment opportunities in a low-yield environment have helped fuel record-high market valuation spurring the emergence of various crypto related initiatives in recent years. A rising number of investment funds has begun to provide institutional and retail investors a way to obtain exposures to cryptos. Assets under management have grown significantly since 2020 (Auer et al, 2022), crypto prices and US stocks (S&P500) both surged amid global financial conditions increasing speculator's appetite for risk.

The arrival of institutional investors has changed the digital asset market. While realloacating resources these investors leave "footprints", captured by BTC price (in USD) and transaction volumes. Analysing periods with relevant measures of cross-correlation between these variables, plus understanding Halving dynamics, produces a picture of when market players are most dynamic over different time frequencies. Wavelet coherence analysis showed short-term movements from small retail investors, added to long-term changes of leveraged speculators.

Access through specialized exchanges and bigger latency of companies that own large sums of Bitcoins, pushed estimations to a long-term trend (lower frequency) in price and transaction correlation. Confirming that co-movements between BTC price and transaction count (quantity) provide an important indication of how flows have been altered by the entrance of these market makers. Wavelet transaction count also corroborates our analysis, giving more precise estimates of retail trading, with stronger relationships at higher frequencies.

Previously uncorrelated to other traditional asset classes, there is indication that Bitcoin has rising interaction with important financial market indicators. Trends have been changing, with short-term and long-term spill overs from risk-free bond markets and the stock market, to the crypto environment. Capturing Bitcoin's real return over the last 10 years, using internal and external independent variables, the second paper arguments towards growing interdependence to US equity markets. Speculator's risk perception and those of US companies are influenced by changes in monetary policy, to such an extent that volume exchanged (transaction count) the S&P500 and the one-year treasury constant maturity rate (1YTCMR) are relevant in estimating non-linear BTC dynamics. Negative shocks (of S&P500 and Transaction Count) have bigger impacts than positive ones, showing Bitcoin's fickle nature to market sentiment.

Stronger correlations suggest that there is a rising probability of contagion between asset markets, confirmed by the IMF and our study. From January 2020 to November 2021, the value of cryptocurrencies rose more than tenfold, peaking at $2.8 trn, before taking a deep dive crashing to $1.2 trn in June 2022 (Boissay et al, 2022). Unconditional correlations computed for the pre-pandemic (Jan 2017-Dec 2019) and post-pandemic (Jan 2020-Nov 2021), show that crypto and equity markets have become much more interconnected over time (Iyer, 2022).

Adoption has been particularly pronounced in emerging market economies (nine of the top 10 major adopters in 2021), confirmed by patterns with equity markets, captured by the MSCI index and Bitcoin[164]. Large, institutional-sized transfers (above $10 million worth of cryptocurrency) represent 42% of transactions sent from India-based addresses. These numbers

[164] Volatility correlation between Bitcoin and Ether and the MSCI index has increased three to four-fold between the pre-and post-pandemic periods (IYER, 2022).

indicate that India's crypto investors are a part of a larger and more sophisticated organization, professionals looking for new asset-types, more focused on speculation[165]. Similar to Brazilian users which also move large institutional type sums (above $10 million worth of cryptos) at 36% of its total transactional volume (CHAINALYSIS, 2021)[166].

Low financial literacy and excessive risk-taking could create bull market-type rewards, with a narrow comprehension of the possible downfalls that are involved. Withal, a sharp decline in Bitcoin prices can increase risk aversion leading to a fall in stock markets, suggesting that investor's sentiments are transmitted in a non-trivial way. Outside regulatory control, market surges raises concerns for price volatility, systemic vulnerability, costumer protection, illicit activities and financial stability.

Should these private alternatives be banned? Knowing that they do have many negative societal consequences, this ultimately could be difficult to enforce (or even be counterproductive) in view of their decentralised and borderless framework. Moving these activities underground, will make them difficult to monitor, especially for use in illegal activities[167].

Although a part of the same ecosystem, cryptos and stablecoins are perceived differently in their functionalities (Kosse & Mattei; 2022). According to central banks cryptocurrencies are mostly used for cross-border payments while single-currency stablecoins have the highest potential in becoming a widely accepted method of payment.

Despite technological progress in information processing and digital technology, the cost of traditional domestic payments has remained high. Credit and debit card fees exceed 1% of GDP in many countries and can be higher in some cases (Alfonso et al, 2020; Duarte et al, 2022). Banks, card networks and payment platforms (Private Payment Service Providers) have entered the market offering services in closed-loop systems (*walled gardens*) that require both payers and payees to be customers of the same institution.

Substantial market power of payment service providers have several undesirable implications (Chen et al, 2022).Through indirect taxation, these costs are partially passed on to consumers through higher prices at checkout. This effectively slows down economic activity

165 Chainalysis (2021); Wheatly & Klasa (2022).

166 Three regulated cryptos ETFs were launched by the Hashdex Asset Management on the São Paulo stock exchange (Brazil), with over 160,000 investors. The HASH11 tracks an index co-developed with Nasdaq on a basket of crypto assets. Charging a management fee of 1.3 percent, it currently has net assets of about R$2.17bn and is the second-most owned ETF. Its growing popularity can be demonstrated by local exchange Mercado Bitcoin, whose total transaction volumes were up seven-fold by the end of August (2021) compared with 2020.

167 Exchanges, markets, even dark-web ones, where trade in illicit goods and services for cryptos popped nearly side-by-side to Bitcoin's online *debut* in January 2009 (*vide*. Silk Road and Mt Gox).

through trade and services are typically “geared” to “high-value” customers and not those that need it the most.

Over observant of international trends, the Brazilian Central bank (BCB), has been studying the need to implement real-time retail payment system, in face of private payment system providers and decentralized financial innovation. The Reserve Bank of India (RBI) has been adopting a similar perspective, but more in tune with local capabilities and infrastructures, through the National Payments Corporation of India (NPCI) since 2008.

A long-term vision is adopted to increase system resiliency through common procedures and standards. Pix is a digital instant payment system similar to CODI in Mexico, Unified Payments Interface (UPI) in India, and even private systems operating on a concessionary basis like Alipay and WeChat Pay in China and the Brazilian PicPay. As it is maintained, operated by the central bank, its regulations are enforced, obliging financial institutions above a certain size to adhere to technical specifications, providing nationwide access.

This study’s novelty is that financial sophistication, economic growth, payment substitutes and relative popularity of banking apps are important variables to understand instant payments dynamics. Used as a study case for the Brazilian Pix, volume of Indian UPI transactions will be positively impacted by credit and debit cards in the short-run showing a complementary nature to this instrument. As expected mobile banking will increase the volume of instant payments. Non-linear results confirmed that the ratio of mobile banking transactions to mobile phone subscription (MB/WLESS) and the level of development of the financial system (M1/GDP) increased instant payment volumes, substantiating a case towards public policies towards telecommunication infrastructure.

In hindsight, the central bank has decided to take on the role of advancing digitalization of payment systems in Brazil, majorly because no private service has managed to so, or could even provide such service with no state driven support. Collective decision-making problems, with different stakeholder positions and short-term profit considerations would not only interfere but hinder a national fast payment system. The same network effects that led to greater concentration and market power of private payment providers were redirected by the Brazilian Central Bank to an open-looped system. Moreover, they reacted proactively, the BCB made the formal decision to develop Pix in 2018, and on November 2020, a period of restricted operation started with a limited number of end users within the PSP’s customer base (DUARTE ET AL, 2022).

Although Pix is not a CDBC (an obligation held against the Central bank) as Kosinski

(2021), we observe a political objective in Pix's institution, which is to maintain the central bank's control over the Brazilian monetary space. A resourceful solution to promote digitalization of means of payment that provides the functionalities of these services but with the legal-political coverage and the prerogatives of state control.

Towards emerging market economies (EMEs) there are clear differences in circumstances (financial inclusion, monetary policy, financial stability, cyber risks, bank disintermediation and cross-border payments efficiency) compared to advanced economies (AEs). Declining cash use plus private payment substitutes puts extra pressure on EMEs' central banks as to provide a suitable answer. Our two best cash usage ratios based on Khiaonarong & Humphrey (2019), plus an extrapolation exercise, illustrates our argument as to without a version of fiat currency, it is possible that cash will be entirely replaced with alternative instruments in the long run.

Facts leads us to argument that CBDCs are an interesting alternative, but only in jurisdictions where digital substitutes are not already universal and needed to promote broader inclusion. The Bahamas Sand Dollar, the Nigerian eNaira and the Eastern Carribbean CBDCs are some examples. Cases for Central Bank Digital Currencies (CBDCs) in Brazil and India encompasses a broader view of what to expect of the future monetary system. In Brazil, the central bank sees it as platform for smart contracts, an environment to foster new financial services, in a continuum of core features in payment infrastructures.

Digital technologies and internet services are important vehicles to promote social inclusion. Infrastructural gaps in lower-income regions need to be addressed by governments through specific state policies, to evenly distribute access across the Brazilian and Indian territory. More directly related to our subject are investments in education to increase digital literacy, policies towards energy distribution and telecommunication rails. Improving and universalizing quality signal in regions that have poor service not only promotes financial deepening but primarily economic development. Low internet connectivity in more impoverished districts have a relevant impact on information access, increasing social differences and exclusion. A fact that was clearly seen through the COVID-19 pandemic. A strategic policy if these countries are to engage productively in the Web 3.0 environment.

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APPENDIX A - PAPER 1

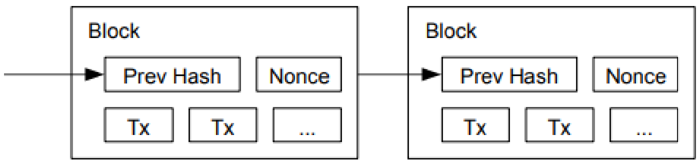
A.1 Nakamoto (2008)

Nakamoto proposed a peer-to-peer (P2P) distributed timestamp server to generate computational proof of the chronological order of transactions. The P2P network ensures that all members are equal and there is no central server to delegate tasks. This is exactly what differentiates Bitcoin as a form of online payment: it distributes the work of verifying transactions among nodes. They are streamed through all participants, creating a dataset of approved exchanges, a giant, shared ledger, where transactions from previous periods are grouped into a “block” and linked to the blockchain (BJERG, 2016; CIAIAN ET AL., 2016; HAYES, 2017; YERMACK, 2013).

In the absence of a "centralized ledger" participants need to agree on a single history and the order in which transactions were received by the network. The timestamp server records time and date in a block's hash and publishes it widely throughout the system. It proves that data must have existed in the network at that specific period. These transactions are hashed into an ongoing chain of proof-of-work (each timestamp includes the previous hash’s timestamp forming a chain) (Figure 1).

Within each block, there is a cryptographic puzzle that, when solved, validates the whole string of transactions. This mathematical problem can only be done through trial and error, requiring great computational power and expanding the machine's “brute force” in calculations to decipher the code (*hash rate*[168]). Using the “proof of work” concept to reach consensus among computers, a block is created, and Bitcoin is generated as a reward (BJERG, 2016; CIAIAN ET AL., 2016; EL MAHDY, 2021; HAYES, 2017; YERMACK, 2013).

Figure 1. Nakamoto’s Representation of the Blockchain



Source: Nakamoto (2008, p.3)

Proof-of-work (PoW) is implemented by incrementing a nonce[169] in the block until a value is found that gives the block's hash the required number of zero bits (binary digit 0 or 1). It is a hash function with a large number of answers, and the "best" is considered to start with 15 zeros. Once a node finds a hash that satisfies the required number of zero bits, solving the cryptographic puzzle it transmits the block to the rest of the network. Each block is algorithmically linked to the previous block, through the hash (Sovbetov, 2018). We can hypothetically represent the hash function as follows:

[168] The number of attempts to find a valid hash.

[169] According to the US National Institute of Standards and Technology (NIST), a cryptographic nonce can be summarized as: "*a random or non-repeating value with the most negligible chance of repeating itself, included in data exchanged by a protocol, usually to guarantee the transmittal of live data* (NIST; 2022). Alternatively, according to Narayan (2016, p.8) “*In cryptography, the term nonce is used to refer to a value that can only be used once.*”

$$Hash = f(\theta, \phi, Z)$$

Where: θ is the hash of the previous block; ϕ is the difficulty[170] level and Z is a random key specific to the block. This unique hash protects the ledger's integrity and new blocks that document recent transactions are added to the blockchain only when a valid hash is found. In a Bitcoin transaction, the current owner validates his ownership using a public key, signing the transaction with his private key. An encrypted instruction is sent with his key, and the system then records the transaction containing the new owner's (receiver's) public key in a new block (Figure 2). In Nakamoto's own words:

> *"We define an electronic coin as a chain of digital signatures. Each owner transfers the coin to the next by digitally signing a hash of the previous transaction and the public key of the next owner and adding these to the end of the coin. A payee can verify the signatures to verify the chain of ownership" (Nakamoto, 2008 p.2).*

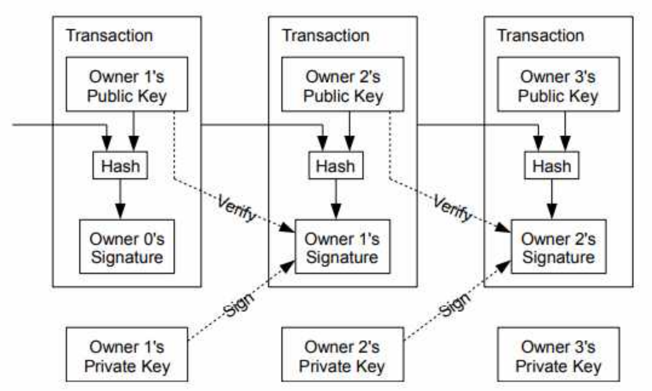
In case two participants broadcast different versions of the next block simultaneously, some may receive one or the other. Collectively nodes will start working on the first one but will save the other in case it becomes longer. When the proof-of-work is found, those that were working on the other will switch to the longer one. As long as new broadcasts reach many computers in the network, transactions will be included in the blockchain before it gets too long. If perhaps a node does not receive a block, it will request it when it realizes that there is one missing, when accepting the newest block (NAKAMOTO, 2008).

Generating a hash using a key (as in Figure 2) is cryptographically easy; however, reverse engineering a key to a hash is difficult. If a malicious user tries to change the hash of the previous block, he will have to do this to the previous block and so on until reaching the first block created by Satoshi himself. Therefore, having a significant number of honest miners investing a large amount of power in hash generation makes it difficult for rogue users to find a valid hash before other miners find the block that contains the real transaction (LI; WANG, 2017; SOVBETOV, 2018).

The longest chain represents network majority and the correct one since it has the greatest proof-of-work invested in it. If more than half of genuine nodes control CPU power, the honest chain will grow faster, imposing to an attacker the extra effort in not only surpassing them but redo the work of the targeted block and the blocks before it. Even though an attacker could assemble more power than the network of trustworthy nodes, he would prefer to play by the rules, since it would favour him with "newly minted coins", and not overthrowing the system to the detriment of his wealth (NAKAMOTO; 2008).

[170] "(…) *difficulty is determined by a moving average that targets an average number of blocks per hour if they are generated too fast, difficulty increases* (Nakamoto, 2008, p.3)".

Figure 2. Nakamoto´s Representation of a Transaction in the Blockchain



Source: Nakamoto (2008, p.2)

Once CPU energy has been expended with proof-of-work (PoW) the block cannot be changed. To be rewarded PoW miners invest in advanced machines that work (consuming energy) to validate transactions (solving hashes) and create new blocks. Crypto asset mining under PoW protocol is competitive, meticulous, expansive and only sporadically rewarding (Sovbetov, 2018). Alternatively, many altcoins have started using proof-of-stake (PoS), which is more cost-effective (cheaper) and greener compared to power-intensive PoW, to solve algorithmic hashes[171].

For overall comprehension of how these payments occur, analysing bitcoin protocol is crucial. They consist of an input and output, where the input is the output of a previous transaction. Transactions take place between Bitcoin addresses, which are similar to email addresses. Each transaction sends a certain balance of virtual currency between addresses, and each individual transaction can have multiple inputs and outputs, either from a larger previous transaction or from multiple inputs combining smaller amounts. There will be typically two outputs: one for the payment, and the other for returning change to the sender, or a fee/block reward (NARAYAN, 2016; HAMPTON, 2016; WISEMAN, 2016).

Figure 3 from Makarov & Shoar (2021) shows an example. Transaction address "17A16Q" sends its balance to three addresses, the amount received is equal to the quantity sent, except for a small fee of 0.01 BTC, which is part of the block reward. The last address is the same as the sending address "17A16Q", resending the remaining balance to itself.

[171] To verify transactions in PoW, the miner is the solver of the mathematical problem, in PoS the creator of the new block is chosen deterministically, according to the stake "wealth" the user holds. The creator of the new block is not rewarded by newly minted cryptocurrencies in PoS, instead, they receive a sum of transaction fees. In PoS all cryptocurrencies were already created in the beginning so there is no money supply through mining, hence miners do not need expensive machines to "mine" newly minted "coins" (ÖZDEMİR et al, 2018; SOVBETOV, 2018).

Figure 3. Bitcoin Transaction on the Blockchain

Note. The figure shows a typical transaction on the Bitcoin blockchain.
Source: Makarov & Shoar (2021, p.37).

The outstanding balance of an address is not stored in the address but imputed from the whole history of transactions involving this address, on the Bitcoin ledger. For computational efficiency, the protocol allows payers to send only amounts that have already been collected by their address. Suppose it had received 5, 7 and 10 Bitcoins, with a total balance of 22 BTCs. If the payer needs to send 8 BTCs he could either send 10 or: 5 + 7, 5 +10, 7 + 10 or 5 + 7 + 10. Considering all the alternatives above the amount is larger than 8 BTCs, and the sender will need to collect the difference. This process creates a large volume of spurious exchanges that obscures the true transaction volume in the blockchain, an important fact underscored by Makarov & Shoar (2021) when dealing with the Bitcoin protocol.

Private keys are what typically allows virtual assets to be spent, while wallets[172] are the user's interface. They enable merchants to display their public addresses to other users, keeping a record of transactions and storing these private keys that protect cryptos. Another important aspect is the pseudonomity of the Bitcoin ledger. Unless information is publicly disclosed, the public Bitcoin address is a string of random characters that nothing reveals about the identity of the user. A user can own several Bitcoin addresses at the same time. While the activity of that particular address can be traced, it is not possible to tell precisely who owns that address (NARAYAN, 2016; HAMPTON, 2016; WISEMAN, 2016).

[172] Bitcoin wallet software are offered with varying options of encryption and security modes. Particularly sought after are "cold wallets" which are stored on a physical device (USB flash drive, or paper representation), secure against internet thieves because they are completely offline and inaccessible unless physically taken (Wiseman, 2016).

A.1 Wavelet Methodology

Most time series techniques interpret data in the short and long run, but do not explain precisely how long is the long run and how short is the short run (Bhuiyan et al (2021). Specific economic phenomena are better addressed through different time scales, while variable decomposition may unveil correlations that are not visible at the aggregate level: "*economic processes are the result of the actions of several agents, who have different term objectives. Therefore economic time-series are a combination of components operating on different frequencies*" (Aguiar-Conraria;Soares, 2011, p.1). Ignoring time and frequency dependence between variables may lead to erroneous conclusions. A more realistic assumption should be to separate different time scales and analyse relationships among variables at each level (GALLEGATTI; SEMMLER, 2014; RAMSEY; 2014).

With a defined number of oscillations, wavelets are a parameter preserving multi-resolution decomposition. They are ideally suited to approximating variables in scale: they can be "stretched" or "squeezed" to mimic the series under investigation. Choosing the appropriate degree and nature of the oscillation within the supports of the wavelet is key. Elementary functions are used (father ϕ and mother wavelets ψ), that being well localized in both time and scale provide a decomposition on a "scale-by-scale" as well as on a frequency basis (CROWLEY; 2007; GALLEGATTI; SEMMLER, 2014; RAMSEY; 2014).

A father wavelet $\phi(t)$ integrates to 1, and a mother wavelet $\psi(t)$ integrates to 0. The father wavelet essentially represents the smooth trend (low frequency) part of the signal, whereas mother wavelets represent the detailed (high-frequency) parts, which is the amount of stretching of the wavelet known as "dilation". Mother wavelets are compressed in the time domain to generate cycles to fit actual data (Crowley, 2007; Ramsey, 2014). Generated from father and mother wavelets through scaling and translation, the approximating functions $\phi_{J,k}(t)$ and $\psi_{J,k}(t)$ are as follows:

$$\phi_{J,k}(t) = 2^{\frac{-J}{2}}\phi\left(\frac{t-2^J k}{2^J}\right) \text{ (1)}$$

And

$$\psi_{J,k}(t) = 2^{\frac{-J}{2}}\psi\left(\frac{t-2^J k}{2^J}\right) \text{ (2)}$$

Where j indexes scale, so that 2^j is a measure of the scale, or width of the functions, and k indexes translation, so that $2^j k$ is the translation parameter. Thus, wavelets will take the following functional form:

$$\psi(t) = \frac{1}{\sqrt{s}}\psi\left(\frac{t-u}{s}\right) \text{ (3)}$$

The u parameter specifies location; the scale parameter s refers to the width of the wavelet indicating how stretched or dilated it is while maintaining its wavelike shape. The $1/\sqrt{s}$ term ensures that the norm of ψ is equal to one[173]. As the wavelet widens, a broad support yields information on a large scale, whereas a small support wavelet yields information on a small scale. Conversely, low scales will allow for analysis of (higher frequency) short-term dynamics of the time-series under consideration, whereas high scales will allow for analysis of (lower-frequency) long-term dynamics. Lastly, if a wavelet is shifted, this is referred to as

[173] Normalization factor to make sure that wavelet transforms are comparable across scales and time series (Lim; Masih, 2017, p.8).

translation or shift of u (RAMSEY; 2014, PHILLIPS; GORSE, 2018).

A wavelet is, therefore, a complex-valued square-integrable function that is rapidly decaying (Kristoufek, 2015). Applying wavelet continuously leads to a complex-valued transform of the time-series at hand, information preserving considering a careful selection of time and frequency resolution parameters. The continuous wavelet transform (CWT)[174] of a given time-series x is:

$$W_x(u,s) = \int_{-\infty}^{\infty} x(t) \frac{1}{\sqrt{s}} \overline{\psi}\left(\frac{t-u}{s}\right) dt, \quad (4)$$

Where s is again the scaling factor that controls the width of the wavelet and u is a translation parameter controlling the location of the wavelet, and the bar over psi Ψ denotes complex conjugate. When the wavelet $\psi(t)$ is a complex-valued function, the wavelet transforms $W_x(u,s)$ are also complex-valued, returning information about amplitude and phase difference. Therefore, it is almost mandatory to use a complex wavelet, when interested in studying oscillatory behaviour of parameters (TORRENCE; COMPO, 1998; AGUIAR - CONRARIA ET AL, 2014).

Assuming that the wavelet (eq.1) has been normalized so that $\int_{-\infty}^{\infty} |\psi(t)|^2 \, dt = 1$. This normalization, $|\psi(t)|^2$ defines a probability density function, with the mean and the standard deviation of this distribution called, respectively, the center, μ_ψ, and radius, σ_ψ, of the wavelet. They are, naturally, measures of localization and spread of the wavelet. The interval $[\mu_\psi - \sigma_\psi, \mu_\psi + \sigma_\psi]$ is set where $\psi(t)$ attains its "most significant" values.

The rectangle $H_\psi := [\mu_\psi - \sigma_\psi, \mu_\psi + \sigma_\psi] \times [\mu_{\grave{\psi}} - \sigma_{\grave{\psi}}, \mu_{\grave{\psi}} + \sigma_{\grave{\psi}}]$[175] is called the Heisenberg box or window for the function ψ. The ψ is localized around the point $(\mu_\psi, \mu_{\grave{\psi}})$ of the time-frequency plane, with uncertainty given by $\sigma_\psi \sigma_{\grave{\psi}}$. The Heisenberg principle establishes that uncertainty is bounded from below by $\frac{1}{2}$ (Aguiar- Conraria; Soares, 2011; Aguiar-Conraria *et al*, 2014).

This lower bound with the Morlet wavelet is where uncertainty attains the minimum possible value while time and frequency radius are equal $\sigma_\psi = \sigma_{\grave{\psi}} = \frac{1}{\sqrt{2}}$. Mathematically the Morlet wavelet builds on a Gaussian-windowed sinusoid that keeps its shape through frequency shifts. Thus, it provides a reasonable separation of contributions from different frequency bands without excessive loss in time resolution (Rösch; Schmidbauer, 2018). The "mother" Morlet wavelet is described as follows:

$$\psi_{\omega_0}(t) = \pi^{\frac{-1}{4}} e^{i\omega_0 t} e^{\frac{-t^2}{2}} \quad (5)$$

ω_0: localization parameter.

Strictly speaking, $\psi_{\omega_0}(t)$ is not a true wavelet, however, for sufficiently large ω_0

[174] The continuous version of the wavelet transform (CWT) assumes an underlying continuous signal, whereas a discrete wavelet transform (DWT) assumes a variable or signal consisting of observations sampled at evenly spaced points in time, which can be referred to as either orthogonal or non-orthogonal wavelets. The use of an orthogonal basis implies the use of a discrete wavelet transform (DWT), while a non-orthogonal wavelet function can be used with either the discrete or the continuous wavelet transform, with smooth variations in wavelet amplitude (TORRENCE; COMPO, 1998; CROWLEY, 2007).

[175] The $\grave{\psi}$, is the Fourier transform of wavelet ψ (AGUIAR-CONRARIA ET AL, 2014).

(e.g. $\omega_0 > 5$) and practical purposes, it can be considered as such. The most common choice of angular frequency ω_0, or rotation rate in radians per time unit, $\omega_0 = 6$ we have that $f \cong \frac{1}{s}$ facilitating the conversion from scales to frequencies, making the Morlet wavelet approximately analytic (AGUIAR- CONRARIA; SOARES, 2011; AGUIAR-CONRARIA ET AL, 2014; RÖSCH; SCHMIDBAUER, 2018).

The set of scales s determines wavelet coverage of the series in the frequency domain. The scale value is a fractional power of 2:

$$s_{min} 2^{j.d_j}, j = 0, \dots, J. \quad (6)$$

One revolution is equal to $2\pi(radians)$; therefore, the period (or inverse frequency) measured in time-units equals $2\,\pi/6$. Inverse frequency or the Fourier Factor is used to convert scales into periods:

$$\lambda(s) = \frac{2\pi}{\omega_\psi} s \quad (7)$$

The minimum (maximum) scale is fixed via the choice of the minimum (maximum) period of interest through a conversion factor of $\frac{6}{(2\pi)}$, giving consistent results for sinus waves of known frequency, which is the relationship between scale and the Fourier frequency, expressed in cycles per unit time:

$$f(s) = \frac{\omega_\psi}{s} \quad (8)$$

Local amplitude of any periodic component of the time series under investigation, and how it evolves with time, can be retrieved from the modulus of its wavelet transform:

$$Ampl(u,s) = \frac{1}{s^{\frac{1}{2}}}.|Wave\ (u,s)| \quad (9)$$

Where:

$$Wave\ = equation(3)$$

Modulus produces “biased” wavelet amplitudes in the sense that high frequency (short-period) phenomena tend to be underestimated.

The square of the amplitude is the time-frequency wavelet energy density, and is called the wavelet power spectrum:

$$Power(u,s) = \frac{1}{s}.|Wave\ (u,s)|^2 \quad (10)$$

Expectation is that at each time and scale corresponds to the series variance (with proportionally factor $\frac{1}{s}$ in this rectified version of the wavelet power).

To compare the frequency contents of two-time series, and to draw conclusions about the series synchronicity at certain periods, the cross-wavelet analysis provides the appropriate tools. The continuous wavelet transform is generalized into a cross wavelet transform as:

$$W_{xy}(u,s) = \frac{1}{s} W_x(u,s) W_y * (u,s) \text{ (11)}$$

Where $W_x(u,s)$and $W_y(u,s)$are continuos wavelet transforms of series *x(t)* and *y(t)*.

While the wavelet power spectrum is depicted as the local variance of a time series, the cross-wavelet power of two-time series depicts the local covariance in the time-frequency space. Cross wavelet power $\left|W_{xy}(u,s)\right|$ is usually used as a measure of co-movement between two series, as it uncovers regions in the time-frequency space where the series have common high power.

With some limitations, wavelet coherency can remediate this as it measures the cross-correlation between two-time series as a function of frequency. Formally and geometrically, coherency is analogue to the classical correlation; it requires smoothing of both the cross-wavelet spectrum and normalizing the individual power spectra. Wavelet coherency is given by the formula:

$$Coherence = \frac{|sWave\ .xy|^2}{sPower.x \cdot sPower.y} \text{ (2) (12)}$$

Or

$$R^2_{xy}(u,s) = \frac{\left|S\left(\frac{1}{s} W_{xy}(u,s)\right)\right|^2}{S\left(\frac{1}{s}|W_x(u,s)|^2\right) S\left(\frac{1}{s}\left|W_y(u,s)\right|^2\right)} \text{ (13)}$$

Where s is the smoothing operator.

Smoothing is necessary because otherwise, coherency would have modulus one at all scales and times. It is important to emphasize that, there is no general agreement in literature neither about the direction of smoothing (scale or time) nor about the amount of smoothing, to obtain an appropriate measure of coherence without loss of information[176].

Analysing equation (13) wavelet coherence is the ratio of the cross-wavelet power to the product of the individual wavelet power, comparable to the squared coefficient of correlation. The squared wavelet coherence ranges between 0 and 1, and it can be interpreted as the correlation coefficient around each moment in time and for each frequency.

The direction of the relationship between the variables is lost, due to the use of the squared coherence, plus the complexity of the wavelets (Kristoufek, 2015; Phillips; Gorse, 2018). To solve this, phase difference is introduced, separating the transform into its real and imaginary parts, providing both local amplitude and instantaneous phase information of the periodic process. An important condition for the investigation of coherency between time series:

$$\varphi_{xy}(u,s) = tan^{-1}\left(\frac{\Im\left[S\left(\frac{1}{s} W_{xy}(u,s)\right)\right]}{\Re\left[S\left(\frac{1}{s} W_{xy}(u,s)\right)\right]}\right) \text{ (14)}$$

[176] The R Package used in our study WaveletComp provides three directional options and a variety of filtering windows over time and scale, but with tunable width to choose from (RÖSCH; SCHMIDBAUER; 2018).

$\Im$ and $\Re$ represent an imaginary and a real part operator.

The angle $\varphi_{xy}$is called the phase difference (phase lead over x over y). In this case, $\varphi_{xy} = \varphi_x - \varphi_y$ estimates the difference of individual phases, justifying its name. This relation holds after $\varphi_x - \varphi_y$is converted to an angle with an interval $[-\pi, \pi]$. If the absolute value is less (larger) than $\pi/2$ indicates that the two series move in-phase (anti-phase). If $\varphi_{xy} \in \left(0, \frac{\pi}{2}\right)$then the series move in phase but time series x leads y, if $\varphi_{xy} \in \left(\frac{-\pi}{2}, 0\right)$ then it is y that is leading. In an anti-phase relation of $\pi, -\pi$ when $\varphi_{xy} \in \left(\frac{\pi}{2}, \pi\right)$, then y is leading; and if $\varphi_{xy} \in \left(-\pi, \frac{\pi}{2}\right)$ x is leading (AGUIAR-CONRARIA; SOARES, 2011; AGUIAR-CONRARIA ET AL, 2014).

A.1 R routine for Wavelet calculations

R Script: Wavelet Calculations for the First Period (2011-2014):

```
#Script Wavelets (2010/2014)
library(WaveletComp) library(readxl) library(dplyr) library(waveslim)

Dados1R2 <- read_excel("C:/Users/Tatiana/Desktop/Thesis/Chapter 1/Dados
2011_2014R2.xlsx", col_types = c("date","numeric", "numeric", "numeric"))

colnames(Dados1R2) <- c("date","dlnbtc","lnbtc", "lntranscount")

dlnbtc <- Dados1R2 %>% select(date,dlnbtc)

lnbtc <- Dados1R2 %>% select(date,lnbtc)

lntranscount <- Dados1R2 %>% select(date,lntranscount)

#Wavelet -> Data 2010/2014 - in log my.wc1 = analyze.coherency (Dados1R2, my.pair =
c("lnbtc","lntranscount"), loess.span = 0, dt = 1, dj = 1/20, window.type.t = 3, window.type.s
= 3, window.size.t = 5, window.size.s = 1, lowerPeriod = 2, upperPeriod = 480, #lowerperiod
= 2dt, #upperPeriod = floor(nrow(Dados_R)/3)dt, make.pval = TRUE, n.sim = 100)
wc.image(my.wc1, which.image = "wc", color.key = "interval", n.levels = 250,
legend.params = list (lab = "Wavelet Coherence Levels"), show.date = T, date.format = "%y-
%m-%d", timelab = "Year", periodlab = "Period (Days)" )

#Wavelet "Transaction Count" -> Data 2011/2014

wt.image (my.wc1, my.series = "lntranscount", n.levels = 250, legend.params = list (lab =
"Wavelet Power Levels"), show.date = T, date.format = "%y-%m-%d", timelab = "Year",
periodlab = "Period (Days)")
```

R Script: Wavelet Calculations for the Second Period (2015 -2018):

```
#Script Wavelets (2015/2018)

library(WaveletComp) library(readxl) library(dplyr) library(waveslim)

Dados2R2 <- read_excel("C:/Users/Tatiana/Desktop/Thesis/Chapter 1/Dados
2015_2018R2.xlsx", col_types = c("date", "numeric","numeric","numeric"))

colnames(Dados2R2) <- c("date","dlnbtc","lnbtc", "lntranscount")
```

dlnbtc <- Dados2R2 %>% select(date,dlnbtc)

lnbtc <- Dados2R2 %>% select(date,lnbtc)

lntranscount <- Dados2R2 %>% select(date,lntranscount)

#Wavelet -> Data 2015/2018 - in log

my.wc1 = analyze.coherency (Dados2R2, my.pair = c("lnbtc","lntranscount"), loess.span = 0, dt = 1, dj = 1/20, window.type.t = 3, window.type.s = 3, window.size.t = 5, window.size.s = 1, lowerPeriod = 2,upperPeriod = 480, #lowerperiod = 2*dt, #upperPeriod = floor(nrow(Dados_R)/3)*dt, make.pval = TRUE, n.sim = 100) wc.image(my.wc1, which.image = "wc", color.key = "interval", n.levels = 250, legend.params = list (lab = "Wavelet Coherence Levels"), show.date = T, date.format = "%y-%m-%d", timelab = "Year", periodlab = "Period (Days)")

#Wavelet "Transaction Count" -> Data 2015/2018

wt.image (my.wc1, my.series = "lntranscount", n.levels = 250, legend.params = list (lab = "Wavelet Power Levels"), show.date = T, date.format = "%y-%m-%d", timelab = "Year", periodlab = "Period (Days)")

<u>R Script: Wavelet Calculations for the Third Period (2019-2021):</u>
#Script Wavelets (2019/2021)

library(WaveletComp) library(readxl) library(dplyr) library(waveslim)

Dados3R2 <- read_excel("C:/Users/Tatiana/Desktop/Thesis/Chapter 1/Dados 2019_2021R2.xlsx", col_types = c("date", "numeric", "numeric","numeric"))

colnames(Dados3R2) <- c("date","dlnbtc","lnbtc", "lntranscount")

dlnbtc <- Dados3R2 %>% select(date,dlnbtc)

lnbtc <- Dados3R2 %>% select(date,lnbtc)

lntranscount <- Dados3R2 %>% select(date,lntranscount)

#Wavelet -> Data 2019/2021 - in log

my.wc1 = analyze.coherency (Dados3R2, my.pair = c("lnbtc","lntranscount"), loess.span = 0, dt = 1, dj = 1/20, window.type.t = 3, window.type.s = 3, window.size.t = 5, window.size.s = 1, lowerPeriod = 2,upperPeriod = 480, #lowerperiod = 2*dt, #upperPeriod = floor(nrow(Dados_R)/3)*dt, make.pval = TRUE, n.sim = 100) wc.image(my.wc1, which.image = "wc", color.key = "interval", n.levels = 250, legend.params = list (lab = "Wavelet Coherence Levels"), show.date = T, date.format = "%y-%m-%d", timelab = "Year", periodlab = "Period (Days)")

#Wavelet "Transaction Count" -> Data 2019/2021

wt.image (my.wc1, my.series = "lntranscount", n.levels = 250, legend.params = list (lab = "Wavelet Coherence Levels"), show.date = T, date.format = "%y-%m-%d", timelab = "Year", periodlab = "Period (Days)")

Angi Roesch and Harald Schmidbauer (2018). WaveletComp: Computational Wavelet Analysis. R package version 1.1. https://CRAN.R-project.org/package=WaveletComp

APPENDIX B - PAPER 2

A.2 Table 1. Unit root tests, in levels (August/2011 - August/2021)

	Test Statistics				
Tests/ Variables	ADF [P-value]	PP [P-Value]	DF-GLS (T-Stat)	KPSS (LM-Stat)	OI
DLN*BTC	(-8,937)** [0,000]	(-8,863)** [0,000]	(-0,560) (-1,943)	(0,055)** (0,463)	S
1 YTCMR	(-1,017) [-0,745]	(-1,269) [0,642]	(-0,906) (-1,943)	(0,470) (0,463)	NS
1 YTCMR POS	(-0,112) (0,94]	(0,235) [0,973]	(0,881) (-1,943)	(1,220) (0,463)	NS
1 YTCMR NEG	(1,933) [0,99]	(1,390) [0,99]	(2,924) ** (-1,943)	(0,939) (0,463)	NS
LN*SP500	(-0,067) [0,949]	(0,430) [0,983]	(2,231)** (-1,943)	(1,288) (0,463)	NS
LN*SP500 POS	(1,484) [0,999]	(1,685) [0,999]	(7,122)** (-1,943)	(1,282) (0,463)	NS
LN*SP500 NEG	(0,818) [0,994]	(0,815) [0,994]	(3,436)** (-1,943)	(1,232) (0,463)	NS
LN TRANSACTION COUNT	(-3,224)** [0,020]	(-3,370)** [0,014]	(0,553) (-1,943)	(1,103) (0,463)	S
LN* TRANSACTION COUNT POS	(-4,703)** [0,00]	(-5,335)** [0,00]	(1,339) (-1,943)	(1,251) (0,463)	S
LN*TRANSACTION COUNT NEG	(-0,359) [0,911]	(-0,442) [0,897]	(1,874) (-1,943)	(1,294) (0,463)	NS
TRENDS	(-2,974)** [0,040]	(-2,937)** [0,044]	(-2,655)** (-1,943)	(0,831) (0,463)	S
TRENDS POS	(0,972) [0,996]	(1,254) [0,998]	(1,921) (-1,943)	(1,183) (0,463)	NS
TRENDS NEG	(1,140) [0,997]	(1,115) [0,997]	(2,094)** (-1,943)	(1,165) (0,463)	NS

Note: Seasonally adjusted with ARIMA-SEATS and x-11 from the Census -13. OI: Order of integration. S: stationary. NS: non-stationary. IC: inconclusive. Estimations indicate with constant and no trend. ()** critical values at 5%. ADF and PP: H0: Unit root (non-stationary). KPSS: H0: No unit root (stationary). DLN*BTC: bitcoin price in dollars, in natural logarithm and first differenced. LN* natural logarithm transformation. Source: Author's elaboration from EViews 10.

A.2 Table 2. Unit root tests, in first differences (August/2011 - August/2021)

Tests/ Variables	Test Statistic ADF[Prob]	PP [Prob]	DF-GLS (T-Stat)	KPSS (LM-Stat)	OI
DLN*BTC	(-8,680)** [0,000]	(-52,68)** [0,000]	(-8,348)** (-1,943)	(0,149)** (0,463)	S
1 YTCMR	(-8,785)** [0,000]	(-9,291)** [0,000]	(-8,810)** (-1,943)	(0,245)** (0,463)	S
1 YTCMR POS	(-4,251)** [0,000]	(-8,118)** [0,000]	(-4,095)** (-1,943)	(0,309)** (0,463)	S
1 YTCMR NEG	(-9,174)** [0,000]	(-9,444)** [0,000]	(-8,913)** (1,943)	(0,518) (0,463)	S
LN*SP500	(-12,542)** [0,000]	(-13,143)** [0,000]	(-0,732) (-1,943)	(0,154)** (0,463)	S
LN*SP500 POS	(-12,798)** [0,000]	(-12,879)** [0,000]	(-0,894) (-1,943)	(0,589) (0,463)	S
LN*SP500 NEG	(-9,063)** [0,000]	(-8,948)** [0,000]	(-8,484)** (-1,943)	(0,234)** (0,463)	S
LN*TRANSACTIO N COUNT	(-9,102)** [0,000]	(-9,086)** [0,000]	(-7,195)** (-1,943)	(0,725)** (0,463)	S
LN*TRANSACTIO N COUNT POS	(-8,901)** [0,000]	(-8,999)** [0,000]	(-8,795)** (-1,943)	(0,962) (0,463)	S
LN*TRANSACTIO N COUNT NEG	(-8,002)** [0,000]	(-7,704)** [0,000]	(-7,495)** (-1,943)	(0,041)** (0,463)	S
TRENDS	(-11,035)** [0,000]	(-11,422)** [0,000]	(-11,082)** (-1,943)	(0,035)** (0,463)	S
TRENDS POS	(-8,284)** [0,000]	(-8,270)** [0,000]	(-8,079)** (-1,943)	(0,350)** (0,463)	S
TRENDS NEG	(-8,391)** [0,000]	(-8,631)** [0,000]	(-8,268)** (-1,943)	(0,320)** (0,463)	S

Note: Seasonally adjusted with ARIMA-SEATS and x-11 from the Census -13. OI: Order of integration. S: stationary. NS: non-stationary. IC: inconclusive. Estimations indicate with constant and no trend. ()** critical values at 5%. ADF and PP: H0: Unit root. KPSS: H0: No unit root (stationary). DLN*BTC: bitcoin price in dollars, in natural logarithm and first differenced. LN*: natural logarithm transformation. Source: Author's elaboration from EViews 10.

A.2 Table 3. Long run estimates. NARDL Model 01 (6 lags) (August/2011 - August/2021)

Model: NARDL (1,0,0,5,6,3)**		
Dependent Variable: BTC real returns (DLNBTC)		
Variable	Coefficient	T-Statistic [Prob]
1 YTCMR	**0,1622**	**2,181 [0,031]**
LNSP500	**0,925**	**3,042 [0,003]**
LNTRANSCOUNT POS	**0,214**	**3,074 [0,002]**
LNTRANSCOUNT NEG	**0,822**	**4,041 [0,000]**
TRENDS	-0,002	-1,086 [0,280]
C	-6,782	-3,043 [0,003]
F-Bounds Test	Critical values (at the 1% level)	
16,36	3,35 - 4,58	
LM Serial Correlation Test [Prob]	F(6,86) 1,13 [0,34]	
White Heteroskedasticity Test [Prob]	F(21,92) 1,17 [0,28]	

Note. NARDL model with maximum of six (6) lags. Model choice based on Akaike Information Criteria. **Case 2: restricted constant and no trend. Source: Author's elaboration (EViews 10).

A.2 Table 4. Short run estimates (Error Correction Regression). NARDL Model 01 (6 lags) (August/2011 - August/2021)

Model: NARDL (1,0,0,5,6,3)**		
Dependent Variable: BTC real returns (DLNBTC)		
Variable	Coefficient	T-Statistic [Prob]
D(LNTRANSCOUNT) POS	0,154	0,638 [0,524]
D(LNTRANSCOUNT) POS (-1)	0,074	0,298 [0,766]
D(LNTRANSCOUNT) POS (-2)	0,516	2,049 [0,043]
D(LNTRANSCOUNT) POS (-3)	**0,524**	**2,118 [0,036]**
D(LNTRANSCOUNT) POS (-4)	**-0,665**	**-2,805 [0,006]**
D(LNTRANSCOUNT) NEG	**1,235**	**3,189 [0,001]**
D(LNTRANSCOUNT) NEG (-1)	-0,195	-0,495 [0,621]
D(LNTRANSCOUNT) NEG (-2)	**-0,934**	**-2,376 [0,019]**
D(LNTRANSCOUNT)NEG (-3)	-0,453	-1,142 [0,256]
D(LNTRANSCOUNT) NEG (-4)	0,426	1,136 [0,258]
D(LNTRANSCOUNT) NEG (-5)	**-1,327**	**-3,864 [0,000]**
D(TRENDS)	0,003	1,507 [0,135]
D (TRENDS) (-1)	-0,002	-1,033 [0,303]
D(TRENDS) (-2)	**0,008**	**2,818 [0,005]**
DUMMY	0,523	7,252 [0,000]
ECM (CointEq (-1))	-1,00	(-11,047) [0,000]

Note. NARDL model with maximum of six (6) lags. Model choice based on Akaike Information Criteria. **Case 2: restricted constant and no trend. Source: Author's elaboration (EViews 10).

A.2 Table 5. Long run estimates. NARDL Model 02 (6 lags) (August/2011 - August/2021)

Model: NARDL (1,0,1,4,6,2)**		
Dependent Variable: BTC real returns (DLNBTC)		
Variable	Coefficient	T-Statistic [Prob]
1 YTCMR	0,0338	0,814 [0,417]
LNSP500 POS	**-1,439**	**-3,648 [0,000]**
LNSP500 NEG	**-1,920**	**-3,079 [0,002]**
LNTRANSCOUNT	**0,196**	**3,830 [0,000]**
TRENDS	**0,004**	**2,770 [0,006]**
C	-2,382	-3,768 [0,000]
F-Bounds Test	Critical values (at the 1% level)	
15,96	3,35 - 4,58	
LM Serial Correlation Test [Prob]	F(6,88)	0,47[0,82]
White Heteroskedasticity Test [Prob]	F(20,94)	0,90[0,58]

Note. NARDL model with maximum of six (6) lags. Model choice based on Akaike Information Criteria. **Case 2: restricted constant and no trend. Source: Author's elaboration (EViews 10).

A.2 Table 6. Short run estimates (Error Correction Regression). NARDL Model 02 (6 lags) (August/2011 - August/2021)

Model: NARDL (1,0,1,4,6,2)**		
Dependent Variable: BTC real returns (DLNBTC)		
Variable	Coefficient	T-Statistic [Prob]
D(LNSP500) POS	1,247	1,083 [0,281]
D(LNSP500) NEG	0,819	0,739 [0,461]
D(LNSP500) NEG (-1)	**3,756**	**3,033 [0,003]**
D(LNSP500) NEG (-2)	0,217	0,200 [0,841]
D(LNSP500) NEG (-3)	**2,432**	**2,298 [0,023]**
D (LNTRANSCOUNT)	**0,598**	**3,263 [0,001]**
D (LNTRANSCOUNT) (-1)	0,076	0,394 [0,694]
D (LNTRANSCOUNT) (-2)	0,106	0,591 [0,555]
D (LNTRANSCOUNT) (-3)	0,277	1,532 [0,128]
D (LNTRANSCOUNT) (-4)	-0,224	(-1,260) [0,210]
D (LNTRANSCOUNT) (-5)	**-0,450**	**-2,510 [0,013]**
D(TRENDS)	**0,006**	**2,393 [0,018]**
D(TRENDS) (-1)	**-0,007**	**-2,716 [0,007]**
DUMMY	0,237	3,317 [0,001]
ECM (CointEq (-1))	-1,02	(-10,902) [0,000]

Note. NARDL model with maximum of six (6) lags. Model choice based on Akaike Information Criteria. **Case 2: restricted constant and no trend. Source: Author's elaboration (EViews 10).

APPENDIX C - PAPER 3

A.3 Table 1. Unit root tests in levels, dataset from Indian payment systems (April/2016 – November/2020)

Tests/ Variables	Test Statistics				OI
	ADF [P-value]	PP [P-value]	DF-GLS (T - Stat)	KPSS (LM-Stat)	
UPI	(4,259) [1,000]	(5,233) [1,000]	(3,806)** (-1,946)	(0,852) (0,463)	NS
M1/GDP	(-1,953) [0,306]	(-1,885) [0,336]	(-1,990)** (-1,946)	(0,756) (0,463)	NS
M1/GDP POS	(0,650) [0,989]	(0,605) [0,988]	(1,745) (-1,946)	(0,803) (0,463)	NS
M1/GDP NEG	(0,525) [0,986]	(0,656) [0,990]	(2,273)** (-1,946)	(0,928) (0,463)	NS
NT1	(-1,997) [0,287]	(-1,892) [0,333]	(-1,074) (-1,946)	(0,781) (0,463)	NS
NT1 POS	(2,366) [1,000]	(2,366) [1,000]	(4,118)** (-1,946)	(0,865) (0,463)	NS
NT1 NEG	(-0,412) [0,899]	(0,5277) [0,986]	(-0,319) (-1,947)	(0,639) (0,463)	NS
NT2	(-2,735)*** [0,074]	(-2,189) [0,212]	(-0,861) (-1,947)	(0,715) (0,463)	NS
D(MB)	(0,050) [-2,928]	(-5,835)** [0,000]	(-5,655)** (-1,946)	(0,499) (0,463)	S
RTGS	(-2,820)*** [0,062]	(-1,963) [0,301]	(-1,462) (-1,946)	(0,829) (0,463)	NS
RTGS POS	(1,567) [0,999]	(1,453) [0,999]	(2,980)** (-1,946)	(0,951) (0,463)	NS
RTGS NEG	(-0,363) [0,907]	(0,595) [0,988]	(0,029) (-1,947)	(0,820) (0,463)	NS
D(MB)/WLESS	(0,095) [0,962]	(-5,830)** [0,000]	(-5,668)** (-1,946)	(0,495) (0,463)	S

Note. Seasonally adjusted with ARIMA-SEATS and x-11 from the Census -13. OI: Order of integration. S: stationary. NS: non-stationary. IC: inconclusive. Estimations indicated are with constant and no trend. ()** critical values at 5%. ()*** critical values at 10%. ADF and PP: H0: Unit root (non-stationary). KPSS: H0: No unit root (stationary). Authors elaboration from EViews 10.

A.3 Table 2. Unit root tests in first differences, dataset from Indian payment systems (April/2016 – November/2020)

Tests/ Variables	Test Statistics ADF [Prob]	PP [Prob]	DF-GLS (LM-Stat)	KPSS (T-Stat)	OI
UPI	(-8,066)** [0,000]	(-8,076)** [0,000]	(-7,534)** (-1,946)	(0,910) (0,463)	S
M1/GDP	(-6,281)** [0,000]	(-12,708)** [0,000]	(-8,270)** (-1,946)	(0,500) (0,463)	S
M1/GDP POS	(-6,230)** [0,000]	(-6,200)** [0,000]	(-6,076)** (-1,947)	(0,204)** (0,463)	S
M1/GDP NEG	(-4,211)** [0,001]	(-8,236)** [0,000]	(-1,975)** (-1,947)	(0,267)** (0,463)	S
NT1	(-7,100)** [0,000]	(-6,623)** [0,000]	(-7,070)** (-1,947)	(0,110)** (0,463)	S
NT1 POS	(-6,206)** [0,000]	(-6,197)** [0,000]	(-5,799)** (-1,947)	(0,515) (0,463)	S
NT1 NEG	(-4,951)** [0,000]	(-4,874)** [0,000]	(-4,945)** (-1,947)	(0,267)** (0,463)	S
NT2	(-6,570)** [0,000]	(-6,029)** [0,000]	(-6,636)** (-1,947)	(0,196)** (0,463)	S
D(MB)	(-7,804)** [0,000]	(-12,694)** [0,000]	(-0,280) (-1,948)	(0,053)** (0,463)	S
RTGS	(-6,701)** [0,000]	(-7,508)** [0,000]	(-6,727)** (-1,947)	(0,124)** (0,463)	S
RTGS POS	(-5,535)** [0,000]	(-5,561)** [0,000]	(-5,590)** (-1,947)	(0,325)** (0,463)	S
RTGS NEG	(-4,656)** [0,000]	(-4,445)** [0,000]	(-4,610)** (-1,947)	(0,198)** (0,463)	S
D(MB)/WLESS	(-7,728)** [0,000]	(-12,682)** [0,000]	(-0,221) (-1,948)	(0,052)** (0,463)	S

Note. Seasonally adjusted with ARIMA-SEATS and x-11 from the Census -13. OI: Order of integration. S: stationary. NS: non-stationary. Estimations indicated are with constant and no trend. ( )** critical values at 5%. ADF and PP: H0: Unit root. KPSS: H0: No unit root (stationary). Authors elaboration from EViews 10.

A.3 Table 3. NARDL Long Run Asymmetric Coefficients (Levels Equation) for the four specified models (dependent Variable UPI), (Indian Dataset)

Model	1	2	3	4
NARDL Model	(6,1,6,6,6)	(6,0,2,6,2)	(1,5,0,4,4)	(6,2,6,0,2)
D(MB)/WLESS	4188.69 [0.169]	1139.37 [0.305]	3730.59 [0.267]	
D(MB)				0.956 [0.295]
NT1 POS		8.21E-06 [0.307]		8.31E-06 [0.288]
NT1 NEG		(-7.90E-06) [0.475]		(-7.67E-06) [0.470]
NT2			(-7.00E-07) [0.802]	
RTGS POS	(-11.633) [0.791]			
RTGS NEG	(-34.692) [0.650]			
M1/GDP	(-1379.84) [0.453]	147.947 [0.676]		146.029 [0.674]
M1/GDP POS			360.355 [0.4439]	
M1/GDP NEG			130.401 [0.8465]	
C	2832.50 [0.465]	(-839.858) [0.164]	503.625 [0.7126]	(-837.905) [0.157]

Note: Software used for estimation EViews 10. ARDL models considered are case II: Restricted Constant and No Trend.

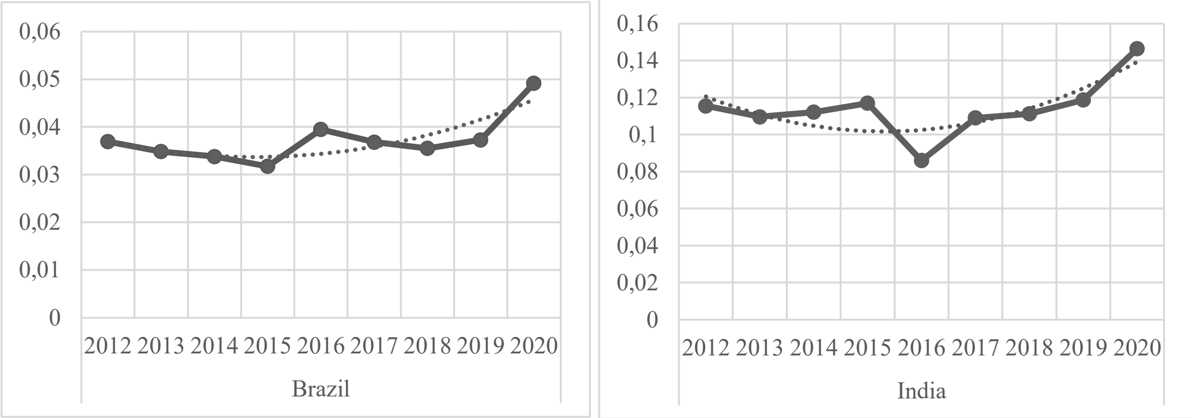
A.3 Table 4. Stepwise Least Squares estimation based on the NARDL coefficients. Statistically significant shocks to the dependent variable (UPI). (April 2016 – November 2020). Dataset from Indian payment systems.

Model	Method	Model Selected	Positive and Negative Shocks	Statistically relevant shock	Coefficient	T-Statistic [Prob]
1	NARDL	(6,1,6,6,6)	RTGS +, RTGS -	RTGS+	0.8354	**1.824 [0.075]***
2	NARDL	(6,0,2,6,2)	NT1 +, NT1 -	NT1+	1.07E-06	**2.193 [0.034]***
3	NARDL	(1,5,0,4,4)	M1/GDP +, M1/GDP -	-	-	-
4	NARDL	(6,2,6,0,2)	NT1 +, NT1 -	NT1+	1.07E-06	**2.184 [0.034]***

Note: Author’s elaboration. Estimation made through EViews 10. * Statistical significance at the 5% and the 10% level.

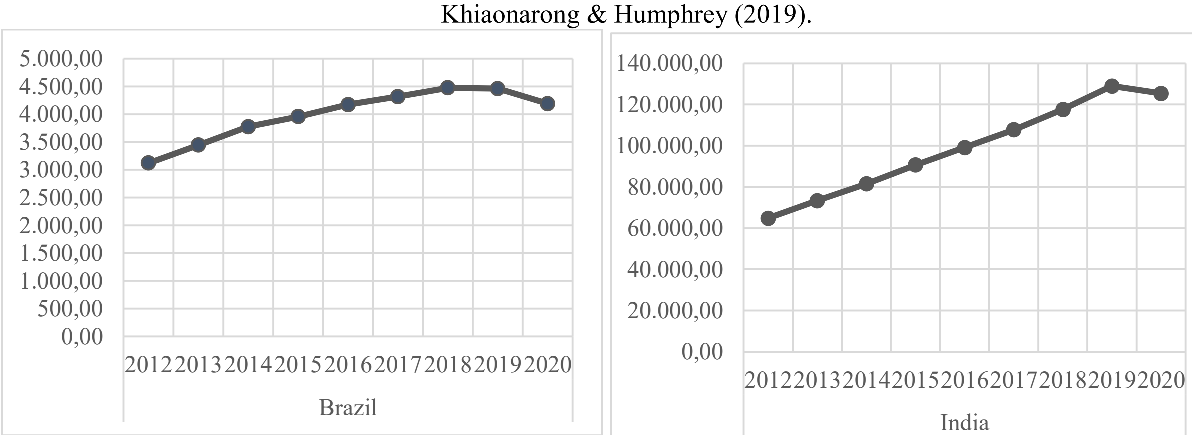
APPENDIX D - PAPER 4

A.4 Graph. 1. CIC/GDP ratio for Brazil and India (2012-2020) based on Khiaonarong & Humphrey (2019).



Source: Bank of International Settlements (BIS) and World Bank (2022). Author's calculations.

A.4 Graph. 2. Residual Cash estimation for Brazil and India (2012-2020) in billions of BRL/INR based on Khiaonarong & Humphrey (2019).



Source: Bank of International Settlements (BIS) and World Bank (2022). Author's calculations.

A.4 Burg's Algorithm:

Linear prediction models estimates the current data sample as a linear combination of the past or future data samples. The optimal prediction coefficients are determined by minimizing the mean-square error. Suppose a signal $x(n), n = 1,2, \dots, N,$ considering the forward and backward linear prediction (LP) estimates of order $m = 1,2, \dots, p$

$$\hat{x}(n) = -\sum_{k=1}^{m} \alpha_m(k)x(n-k), \qquad (1.1)$$

$$\hat{x}(n-m) = -\sum_{k=1}^{m} \beta_m(k)x(n+k-m), \qquad (1.2)$$

Where $\alpha_m\,(k)$ and $\beta_m\,(k)$ are the forward and backward prediction coefficients, $x^t(n) = [x(n), x(n-1), \dots, x(n-m)]$. The Burg method is based on the concept of forward and backward finite impulse response (FIR) filters of the signal $x(n)$.

$$f_m(n) = x(n) - \hat{x}(n) = \sum_{k=0}^{m} \alpha_m\,(k)x(n-k), \qquad (2.1)$$

$$b_m(n) = x(n-m) - \hat{x}\,(n-m) = \sum_{k=0}^{m} \beta_m\,(k)x(n+k-m), \qquad (2.2)$$

Where $f_m(n)$ and $b_m(n)$ are the forward and backward prediction errors (residuals). Note that $\alpha_m\,(0) = \beta_m(0) = 1$ by definition. The forward filter output $f_m(n)$ and the backward filter output $b_m(n)$ depend on the column $(m+1)$ dimensional vector $x(n)$. In practice, we must choose $m < N$. Assuming that $x(n)$ is only available over the interval $m+1 \le n \le N$. (KAZLAUSKAS, 2011, p.179).

An essential characteristic of the algorithm is that the number of residuals decreases with each recursion step, calculating the reflection coefficients K_m so that they minimize the sum of the forward and backward residual errors. The prediction error filter estimated coefficients are found at the end of the recursions. The absolute value of K_m is always smaller than unity. Therefor the stability of the estimated AR model is guaranteed. The Burg method not only minimizes the combined global error, but also gives better estimates, resulting in high frequency resolution through efficient recursive implementation. Limitations of the algorithm for the autoregressive estimation are basically for engineering implementations such as frequency bias and line-splitting in processing the sinusoidal signals in noise.

ANNEX - PAPER 4

Table 1. Factors that support the adoption of digital money

Supply factors	Description	Indicators
Infrastructure for adoption	Digital money requires a network and digital infrastructure, such as mobile phone coverage and retail agent networks, for adoption.	Share of population with mobile phone subscription, share of population with access to internet, avalibility of exchanges.
Traditional payment service provider profitability and costs.	Incumbent financial institutional cost structures are high, making financial institutions unattractive. Digital money providers may not be subject to the same requirements or could have lower compliance costs.	FATF AML/CFT high-risk designation (proxies for higher KYC and risk management costs to banks); measure of off-shore/tax haven status (higher risk); incumbent financial institution profitability; level of interchange by payment card providers.
Public sector desire to improve payments and financial systems.	Improvements in domestic payments efficiency, payments safety and financial inclusion, reliance on cash use.	Low share of population with transaction account; high reliance on cash or very low cash usage.
Demand factors	**Description**	**Indicators**
Cost and convenience	Cost and speed of digital currency transfer or exchange may differ from traditional payments with a bank.	Cost of receiving remittances, current speed of receiving payments.
Confidence in incumbent banking system	Trust in incumbent financial institutions, could be undermined by crises and concentrated markets or monopoly power.	Incidence of financial crises over the years, concentration of banking system in local market, shadow economy.
Confidence in government	Trust in the public sector, including the public's expectation of sustainable monetary and fiscal policy may support CBDCs. While financial repression and weak macro-financial policies may support private stablecoins.	Trust in government index, corruption perception index, to proxy for poor rule of law and higher risk countries, controls on domestic currency.
Macroeconomic factors	Poor growth and large fluctuations in the value of the domestic currency may make private alternatives, more attractive to users.	Growth, foreign exchange, volatility, inflation and trade flows.

Source: Feyen et al (2021, p. 10).