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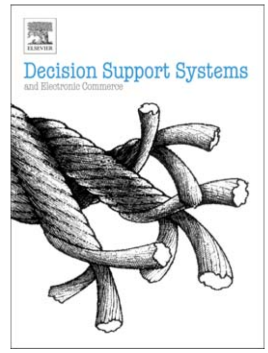

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The Technology and Economic Determinants of Cryptocurrency Exchange Rates: The Case of Bitcoin

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Abstract

Cryptocurrencies, such as Bitcoin, have ignited intense discussions. Despite receiving extensive public attention, theoretical understanding is limited regarding the value of blockchain-based cryptocurrencies, as expressed in their exchange rates against traditional currencies. In this paper, we conduct a theory-driven empirical study of the Bitcoin exchange rate (against USD) determination, taking into consideration both technology and economic factors. To address co-integration in a mix of stationary and non-stationary time series, we use the autoregressive distributed lag (ARDL) model with a bounds test approach in the estimation. Meanwhile, to detect potential structural changes, we estimate our empirical model on two periods separated by the closure of Mt. Gox (one of the largest Bitcoin exchange markets). According to our analysis, in the short term, the Bitcoin exchange rate adjusts to changes in economic fundamentals and market conditions. The long-term Bitcoin exchange rate is more sensitive to economic fundamentals and less sensitive to technological factors after Mt. Gox closed. We also identify a significant impact of mining technology and a decreasing significance of mining difficulty in the Bitcoin exchange price determination.

***Keywords*:** Cryptocurrency; Bitcoin; Exchange rate; Technology-economic perspective; Mining technology

1. Introduction

Blockchain technologies and cryptocurrencies,[1] such as Bitcoin, Litecoin, and Ethereum, have attracted significant attention in recent years. Some have expected that cryptocurrencies would cast disruptive impacts on the financial systems [1]. To date, Bitcoin is the most significant example of blockchain-based cryptocurrencies. According to some recent reports, Bitcoin transaction values could reach $92 billion bitcoins in 2016.[2]

Despite rising economic significance and expressed enthusiasm, academic research concerning cryptocurrencies has only started to emerge [2–8]. A pressing question in the emerging blockchain ecosystem which is related to investment decision making is how a cryptocurrency would be priced. Dramatic price fluctuations in Bitcoin exchange markets have resulted in extensive debates and doubts about using cryptocurrencies as a transaction medium.[3] Some early research considered Bitcoin as a speculative bubble rather than a proper currency system [6, 9]. Still today, there is not a consensus about the real value of cryptocurrencies that can direct investment decision making.

The current study pioneers a theory-driven discussion regarding the market value determination of cryptocurrencies, using Bitcoin as a primary example. Theoretically, we root the discussion in the literature on technology acceptance and monetary economics theories, recognizing that a cryptocurrency is both a technology artifact and an economic instrument of value transaction. Such a multi-perspective framework not only enables a systematic discussion that helps synthesize existing evidence but also provides a logical foundation for future research and model extensions. Empirically, we adopt an Autoregressive Distributed Lag (ARDL) model with a bounds test approach [10] to identify the dynamics of the Bitcoin exchange rate. The model addresses empirical issues in existing studies and enables us to understand the long-term relationship between the exchange value and the determinants that take short-term fluctuations into consideration. In addition, we compare

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[1] Cryptocurrency is a new breed of digital currencies that derived from the blockchain technology. The Bitcoin system was proposed in a paper by Satoshi Nakamoto in 2008 [65].

[2] "'Trump-Brexit' Factors Could Triple Bitcoin Transactions but Where's the Price Heading?" Forbes, http://goo.gl/IEa8lx.

[3] For example, John Quiggin, "The Bitcoin Bubble and a Bad Hypothesis," http://goo.gl/qbV6Z; and Mark T. Williams, "Bitcoin Will Crash To $10 By Mid-2014," http://goo.gl/9E0Hbh.

model estimates from two consecutive time periods separated by the closing down of Mt. Gox (the largest Bitcoin exchange marketplace at the time). We name the Mt. Gox period as the early market and the post-Mt. Gox period as the later market. The comparison allows us to shed light on the speculative nature of Bitcoin price movement in the early market and discover a trend towards more rational price dynamics.

Our investigation yields interesting findings. Specifically, there is a salient contrast between estimates from the early market and those from the later market. First, public interest-related variables have more significant long-term impacts in the early market, while economic factors become more significant in the later market. Second, while trading activities play a significant role in the early market, their significance declines in the later market. This indicates that as public recognition increases, speculative trading becomes less prominent. Third, as mining technology progresses, the marginal impact of mining difficulty on price reduces. Fourth, the short-term adjustment against the public interest reduces in the later market. Overall, the analysis suggests that: (1) technology factors play important roles in determining the Bitcoin exchange rate in terms of both mining technology and public recognition; and (2) the Bitcoin valuation gradually evolves to a "mature" state, which resembles other monetary instruments and aligns with economic fundamentals in the long term.

This study makes several contributions to the information systems (IS) literature in developing a comprehensive theoretical explanation of the exchange value of Bitcoin. First, answering the call for modeling cryptocurrency exchange rates and building powerful investment decision support tools, we propose and test a theoretical model in the context of the Bitcoin exchange market using an advanced econometric modeling technique (ARDL bounds test approach) that helps address empirical issues in existing studies. The empirical results prove the utility of the model. Second, unlike other studies in this emerging literature, our theory recognizes the dual nature of cryptocurrencies and includes the joint determination of technology and economic factors. It thus offers a more comprehensive model and serves as a good foundation for subsequent research. Third, our empirical investigation compares estimates from two consecutive periods. It generates insights on investor decision making in emerging financial markets by revealing the phasing out of market speculation and the emerging significance of technology factors in driving the fundamental value of cryptocurrencies.

Financial instrument valuation has always been an important area in decision support research [11, 12], and there has been continuous interest in price dynamics in exchange markets [13, 14]. Results from this research contribute to our understanding of the market dynamics of cryptocurrencies. They reveal important managerial insights and are useful in enabling more efficient, data-driven investment decision making. Further, cryptocurrencies and other disruptive financial technologies are active areas in IS research (see for instance, [15–18]). This research thus fits into and contributes to the decision support literature. Given the rapid development of the technology and growing market recognition,[4] it is foreseeable that cryptocurrency systems could cause disruptive changes in financial industry, making it critical to build up a solid theoretical foundation.

In the following, we first briefly introduce the cryptocurrency technology and the Bitcoin exchange market. After establishing a basic understanding of Bitcoin, hypotheses are developed. We then report an empirical study with a few robustness checks. The paper concludes with a discussion of theoretical contributions and practical implications.

2. Background and Literature Review

This paper proposes a model for understanding the value of cryptocurrencies and empirical validating the model using observations of Bitcoin exchange rates. We begin by introducing the general background of Bitcoin.

2.1 Blockchain, Ledger Protection, and Mining

Cryptocurrencies, such as Bitcoin, are a new breed of digital currency systems built on computer cryptology and decentralized (peer-to-peer) network architecture. To serve as a payment medium and value storage, Bitcoin creates a decentralized authentication system to deal with counterfeits and double-spending problems, whereas modern fiat monetary systems and early digital payment systems require central institutions to authenticate transactions and serve as repositories (see

[4] In May 2015, the New York Stock Exchange officially launched its own Bitcoin index. http://www.bizjournals.com/newyork/news/2015/05/19/new-york-stock-exchange-bitcoin-exchange.html.

also, [4, 19]).[5]

Bitcoin is essentially a large, distributed public ledger of validated transactions. The ledger is organized as a chain of "blocks." The blockchain contains "blocks" of validated transaction records to track the ownership of every bitcoin. Each transaction record contains the receiver's public key. In a Bitcoin transaction, the current owner validates his/her ownership using the private key and sends a transaction instruction encrypted with his/her private key. The system then records the transaction instruction that contains the public key of the receiver (the new owner) in a new block.

To protect the ledger's integrity, the system labels and thus protects each block with a unique hash. The hash is generated based on the information on the block and an integer key. The generated hash needs to meets a "hash-rate criterion" set by the system. A new block that documents recent transactions is confirmed and added to the blockchain only when a valid hash is found. Generating a hash using a key is easy. Reverse engineering a key from a hash, however, is cryptographically difficult. A valid hash that meet the hash-rate criterion is discovered through trial and error, which requires significant computing power. The Bitcoin system crowdsources the hash-generating process from specialized users, called miners. By having a large number of miners investing a large amount of computational power on hash-generating, Bitcoin makes it difficult for ill-intentioned users to find a valid hash for their altered blocks before other miners finding a valid hash for the block that contains real transactions.

Miners are incentivized to contribute computational power in generating hash and validating blocks by receiving new bitcoins. Mining is the only way that new bitcoins are introduced. By design, the number of bitcoins generated per block starts at 50 and decreases by a half every 210,000 blocks. A block is generated approximately every ten minutes. To control block generation speed, the hash-rate criterion, and thus the mining difficulty, adjusts every 2016 blocks. Higher mining difficulty is associated with more computing power investment per bitcoin. Under this mechanism, the Bitcoin

[5] The two basic promises of any currency system are (1) users should be guaranteed to receive authentic currency that can be spent in future transactions, and (2) each unit of the currency can only be spent once by the owner, i.e., no double-spending. Paper-based currencies use multiple counterfeit measures in their production and are immune to the double-spending problem. Digital currency systems rely on central institutions as trusted issuers and bookkeepers to avoid the double-spending problem.

mining yield starts at roughly 7200 blocks per day initially and reduces by one half approximately every 4 years.

Besides the mining difficulty, the computational power cost in mining also depends on mining technology. Since the introduction of Bitcoin, there have been four generations of mining devices, namely, Central Processing Units (CPUs), Graphics Processing Units (GPUs), Field Programmable Gate Arrays (FPGAs), and ASIC- Application-Specific Integrated Circuits (ASICs), where each generation is successively more efficient in Bitcoin mining. GPU-based devices gradually replaced CPU-based devices in 2011. FPGA devices were first offered in January 2012. By 2014, FPGA mining devices dominated the market. ASIC devices were introduced in early 2013 but received less adoption than FPGA devices until 2014, because they require a higher initial investment. As we will discuss later, these technical features of cryptocurrency systems have critical implications for its value.

2.2 Exchange Markets

The value of Bitcoin (and other cryptocurrencies) could be expressed as its exchange rate against other currencies. Most Bitcoin users do not engage in mining. They purchase bitcoins from others with “local currencies” (fiat money systems). Online exchanges, where users trade bitcoins with other currencies, are important components of the cryptocurrency ecosystem. They connect Bitcoin with the real economy, in which transactions are denominated in local currencies.

There have been a few major exchange venues in Bitcoin’s short history. In the current paper, we focus on the exchange between Bitcoin and USD. Mt. Gox, opened in July 2010, was the earliest Bitcoin exchange and the leading exchange market for USD for several years [4, 19]. Later, exchange trading volumes at BitStamp, BTCe, and BiFinex[6] (referred to as the Big3 hereafter) rose as Mt. Gox’s fell, due to several technical incidents and legal issues. In the latter half of 2013, the Big3 took more than 50% of the Bitcoin-USD exchange market share. Mt. Gox suspended all transactions in February 2014 after a serious security breach.

[6] BitStamp, BTCe, and BiFinex opened in Sep 2011, Aug 2011, and Apr 2013, respectively.

2.3 Academic Literature on Bitcoin

The growing significance of blockchain technology and cryptocurrencies has implications for various academic disciplines. There is emerging research attention on Bitcoin, including discussions on technical features (for example, [20, 21]), security and legal issues in cryptocurrency systems (for example, [2, 22]), and analytics on the information contained in the blockchain (for example, [23–25]).

Closely relevant to the current study, a stream of research discusses economic issues in cryptocurrency systems. Research in this stream discusses the economic function, mechanism, and value of cryptocurrencies (for example, [8, 26, 27]). A few studies have investigated Bitcoin exchange markets. Early studies focus on the question about bubbles in Bitcoin exchanges. Cheah and Fry, for example, argue that Bitcoin exhibits speculative bubbles and that the fundamental price of Bitcoin is zero [3]. Cheung et al. detected a number of short-lived bubbles and three huge bubbles in the period between 2011 and 2013 [28]. Glaser et al. discusses the intentions of investors in using Bitcoin and raised concern about limited adoption of Bitcoin and the resemblance of its exchange activities to speculative trading [29]. Adding to this stream of research, we discuss and empirically investigate the significance and impact of market speculation in different periods of Bitcoin exchange history.

Some recent studies have conducted econometric analyses regarding the determinants of the Bitcoin exchange rate. Kristoufek, for example, studied the impact of Google search volume and daily views on Wikipedia. He found a significant correlation between search and price [6]. In a later study, he conducted a wavelet coherency analysis to identify the correlation between Bitcoin exchange prices and various factors [30]. The estimation result revealed that such factors as the exchange-trade ratio and speculative behavior play a significant role in lower frequencies. Researchers also have suggested that the Chinese market index may be a main driver of Bitcoin price. Garcia et al. looked at the effect of online word-of-mouth (Twitter and Facebook) on top of search [7]. Bouoiyour and Selmi identified a set of determinants, including Google Search, ratio of exchange-trade volume, the hash rate, and stock market, using the ADRL bounds test approach [5]. Ciaian et al. found that transaction volume, user volume, and attractiveness (measured by forum postings and Wikipedia views) have significant impacts on Bitcoin price. They also found significance changes over time [9]. Polasik et al. studied the impact of news articles volume, sentiment, Google search, transaction amount, number of bitcoins, and economic factors (industrial production growth, unemployment, and inflation) on the monthly return of Bitcoin and found that returns are driven primarily by news volume, news sentiment, and the total number of transactions [4].

<<Insert Table 1 around here>>

Table 1 summarizes the extant literature on the Bitcoin exchange market. Several variables have been identified, including public recognition and interest measured by Google search and Wikipedia views, market trading activities, and economic fundamentals. The current study builds on this foundation and aims at a systematic theory-driven discussion. Not only does the paper add to the collection of empirical evidence, it improves upon previous research in major aspects. Theoretically, the current study summarizes existing evidence and provides a comprehensive theory-driven discussion. The proposed multi-perspective framework emphasizes the dual nature of cryptocurrencies and the utility of combining economic and IS theories. Empirically, leveraging on the closing down of Mt. Gox, the current study examines two consecutive periods of Bitcoin trading history, which helps shed light on the evolution of bitcoin valuation. Methodologically, the current study adopts an advanced econometric modeling approach addressing the empirical issue caused by a mix of both stationary and non-stationary variables and offering rigorous identification. The paper thus synthesizes and extends current studies on the Bitcoin pricing.

3. Hypotheses Development

In this section, we present a theoretical discussion that synthesizes and extends extant literature and existing empirical evidence concerning the determinants of the Bitcoin exchange rate. Bitcoin's exchange rate deserves a separate discussion for a few reasons. First, Bitcoin is a new breed of IT-enabled payment medium with a unique decentralized verification system – the mining system. The system depends on the computing power contributed by Bitcoin miners to ensure its successful operation. It is thus critical to study technology determinants on top of economic factors. Second, trust building in the Bitcoin system relies on no central authority. On one hand, potential adopters need time to fully appreciate the power of new systems. On the other hand, the real potential of the system is obscure, making the exchange price sensitive to market speculation. It is thus interesting to examine the impact of speculative trading in the exchange rate determination. Third, different from fiat money, as a peer-to-peer system, the diffusion of Bitcoin and the increase in public awareness could also play a role in valuation.

We propose that the exchange rate between Bitcoin and another country's currency should change under the influence of two general categories of factors: technology factors and economic factors. On the technology side, based on the literature on security and technology adoption, we expect that the exchange price is subject to the impacts of mining and public recognition. From the perspective of economic theories, both economic fundamentals and speculative trading should play significant roles. Following the literature, our theoretical discussion focuses on long-term (equilibrium) impacts.

3.1 Technology Factors

3.1.1 Mining & Ledger Protection

At the core of the Bitcoin system is the mining process. As we introduced in section 2.1, Bitcoin miners invest computing power to enable transaction record protection through hashing, and new bitcoins are generated as rewards to the miners. The unique Bitcoin mining process influences the formation of Bitcoin price.

First, regarding the mining process, Bitcoin shares features with commodity money, such as gold. Researchers have found that mining cost affects the price of commodity money [31]. In the IS literature, extant research indicates that the value of virtual currencies depend on players' time and monetary investments [32]. As the mining of bitcoins incurs significant costs in hardware purchase and maintenance, electricity, and human resources, the exchange value should reflect such costs. In the Bitcoin system, a measure, mining difficulty[7] indicates the average amount of calculation required to find a valid hash. Although it is impossible to track the actual costs incurred by individual miners, mining difficulty serves as a good proxy of the average mining cost of miners.

Second, mining difficulty also captures the robustness of the Bitcoin system. As we

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[7] As introduced in section 2.1, the system uses a target hash rate to control the speed of Bitcoin generation. When more computing power is devoted to the validation, the target rate is set higher and lead to higher mining difficulty.

introduced in section 2.1, mining is also the process of validating and securing recent transactions in the Bitcoin system. A higher standard for target hash rate means a lower chance to recover a valid hash and change the transaction records, which translates to a higher level of system security. Prior literature suggests that security is a critical component of system valuation [33]. Thus, the exchange value of Bitcoin as a payment system should increase with mining difficulty.

We thus have the following hypothesis:

H1a: Mining difficulty has a positive impact on Bitcoin's exchange rate.

Although mining difficulty serves as a good proxy of the cost of mining, its relationship with mining cost depends on the efficiency of mining technology. That is, the same amount of investment in equipment and electricity could generate more computing power for mining when the technology becomes more efficient. As discussed in section 2.1, Bitcoin mining technology has made significant improvements over the years. The adoption of more advanced mining devices makes hash calculation faster while requiring less electricity. As a result, we expect the marginal impact of mining difficulty on the exchange rate to weaken as mining technology evolves. We thus have the following hypothesis:

H1b: The impact of mining difficulty on Bitcoin's exchange rate decreases over time.

3.1.2 Public Recognition

Bitcoin is a payment network based on blockchain technology, a peer-to-peer system. As with any network product and peer-to-peer system, its value exhibits network externality. That is, the more users are using the system, the more valuable the system becomes to each of the users [34]. As a result, it is expected that the value of Bitcoin depends on transaction capability resulting from public recognition and adoption. According to the technology acceptance model [35, 36], an individual's intention to adopt is shaped by her perception of the technology, which depends on external environment conditions, such as information provision and social norms. The overall public recognition thus would affect the overall value of the Bitcoin system and the exchange rate of Bitcoin. We thus have the following hypothesis.

H2: Public recognition has a positive impact on the Bitcoin exchange rate.

There has been some empirical evidence concerning the impact of public recognition (such as Google search, Wikipedia views, Tweets, etc.) on the Bitcoin exchange rate [6]. We thus follow the literature and use Google search and Tweets as a proxy of public recognition. However, it worth noting that most previous studies adopt a rationale that public recognition reflects the market demand for Bitcoin and that an increase in the demand for a currency can lead to appreciation [37]. According to our theory, although temporary market demand change can have a short-term price effect, the long-term appreciation is due to the improved value caused by network externalities.

3.2 Economic Factors

3.2.1 Economic Fundamentals

As a currency, the exchange value of Bitcoin should follow predictions from economic theories. An intensive literature has addressed the exchange rates of traditional currencies, for example [38, 39].[8] According to the theory of purchasing power parity (PPP), the long-term real purchasing power in any two countries should be equivalent, despite any difference in the nominal currency [40]. Given long-term purchasing power parity, the exchange rate between two countries should be proportional to the ratio of the Consumer Price Index (CPI). Based on this rationale, the sticky-price monetary model posits the impacts of indicators of economic conditions and monetary policy, i.e., money supply, Gross Domestic Product (GDP), inflation, and the interest rate [39, 41, 42]. Following this literature, we propose that the exchange rate between Bitcoin and another currency is determined by monetary policy factors and economic condition factors in both the Bitcoin economy and the foreign economy, respectively.

Measures of economic fundamentals are readily assessable and require no further discussion. Economic fundamentals in the Bitcoin economy, however, are of a different flavor. Credit in the Bitcoin system is enabled by the blockchain technology and requires neither national or institutional credits nor any linkage to valuable commodities. Due to the difficulty in measuring commercial activities in the Bitcoin economy, it is hard to define and measure the Bitcoin economy's inflation rate.

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[8] We conducted a comprehensive review of exchange rate models in the economics literature, including the Balassa-Samuelson model [66], the fundamental equilibrium exchange rate model [67], the behavioral equilibrium exchange rate model [68], and the real equilibrium exchange rate model [69]. These models include such factors as productivity, traded/non-traded goods, and remittance. From the perspective of international trade economics, researchers also have examined the roles of the prices of oil and precious metals in the determination of exchange rates [70, 71]. In the current study, we adopted the most widely tested exchange rate model.

Discretionary monetary policies are also absent in the Bitcoin economy. Meanwhile, Bitcoin supply follows a fixed schedule and is subject to natural deflation [8]. As the total amount of bitcoins in circulation is capped, the current Bitcoin supply may indicate the relative scarcity of future supply, which results in appreciation in the exchange value. Meanwhile, as a transaction medium, the boundary of the Bitcoin economy is the commercial transactions it facilitates. The scale of the Bitcoin economy can be reflected by the total Bitcoin transactions. Thus, from the perspective of economic fundamentals, we have the following hypotheses.

H3a: The Bitcoin exchange rate reacts to economic indicators of the foreign country, including money supply, GDP, inflation, and interest rate.

H3b: The Bitcoin exchange rate reacts to total number of bitcoins in use and transaction volume.

3.2.2 Speculation and Exchange Market Activities

There has been discussion about the (early) trading of bitcoins being driven by speculative trading [3, 5]. Speculative trading activities, such as investment decisions that are based on inconsequential information and Chartism, are commonly observed in commodity, security, and foreign exchange markets [43]. While considered as less rational decisions, speculative trading represents an important aspect of financial exchanges, especially during a period of high market uncertainty. To some extent, speculation promotes transactions among market participants, inflates liquidity, and may help to enhance market efficiency. Theoretically, short-term impact of market speculation would be more significant than the long-term impact. In a market where trading is infrequent and there is significant uncertainty about asset valuation, however, speculation may have a lasting impact on price. As a new currency system, Bitcoin has attracted significant media attention. Yet the market has lacked proper understanding about the technology, and there has been no consensus about the prospects, making the Bitcoin exchange market susceptible as a target of speculative investments [8, 29]. This was especially true in the early days of Bitcoin. A common approach to capture the impact of speculative trading is to employ market activity indicators, such as trading volume and volatility, in the exchange price model [44, 45]. We thus have the following hypothesis:

H4: Trading volume and price volatility have significant impacts on the Bitcoin exchange rate (in the early market).

3.3 Research Framework

<<Insert Figure 1 around here>>

Figure 1 summarizes our research framework. From the technology perspective, we propose that the Bitcoin mining cost has a time-varying effect on the exchange rate based on inspections. Meanwhile, similar to existing studies, we include factors that capture public recognition. From an economic perspective, economic fundamental factors of both the Bitcoin economy and the foreign country are included. Meanwhile, trading volume and price volatility are included to capture the impact of market speculation. Not only does the framework generate a systematic view; it also includes a more comprehensive set of factors synthesizing and extending existing studies. We further summarize our theoretical rationale in the Appendix for easy reference (Table A.1).

4. An Econometric Analysis of the Bitcoin Exchange Rate

4.1 Data and Variables

Our econometric study focuses on the exchange rate between Bitcoin and the US Dollar (USD). We collected price and trading volume data from Bitcoincharts.com. The data cover multiple Bitcoin exchanges.

Considering the rise and fall of Mt. Gox as a major exchange market between Bitcoin and USD, we separate our analysis into two parts. In the first part, we analyze the exchange rates on Mt. Gox between January 1, 2011 and December 31, 2013 (the early market), which is the longest continuous observation of exchange rates between Bitcoin and the USD on a single exchange market available at the time of this study.[9] In the second part, we study the volume-weighted average price on three major exchange markets, BitStamp, BTCe, and BiFinex (the Big3), between July 1, 2013 and December 31, 2014 (the later market). During this period, the Big3 collectively gained a significant

[9] We omit the period before 2011, when exchange trading was rare. There were some incidents of temporary market anomalies. A security breach, for example, caused the nominal price of a bitcoin to drop to one cent on the Mt. Gox exchange on June 19, 2011 for about one week. We carefully identified and adjusted anomalous exchange rates by interpolation.

market share and eventually dominated the Bitcoin (to USD) exchange.

Separating the empirical analysis into two parts allows us to detect potential changes in exchange rate dynamics as Bitcoin matured. At the same time, this operation enables us to get the most out of the available data. To ensure that the observed patterns were indeed systematic differences in exchange rate dynamic, we also collected prices on the Big3 before July 2013 to validate the consistency between exchange dynamics on Mt. Gox and the Big3 in the early market.

We collected observations on proposed independent variables from multiple sources. First, we retrieved historical observations of mining difficulty from blockchain.info, a website that parses all Bitcoin transactions and generates Bitcoin statistics from the public ledger.

Second, we consider two technology factors as measures of public recognition: search intensity and social media mention. Both factors reflect public recognition while having subtle differences. Search intensity focuses on recognition driven by information retrieval. It indicates the expressed intention to learn about Bitcoin. Meanwhile, social media mention focuses on information sharing and provision. It is a measure of expressed willingness to engage in conversations about Bitcoin. We collected daily Google search numbers for the keyword “Bitcoin” from Google Trends [46, 47]. The search volume was normalized by the search volume on February 25, 2014 (the last day of Mt. Gox’s operation).[10] To measure social media mention, we collected the daily number of Twitter posts mentioning Bitcoin from Bitcoinpulse.com. The website counts all tweets, excluding retweets, that contain the keyword “Bitcoin,” using a service provided by Topsy, which archives all tweets under a contract with Twitter.

Third, for the economic indicators, we collected federal fund interest rates and monthly USD money supply observations from the Federal Reserve, quarterly GDP observations from the US Department of Commerce, and the monthly inflation rate from usinflationcalculator.com. We also collected data on the total number of bitcoins in circulation as a measure of Bitcoin supply, and we collected both the total number of Bitcoin-supported transactions and the total value of daily Bitcoin

[10] In other words, if the Google search variable value on February 25, 2014 was 100 and an observation has a search value of 200, it means the search volume on the day of the observation was twice as much as the search volume on that day.

transactions from blockchain.com to measure the size of the Bitcoin economy.

Fourth, to measure market activities, we collected data on daily trading volume and calculated price volatility. Since transaction-level data are not available, we calculate the rolling variance of the market price as a measure of market volatility. We choose a lagging window of 30 days for the rolling variance calculation [48, 49].

<<Insert Table 2 around here>>

Table 2 summarizes the variables in our dataset. In our estimation, all variables except price volatility were log-transformed, following the exchange rate literature.[11] As a reference, Figure A.1 in the Appendix visualizes the time-series data we collected. In general, during our observation period, the Bitcoin exchange rate kept rising until the end of 2013. The exchange rate then showed a moderate decreasing trend.

4.2 Econometric Analysis

4.2.1 Integration and Unit-Root Tests

Following the empirical literature on foreign exchange rates, we first examine the stationarity of the time-series data using the Augmented Dickey-Fuller (ADF) test, and we base our choice of lags on the Akaike Information Criterion (AIC) [50]. Table 3 reports the results of ADF tests on the two sets of observations (the Mt. Gox data in early market and the Big3 data in later market). Findings from the ADF tests suggest that the Bitcoin exchange rate, USD supply, US GDP, US interest rate, US inflation, number of Bitcoin-supported transactions, number of Twitter mentions, and mining difficulty exhibit non-stationarity and could be considered as a I(1) time series.

<<Insert Table 3 around here>>

4.2.2 Co-Integration and the ADRL Model with Bounds Test

Because the Bitcoin-USD exchange rate and some of the independent variables are non-stationary, ordinary time-series regression analysis could result in spurious correlations and inconsistent estimates. One way to address the issue is to apply first difference on the variables before analysis. The first-difference model, however, may still fail in identification if the variables are co-

[11] Following common practice, for variables that have zero values, we add 0.001 before the log transformations.

integrated and exhibit long-term equilibrium relationships. To assess the extent of co-integration in our data, we take a Vector Error Correction Model (VECM) approach and apply Johansen's test on the I(1) variables [51]. The VECM model, which requires all variables examined to be I(1)), has been used extensively in studies of exchange rates [39, 52, 53]. The model is specified as:

$$\Delta Y_t = \sum_k \Delta Y_{t-k} \Gamma_k + \Pi Y_{t-1} + \mu_t \,, \tag{1}$$

where Y=[s, X] is the set of variables to be examined, including the Bitcoin exchange rate. In the model, the number of co-integration relationships corresponds to the rank of coefficient matrix Π. Mathematically, if Π has a reduced rank, it can be represented as a multiplication of loading coefficients $\boldsymbol{\alpha}$ and a matrix of co-integration vectors $\boldsymbol{\beta}$, that is $\Pi = \alpha\beta'$, where $\boldsymbol{\alpha}$ represents the speed of adjustment towards the long-term relationship following a deviation and $\boldsymbol{\beta}$ represents the long-term relationship.

<<Insert Table 4 around here>>

Table 4 reports the results of the Johansen test. Following standard procedure of the VECM model, we set the number of lags to six according to the AIC value. The rank of the Π matrix is three, indicating that co-integration exists in the data. As a result, it is not appropriate to use the first-difference approach in the estimation. Meanwhile, as there are both I(0) and I(1) variables in our full model, it is also not appropriate to apply the VECM model directly. It worth noting that previous research has applied both ordinary regression and VECM models. Yet, the properties of the time series in our data set indicate the need for a more advanced approach. This is a unique econometric challenge when we consider a more comprehensive set of independent variables.

To achieve econometric identification in a time-series regression model with a mix of I(0) and I(1) variables and co-integration, we adopt the ARDL model with a bounds test approach [10]. The ARDL bounds test approach has been frequently adopted to study co-integration relationships in financial time series [54, 55]. It allow us to visit the long-term equilibrium relationship between the time series, as well as the short-term adjustment, simultaneously. Equation (2) shows the setup of the ARDL model.

$$\Delta s_t = \sum_j \Delta s_{t-j}\xi_j + \sum_k \Delta X_{t-k}\Gamma_k + \gamma s_{t-1} + X_{t-1}\theta + \alpha + \mu_t \quad (2)$$

In the model, ξ_j captures the autoregressive component, Γ represents the short-term relationship, γ represents adjustment speed, and $\frac{\theta}{\gamma}$ represents the long-term relationship. We also include trend and intercept items in the estimation. In all model estimations, we chose to use a lag length of 6 in the adjustment equation, based on the AIC values and results from LM tests. This ensures serial correlations in the error terms are properly controlled.

We posit that the impact of mining difficulty will depend on the mining technology. Since we cannot directly observe a quantitative measure of mining technology, we explore the temporal trend in the marginal impact of mining difficulty. In the estimation, we try to detect the time-varying effect of mining difficulty on the exchange rate using two orders of polynomials [56]. We allow the long-term effect ($\frac{\theta}{\gamma}$) of mining difficulty to change with time *t* [57]. Following previous works, we normalize the variable *t* on the interval between 0 (corresponding to July 7, 2010) and 1 (corresponding to December 31, 2014).

5. Results & Discussion

Tables 5 and 6 report the estimation results. Table 5 reports estimates of the long-term equilibrium relationship. It serves as the principal empirical evidence for supporting the theoretical hypotheses. For completeness, Table 6 reports the short-term adjustment effects, which could be useful in prediction. In both tables, Models I and II report estimates regarding the early market; and Models III and IV report estimates from the later market. Compared to Model I (Model III), Model II (Model IV) allows time-varying coefficients of mining difficulty, which provides support for the moderating role of mining technology (H1b).

5.1 Long-term Relationship

<<Insert Table 5 around here>>

Model I in Table 5 reports the estimates concerning the long-term relationship without time-varying coefficients. We can see that in the early market, besides the amount of bitcoins in circulation (m_t^B), the long-term price of Bitcoin reacts primarily to measures of market activity, i.e., trading volume (v) and market volatility (σ^2). This indicates that the exchange price during this period is subject to a significant influence from speculative trading and does not closely follow economic fundamentals in the foreign economy. Meanwhile, it appears that the market price does not reflect the scale of the Bitcoin-supported economy. In general, the force of speculative trading dominates the early market.

Models III and IV in Table 5 report the long-term relationship in the later market (on Big3). We observe significant changes in how the Bitcoin exchange rate responds to economic factors in the long-term equilibrium. On one hand, the exchange rate shows a significant reaction to economic fundamentals, such as the supply of USD (m^A), interest rate (i^A), and number of Bitcoin-supported transactions (n^B), consistent with the theoretical predictions (H3a and H3b). On the other hand, we can no longer observe significant long-term influences from exchange market activities. This indicates that as Bitcoin continues to diffuse as an alternative medium for exchange, exchange market participants are becoming more rational and the exchange market is less driven by market speculation.

Regarding mining, we find that mining difficulty drives the exchange price upward in the early market, confirming H1a. Estimation results from Model II, in which we allow the coefficient for mining difficulty to change over time, suggest that the impact of mining difficulty on the exchange rate weakens. This is consistent with our expectation that the progression in mining technology reduces the significance of mining costs and weakens the impact of mining difficulty on the Bitcoin exchange rate (H1b). The decline in the relevance of mining cost continues in the later market according to estimates from Model IV. We also find some evidence that the market overcompensated miners, leading to a negative long-term relationship between mining difficulty and the exchange rate when time trends are not considered. It is worth noting that the short-term adjustment in the exchange rate responds positively to the temporal increase in mining difficulty.

Results concerning the long-term effects of public recognition variables are a bit obscure. Both variables generally capture short-term shocks in public interest, and their impacts are more significant in the short term. In the long term, Twitter mention does not have a significant impact on the Bitcoin exchange rate, while Google search appears to have a positive impact on the long-term Bitcoin value. An explanation for this observation is that, compared to search, social media mentions are passive and are less effective in boosting general public recognition.

We find all F-statistics for the bounds test, an indicator of the existence of long-term equilibrium, significant at the 99% level for models with a mix of I(0) and I(1) variables [10]. The statistical significance level of the adjustment coefficient (γ) is marginal, and we can confirm significance at the 95% level only if we assume all variables are I(0). This indicates that the time series exhibits a slow adjustment towards the long-term relationship. Statistical significance of adjustment coefficients also increases in the later market. Thus, as the market develops, the Bitcoin exchange rate exhibits a clearer long-term pattern and adjusts more quickly from temporary shocks.

5.2 Short-term Adjustment

<<Insert Table 6 around here>>

Table 6 shows estimates concerning the short-term adjustment effects. Models I and II in Table 6 report estimation results in the early market. During this period, we find that changes in the US money supply (m^A) have a positive impact (with 4-day lag); the US interest rate (i^A) has a negative impact (with 5- and 6-day lags); and the total value of transactions (r^B) has a significant negative impact (with 5- and 6-day lags).[12] We also find that Bitcoin price responds actively to exchange market volatility (σ^2) with significant coefficients at different lags.

In terms of technology factors, the Bitcoin exchange rate responds promptly to changes in mining difficulty. As we discussed, we also observe over-compensation for mining difficulty change in the market regarding the long-term effect. Public recognition factors show a significant impact on short-term price changes. Interestingly, Google search shows a significant positive impact (with a 3-day lag), while Twitter mention has a significant negative impact (with a 5-day lag). It appears that Google search serves as a better lead index for market movement.

According to Models III and IV, short-term changes in Bitcoin exchange rates continue to be sensitive to economic fundamentals and market activities in the later market, consistent with extant economic literature on exchange price dynamics. Interestingly, we find no significant short-term

[12] In the early stage of Bitcoin, many merchants used Bitcoin as a payment method and exchanged it for domestic currency after the transaction. A temporary increase in the Bitcoin value transacted introduces sell pressure on the exchange market and reduces the exchange rate in the short term.

effect regarding public recognition variables. This indicates that as Bitcoin users and investors become familiar with the system, the market becomes more prudent and less sensitive to temporary hype in social media.

5.3 Discussion

5.3.1 Comparison between the early market and the later market

To understand how Bitcoin exchange rate dynamics evolved between the early and later markets, we summarize the main findings from Models II and IV in Figure 2. In the figure, we use color to denote the significance level, and we aggregate estimates in the same categories and across lags so that the general patterns stand out.

<Insert Figure 2 around here>>

From the economic perspective, during the early market, the long-term exchange rate reacted primarily to market activities, indicating that speculative investment activities dominated value-based investment in the exchange market during this period. In the later market, the dependence of the Bitcoin exchange rate on economic fundamentals in both the foreign country and the Bitcoin economy was more significant, and market speculations stopped driving the long-term exchange rate. Short-term exchange rate fluctuations also began to react to changes in economic conditions in the later market. Meanwhile, as in other exchange markets for financial instruments, the short-term exchange rate fluctuations respond to exchange market activities.

From the technology perspective, it appears that search and social media activities have no significant impact on the Bitcoin exchange rate in the long term. Yet, the short-term exchange rate reacts to public recognition indicators in the early market, which indicates that hype in public interest may drive temporal market fluctuations when the market lacks a proper understanding of the new technology. We observe a weakening impact of mining difficulty on the long-term exchange rate. Meanwhile, mining difficulty shows a persistent short-term impact on the exchange rate, indicating that exchange price does anchor on production cost.

This comparison sheds light on the rapid rise and excessive fluctuation of Bitcoin price in the early markets. Consistent with early research [6, 9], we find evidence that speculative investment is indeed a major component of Bitcoin exchange activities in the early market. The long-term market price dynamics was dominated by speculations, and deviated from predictions from economics and IS theories. The market also exhibits excessive responses to short-term variations in social media exposure and market trading activities. Promisingly, exchange price behavior in the later market is more in line with theoretical predictions. Price fluctuations become less sensitive to temporary hypes and the long-term price exhibits no sign of being driven by market speculation.

5.3.2 Robustness Checks

We conducted a few robustness checks. First, we replaced 30-day rolling variance, the price volatility measure we adopted in the main models, with estimated daily price volatility using generalized autoregressive conditional heteroscedasticity (GARCH) model. Both rolling variance and volatility estimate from GARCH model are commonly adopted measures of price volatility in literature [58].[13] The robustness check generated the same findings as in our main analysis. Second, to ensure that the differences we observed between the two datasets are indeed systematic changes rather than differences between exchange markets, we estimated the same models using exchange rate observations from the Big3 between September 2011 (the first available Big3 data) and July 2013. Although the market share of the Big3 is significantly smaller than Mt. Gox during this period, the results are consistent with what we found in the early market. Third, we estimated a model in which we set the coefficient of mining difficulty to vary with $\log(t)$ instead of using polynomial forms. The results are consistent with our findings in Models II and IV. We also conducted a rolling regression analysis on shorter time windows and found a positive significant effect of mining difficulty in earlier regression results, yet insignificant coefficients in later regression results. These tests corroborate our findings regarding the diminishing impact of mining difficulty on the exchange rate as mining technology progresses.

6. Conclusion

In this research, we empirically examine the determinants of the Bitcoin exchange rate, a representative of emerging cryptocurrencies. There are three main research objectives. First,

[13] We choose an AR(3)-GARCH(1,1) model for estimating variance from observed price dynamics according to model fit. We use this measure in our robustness check.

recognizing that a cryptocurrency is both a medium for economic transactions and a technology artifact derived from blockchain technology, we propose a framework to explain the Bitcoin exchange rate from the perspectives of technology and economics. Second, we conduct a rigorous time-series analysis on the exchange rate between Bitcoin and the USD using the ARDL model with a bounds test. Third, to detect the evolution in market dynamics, we separately estimate the model with data from the early market and the later market, respectively.

The empirical analysis confirmed the relevance of both the technology factors and the economic factors. Interestingly, although the market price does anchor on mining cost, the long term impact of mining difficulty diminishes over time as mining technology becomes more efficient. We also found a systematic difference between the early market and the later market. The early market exchange rates are driven predominantly by speculative investment and deviate from economic fundamentals. Later, the market matured and the price dynamic followed more closely with changes in the economic factors, while market speculation cast no significant impact in the long term.

This paper contributes to the IS literature in several ways. First, it pioneers a systematic discussion of the determinants of exchange rates of cryptocurrencies from both technology and economic perspectives. The proposed framework builds up a foundation for future theoretical discussions and highlights the importance of combining economic theories with technology considerations to understand IT-enabled financial innovations. Second, this paper presents a comprehensive formal empirical analysis of the Bitcoin exchange rate. It not only synthesizes and extends existing empirical evidence in the area but also adopts an advanced empirical analysis methodology addressing issues in previous models. Third, the study features a comparison between the early market and the later market. The comparison reveals an evolution in exchange market dynamics. It confirms excessive speculation in the early market and provides evidence of the maturity of the later market. In addition, this study contributes to the economics and finance literatures on exchange market dynamics and speculative trading.

The study has important managerial implications. For investment managers, the paper offers a comprehensive discussion about the factors they need to consider in the valuation of a cryptocurrency. First, the paper presents a explanation of the unique features of the cryptocurrency systems and provides an overarching multi-perspective framework that can direct the design and implementation of financial decision support systems in the emerging cryptocurrency markets [13, 14]. As shown in literature, multi-perspective models are often used in understanding complex financial-technology phenomena [59] and can be extended when new observations become available. Second, the paper indicates excessive speculation in early market. Such speculative trading activities need to be appropriately monitored [60]. Third, the paper shows that the later market price closely tracks economic fundamentals, making Bitcoin a good instrument for hedging to be considered in portfolio management decision support systems [61]. The study shows that investment in mining technology is properly rewarded, which is a unique decision factor for cryptocurrency investments. For regulators, our study suggests that the Bitcoin market has shown evidence of maturity in recent years, thus strengthening confidence in the system's legitimacy as a payment channel. As cryptocurrencies continue to gain economic significance, it would be critical to monitor exchange market activities in economic decision-making. Meanwhile, regarding the parallel development of other cryptocurrency systems, policy makers may need proper regulatory instruments to contain excessive speculation and stabilize technology investments.

The study leaves some room for extensions in the future. First, it would be interesting to explore other factors in the proposed framework. For example, factors such as social media sentiment or location-related information could be added to the model [62–64]. Second, since huge transaction-level data is publicly accessible from the blockchain files, it would be interesting to explore the relationship between the structural properties of the transaction network and exchange rates. Third, Bitcoin is still a young currency. While it is valuable at this stage to establish a research framework and test its utility to provide a foundation for future works, the relationships we identified could be subject to further changes as exchange markets develop. It will be necessary to revisit the model at some future time and consider the possibility of multiple regime changes in exchange rate dynamics.

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Figures and Tables

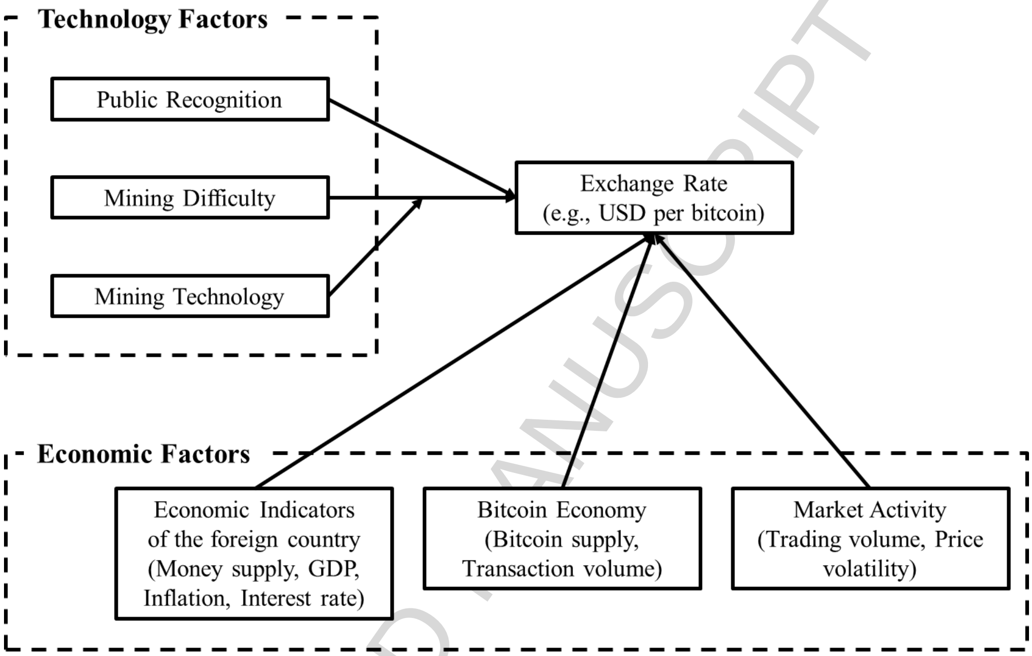
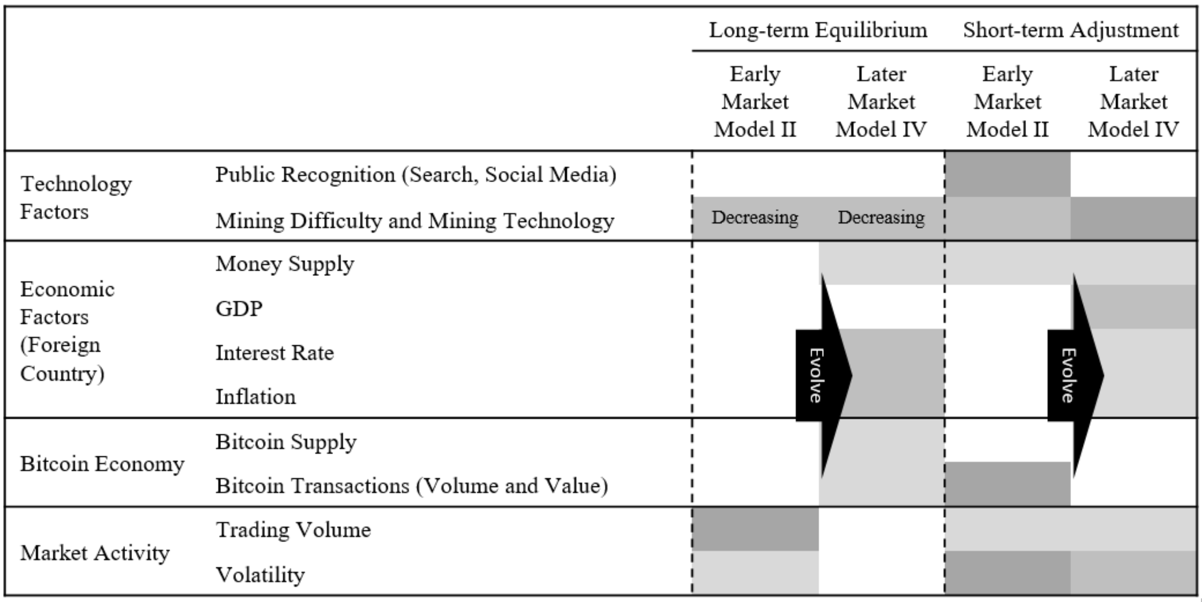


Figure 1. Research Framework



Note: Cells with gray color indicate statistically significant coefficients. Darker cells have higher significance. The arrows represent time sequence. The long-term impacts of mining difficulty decrease over time.

Figure 2. Comparison between the Early Market and Later Market

Table 1. Summary of Existing Studies on Bitcoin Exchange Rate

Studies	News	Public Interest (Google Search, Wiki Views)	WOM (Twitter, Facebook, Forum)	User Volume	Trading (Volume, Frequency)	Bitcoin Amount	Hash rate	Difficulty	Other Markets (Gold, Stock)	Financial Stress	Economy Fundamentals	Model
Kristoufek, 2013		√										VECM
Garcia et al. 2014		√	√	√								VAR
Bouoiyour et al. 2015		√	√		√		√		√			ARDL Bounds Testing
Kristoufek 2015		√			√		√	√	√	√		Wavelet Analysis
Ciaian et al. 2016		√	√	√	√	√			√			VAR, VECM, ARDL
Polasik et al. 2016	√	√			√	√					√	Regression

Table 2. List of Variables

	Name	Period	Definition
s_t	Exchange Rate	daily	Bitcoin - USD exchange rate
$m^A{}_t$	USD Supply	weekly	USD money supply
$y^A{}_t$	US GDP	quarterly	US GDP
$i^A{}_t$	US Interest	daily	US federal fund interest rate
$\pi^A{}_t$	US Inflation	monthly	US inflation rate
$m^B{}_t$	Bitcoin Supply	daily	Total amount of bitcoins in circulation
$r^B{}_t$	Bitcoin Transaction Value	daily	Total value of Bitcoin-supported transactions
$n^B{}_t$	Bitcoin Transaction Volume	daily	Number of Bitcoin-supported transactions
v_t	Trading Volume	daily	Total value of traded bitcoins in the exchange
σ_t^2	Volatility	daily	Variance of Bitcoin exchange rate
g_t	Google Search	daily	Google Trends index on the term "Bitcoin" (normalized to the search volume on February 25, 2014)
w_t	Tweets	daily	Number of tweets mentioning the term "Bitcoin"
d_t	Mining Difficulty	daily	Bitcoin mining difficulty

Table 3. Augmented Dickey-Fuller Tests

	Early Market			Later Market		
	Lag	Tau	P-value	Lag	Tau	P-value
s_t	21	-0.683	0.8510	18	-2.153	0.2239
Δs_t	20	-5.186***	0.0000	17	-4.308***	0.0004
$m^A{}_t$	21	-1.439	0.5634	7	-1.233	0.6592
$\Delta m^A{}_t$	1	-23.639***	0.0000	18	-6.589***	0.0000
$y^A{}_t$	1	-0.080	0.9514	1	-1.553	0.5071
$\Delta y^A{}_t$	17	-7.913***	0.0000	9	-7.609***	0.0000
$i^A{}_t$	8	-2.404	0.1405	7	-3.046**	0.0308
$\Delta i^A{}_t$	21	-9.228***	0.0000			
$\pi^A{}_t$	1	-1.358	0.6024	1	-1.075	0.7250
$\Delta \pi^A{}_t$	17	-6.984***	0.0000	15	-5.831***	0.0000
$m^B{}_t$	17	-3.950***	0.0017	14	-4.781***	0.0001
$\Delta m^B{}_t$						
$r^B{}_t$	19	-3.904***	0.0020	13	-2.201	0.2060
$\Delta r^B{}_t$				16	-7.693***	0.0000
$n^B{}_t$	21	-2.785*	0.0604	16	-2.163	0.2201
$\Delta n^B{}_t$	1	-30.796***	0.0000	18	-7.097***	0.0000

v_t	20	-3.201**	0.0199	13	-3.253**	0.0171
Δv_t						
σ_t^2	17	-3.521***	0.0075	10	-2.723*	0.0701
$\Delta \sigma_t^2$						
g_t	9	-3.437***	0.0098	5	-1.813	0.3742
Δg_t				15	-6.150***	0.0000
w_t	21	-1.534	0.5165	17	-1.984	0.2938
Δw_t	21	-8.099***	0.0000	14	-6.486***	0.0000
d_t	21	-0.047	0.9544	15	-3.790***	0.0030
Δd_t	18	-3.599***	0.0058			

Note:
This table reports test results from the Augmented Dickey-Fuller test for stationarity.
* p<0.10 ** p<0.05 *** p<0.01

Table 4. Johansen Tests for Co-integration of the I(1) Variables

Rank	Parms	Log-likelihood	Eigenvalue	Trace statistic	Critical value
0	328	17685.28	.	277.2575	182.82
1	344	17733.18	0.08369	181.4648	146.76
2	358	17761.21	0.04986	125.4101	114.9
3	370	17784.07	0.04086	79.6851*	87.31
4	380	17799.88	0.02843	48.0707	62.99
5	388	17808.66	0.01589	30.5133	42.44
6	394	17816.92	0.01496	13.9909	25.32
7	398	17822.4	0.00995	3.0318	12.25
8	400	17823.91	0.00276		

Number of observations = 1096
Lag length = 6

Note:
This table reports test results from the Johansen test based on the VECM model.
We use a lag length of 6 in the model based on the AIC value.
* p<0.10 ** p<0.05 *** p<0.01

Table 5. Long-term Relationship

	I (Early Market)		**II (Early Market)**		**III (Later Market)**		**IV (Later Market)**	
	Coef.	***t-static***	***Coef.***	***t-static***	***Coef.***	***t-static***	***Coef.***	***t-static***
$m^A{}_t$	-10.871	-1.437	-9.193	-1.291	-15.156**	-2.106	-11.793*	-1.790
$y^A{}_t$	-28.281	-1.052	-16.948	-0.630	23.381	1.552	21.186	1.520
$i^A{}_t$	-0.235	-0.649	-0.300	-0.738	1.354**	2.418	1.148**	1.985
$\pi^A{}_t$	0.249	0.637	-0.522	-1.062	0.386	1.590	0.889**	2.456
$m^B{}_t$	-5.939**	-1.992	22.357	1.571	700.568**	2.557	978.691*	1.752
$r^B{}_t$	-0.018	-0.134	-0.040	-0.317	0.153	0.720	0.094	0.479
$n^B{}_t$	0.355*	1.724	-0.057	-0.204	-0.965*	-1.664	-1.015*	-1.822
v_t	0.409***	2.609	0.480***	2.869	0.043	0.389	0.043	0.412
σ_t^2	3.800**	2.416	2.902*	1.917	-2.173	-0.915	-1.523	-0.696
g_t	-0.096	-1.312	-0.126*	-1.680	0.970***	2.793	0.557	1.567
w_t	0.231*	1.772	0.213	1.613	0.019	0.055	0.386	1.059
d_t	0.226**	2.104	1.095**	2.208	-3.371**	-2.148	1.324	0.501
d_t*t			-5.642**	-2.357			-11.001**	-1.969
d_t*t^2			4.692**	2.317			5.691	1.590
Adj. Par.	-0.035[**~]	-3.728	-0.037[**~]	-3.568	-0.055[**~]	-3.799	-0.058[**~]	-3.934
F Stats.	3.206[***~*]		3.349[***~*]		3.744[***~**]		3.625[***~**]	
N. Obs.	1096		1096		549		549	

Note:
This table shows the results concerning the long-term equilibrium relationship in the ADRL model. We omitted the coefficients on intercept and trend. Models I and II are based on the data in the early market. Models III and IV are based on the data in the later market. Compared to Model I (Model III), Model II (Model IV) further allows the long-term effect of mining difficulty to vary over time.

Statistical significance of F-statistics of the bounds test is derived from Table CI-(v) in Pesaran et al. (2001). The table contains a lower bound and a higher bound at each significance level, given a certain model set up. The lower bounds are critical values when all variables are I(0), while the higher bounds are critical values when all variables are I(1). Given a mixture of I(0) and I(1) variables, the critical value should be between the two bounds. We conservatively code the significance levels using the critical values for 10 variables (we have more than 10 variables, which makes the coding conservative). Our final significance levels of the F-Statistics are coded using the following intervals.
10% interval [2.07; 3.16]; 5% interval [2.33; 3.46]; 1% interval [2.84; 4.10]
* p<0.10 ** p<0.05 *** p<0.01

Table 6. Short-term Adjustment

	I (Early Market)		**II (Early Market)**		**III (Later Market)**		**IV (Later Market)**	
	Coef.	***t-static***	***Coef.***	***t-static***	***Coef.***	***t-static***	***Coef.***	***t-static***
Δs_{t-1}	0.175***	5.065	0.169***	4.878	0.068	1.374	0.060	1.216
Δs_{t-2}	0.000	-0.007	-0.004	-0.115	-0.137***	-2.684	-0.140***	-2.765
Δs_{t-3}	-0.111***	-3.162	-0.114***	-3.241	-0.005	-0.093	-0.005	-0.096
Δs_{t-4}	0.082**	2.363	0.078**	2.248	0.037	0.741	0.034	0.666
Δs_{t-5}	-0.002	-0.067	-0.005	-0.135	0.033	0.668	0.030	0.592
Δs_{t-6}	0.050	1.509	0.047	1.421	0.054	1.076	0.047	0.948
Δm^A_{t-1}	0.044	0.074	0.016	0.026	1.177*	1.711	1.105	1.609
Δm^A_{t-2}	0.231	0.386	0.187	0.314	0.255	0.369	0.146	0.210
Δm^A_{t-3}	0.326	0.546	0.321	0.539	0.236	0.340	0.140	0.202
Δm^A_{t-4}	1.100*	1.844	1.089*	1.831	-0.317	-0.454	-0.414	-0.594
Δm^A_{t-5}	-0.434	-0.733	-0.449	-0.761	0.746	1.079	0.671	0.971
Δm^A_{t-6}	0.829	1.405	0.795	1.352	1.270*	1.841	1.199*	1.741
Δy^A_{t-1}	-0.834	-0.286	-1.086	-0.374	-4.665**	-2.114	-4.598**	-2.090
Δy^A_{t-2}	-1.446	-0.494	-1.642	-0.562	-2.877	-1.294	-2.868	-1.293
Δy^A_{t-3}	-2.601	-0.886	-2.894	-0.988	-3.141	-1.423	-3.081	-1.399
Δy^A_{t-4}	-4.126	-1.411	-4.624	-1.583	-4.561**	-2.063	-4.707**	-2.133
Δy^A_{t-5}	1.720	0.590	1.146	0.394	-3.082	-1.381	-3.124	-1.404
Δy^A_{t-6}	0.734	0.255	0.223	0.078	0.228	0.103	0.176	0.080
Δi^A_{t-1}	0.016	0.620	0.016	0.628	-0.076**	-1.997	-0.067*	-1.729
Δi^A_{t-2}	0.038	1.484	0.039	1.532	-0.046	-1.186	-0.036	-0.914
Δi^A_{t-3}	-0.002	-0.087	-0.001	-0.024	-0.046	-1.220	-0.036	-0.937
Δi^A_{t-4}	-0.015	-0.578	-0.013	-0.514	-0.076**	-2.087	-0.066*	-1.800
Δi^A_{t-5}	-0.034	-1.397	-0.034	-1.367	-0.019	-0.534	-0.010	-0.288
Δi^A_{t-6}	-0.037	-1.535	-0.037	-1.519	-0.060*	-1.827	-0.054	-1.632
$\Delta \pi^A_{t-1}$	-0.054	-0.878	-0.034	-0.548	-0.005	-0.096	-0.019	-0.387
$\Delta \pi^A_{t-2}$	-0.074	-1.205	-0.055	-0.888	-0.023	-0.473	-0.038	-0.764
$\Delta \pi^A_{t-3}$	0.050	0.825	0.067	1.093	0.017	0.331	0.002	0.038
$\Delta \pi^A_{t-4}$	-0.086	-1.403	-0.072	-1.174	-0.062	-1.238	-0.074	-1.482
$\Delta \pi^A_{t-5}$	-0.037	-0.614	-0.026	-0.426	-0.039	-0.778	-0.053	-1.067
$\Delta \pi^A_{t-6}$	-0.049	-0.795	-0.038	-0.620	-0.084*	-1.708	-0.096*	-1.938
Δm^B_{t-1}	9.135	0.491	14.034	0.750	-47.974	-0.681	-56.529	-0.763
Δm^B_{t-2}	6.672	0.323	8.463	0.411	-61.137	-0.854	-74.092	-0.974
Δm^B_{t-3}	-16.984	-0.814	-15.682	-0.753	-22.691	-0.316	-34.616	-0.454
Δm^B_{t-4}	-2.275	-0.109	-2.249	-0.108	-70.957	-0.984	-86.407	-1.125
Δm^B_{t-5}	-9.110	-0.436	-9.379	-0.450	-11.175	-0.155	-27.874	-0.368
Δm^B_{t-6}	12.644	0.649	12.668	0.648	-41.016	-0.571	-63.962	-0.837
Δr^B_{t-1}	-0.005	-0.914	-0.004	-0.757	-0.012	-1.103	-0.010	-0.897
Δr^B_{t-2}	-0.009	-1.471	-0.008	-1.352	-0.009	-0.818	-0.007	-0.673
Δr^B_{t-3}	-0.010*	-1.734	-0.009	-1.637	-0.012	-1.086	-0.011	-1.013
Δr^B_{t-4}	-0.006	-1.072	-0.006	-1.016	-0.010	-0.957	-0.009	-0.927
Δr^B_{t-5}	-0.009*	-1.779	-0.009*	-1.781	-0.001	-0.139	-0.002	-0.182
Δr^B_{t-6}	-0.012**	-2.532	-0.012***	-2.589	0.001	0.099	0.000	0.053
Δn^B_{t-1}	-0.009	-0.635	0.002	0.143	0.024	0.662	0.029	0.803
Δn^B_{t-2}	-0.004	-0.283	0.006	0.387	0.033	1.001	0.037	1.134
Δn^B_{t-3}	0.017	1.142	0.026*	1.686	0.019	0.623	0.023	0.742
Δn^B_{t-4}	0.001	0.062	0.008	0.544	0.014	0.499	0.018	0.623

Δn^B_{t-5}	0.009	0.657	0.015	1.017	-0.005	-0.207	-0.002	-0.080
Δn^B_{t-6}	0.002	0.180	0.005	0.404	-0.020	-0.774	-0.017	-0.650
Δv_{t-1}	-0.006	-1.244	-0.009*	-1.763	0.000	-0.070	0.000	-0.040
Δv_{t-2}	-0.005	-1.034	-0.008	-1.508	0.000	0.015	0.001	0.120
Δv_{t-3}	-0.006	-1.179	-0.008	-1.593	0.001	0.119	0.002	0.273
Δv_{t-4}	-0.004	-0.965	-0.006	-1.320	0.009	1.638	0.010*	1.811
Δv_{t-5}	-0.001	-0.360	-0.003	-0.656	0.005	1.066	0.006	1.226
Δv_{t-6}	0.001	0.287	0.000	0.096	0.004	1.027	0.005	1.138
$\Delta \sigma^2_{t-1}$	2.664***	3.013	2.668***	3.026	1.646	1.095	1.655	1.104
$\Delta \sigma^2_{t-2}$	-4.119***	-3.133	-4.090***	-3.120	-0.890	-0.448	-0.871	-0.440
$\Delta \sigma^2_{t-3}$	2.858**	2.104	2.846**	2.101	-2.392	-1.200	-2.379	-1.198
$\Delta \sigma^2_{t-4}$	-0.275	-0.201	-0.216	-0.158	4.631**	2.303	4.702**	2.347
$\Delta \sigma^2_{t-5}$	0.594	0.449	0.592	0.449	-0.137	-0.068	-0.089	-0.044
$\Delta \sigma^2_{t-6}$	-2.020**	-2.335	-1.892**	-2.189	0.524	0.336	0.735	0.472
Δg_{t-1}	-0.003	-0.663	-0.003	-0.540	-0.032	-1.444	-0.018	-0.763
Δg_{t-2}	0.000	0.002	0.000	0.085	-0.027	-1.270	-0.015	-0.682
Δg_{t-3}	0.009*	1.691	0.009*	1.753	-0.016	-0.767	-0.006	-0.297
Δg_{t-4}	0.005	0.981	0.005	1.020	-0.027	-1.322	-0.019	-0.935
Δg_{t-5}	0.004	0.907	0.004	0.901	-0.015	-0.799	-0.011	-0.565
Δg_{t-6}	0.004	0.795	0.004	0.763	0.001	0.071	0.004	0.232
Δw_{t-1}	-0.004	-0.651	-0.004	-0.693	0.016	0.869	-0.002	-0.085
Δw_{t-2}	-0.001	-0.161	-0.001	-0.227	-0.003	-0.182	-0.018	-0.987
Δw_{t-3}	0.000	-0.034	0.000	-0.070	0.001	0.091	-0.010	-0.641
Δw_{t-4}	0.000	0.088	0.000	0.036	-0.004	-0.299	-0.013	-0.905
Δw_{t-5}	-0.014***	-2.883	-0.014***	-2.925	-0.005	-0.401	-0.011	-0.901
Δw_{t-6}	-0.002	-0.386	-0.002	-0.439	0.002	0.225	-0.002	-0.156
Δd_{t-1}	0.011	0.291	0.017	0.425	0.218***	3.040	0.243***	2.752
Δd_{t-2}	-0.004	-0.106	0.003	0.069	0.093	1.332	0.120	1.432
Δd_{t-3}	0.100**	2.320	0.108**	2.473	0.132**	2.045	0.154**	2.077
Δd_{t-4}	0.016	0.370	0.024	0.549	0.057	0.961	0.077	1.182
Δd_{t-5}	-0.027	-0.641	-0.020	-0.481	0.037	0.710	0.051	0.930
Δd_{t-6}	0.034	0.879	0.038	0.974	0.038	0.862	0.045	1.015
R^2	0.172		0.179		0.276		0.284	

Note:
This table shows the results concerning the short-term adjustment effects in the ADRL model. We omitted the coefficients on intercept and trend. Models I and II are based on the data in the early market. Models III and IV are based on the data in the later market. Compared to Model I (Model III), Model II (Model IV) further allows the long-term effect of mining difficulty to vary over time.
* p<0.10 ** p<0.05 *** p<0.01

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Highlights

- We theoretically discuss the technology and economic determinants of the Bitcoin exchange rate
- To address co-integration in a mix of stationary and non-stationary time series, we use the autoregressive distributed lag (ARDL) model with bounds test in the estimation
- We find that the long-term Bitcoin exchange rate becomes more sensitive to economic fundamentals and less sensitive to technological factors as Bitcoin evolves
- We find that the impact of computational capacities on Bitcoin is decreasing as technology progresses