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# STABILITY OF TRANSACTION FEES IN BITCOIN: A SUPPLY AND DEMAND PERSPECTIVE[1]

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*Cryptocurrencies such as Bitcoin are breakthrough financial technologies that promise to revolutionize the digital economy. Unfortunately, their long-term adoption in the business world is imperiled by a lack of stability that manifests as dramatic swings in transaction fees and severe participant dissatisfaction. To date, there has been little academic effort to study how system participants react to volatility in fee movements. Our study addresses this research gap by conceptualizing the Bitcoin platform as a data space market and studying how market equilibrium forms between users who demand data space while trying to avoid transaction delays, and miners who supply data space while trying to maximize fee revenues. Our empirical analysis based on past bitcoin transactions reveals the existence of a relatively flat downward-sloping demand curve and a much steeper upward-sloping supply curve. Regarding users, the inelastic nature of demand signals the utility of Bitcoin as a niche platform for transactions that are otherwise difficult to conduct. This result challenges the belief that users may easily abandon Bitcoin technology given rising transaction costs. We also find that the use of bitcoins as a trading asset is associated with higher levels of tolerance to fees. Regarding miners, the comparatively elastic nature of supply indicates that higher fees stimulate mining by a larger magnitude than suppressing demand. This finding implies that, ceteris paribus, the Bitcoin system turns to self-regulate transaction fees in an efficient manner. Our work has implications for the management of congestion in blockchain-based systems and more broadly for the stability of cryptocurrency markets.*

**Keywords**: Fintech, blockchain, cryptocurrency, transaction fee, supply and demand, Bitcoin

[1]Sunil Mithas was the accepting senior editor for this paper. Ali Tafti served as the associate editor.

## Introduction

Cryptocurrencies such as Bitcoin are breakthrough financial technologies that promise to revolutionize the digital economy (Li and Wang 2017; Zhao et al. 2016). It is argued that cryptocurrencies will replace traditional methods of payment (e.g., cash and credit cards) because of their advantages in terms of transaction cost, processing speed, disintermediation, and decentralization of control (Grinberg 2011). Unfortunately, recent drastic turbulences in transaction fees and processing times have revived concerns about the stability of cryptocurrencies while propelling businesses to back away from cryptocurrency adoption and leading to the so called "transaction fee crisis" (Huo 2017; Lee 2018; Master 2018). Research suggests that swift surges in transaction fees might deter cryptocurrency usage and prompt regular users (i.e., transaction senders) to abandon this technology (Basu et al. 2018; Easley et al. 2019), and that, conversely, the sharp and unpredictable drops in fees paid to "miners"—i.e., a special type of users who contribute computing power to verify the transactions—might discourage miner participation, leading to security and stability concerns (Carlsten et al. 2016). Consequently, how transaction fees are determined in an equilibrium between the system participants with contradictory fee attitudes remains an open but important question (Huberman et al. 2017).

Our paper fills this void in the literature by studying the relationship between transaction fees and transaction data amount (i.e., quantity) published on Bitcoin's blockchain. These two factors are jointly determined through participation in the system. Accordingly, we aim to provide insights into the behaviors of both the users utilizing the system for conducting transactions and the miners providing the computing power for processing the transactions. Given the cross-side network dynamics between these two system participants, we conceptualize the cryptocurrency platform as a marketplace that is facilitated by the basic market forces of data space demand and supply. An investigation into the fee-quantity relationship in this market allows us to: (1) estimate and contrast the fee elasticities of data space demand (users) and data space supply (miners), and (2) study the impact of fees on processing (i.e., confirmation) time and how the equilibrium data quantity functions as the underlying mechanism for this impact.

Our research aims to strengthen both the practical relevance and theoretical significance of the nascent literature on blockchain-enabled cryptocurrencies. From a practical perspective, our contextual focus is motivated by the fee and data quantity volatility observed in the Bitcoin network, which is the original and the most popular cryptocurrency system in use today.[2] During the period of October 2017 to March 2018, the average daily transaction fee per byte in the Bitcoin network fluctuated wildly, with the highest point almost ten times higher than the lowest point, as it can be seen in Figure 1a. During this time, the transaction data quantity published on Bitcoin's blockchain, which is a function of data space supply and demand, also experienced large oscillations, as shown in Figure 1b.

These two figures allude to the lack of transparency in Bitcoin's fee mechanism that can distort a system participant's financial and performance expectations in the marketplace. For instance, miners might overestimate their expected rewards due to temporary fee hikes and therefore incur costly operational expenses (e.g., purchasing additional mining hardware), whereas users might pay high fees without receiving confirmation speed benefits due to reduced data space availability. Prior research in information systems (IS) literature has shown that reducing uncertainty and improving transparency in electronic markets have significant welfare ramifications for market participants. Arora et al. (2007) consider the uncertainty about the number of competitors in the market (referred to as the market-structure) and demonstrate that information revelation policies that generate the least amount of market-structure uncertainty maximize buyer (i.e., user) surplus. Similarly, Greenwald et al. (2010) show that in a reverse electronic marketplace with a single procurer and many suppliers, revealing more information about the bids at the end of a market session is a better policy to improve the procurer's welfare. Dimoka et al. (2012) focus on uncertainty about the characteristics, condition, and performance of products sold in online markets (referred to as product uncertainty) and find that reducing product uncertainty can have substantial economic benefits. This finding is especially relevant within the Bitcoin context, where product uncertainty closely resembles users' inability to accurately estimate what they might gain by increasing their fee offerings.

[2] According to a recent study (Easley et al. 2019), it is estimated that 35 million Bitcoin wallets were held worldwide with 100,000 businesses accepting payments in bitcoins. For further details about the Bitcoin system and the concept of blockchain, please see Section 2.

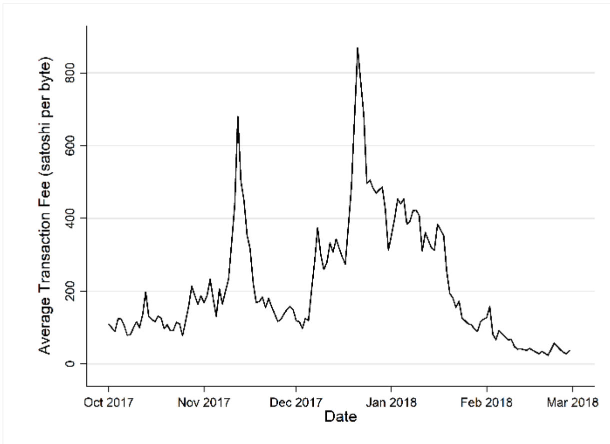


**Figure 1a. Average Daily Transaction Fee**

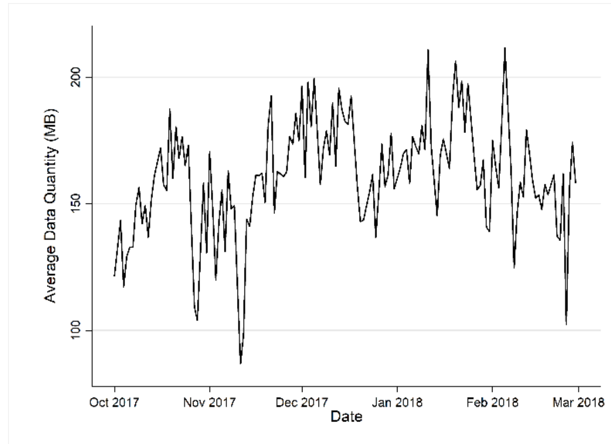


**Figure 1b. Average Daily Data Quantity**

Following this literature stream (see Pavlou et al. 2007; Xu and Zhang 2013 for additional examples), our study concentrates on the uncertainty surrounding the fee-data space quantity relationship in Bitcoin. Considering that: (1) in 2018, over $286 million in fees has been paid by the users of the Bitcoin network alone,[3] and (2) the role of transaction fees as a reward mechanism is known to periodically increase due to a limited coin supply design (Lavi et al. 2017), a better understanding of the factors affecting the movement in fees and data quantity is paramount to improving the transparency in the Bitcoin marketplace and hence the long-term stability of this emerging technology.

In addition to practical considerations, our study is also motivated by theoretical aspects of cryptocurrency market design. From an operational standpoint, it is reasonable to expect that increasing transaction fees will entice more miners to join the system as it gets more rewarding to mine. With more miner participation, and hence increased cumulative computing power in the system, more data can theoretically be published on the blockchain (i.e., supplied) per unit of time. However, two factors counter this expectation. To begin with, rising fees might urge users to abandon the network (possibly by switching to other methods of payment), thereby lessening the demand for the data space. The negative price-demand relationship for a wide range of products is well-established in earlier work and known as the "law of demand" in the classical economics literature (Gale 1955). In addition, for various reasons (to be discussed in detail in the Operational and Theoretical Foundations section below), many cryptocurrency protocols employ policies to stabilize the amount of data space supplied to the network per unit of time.[4] Basu et al. (2018) argue that given fixed protocol limits on the data space release rate and size, transaction fees serve merely as a queue-sorting mechanism and should therefore be considered as "social waste."[5] However, as Figure 1b implies, the effectiveness of such policies in keeping the data flow stable is questionable and, to our knowledge, has not yet been studied. Accordingly, an empirical investigation into the formation of the fee-quantity equilibrium should help bridge the gap between theoretical expectations based on system policies and observed reality based on market behavior.

Our empirical context for this investigation is the Bitcoin system. Bitcoin is the first decentralized cryptocurrency, released as an open-source software in 2008 (Nakamoto 2008). According to Hileman and Rauchs (2017), in March 2017, it accounted for 72% of the total cryptocurrency market that had a combined market capitalization of 25 billion USD. During this period, there

[3] This number is based on the information provided on the www.blockchain.com website and it is validated using the raw transaction level data collected from Bitcoin's blockchain.

[4] For instance, the Bitcoin protocol aims to release 1 megabyte (MB) of data space every 10 minutes (Arvind et al. 2016).

[5] The authors clarify that this argument applies assuming that there is enough mining revenue potential to provide sufficient security for the system.

were over 280,000 average daily transactions conducted in the Bitcoin network. Our main data source is the public ledger (i.e., blockchain) of Bitcoin, which records and broadcasts all verified transactions that have occurred in the network. Our discussion so far articulates that the transaction fees and the data quantity in the Bitcoin system are jointly determined by the decisions made by users and miners. Accordingly, we develop a simultaneous equations model to study the relationship between fees and data quantity observed in equilibrium. In this model, users represent the demand side (as they demand data space for their transactions) and miners correspond to the supply side (as they provide data space through mining). Given the anticipated differences of the two sides with respect to fees, we separate the supply and demand equations and estimate each one individually. For identification purposes, we make use of two exogenous variables: the price of a popular hardware device used for bitcoin mining as a supply shifter and the popularity of the Bitcoin system based on web searches as a demand shifter. We meticulously discuss the relevance and exogeneity conditions for these variables to establish instrument validity and show that the results are robust to alternative specifications as well as to other potential concerns such as protocol updates and the collider bias.

Our analysis yields several key findings. First, we document the existence of an upward-sloping supply curve and a downward-sloping demand curve for the transaction fee-data quantity relationship. The supply-side results show that transaction fees have a positive effect on the amount of data supplied on the network per unit of time. This is a surprising finding that questions the effectiveness of Bitcoin protocol policies aimed at imposing limits on the rate of releasing data space. The demand-side results reveal that transaction fees have a weak negative effect on the amount of data demanded to be placed on the blockchain. The fee elasticity of demand (by users) is considerably lower than that of supply, as indicated by the slope differences between the curves. This result challenges the expectation that users can easily abandon Bitcoin technology if transaction costs rise (Basu et al. 2018; Easley et al. 2019). Further, given that a common key reason behind the inelastic demand is the lack of substitute goods, it implies that the Bitcoin system serves as a unique mechanism for processing transactions that are difficult to conduct using conventional transaction methods. Second, our demand-side results identify a moderation effect exercised by the use of bitcoins as a trading asset. In particular, we find that when there is a higher level of bitcoin trading activity in the network, the overall user population exhibits increasing levels of tolerance to transaction fees. This finding is in parallel with the observations in the finance literature that show that financial traders' sensitivity to trading costs is higher than that of regular users. Third, we find that transaction fees have an accelerating effect on confirmation times and that this effect disseminates through the fee's stimulating impact on data space supply and suppressing impact on data space demand. Combined with earlier findings on the positive effect of confirmation time on fees (Easley et al. 2019), this result alludes to the existence of a fee-confirmation time feedback loop that can act as a mechanism regulating transaction fees. Collectively, our findings provide insights into the extent and the manageability of the surging fee conundrum, such as the one occurring at the end of 2017, which media outlets called the "transaction fee crisis" (Huo 2017; Lee 2018; Master 2018). Fee hikes are usually caused by an influx of high willingness-to-pay users. The fear is that such fee hikes could suppress other users' motivation to transact and ultimately harm the long-term attractiveness of Bitcoin. Our results alleviate this concern from two perspectives. First, the ability of fee hikes to suppress demand might not be as high as imagined. Second, the amount of additional mining capacity "turned on" by miners in response to fee hikes will likely bring down the necessity of subsequent high fees. In essence, we infer that as long as the driving forces underlying the steep supply curve and the flat demand curve remain unchanged, the Bitcoin system will "self-regulate" transaction fees and sustain long term stability in its fee marketplace.

The remainder of the paper is organized as follows: In the Operational and Theoretical Foundations section below, we describe the operational and theoretical fundamentals of the Bitcoin system and review the relevant IS literature within this context. Next, in the Hypothesis Development section, we discuss supply- and demand-side mechanisms that underlie the transaction fee-data quantity relationship and develop hypotheses based on these mechanisms. Then, in the Data and Variables section, we define data and variables used in our estimations, and present the main model and estimation results in the Empirical Analysis section. We provide results from our additional analyses, including supply and demand elasticity estimations and the impact of fees on confirmation times in the Additional Analyses section, and conclude by discussing the implications of our findings and offering some final remarks.

## Operational and Theoretical Foundations

### *Bitcoin System*

In this section, we provide an overview of the Bitcoin system that facilitates the use of a digital currency for electronic payments and the blockchain protocol that underlies this technology. Our focus is on the economic components of this system and we refer readers to Nakamoto's study (2008) for its technical and cryptographic details. At its core, Bitcoin functions as a distributed public ledger (i.e., record) of financial transactions between two or more accounts. Accounts are anonymous and can be created without the need of vetting from any centralized authority (Zohar 2015). Users can debit the balances in their accounts and credit the debited amount to any other account in the form of bitcoins.[6] Each transaction record contains the sender(s) and receiver(s) public account information (e.g., public address) as well as transaction details such as the amount transferred. Transactions are not finalized (i.e., validated) until they are added to the ledger, which is duplicated among all participating users across a peer-to-peer network.

The ledger is organized as a chain of blocks (and fittingly named as the blockchain) that is periodically updated with a block of recent transactions. The blockchain is central to the functioning of the Bitcoin system as, given the lack of a centralized authority to store user information and balances, this ledger is used to authenticate the validity of the transactions (i.e., making sure that the sender holds enough bitcoins to complete the transfer). In that aspect, the blockchain can be seen as a public good that keeps the transaction records up to date and the system operational (Zohar 2015). The transaction validation process is significantly different from those in traditional payment processing systems and it requires the assistance of a special type of users in the network known as miners.

It is the role of miners to confirm and insert valid transactions into the blockchain. Miners achieve this by compiling recent valid transactions into blocks and solving a computationally difficult mathematical problem—i.e., providing proof-of-work. This problem requires generating a hash that meets the "hash-rate criterion" set by the system, which is a trial-and-error process that requires significant computing power (Li and Wang 2017). Coupled with the embedding of cryptographic hash of previous blocks into the current block, proof-of-work makes it difficult for ill-intentioned users to cheat the system with forged transactions, thereby overcoming potential fraud and double spending issues. The first miner who successfully solves the proof-of-work problem gets the right to broadcast and publish its block (i.e., the transactions in the block) on the blockchain. Miners have total control over which transactions to include in the newly discovered block and they are expected to maximize their financial gains during the transaction selection process (Sompolinsky and Zohar 2018).

An ingenuity of the Bitcoin system is that it provides financial incentives for miners solely acting on their self-interest to participate in the network. The trustworthiness of individual actors within the system is irrelevant and the ledger's integrity is protected as long as miners respond to incentives in a profit-maximizing way (Huberman et al. 2017). There are two main reward mechanisms for miners—i.e., new coins and transaction fees. First, each miner that successfully adds a legitimate block to the blockchain is awarded a predetermined quantity of newly minted bitcoins (i.e., the coinbase). In fact, this is the only way of adding new bitcoins into circulation. Based on Bitcoin protocols, the number of bitcoins minted per block starts at 50 and decreases by one half every 210,000 blocks. The number of all bitcoins that can be circulated in the system is therefore capped at 21 million. In other words, Bitcoin protocol uses a controlled mechanism for the expansion of the currency and the limits the total number of bitcoins that will ever be issued (Li and Wang 2017). To supplement miners' minting rewards that decrease over time, the Bitcoin protocol also uses transaction fees as a second reward mechanism. Transaction fee is an optional fee offered by the sender of a transaction with the aim of enticing the miner to select his/her transaction into the next discovered block. A miner collects all fees attached to transactions that are included in the block. Given that the protocol prescribes diminishing returns from minting rewards, transaction fees are expected to play an increasingly important role to incentivize miners for participating in the transaction validation process and therefore ensuring the security and reliability of the Bitcoin system in the long run (Huberman et al. 2017).

There are two important features in the Bitcoin protocol that affect how transaction fees are determined and realized. First, the maximum size of block that can be added to the blockchain is set to a fixed parameter by the protocol.

[6] Following convention, we use the capitalized Bitcoin to refer to the system and lowercase bitcoin to refer to the unit of currency.

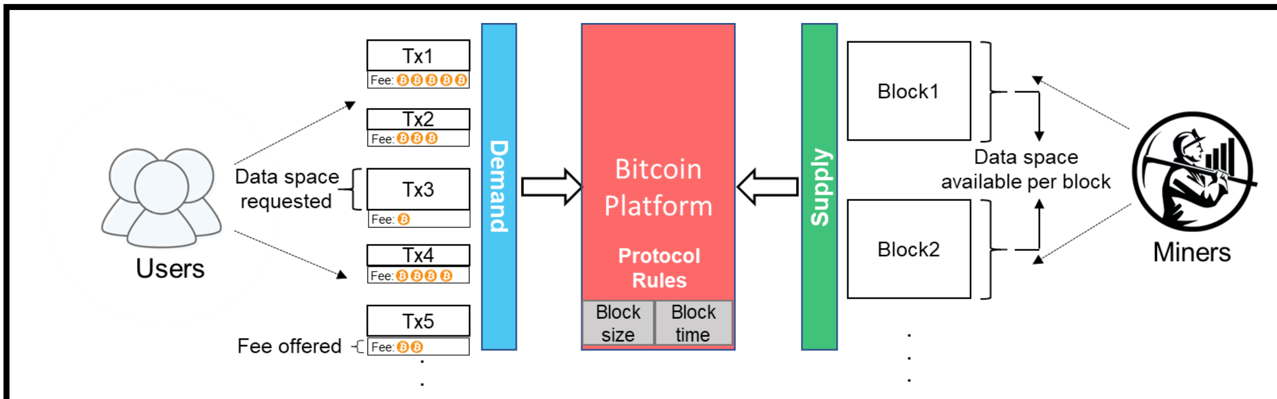


**Figure 2. Bitcoin as a Data Space Marketplace**

In other words, there is a limit on the number of bitcoin transactions (i.e., throughput) that can be processed by the system over a given time interval. Second, as mentioned above, the protocol gives miners the flexibility to select which transactions to include in the blocks that they discover. Together, these two characteristics lead to an interesting market mechanism for users who might have varying levels of transaction delay preferences and are hence willing to offer different amounts of optional transaction fees. We discuss the dynamics of this marketplace in more detail in the following subsection.

### *Bitcoin's Data Space Marketplace*

The operational overview of the Bitcoin system highlights the roles of the two types of system participants. In brief, "users" utilize the Bitcoin platform for sending and/or receiving bitcoins (i.e., conducting transactions) whereas "miners" validate the transactions and record them in the blockchain using blocks. The dynamics between these two types are affected by the number of participants as well as the protocol rules embedded in the Bitcoin platform. For instance, when the user base (users who are sending transactions in the cryptocurrency network) grows, miners gain access to a greater number of transactions to confirm in the network. However, the Bitcoin protocol confines the number of transactions that can be processed in the system (i.e., the throughput) by setting block size and block discovery interval limits. The transaction congestion in the network due to these limits prompts users to compete with each other for a space in the block. As a result, users might offer higher transaction fees to influence miners' selection decisions. When the transaction fees grow, more miners are motivated to join the system as it gets more rewarding to mine. Yet higher transaction fees might also deter bitcoin usage and cause users to exit the Bitcoin network (Easley et al. 2019), which in turn reduces the congestion in the network. The process outlined above paves way to a marketplace, illustrated in Figure 2, that is regulated by the Bitcoin platform and facilitated by the basic market forces of supply and demand.

Within this context, we define the market commodity as the "data space" (i.e., unit of storage available to hold transaction data in a block) and users and miners as the "buyers" and "sellers" of this commodity, respectively. The fundamental reason behind this conceptualization is that users require data space to post their transactions on the blockchain, and miners are the producers of this data space—i.e., they generate space storage on the blockchain by mining blocks through solving the proof-of-work problem. Note that from an operational standpoint, a transaction is nothing but digital information that stores details about the sender-receiver interaction such as input/output addresses. Our empirical analysis reveals that the average size of a transaction during our data time period was 500 bytes. In other words, the sender of an average size transaction requests 500 bytes of data space in the next available block when the transaction is submitted to the network. In return for being awarded space in a block, the user promises to pay the miner a transaction fee amount, which serves as the price of this data space. As discussed above, the scarcity of data space (due to block size and block discovery interval limits) commonly leads to price competition among users. The Bitcoin protocol allows users to name their own prices with the expectation that low willingness-to-wait users will offer higher fees to gain priority in the transaction validation process.

## Related Literature

Following the earlier conceptualization, we draw on three streams of IS research that can contribute to our understanding of the commodity and pricing dynamics in the data space marketplace: (1) the pricing of data storage services, (2) online auctions, and (3) two-sided markets. Next, we review some of the relevant work in these areas and discuss their relationship to the Bitcoin system.

The first stream is related to the pricing of data storage services. At its core, a blockchain is a data management system where information about transactions (e.g., financial records) is stored in a distributed online environment (Yli-Huumo et al. 2016). Accordingly, the fees paid for a confirmed Bitcoin transaction can simply be considered as the price of the data storage reserved for this transaction on the Bitcoin's blockchain. Earlier research that considered the pricing of online computing resources includes the works of Jain and Kannan (2002), who analyze the conditions under which different pricing schemes might be optimal for online servers, and of Das et al. (2011), who identify optimal pricing strategies for online storage service providers under demand uncertainty. More recent studies in this area focus on pricing issues in the "cloud computing" nomenclature such as software-as-a-service (SaaS), infrastructure-as-a-service (IaaS), and platform-as-a-service (PaaS). Examples include Feng et al. (2018), who identify optimal market strategies for SaaS providers newly entering the market, Cheng et al. (2016), who account for the latency caused by geographical differences in spot pricing dynamics of Amazon's Elastic Compute Cloud service, and Chen and Huang (2016), who compare three different pricing strategies (by minutes, by gigabytes, and by megabytes per second) for data services. While there exist similarities between the distributed computing environments considered in these studies and the blockchain technology, the Bitcoin context diverges from most of the earlier work on data storage pricing in two aspects. First, many of the operational policies such as resource availability limits and connection protocols in the Bitcoin network are controlled by the rules embedded into the system, whereas service providers in former computing environments have more flexibility in terms of customizing their services. For instance, while it is impossible for a miner to override the 1 MB data size limit of a Bitcoin block, a traditional service provider can more easily scale up (down) the online service based on demand. Second, pricing schemes in traditional computing environments are primarily determined by service providers. However, given the lack of a single, centralized authority, transaction fees in Bitcoin are eventually decided by users who differ in terms of their confirmation time expectations and hence their fee offerings. Thus, our study complements the existing literature by investigating a data storage environment where the service provider (miner) has limited influence on pricing.

Users' ability to name their own fees based on their willingness-to-wait and the scarcity of the data space resources lead to a competitive setting that resembles online auctions. IS researchers have studied many different types of auctions in IT-enabled marketplaces, such as Yankee auctions (Bapna et al. 2004), combinatorial auctions (Adomavicius et al. 2019), and business-to-business auctions (Lu et al. 2016; Mithas et al. 2008). The Bitcoin transaction process is most similar to the multi-unit sequential auction (Lu et al. 2016), where there are multiple rounds of auctions and multiple units of goods sold in each round. The former characteristic (i.e., multiple rounds) resembles the continuous block generation process of Bitcoin (with an average of 10 minutes between block discoveries) and the latter characteristic (i.e., multiple units) resembles the 1 MB of data space allocated to transactions in each block. In a sequential auction setting, the amount of information to release about the auction process is a critical decision for market designers because bidders can learn from earlier auctions and change their bidding strategies. For example, Arora et al. (2007) and Greenwald et al. (2010) show that in a reverse electronic marketplace with one buyer and multiple sellers, complete information policy minimizes the uncertainty on market structure and opponents' cost structure and generates a higher buyer surplus in sequential procurement auctions. In the Bitcoin context, users can also learn from the information about confirmed transactions in previous blocks and use this information to decide the amount of transaction fees they are willing to pay. This is, in fact, a common strategy implemented by many fee recommendation systems embedded in popular Bitcoin wallets (e.g., Bitcoin Core). This insight provides guidance on the choice of instrumental variables in our supply-demand simultaneous equation system.

The third relevant stream is IT-enabled two-sided markets. Following the advances in mobile and internet technologies, applications of two-sided markets have expanded to many business sectors ranging from housing (e.g., Airbnb) and transportation (e.g., Uber and Lyft) to e-commerce (e.g., Amazon and eBay). The Bitcoin system is similar to these applications with respect to providing an online, peer-to-peer platform to enable user and miner interaction. Existing research in this area has primarily focused on the network effects observed in the markets. For instance, Parker and van Alstyne (2005) propose a model to explain how the size and direction of network effects influence firms' pricing strategies in a two-sided market. Bakos and Katsamakas (2008) argue that the network effect is actually an endogenous factor that is determined by the design of the two-sided network. Song et al. (2018) demonstrate that the cross-side network effects in two-sided markets can be temporally asymmetric, with provider-to-user effect developing in the short term and user-to-provider effect materializing in the long-term. Within the context of Bitcoin, we expect to observe a negative same-side network effect due to the fee (block generation) competition among the users (miners). In addition, a fundamental difference between the Bitcoin's data space market and most existing two-sided markets is platform ownership. In a conventional market, there are buyers, sellers, and an intermediary firm who owns the IT platform and designs the market structure. However, the Bitcoin system is an open source platform that is not owned by any entity. Therefore, the primary concern for Bitcoin is not to design an optimal pricing strategy for any intermediary firm to maximize its profit, but to study whether the operational mechanisms (such as data space limitations) embedded in the Bitcoin source code will maintain stability in the long term.

To summarize, our survey of the IS literature has identified similarities as well as differences between the Bitcoin context and the existing research on data storage pricing, online auctions, and two-sided markets, which lay out the foundation for the theoretical contribution of our fee- data quantity analysis (Rai 2017a, 2017b).

## Hypothesis Development

In this section, we provide a discussion on the mechanisms that underlie the transaction fee-data quantity interaction and develop hypotheses based on these mechanisms. Given the two-sided nature of the data space market, we separate miner (supply) and user (demand) mechanisms and discuss each side in turn.

### *Miner Side (a.k.a. Supply Side)*

A survey of the cryptocurrency literature affirms that the current research efforts on Bitcoin transaction fees are aimed at designing alternative fee setting and market clearing mechanisms for transactions submitted to the network (Basu et al. 2018; Carlsten et al. 2016; Lavi et al. 2017; Master 2018). A majority of these studies focus on the role of fees on increasing the security in the system by attracting miners (hence computational power) under system-imposed block discovery interval and block size limits. For instance, Lavi et al. (2017) find that the current fee regime heavily relies on artificially created congestion in the network and on "addressing" how the congestion problem (e.g., by increasing the block size limit) might compromise the security of the system by diminishing the monetary incentives for miners. To address this issue, they propose a new fee market mechanism that can sustain miners' revenues under increasing block sizes. Similarly, Carlsten et al. (2016) show that a transaction fee regime alone cannot guarantee the security of the system without the help of a block reward regime, which is only a temporary incentive mechanism in the current state of the Bitcoin system. They argue that designers of new cryptocurrencies may need to consider the inevitability of monetary inflation by making the block rewards permanent. Tsabary and Eyal (2018) develop a model to study miners' decisions to switch on and off their computing resources in the system to maximize the difference between their income and expenses (capital and operational expenditures such as electricity costs) under varying fee amounts. The authors find that, as expected, miners refrain from contributing computing power to the system when the transaction fees are small and the operational expenses are large. However, more interestingly, they also show that miners can be heterogeneous in their participation decisions even when their computing hardware is identical.

A separate stream of work related to miners and transaction fees has focused on the social costs of the congestion-dependent market clearing mechanism that is essential in the current state of the Bitcoin system. For example, Basu et al. (2018) argue that the fees in the current first price auction type system are "social waste," given that the average block discovery interval and the block size are set to 10 minutes and 1 MB, respectively, and that these limits have been established and controlled by the Bitcoin protocol. Accordingly, they propose a new fee mechanism based on second price auctions to decrease the volatility in the fee market. Similarly, Huberman et al. (2017) argue that protocol-induced transaction delays generate significant waste, as they serve no purpose other than inflating transaction fees. Yet, they also recognize delay costs to be a necessary condition in order to raise revenue from users to fund miners.

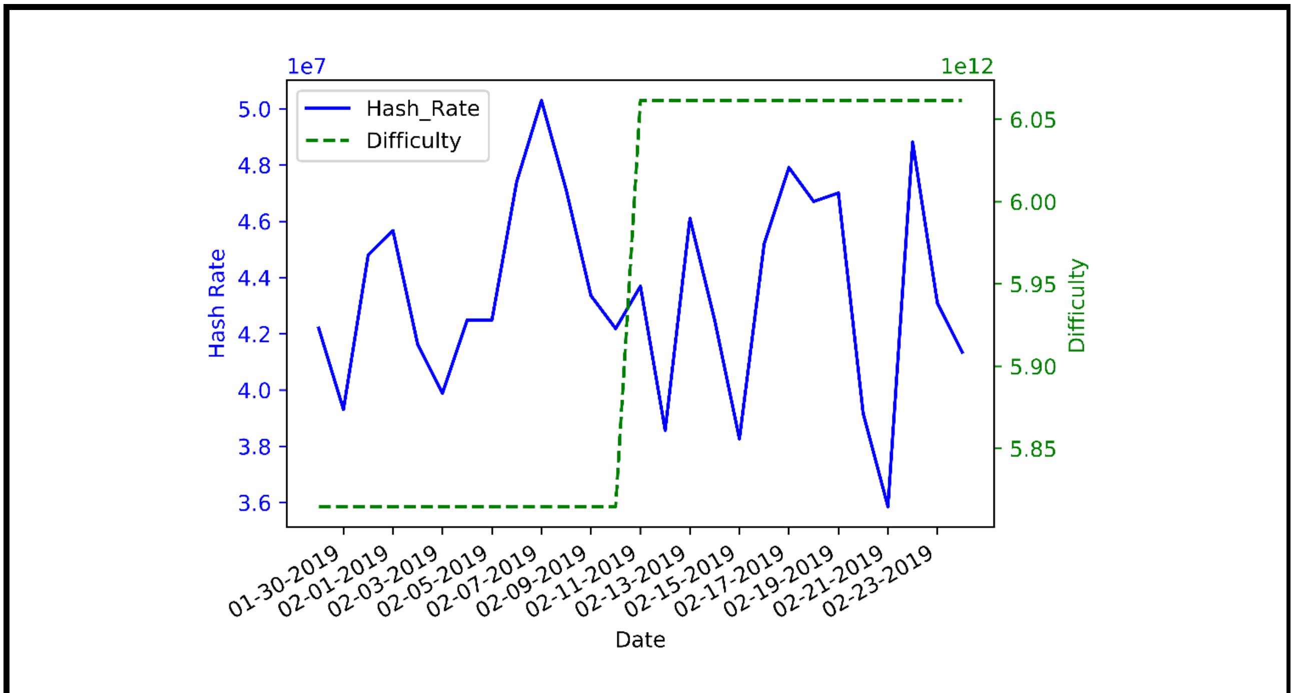


**Figure 3. Average Daily Hash Rate Between Two Difficulty Updates**

An important avenue of discussion that has been absent in aforementioned studies is the impact of transaction fees on the block supply. While it is conventional to define the long-term average throughput in the Bitcoin system as a constant due to fixed protocol limits (Croman et al. 2016), the implementation details of these limits allow for variation in the number of transactions entering the Bitcoin blockchain in the short term. The reasoning behind this counterintuitive argument is multifaceted. First, it is well-known that the aggregate computational power in the network is dynamic and contingent on miners' participation decisions. As indicated by Huberman et al. (2017), miners enter and exit the system at will while responding to perceived profit opportunities that can change dynamically (e.g., variations in electricity costs during the day). When the computational power in the system changes (due to fluctuations in the number of miners), the block time interval will vary since the proof-of-work problem would be solved at different speeds (Tsabary and Eyal 2018). Second, in theory, the Bitcoin protocol aims to counteract this variation issue by automatically adjusting the difficulty of the proof-of-work problem so that the time between two block discoveries stays constant (10 minutes on average). However, a more detailed analysis of the protocol implementation reveals that these adjustments only occur once every 2,016 blocks. In other words, there is a significant and recurrent time period in which the problem difficulty is fixed while the computational power fluctuates. To further illustrate, consider Figure 3, which superimposes the average daily hash rate[7] in the Bitcoin network between January 30, 2019 and February 23, 2019 onto the problem difficulty level during the same period.

The discrepancy in these two lines alludes to the existence of variation in block discovery intervals that can influence how much data (as a function of submitted transactions) can be published on the Bitcoin blockchain. Finally, we also know that an increase in transaction fees leads to more miner participation in the network (Carlsten et al. 2016; Houy 2016). Combining these arguments, we postulate the supply-side impact of transaction fees as follows: higher fees attract more computing power in the network and hence decrease block discovery times, which then leads to an increase in the amount of data added to the blockchain during a given time period. Accordingly, we form the following hypothesis:

[7] The hash rate refers to the number of hashes conducted per second and is a function of the aggregate computational power available in the network.

**H1:** *Holding difficulty level constant, an increase in transaction fees is associated with an increase in the amount of data published on the blockchain per unit of time.*

## User Side (a.k.a. Demand Side)

It is well-established in classical economics literature that for many ordinary goods, the demand curve is downward sloping—i.e., *ceteris paribus*, the quantity of a good demanded decreases when its price increases (Borjas 2003; Burnetas and Ritchken 2005). This observation is also known as the "law of demand" in microeconomics (Gale 1955). Considering the similarities between the market economies of ordinary goods and Bitcoin's data space market (as discussed in the Related Literature subsection above), it is logical to expect the law of demand to be applicable in the cryptocurrency context. This rationale has been adopted in a recent stream of studies. For instance, Easley et al. (2019) develop a game-theoretic model to investigate the evolution of the transaction fees in equilibrium and explain the interactions between miners and users. They postulate that higher transaction fees discourage bitcoin usage and cause users to leave the Bitcoin ecosystem. Kasahara and Kawahara (2019) model the transaction confirmation process as a priority queueing system with batch service. Through numerical experiments, they find conditions where transactions with small fees suffer from extremely long delays that drastically undermine the possibility of using bitcoins for micropayments (e.g., for purchasing daily items) in the real-world. Huberman et al. (2017) develop an economic model to study how transaction fees and miner participation are determined in an equilibrium of a congestion queueing game.

While this stream of research instinctively affirms the idea that there exists a downward-slope demand curve that allows for the equilibrium in the system, the "steepness" of the slope— i.e., the "fee elasticity" of the demand, is an important empirical question that has not been explicitly considered in prior literature. There are two reasons that can differentiate the behavior of the demand curve in the Bitcoin context from the demand curves observed in more traditional markets. First of all, a majority of Bitcoin wallet software in use today implements "fee calculators" that can dynamically set the fees for transactions that are instigated with the software. These calculators utilize heuristics based on blockchain history and the queue of pending transactions to determine transaction fees as a response to the current congestion level (Lavi et al. 2017). While providing user convenience by automating the fee setting process, such mechanisms are problematic from a market clearing perspective because the fees set by these calculators purely depend on the congestion levels in the system and hence do not reflect the users' true valuation of transaction confirmation delays.

Second, it is known that the Bitcoin system has been subject to substantial speculative activity (Griffin and Shams 2018) and a majority of bitcoin transactions are conducted for trading and investment purposes, rather than serving as a medium of exchange. Baur et al. (2018) categorize bitcoin users into six groups (active investor, passive investor, hybrid, currency user, miner, and tester). They discover that currency users—i.e., those who were identified to have acted as both sender and receiver for small size transactions—only constituted between 2-7% of the total user population between 2011 and 2013. Similarly, an industry report by Chainalysis Inc. (Chainalysis 2018) found that only 11% of bitcoins in circulation are used for "service transactional" activity and the rest are mostly speculative or investment coins. This situation raises concerns regarding the applicability of the microeconomic "law of demand" in the Bitcoin context.

There have been mixed findings in the finance literature with respect to financial traders' sensitivity to trading costs (Admati and Pfleiderer 1988; Foster and Viswanathan 1993). In particular, Foster and Viswanathan (1993) find that trading volume can increase during the times of day when adverse selection costs[8] (Glosten and Harris 1988; Stoll 1989) are high. Considering that trading costs are comparable to transaction fees in the Bitcoin system, bitcoin trading users' tolerance level to transaction fees might be higher than that of regular users. It should also be noted that trading orders executed over cryptocurrency exchange platforms (e.g., Coinbase, Bitfinex, etc.) are not submitted to the Bitcoin network individually, but rather are written to the blockchain periodically after account balancing and bookkeeping by the exchange platform. During this process, the platform incurs and pays transaction fees on their users' behalf (Coinbase 2019). However, these fees are commonly passed to users as additional charges (Houy 2016), and therefore the platform might not be concerned about transaction fees. As a result, we posit that it is possible to observe more transaction activity in the network even if the transaction fees are increasing.

[8] Adverse selection costs is one of the three components of trading costs as identified by Glosten and Harris (1988).

Overall, the first argument (automated fee mechanism) suggests a downward-sloping yet relatively inelastic demand with respect to Bitcoin transaction fees. The second argument (trading activity) suggests that this relationship will be further moderated by the use of bitcoins as a trading asset rather than a medium of exchange. Thus, we hypothesize the following:

**H2a—Main Effect:** *An increase in transaction fees is associated with a weak decrease in the amount of data demanded to be published on the blockchain.*

**H2b—Moderation Effect:** *The use of bitcoins as a trading asset dampens the association between transaction fees and the amount of data demanded to be published on the blockchain.*

## Data and Variables

### Data Collection and Processing

We collected and merged data from four sources to conduct our empirical analysis. The first and main data source is the Bitcoin blockchain—i.e., the digital ledger that records information about all published blocks and confirmed transactions in the Bitcoin network. We used the public API provided by the block explorer website www.blockchain.com to download transaction details, including the size of the transaction, fees paid to miners, and the proof-of-work difficulty level at the time of confirmation, for all transactions in all blocks published in the blockchain from the inception of the Bitcoin network until February 28, 2019. Given that the data supply variation can only be observed over a period of time due to protocol limits, as discussed in the previous subsection discussing the miner side (a.k.a supply side), we aggregated the transaction data at daily time intervals to calculate the total data published and average transaction fees paid per day. We expected each day to include an average of 144 blocks published in the blockchain; hence, using the day period as the time scale provides a good balance between the granularity of observations and the level of within-period variation. Furthermore, using the daily time interval also allowed us to conveniently merge external data sources that record daily information (e.g., exchange rate, internet search popularity) with the blockchain data. It should be noted that the Bitcoin system operates worldwide and continuously (24 hours a day); therefore, a consideration during the aggregation process is identifying the start and the end times of a day. To establish consistency with the other data sources, we used the Central Time Zone for dividing the Bitcoin data into individual days.

The remaining three data sources are utilized for constructing the exogenous variables used in our estimations. Specifically, we obtained the daily average price information for a specialized bitcoin mining hardware device from the Amazon.com e-commerce platform[9] to proxy for supply production costs. In addition, we utilized the Google Trends service to obtain the search popularity of the keyword "bitcoin." Finally, we used the bitcoinity.org website to obtain trading information regarding bitcoin exchanges. After merging the data from these separate sources, our consolidated data set covers the period between April 18, 2017[10] and February 28, 2019. We note that during this time frame, the minting reward (i.e., the reward for publishing a block on the blockchain) remained stationary at 12.5 bitcoins per block. Next, for data cleaning purposes, we removed 55 observations in which the difficulty level of the proof-of-work problem had been updated by the system on those particular days. It likely took a take a while for users and miners to realize these difficulty level changes and adjust their activities accordingly. As a result, observed variable values on those days might not reflect system participants' typical behavior on regular days with a fixed within-the-day difficulty level. Next, we discuss the construction of variables from these data sets in more detail.

### Variable Definitions and Measurement

***Quantity:*** Our first endogenous variable of interest is *Quantity*, which refers to the amount of transaction data published on the Bitcoin's blockchain per day. The unit of measurement is megabytes (MB). As discussed in the previous subsection, our analysis is conducted at the day level.

[9] To obtain historical price information, we utilize an API provided by Keepa.com, which is a data repository that tracks and records the historical prices of the products sold on Amazon.com.

[10] April 18, 2017 is the start of the daily hardware price information, therefore the consolidated data set begins from this date.

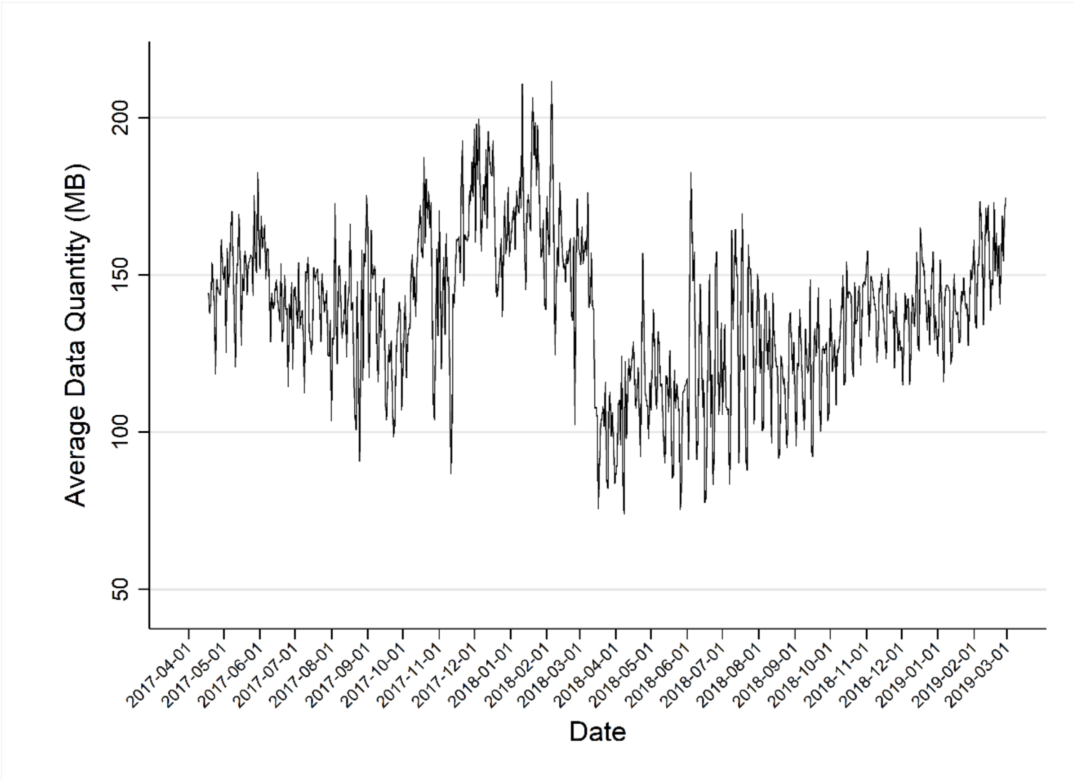


**Figure 4. Daily Average Data Quantity in the Observation Time Window**

Thus, we divided the continuous "string of blocks" into respective individual days. To calculate the *Quantity* values, we downloaded all the blocks that were mined between the start-end times of each day and accumulate the data size of all transaction included in these blocks. A transaction's data size is a function of the input and output addresses included in the transaction and can vary widely across transactions. Due to this variation and the variation in the number of blocks generated each day (caused by fluctuating computing power in the network), the amount of daily data published in the blockchain can differ significantly. Figure 4 plots the daily quantity amounts over the data time period. We observe that there exist considerable daily fluctuations in *Quantity* and the difference between highest and lowest amounts of data published per day is almost three times.

***Fee:*** The variable *Fee* refers to the daily average fees paid by users for the transactions that were published on the blockchain. The unit of measurement is satoshi(s)[11] per byte. It is calculated as the total amount of transaction fees paid divided by the total amount of data published (in bytes) per day. We emphasize that the daily average fees were computed at the data size level but not at the transaction level, because miners are limited by the block size (1MB) and the ideal transaction selection strategy for block formation involves maximizing the fees gained per unit of data, regardless of the number of transactions included in the block (Lavi et al. 2017). Figure 5 plots the daily average transaction fees per byte and the daily transaction volume (measured as the number of transactions confirmed per day) over the data time window.

[11] Satoshi is the smallest unit of currency in the Bitcoin system: 1 satoshi = $10^{-8}$ bitcoin.

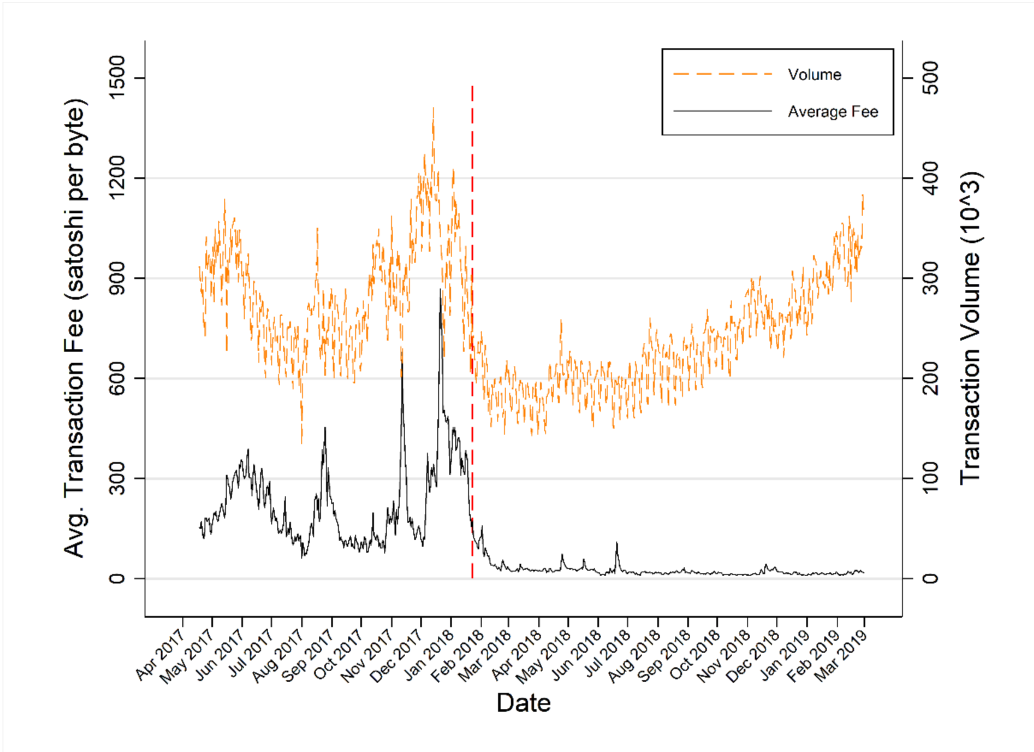


**Figure 5. Daily Average Fee and Volume in the Observation Time Window**

The fee and volume movement differences before and after January 23, 2018 (separated by the vertical dashed line in Figure 5) indicate that the data window covers the state of the Bitcoin network under varying congestion conditions. In particular, the period before January 23, 2018 exhibits a large variation in transaction fees, which can assist the identification of the *Fee's* true impact on user and miner behavior. However, such a difference can also signal unobserved heterogeneity across different time periods. To account for possible congestion related heterogeneity that might be potentially correlated with both *Fee* and *Quantity*, we utilize a dummy variable, *PeakPeriod*, defined by the date. The value of *PeakPeriod* is "1" is the date is before January 23, 2018 and "0", otherwise.

***Fx:*** The variable *Fx* refers to the daily average exchange rate between 1 bitcoin and 1 USD. Considering the prevalent use of bitcoins as a trading asset (Baur et al. 2018), the exchange rate might be correlated with *Fee* because when the exchange rate is high, more users might want to conduct transactions in the network, which would create congestion and increase the transaction fees offered to miners. The exchange rate might also be correlated with *Quantity* because when the exchange rate is high, miners' net USD revenue from mining a block would be higher and therefore more computing resources might flow into the system, which would reduce the block discovery times and increase the amount of data published in the blockchain. To address the possible bias caused by these potential correlations, we include *Fx* in both supply and demand equations as a control variable.

***HardwareCost:*** We use the *HardwareCost* variable as an exogenous supply shifter that can help identify the demand function in our simultaneous equations model, (details of which are discussed in the Model subsection below). *HardwareCost* refers to the daily average price of a highly popular bitcoin mining hardware device—i.e., the AntMiner S9. According to Techradar website (Techradar 2018), S9 is one of the most widely used bitcoin mining hardware devices in the world and was considered the most energy efficient miner on the market during our data time frame (April 2017 to March 2019). Accordingly, we consider the cost of the AntMiner S9 to be a good proxy for the cost of "data space production" from the miners' (i.e., suppliers') perspective. *HardwareCost* is measured in USD and the price data for the S9 miner was collected from Amazon.com via a third-party tracking service, as discussed in the Data Collection and Processing subsection above.

***Difficulty*** is a measure of the computational complexity associated with mining a block by finding a hash value below a given target threshold (i.e., solving the proof-of-work problem). It is a value determined automatically by the Bitcoin protocol and is adjusted periodically (every 2,016 blocks) with the goal of keeping the block discovery interval stationary at 10 minutes. Given that the difficulty level has a direct impact on the number of blocks generated during a given time period, it is expected to affect the amount of data published on the Bitcoin's blockchain. Accordingly, we include *Difficulty* as one of the control variables in our supply equation. By default, difficulty levels are represented using large numeric values (e.g., thirteen-digit numbers). For cleaner exposition, we scale these values down by a factor of $10^{-12}$.

***Popularity*** is defined as the recognition and the reputation of the Bitcoin system by the public. We expect that the more well known Bitcoin is, the more it will be used as a transaction medium and therefore the more data space demand will be observed in the network. As a result, we propose to employ it as an exogenous demand shifter that can help identify the supply function in the simultaneous equations model. To measure Bitcoin's popularity over time, we used Google Trends, an online analytics service that provides information on the relative popularity of a search term queried in the Google search engine, which is used in various research domains ranging from healthcare (Nuti et al. 2014) to economics (Vosen and Schmidt 2011) and finance (Preis et al. 2013) to estimate aggregate-level interest and behavior. To extract the popularity information, we used the keyword "bitcoin" and obtained the Google Trends scores of this keyword during our data time period—i.e., between April 18, 2017 and February 28, 2019. For an extended time period such as ours, Google Trends scores are only provided on a weekly basis and we thus used the same score for all days in the same week. The scores were calculated by dividing the number of queries made including this keyword by the total number of all queries made in the Google search engine, normalized between 0 and 100.

***Trading:*** To test for the hypothesis that Bitcoin's use as a trading asset can moderate the impact of transaction fees on data space demand, we include a variable (*Trading*) that can proxy for the trading activity in the Bitcoin network. Specifically, we obtained information about the trading volume on the Coinbase cryptocurrency exchange platform.[12] Coinbase is one of the oldest cryptocurrency exchange platforms with the largest market share in terms of trading volume in April 2019 (Bitcoinity 2019). The *Trading* variable is measured as the daily average number of trading orders executed per minute on this exchange platform.

***DaysSinceUpdate:*** As discussed in earlier sections, the Bitcoin protocol updates the difficulty level of the proof-of-work problem every 2,016 blocks. From a system standpoint, the ramification of these periodic updates is instantaneous—i.e., *ceteris paribus*, the time to discover a block changes at the instant that the difficulty level gets updated. Yet, from a participant standpoint, it is unlikely that miners or users will adjust their operations and expectations immediately. For instance, some miners might consider increasing their computational power in the network in response to a difficulty level surge; however, it might take some time to turn on additional machines. To account for the possible time-related heterogeneity caused by difficulty changes, we include a time variable called *DaysSinceUpdate* in our models. This control variable is defined as the number of days that have passed since the proof-of-work problem difficulty was last updated. Its values start at 1[13], with an increment of 1 for each day that the difficulty level stays the same. Once the difficulty level gets updated, the value of *DaysSinceUpdate* resets to 1.

***DayOfWeek:*** To control for possible temporal-specific user variation across different days of the week, we include *DayOfWeek* dummies in our models.

***PeakPeriod:*** As discussed in the *Fee* variable discussion above, the congestion level in the Bitcoin network considerably changed after January 23, 2018. To account for possible congestion related heterogeneity that might be potentially correlated with both *Fee* and *Quantity*, we utilize a dummy variable, *PeakPeriod*, defined by this date. The value of *PeakPeriod* is "1" is the date is before January 23, 2018 and "0" otherwise.

[12] https://pro.coinbase.com/trade/BTC-USD

[13] There are no zero values because the same day updates are dropped from the analysis during data cleaning.

**Table 1. Descriptive Statistics**

| | N | Mean | St. Dev. | Min | Max |
|---|---|---|---|---|---|
| ***Quantity*** | 627 | 138.38 | 24.53 | 74.07 | 211.58 |
| ***Fee*** | 627 | 106.55 | 127.27 | 9.32 | 868.35 |
| ***Fx*** | 627 | 6296.78 | 3376.26 | 1210.65 | 19206.16 |
| ***Difficulty*** | 627 | 3.55 | 2.36 | 0.52 | 7.45 |
| ***HardwareCost*** | 627 | 1836.95 | 1452.11 | 244.32 | 6347.99 |
| ***Popularity*** | 627 | 18.49 | 17.45 | 5.00 | 100.00 |
| ***Trading*** | 627 | 65.84 | 48.67 | 16.46 | 405.16 |
| ***DaysSinceUpdate*** | 627 | 6.74 | 3.65 | 1.00 | 16.00 |

**Table 2. Correlation Scores**

| | | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|---|
| **(1)** | *Quantity* | | | | | | | |
| **(2)** | *Fee* | 0.337 | | | | | | |
| **(3)** | *Fx* | 0.179 | 0.203 | | | | | |
| **(4)** | *Difficulty* | -0.294 | -0.678 | 0.063 | | | | |
| **(5)** | *HardwareCost* | 0.432 | 0.797 | 0.440 | -0.792 | | | |
| **(6)** | *Popularity* | 0.445 | 0.566 | 0.739 | -0.356 | 0.756 | | |
| **(7)** | *Trading* | 0.400 | 0.454 | 0.688 | -0.152 | 0.552 | 0.794 | |
| **(8)** | *DaysSinceUpdate* | 0.042 | -0.075 | -0.038 | 0.031 | -0.053 | -0.051 | -0.073 |

***Regulatory:*** The administrative and operational complications arising from rapid adoption of cryptocurrencies have prompted various legal authorities to regulate cryptocurrency related operations. Considering that regulatory actions can affect user behavior while also being correlated with *Fee* and *Quantity*, they might lead to omitted variable bias if unaccounted for. To address this issue, we introduce a control variable related to bitcoin mining in China. According to industry reports, mining operations that originate in China constitute the majority—as much as 65%—of all the mining activity in the Bitcoin network (Bendiksen and Gibbons 2019). Within this context, a major regulatory measure taken against cryptocurrency mining in China is the central government's ban on local governments providing subsidies and preferential policies for bitcoin mining companies (Zhang 2018). The new rule has also pressured local authorities to increase reporting on bitcoin mining operations in their jurisdictions. This regulation has been in effect since January 4, 2018 and, as a result, many bitcoin miners in China have ceased operations. We note that while similar regulatory options have been explored by other governments (e.g., United States), to our knowledge, there has not been any other major regulations passed with respect to bitcoin mining activity during our data period. To account for this particular mining related regulatory action in our analyses, we create a before/after dummy based on the date of its introduction. Descriptive statistics and correlation scores for the variables discussed above are provided in Tables 1 and 2.

## Empirical Analysis Model

The daily data amount published and the daily average fees paid are a consequence of the simultaneous decisions made by miners and users. Accordingly, we propose approximating the market equilibrium for the data space via a simultaneous equations model. The complete specification of the base model is as follows:

$$\text{Supply: } \begin{aligned} Quantity_t^S &= \alpha_0 + \alpha_1 \log(Fee_t) + \\ &\alpha_2 \log(Fx_t) + \alpha_3 Difficulty_t + \\ &\alpha_4 \log(HardwareCost_t) + \\ &\alpha_5 DaysSinceUpdate_t + \\ &\alpha_6 PeakPeriod_t + \alpha_7 Regulatory + \\ &+ \mu_d + u_t^S \end{aligned} \tag{1}$$

Demand:
$$Quantity_t^D = \beta_0 + \beta_1 \log(Fee_t) + \{\beta_2 \log(Fee_t) \times \log(Trading_t)\} + \beta_3 \log(Fx_t) + \beta_4 Popularity_t + \beta_5 \log(Trading_t) + \beta_6 PeakPeriod + \beta_7 Regulatory + \mu_d + u_t^D \quad (2)$$

Equilibrium Condition:
$$Quantity_t = Quantity_t^S = Quantity_t^D, \quad (3)$$

where $S$ and $D$ are indicators of supply and demand structural equations, respectively; $t$ is the period (day) index, $\mu_d$ depicts the day of week fixed effects, and $u_t$ is the error term. Due to the skewed distributions of *Fee*, *Fx*, *HardwareCost*, and *Trading*, log-transformed versions of these variables are used in the equations. Equation (3) in the model indicates that the observed quantity (and fee as a result) are determined in equilibrium by the intersection of supply and demand curves. For notational brevity, we drop the superscripts and denote the observed quantity at each $t$ by $Quantity_t$.

In this model, the endogenous variables are $Quantity_t$ and $\log(Fee_t)$. Both equations include exclusion restriction variables for identification purposes. Specifically, the supply equation has three exogenous variables (supply shifters)—i.e., *Difficulty*, log(*HardwareCost*), and *DaysSinceUpdate*, excluded from the demand equation and the demand equation has two exogenous variables (demand shifters)—i.e., *Popularity* and log(*Trading*) excluded from the supply equation. Both equations also include a common set of control variables, namely log(*Fx*), *PeakPeriod*, *Regulatory,* and *DayOfWeek* dummies.

The key parameters of interest are $\alpha_1$ in Equation (1)—miner's fee sensitivity and $\beta_1$ in Equation (2)—user's fee sensitivity. The most common identification approach is the two-stage least squares estimator (2SLS). In the first stage, $\log(Fee_t)$ is regressed on all control variables and its predicted value is calculated. The second stage is carried out separately for the supply and demand equations. On the supply side, Equation (1) is estimated by replacing the $\log(Fee_t)$ with its predicted value. In essence, the two exogenous demand shifters discussed above act as instrumental variables for the supply estimation. On the demand side, Equation (2) is estimated in a similar fashion where the three exogenous supply shifters are de facto instruments.

## Miner-Side Results

Columns (1) and (2) in Table 3 present miner-side results using 2SLS estimator. As a comparison, results from ordinary least squares (OLS) estimator are also presented in Column (3). Let us start with examining the relevance of the instruments. The two exogenous demand shifters that were held out from the second-stage supply estimation are *Popularity* and log(*Trading*), both of which register positive and significant effects in predicting log(*Fee*) in the first stage. This result is in line with the theoretical expectation that an increase (decrease) in either the popularity of Bitcoin for to the general public or the trading intensity of Bitcoin for traders leads to a lift in Bitcoin transaction demand (i.e., number of transactions submitted to the network). This upwardly shifted demand curve intersects with the supply curve at a higher equilibrium fee, creating a positive correlation between the two demand shifters and log(*Fee*). Comparing the first-stage regression with and without the demand shifters, we observe an incremental *F*-statistic of 24.340, which is larger than the suggested cutoff value of 10 (Stock et al. 2002). Furthermore, to investigate whether a "weak instrument" problem exists, we conduct two frequently used statistical tests. The first one is the Stock-Yogo (Stock and Yogo 2005) test, which compares the Cragg-Donald *F*-statistic (70.890) with a predetermined critical value (19.930). The second one is the Kleibergen and Paap (2006) rank test which computes a Lagrangian Multiplier statistic (38.661) and determines a *p*-value from the $\chi^2$ distribution ($p < 0.001$). Both tests reject the null hypothesis that the instruments are weak and collectively, we find strong support for instrument relevance in the supply model.

Next, we discuss the other condition of instrument validity: exogeneity. Unlike the relevance condition, the exogeneity condition cannot be fully verified by statistical tests (Rossi 2014). However, it is possible to perform an overidentifying restrictions test—i.e., check if additional instruments used are exogenous when coefficients are overidentified (Stock and Watson 2012). Given that we have two demand shifters and only a single endogenous regressor (*Fee*), our model is overidentified and allows for the computation of the Hansen *J*-statistic (1.825) and its *p*-value (0.177) via an overidentifying restrictions test. The insignificance of the *p*-value indicates the null hypothesis that all instruments that are exogenous cannot be rejected. The next assessment regarding the exogeneity condition involves considering theoretical arguments against the exclusion of instrument variables from the supply equation.

**Table 3. Miner-Side Results: Quantity Supplied**

| Variables | (1) 2SLS 1st Stage log(*Fee*) | (2) 2SLS 2nd Stage *Quantity* | (3) OLS *Quantity* |
|---|---|---|---|
| *Popularity* | 0.006* (0.003) | | |
| log(*Trading*) | 0.328*** (0.065) | | |
| log(*Fee*) | | 52.973*** (10.957) | 3.013 (2.476) |
| log(*Fx*) | -0.489*** (0.126) | 18.086* (7.891) | 11.952*** (3.255) |
| *Difficulty* | 0.022 (0.050) | -3.111 (3.752) | -2.722* (1.266) |
| log(*HardwareCost*) | 0.588*** (0.126) | -40.516*** (11.429) | -11.187** (3.787) |
| *DaysSinceUpdate* | -0.007 (0.005) | 0.812* (0.412) | 0.440 (0.240) |
| *PeakPeriod=1* | 1.475*** (0.194) | -41.294 (23.143) | 43.219*** (8.067) |
| *Regulatory=1* | 0.329† (0.184) | 4.667 (14.253) | 2.658 (5.366) |
| *DayOfWeek FE* | Included | Included | Included |
| Constant | 1.689* (0.754) | 89.029* (41.536) | 84.813*** (14.704) |
| *N* | 627 | 627 | 627 |
| $R^2$ | 0.914 | | 0.275 |
| Instrument Strength | | | |
| Incremental $R^2$ | 0.030 | | |
| Incremental F | 24.340 | | |
| Cragg-Donald Wald F Stat. | | 70.890 | |
| Stock-Yogo Critical Value | | 19.930 | |
| Kleibergen-Paap LM Stat. | | 38.661*** | |
| Hansen J Stat. | | 1.825 | |

**Note:** Heteroskedastic and autocorrelation consistent (HAC) standard errors are shown in parentheses, where the optimal bandwidth (5) is calculated following Newey and West (1987). † $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Based on our contextual knowledge of the Bitcoin system and previous literature (Carlsten et al. 2016; Easley et al. 2019; Houy 2016), it is reasonable to assume that miners are rational agents who base their mining decisions primarily on financial incentives. A possible concern is the correlation between the instrumental variables (e.g., *Popularity*) and the bitcoin exchange rate (*Fx*), since the latter translates miner rewards into USD. However, given that *Fx* is included as a control variable in both supply and demand equations, the two demand shifters are unlikely to influence mining decisions through means other than transaction fees. Thus, it is theoretically highly plausible to exclude *Popularity* and log(*Trading*) from the supply equation. Finally, we contrast 2SLS with OLS estimates—Column (2) vs Column (3). A positive unobserved supply shock shifts the supply curve upward, intersecting with the demand curve at a lower price. Thus, the error term in Equation (1), $u_t^S$, is negatively correlated with equilibrium fee, log(*Fee*). This in turn leads to a downward bias in the OLS estimates when endogeneity in log(*Fee*) is not controlled for. Our results verify this theoretical expectation: the magnitude of log(*Fee*)'s effect is noticeably larger and statistically significant with the 2SLS estimator (52.973 vs. 3.013). The Hausman test also rejects the null hypothesis that log(*Fee*) is exogenous ($p < 0.001$). Taken together, the above evidence regarding relevance and exogeneity suggests that the two demand shifters act as valid instruments for identifying the supply equation.

We now interpret log(*Fee*)'s effect based on Column (2). Its direction and statistical significance indicate that higher (lower) transaction fees lead to an increase (decrease) in the amount of data published by miners on the blockchain. Considering that Equation (1) is a linear-log model, the coefficient value of 52.973 for the log(*Fee*) can be interpreted as a 10% increase in the daily average transaction fee, translating into an approximately 5 MB

$(52.973 \times \log(1.1))$ of additional data (or five additional blocks), everything else held constant. For an average day seeing 138.4 MB of data activity, this corresponds to a 3.6% increase in the amount of data published on the blockchain, or approximately 10,000 additional transactions per day.[14] This finding provides support for H1 and challenges the notion that transaction fees merely function as a sorting mechanism to determine which transactions get processed first and do not alter the state of the system otherwise (Basu et al. 2018).

## User-Side Results

Estimation results for the user-side (i.e., the demand equation) are presented in a similar format: Columns (1) and (2) of Table 4 contain the 2SLS results, while Column (3) shows the OLS estimator. To test Hypothesis 2(b), we consider one more specification of the 2SLS estimator with the interaction term between log(*Fee*) and log(*Trading*), which is shown in Column (4). Note that, as discussed in the Model subsection above, the simultaneous equation model uses the same first stage for both supply and demand estimation. Thus, coefficient estimates in Column (1) are merely a reorganized version of those in Table 3's Column (1), where the three supply shifters (i.e., *Difficulty*, log(*HardwareCost*), and *DaysSinceUpdate*), acting as demand equation's instrumental variables, are presented at the top of the table. The instrument strength statistics are, however, specific to the estimation of the demand equation.

Following the structure of our discussion for miner-side results, we first comment on instrument validity, starting with the relevance condition. Column (1) results indicate that one of the instruments, *HardwareCost*, exhibits a statistically significant and positive association with *Fee*. Although the other two variables are not significant, we choose to keep them in our estimation since they are theoretically relevant in the supply model specification. In addition, when considering *Fee*'s interaction with *Trading*, we are faced with two endogenous regressors. Thus, performing Hansen's overidentification test requires at least three instruments. All else being equal, if mining equipment becomes more costly, then less miners are expected to participate, leading to a downward shift of the supply curve. This makes it intersect with the demand curve at a higher equilibrium fee—an expected positive correlation between *HardwareCost* and *Fee*. This is exactly what the first-stage estimation shows in Column (1). In terms of instrument strength, the incremental *F*-statistic and $R^2$ are 26.020 and 4.1%, respectively, which indicate that the joint inclusion of the three instruments is meaningful. Further, both Cragg-Donald Wald *F*-test and the Kleibergen-Paap LM scores reject the null hypothesis that there exists a weak instrument concern. The findings above provide support for the relevance of the instruments.

Regarding the exogeneity condition, our theoretical argument is straightforward—that is, bitcoin mining hardware is simply a "production factor" for miners. Its cost is unlikely to be tracked by majority of the Bitcoin users. Even if tracked, this information is almost meaningless in a specific user's decision to conduct a transaction because there many active miners on Bitcoin are likely to possess varying degrees of production cost sensitivity. Predicting which miner mines the blocks relevant for the user is a fruitless task, given the strong randomness inherent in mining's proof-of-work process; hence, production costs for Bitcoin should be irrelevant to demand. Hansen's overidentifying restrictions shows a *J*-statistic of 3.166 and a *p*-value of 0.205, failing to reject the null hypothesis that error term ($u_t^D$) is uncorrelated with the instrumental variables (Tan and Netessine 2014). Thus, it verifies our theoretical expectation.

Finally, we observe that, albeit negative, the OLS estimate is smaller in size than the 2SLS estimate: -8.586 vs. -9.177 (Hausman test $p < 0.001$). Such attenuation of the effect size when not controlling for fee endogeneity can be explained as follows. A positive unobserved demand shock shifts the demand curve upward, which intersects with the supply curve at a higher equilibrium fee. As a result, *Fee* and $u_t^D$ are positively correlated, "shrinking" the negative true effect of *Fee* on demand. Having verified instrument validity, we now interpret the effect size of log(*Fee*) based on Column (2). A coefficient value of -9.177 implies that a 10% increase in the daily average transaction fee decreases the amount of data demanded (by users) to be put on the blockchain by 0.87 MB—i.e., a decrease of roughly 1,740 transactions[15] submitted by users per day. The coefficient value is negative ($p < 0.1$) and considerably smaller than that of the supply-side. This finding supports H2(a) and affirms the expectation that increasing transaction fees have a weak negative impact on the amount of data demanded to be published on Bitcoin's blockchain.

[14] Transaction level analysis on the data set reveals that the average size of a transaction during our data time period is 500 bytes.

[15] Considering an average transaction size of 500 bytes.

**Table 4. User-Side Results: Quantity Demanded**

| Variables | (1) 2SLS 1st Stage log(*Fee*) | (2) 2SLS 2nd Stage *Quantity* | (3) OLS *Quantity* | (4) 2SLS with Interact. *Quantity* |
|---|---|---|---|---|
| *Difficulty* | 0.022 (0.050) | | | |
| log(*HardwareCost*) | 0.588*** (0.126) | | | |
| *DaysSinceUpdate* | -0.007 (0.005) | | | |
| log(*Fee*) | | -9.177† (5.000) | -8.756*** (2.651) | -19.993* (8.030) |
| log(*Fee*) x log(*Trading*) | | | | 3.527† (2.088) |
| log(*Fx*) | -0.489*** (0.126) | -17.981*** (3.832) | -17.967*** (3.825) | -18.407*** (2.945) |
| *Popularity* | 0.006* (0.003) | 0.673*** (0.138) | 0.671*** (0.137) | 0.567*** (0.124) |
| log(*Trading*) | 0.328*** (0.065) | 14.551*** (3.625) | 14.368*** (3.143) | -1.159 (9.559) |
| *PeakPeriod=1* | 1.475*** (0.194) | 47.854*** (13.497) | 46.926*** (9.681) | 38.747*** (10.994) |
| *Regulatory=1* | 0.329† (0.184) | 26.786*** (8.093) | 26.763*** (8.082) | 23.971*** (6.476) |
| *DayOfWeek FE* | Included | Included | Included | Included |
| Constant | 1.689* (0.754) | 229.258*** (32.585) | 228.642*** (31.866) | 289.841*** (44.769) |
| *N* | 627 | 627 | 627 | 627 |
| $R^2$ | 0.914 | | 0.430 | |
| Instrument Strength | | | | |
| Incremental $R^2$ | 0.041 | | | |
| Incremental F | 26.020 | | | |
| Cragg-Donald Wald F | | 94.723 | | 57.069 |
| Stock-Yogo Crit. Val | | 13.910 | | 11.040 |
| Kleibergen-Paap LM | | 51.555*** | | 55.019*** |
| Hansen J Stat. | | 3.166 | | 3.936 |

**Note:** Heteroskedastic and autocorrelation consistent (HAC) standard errors are shown in parentheses. † $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Finally, we test the demand-side moderation effect posited in H2b. Recall that intensity of bitcoin trading on a given day is represented by the variable, *Trading*. Thus, the coefficient on the log(*Fee*) x log(*Trading*) interaction in Column (4) captures whether the fee's effect on demand is strengthened or dampened by a higher level of trading activity. Since log(*Fee*) is endogenous, it follows that the interaction term is endogenous as well. Given the relevance and strength of log(*HardwareCost*) discussed above, following common practice in the literature (Aghion et al. 2005; Rajan and Zingales 1998), we further construct log(*HardwareCost*) x log(*Trading*) interaction as an additional instrument to assist identification. The log(*Fee*) x log(*Trading*) interaction registers a positive effect (3.527, $p < 0.1$), demonstrating that when there is a higher level of bitcoin trading activity, the overall user population exhibits a smaller sensitivity to higher transaction fees. To better understand the magnitude of this moderation effect, we construct a confidence band plot (a.k.a. Johnson-Neyman technique) advocated by Bauer and Curran (2005). As shown in Figure 6, this visualization approach has a clear advantage over the conventional interaction plot (Aiken and West 1991) in that it provides information on the region of significance, which, in turn, spurs many applications in the recent literature (Lu and Shang 2017; Malhotra et al. 2017; Shang et al. 2017). The construction process starts with quantifying the marginal effect of log(*Fee*), $\theta_t = \frac{\partial E(Quantity_t^D)}{\partial \log(Fee_t)} = \beta_1 + \beta_2 \log(Trading_t)$, and its standard error, $\sigma_{\theta_t}$, for each observation in our sample through the Delta Method (Oehlert, 1992). Assuming $\theta_t$ is normally distributed, its 95% confidence interval is simply $[\theta_t - 1.96\sigma_{\theta_t}, \theta_i + 1.96\sigma_{\theta_t}]$. Within the 627 observations in the sample, 284 or 45% have a negative and significant effect (i.e., $\theta_t + 1.96\sigma_{\theta_t} < 0$), while 343 or 55% register an insignificant effect ($\theta_t + 1.96\sigma_{\theta_t} > 0 > \theta_t - 1.96\sigma_{\theta_t}$). These statistics are marked on top of Figure 6. Next, we provide more general insights on when the demand effect of transaction fee "shifts zones." As shown in the figure, the effect of *log(Fee)* switches from negative to insignificant when the upper bound of its 95% confidence interval hits zero at log(*Trading*) = 3.85. Given the distribution of *Trading* in our sample, this corresponds to a medium level of trading intensity. Thus, our results not only confirm that bitcoin traders share a common trait of traders observed in other financial markets such as stocks and investment funds, but also imply that the fee-insensitivity of bitcoin traders might be even more pronounced than in traditional markets.

## Additional Analyses

### Supply versus Demand Elasticities

Having estimated the simultaneous supply-demand equation system, we are afforded with the opportunity to contrast fee elasticities of supply versus demand of the Bitcoin transaction market. We also compare these estimated elasticities with those of other goods and services. To estimate the fee elasticity of demand, we extend the idea of average marginal effect: for each observation we calculated the percentage change in predicted quantity demanded for a 1% increase in *Fee* from its current value, with all other variables held constant (i.e., the point demand elasticity for this observation). This was then averaged across the sample to obtain the sample average demand elasticity: -0.067. A popular classification scheme (Frank 2008) categorizes this as highly inelastic demand (the boundary of between elastic and inelastic demand is at -1). Such a high degree of price insensitivity is parallel to what has been observed in the consumption of "critical goods" such as gasoline and eggs, where the short-run elasticity of demand is reported to be around -0.1 (Havranek et al. 2012; Krugman and Wells 2009). Since a key reason behind inelastic demand is the lack of substitutes, our results imply that Bitcoin provides its users with a unique means to conduct transactions that are otherwise difficult to make. Note that this inelastic demand is unlikely to be completely driven by traders, as Figure 6 shows that even if trading activity is low, users remain fairly insensitive. Therefore, while it is theoretically plausible that Bitcoin could become a disruptive innovation (Tapscott and Tapscott 2016) that cannibalizes established means of sending money (e.g., wire and ACH transfers), it is currently only serving a niche market of users whose money transfer needs are unlikely to be satisfied by established means.

The sample average fee elasticity of supply is estimated in a similar fashion at 0.392. Comparable numbers are found in staple food items such as milk, where its long-run price elasticity of supply is estimated at 0.5 (Adelaja 1991), as well as in the labor supply of young female physicians (Rizzo and Blumenthal 1994). A common characteristic of supply cost structure shared across these industries is that the fixed cost is relatively high: mining machines for Bitcoin, cow farming for milk, and medical school training for physicians. One additional explanation for a large supply of elasticity (relative to its demand counterpart) comes from the dual-source mining reward. During the time frame of our data, the minting reward was 12.5 bitcoins per block, while the average transaction fee reward was much smaller—i.e., less than 1 bitcoin per block. Thus, a decrease in transaction fees offered by users only marginally turned away mining activity.

While both supply and demand are fairly inelastic for the Bitcoin transaction market, fee elasticity of supply is considerably larger than that of demand. When a (comparatively) steep supply curve is jointed with a flat demand curve, the consequence is a low equilibrium transaction fee, as shown in Figure 7. To construct this figure, we use Equations (1) and (2) with coefficient estimates from Column (2) of Tables 3 and 4. We fix all variables, except for *Fee*, at their average values and let *Fee* vary between its observed values in the data. The intersection of the curves marks the equilibrium point, which occurs at $Quantity = 140.2$ MB and $Fee = 32.8$ satoshi per byte.

We make two observations. First, non-fee factors shifting the supply curve, such as electricity and mining machine costs, are much less volatile in the short run than those shifting the demand curve, such as exchange rates and trading intensity. Over a longer time horizon, supply curve is further regulated by difficulty level adjustments. Thus, fluctuations in the equilibrium fee are much more likely caused by shifts in the demand curve. Given its flatness, an upward (downward) shift in the demand curve will only result in a small increase (decrease) in the equilibrium fee. Second, we consider deviations from equilibrium fee, as shown by the three-arrow triangle in Figure 7.

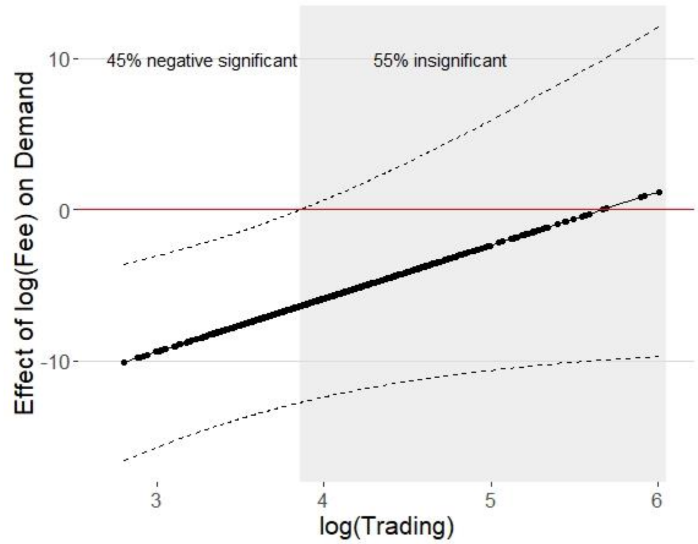


**Figure 6. Confidence Band Plot for The Moderating Effect**

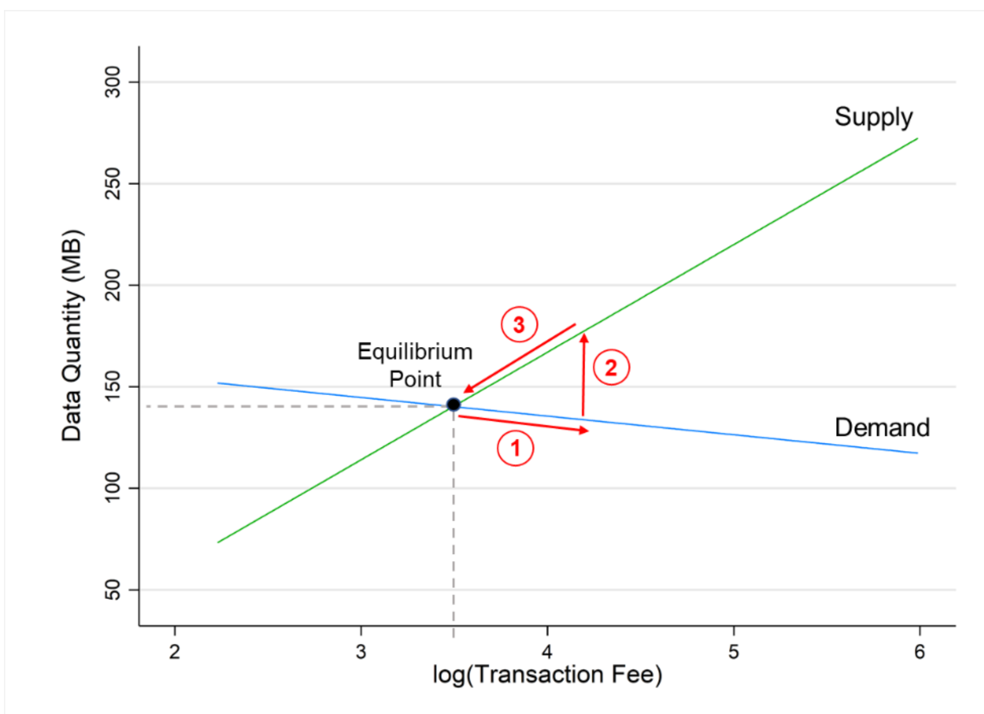


**Figure 7. Estimated Supply and Demand Curves**

Since transaction fees are offered by users on Bitcoin, a "wave" of high-fee users will suppress demand by deterring low willingness-to-pay users from sending transactions (Arrow 1). Interestingly, a higher fee stimulates supply by a much larger magnitude than suppressing demand (Arrow 2), due to the relative slopes of the supply and demand curves. The extra data space opened up by increased mining capacity will process pending transactions at a faster speed and hence lower subsequent users' willingness to pay a high fee (Arrow 3). This feedback loop ensures that the Bitcoin system "self-regulates" the average transaction fee in an efficient manner. To summarize, our empirical results, when taken together with the contextual knowledge of Bitcoin's transaction market, suggest that steep surges in transaction fees should be temporary and can be curbed by miners' reaction to fee increases, while the proof-of-work problem difficulty level stays stationary. This finding has practical implications regarding the development of cryptocurrency systems. In recent years, there has been a growing concern over Bitcoin's scalability and stability (Eyal et al. 2016; Yli-Huumo et al. 2016). The drastic volatility in fees at the end of 2017, an event labeled as the transaction fee crisis by the media outlets (Huo 2017; Lee 2018; Master 2018), has befittingly incited these concerns and accelerated the efforts to substantially redesign the Bitcoin ecosystem (e.g., the inception of Bitcoin Cash). Our finding implies that the mechanism to financially incentivize miners in Bitcoin and similar systems is fundamentally sound. As long as the driving forces underlying the steep supply curve and the flat demand curve remain unchanged, we believe that the Bitcoin market is likely to sustain its low transaction fee status.

## *The Impact of Fee on Confirmation Time*

In addition to fee elasticity, the insights from the supply-demand structural model also shed light on the transaction confirmation time dynamics in the Bitcoin system. From the user's perspective, the quality of the transaction service received is primarily gauged on speed. That is, faster confirmation times improve user satisfaction and welfare while the base service product—the bitcoin exchange between the sender and the receiver—remains unchanged. As explained in the previous subsection, an increase in fee creates two opposing effects: demand is suppressed by less user participation and supply is stimulated by additional miner (mining resource) contribution. Both effects should, in turn, reduce the waiting times experienced by users. Specifically, lower user participation leads to less congestion and hence faster processing for transactions pending publication. Higher computing power means shorter block discovery intervals, which also leads to faster processing. As a result, we expect a negative effect of transaction fees on confirmation time.

While the fee-to-time relationship is mainly driven by the changes in supply and demand, confirmation time can reversely affect fees by influencing user expectation. This is the focus of a recent study by Easley et al. (2019). They theorize and empirically show that, in the presence of elongating confirmation times, users will strategically offer higher transaction fees. Figure 8 stitches our proposed fee-to-time and their time-to-fee relationships together, creating a complete feedback loop. For notational consistency with Easley et al (2019), we use *TxFee* to represent the daily average fee per byte for the transactions that arrive on the network,[16] and *MWT* to represent the daily median confirmation times of these transactions.[17] As shown in Figure 8, an increase in *TxFee* reduces *MWT*, which in turn lowers *TxFee* for later transactions. Such counterbalancing dynamics between fees and time offer yet another theoretical reason why steep surges in transaction fees—the phenomenon giving rise to the name "transaction fee crisis" —should be temporary, and the fee stability of Bitcoin might be stronger than suggested (Browne 2017; Qureshi 2019; Thomson 2019).

Next, we present empirical evidence for the *TxFee* → *MWT* effect. The key empirical challenge, as shown in Figure 8, is the simultaneous determination of *TxFee* and *MWT*—a common reason behind endogeneity (Chen et al. 2017; Lin et al. 2017). To address this, we propose using the SegWit protocol adoption rate among transactions (*SegWitRate*) as an instrumental variable for *TxFee*.

[16] We note that there is a subtle difference between *TxFee* and the variable *Fee*, which was used in the supply-demand structural model. The former is calculated from the transactions arrived on the network on day *t*, whereas the latter is calculated from the transactions confirmed (i.e., published) on day *t*.

[17] The rationale for measuring daily confirmation time by median rather than mean is given by Easley et al. (2019 p. 100): mean waiting times are sensitive to outliers and therefore are less reliable. Different from their study, we rely on the raw transactions data embedded in the bitcoin blockchain to more precisely measure *TxFee* and *MWT*.

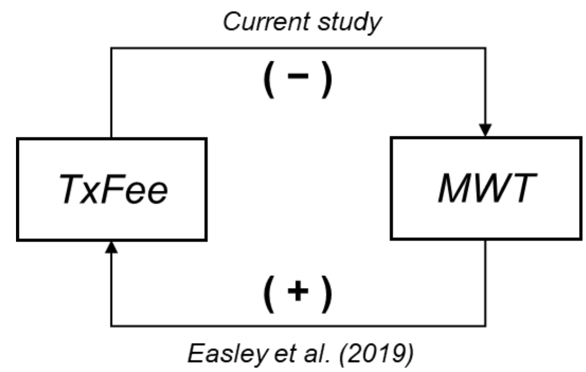


**Figure 8. Feedback Loop between Fee and Confirmation Time (MWT)**

SegWit protocol is a technological update in the Bitcoin system that reduces the effective size of a transaction.[18] When initiating transactions, users can choose whether to adopt the SegWit protocol or not. Since SegWit compresses the file size of an otherwise identical transaction, it allows the user to offer a higher "fee per byte," even if the total fee remains unchanged. This behavior is indeed observed in practice and encouraged by expert Bitcoin users.[19] Accordingly, we expect *SegWitRate* to be correlated with *TxFee*, while being exogenous to *MWT*. The sample correlation scores of -0.696 between *SegWitRate* and *TxFee*, and -0.002 between *SegWitRate* and *MWT* are in line with this theoretical expectation. Furthermore, the Bitcoin system allows for both types of transaction (SegWit and no SegWit) to coexist in the blockchain; hence, we observe a varying degree of SegWit adoption over time. These two conditions make *SegWitRate* an ideal instrumental variable and allow us to estimate the following regression via the 2SLS estimator with *SegWitRate* as an instrument for *TxFee* in the first stage:

$$MWT_t = \alpha_0 + \alpha_1 TxFee_t + \alpha_2 \log(Fx_t) + \alpha_3 PeakPeriod + \varepsilon_t, \quad (4)$$

where *MWT* and *TxFee* are the endogenous variables that depict the daily median confirmation times and daily average fees paid per byte for transactions that arrived at the Bitcoin network on day *t*, respectively. To account for the potential endogeneity due to the correlation of network congestion and bitcoin prices with both *MWT* and *TxFee*, we include log(*Fx*) and *PeakPeriod* controls to the model. *Fx* refers to the daily average exchange rate between 1 Bitcoin and 1 USD, and *PeakPeriod* is the network congestion dummy, as discussed in the Variable Definitions and Measurement subsection above.

We note three data processing/cleaning issues. First, the SegWit update was introduced to the Bitcoin system on August 23, 2017 and hence we trim off observations prior to this date from the original data set (see the Data and Variables section above). Second, the exact time a user submits a transaction is unobservable even with our granular raw data. We approximate it by the time this transaction is received by a major mining node in the network. The discrepancy between the two timestamps should be negligible in most cases, due to the speed of information propagation in the Bitcoin network (Donet et al. 2014, p. 96). Confirmation time is then calculated as the time elapsed between when the transaction is received by the node (e.g., blockchain.com) and when the transaction is included in a block. To our knowledge, this is the standard approach to measure confirmation time in the literature (Easley et al. 2019; Möser and Böhme 2015). Third, we filter out 39 observations from the data set that have a median confirmation time of zero, which is caused by missing timestamps in the mining node data. The resultant data set used for regression has 470 observations.

[18] For further details about the SegWit update, please see the Controlling for the SegWit Protocol Update subsection below or https://en.wikipedia.org/wiki/SegWit.

[19] https://blog.blockonomics.co/saving-transaction-fee-using-segwit-how-to-be-a-bitcoin-ninja-78d8416375db

**Table 5. Fee-Confirmation Time Analysis Results**

| Variables | (1) 2SLS 1st Stage log(*TxFee*) | (2) 2SLS 2nd Stage *MWT* |
|---|---|---|
| log(*TxFee*) | | -128.464** (43.941) |
| *SegWitRate* | -3.238*** (0.538) | |
| log(*Fx*) | 0.664*** (0.091) | 42.307 (42.222) |
| *PeakPeriod=1* | 1.281*** (0.154) | 331.739*** (92.787) |
| Constant | -1.634† (0.860) | 527.061* (266.994) |
| *N* | 470 | 470 |
| $R^2$ | 0.868 | |
| Instrument Strength | | |
| Incremental $R^2$ | 0.034 | |
| Incremental F | 35.910 | |
| Cragg-Donald Wald F Stat. | | 119.670 |
| Stock-Yogo Critical Value | | 16.38 |
| Kleinbergen-Paap LM Stat. | | 26.831*** |

**Note:** Heteroskedastic and autocorrelation consistent (HAC) standard errors are shown in parentheses. † $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 5 presents 2SLS estimation results for Equation (4). *SegWitRate* registers a negative and significant effect in predicting log(*TxFee*) in the first stage, confirming our a priori expectation that the adoption of *SegWit* protocol has a relieving effect on the transaction fees offered by users. We also observe that the Stock-Yogo critical value is above the recommended threshold and the Kleibergen-Paap rank test rejects the null hypothesis, both providing evidence against the weak instrument concern. Regarding the main effect, Column (2) indicates that log(*TxFee*) registers a negative and significant impact in the second stage. That is, a higher average transaction fee paid by users shortens median transaction confirmation time. Coupled with Easley et al. (2019)'s finding that the reverse *MWT* → *TxFee* effect is more pronounced during time periods when the Bitcoin system is more congested, our results suggest that the feedback loop in Figure 8 indeed functions as a regulating mechanism that prevents transaction fees from growing uncontrollably and hence maintains the long-term stability of the Bitcoin transaction market.

## *Robustness Checks*

In the next two subsections, we test the robustness of our findings against a technological change in the system and various alternative specifications. We report two additional robustness checks that consider potential collider bias (Tafti and Shmueli 2019) and an alternate measure for quantity demanded in an appendix available upon demand.

### Controlling for the SegWit Protocol Update

Activated on August 23, 2017, the Segregated Witness (abbreviated as SegWit) is a protocol update in the Bitcoin system designed with two main improvements in mind: (1) increasing the security of the system by providing additional protection from transaction malleability, and (2) reducing the congestion in the system by relaxing the 1 MB block size limit (to a certain extent) without fundamentally changing the existing Bitcoin protocol. Specifically, the SegWit mechanism increases the effective block size limit to approximately 1.6 - 2 MB (BitcoinCore 2016). The time frame of our data covers dates both before and after SegWit activation in the network, raising a potential endogeneity concern. We aim to alleviate this concern by controlling for the activation of SegWit. To achieve this, we introduce an activation dummy variable (*SegWitActivated*) in both equations that takes the value of 0 for the days before August 23, 2017, and 1 otherwise. The estimation results for specifications that include this control variable are provided in Table 6. Overall, we find the results to be consistent with our main results and do not observe any changes in the direction or the statistical significance of the impact of *Fee* on *Quantity* for supply or demand estimations.

**Table 6. Robustness Check for the SegWit Protocol Update**

| **Variables** | **Supply 2SLS *Quantity*** | **Demand 2SLS *Quantity*** |
|---|---|---|
| log(*Fee*) | 53.306*** (10.875) | -9.005† (4.792) |
| log(*Fx*) | 5.510 (9.531) | -17.482*** (4.773) |
| *Difficulty* | -2.693 (3.697) | |
| log(*HardwareCost*) | -35.584** (10.972) | |
| *DaysSinceUpdate* | 0.825* (0.409) | |
| *Popularity* | | 0.674*** (0.139) |
| log(*Trading*) | | 14.742*** (3.870) |
| *PeakPeriod=1* | -40.798 (22.758) | 48.628*** (14.718) |
| *Regulatory=1* | 6.541 (13.977) | 26.809*** (8.102) |
| *SegWitActivated=1* | 20.888* (10.334) | -1.182 (6.919) |
| *DayOfWeek FE* | Included | Included |
| Constant | 141.205** (48.591) | 226.810*** (34.728) |
| *N* | 627 | 627 |

**Note:** Heteroskedastic and autocorrelation consistent (HAC) standard errors are shown in parentheses.
† $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p<0.001$

**Table 7. Regression Results with Additional Alternative Measures**

| **Model: variables** | **(A1) Alternate log(*Trading*)** | **(A2) Alternate *Popularity*** | **(A3) Alternate log(*HardwareCost*)** | **(A4) Subsample *5th-95th*** | **(A5) Subsample *PeakPeriod=0*** | **(A6) Subsample *PeakPeriod=1*** |
|---|---|---|---|---|---|---|
| Supply: log(*Fee*) | 50.107*** (11.644) | 46.805*** (9.987) | 47.303*** (10.852) | 52.961*** (10.503) | 48.104*** (14.257) | 28.022** (8.715) |
| Demand: log(*Fee*) | -10.943† (6.112) | -9.953† (5.570) | -4.330 (5.802) | -7.684† (4.645) | -44.239 (28.001) | -32.291* (14.184) |
| Dem. Int.: log(*Fee*) | -46.732*** (11.892) | -34.647*** (10.001) | -11.673 (10.700) | -33.650** (10.909) | -193.249** (66.218) | -19.213 (38.279) |
| Dem. Int.: log(*Fee*) x log(Trading) | 8.680*** (2.466) | 8.477*** (2.347) | 2.504 (2.545) | 8.079** (3.130) | 51.823† (28.921) | 8.746 (7.502) |
| *N* | 627 | 625 | 627 | 505 | 371 | 256 |

**Note:** Heteroskedastic and autocorrelation consistent (HAC) standard errors are shown in parentheses.
† $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

## Alternative Measures and Samples

Next, we test the robustness of our results against a number of alternative measures and samples. For conciseness, we only provide the coefficient estimates for *Fee* (in supply and demand equations) and its interaction with *Trading* (in demand equation). Specification (A1) uses the sum of the daily trading orders executed on six different cryptocurrency exchange platforms (i.e., Bitfinex, Bitflyer, Kraken, Bithumb, and Bitstamp in addition to Coinbase) to proxy for the trading activity in the Bitcoin network. We collected the trading information on these exchanges from the bitcoinity.org website. In Specification (A2), we used the growth in the number of brick-and-mortar stores that accept bitcoin as a method of payment to proxy for the popularity of the system. This information was gathered from coinmap.org, which is a crowdsourced mapping service for identifying bitcoin accepting businesses. Coinmap.org provides the count of such venues around the world on a weekly basis. We calculated the difference between the start and the end day of a given week to find the weekly growth in the number of bitcoin accepting venues and distributed this value uniformly across the days in the week to obtain the daily scores. In Specification (A3), we consider a different bitcoin mining hardware—i.e., AntMiner S7, to proxy the cost of data space production. This equipment is an earlier version of AntMiner S9 and is still used by many miners because of its lower purchase price (Chi 2019). The price of a new/unused equipment is not always available on Amazon.com for older products; therefore we collected the daily used condition prices of this product from Amazon via the Keepa.com API. Finally, Specifications (A4) through (A6) consider modifications to the data sample. In (A4), we exclude observations with extreme values for *Quantity* and *Fee*, using 5th and 95th percentile as the cutoff, to account for their potential disproportionate influence. Specifications (A5) and (A6) use subsamples of the data based on the *PeakPeriod* variable. Considering the substantial drop in transaction fees after late January, 2018 (as shown in Figure 5), *PeakPeriod*=1 refers to the daily observations before January 23, 2018, and *PeakPeriod*=0 refers to the observations afterward.

Overall, the results in Table 7 are consistent with our previous findings. There are no changes in the direction of the coefficients and a majority of the coefficients keep their significance level similar to those reported in Tables 3 and 4. It should be noted that while we observe some variation in coefficient values for subsample specifications, this situation is not unexpected given that the sample size, *N*, changes considerably under these specifications.

## Conclusion

Blockchain-enabled cryptocurrencies have the potential to revolutionize many business sectors, ranging from finance, to e-commerce, and to healthcare (Tapscott and Tapscott 2016). However, it is evident that this technology is still in its infancy. The swift and unpredictable movements in transaction fees, such as those that occurred at the end of 2017, have prompted many to question whether Bitcoin and similar cryptocurrencies (e.g., Litecoin and Bitcoin Cash) are headed toward an inevitable crisis due to their lack of scalability (Blenkinsop 2018). This question is particularly concerning given that miners' financial incentives continue to tilt away from minting rewards and toward transaction fees (Lavi et al. 2017).

This paper contributes to the debate about the stability of Bitcoin's fee mechanism by studying system participant (user and miner) behavior under varying transaction fees. Considering that increasing fees is a manifestation of the difference between the data space need for incoming transactions and the data space availability on the blockchain, we conceptualize the exchange of data space between users and miners as a data space market and the transaction fee as the price. In this market, the demand side is represented by users because their transactions demand data space on blockchain, and the supply side is represented by miners because they supply this data space via mining activities. Given that posted data quantity and fees are jointly determined and are observed in equilibrium, we follow a structural approach to model user and miner behavior from a supply and demand perspective. Based on the findings from this model, we further study how transaction fees might impact confirmation times that users experience in the Bitcoin network.

Our empirical findings contribute to the literature in several ways. First, our analyses identify the existence of an upward-sloping supply curve and a downward-sloping demand curve for the transaction fee-data quantity relationship. The shape of the former curve is contradictory to protocol policies that aim to stabilize the data amount published on the Blockchain and is caused by policy implementation gaps that allow for temporary increases in the data space supply. While the shape of the latter curve is consistent with traditional microeconomics theories, we find the fee elasticity of demand to be very small—i.e., in parallel to what has been observed in the consumption of critical goods such as gasoline and eggs (Havranek et al. 2012; Krugman and Wells 2009). Given that a typical reason behind the inelastic demand is the lack of substitute goods, this finding implies that the Bitcoin system might be serving a niche market of users whose money transfer needs are unlikely satisfied by established means. Collectively, these results suggest that it is the update frequency feature in the supply limitation policy (i.e., the gaps between problem difficulty updates) but not the fee averseness of users (i.e., fee elasticity of demand) that might be acting as the main relief valve that prevents transaction fees from growing uncontrollably during heavy congestion in the network. This is an interesting finding that implies that the lenient implementation of the block discovery interval limit (i.e., gaps between proof-of-work problem difficulty updates) might be positively contributing to the stability of the system.

Second, our demand-side results identify a moderation effect exercised by the use of bitcoins as a trading asset. In particular, we find a positive association between higher levels of bitcoin trading activity in the network and greater levels of tolerance to transaction fees. This is a finding that was postulated but rarely observed in the finance literature (Foster and Viswanathan 1993). Third, our findings on Bitcoin's fee-quantity dynamics provide insights on the possible effects of relaxing the limit on the block size. Over the past few years, there has been a growing concern about Bitcoin's scalability—i.e., its ability to handle an increasing number of transactions. A redesign of the Bitcoin protocol has been suggested to address this concern by influential members of the cryptocurrency community (Croman et al. 2016), which led to the creation of spin-off cryptocurrencies with larger block sizes such as Bitcoin Cash (Bogart 2017). Our findings indicate that an increase in the block size should not affect the fee elasticity of demand, since this is mostly driven by customers' innate sensitivity to fee changes. However, a larger block size causes cumulative fees per-block to become larger, which should, in turn, create an even stronger incentive for suppliers (miners) to open up additional mining resources in light of higher fees so that a block could be mined faster. This would shift the supply curve upward, leading to a smaller equilibrium fee and larger equilibrium quantity.

Finally, we theoretically establish and empirically validate that transaction fees have a dampening effect on confirmation times that users experience, and this effect disseminates through the fee's stimulating impact on data space supply and suppressing impact on data space demand. Prior research has shown that under prolonging confirmation delays, users will strategically offer higher transaction fees (Easley et al. 2019). We expand this relationship to both directions and demonstrate that a directionally opposite effect, which diffuses from fee to confirmation time, also exists. This finding affirms that there is a feedback loop between fees and confirmation times which acts as a transaction fee regulating mechanism.

As with any empirical work, our analysis is not exempt from limitations. First, our data observations are defined at the daily level, based on the assumption that daily intervals provide a good balance between the total number of observations and the level of variation. However, there might be heterogeneity in the time it takes for users and miners to react to changing fees. Future research could consider different levels of data granularity and/or incorporate such heterogeneity in the model. Second, we also do not consider decision-making heterogeneity among miners. In reality, not all miners are likely to be rational economic actors who purely follow financial incentives. Participation in mining pools can also affect a miner's behavior. An interesting venue for future research would be to consider the mining pool mechanism as a research setting. Third, our study focuses on proof-of-work type of cryptocurrencies—in particular the Bitcoin system. Proof-of-stake systems such as Dash, Neo, and Ethereum's Casper protocol employ different validation and incentive mechanisms than their proof-of-work counterparts, hence our results and implications might not hold within the proof-of-stake context. We leave the extension of our models to such systems as future work. Finally, certain technological updates that are currently in development for proof-of-work platforms (e.g., Lightning Network), once widely adopted, might alter system participant behavior regarding transaction fees. Due to their experimental nature and limited adoption, we do not explicitly consider these potential modifications to the system in the current paper. However, future research can monitor the evolution of these technologies and assess how new findings might ensue if the Bitcoin system goes through fundamental technological modifications in the future.

To conclude, our investigation provides insights on the extent and manageability of the transaction fee stability in the Bitcoin ecosystem. While we cannot be sure of the timing of another "fee crisis" that is caused by unexpected surges in data space supply and demand limitations, our study implies that the fee mechanism to financially incentivize miners is fundamentally sound and should maintain an inherently stable marketplace, as long as the driving forces underlying the steep supply curve and the flat demand curve remain unchanged (e.g., the time gap between problem difficulty updates). This stable nature of the Bitcoin-type cryptocurrency market provides a possible explanation for why sudden fee surges at the end of 2017 were rapidly followed by sharp declines and why fees did not explode, although their extreme swings did cause anxiety among users and miners. We conclude that even if extreme swings in transaction fees may appear again in the future, the fear of a market crash due to transaction fees is unfounded based on our findings in this paper.

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