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Impact of total transaction fees on the price of Bitcoin and Ethereum

Bachelor thesis

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Prague, July 31, 2023

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Abstract

The aim of this thesis is to explore the price dynamics of Bitcoin and Ethereum with special emphasis on the role of transaction fees, which can provide insight into network congestion and user behaviour, and may also reflect the future economic viability of these networks. Previous research has shown intertwining relationships between variables and suggested possible endogeneity in a cryptoasset environment. For these purposes, a system of two simultaneous equations for transaction fees and price was developed and subsequently estimated using the 2SLS method. The analysis covers relationships from both long-term and short-term perspectives. It turns out that the price dynamics of both assets is determined by a diverse mix of fundamental, economic and speculative factors, despite the narrative that the price of cryptoassets is primarily driven by speculative factors. Furthermore, in the context of the fee-price relationship, it turned out that the relationship is a priori that the price impacts the fees, however, at some intervals, the opposite relationship is also shown, which is rather an exception. An important contribution could be the finding of a stable positive effect of the total number of active addresses in Bitcoin on transaction fees, which might bring new insights to the discussion on Bitcoin's sustainability.

Keywords Cryptoassets, Bitcoin, Ethereum, time series, transaction fees

Title Impact of total transaction fees on the price of Bitcoin and Ethereum

Abstrakt

Cílem této práce je prozkoumat cenovou dynamiku Bitcoinu a Etherea se zvláštním důrazem na roli transakčních poplatků, což může poskytnout vhled do přetěžování sítě a chování uživatelů, a může také odrážet budoucí ekonomickou životaschopnost těchto sítí. Předchozí výzkum ukázal vzájemně se prolínající vztahy mezi proměnnými a naznačil možnou endogenitu v kryptoaktivovém prostředí. Pro tyto účely byl vytvořen systém dvou simultánních rovnic, pro transakční poplatky a cenu, který byl následně odhadnut metodou 2SLS. Analýza pokrývá vztahy z dlouhodobého i krátkodobého hlediska. Ukázalo se, že dynamika cen obou aktiv je určována různorodým mixem fundamentálních, ekonomických a spekulativních faktorů, a to navzdory narativu, že cena kryptoaktiv je primárně řízena spekulativními faktory. Dále se v souvislosti se vztahem poplatků a ceny ukázalo, že a priori platí, že cena ovlivňuje poplatky, nicméně na některých intervalech se ukazuje i opačný vztah, což je ale spíše výjimka. Důležitým přínosem by mohlo být nalezení stabilního pozitivního vlivu celkového počtu aktivních adres v bitcoinové síti na transakční poplatky, což by mohlo přinést nové poznatky do diskuse o udržitelnosti Bitcoinu.

Klíčová slova Kryptoměny, Bitcoin, Ethereum, časové řady, Transakční poplatky

Název práce Vliv celkových transakčních poplatků na cenu Bitcoinu a Etherea

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Chapter 1

Introduction

The cryptoasset environment has received a lot of attention in recent years. Cryptoasset investment is unique due to its massive volatility and extreme returns, which are offset by the risk of substantial price drops. The first and so far most successful representative of this ecosystem is Bitcoin introduced by Nakamoto (2008). Bitcoin is an open-source protocol that forms a peer-to-peer decentralized network, that allows users to conduct digital transactions all around the world. All transactions are stored in a distributed database called blockchain. Network security is continuously maintained by a process referred to as mining, when participants (miners) perform a large amount of work reflected by a large electricity consumption, in order to fold a block with new transactions to the blockchain. Miners are incentivized with a two-component reward in the form of newly created bitcoins and transaction fees collected from users. Inflation in the form of newly created bitcoins is determined by the diminishing function, which is encoded in the Bitcoin protocol. It is clear from the monetary rules that in the future the Bitcoin network will have to survive purely on transaction fees. Thus, the transaction fees will have to be high enough, otherwise miners will not be sufficiently incentivised and the network will be heavily vulnerable to external or internal attacks. Thus, the role of transaction fees in Bitcoin will most likely become crucial in the future. Examining fee dynamics can not only give us clues about the long-term sustainability of Bitcoin, but also shed light on network congestion and user behaviour. The role of transaction fees in the case of Ethereum is slightly different due to the fact that it does not have a limited money supply by design and there will not be a situation in the future when the network will have to survive purely on transaction fees. Thus, in the case of Ethereum, we do not address the issue of the long-term sustainability of the network, since it is not dependent on transaction fees.

The economics of transaction fees has been previously discussed (Houy 2014; Easley *et al.* 2019), however, the analysis of transaction fees in the context of price dynamics has not, to the best of our knowledge, been properly conducted. The purpose of this paper is to investigate the price dynamics of Bitcoin and Ethereum, the second largest cryptoasset introduced by Buterin *et al.* (2014), with an emphasis on the role of transaction fees and thus adding a new dimension to fee analysis.

Our work builds on Kubal & Kristoufek (2022), who point out the interconnectedness of relationships and a possible endogeneity, and further showed how to deal with such a finding. To capture a potential bidirectional price-fee relationship and to account for possible endogeneity, we developed a system of two simultaneous equations (with an equation for price and an equation for fees), which allows us to test the presence of endogeneity by statistical tests and choose between OLS and 2SLS estimators. For the purpose of the analysis, we use data from January 1, 2016 to August 31, 2022, which is motivated by the comparability of Ethereum and Bitcoin, because in September 2022 Ethereum moved to version 2.0, which makes the comparison of the two assets significantly more challenging due to the different consensual algorithm and mechanics of transaction fees. We further divide the global interval into 3 different subintervals in order to capture long-term and short-term relationships.

The work is structured as follows: Chapter 2 provides a brief description of Bitcoin and Ethereum fundaments and further summarizes existing knowledge in the area of transaction fees and cryptoasset price dynamics. Chapter 3 focuses on model selection and describes the econometric methods used. Chapter 4 presents the statistical tests that preceded the choice of the resulting estimation method, followed by the results of the analysis and the corresponding implications. Finally, Chapter 5 concludes the thesis, summarizes the findings, and suggests possible future extensions of the research.

Chapter 2

Literature review

The summary of existing knowledge takes the following structure. Firstly, the development preceding the emergence of Bitcoin and today's cryptoasset ecosystem is discussed. Then the technological aspects of Bitcoin are introduced, which is followed by a summary of relevant literature regarding transaction fees. The technology aspects are briefly discussed also for Ethereum. Finally, we summarize the existing knowledge regarding the price dynamics of the cryptoasset ecosystem.

2.1 Precursors of modernday cryptoasset enviroment

Although the first so far successful attempt to create digital money was Bitcoin, introduced by an unknown person with the pseudonym Satoshi Nakamoto (2008), the first projects of this nature appeared even earlier and were mostly linked by various criticisms of the fiat money.

Chaum (1983) argues that bank systems lack sufficient privacy, thus proposes the concept of double signatures to ensure secure and anonymous payments. This concept called *blind signature* allows a user to obtain a valid signature from a bank or other trusted party without revealing any information about the transaction. The project was named *DigiCash* and eventually went bankrupt in 1998 (Pitta 1999).

In his article Dai (1998) proposed the pseudonymous (the users interact under pseudonyms) payment network named *b-money.* The network is based on a distributed database, which stores the balances of user accounts.

Szabo (2005) criticized traditional currencies because of the need for a trusted third party to ensure monetary value. Szabo claims that this centralizing element can be abused, as could be demonstrated by periods of hyperinflation in the 20^{th} century. In order to remove the trusted party, he proposed the concept of *bit gold*, based on the algorithm called *Reusable Proofs of Work*[1], introduced by Finney (2004).

2.2 Bitcoin summary

Bitcoin is an open-source communication protocol designed to serve as digital money. Users of the Bitcoin protocol together form a peer-to-peer decentralized network, which allows users to send and receive irreversible transactions from anywhere in the world, all they need is an internet connection. The monetary unit of the payment system is 1 *bitcoin* [2], which consists of 10^8 *satoshi* (the smallest unit, which cannot be further divided [3]). Bitcoin money supply is limited by design (which is shown in the following section) and the total amount of bitcoins in circulating supply will never be larger than $2.1 * 10^7$ coins [3]. Transactions are stored into distributed ledger, which can be accessed from any computer with installed Bitcoin software client. The overall history of all transactions is stored into data structure *blockchain*, which consists of blocks with processed transactions. The security of the blockchain is maintained by the algorithm *PoW* (Proof of Work), sometimes referred to as mining (Nakamoto 2008).

2.2.1 Bitcoin security

A typical problem digital cash systems must tackle is *double spending* - a situation, when one transaction input is spent multiple times (the most common solution is the introduction of a trusted third party). To prevent double spending, without the loss of decentralization, Bitcoin uses cryptography. Each unique address is assigned two cryptographic keys - *public key* and *private key*. The public key is used as a verification of incoming transactions. The private key allows the user to manipulate the bitcoin balance of the related address

[1] Precursor of the algorithm Proof of Work, which will be discussed in section Bitcoin security.

[2] Note that bitcoin as a monetary unit is written with lowercase "b", but Bitcoin as the network with capital "B".

[3] Assuming the protocol remains unchanged, technically this could happen by *hardfork*, for more see Antonopoulos (2017).

and serves as the transaction signature. The problem is that cryptographic keys are not able to verify that there is no history of double spending, thus at each block closure time the network must reach consensus, which is obtained by PoW algorithm, using hashing.

Hash function is a function, which transforms input of any length into an integer with specific bit length (called hash). For instance, the SHA256 algorithm transfers input into a 256 bit integer. The hash function is not invertible, and compute inverse function is *NP hard* - cannot be solved in polynomial time (Sobti & Geetha 2012; Loe & Quaglia 2018).

For each block, miners solve a computationally challenging problem, which consists of a folding block with the format of a header with previous block hash and nonce - 32 bit integer chosen by the miner, followed by new transactions from mempool [4]. The header is then hashed by hash function *SHA256* and if the hash starts with a sufficient amount of zeros *i.e.* it is a sufficiently small number, the miner obtains a right to store transactions into the blockchain, otherwise the miner should change the nonce and repeat process until the resulting hash meets the criterion above. The mining is very computationally intensive, but when the hash is found, it is straightforward for other Bitcoin users, *nodes*, to verify the solution. The *difficulty* of the challenge is adjusted every 2016 mined blocks, so the mean value of the difference between the blocks would be 10 minutes. (Nakamoto 2008; Antonopoulos 2017).

In order to incentivize miners to participate in the mining process, the one who mined the block obtains a two-component reward.

1. The first component is a reward in the form of newly created bitcoins (the transaction is classified in the block as *coinbase transaction*). The amount of newly created Bitcoins is designed to be diminishing. When Satoshi Nakamoto mined the first block (called *Genesis block*), the reward was 50 bitcoins, but this reward is halved every 210 000 blocks (approximately every 4 years), an event referred to as *Bitcoin Halving*.

   From this definition, we can obtain a formula for the total monetary supply of Bitcoin, as a sum of the infinite series. The resulting sum is

[4] Mempool is a place where all transactions, already verified by nodes, are collected before they are put into the blockchain (Antonopoulos 2017).

equal to $2.1 * 10^7$ bitcoins:

$$\sum_{k=0}^{\infty} 210,000 * \frac{50}{2^k} = 210,000 * 50 * \underbrace{(1 + \frac{1}{2} + \frac{1}{4} + \frac{1}{8} + \frac{1}{16} + \dots)}_{=2} = 21,000,000 \text{ bitcoins} \tag{2.1}$$

Although, technically, the halving will be stopped when the reward would be less than 1 satoshi. This should occur exactly after 32 halvings, at the block number 6,720,000 mined approximately in the year 2137. Thus the formula 2.1 should be slightly modified and the theoretical total supply should be slightly less than 21 milion bitcoins (Antonopoulos 2017).

$$\sum_{k=0}^{32} 210,000 * \left\lfloor \frac{50 * 10^8}{2^k} \right\rfloor = 2,099,999,997,690,000 \text{ satoshis}$$

Since in the future the mining will be stopped, this implies that it is impossible to incentivize miners just with reward from newly issued bitcoins, and another reward component is required.

2. Together with newly issued bitcoins the miners are rewarded by *transaction fees*. Each time a user sends a transaction, the transaction must be accompanied by a transaction fee for the miner, who mines the upcoming block. The amount of the transaction fee is arbitrarily chosen by the user. Since the capacity of one block is limited by the upper bound of 1 megabyte (MB), the users face a trade-off between paid amount and the speed at which the transaction is processed.

A significant threat that could compromise the reliability of the Bitcoin network is *majority attack* (also sometimes referred to as *51% attack*), which consists of an attacker, who has more than a 50% share of the total Bitcoin *hashrate* (variable indicating how many hashes are computed per second), taking control of the network. The attacker can then theoretically carry out double spending or even rewrite the history of the blockchain. In order to prevent such a threat it is desirable to sufficiently incentivize miners with high rewards, as the prevailing view is that the higher the total hashrate of the network is, the more difficult it is to perform a potential attack (Aponte-Novoa *et al.* 2021).

Aponte-Novoa *et al.* (2021) analyzed the risk of a 51% attack and the centralization of the Bitcoin. The result shows that the threat is not negligible, since 18 miners (less than 0.01% of the total number of miners) represent slightly more than 51% of the total hashrate [5].

On the other hand this might be caused by the fact that miners usually maximize expected reward and for small miners, it is more effective to join *mining pool*, which is an entity that gathers miners. In the case of successful block mining, the block reward is divided among pool participants proportionally to the computational power provided [6] (Lewenberg *et al.* 2015).

2.2.2 Bitcoin transaction fees

The amount of newly created bitcoins plus the sum of the individual fees of all transactions, i.e. total fees, included in the new block is referred to as security budget (Pagnotta 2022). The amount of newly created bitcoins will diminish every 210,000 blocks (approximately 4 years). This implies that without a change of the protocol, the Bitcoin will cease to be inflationary in the future, therefore the network will have to survive on a security budget consisting of fees only. In order to ensure security of the network, transaction fees have to be large enough, otherwise there is a significant security risk. For example, with a too low security budget the network will be more vulnerable to double-spend. The fact that the fees must not be too small might be obvious, although what is the optimal level and how to achieve it is a matter of discussion.

In the early stage of adoption transaction fees were near zero, which as Kaşkaloğlu (2014) argues cannot last forever. Kaşkaloğlu believes that in the future a change of the protocol is inevitable and proposes to fix the transaction fees amount to a specific level instead of the current voluntarily based fee mechanism (Kaşkaloğlu 2014). Later in their study Möser & Böhme (2015) found that as the Bitcoin network grew, the percentage of zero-fee transactions dropped significantly, although they rejected the hypothesis that mining pools systematically enforce non-zero fees. The factors affecting the percentage of zero-fee transactions were then investigated by Easley *et al.* (2019). The results indicated that the percentage of zero-fee transactions should be driven mainly by median waiting time for transaction approval. The relationship between these two variables turned out to be negative, i.e. with higher median waiting time comes a lower proportion of zero-fee transactions, suggesting that the

[5] Aponte-Novoa *et al.* (2021) analyzed data from blockchain throughout the period 2009-2021, the given statistics are from 9.5.2021

[6] How the block reward is divided depends on the mining pool policies.

decrease in the percentage of zero-fee transactions might be attributed to the escalating competition for block space.

Houy (2014) examined the economics of bitcoin transaction fees using game theory and static partial equilibrium model. According to Huoy's model, limiting the block size or introducing a mandatory fee can achieve equivalent results in terms of securing network security. On the other hand, if the size of the transaction fee is determined by market mechanisms without a limited block size, then the security of the network might be insufficient, since the users would stop facing the trade-off between paid amount of fees and speed of transaction processing.

Furthermore, the crucial aspect of transaction fees has been described by Easley *et al.* (2019)[7], who firstly analyzed the transaction fees using game theory and then supported the findings empirically. They point out that the diminishing reward in the form of new bitcoins does not have a significant impact on the increase in transaction fees, which should be driven primarily by the large number of users struggling to push their transaction into the *mempool* at the same time.

2.3 Ethereum

The proposal of the second most successful cryptoasset [8], Ethereum, was published in late 2014 and the project was launched on 30 July 2015. Ethereum founder Buterin *et al.* (2014) criticizes Bitcoin for using blockchain only as digital currency, while arguing that the technology has a range of other potential use cases. Thus, Ethereum is not just a protocol providing a peer-to-peer transaction system, but an entire platform that enables creation and execution of smart contracts - digital contracts written in associated turing-complete programming language *Solidity*, stored in a blockchain without the need for a central authority enforcing the terms of the contract - and decentralized applications, providing a more extensive range of applications beyond just a digital currency (Buterin *et al.* 2014).

All transactions in Ethereum network are processed by the Ethereum virtual machine (EVM), which is stack-based *state machine*. The state machine

[7] The same paper that investigated the percentage of zero-fee transactions.

[8] As of July 5, 2023, Ethereum was the second largest cryptoasset by market capitalization, where Ethereum's market capitalization was approximately $229 billion, which is slightly less than 40% of the market capitalization of Bitcoin (`https://coinmarketcap.com/`).

is powered by a utility token called *ether* (ETH). Similarly, as the smallest monetary unit of the Bitcoin network is not bitcoin, but satoshi, the smallest monetary unit of the Ethereum network is 1 wei, where 1 ETH = 10^{18} wei (Wood *et al.* 2014; Buterin *et al.* 2014).

Ethereum, similar to Bitcoin, is an open-source protocol, whose source code evolves over time through so-called Ethereum Improvement Proposals (EIP) [9]. Ethereum has undergone many protocol changes during its existence. Paris EIP (implemented September 15, 2022) was probably the most discussed change. The proposal consisted of hard fork [10] to version Ethereum 2.0. The key difference between these versions is primarily in the consensus algorithm. The original version of Ethereum uses the Proof of Work (PoW) algorithm (described in 2.2.1), while the newer version implements Proof of Stake (PoS) algorithm (Ethereum.org 2023).

The transition to PoS was described by Buterin & Griffith (2017), who criticize PoW algorithm for its high electricity demand and high barriers to entry in the form of the need to invest into a mining technology. The new mechanism is that validators, who have the right to assemble a new block, are always chosen randomly among stakeholders, who were willing to stake a given amount of ether at risk. If the stakeholders are not 'honest', their entire stake could be destroyed (Buterin & Griffith 2017).

Nevertheless, the Ethereum 2.0 version is not the subject of this paper, since the fee mechanism is completely different from Bitcoin and hardly comparable. Thus the following section, in which the monetary policy of Ethereum is discussed, will cover the period up to the Paris EIP, i.e. the period when PoW served as a consensual algorithm.

2.3.1 Ethereum mining

The Ethereum blockchain can be viewed as a collection of stored global states of the users' accounts. The global state is modified by newly created transactions in each block. Transactions could be divided into two types according to their purpose. *Message call transactions* are transactions, which transfer value between accounts, similarly to transactions in Bitcoin. *Contract creation transactions* are transactions, which create a smart contract. Each computational

[9] Parallel to Bitcoin Improvement Proposals (BIP) in Bitcoin.

[10] The hardfork is a divergence from the current version of the software, i.e. an upgrade that is not compatible with the older version of the Ethereum client (Antonopoulos & Wood 2018).

operation of EVM is denominated in units called *gas* (gas price is denominated in *qwei*, which equals 10^6 wei). Thus, the price of a transaction could be calculated as the gas amount of a given operation multiplied by the current gas price, which, similarly to Bitcoin transaction fees, is determined by the Ethereum users. Unlike Bitcoin, the Ethereum block is not limited by memory usage, but is limited by the block's gas limit, which could be voted down or up by miners to some extent (Bashir 2017; Tikhomirov 2018).

From inception to the transition to version 2.0 consensus of the network was achieved by the PoW algorithm with an underlying hashing function *Ethash*. The mean time of block mining is between 10 and 19 seconds, which is much shorter than in case of Bitcoin. If the block is mined at a time outside this range, the difficulty will be adjusted. The reward for miners has two components - newly created ethers and gas fees. The amount of newly created ethers was fixed until the transition to version 2.0. At the inception of Ethereum it was 5 ETH, which was later reduced to 3 ETH. In addition, miners receive the gas fees associated with the transactions included in their block. Thus the block reward mechanism implies that the monetary policy of the ether is strictly inflationary. Nevertheless, in 2021, Ethereum underwent an upgrade with EIP-1559, changing the existing transaction fee mechanism. With this change a base gas fee is burned and only an optional tip goes to miners. Thus the change has brought another dynamic factor to the monetary policy of ether, and whether the monetary supply will fall or rise might change for each block (Wood *et al.* 2014; Bashir 2017; Tikhomirov 2018; Leonardos *et al.* 2021).

2.4 Price Dynamics of Cryptoasset Market

For the purpose of our work it is essential to be able to describe the relationships in the ecosystem of cryptoassets and especially which variables form their price.

There is a common narrative that the cryptoasset market is driven by Bitcoin price movements. This narrative might be supported by Qiao *et al.* (2020), who discovered that Bitcoin shows a positive correlation with all other cryptocurrencies studied [11] and at the same time as a cryptoasset with a large market capitalization and a long history can influence the development of other cryptoassets.

[11] The dataset included the cryptoassets with the largest market capitalization (including Bitcoin and Ether), which together accounted for 86% of the entire market capitalization of the whole crypto market.

One of the first to address what drives the Bitcoin price was Kristoufek (2013). According to his paper, the standard models used for stock pricing cannot be used to describe the price of Bitcoin, since the price is determined purely by the forces of supply and demand. Therefore data from Google searches and Wikipedia queries were used as a proxy variable representing the public interest. The analysis was concluded using Vector Autoregression (VAR) and Vector Error Correction (VACM) methods. The author also wanted to distinguish whether Bitcoin is in a growing bubble or in its bursting. For this purpose a dummy variable was created to determine whether the price of Bitcoin is below or above the moving average. The results indicated the existence of a bidirectional relationship between the Bitcoin price and public interest. If the price was above the moving average, then the price was positively affected by the public interest and vice versa, conversely, if the price was below the moving average, then again there was a bidirectional relationship, but a negative one.

The relationship between bitcoin price and public interest was further supported by Kristoufek (2015), along with other findings. Wavelet coherence analysis was used, which essentially examines the correlation and its changes between two time series across different time frequencies. The author reveals that the price of bitcoin is not driven by purely speculative factors, but is also influenced by fundamental drivers. The hypothesis of whether the behavior of bitcoin corresponds to the behavior of currency according to economic theories has been tested. According to the *quantitative theory of money* should hold, the higher the use of a currency, the higher the price. Variable *trade-exchange ratio* was created as a proxy for currency usage, the lower the ratio, the higher the Bitcoin usage. Bitcoin has been shown to actually behave in accordance with this theory, i.e. the negative correlation between the trade-exchange ratio and price was shown. It was also shown that bitcoin follows the *Law of One Price*, or equivalently that there is a negative relationship between price and price level. According to the results, the money supply appears to be slightly positively correlated with price, although according to economic theory there should be a negative relationship. Finally, the author examined technical factors, hashrate and difficulty, related to the mining mechanism, where a positive relationship was found.

Ciaian *et al.* (2016) was inspired by Barro's (1979) gold standard model, based on which he derived hypotheses, which were further tested empirically on daily data between 2009 and 2015 using Vector Autoregression (VAR), Vector Error Correction (VAC) and Autoregressive Distributed Lag (ARDL) approaches. The author divided drivers of bitcoin price into 3 sets:

1. **Market forces of supply and demand**. This set contained demand side variables such as the number of transactions, number of addresses etc., and the supply side was represented by the number of bitcoins in circulation. The results indicated that demand side variables show a positive significant relationship with price, while the relationship between bitcoin supply and price turned out to be negative with statistical significance.

2. **Public interest**, which is captured similarly as in Kristoufek (2013), but without data from Google searches and with the newly added proxies, which is the number of new members and the number of new posts on the `bitcointalk.com` website. Although in the short run all variables were significant, in the long run the only significant relationship turned out to be the positive effect of the number of new posts on the price.

3. **World economic growth**, i.e. the assumption that bitcoin price dynamics could be driven by the global macroeconomic factors. For this purpose, the Dow Jones index and oil price were chosen as proxies. The analysis in this case did not reveal any statistically significant relationship in the long run.

Kristoufek (2019) built upon his previous research and further explored bitcoin price in terms of economic theories, namely *Law of One Price* and *Equation of Exchange*. The Law of One Price states that

$$P = EP^*$$

where in this case P is the Price Level of bitcoin, P^* is Price Level of \$USD and E is exchange rate between \$USD and bitcoin, i.e. bitcoin price in \$USD. Bitcoin Price level was extracted from the Equation of Exchange as the ratio of the total transaction volume and the number of transactions. Due to the open-source nature of Bitcoin, there was no problem to receive daily data of price level, although US price level, which was used as a benchmark, is at our disposal only on a monthly basis, therefore it was necessary to transform the Price Level to monthly data, which was done as a mean of daily data. The results revealed that the bitcoin exchange rate is proportional to the ratio of the \$ USD price level to the bitcoin price level, from which the author, using two time series log-log regression (one with added time trend and one without it), estimated the relationship between the estimated exchange rate and the actual bitcoin price. The results of the final models showed a relatively tight following of the current price, with R^2 coefficient of 0.9 for model with added time trend and 0.88 for the second one.

Kubal & Kristoufek (2022) intended to describe dynamic aspects of the relationship between bitcoin price and hashrate. In the previous works numerous variables were suspected to be endogenous, which was later confirmed in this paper and therefore a system of **simultaneous equations** was applied. A separate equation was created for each variable that was assumed to be endogenous - price, hashrate, transaction fees, and Google searches. Each equation was estimated separately using the **2SLS** method, which turned out to be more consistent than **OLS** or **3SLS** approaches. In our thesis we are motivated by this paper and we build on it, especially how it addresses endogeneity and interconnectedness of variables in a cryptoasset system, and thus describe the findings in more detail:

1. **Price equation** contained variables such as hashrate, Google searches and transaction fees (all assumed to be endogeneous), price level, exchange ratio, i.e. variables suggested by Kristoufek (2019) and S&P500, index, which is generally considered as an indicator of world economic growth. The results revealed that just hashrate, Google searches and S&P500 affect the price significantly. For the purpose of our work it is important to emphasize that no significant relationship was found for transaction fees.

2. In the case of **hashrate equation** the model surprisingly implied that the only significant factor at the 0.05 level of significance were transaction fees, with p-value approximately 0.0345. Moreover, the relationship between hashrate and price shows that only the price is affected by the hashrate, not the other way around, which would be expected from Kristoufek (2015).

3. As outlined in the section 2.2.2, Bitcoin users face the trade-off between the amount paid and the speed of transaction confirmation, which should imply that the demand for fast transaction execution should have a crucial impact on the amount of the fee. This observation was in line with the approach chosen by Kubal & Kristoufek (2022) in the **Transaction fees**

equation. The authors selected price, Google searches and total number of addresses as explanatory variables. All variables were found to be significant at any reasonable level. The total number of addresses and Google searches turn out to have a positive effect, but the effect of price surprisingly turned out to be negative, which was attributed to the fact that the variable was denominated in the bitcoin base. Thus, when the price increases, from a psychological point of view, users are not inclined to pay the same fee, because in a dollar base the paid amount might increase substantially.

4. Google searches were standardly used as an explanatory variable since Kristoufek (2013), however the authors pointed out that the common exogenous assumption does not hold and Google searches appear to be endogenous. Therefore **Google searches equation** was added. Results showed that Google searches are positively driven by price (as was indicated by Kristoufek (2013)), bitcoin daily volatility and the total number of addresses.

Kukacka & Kristoufek (2023) analyzed the price dynamics of major cryptoassets - Bitcoin, Ethereum, Litecoin, XRP and Dogecoin - utilizing the cusp catastrophe approach, which could represent the sudden shifts in the market, such as crashes or booms. According to the authors, factors affecting the price of bitcoin can be divided into 3 groups: **Technical** factors, usually blockchain metrics such as total number of addresses, transaction fees, hashrate or newly emitted coins. **Economic** indicators such as S&P500 index or USD/EUR exchange rate. And **information demand-related** factors - usually speculative factors such as data about Google searches or Chicago Board Options Exchange's CBOE Volatility Index (VIX). The first two groups could also be considered as fundamental factors and the last one as a speculative factor. It turned out that for all assets (except for Dogecoin, which price is driven a priori by speculative factors) the price is determined by a complex interaction of speculative and fundamental factors. A very interesting implication of the model for Bitcoin was the prominent role of transaction fees as a significant price driver, which is in contradiction with Kubal & Kristoufek (2022), where the transaction fees were not significant at all. Furthermore, the number of active addresses, S&P500 (as a fundamental influences) and the VIX index and standardly used variables - Wikipedia queries and Google searches (as a speculative influences) had a significant effect on bitcoin price. Surprisingly, the only significant technical influence for Ethereum turned out to be transaction fees, however, Ethereum has also been shown to be significantly affected by S&P500, Exchange Ratio and Google searches.

Chapter 3

Methodology

This chapter first outlines the reasons that motivated the direction of our research and the choice of econometric methods. This is followed by a description of the data and finally a detailed description of the econometric methods used.

3.1 Motivation

Many authors have tried to describe the price dynamics of bitcoin using various methods. However, to the best of our knowledge, no research has yet been conducted that would attempt to comprehensively describe the price dynamics of bitcoin with an additional emphasis on transaction fees. In section 2.2.2 it was described that transaction fees play a critical role in Bitcoin (and in Ethereum until the transition to version 2.0), and without high enough fees, the network will not be secure and will be susceptible to all sorts of attacks. We believe that exploring the relationship between price and transaction fees, and vice versa, could be of great benefit not only to investors, but can also be fundamental to the discussion about the long-term sustainability of Bitcoin and other cryptoassets.

The endogenous nature of transaction fees in the cryptoasset system emerges quite unambiguously from previous research. In order to obtain unbiased estimates, endogeneity needs to be accounted. Kubal & Kristoufek (2022) found a negative impact of price on transaction fees, however, the effect seems to be only one-sided. Nevertheless, Kukacka & Kristoufek (2023) found a significant positive relationship between transaction fees and price, both for Bitcoin and Ethereum. Another contribution of our work might be to explain the discrepancy between these two recent papers and to build on them.

3.2 Benchmark Model

Our choice of research procedure and model is essentially based on Kubal & Kristoufek (2022) (described in 2.4), which gives great guidance on how to work with endogeneity in a cryptoasset system. Kubal & Kristoufek (2022) created a system of simultaneous equations, where each equation belongs to one endogenous variable. Within the scope of our work we propose a system of only 2 equations, one for transaction fees and one for price, since we are interested just in the price-fees relationship. Our system also differs from Kubal & Kristoufek (2022) by adding volatility to both equations, and conversely, some explanatory variables, such as exchange-ratio and US M2 money supply have been removed, because previous work did not find them significant. The choice of variables and a description of both equations will be described in detail in the following section. The proposed benchmark system of equations is defined as follows:

$$\begin{aligned} \log(close_t) = \alpha_0 &+ \alpha_1 \log(total\_fees_t) + \alpha_2 \log(total\_addresses_t) \\ &+ \alpha_3 \log(hash\_rate\_mean_t) + \alpha_4 \log(google\_trends_t) \\ &+ \alpha_5 \log(sigma_t) + \alpha_6 \log(sp500_t) + \epsilon_{1_t} \end{aligned} \tag{3.1}$$

$$\begin{aligned} \log(total\_fees_t) = \beta_0 &+ \beta_1 \log(close_t) + \beta_2 \log(total\_addresses_t) \\ &+ \beta_3 \log(google\_trends_t) + \beta_4 \log(sigma_t) + \epsilon_{2_t} \end{aligned} \tag{3.2}$$

where $t \in \{1, ...T\}$ is a time index, β_i, $i \in \{0, ...6\}$ and α_j, $j \in \{0, ...4\}$ are standard regression coefficients and ϵ_1 and ϵ_2 are a residuals of each equation.

Table 3.1: The structure of the benchmark system.

Equation	**Exogeneous**	**Endogeneous**	**Instrument**
close	total_addresses sigma sp500	total_fees hash_rate_mean google_trends	gold vix total_supply transfers_med
total_fees	sigma total_addresses	close google_trends	gold vix total_supply transfers_med sp500

Model description

The proposed system consists of two equations. Equation 3.1 will be referred to as **price equation** and equation 3.2 as **transaction fees equation**. For both equations in the system we use log-log transformation, since the elasticity representation better captures the nature of the cryptoassets environment, where variables often grow exponentially and suffer from heteroscedasticity.

Price equation

The price is denoted as *close* in our model. Similar to Kukacka & Kristoufek (2023) and Ciaian *et al.* (2016), we distinguish 3 types of factors driving the cryptoasset price. Among the fundamental technical factors we include **total transaction fees** (denoted as *total_fees*), **total number of active addresses** (denoted as *total_addresses*) and **mean hasrate** (denoted as *hash_rate_mean*) in the price equation. We further included data about **Google searches** (denoted as *google_trends*) and **volatility** (denoted as *sigma*) as a proxy for public interest. Finally, we included **S&P 500** index data as an indicator of global economic growth.

The effect of Google searches and S&P 500 on the price of both bitcoin and ether was found to be significant and positive by Kukacka & Kristoufek (2023), which is in line with Kubal & Kristoufek (2022). The Google searches as an explanatory variable have been part of early Bitcoin models (Kristoufek 2013; 2015) and intuition behind is quite clear - the more interest in a given cryptoasset, the more people buy. On the other hand, the effect of S&P500 can be described as the effect of global economic growth on cryptoasset prices. Google searches are further assumed to be endogenous, since it is indicated by Kubal & Kristoufek (2022), which we see as reasonable with respect to possible simultaneity error.

The effect of transaction fees on the price of an asset is practically the effect of network clogging. We assume the endogeneity of transaction fees, since the transaction fees are determined primarily by the demand for fast transaction execution. This demand could be influenced by factors such as the number of addresses etc., which is further discussed in section describing transaction fees equation.

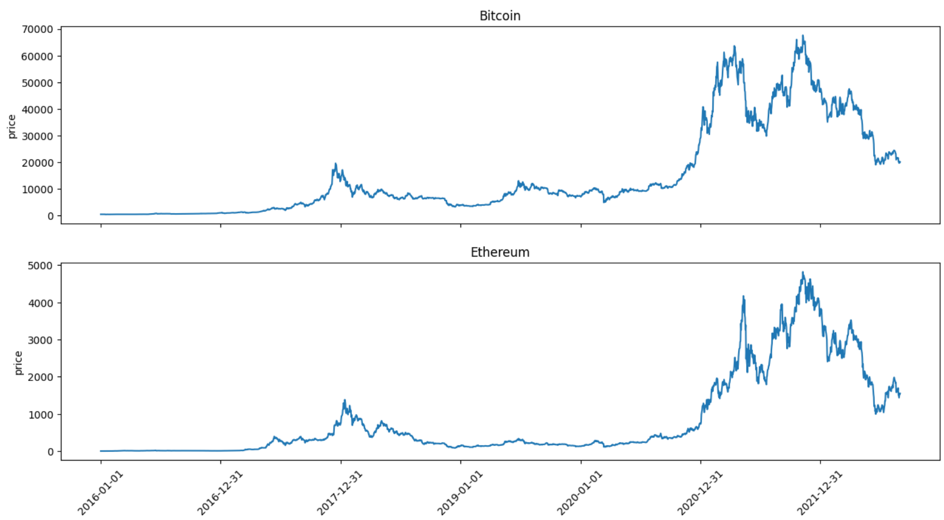
The total number of active addresses could be considered as a proxy variable indicating the activity of the network. A larger number of addresses should indicate a larger user activity a higher rate of adoption. Intuitively we expect that the more active users the asset has, the higher the price will be, which should be in line with the findings of Ciaian *et al.* (2016) and Kukacka & Kristoufek (2023).

Hashrate is considered as a metric indicating the network security - the higher the hashrate, the more difficult and expensive it is for a potential attacker to successfully control the network. Kubal & Kristoufek (2022) found a positive effect of hashrate on the price of bitcoin, which might be intuitively explained as the more secure the network is, the higher its price.

We believe that volatility could explain some of the variance in the price equation. We expect that volatility could have a similar effect as Google searches, given that the high volatility may be a factor that attracts new investors to the cryptoasset market, as investors might be attracted by higher profits than in the standard stock market.

The positive correlation between the price of bitcoin and ether is indicated by Qiao *et al.* (2020) (described in section 2.4) and could be clearly visible in figure 4.2. For the purposes of our work, we will assume that bitcoin might be the prime driver of the cryptoasset market, i.e. that bitcoin sets the price trend. For this reason, the equation 3.1 will be slightly modified for ether - the bitcoin price will be added as an explanatory variable.

Figure 3.1: Bitcoin and Ethereum price in $USD



Transaction fees equation

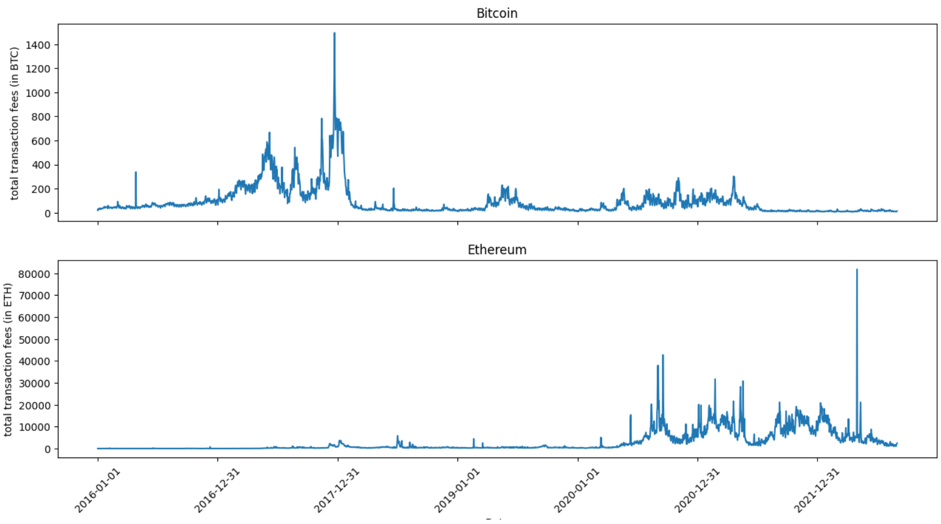
The main objective of this paper is to examine the relationship between transaction fees and price. The price equation should answer the question of what effect transaction fees have on price, but there is strong reason to believe that the relationship might be bidirectional. Thus, the first possible influence that could affect the demand after a fast execution of the transaction might be the asset price. Initial intuition suggests that a high asset price could cause network clogging and vice versa, i.e. have a positive effect on transaction fees. However, it is necessary to remember that transaction fees are denominated in the relevant asset (i.e. ether/bitcoin), not in $USD or another fiat currency. Thus, the effect of price might struggle with the psychological reluctance of users to set the same or higher fee as before the price increase. Mentioned effect served as an explanation of the negative effect of bitcoin price on transaction fees in Kubal & Kristoufek (2022).

Kubal & Kristoufek (2022) also found a positive effect of Google searches and total number of active addresses. The interpretation of both variables appears to be quite straightforward. The number of addresses represents the activity of the network, so transaction fees increase with larger amounts of active users. On the other hand, Google searches serve as a proxy for public interest, which can motivate investors to buy or sell quickly - thus influencing demand for fast confirmation of a transaction.

Above-standard volatility is one of the factors that differentiate the cryptoasset market from the standard stock market. The volatility effect can be perceived similarly to the Google searches effect. Volatility can be upside or downside, but in both cases it could affect user activity - upside volatility might motivate investors to buy, downside volatility might motivate investors to sell, nevertheless, in both cases it could lead to an increase in demand for a quick transaction execution. For this reason volatility can be expected to positively impact transaction fees.

A possible future extension could be to include the median transaction waiting time in the mempool, which Easley *et al.* (2019) found significant in his empirical model of Bitcoin transaction fees. However, these data are not directly observable and were derived from a theoretical model. In our case it would be necessary to develop a different theoretical model for Ethereum, due to the different fee mechanism, which would further complicate the acquisition of this data. Easley *et al.* (2019) also included the factor of diminishing block reward in his model, which was not found to be significant, thus for this reason we decided not to include it. Nevertheless, given the rapidly evolving dynamics, it might be worthwhile to test this hypothesis again in the future.

Figure 3.2: Bitcoin and Ethereum total transaction fees



3.3 Data

The cryptoasset market is unprecedented in terms of data availability. Cryptoassets are traded continuously 24 hours a day, 7 days a week and due to the open-source nature, most of the necessary metrics are easily accessible. For the purpose of modelling the daily data from January 1, 2016 to August 31, 2022 will be used. The choice of the data range is motivated by the duration of the PoW consensus algorithm on Ethereum [1] - to be able to meaningfully compare both assets.

The data importing pipeline data consists of 3 sources - **blockchain metrics**, **economic metrics** and **Google searches** - which will be described in the following subsections.

[1]As mentioned in the section 2.3, Ethereum was launched on July 30, 2015 and the transition to version 2.0 occurred on September 15, 2022.

3.3.1 Blockchain metrics

All blockchain metrics were obtained from glassnode.com[2]. Blockchain metrics include the following variables:

Price OHLC: Daily $USD price data including the highest (high) and lowest (low) daily price achieved, the price at the beginning of the day (open) and the price at the end of the day (close). We use the close price as the price in the proposed model.

Total transaction fees: The sum of the transaction fees of all blocks mined on a given day.

Hashrate: Mean daily hashrate.

Total number of active addresses: Number of addresses involved in completed transactions.

Total supply: The current number of mined coins - bitcoins/ethers.

Median Transfer volume: Median amount of coins transferred between addresses in one transaction.

Volatility: Volatility, unlike the other data, was not downloaded from glassnode.com, but was estimated from the price data according to Garman & Klass (1980) as follows:

$$\sigma_t = \sqrt{\frac{1}{2} * \left[\log\left(\frac{h_t}{l_t}\right)\right]^2 - [2\log 2 - 1] * \left[\log\left(\frac{c_t}{o_t}\right)\right]^2} \tag{3.3}$$

where o, h, l, c are OHLC price data described above.

3.3.2 Economic metrics

To download data about financial indicators we used a connector built on top of the yfinance library[3], which is a python integration of Yahoo Finance[4]. For all used metrics we had to tackle the problem that data is available only for weekdays, which we decided to solve by approximating the missing data by the last available value. From the economic metrics we used the following variables:

S&P 500: Daily close prices of the Standard and Poor's 500 (S&P 500) index.

VIX: Daily values of the Chicago Board Options Exchange's CBOE Volatility Index (VIX).

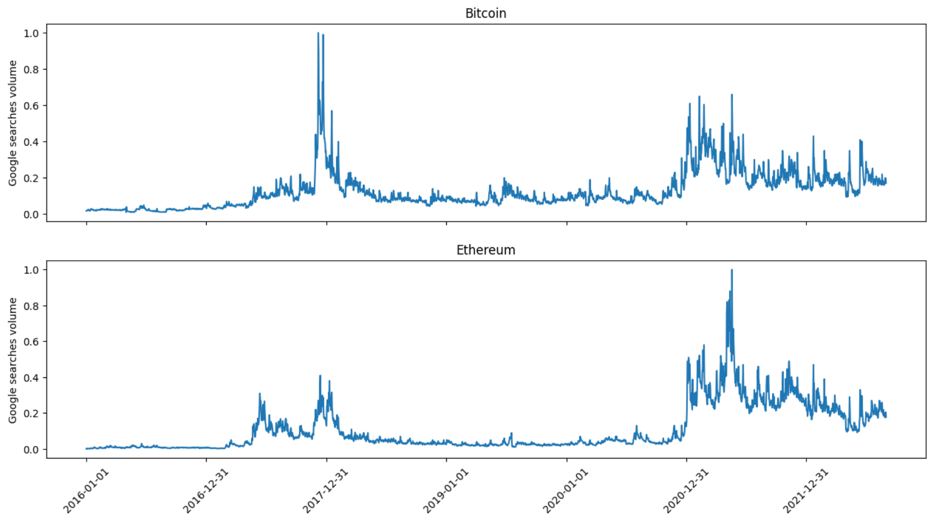
[2] `https://glassnode.com/`
[3] `https://pypi.org/project/yfinance/`
[4] `https://finance.yahoo.com/`

Gold: The traded price of a troy ounce of gold.

3.3.3 Google Searches

Google search volume for the keywords 'bitcoin'/'ethereum' was obtained from Google Trends[5]. Google searches data is scaled to values between 0 and 100 by default and is only available on a monthly, not daily, basis for large time frames. To estimate daily data, we first imported daily data in monthly intervals (daily data are available for such a short interval), subsequently imported monthly data for the whole interval, and rescaled all daily data according to the corresponding month. Obtained values were further rescaled into the range of 0 to 1. Finally, it was necessary to avoid the case when the value is equal to zero which would prevent the logarithmic transformation, for such case the zero values were mapped to the smallest non-zero value.

Figure 3.3: Google searches volume



3.4 Estimation methods

When estimating a system of two simultaneous equations it is usually done by estimating each equation separately. The standard OLS approach could be used to estimate the equations, however, assuming that endogeneity actually occurs in our system, the OLS estimator might be biased and inconsistent.

[5]https://trends.google.com/trends/

This problem could be solved by approaches based on instrumental variables, for example 2SLS method (Wooldridge 2015).

3.4.1 Exogeneity assumption

The crucial assumption for the Ordinal Least Squares (OLS) estimator of time series regression to be unbiased is the exogeneity assumption. Exogeneity implies that the error terms are not correlated to the explanatory variables. Mathematically expressed as:

$$\mathbb{E}[\epsilon_t|\boldsymbol{X}] = 0, t = 1, 2, ..., T \tag{3.4}$$

Together with the assumptions of linearity of parameters and no perfect collinearity of the explanatory variables, form the basic assumptions which, if valid, imply the unbiasedness of the OLS estimator. Otherwise, if exogeneity assumption is not valid, i.e. at least one variable is endogenous, then the OLS estimator does not have to be unbiased (Wooldridge 2015).

3.4.2 2SLS

If assumption 3.4 does not hold one of the possible solutions is to use Two Staged Least Squares (2SLS) approach. Assume a standard linear regression model:

$$y_1 = \beta_0 + \beta_1 y_2 + \beta_2 z_1 + \epsilon \tag{3.5}$$

where

$$Cov(\epsilon, y_2) \neq 0 \implies \mathbb{E}[\epsilon|y_2] \neq 0 \tag{3.6}$$

y_2 is endogenous, therefore OLS estimator might be biased. For the endogenous variable it is first necessary to find the instrumental variables, where instrumental variable z is a variable that meets two conditions:

1. z is not correlated with error term: $Cov(z, \epsilon) = 0$,
2. Non-zero correlation with y_2: $Cov(z, y_2) \neq 0$

Assume that z_2 and z_3 are instruments for y_2. The whole 2SLS procedure can be divided into 2 stages:

First Stage

The endogenous explanatory variables are regressed on all exogenous variables in the system (instrumental variables included) and the predicted values of the endogenous explanatory variables are obtained using an OLS estimator.

$$\hat{y}_2 = \hat{\pi}_0 + \hat{\pi}_1 z_1 + \hat{\pi}_2 z_2 + \hat{\pi}_3 z_3 \tag{3.7}$$

Second Stage

The endogenous variables from equation 3.5 are replaced by the reduced form from equation 3.7 and subsequently the regression coefficients from equation 3.5 are estimated using OLS.

$$y_1 = \beta_0 + \beta_1 \hat{y}_2 + \beta_2 z_1 + \epsilon \tag{3.8}$$

(Wooldridge 2015)

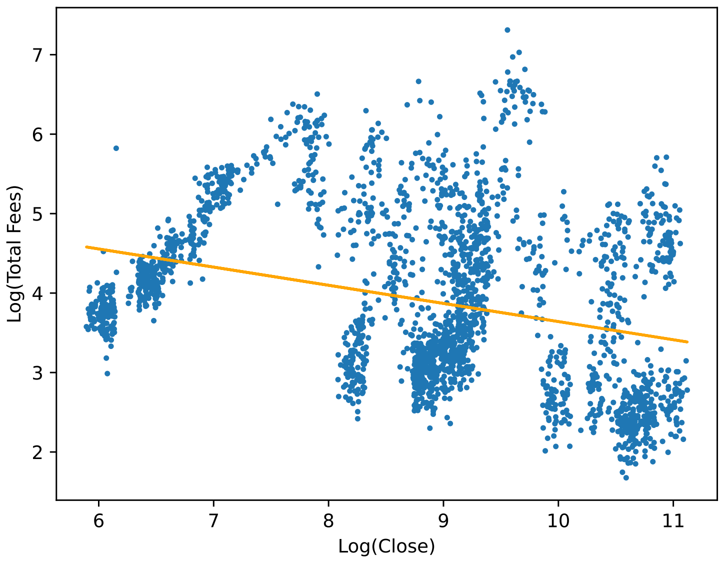
When choosing between OLS and 2SLS approach Hausman (1978) test can be applied. Under the null hypothesis (H_0) the OLS estimator is efficient and consistent without present endogeneity, otherwise, under the alternative hypothesis (H_A) the OLS estimator is inconsistent due to endogeneity, thus the 2SLS is the preferred method.

Chapter 4

Results and Discussion

This chapter goes through the whole modeling procedure in detail, i.e. selection of appropriate econometric methods, statistical testing, presentation of results, and subsequent implications. A dataset of 2435 observations between 2016 - 2022 is used for the empirical analysis, as described in section 3.3.

Figure 4.1: Bitcoin: Transaction Fees vs Close Price with regression line.



The very first glance at the scatter plot in figure 4.1 might raise two questions:

1. Almost 7 years of data is collected. The relationships between variables

in a rapidly evolving environment such as cryptoassets may have changed substantially in that time.

2. On the whole interval a decreasing trend of transaction fees with respect to the price (both variables in logarithmic transformation) can be seen. However, there are relatively large intervals where an increasing trend is visible, which can be selected from the chart. One possible explanation is that these positive trends might occur in the short term in a growing or bursting bubble. Conversely, in the long term, the trend might be negative because of the encounter with the factor of transaction fee appreciation[1]. Note that the problem is purely Bitcoin - for Ethereum the trend between price and fees is purely positive and with no obvious intervals of reverse trend.

In order to mitigate the above mentioned problems, we divide our analysis into two parts - **analysis from a long-term perspective**, i.e. the analysis of the whole interval and **analysis from a short-term perspective**. In the analysis from the short-term perspective, we divide the whole interval into 3 subintervals according to 2 arbitrary breakpoints (January 21, 2018, February 10, 2020).

Figure 4.2: Bitcoin: Transaction Fees and Close Price in time with division into subintervals.

[1]We define **transaction fee appreciation factor** as a psychological factor which, when the cryptoasset price increases, discourages users from paying the same fee as before, as they might pay significantly higher amounts in the fiat base.

4.1 Long-Term analysis

To analyze the whole interval between 2015-2022, we use the benchmark system of simultaneous equations 3.1, 3.2. Both equations are estimated separately and OLS and 2SLS approaches are considered for estimation. The OLS and 2SLS approaches were tested by Hausman test (Hausman 1978) for both assets with the result of rejecting the null hypothesis at any reasonable level, which implies inconsistency of OLS. Therefore it is appropriate to stick with the 2SLS approach.

The Wu-Hausman test (Wu 1973) was further used to test the assumed endogeneity of the explanatory variables. The Wu-Hausman test is designed to test whether it is necessary to use an instrumental estimator, i.e. whether there is an endogenous variable in the system. The null hypothesis is that explanatory variables can be considered exogenous. In our analysis, we rejected the null hypothesis, which implies that the variables in our system are indeed endogenous.

Table 4.1: Bitcoin: Endogeneity tests.

	df1	**df2**	**statistic**	**p-value**
Price equation:				
Wu-Hausman	3	2427	187.23	<0.001 ***
Weak instruments (log(total_fees))	4	2429	340.09	<0.001 ***
Weak instruments (log(hash_rate_mean))	4	2429	3753.20	<0.001 ***
Weak instruments (log(google_trends))	4	2429	84.67	<0.001 ***
Transaction Fees equation:				
Wu-Hausman	1	2430	1497.10	<0.001 ***
Weak instruments	5	2427	3179.00	<0.001 ***

Table 4.2: Ethereum: Endogeneity tests.

	df1	**df2**	**statistic**	**p-value**
Price equation:				
Wu-Hausman	2	2427	47.86	<0.001 ***
Weak instruments (log(total_fees))	4	2427	345.11	<0.001 ***
Weak instruments (log(google_trends))	4	2427	249.28	<0.001 ***
Transaction Fees equation:				
Wu-Hausman	1	2430	231.10	<0.001***
Weak instruments	4	2428	1381.10	<0.001 ***

As described in section 3.4.2, for the 2SLS approach it is necessary to select appropriate instrumental variables, i.e. those that are not correlated with residuals and at the same time have a non-zero correlation with endogenous variables. Testing for weak instruments together with the Wu-Hausman test results is presented in table 4.1 and 4.2.

Subsequently, it is necessary to exclude that the residuals contain unit root. If we cannot exclude the unit root, spurious regression might occur. Spurious regression is a phenomenon where regression estimates suggest a causal relationship between a dependent and an independent variable because of a trend or correlation with a non-included variable, even though there is actually no relationship between them (Wooldridge 2015). To test the unit-root of residuals we used Augmented Dickey-Fuller test (ADF) (Fuller 2009) and Kwiatkowski-Phillips-Schmidt-Shin test (KPSS) test (Kwiatkowski *et al.* 1992). The null hypothesis of the ADF test is that the residuals contain a unit root, thus rejection is crucial for our analysis. On the other hand, the null hypothesis of the KPSS test is that the residuals are stationary. Ideally, it is appropriate not to reject the null hypothesis, but if stationarity is rejected, then non-stationarity does not imply unit root. In our analysis, the unit root was rejected for the price and fee equations for both assets. The results of the unit root tests are presented in Table 4.3.

Table 4.3: Unit-Root tests.

Equation	ADF	KPSS
Bitcoin:		
Price	≤ 0.01	≤ 0.01
Fees	≤ 0.01	≤ 0.01
Ethereum:		
Price	≤ 0.01	0.02
Fees	0.01	≤ 0.01

Note: The table presents p-values for specified tests.

So far we have tested the first three assumptions of the time series regression, which should imply unbiasedness of the estimates. Furthermore, it is necessary to perform tests for homoskedasticity and no serial autocorrelation. Homoskedasticity states that regardless of time the variance of the residuals is constant. Expressed mathematically:

$$Var(\epsilon_t|\mathbf{x}_t) = \sigma^2 \tag{4.1}$$

Further, no serial correlation demands a correlation between a variable and its own lagged values equal to zero. Formally expressed:

$$\mathbb{E}\left[\epsilon_t, \epsilon_s | \mathbf{x}_t, \mathbf{x}_s\right] = 0, \forall t \neq s \tag{4.2}$$

Both assumptions are essential to the validity of standard errors and t-statistics (Wooldridge 2015).

To test for homoscedasticity we used the Breusch-Pagan test (Breusch & Pagan 1979), with the null hypothesis of constant variance of residuals, and to test for serial autocorrelation we used the Durbin-Watson test (Durbin & Watson 1950), with the null hypothesis that the true autocorrelation is equal to zero.

Table 4.4: Breush-Pagan test.

Equation	χ^2	df	p-value
Bitcoin:			
Price	138.83	4	< 0.001
Fees	177.12	3	< 0.001
Ethereum:			
Price	100.76	5	< 0.001
Fees	35.461	3	< 0.001

Breusch-Pagan test revealed heteroscedasticity for each of the two equations for both cryptoassets at any statistically reasonable level.

Table 4.5: Durbin-Watson test.

Equation	DW	p-value
Bitcoin:		
Price	0.208	< 0.001
Fees	0.339	< 0.001
Ethereum:		
Price	0.156	< 0.001
Fees	0.163	< 0.001

Similarly, the Durbin-Watson test suggested non-zero autocorrelation for all equations examined. To obtain valid t-statistics, we followed MacKinnon & White (1985) and used heteroscedasticity and autocorrelation consistent standard errors (HAC).

Due to the sufficient sample size, it was not necessary to test the normality of the residuals, but we still performed a Shapiro-Wilk test (Shapiro & Wilk 1965) with the null hypothesis that the residuals are normally distributed. Given the volatile nature of the cryptoasset environment and the typically skewed and heavy-tailed data, we expected the rejection of normality. Normality was indeed rejected for all 4 tested equations.

Table 4.6: Shapiro-Wilk test.

Equation	W	p-value
Bitcoin:		
Price	0.997	<0.001
Fees	0.994	<0.001
Ethereum:		
Price	0.997	<0.001
Fees	0.954	<0.001

Discussion of long-term relationships

This section contains the interpretation and implications of the results of the long-term analysis. The resulting estimates together with the HAC standard errors and the corresponding statistical values are shown in Table 4.7 and Table 4.8.

Bitcoin Results

Bitcoin's price has been shown to be driven by a diverse range of factors.

Table 4.7: Bitcoin: 2SLS estimator.

	Estimate	Std. Error	t-statistic	Pr(>|t|)
Price equation:				
(Intercept)	-19.222	3.877	-4.958	<0.001 ***
log(total_fees)	-0.081	0.049	-1.637	0.102
log(hash_rate_mean)	0.198	0.045	4.413	<0.001 ***
log(google_trends)	0.597	0.174	3.421	<0.001 ***
log(sp500)	2.611	0.452	5.775	<0.001 ***
Transaction Fees equation:				
(Intercept)	-40.092	4.171	-9.613	<0.001 ***
log(close)	-0.844	0.073	-11.609	<0.001 ***
log(sigma)	0.515	0.075	6.862	<0.001 ***
log(total_addresses)	4.045	0.338	11.984	<0.001 ***
		R^2	Adj. R^2	
Price Equation		0.965	0.965	
Transaction Fees Equation		0.502	0.502	
Number of observation				2435
Note:	*p<0.1; **p<0.05; ***p<0.01			

The representative of the fundamental factors is the positive impact of the mean hashrate. The hashrate effectively serves as a proxy for network security because the higher the hashrate, the more difficult it is to successfully control the network. Thus, network security plays a significant role in bitcoin price dynamics, which is logical given that the moment the hashrate is too low, it will be easy to attack the network and the price of bitcoin can be expected to become negligible compared to today's values.

Furthermore, it turns out that in the long term, bitcoin reacts most strongly to global economic development, represented by the S&P500 index, with an elasticity of 2.611. It will be convenient to compare the impact of the S&P500 from a short-term perspective, as we believe that this effect is due to the popularization of Bitcoin and the arrival of investors from the standard markets. Further, this effect might contradict the safe haven narrative of Bitcoin.

The influence of Google searches as a traditional proxy for public interest (used since Kristoufek (2013)) comes out positively as expected. We consider this influence to be representative of speculative factors. The higher the Google searches, the greater the public interest, which might increase the demand for buying bitcoin, which according to Law of Demand and Supply should increase the price *ceteris paribus*.

Finally, the impact of transaction fees turned out to be negative, however with a p-value of 0.102 the effect is not significant. The finding contradicts Kukacka & Kristoufek (2023), although this is likely to be explained by a different base currency (mentioned paper use $USD base). Since Bitcoin has a relatively short history and the majority of block rewards consists of newly mined bitcoins, we predict that the larger the share of fees in the security budget, the more significant their impact on the Bitcoin price will be. Considering that the moment Bitcoin inflation becomes negligible, the transaction fees will become closely linked to the security of the network, as they form the only motivation for the miners.

Overall, the estimates of the long-term price dynamics are in line with Kubal & Kristoufek (2022), who also revealed that the bitcoin price is positively driven by network security, stock market trends and public interest.

In the case of the fees equation, it should be repeated that the dynamics of transaction fees is in principle driven by the demand for fast transaction execution, thus in this framework, the interpretation of the results is relatively straightforward.

The strongest effect with elasticity 4.045 is the effect of the number of active addresses, as a proxy for the network activity. The number of active addresses can provide insight into the level of interest, adoption and engagement in the Bitcoin network. The model shows that the higher the network activity and adoption, the higher the transaction fees, which might bring a crucial contribution to the discussion about the future of Bitcoin, given that fee growth with a higher user adoption tends to ensure a sufficient security budget.

We believe that the negative effect of the price on the transaction fees (elasticity -0.844) is due to the *factor of the transaction fees appreciation*. The problem is that when the price of Bitcoin rises, the potential profit for the attacker also rises and therefore at the moment when the network will live primarily from the transaction fees, the value of the fee needs to increase at such a moment. In principle, this finding does not contribute much to the discussion of Bitcoin's long-term sustainability because, although we found a negative relationship, we expect that the majority of Bitcoin users still consider fiat currency (instead of bitcoin or satoshi) to be their unit of account[2], and therefore it would be more beneficial in this context to examine the effect between price and fees in a fiat basis.

Finally, the positive effect of volatility was expected, given that high volatility can motivate bitcoin holders to either buy or sell quickly, depending on the market phase, but in any case, it can motivate users to make a transaction quickly, which can result in a network clogging, thus increase transaction fees.

Ethereum Results

Compared to Bitcoin, speculative factors play a much bigger role in the price dynamics of Ethereum, which can be explained by the fact that Ethereum has a shorter history than Bitcoin and at the beginning of the analyzed period was shortly after the launch, and it could be assumed that for new cryptoassets speculative factors play a major role in price formation, and the fundamental factor will begin to develop during stabilization.

The strongest speculative factor turns out to be Google searches with an elasticity of 0.780, which is a slightly stronger relationship than 0.597 in the case of Bitcoin. This difference might again point to the more speculative nature of Ethereum, and it can be assumed that the effect of Google searches may decrease over time as both cryptoassets become more and more widely known.

[2] One of the three basic characteristics of money, the unit in which an individual operates.

Table 4.8: Ethereum: 2SLS estimator.

	Estimate	Std. Error	t-statistic	Pr(>|t|)
Price equation:				
(Intercept)	-0.935	1.173	-0.796	0.426
log(total_fees)	-0.131	0.117	-1.126	0.260
log(btc)	0.481	0.139	3.452	<0.001 ***
log(google_trends)	0.780	0.150	5.209	<0.001 ***
log(sigma)	-0.194	0.053	-3.688	<0.001 ***
log(total_addresses)	0.391	0.088	4.425	<0.001 ***
Transaction Fees equation:				
(Intercept)	0.832	2.097	0.397	0.692
log(close)	0.886	0.138	6.406	<0.001 ***
log(sigma)	0.042	0.078	0.534	0.593
log(total_addresses)	0.080	0.229	0.351	0.726
		R^2	Adj. R^2	
Price Equation		0.967	0.967	
Transaction Fees Equation		0.807,	0.807	
Number of observation				2435
Note:	*p<0.1; **p<0.05; ***p<0.01			

Volatility as another speculative factor has turned out to have a negative effect on the price of ether. Thus, high volatility brings uncertainty among investors, and due to high liquidity, investors may, for example, look for a temporarily more stable asset to store value - for example, bitcoin or stablecoins[3].

Another important finding is that Ethereum appears to be positively driven by the price of bitcoin (elasticity 0.481), which supports the nature of bitcoin as the primary driver of the cryptoasset market, which is consistent with our initial hypothesis in the model proposal and in line with Qiao *et al.* (2020). We classify the impact of bitcoin price as an economic factor and might be analogous to the impact of the S&P500 on bitcoin price.

It turns out that Ethereum responds positively to the total number of active addresses, which is the only representative of the fundamental factors. The interpretation of this effect is relatively straightforward. The number of active addresses can be understood as a proxy of the Ethereum demand side and should according to the law of supply and demand increase the price of ether *ceteris paribus*.

In the transaction fee equation, only the effect of price appears to be significant. In contrast to Bitcoin, the price effect has been shown to be positive. One possible explanation is that Ethereum indicates a weaker *transaction fee appreciation factor* than Bitcoin, which may be due to two factors:

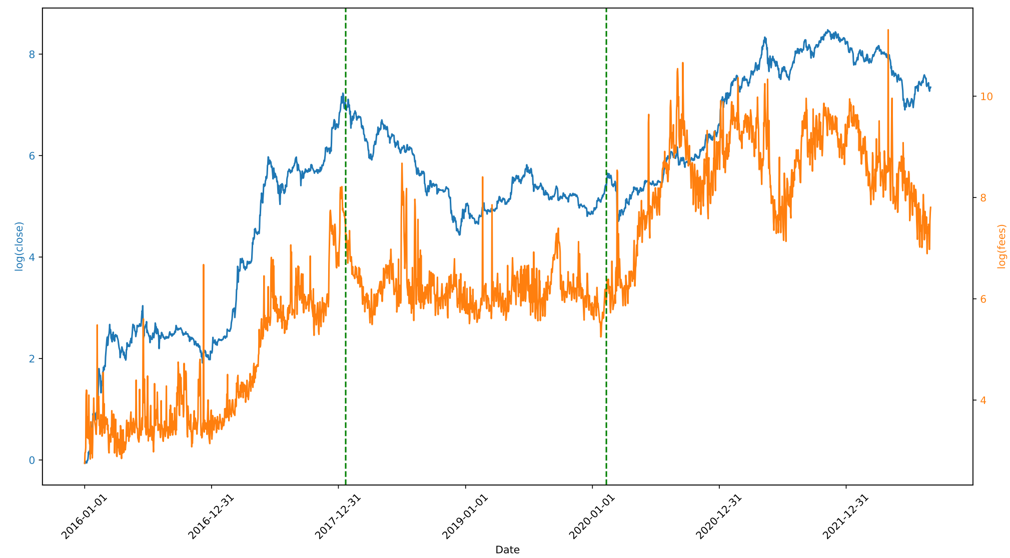
[3]Cryptoassets, which aim to peg their value to another asset, usually fiat currency.

The block time is much shorter for Ethereum than for Bitcoin (about 15s vs 10 min), so Ethereum scales better and has more network activity, for this reason, there might be larger competition for the transaction execution.

One of Ethereum's main features is support for smart contracts, which are technically a type of transaction. Thus, transactions on Ethereum have a wider scale of use cases than just peer-to-peer transfers in Bitcoin. This factor is likely to increase the demand for transaction execution, as more than just value transfer is at stake. Even though it can be assumed that if the price of bitcoin drops significantly, fees and network activity will drop significantly as well, in the case of Ethereum this effect is likely to be mitigated, as many smart contracts transactions can operate regardless of price.

These factors could also partially explain the difference between the overall trend of transaction fees between Bitcoin and Ethereum (shown in Figure 4.3).

Figure 4.3: Ethereum: Transaction Fees and Close Price in time with division into subintervals.



4.2 Short-Term analysis

The analysis of short-term effects was performed separately by subintervals, defines arbitrary as follows: **Interval I** from January 1, 2016 to January 21, 2018. **Interval II** from January 22, 2018 to February 10, 2020. **Interval III** from February 11, 2020 to August 31, 2022. In this section, we first describe the characteristics of the individual inter, then the modeling process and finally a discussion of the results.

Interval I can be characterized by the cryptoasset environment becoming more mainstream and rapid price growth. During this period, Bitcoin halving occurred, i.e. inflation decreased. Subsequently, both assets struggled with internal issues that escalated into hardfork [4]. Furthermore, the year 2017 is notable for emerging ICO[5] bubble, which fueled the 2017 crypto bull run. Both assets underwent astronomical growth during this period, which is shown in Table 4.9.

Table 4.9: Subinterval characteristics.

	Interval I	**Interval II**	**Interval III**
Bitcoin:			
Total Returns	2547%	-23%	98%
Volatility	0.0303	0.0260	0.0282
Ethereum:			
Total Returns	110006%	-81%	579%
Volatility	0.0558	0.0343	0.0372

Interval II begins with the bursting of the ICO bubble. The whole interval is characterized by a market crash and gradual recovery. This period turned out to be less volatile than the previous interval and at the same time for both assets the price failed to return to the original values before the crash. About halfway through the interval, the price of Bitcoin began to stabilize and rise again and recovered significantly more than in the case of Ethereum, which was nowhere near its original values.

Finally, the interval III is characterized by the colorful events in the cryptoasset markets. The interval starts with a Covid19, from which, however, the cryptasset market was able to quickly recover. Further In May 2020, the third bitcoin halving occurred, which, together with the growing interest of institutional investors associated with a new wave of quantitative easing and fiscal stimulus in the US, started a rapid growth, which inflated the first bubble that escalated to all time high (ATH) of both Ethereum and Bitcoin. The

[4] Ethereum experienced an event called the Dao hack, where a vulnerability in smartcontact was exploited and an anonymous hacker stole $60 million worth of ethers. The stolen Ether was subsequently returned by a rollback that was performed by a hardfork (Morrison *et al.* 2020). Bitcoin experienced an event called blocksize wars, which was a discussion about Bitcoin scaling, which resulted in a hardfork on Bitcoin core - the original version, and Bitcoin Cash, which solve scaling by increasing the block from 1MB to 4MB (Morgan 2017).

[5] Initial Coin Offering (ICO) is a process of raising capital for cryptoasset projects analogous to a standard IPO on the stock market.

bubble then quickly burst, which may have been influenced by the cryptoasset ban in China, which was followed by a massive drop in hashrate [6]. However, the crypto environment quickly stabilized and by the end of 2021, Bitcoin and Ethereum made a new ATH. There was a major correction at the end of the interval, followed by the crash of the Terra Luna[7], which brought panic to the cryptoasset environment.

Discussion of short-term relationships

The modeling process was carried out in an analogous way as in the case of the analysis from a long-term perspective. We used the same methods to choose between OLS and 2SLS approaches, and we also used the same statistical tests to verify the assumption of time series regression. In principle, the statistical tests led us to the same choice of model as in the first analyzed part, with only a minor problem, when on interval II for Ethereum the p-value of the ADF test was 0.05092, which did not allow us to reject the null hypothesis at conventional 0.05 significance level, however, at any other conventional significance level the unit-root of residuals can be rejected and the p-value is very close to rejection, thus we decided to assume that the unit-root is not present and proceeded accordingly. Thus, all models in this section were estimated using the 2SLS approach with HAC standard errors.

Bitcoin results

The only significant effect on Bitcoin price that is present across all intervals is the positive effect of public interest, represented by Google searches. It might be difficult to interpret the difference in effect strengths. Public interest showed the strongest impact (elasticity 0.977) at the second interval, which captures the bear market. This finding is contrary to our intuition, given that the strongest influence of the Google searches was expected in the bull market where sentiment is rising. However, a possible explanation could be that the public interest in this period was the least 'volatile', and therefore the respective outliers could cause a big shock and therefore have a relatively large impact on the price.

An interesting finding is the strong positive relationship of the hashrate (elasticity 0.957, close to unit elasticity) on interval I, which shows that the

[6]For more see Cox (2021).

[7]for more see Kharpal & Browne (2022)

Table 4.10: Bitcoin: Short-term analysis results.

Equation	**Interval I**	**Interval II**	**Interval III**
Price equation:	(2SLS)	(2SLS)	(2SLS)
(Intercept)	-31.198 ***	-14.273 *	2.115
log(total_fees)	-0.183	0.001	-0.288 ***
log(hash_rate_mean)	0.957 ***		-0.651 *
log(google_trends)	0.480 ***	0.977 ***	0.559 ***
log(sigma)		-0.143 *	
log(sp500)		3.133 *** .	2.354 ***
log(total_addresses)			1.560 **
R^2	0.958	0.331	0.842
Transaction Fees equation:	(2SLS)	(2SLS)	(2SLS)
(Intercept)	-13.576 *	-24.896 ***	-40.7334 ***
log(close)	0.484 ***	-0.367	-0.967 ***
log(sigma)	0.066	0.443 ***	0.420 ***
log(total_addresses)	1.158 *	2.550 ***	4.153 ***
log(google_trends)			
R^2	0.792	0.4275	0.411
Number of observation	750	750	935

Note: *p<0.1; **p<0.05; ***p<0.01

Bitcoin price was driven at an early stage also by fundamental factors and even more so than speculative factors. In the context of the bullrun 2017, we can suspect a bidirectional relationship between the hashrate and the price (which cannot be shown by our model, because it is not the purpose of our work to explore hashrate through separate equation) given that a rapid rise in price can strongly incentivize the miners, which increases the hashrate and conversely the price is likely to further react to increased network security. Significant influence of the hashrate was further shown at interval III. The effect turned out to be negative, which is a very unexpected and counterintuitive finding. It can be assumed that this effect might be related to the fact that at the end of the interval, the hashrate was continuously rising steeply towards its maximum at the time when the price significantly dropped from ATH.

On Interval II, the price was mostly driven by S&P500 (elasticity 3.133). The significant influence of S&P500 begins in this interval and continues with a substantially strong effect (elasticity 2.354) in the last interval. We interpret this phenomenon to mean that at this time Bitcoin is no longer the domain of enthusiasts and fundamentalists, but is beginning to attract mainstream investors from the stock market.

Furthermore, interval II indicates a negative impact of volatility, which makes sense given that interval II is characterized by a deep bear market and high fear after the bursting of the ICO bubble, and thus increased volatility can scare investors who start panic selling.

A relatively strong effect of the number of active addresses was in interval III. During this period there was a rapid price rise that went up to the ATH and thus this finding shows that this rise was strongly driven by the network activity and adoption rate.

Finally, a significant impact of transaction fees was discovered only in the last period. The effect turns out to be negative, bidirectional and relatively weak (elasticity -0.288 in the opposite direction is the elasticity of almost unit -0.967), which means that clogging lowers its price and at the same time increasing the price lowers its clogging. At the end of interval III, fees were the lowest of the whole global interval, indicating a strong effect of the transaction fees appreciation factor - the Bitcoin price is at an ATH and therefore transaction fees are logical. In this context, there is again a potential future research direction, where it might be appropriate to conduct a similar research with the use of transaction fees in the fiat base.

In the case of the transaction fees equation, it turns out that the dynamics is determined primarily by the total number of active addresses with a gradually increasing positive elasticity effect (1.158, 2.550, 4.153), which further confirms the strong long-term influence of addresses found on the global interval.

The negative effect of the price in interval III was discussed above, however, the price turned out to be a significant driver also in the first epoch. It turns out that transaction fees on the interval I reacted positively to the price increases. This period is practically the first Bitcoin bullrun that started to catch the attention of mainstream investors. The positive effect is likely to be explained by the perception of new investors who could see Bitcoin as a 'get-rich-quick' scheme with the prospect of unprecedented astronomical returns, which could mitigate the transaction fee appreciation factor, i.e. investors probably do not attribute much importance to the appreciation of fees in the fiat base.

The last factor with a positive impact on transaction fees turns out to be volatility. The positive impact of volatility is not surprising for the same reason as described in the long-term analysis, i.e. that volatility can increase the demand for buying/selling, i.e. for carrying a transaction. An interesting finding is that volatility was not found to be significant in the first interval, nor had any significant effect on price found in this interval. This phenomenon is expected to be explained by the fact that the first interval is characterized by the highest volatility of the whole global interval and due to its commonness investors may not have reacted to its increase.

Ethereum results

The price dynamics of the ether turned out to be quite diverse, none of the variables appears to be significant for all intervals.

Table 4.11: Ethereum: Short-term analysis results.

Equation	Interval I	Interval II	Interval III
Price equation:	(2SLS)	(2SLS)	(2SLS)
(Intercept)	6.406 **	-38.560 *	-31.817 ***
log(total_fees)	0.141	0.668 .	-0.014
log(hash_rate_mean)		1.034 *	0.406 ***
log(google_trends)	1.212 ***	0.763 ***	
log(sigma)	-0.385 ***	0.045 .	
log(sp500)			2.185 ***
log(total_addresses)		0.612 .	
log(btc)			0.731 ***
R^2	0.426	0.560	0.986
Transaction Fees equation:	(2SLS)	(2SLS)	(2SLS)
(Intercept)	6.523	2.492	-48.181 *
log(close)	0.096	0.121	0.902 *
log(sigma)	-0.114	0.104 **	0.691 *
log(total_addresses)	0.023	0.273	3.815 **
log(google_trends)	0.768 *		-1.493 .
R^2	0.832	0.141	0.259
Number of observation	750	750	935

Note: *p<0.1; **p<0.05; ***p<0.01

On interval I it is visible that Ethereum reacts purely to speculative factors, which is logical given its very short history. The most significant effect is the effect of public interest, i.e. Google searches (elasticity 1.212). Furthermore, Ethereum reacts negatively to increased volatility, which is surprising given that Bitcoin did not react to volatility at all during this period. However, it can be assumed that Ethereum showed the highest volatility relatively shortly after the launch - i.e. at the beginning of the interval - and then volatility stabilized, which could lead to a slightly lower volatility than at the beginning of the interval and thus a negative effect when the ICO bubble grows.

Interval II is very diverse, mixing fundamental factors with speculative factors represented by volatility and a very strong public interest effect, which is the only one that remains significant at any conventional significance levels. Of the fundamental factors, the most important for the purposes of our work is the positive impact of transaction fees. This relationship appears to be only unidirectional with an elasticity of 0.668 and p-value of 0.0745. As described in the long-term analysis, it can be assumed that the influence of the transaction appreciation factor is smaller in the case of Ethereum than in the case of Bitcoin, which is better observable in the opposite direction, but also in this direction can be seen that the clogging of the network, which only reflects the demand for fast transaction execution, is likely to be more continuous as Ethereum users react less to the appreciation of fees, and thus be reflected in the price increase.

In the last interval, there is an obvious reduction of speculative factors, which may be due to the stabilization of Ethereum's position as number two on the market, and therefore investors are beginning to see its fundamental value. It turns out that Ethereum reacts the strongest to the economic factor - Bitcoin, an indicator of cryptoasset market growth, and S&P500, an indicator of global economic growth. The price of bitcoin positively affects the dynamics of ether with an elasticity of 0.731, which means that with a 10% increase in the price of bitcoin we predict a 7.31% increase in the price of Ethereum, which supports the results of the long-term analysis. Further, the positive impact of the S&P500 (elasticity 2.185) is likely to indicate that Ethereum has also attracted the attention of mainstream investors. Finally, the positive effect of the hashrate proved to be significant (in contrast to the previous interval it is significant at any conventional level), which only shows that Ethereum users value higher network security. An interesting observation is that the influence of Google searches has ceased to be significant. We do not believe that the public interest factor has ceased to be significant, but rather has begun to be captured by a different proxy than Google searches. Google might be replaced by, for example, Discord, Telegram or Twitter, since these platforms are now primarily used for discussion of cryptoasset environment.

In the case of the fee equation, as in the analysis of the long-term perspective, it appears that Ethereum's fees are driven by a single prevailing factor rather than a diverse mix. In interval I, this factor is the influence of the public interest, which we interpret that with higher public interest more users are motivated to conduct a transaction, which according to the law of supply and demand should *ceteris paribus* increase transaction fees. In interval II this effect is captured by the effect of volatility, with essentially the same interpretation as before.

Finally, Interval III revealed the significance of all variables included in the benchmark model. The positive impact of price and volatility is not a big surprise, the interpretation of both variables has already been discussed and remains the same. The negative relationship of Google searches is surprising, especially because it does not play a significant role in price dynamics. With a p-value of 0.0898, it is close to the rejecting of significance and no logical explanation for negative trend appears to us. Further, a very strong positive effect of the total number of active addresses (elasticity 3.815) is shown, which logically implies that the fees on interval III reacted most to the activity of the network. In contrast to Bitcoin, this effect is not omnipresent, but only occurs at the most recent interval - interval III. All of this likely demonstrates that Ethereum's fee drivers are dynamic and rapidly changing, while Bitcoin fee dynamics appear to be relatively more stable, as shown for example by the constant influence of the total number of active addresses.

Chapter 5

Conclusion

The aim of this work was to shed light on the role of transaction fees in the cryptoasset ecosystem, namely Bitcoin and Ethereum, and to further identify the factors driving the dynamics of transaction fees and price. Previous research, such as Kubal & Kristoufek (2022), has shown that variables in the cryptoasset environment are interconnected and exhibit signs of endogeneity, and in order to reflect this nature a system of two simultaneous equations - one for price and one for transaction fees - was developed and further estimated using 2SLS method. Given the dynamically evolving cryproasset sentiment, it cannot be assumed that the relationships between variables remain stable over the entire interval, but rather evolve. In order to capture this feature we divide our empirical research into an analysis of the long-term and short-term perspective. The analysis of the long-term relationship is conducted on the data between January 1, 2016 and August 31, 2022. In contrast, the analysis of the short-term relationship is conducted on 3 approximately 2 year intervals, where each of them differs in market sentiment.

It has been shown that the price dynamics of both assets is determined by a diverse range of factors that could be categorized into fundamental, economic and speculative influences. The fundamental difference is that speculative factors play a slightly bigger role in the dynamics of Ethereum, which might be expected due to the more stable market position of Bitcoin. It is worth mentioning that the price of both assets reacts substantially to events in the more developed markets. In the case of Bitcoin, it is the stock market represented by the S&P500, while Ethereum is influenced by Bitcoin over the long term and mostly in the most recent examined period. One of our research questions was how transaction fees impact the price. This effect did not prove to be systematically significant, except for one short-term interval for both assets. For Bitcoin, it was the period between 2020 and 2022 where the negative impact is evident, indicating that network clogging discourages users from conducting transactions. On the contrary, for Ethereum it is the period after the bursting of the ICO bubble until the beginning of 2020, where the positive impact of fees is shown, indicating that the clogging of the site does not discourage investors to continue buying, but instead drives the price.

We were also interested in what variables drive the fee dynamics. In particular, whether and how the price of the asset, the total number of active addresses and volatility affect the fees. The fee dynamics of Ethereum and Bitcoin differ significantly. The dynamics of Bitcoin is quite stable and there was found to be a long-term and short-term influence of all the mentioned variables. The effect of the price turned out to be rather negative, which is explained by the transaction fee appreciation factor, i.e. the fees are denominated in the base currency of the network (bitcoin), and therefore in case of a price increase the same value of the fee might mean a significant increase in the fee in the fiat base, which can motivate users to lower the fees. The positive effect of volatility is also practically omnipresent, which is very logical, since volatility drives investors to buy/sell, which according to the law of supply and demand should increase the demand for fast execution of the transaction, which can increase the clogging of the network. The strongest driver is the positive effect of the total active addresses, which is significant in the long and short term, which implies that with increasing network activity and higher adoption rates, transaction fees increase. This finding is very important for the future discussion about the sustainability of Bitcoin, because without a change in the protocol, in the future, miners will only be incentivized by rewards in the form of transaction fees, i.e. the transaction fees will have to be large enough, otherwise the network cannot survive, and therefore the found growing trend can play a significant role. On the other hand, Ethereum's transaction fee dynamics appear to be rapidly evolving, less structured, and more influenced by one prevailing factor rather than a mixture of them. From a short-term perspective, all of the examined variables turned out to be significant, but none of them seems to have a consistent effect. There is no structural difference in the effect of individual variables compared to Bitcoin, except for the price effect, which is the only factor that is significant in the long term. The price effect turns out to be positive, which we attribute to the fact that the transaction fee appreciation factor is mitigated in the case of Ethereum, primarily due to a different fundament which implicitly results in systematically higher activity on the network, which might play a role in the higher demand for fast transaction execution, which could exceed the fee appreciation factor.

We would also like to highlight the space for future extension of our work. One extension could be the inclusion of additional explanatory variables that could explain further variance in our model. One example might be the new proxy for public interest, given that we believe that the influence of Google searches is beginning to diminish and the cryptoasset discussion is moving to platforms such as Twitter, Discord or Telegram, where it is much more difficult to extract relevant data. It might also be useful to include a proxy for crosschain dynamics that could account for the substitution factor between other cryptoassets. Furthermore, it can be assumed that transaction fees can be determined by the average waiting time for transaction execution, which is unobservable, although it is possible to estimate this variable according to a theoretical model similar to Easley *et al.* (2019). Another logical extension could be a higher data frequency, which could better describe the dynamic environment of transaction fees and network clogging. Given that the relationship between price and fiat has been shown to be quite strongly influenced by the transaction fee appreciation factor, it may be beneficial to mitigate this factor and perform an analysis with transaction fees in the fiat base. Finally, it is recommended to update the dataset and possibly add more cryptoassets. In this respect, it is important to be aware of the circumstances of Ethereum transition to the PoS consensus mechanism, and although transaction fees in version 2.0 still play the same role in principle, these intervals cannot be combined due to the significantly different functioning of the whole network.

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Appendix A

Additional materials

All the necessary material to replicate the work, together with an R script to retrieve data from google trends and a python connector to the Glassnode API is publicly available and easily accessible at `https://github.com/cedav12/Impact-of-total-transaction-fees-on-the-price-of-Bitcoin-and-Ethereum`