Arbitrage Opportunities in Ethereum Markets

A study of price deviations and the practical exploitation of arbitrage opportunities in Ethereum markets.

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Preface

Our thesis marks the end of our master's programme in Business Administration at the University of Agder (UIA).

The topic for our thesis was motivated by our interest in cryptocurrencies. Although our interest was personal at first, we found inspiration in applying quantitative methods derived from our specialization in Analytical Finance.

We wish to thank our supervisor Steen Koekebakker for guidance throughout the process. His input contributed to interesting discussions, which in return increased our knowledge and broadened our perspective on the subject.

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Abstract

This paper is an examination of the exploitability of arbitrage opportunities in Ethereum markets. Using 1-minute candlestick data from 2021 on three cryptocurrency exchanges we find substantial and frequent price deviations. However, these deviations are of a much smaller magnitude compared to the findings in recent research. By using data on trading fees and volume, we find the arbitrage profits. We interpret our findings through strategies for exploitation and find that exploitable arbitrage opportunities do exist in Ethereum markets.

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1 | Introduction

In light of recent market volatility and previous research, we found interest in examining arbitrage opportunities in Ethereum markets. Recent research suggests that cryptocurrency markets experience substantial price deviations at times. However, some researchers argue that there are barriers to the practical implementation of arbitrage trading in cryptocurrency markets. While previous research has focused more on Bitcoin markets, we turn our attention to Ethereum markets. Our paper aims to investigate the price deviations and practical exploitation of arbitrage. This gives us the research question; "Do viable arbitrage opportunities exist in Ethereum markets?".

When conducting our research on arbitrage in Ethereum markets we use 1-minute price data from 2021 on three exchanges. The data is analyzed and explained with descriptive statistics throughout this paper. Furthermore, the collected data is used in the development of an arbitrage index to identify price deviations between exchanges. We then identify important attributes of cryptocurrency transactions, including transfer speed, volume, and trading fees. Additionally, we differentiate trading fees based on the volume traded by the investor and calculate arbitrage profits. Finally, we investigate how long the arbitrage opportunities are available before the price deviations converge. We then present two strategies for implementation of arbitrage trading and discuss practical concerns and risk connected with exploitation.

Our findings include recurring price deviations between exchanges. These deviations are substantial also when accounting for trading fees. The calculation of arbitrage profits shows that with full exploitation during 2021, 5 057 247 USD were available to smaller investors, while 10 821 235 USD were available to larger investors. The supplemental analysis of the duration of arbitrage opportunities shows that the majority of opportunities available to small investors are very short-lasting. On the other hand, opportunities available to large investors take somewhat longer to converge. Finally, we discuss the important implications these findings have for the implementation of a trading strategy.

Our paper is designed as a descriptive study, where we intend to explain and describe the characteristics of a phenomenon. With this in mind, we have structured our paper as follows. In the second chapter, we approach the relevant theory and aspects of blockchain technology, cryptocurrencies, and cryptocurrency exchanges. Furthermore, in the third chapter, we introduce relevant financial theory concerning arbitrage as well as the latest research on arbitrage in cryptocurrency markets. We follow up by introducing and describing the data in chapter four. In the last chapters, five and six, we present the results, interpret them, and conclude the paper.

2 | Blockchain Technology

Since there are several different ways of exploiting arbitrage in cryptocurrency markets, we have dedicated this section to elaborate on possible limitations along the way. Such limitations are related to the blockchain technology, the cryptocurrency at hand, and the exchanges used. Therefore, it is necessary to understand the basics of them all. We define a blockchain as a distributed ledger technology that operates on a computer network. A blockchain offers the ability to perform, record, and share information about transactions securely and simultaneously across the network and it is governed by the contributors on the network itself (Houben & Snyers, 2018, p. 15). As Bitcoin is one of the most used and understandable blockchains we utilize literature about its structure to increase the reader's understanding of blockchains, before introducing more advanced topics. Furthermore, we define a cryptocurrency as a peer-to-peer digital or virtual currency that operates on and utilizes the cryptographic nature of the blockchain network (Houben & Snyers, 2018, p. 23).

2.1 | Blockchain

The popularization of blockchains came after the infamous Satoshi Nakamoto published his paper *Bitcoin: A Peer-to-Peer Electronic Cash System* in 2008. Nakamoto's paper focuses on the need for a trust-less system for financial transactions on electronic platforms. Instead of trusting a third-party involvement such as banks or an intermediary, the blockchain network uses cryptography to solve transactions (Nakamoto, 2008, p. 1). Such transactions on the Bitcoin blockchain happen through coins that function on the network. These coins are defined by Nakamoto *"…as a chain of digital signatures. Each owner transfers the coin to the next by digitally signing a hash of the previous transaction and the public key of the next owner and adding these to the end of the coin. A payee can verify the signatures to verify the chain of ownership."* (Nakamoto, 2008, p. 2).

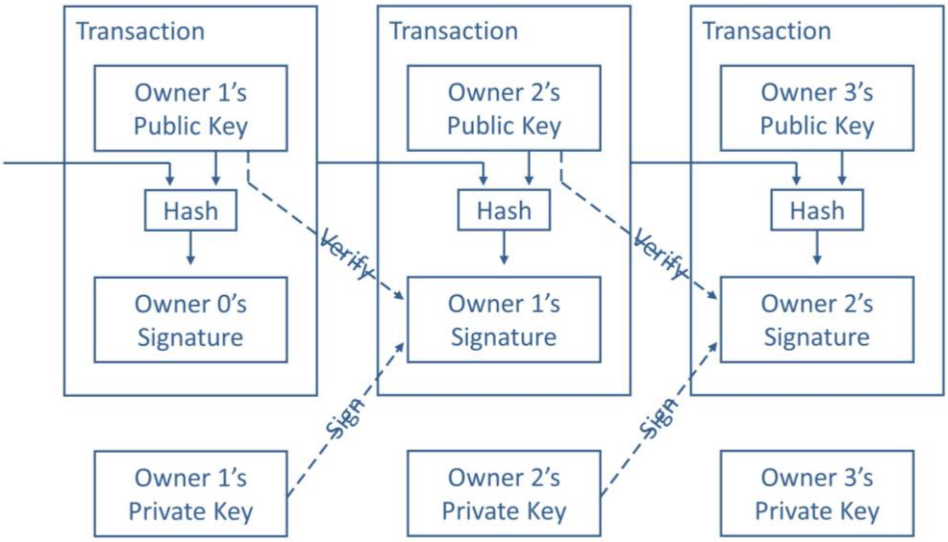

Figure 1 – Transactions | Chain of digital signatures (Nakamoto, 2008, p. 2)

We define a hash as a one-way process of encrypting a data input of undefined length into a string of defined length (Bybit Learn, 2020). Furthermore, the public key is a publicly available destination address for the wallet of an entity that is connected to the network. On the other hand, a private key is the entity's private access code to its wallet. It is known only by the creator of the wallet and is used for creating digital signatures and storing the coins (Coinbase, n.d.). To verify that transactions are not being double-spent in the network, Nakamoto introduces the process of timestamp servers. This process involves timestamping the hash of a block and then spreading the information about the timestamp across the network simultaneously (Nakamoto, 2008, p. 2). The block being timestamped can be described as a package of information that contains the transactions performed on the network within a given timeframe. Each block that is created on the network is linked with the previous block, and the previous block is connected to the one before that. Therefore, it could also be viewed as a chain of blocks, hence the term blockchain.

2.2 | Processing of transactions in the network

To further understand the speed of processing transactions, a walkthrough of blocks and block validation is needed. The following section goes into a surface-level explanation of block validation. For readers that want a more technical and detailed explanation, we recommend the articles *Distributed ledger*[1] and *Blockchain*[2] which parts of this section are built upon.

We define a block as a package of information that contain *n* number of transactions. In addition to this, it holds the timestamp, a hash value of the last block, and a random number called the nonce (Nofer et al., 2017, p. 2). The maximum number of transactions in each block is a fixed amount based on the maximum byte size of the block, meaning how much data it can contain. For a new block to be proposed to the network, the block needs to meet a specific criterion for its hash value, called the hash target. This criterion is set by the network and could for example include that the hash value of a block needs to start with four zeros. A hash is deterministic, meaning that a specific dataset always returns the same specific hash value. Therefore, to meet the criterion set by the network the nonce is introduced. A block is proposed to the network only when a miner has guessed the right nonce. This nonce will in combination with the hash value, produced from the block data, fulfil the hash target set by the network. With this structure, all blocks and the transaction within are linked to their previous block. This linkup goes back to the first block created on the network called the genesis block.

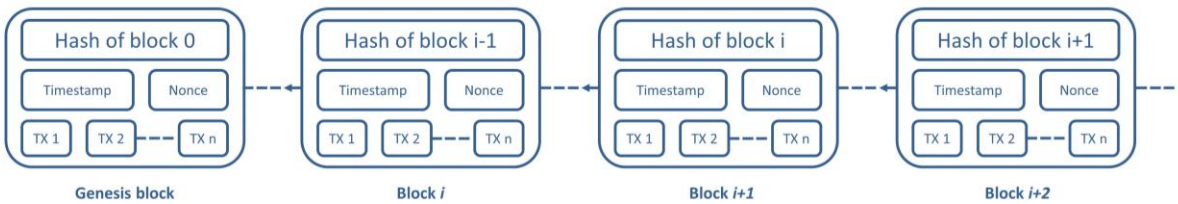

Figure 2 - Bitcoin block architecture (Zheng et al. 2016)

In addition to the hash target, a block needs to be validated by the majority of the nodes in the network before it is accepted as a new part of the blockchain (Nofer et al., 2017, p. 2). A *full node* is regarded as an individual participant that downloads all data on the blockchain and contributes computational power to the network through their hardware. While doing so they contribute to the validation of blocks and transactions. Furthermore, a *light node* is often regarded as an individual that downloads parts of the blockchain to utilize it for transactions (Cryptopedia Staff, 2021). However, they do not contribute any computational power. While

[1] Burkhardt, Weling & Lasi (2018)
[2] Nofer, Gomber, Hinz & Schiereck (2017)

it is common to use the terms *full nodes* and *light nodes,* we simplify this by referring to full nodes simply as nodes, and light nodes as wallet holders. For a more technical description of nodes, how they operate, and what types there are, we recommend reading *Types of Nodes: Light Nodes, Full Nodes, and Masternodes* by Cryptopedia. Each block is accepted by nodes either through the proof-of-work or the proof-of-stake mechanism, which can be read about in the paper *Cryptocurrencies and blockchain* by Houben & Snyers. Nodes are paid for the computational power they offer with the fees that a transferring party spends when performing transactions. In addition to this, they also receive other mining rewards that are offered by the network (Houben & Snyers, p. 25).

The Ethereum blockchain structure is quite similar to the one illustrated in Figure 2. One of the main differences, however, is that Ethereum focuses more on smart contracts and the ability to build decentralized apps. Smart contracts are defined as "…a set of cryptographic rules that are executed only if certain conditions are met" (Vujičić et al., 2018, p. 4). We define decentralized apps as applications that operate on the blockchain network and utilize smart contracts for their operations. A good example of a decentralized application is a decentralized exchange (DEX) where trading happens through liquidity pools and is based on the set of rules in the smart contract. Meaning that the trading happens through the network which does not involve a third party. These extra attributes contribute to a more complex block structure in the Ethereum network. However, our paper does not involve the use of decentralized apps and therefore we limit ourselves to the already established block structure with transactions and validation.

Transaction speed on the network can vary between seconds to minutes depending on the time it takes to create a new block and the number of block confirmations the receivers require. These criteria are also dependent on which blockchain you use since different blockchains have different data sizes on their blocks. The bitcoin blockchain uses about 10 minutes for each block creation (Bitinfochart, n.d). After a varying number of block confirmations, the centralized receivers regard transactions as safe. Because of the varying requirement of block confirmations, we simplify this number as to each exchange requiring three confirmations. This means that in addition to the block that contains your transaction, three new blocks need to be added to the blockchain before the transaction is regarded as verified and the receiver accepts the transaction. With this in mind, the transaction speed on the bitcoin network becomes about 40 minutes. The Ethereum blockchain, on the other hand, processes blocks in about 13 seconds (Etherscan, n.d). Centralized receivers have no commonly established standard for block confirmations here either. Therefore, we simplify this as a requirement of 20 block confirmations giving Ethereum a transaction speed of about 4-5 minutes. In comparison, an international transfer of USD could take anywhere from a couple of hours to almost a week when using a bank.

The transaction speed is based upon the assumption that the demand for transactions does not exceed the maximum amount a block can contain, within the timeframe of a block creation. In periods where the demand, within the given timeframe of block creation, exceeds the maximum number of transactions a block can contain, the network will become congested. This means that transaction time will exceed the normal standard. Within such periods there will be an increase in the network fee to reduce the demand for transactions. This mechanism also prevents an attack from malicious actors, since exceeding the transaction maximum number would cost them increasingly more money. With this distributed structure, where every node in the network holds the same continuously updated data, and they a form consensus about block addition, the technology is viewed as transparent and secure for performing transactions. Secondly, a key aspect of it all is that every contributor in the network is hidden behind their public and private keys.

2.3 | Structure of the network

In the world of blockchain and cryptocurrencies, one often hears about the terms centralized, decentralized, and distributed. If we consider these terms concerning the blockchain, it usually refers to how the blockchain network and its ledger are structured. A *centralized network* can be defined as a network where the operational power or decision-making lies with one entity, and users can only be connected through this entity (Burkhardt et al., 2018, p. 3). Within the traditional financial system, this network type is the typical structure. If we send money electronically, the processing goes through the bank, with all the responsibility and trust of the transaction lying in the hands of the bank. In such a network a transaction can be blocked, and accounts can be frozen by the controlling entity.

In a *decentralized network*, on the other hand, the operational power or decision-making lies with several entities that are separated from each other but connected to the same network. Users of the network are connected to one of the decision-making entities. They can switch entities if they wish to, and if one entity goes down, the rest of the network does not necessarily follow.

Furthermore, in a *distributed network* all participants are connected equally across the network. This is the case for most blockchain ledgers, which contain records of everything that has and is happening on the network, it is shared equally and simultaneously between participants on the network (Burkhardt et al, 2018, p. 3). This means that several of the users can go down without affecting the ledger and that everyone has equal access to the information from the blockchain. With regards to the blockchain, we separate the terms decentralized/centralized as the control of the network while distribution focuses on how the network is shared.

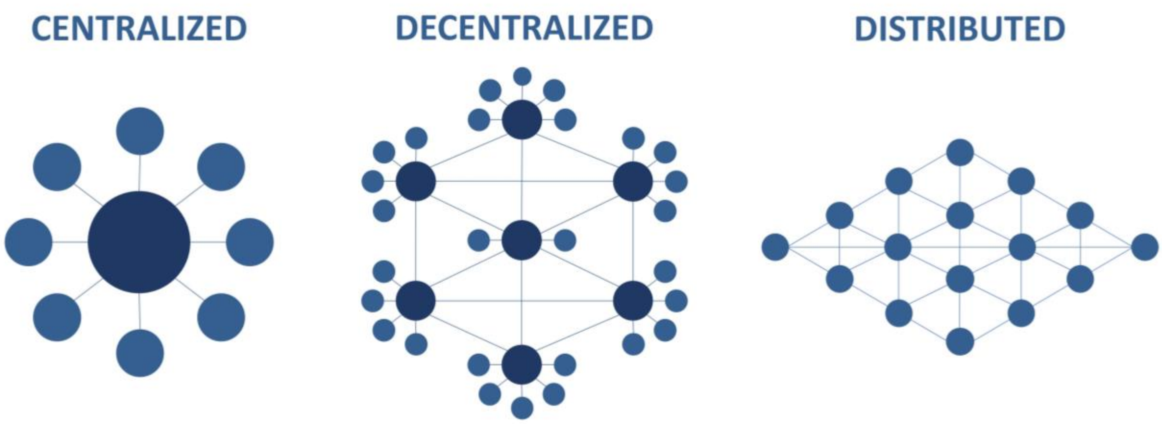

Figure 3 - Network types (Burkhard et. al., 2018, p. 3)

For a blockchain ledger, the distributed network structure offers the ability to share information equally and simultaneously between all participants. This includes both nodes and wallet holders. Furthermore, the blockchain network itself processes transactions made by wallet holders through blocks that are validated by nodes. In other words, the *decision-making* on the blockchain is structured similarly to a decentralized network, since there are several different entities that function as nodes. Anyone can become a node if they have the hardware needed, and they collectively make a consensus of transactions and blocks without involving a third party. When each block has enough validation, and a consensus is made, the block is added to the previous one (Burkhardt et al, 2018, p. 4). This decentralized and distributed structure is common for most blockchains such as for Bitcoin and Ethereum. However, one cannot conclude that a blockchain is decentralized or distributed just because it is a blockchain.

Even though third-party involvement is not a necessity for a decentralized and distributed blockchain, a lot of utility and infrastructure have been provided by them. Such infrastructure includes centralized cryptocurrency exchanges, which we view as centralized entities. On the contrary, we view the blockchain network itself as decentralized and distributed. This is an important distinction as centralized exchanges offer the opportunity for trading cryptocurrencies with customers off-network, on their platform. On the other hand, decentralized and distributed blockchain networks offer the opportunity to perform transactions of assets across the network, such as between centralized entities, and all information is publicly available.

2.4 | Cryptocurrencies

With the introduction of blockchain and the proposal of electronic cash, the term cryptocurrency was born. A cryptocurrency utilizes the blockchain when performing operations such as transactions, payments, and trading of the cryptocurrency. Furthermore, the currency inherits the key attributes of the network such as anonymity, security, trustlessness, and speed. Cryptocurrency is by definition intangible and holds no inherent value, as it is not backed by any government entity or commodity. Instead, the currency is created and distributed by the network itself when a node mines a block that matches certain criteria. In other words, if a node creates a new block on the network, they are rewarded with a piece of cryptocurrency. Considering this, the value of the currency itself is speculative, since it is not connected to an economy like the US dollar is linked to the US economy.

The native currency of the Ethereum blockchain is defined as Ether, which is the second-largest cryptocurrency measured in market capitalization (Coinmarketcap, 2022). To own a unit of Ether, one must create a wallet connected to the Ethereum network. These wallets are categorized as custodial and non-custodial. The former represents a wallet where the owner is solely responsible for their private keys, while the latter represents a wallet on a centralized platform. On a centralized platform, it is the controlling entity that holds your private keys. Ether itself is a speculative asset as it is not backed by any commodity or government. It can be traded both on centralized and decentralized exchanges where the value per unit fluctuates with demand and supply. Furthermore, it inherits the transaction speed of the network, meaning that if one were to transfer a unit of Ether from one wallet to another, it involves the transaction speed of around 4-5 minutes.

Another currency that operates on the Ethereum network is the stable coin Tether (USDT). We define a stable coin as a cryptocurrency that is backed by an underlying asset such as a commodity, cash, or cash equivalents. The intention of Tether is that the underlying assets keep the value of the currency linked in a 1:1 relationship with the US dollar (Tether, n.d). In other words, 1 USDT is regarded as the equivalent of 1 USD. One of its main differences, however, is that USDT evades the old and traditional way of performing transactions through banks. This is due to the currency being built upon the Ethereum blockchain, which means that it can be transferred, stored, and traded with the same principles and attributes as Ether. Stable coins create the opportunity for an exchange to offer faster trading and the ability to cash out without removing the customers' funds from the platform. It also gives the customer an opportunity to send transactions of a fixed amount equivalent to dollars across exchanges without the hassle of involving a bank.

2.5 | Cryptocurrency exchanges

We define a cryptocurrency exchange as a platform where users can trade and store different types of cryptocurrencies. These exchanges can be structured as a centralized exchange (CEX) or a decentralized exchange (DEX). The former is controlled by a known company or entity, while the latter operates on the blockchain network through smart contracts which are not governed by a single entity and do not need intermediaries (Houben & Snyers, 2018, p. 26-27).

On a CEX the user can benefit from spot trading, leverage trading, and other common trading types. A common way to exploit arbitrage in the cryptocurrency market is to utilize spot trading, meaning exploiting differences in the exact market price of a given cryptocurrency between exchanges. The common way for a CEX to operate is through off-chain operations. In this paper, we assume that all the chosen cryptocurrency exchanges we look at utilize what is called an *I owe you* (IOU) system (Coinmarketcap Alexandria, n.d.).

Using an IOU system gives a CEX the ability to become an off-chain marketplace, where the trading does not involve the blockchain network directly. In figure 4 we show how a wallet holder on the Ethereum blockchain transfers funds and utilizes an exchange with the IOU structure for spot trading. First, the wallet holder creates an account on the platform, and then they transfer their funds from their custodial Ethereum wallet into their non-custodial wallet connected to the platform. While doing so the exchange takes control of the wallet holder's funds and returns an IOU document. This document explains how much the platform owes the trader when they wish to withdraw their cryptocurrency (Coinmarketcap Alexandria, n.d.).

When the user wishes to trade their deposited cryptocurrency for another type, they exchange parts of or the full IOU document with the counterpart's IOU documents. Therefore, we define a trader's wallet on the cryptocurrency platform as an IOU wallet. This wallet tracks the IOU holdings from the time of deposit to the time of withdrawal. Profit or loss will be added or deducted to said IOU documents when trading happens on the platform. If the trader wishes to withdraw the cryptocurrency back into the network, they request the cryptocurrency from the platform using their IOU document. The funds are then transferred from the platform's wallet to the user's on-chain wallet, and the platform deducts said transfer from the IOU document.

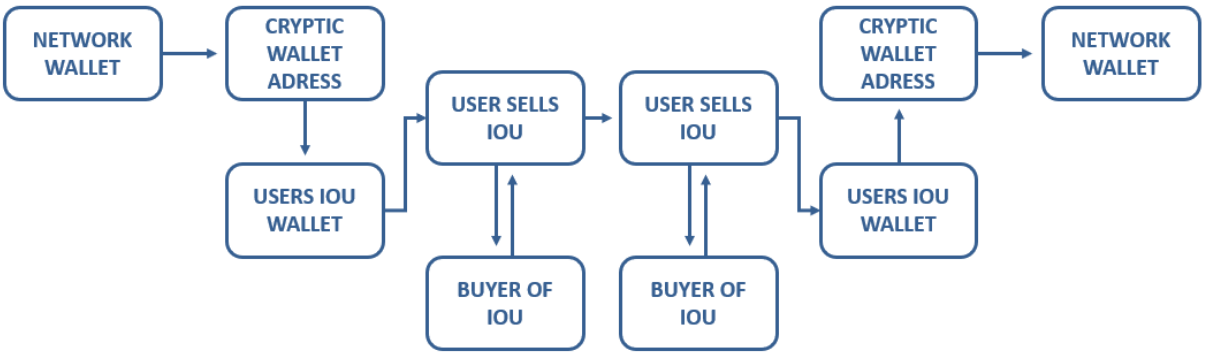

Figure 4 - Illustrating the IOU system

A decentralized exchange (DEX) on the other hand, is a type of smart contract-based marketplace. Trades are automated and happen on-chain, which means that there are no intermediaries, as the liquidity in the market comes from liquidity pools (Coinmarketcap Alexandria, n.d.). On these platforms, individuals can deposit liquidity for a certain trading pair, for example, ETH – USDT, in exchange for parts of trading fees and other rewards. In contrast to a CEX, a trade on a DEX is publicly available as they become part of the blocks on the blockchain network. With this structure, it is possible to use your custodial wallet on the Ethereum blockchain on several different DEXs without transferring your funds. This is possible because both your wallet and the trading on a DEX are on-chain. However, analyzing such trades can be quite time-consuming as they require both advanced knowledge about how to read information from the blockchain and how to retrieve the correct data.

3 | Arbitrage in Cryptocurrency Markets

Two assets that are equivalent in all the economically relevant aspects should have the same market price. This is stated by the Law of One Price. If the prices differ, then the Law of One Price is being violated, and arbitrage trading might be possible. An arbitrage opportunity is present when it is possible to make a profit without risk. This can be a stock trading for different prices on different exchanges. Arbitrageurs can take advantage of this by buying the stock where it is cheap and selling where it is expensive. Given that arbitrage opportunities are opportunities for profit without risk, any investor will want to take an infinite position. Therefore, the prices will move quickly until the opportunity is gone (Bodie, et al., 2014, p. 328). This is the mechanism through which the arbitrageurs enforce the Law of One Price.

Previous research has studied the potential for arbitrage in cryptocurrency markets. Krückeberg and Scholz (2020) found substantial and increasing opportunities for arbitrage exploitation in Bitcoin markets during the years 2015 to 2018. These results are supported by Makarov and Schoar (2020) who also found large and increasing price deviations in Bitcoin, Ethereum, and Ripple markets between January 2017 and March 2018. This includes the potential for 1.275 billion USD in arbitrage profits in Bitcoin markets just between November 2017 and February 2018. The trend of increasing arbitrage opportunities found by Krückeberg and Scholz (2020) as well as Makarov and Schoar (2020) was contradicted by Crépellière and Zeisberger (2020) who found much lower price deviations with data from October 2018 to June 2019. Further findings included that after accounting for transaction costs and the practical concerns of implementing a strategy for exploitation in Bitcoin markets, only negligible arbitrage opportunities were identified.

Our contribution to this body of research is a study examining the price deviations in Ethereum markets throughout the year 2021. We account for trading and transaction costs similarly to Krückeberg and Scholz (2020), as well as Crépellière and Zeisberger (2020). However, we differentiate between smaller and larger investors by applying different fees and present arbitrage profits for the two groups. Our research is then supplemented with an analysis of the duration of exploitable price deviations. Finally, we discuss implementation of arbitrage trading using two strategies. The first is simple, while the second is an advanced strategy that is different from the one employed by Crépellière and Zeisberger (2020).

4 | Data

We define the research design to regard the questions of what, why, when, and how to structure our project (Kothari, 2004, p. 31). In contrast, research methodology can be defined as looking at not only the methods of collecting, transforming, and processing the data but also the reasoning behind the different methods in our study (Kothari, 2004, p. 8). Furthermore, validity and reliability are defined as how accurate and reliable our approach is. We will in the following chapter walk the reader through our choice of research design and methodology, while we emphasize how our choices lead to valid and reliable results.

4.1 | Research design

With regards to our research question *"Do viable arbitrage opportunities exist in Ethereum markets?"* we seek not only to extend our knowledge within the field but more importantly to describe the characteristics of the phenomenon. With this approach in mind, we perform what is called a descriptive study. This study type differs from the two other common types; exploratory studies and hypothesis-testing studies. A descriptive study focuses more on quantitative research and the characteristics of a phenomenon (Kothari, 2004, p. 37-39). Therefore, we have a strict path to follow during our research. This path involves a pre-determined structure where after defining the problem at hand we focus on designing methods to collect, sample, and process data before we eventually report our findings and discuss them (Kothari, 2004, p. 37). To increase our knowledge on the subject before entering the process of collecting and analyzing data we used financial theory and previous research. This includes theory about arbitrage, research about blockchain technology, and previous studies of arbitrage trading in cryptocurrency markets. Based on previous research and the models we wish to use, we have found it sufficient to use secondary data in the form of 1-minute trading data collected by the open-source provider CryptoDataDownload.

4.2 | Quantitative method

The descriptive research design is a structure that builds upon quantitative methodology, which seeks to explain the unknown with the use of quantitative data. Furthermore, it utilizes different methods and models to process it. Our research consists of what is called *ex post facto research*, which means that we as researchers do not control the variables collected in the study, we only report their characteristics (Kothari, 2004, p. 3). We seek to explain, understand, and report on the phenomenon. The nature of trading data is continuous and changes within seconds. We chose to conduct our research with the use of OHLCV-data collected by CryptoDataDownload. Our dataset is classified as historical online trading data, which happens on centralized exchanges. It contains the open, high, low, and close price for the trading pair as well as the traded volume within the given interval. Furthermore, we collect data about transaction speed and network fees on the Ethereum blockchain from Etherscan. The trading data we have collected comes from three of the biggest cryptocurrency exchanges in the world; Binance, Kucoin, and FTX. Data from these three exchanges were chosen because of their high liquidity and the ability to coordinate the data across time zones.

4.3 | Validity and reliability

To ensure the validity of our results, meaning that we measure what we intended to measure, we base parts of our studies on previous research on the topic (Kothari, 2004, p. 73). This includes the use of an arbitrage index based upon 1-minute intervals which have been presented both by Makarov and Schoar (2020) and Crépellière and Zeisberger (2020). Furthermore, reliability is about ensuring that a study has accuracy and precision (Kothari, 2004, p. 73). If our study is reliable, others should be able to replicate it and come up with the same results as we did. To ensure that the data collected in our study is reliable and replicable, we have chosen to use historical trading data supplied by CryptoDataDownload. This has been a free and publicly available platform since 2017 and it tracks trading data across exchanges with the same format. This means that exchanges that operate in different time zones have been converted to NY-EST time zone by CryptoDataDownload. We would like to note that a while after we gathered 1-minute datasets from CryptoDataDownload, they removed them from the site. Should readers be interested in accessing our raw data, it is available using this link.

4.4 | Data collection

To perform our analysis, we collected 1-minute historical trading data on the trading pair Ether – Tether denoted as ETH-USDT. This trading pair offers an advantage compared to Ether – US Dollars. The reason is that USDT has the assumption of a 1:1 relationship with the dollar and can be transferred between exchanges on the Ethereum network. In other words, a transfer between exchanges can happen within minutes compared to USD which can take days. We use USDT as a proxy for USD. Therefore, we report in results in USD. Our price data originates from the exchanges Binance, Kucoin, and FTX through our third-party supplier.

4.5 | From raw to applicable data

Our data is obtained from the platform CryptoDataDownload. It is formatted in the form of minute-level price and volume data denoted as historical OHLCV data. The data covers the entire year 2021. The raw datasets contain ten columns of information which are illustrated in Table 1. It starts with the Unix and timestamp of the 1-minute interval. Our data is time-stamped in New York Eastern Standard Time (NY EST). Furthermore, the third column contains abbreviations indicating the reported trading pair. In the following columns thereafter, the price and volume data are reported. While the price data is given in open, high, low, and close. The volume is given in both Ether and USDT. In the very last column, the number of trades for the given time period is noted.

Unix	Date	Symbol	Open	High	Low	Close	Volume ETH	Volume USDT	TRADECOUNT
1643681160000	01.02.2022 02:06:00	ETH/USDT	2685.04	2686.06	2683.57	2683.66	70.05	188104.49	138
1643681100000	01.02.2022 02:07:00	ETH/USDT	2686.48	2689.87	2684.82	2685.04	675.21	1814614.12	635
$UNIX_n$	$Date_n$	ETH/USDT	$Open_n$	$High_n$	Low_n	$Close_n$	Vol ETH_n	Vol $USDT_n$	$Count_n$

Table 1 - Raw data

Although the supplied raw data contains all the mentioned columns, when conducting our research, we have no use for several of them. In the process of sorting out unnecessary data, producing our data, and calculating the results we utilize the programming environment R studio. The script to perform the following programming is attached in the appendix of this study. Since we are studying the year 2021, we removed all datapoint outside the selected timeframe from 2021-01-01 00:00:00 to 2022-01-01 00:00:00. Furthermore, we removed the columns Unix, Open, Volume ETH, and Tradecount. Thus, we are left with observations from the columns Timestamp, Symbol, High, Low, Close, and Volume USDT within the given timeframe. With this sorted data set we controlled for missing observations, meaning that rows where timestamps did not produce numeric variables for trading, were removed. Furthermore, for time periods where at least one exchange had missing observations, the same time period was deleted across all exchanges. We are left with 520 456 observed rows each representing a 1-minute interval, which cover 99.02% of the year.

4.6 | Price data

Using our revised data, we plot the closing price of Ether taken from Binance in Figure 5. This exchange has the largest volume of the three objects and thus represents the most liquid market. In the plot, we observe that the price of Ether has been quite volatile throughout 2021. Although the price peaked at 4865 USDT per unit on the10th of November 2021, we observe that there are several months where the price rapidly spikes. These spikes happened in the month of May as well as in the months between July and November. Furthermore, one can observe rapidly decreasing prices in the months of May, June, and September.

Figure 5 - Ether price 2021

Using the closing price per minute from all three exchanges we calculate the descriptive statistics on the returns. Furthermore, the return of a buy-and-hold strategy between the first and last observation is calculated. In table 2 we can see that the returns from each exchange follow what could be argued as similar distributions. The observed skewness is negative for Binance and Kucoin, while it is positive for FTX. However, the value of this skewness is quite close to zero, indicating that the distribution is nearly symmetrical. Furthermore, the distribution bells have quite heavy tails, as indicated by their extremely positive kurtosis values. These heavy tails indicate that there have been observations of extreme returns across the dataset. This is also indicated by the range of around 17.8%. Given these observations, we can conclude that returns are normally quite close to the mean. However, the returns are more extreme both negatively and positively in some periods.

	Binance	Kucoin	FTX
Mean %	0.0005	0.0005	0.0005
Standard deviation %	0.1641	0.1632	0.1612
Skewness	-0.15	-0.66	0.17
Kurtosis	90.56	84.66	72.1
Minimum in %	-9.2773	-9.472	-6.3804
Maximum in %	8.5262	6.1518	6.7471
Buy-hold return %	499.96%	500.15%	499.84%

Table 2 - Descriptive statistics on returns

4.7 | Volume data

A stacked plot of the volume traded on the exchanges is presented in Figure 6. If we compare the price development with the volume traded, we observe that they tend to spike at the same time. This indicates that with a sudden increase in the volume demanded of Ether, the price spikes accordingly. Furthermore, within our observed time period a sudden spike in the price seems to be followed by a downturn in the price shortly after. The combined volume traded is reported to be around 870 674 000 000 USDT. Binance stands for 87.5% of the total, Kucoin for 9.8%, and FTX for 2.7%.

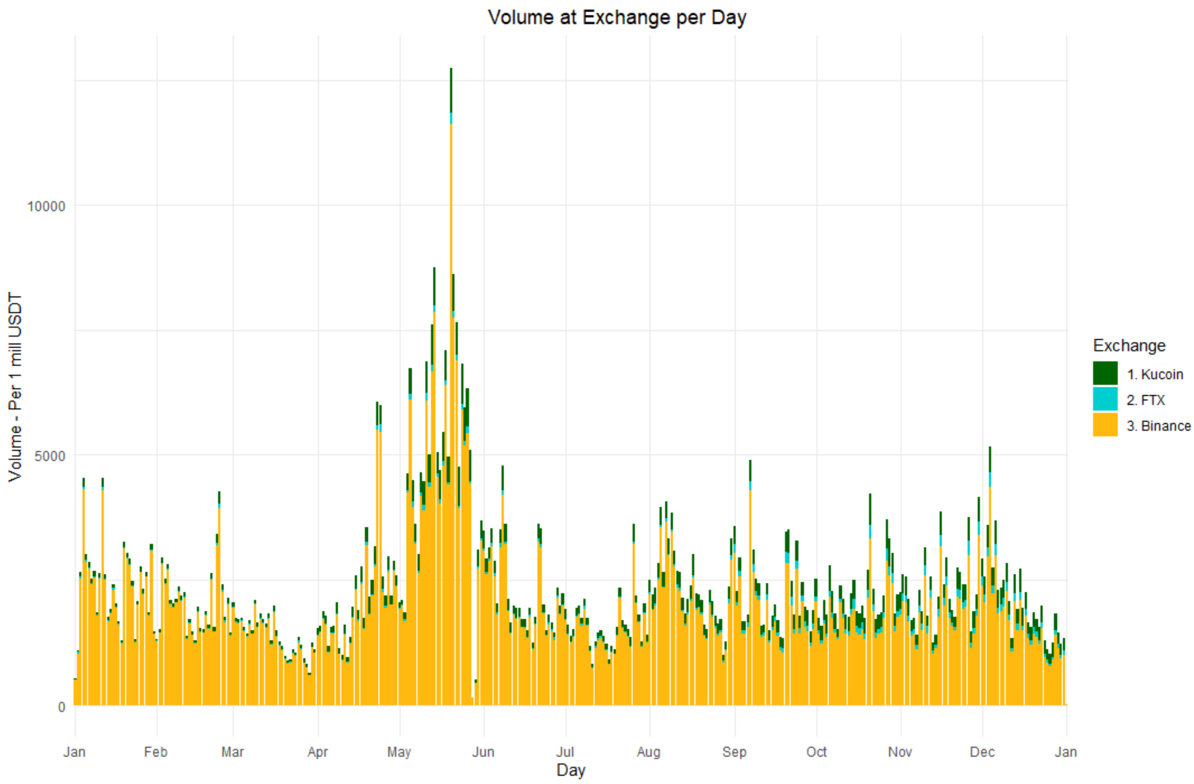

Figure 6 - Volume per day

4.8 | Blockchain data

The transaction fee from the Ethereum Network, presented in figure 7, indicates that there is a correlation between the price of Ether and the price of a transaction in the network. This can be observed in the month of May when the Ether price spiked the transaction fee spiked accordingly. The observed mean for the period is 9.88 USD, while the maximum and minimum value is reported as 68.72 and 1.82 USD. Furthermore, another key attribute of the network is the transaction speed. For the entirety of 2021, the average block creation speed was approximately 13 seconds. We assumed a block confirmation of 20 blocks. Therefore, in a normal scenario, a transaction uses around five minutes to be sent through the network. However, the transaction can take longer than the normal five minutes when there is a spike in the transaction demand. If the demanded transactions per 13 seconds exceed the maximum number of transactions a block can carry, the transaction fee becomes more expensive as a safety mechanism to regulate demand. Thus, we can observe that during large price movements in Ether, the transaction fee is observed to be higher because of the high demand for transactions, and we assume the transaction speed to be slower than usual.

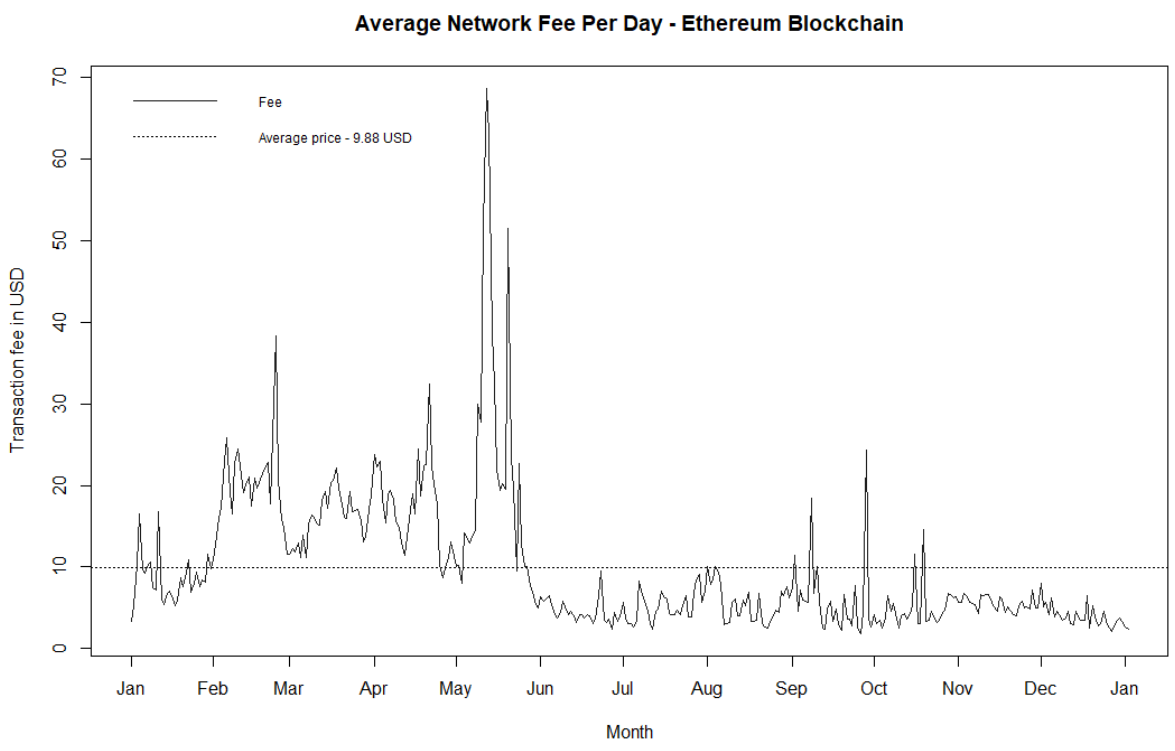

Figure 7 - Network fee

4.9 | Trading fees

When buying or selling cryptocurrencies on an exchange the trader is subjected to trading fees, which are divided into maker and taker fees. The maker fee is applied when the trader creates an order to buy or sell an asset, while the taker fee is applied when accepting an already created order. Binance and Kucoin have somewhat more expensive trading fees than FTX[3]. They operate with a 0.1% fee for both makers and takers. We simplify this and use a 0.1% fee per trade regardless of exchange. Furthermore, exchanges also lower the trading fees for accounts with higher traded volumes in the past 30 days. We simplify and use 0.01% as

[3] Sourced here.

the fee for the largest traders. Any arbitrage exploitation will need a purchase and a sale. Therefore, we refer to 0.2% and 0.02% as the trading fees for arbitrage trading.

4.10 | Arbitrage Index

The arbitrage index is a tool used in Makarov and Schoar (2020) as well as Crépellière and Zeisberger (2020) to measure price deviations between exchanges. The index is created by programming a script that looks through the observed price from each exchange at each time interval. Before we do this, we create average prices for each minute. This is achieved by adding high, low, and close prices before dividing by three. The script for the arbitrage index then selects the highest and lowest average price across the exchanges at each minute, before dividing the highest price by the lowest. This returns a vector of relative price deviations. These deviations can also be interpreted as the arbitrage return at each minute.

5 | Results

The arbitrage index in figure 8 shows the continuous relationship between the price on the more expensive of the three exchanges and the price on the cheaper of the three exchanges. The graph shows that for most observations, the price difference is quite low. It is not negligible, although it seems to be lower than 1% for the vast majority of observations. Furthermore, the figure shows that spikes in price deviation are not all that uncommon. There are many spikes showing price differences of around 1% and 2%. The most extreme observations show price deviations beyond 3% and up to around 9%. We would like to note at this point that it seems like there is a connection between the arbitrage index and the price index in figure 5. When comparing these two, it looks like price deviations and high volatility appear together. We already know from our preliminary data analysis that high volatility appears together with higher network fees and longer transaction times. Therefore, we assume that higher network fees and longer transaction times also appear together with price deviations. The following two tables expand on the properties of the arbitrage index. We also report the arbitrage index for each pair of exchanges in the appendix.

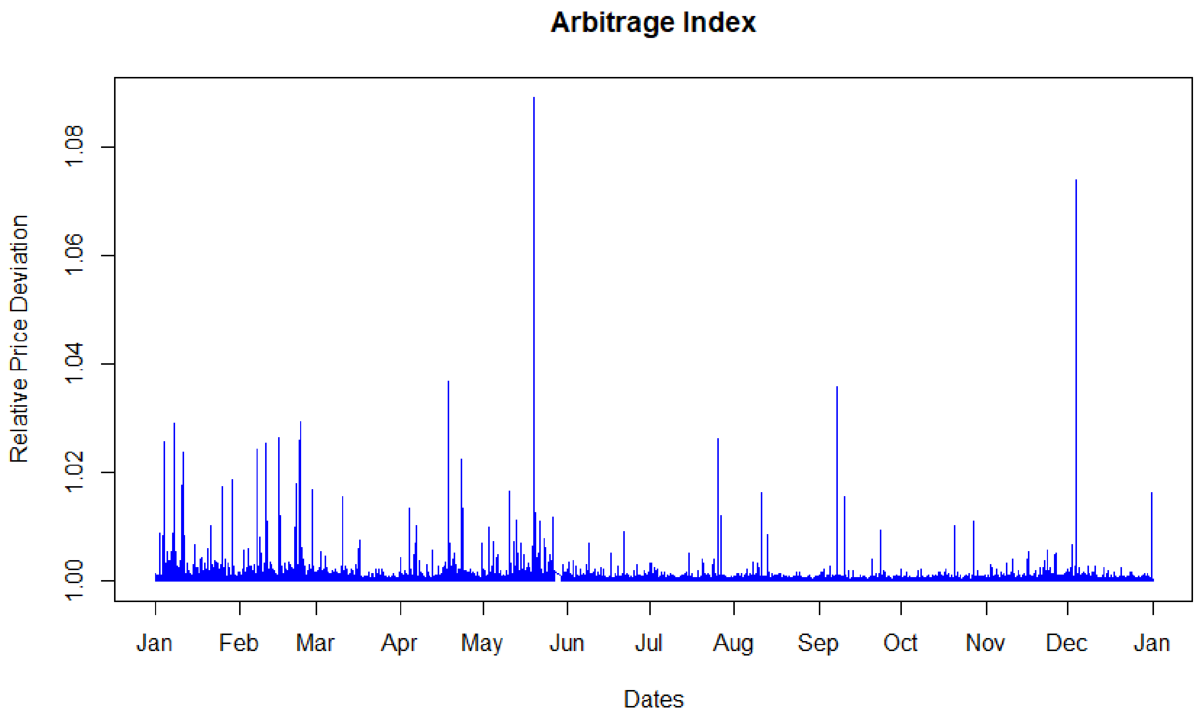

Figure 8 - Arbitrage index

Table 3 contains descriptive statistics showing the characteristics of the arbitrage index. The mean of the arbitrage index is 1.000267, which means that 1.00027 is the central location of the density. The standard deviation of 0.00075 is the average difference between a value on the arbitrage index and the mean. With a skewness of 39.77, the data is substantially skewed to the right. The very high kurtosis of 2589.59 is evidence of very heavy tails. The minimum observation is 1, which is the case for all minutes in which the prices are identical. The maximum observation on the arbitrage index is 1.089, resulting from the largest price deviation across the cryptocurrency exchanges throughout the year.

	Arbitrage Index
Mean	1.00027
Standard Deviation	0.00075
Skewness	39.77
Kurtosis	2589.59
Min	1
Max	1.089

Table 3 - Descriptive statistics on the arbitrage index

Table 4 further elaborates on the density of the arbitrage index and how it relates to the possibilities of arbitrage. Out of the 504 344 observations, 270 455 have price deviations lower than 0.02 %. The trading fees on the cryptocurrency exchanges remove the possibility of any arbitrage exploitation on these observations. 232 256 observations have a price deviation of between 0.02 and 0.2%, meaning that arbitrage exploitation is a possibility for a larger investor. The remaining categories are meant to give a sense of the magnitude of the arbitrage possibilities. 1 058 observations have price deviations between 0.2 and 0.5%, while 317 are between 0.5 and 1%. 154 are between 1 and 2%, 39 between 2 and 3%, and 27 between 3 and 4%. There are 11 observations between 4 and 5 % while the most extreme arbitrage opportunities of above 5% were found 15 times.

	Number of Observations
Price deviation, above 5 %	15
Price deviation, 4-5 %	11
Price deviation, 3-4 %	27
Price deviation, 2-3 %	39
Price deviation, 1-2 %	154
Price deviation, 0.5-1 %	317
Price deviation, 0.2-0.5 %	1 058
Price deviation, 0.02-0.2 %	232 256
Price deviation, below 0.02 %	270 455
Total Observations	504 334

Table 4 – Observed price deviations

Figure 9 illustrates the total profits of each arbitrage opportunity. It is a function of both the price deviations from the arbitrage index and the volume traded. We choose the lower volume from the exchanges whose prices deviate at each minute. This is done to ensure that buying and selling the entire volume would have been possible. Opportunities on the arbitrage index during periods with zero traded volume are removed. The trading fees of 0.2% are also taken into account, meaning that the investor is assumed to have traded a lower volume. The possible profits from most of the opportunities are quite low. The vast majority of them appear to be below 10 000 USD. Spikes in possible profits are quite uncommon, although they do happen. Opportunities between 10 000 USD and 50 000 USD seem to be somewhat common. There are also several opportunities that surpass 50 000 USD. A very select few of the opportunities surpass 100 000 USD, and the most extreme spikes go beyond 200 000 USD.

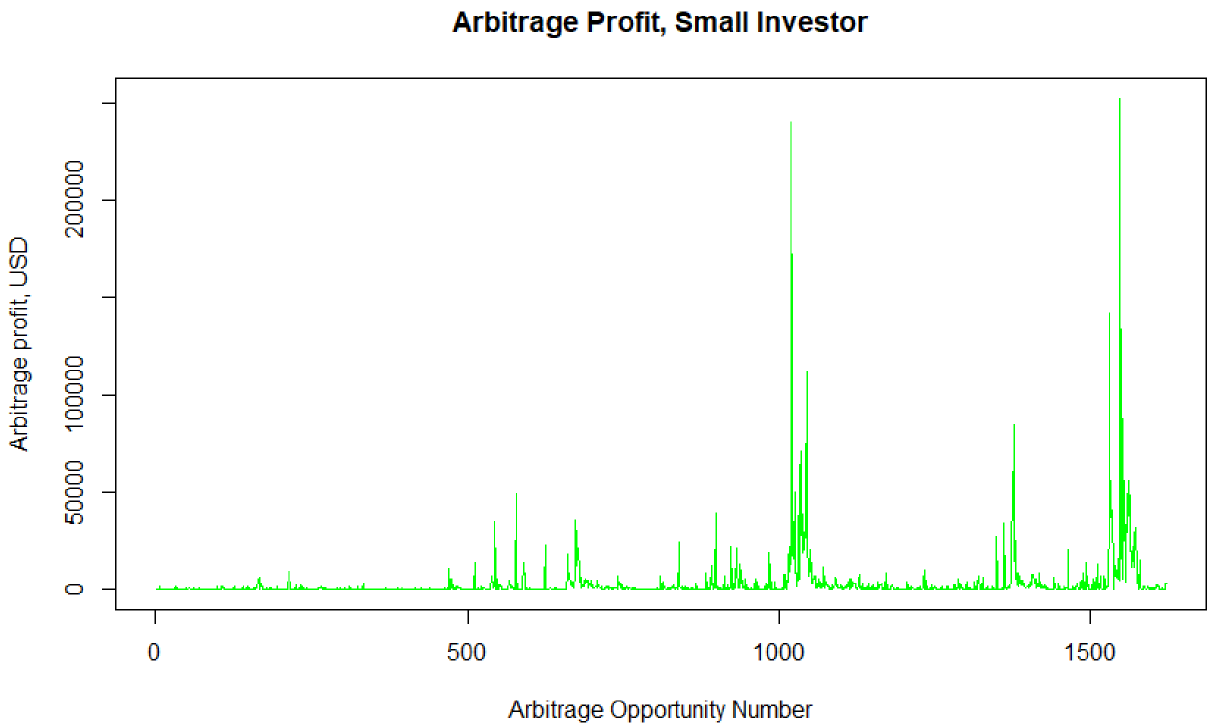

Figure 9 - Arbitrage profits, small investor

Figure 10 is similar to Figure 9, although the trading fees are different. In this case, the investor is assumed to have traded a larger volume, resulting in trading fees of only 0.02%. The profits from most of the opportunities seem to be even lower than for the smaller investor. A key difference here is the difference in scale on the x-axis. Therefore, the number of opportunities is far greater for the larger investors. They have more than 200 000 opportunities, as opposed to a little over 1 500 for the smaller investors. The majority of the extra opportunities seem to be very low, and the chances for bigger profit on opportunities seem similar to the ones available also to the smaller investors.

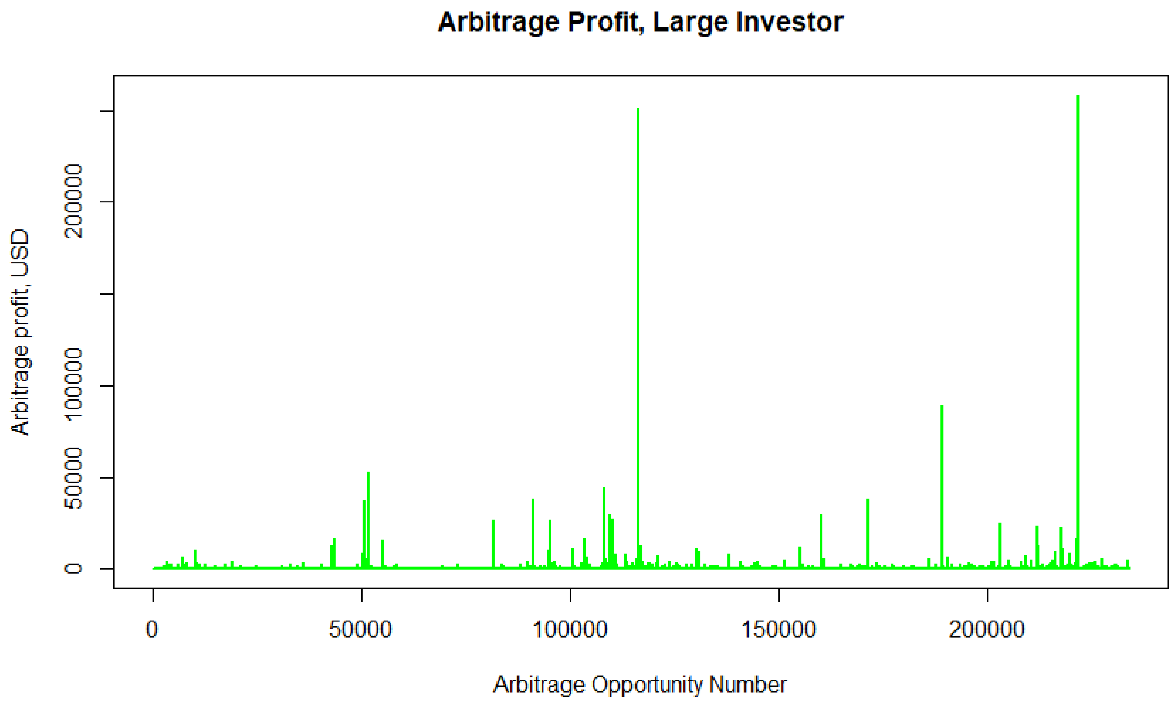

Figure 10 - Arbitrage profits large investor

Table 5 further elaborates on the magnitude of the possible profit for each observation on the arbitrage index. The middle column presents the opportunities for a smaller investor. A total of 495 opportunities yield a profit of below 100 USD. Furthermore, 397 of them are between 100 and 500 USD, 225 between 500 and 1 000 USD, while 402 are between 1 000 and 10 000 USD. In addition to this, 54 opportunities lie between 10 000 and 25 000 USD, 35 between 25 000 and 50 000 USD, 8 between 50 000 and 100 000 USD, while three are between 100 000 and 200 000 USD. Finally, the most extreme profits of above 200 000 USD are available from two opportunities. All the observed arbitrage opportunities exploited with the full volume possible throughout the year would yield arbitrage profits totalling 5 057 247.45 USD.

The right column presents the opportunities for a larger investor. A total of 224 284 opportunities yield a profit of below 100 USD. Furthermore, 7 309 of them are between 100 and 500 USD, 1 069 between 500 and 1 000 USD, while 1 084 lie between 1 000 and 10 000 USD. In addition to this, 75 opportunities lie between 10 000 and 25 000 USD, 40 between 25

000 and 50 000 USD, 11 between 50 000 and 100 000 USD, while three are between 100 000 and 200 000 USD. Finally, profits surpassing 200 000 USD are possible with two opportunities. The total arbitrage profits given full exploitation in the entire year equals 10 821 234.84 USD. The major difference between the opportunities of the investors is that the larger investors have access to a far greater number of opportunities that yield small profits. We also report the arbitrage profits for each pair of exchanges in the appendices.

Profit from Arbitrage Opportunities	Small Investor	Large Investor
Above 200 000 USD	2	2
100 000 - 200 000 USD	3	3
50 000 - 100 000 USD	8	11
25 000 - 50 000 USD	35	40
10 000 - 25 000 USD	54	75
1 000 - 10 000 USD	402	1 084
500 - 1 000 USD	225	1 069
100 - 500 USD	397	7 309
Below 100 USD	495	224 284
Total Arbitrage Profits	**5 057 247.45 USD**	**10 821 234.84 USD**

Table 5 - Arbitrage profits

Table 6 contains an overview of the duration before exploitable price deviations converge. For the smaller investor, those are the opportunities with price deviations surpassing 0.2%. The analysis shows that 78.4% of these deviations converge after 1 minute, while 10.6% of deviations converge in 1-3 minutes. In addition to this, 3.7% of the deviations converge in 3-10 minutes, 2.4% in 10-50 minutes, while 0.6% of price deviations last for more than 50 minutes. The mean exploitable price deviation lasts for 2.3 minutes, while the maximum deviation converged after 135 minutes.

For the larger investor, there are far more opportunities. It is therefore natural that the exploitable price deviations of more than 0.02%, last somewhat longer. The analysis shows that 33.2% of those opportunities last only for 1 minute. At the same time, 18.9% converge in 1-3 minutes, 22.4% converge in 3-10 minutes, and 12.5% converge in 10-50 minutes. Exploitable opportunities lasting for more than 50 minutes account for 1.7% of the total amount of opportunities. The mean exploitable deviation lasts for 6.97 minutes, while the maximum converged after 248 minutes.

Time until convergence	Small Investor	Large Investor
1 minute	78.4 %	33.2 %
1-3 minutes	10.6 %	18.9 %
3-10 minutes	3.7 %	22.4 %
10-50 minutes	2.4 %	12.5 %
Above 50 minutes	0.6 %	1.7 %
Mean	2.3 minutes	6.97 minutes
Max	135 minutes	248 minutes

Table 6 - Time until price deviations converge

5.1 | Arbitrage opportunities

Our results show that price deviations between exchanges exist and that they quite often are sizable enough to cover the fees that one must pay to trade. Furthermore, the results indicate that smaller investors stand to make 5 million USD on arbitrage exploitation, while larger investors can make 11 million USD. However, it is important to note that we cannot assume that one investor is able to capitalize on all or even most of the profits. It is reasonable to assume that the arbitrage profits will be, and already are being, competed for.

Another important caveat is that more competition for the arbitrage profits would reduce them. This is due to arbitrage trading exerting pressure on the prices and making them converge faster. It is therefore likely that if we joined in the competition for arbitrage profits in 2021, they would be somewhat reduced. What we can say for sure, however, is that these amounts were lost and won by players in the market. This is due to the currency being sold and bought at the 'wrong' prices. The following two segments will discuss the practical possibilities of arbitrage exploitation as well as the risk that comes with it. No matter the viability of exploitation, this market perspective on price deviations is applicable. Since arbitrage is the means through which the arbitrageurs enforce the law of one price, this perspective shows the usefulness of arbitrage exploitation. Engaging in arbitrage trading ties markets together, strengthens exchanges, and lowers risk for the common investor.

5.2 | Arbitrage strategies

When attempting to exploit an arbitrage opportunity using spot trading on a cryptocurrency exchange, a trader has two possible strategies to choose from. The first strategy consists of buying on the cheaper exchange, transferring, and then selling on the more expensive exchange. We refer to this as the simple strategy. The second strategy is more complicated. It requires holding both USDT and Ether on all the exchanges. When a price deviation is identified, the trader then uses USDT to buy Ether on the exchange with the lower Ether price. Simultaneously, the trader sells Ether for USDT on the more expensive exchange. To maximize payoff, the amount of Ether bought should equal the amount sold. The investor is then left with the same amount of Ether, while their USDT holdings have increased. We refer to this as the advanced strategy. When the prices converge, the reverse trades can be made so that the investor is again holding USDT and Ether on all exchanges. We call this rebalancing.

These strategies have different barriers to arbitrage exploitation. The simple strategy is sensitive to the speed of transfers between the cryptocurrency exchanges. The durations of the price deviations are not long. Because of the transaction time of around five minutes on the Ethereum network, this strategy is only useful for the fewer long price deviations. This means that the advanced strategy must be employed for the majority of arbitrage opportunities. This strategy circumvents the issue of transaction speed, as it allows for near-instant exploitation, unlike the simple strategy. It does, however, have its drawbacks. These drawbacks include the requirement of holding a substantial amount of capital across the cryptocurrency exchanges. For full exploitation, one would need to hold an amount large enough to allow for both purchase and sale of Ether equal to the unknown possible trading volume at each arbitrage opportunity, on every exchange. The possible trading volume is unknown because we do not know the volume that can be traded before the price pressure removes the price deviation between exchanges. Allowing for purchase and sale of Ether at any point entails holding the possible trading volume in both Ether and USDT.

Another drawback of this strategy is the need for rebalancing the holdings across the exchanges after making the trades. Depending on the capital held on the exchanges, the need for rebalancing might hinder trading during periods of frequently appearing arbitrage opportunities. As long as there are periods between the arbitrage opportunities in which the prices converge, rebalancing is possible and will not hinder arbitrage exploitation. The results containing the duration of the price deviations tell us that most arbitrage opportunities are followed by a chance to rebalance. Increasing the amount of capital held on each exchange is an option for mitigating the risk of imbalanced holdings hindering arbitrage exploitation. It is also worth noting that rebalancing the holdings is only needed if the price deviations move in the same direction. Let us illustrate with an example where Ether is cheaper on Kucoin than on one of the other exchanges. Ether is then bought on Kucoin as part of arbitrage exploitation. The holdings on Kucoin are now imbalanced, which limits the possibilities of future exploitation involving Kucoin. If there is a price deviation between the two other exchanges, then arbitrage exploitation is of course still possible. Should Kucoin become the more expensive exchange, then arbitrage exploitation itself will contribute to rebalancing the holdings.

5.3 | Risk exposure

The risk associated with exploiting the arbitrage opportunities is compound. A substantial amount of this risk is inherent to trading in the cryptocurrency market. It is also affected by the strategy chosen to exploit the arbitrage opportunities. When using the simple strategy, one is exposed to the risk of the prices converging during the time it takes to complete the trades and the transaction. This is a major and immediate risk. Given the typical duration of a price deviation, it is quite likely that they disappear too quickly to allow for exploitation using this method. Another cause for concern relating to the duration of price deviations is the varying transfer time. In our results, we assumed that high network fees and longer transaction time appear together with price deviations. One could speculate that the high volatility, which appears together with price deviations, also creates a transaction demand above the capacity of the network. Thus, it results in longer transaction times and higher network fees. Therefore, in periods when the arbitrage opportunities appear, we have a strong suspicion that the network is so congested that a transaction would not be completed within the duration of the price deviation.

Should the price deviation sustain long enough to allow for purchase, transfer, and sale, the unknown possible trading volume will be a limiting factor. The following scenario is conceivable: A price deviation is identified, and one buys a certain amount at the cheaper exchange, before transferring and attempting sale at the more expensive exchange. Then, one is not able to sell the full amount of Ether units that were bought. This leads to a reduced pay-out and possibly a net loss after accounting for the required fees. This strategy is also exposed to the uncertainty of the Ether price itself. Even though a price deviation is identified and exploited, a negative movement in the Ether price during the period when the cryptocurrency is owned can cause a net loss. However, this effect can also work in favour of the arbitrageur. All of this points to the simple strategy being far too risky and that this type of exploitation can hardly be called arbitrage.

When deploying the advanced strategy, one circumvents the risk of price deviations closing, as one can complete both purchase and sale near instantly. With this strategy, however, one is exposed to risk due to the capital that needs to be held on the exchanges. This includes the risk of negative price development on Ether and the risk of the exchange failing. Given the historical volatility of the Ether price, especially the former is a substantial risk. The previously mentioned need for rebalancing and the fact that the possible trading volume is unknown are limiting factors only for this strategy. They can hinder arbitrage exploitation and limit the volume traded, but there is no risk that they will turn profitable exploitation into a loss. This assumes that the trader sets a fixed price and stops trading when the price deviation converges. All of this points to the advanced strategy having much lower risk. This does not mean that it fulfils the theoretical definition of arbitrage since it is not risk-free. However, we think the advanced strategy is very much viable in Ethereum markets and worthy of implementation.

6 | Conclusion

This paper examines price deviations and aims to answer the research question “Do viable arbitrage opportunities exist in Ethereum markets?” This is achieved through analysis of the Ether - USDT trading pair on three exchanges. Using price data from 2021 on these trading pairs, we create an arbitrage index showing the largest price deviations between exchanges at any point in time. Findings show substantial and recurring price deviations. In addition to this, we find a select number of more extreme deviations of up to 9%. Still, findings contradict the trend of increasing price deviations found by Krückeberg and Scholz (2020), as well as Makarov and Schoar (2020). Our findings support the results from Crépellière and Zeisberger (2020), in that they show much smaller price deviations than what was found in earlier years. We supplement with an analysis of the arbitrage profits by subtracting trading fees and multiplying with the volume traded. The fees are differentiated based volume traded by the investors, and we find that 5 057 247.45 USD in arbitrage profits were available to smaller investors, while 10 821 234.84 USD were available to larger investors. We find a curious pattern of price deviations appearing together with volatility and network congestion. This relationship could be the subject of further research. Finally, we interpret our results through a discussion including strategies for exploitation. Contradicting the findings of Crépellière and Zeisberger (2020), we find that the arbitrage opportunities during 2021 were practically exploitable without large amounts of risk. We conclude that viable arbitrage opportunities exist in Ethereum markets.

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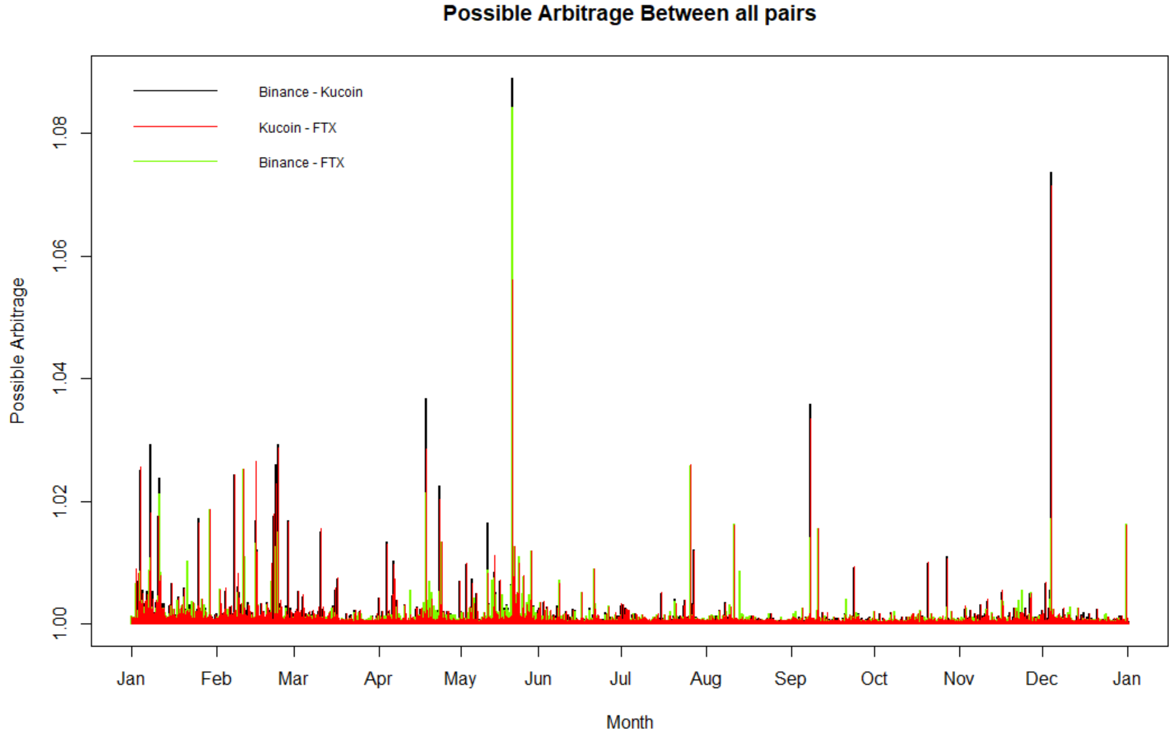
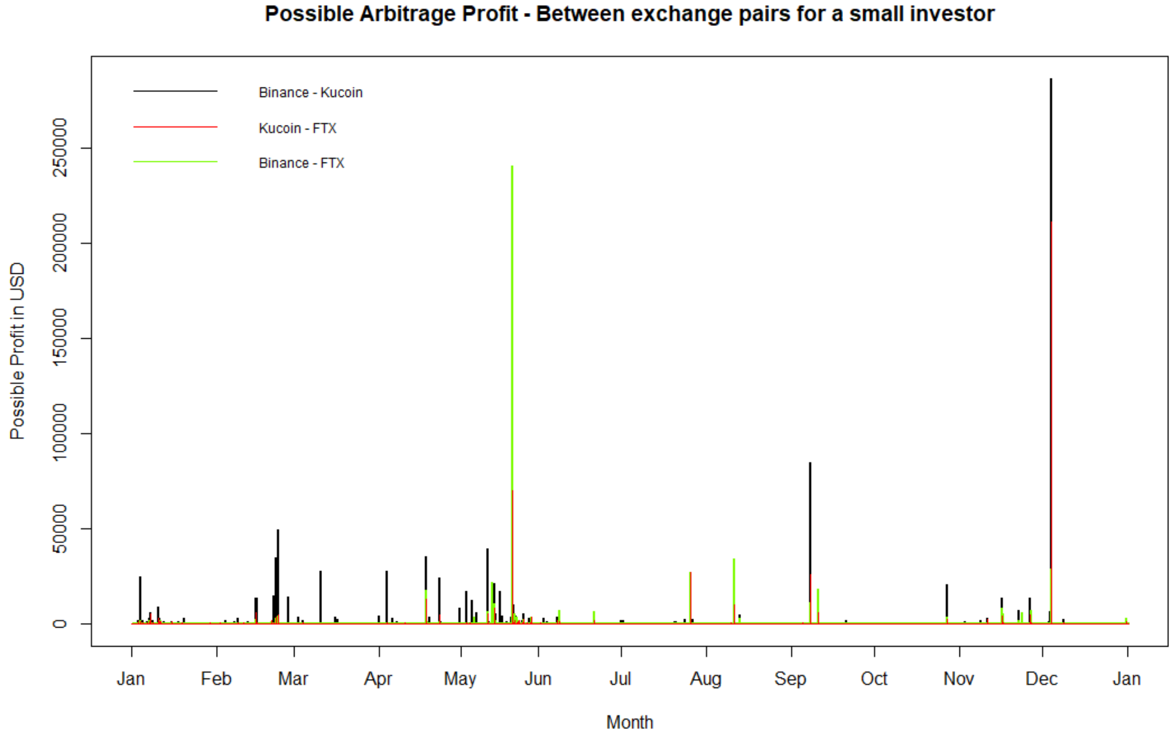
Appendix

A1 | Arbitrage index measured between exchange pairs

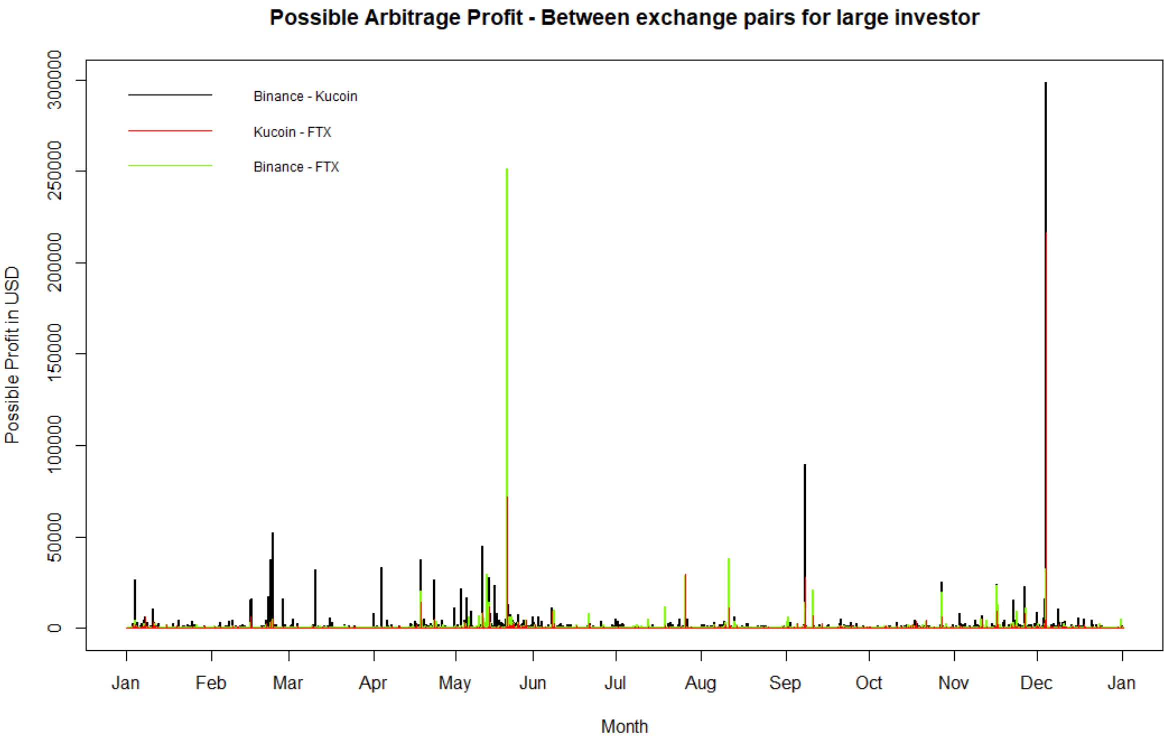


A2 | Arbitrage profits between exchange pairs – Small investors



Profit from Arbitrage Opportunities	Binance – Kucoin	Kucoin – FTX	Binance - FTX
Above 200 000 USD	2	1	1
100 000 - 200 000 USD	2	0	1
50 000 - 100 000 USD	12	6	1
25 000 - 50 000 USD	34	17	6
10 000 - 25 000 USD	66	30	8
1 000 - 10 000 USD	461	262	113
500 - 1 000 USD	151	152	85
100 - 500 USD	254	311	247
Below 100 USD	127	449	295
Total Arbitrage Profits	**5 548 412.38 USD**	**2 590 709.91 USD**	**1 230 123.73 USD**

A3 | Arbitrage profits between exchange pairs – Large investors



Profit from Arbitrage Opportunities	Binance – Kucoin	Kucoin – FTX	Binance - FTX
Above 200 000 USD	2	1	1
100 000 - 200 000 USD	2	0	1
50 000 - 100 000 USD	14	7	1
25 000 - 50 000 USD	41	16	7
10 000 - 25 000 USD	93	33	23
1 000 - 10 000 USD	1317	463	354
500 - 1 000 USD	1216	356	448
100 - 500 USD	7762	2474	2927
Below 100 USD	10051	15263	12816
Total Arbitrage Profits	**11 953 218.54 USD**	**4 578 342.22 USD**	**3 471 510.48 USD**

A5 | R studio – Script containing each self-created function used in our computation

```
###SCRIPT CONTAINING FUNCTIONS USED IN OUR R-COMPUTATIONS

#Function to choose time of the dataset
df.between.date<-function(start, end, column, df) {
  between<-which(column>=start & column<=end)
  df.between<-df[between,]
  return(df.between)

  #This function returns a dataframe where the rows that lies between the wished
  #dates. Say you have a dataset with dates and values between 2020-01-01 and
  #2022-01-01, but you wish to only have the rows that include 2021-05-05 to
  #2021-06-06, then this is the right function for you.

  #The new data will be returned in a dataset named "df.between".

  #Explanation of variables
  #Notice that variables could be either numeric or character based.
  #You might need apastrophe on the date if it is charater based.
  #   start = start date, including time
  #   end = end date, including time
  #   column = column of the dates in your dataset
  #   df = data-frame of which you which to sort from

}


#Function to choose the columns you need
column.extract<-function(df) {
  date<-as.POSIXct(as.vector(df$date), format="%Y-%m-%d %H:%M:%S", tz="UTC")
  extracted.df<-merge.zoo(df$date, df$symbol, df$high, df$low, df$close, df$Volume.USDT)
  index(extracted.df)<-date
  #extracted.df<-as.data.frame(extracted.df)
  colnames(extracted.df)<-c("date", "symbol", "high", "low", "close", "volume.USDT")
  return(extracted.df)

  #This function provides the ability to merge certain columns from your dataset
  #it will only merge the variables; symbol, high, low, close, Volume.USDT"
  #Thereafter it will index the new dataframe with the dates that belong to them.
}



#Function to calculate daily Volume
Volume1day  <- function(df, dates) {
  df<-as.numeric(df$Volume.USDT)
  dates<-substr(dates, 1, 10)
  u<-data.frame(unique(dates))
  zero<-rep(0, 365)
```

```
  for (i in 1:length(zero)) {
    zero[i]<-max(which(dates==u[i,]))
  }
  l<-c(1, (zero[1:length(zero)-1]+1))
  vol<-rep(0, 365)
  for (i in 1:length(vol)) {
    vol[i]<-sum(df[l[i]:zero[i]])
  }
  return(vol)
  #This function calculates and returns the volume traded within
  #a given day on the given exchange.
  }

#Function to calculate 1-min Average HLC
AverageHLC<-function(df) {
  typical<-(as.numeric(df$High)+as.numeric(df$Low)+as.numeric(df$Close))/3
  return(typical)
  #This function returns the Average HLC on a 1-minute interval
}

#Create a table for real profit statistics
proftable<-function(realprof) {
AboveTwoHundred<-length(which(realprof>200000))
AboveHundred<-length(which(realprof<200000 & realprof>100000))
AboveFifty<-length(which(realprof<100000 & realprof>50000))
AboveTwentyFive<-length(which(realprof<50000 & realprof>25000))
AboveTen<-length(which(realprof<25000 & realprof>10000))
AboveOne<-length(which(realprof<10000 & realprof>1000))
AboveFiveHundred<-length(which(realprof<1000 & realprof>500))
AboveOneHundred<-length(which(realprof<500 & realprof>100))
BelowHundred<-length(which(realprof<100 & realprof>0))
Sumprof<-sum(realprof)
Profitsize<-rbind(AboveTwoHundred, AboveHundred, AboveFifty, AboveTwentyFive,
AboveTen, AboveOne, AboveFiveHundred, AboveOneHundred, BelowHundred, "-",
Sumprof)
colnames(Profitsize)<-c("Number of Arbitrage Opportunities")
rownames(Profitsize)<-c("Above 200 000 USD", "100 000 - 200 000 USD", "50 000 - 100
000 USD", "25 000 - 50 000 USD", "10 000 - 25 000 USD", "1 000 - 10 000 USD", "500 - 1
000 USD", "100 - 500 USD", "Below 100 USD", "-", "Total Arbitrage Profits")
x<-reactable(Profitsize)
return(x)
#This function returns a table of the profit within each interval
}
```

A6 | R studio – Computational script

```
###R script - Master Thesis

##STEP 1 - SET DIRECTORY FOR WHERE WE RETRIEVE FILES
rm(list=ls(all=TRUE)) #To clear R environment
setwd("C:/Users/jorge/Documents/ØKAD Master/Masteroppgave/Data") #Where to retrieve files from
source("C:/Users/jorge/Documents/ØKAD Master/Masteroppgave/Crypto.R") #Script with constructed functions



##STEP 2 - CREATING DATAFRAMES FROM EXCHANGES
library(zoo)
library(dplyr)
s<-"2021-01-01 00:00:00" #Start of the datapoints
e<-"2022-01-01 00:00:00" #End of the datapoints
controldate<-read.zoo("Datoer.csv", header=TRUE, sep=";") #Dataframe with all continous dates on minute interval within the year 2021
binance.df<-read.zoo("Binance_ETHUSDT_minute.csv", header=TRUE, sep=",", dec=".") #Exchange data Binance
kucoin.df<-read.zoo("Kucoin_ETHUSDT_minute.csv", header=TRUE, sep=",", dec=".") #Exchange data Kucoin
ftx.df<-read.zoo("FTX_ETHUSDT_minute.csv", header=TRUE, sep=",", dec=".") #Exchange data FTX
binance<-as.data.frame(binance.df) #Convert from zoo to dataframe
kucoin<-as.data.frame(kucoin.df) #Convert from zoo to dataframe
ftx<-as.data.frame(ftx.df) #Convert from zoo to dataframe
binance<-df.between.date(s, e, binance$date, binance) #Retrieve only data within given timeframe
kucoin<-df.between.date(s, e, kucoin$date, kucoin) #Retrieve only data within given timeframe
ftx<-df.between.date(s, e, ftx$date, ftx) #Retrieve only data within given timeframe
class(binance) #Identify class for the dataset
class(kucoin) #Identify class for the dataset
class(ftx) #Identify class for the dataset

#Extract the columns we want to work with using column.extract function
binance<-column.extract(binance)
kucoin<-column.extract(kucoin)
ftx<-column.extract(ftx)


#Using the "controldate" dataframe to sort out missing dates,
#and minutes from our exchange data.
date<-as.POSIXct(as.vector(controldate$date), format="%Y-%m-%d %H:%M:%S", tz="UTC")
index(controldate)<-date
date<-as.POSIXct(as.vector(binance$date), format="%Y-%m-%d %H:%M:%S", tz="UTC")
index(binance)<-date
```

```
date<-as.POSIXct(as.vector(kucoin$date), format="%Y-%m-%d %H:%M:%S", tz="UTC")
index(kucoin)<-date
date<-as.POSIXct(as.vector(ftx$date), format="%Y-%m-%d %H:%M:%S", tz="UTC")
index(ftx)<-date
after<-merge.zoo(controldate, binance[,2:6], kucoin[,3:6], ftx[,3:6])
index(after)<-as.POSIXct(as.vector(controldate$date), format="%Y-%m-%d %H:%M:%S",
tz="UTC")
nan.rows<-which(complete.cases(after)=="FALSE") #Identify which rows has missing values
n.nan<-length(nan.rows) #Number of missing rows
after<-after[complete.cases(after),] #Remove rows that are not complete cases
after<-after[,3:ncol(after)] #Extract columns we want to work with
name<-names(binance[,2:6]) #Create name-variable for column names
dfnames<-c(deparse(substitute(binance)), deparse(substitute(kucoin)),
deparse(substitute(ftx)))
colnames(after)<-c(paste(dfnames[1], name, sep="."), paste(dfnames[2], name[2:5], sep="."),
         paste(dfnames[3], name[2:5], sep="."))
after
dates<-index(after)

binance<-merge(after$binance.symbol, after[,2:5])
index(binance)<-dates
kucoin<-merge.zoo(after$binance.symbol, after[,6:9])
index(kucoin)<-dates
ftx<-merge(after$binance.symbol, after[,10:13])
index(ftx)<-dates
shlcv<-c("Symbol", "High", "Low", "Close", "Volume.USDT")
colnames(binance)<-shlcv #Naming columns from SHLCV
colnames(kucoin)<-shlcv #Naming columns from SHLCV
colnames(ftx)<-shlcv #Naming columns from SHLCV

##STEP 3 - CALCULATING RETURNS FROM CLOSE-PRICE 1-MINUTE INTERVAL
n<-length(binance$Close)-1 #How many observations
ret.b<-diff(as.numeric(binance$Close))/as.numeric(binance$Close[1:n]) #Return on Binance
ret.k<-diff(as.numeric(kucoin$Close))/as.numeric(kucoin$Close[1:n]) #Return on Binance
ret.f<-diff(as.numeric(ftx$Close))/as.numeric(ftx$Close[1:n]) #Return on Binance

#We need to remove returns that were calculated on a period where rows
#were previously deleted because of missing values. The reason being
#that a jump in time could lead to extreme observed values
interval.nan<-split(nan.rows, cumsum(c(1, diff(nan.rows) != 1)))
interval.length <-rep(0, 32)
for (i in 1:length(interval.length)) {
  interval.length[i]<-length(unlist(interval.nan[i]))
}
interval.length<-cumsum(interval.length)
x<-c(59261, 61364-80, 64889-82, 71421-83, 73526-111, 92281-112, 96604-202, 116528-204,
139627-205, 145447-206, 146042-207, 157081-208, 164402-358, 199505-642, 202519-643,
210278-644, 216520-4708, 322681-4710, 359585-4980, 363332-4981, 363339-4983,
390661-4984, 423817-5104, 451926-5110, 485880-5111, 486634-5114, 494365-5123,
494372-5125, 495035-5128, 495544-5131, 510293-5138, 524344-5139, 524350-5146)
```

```
x1<-x+1

ret.b<-ret.b[-x] #Remove the unwanted values from our returns data
ret.k<-ret.k[-x] #Remove the unwanted values from our returns data
ret.f<-ret.f[-x] #Remove the unwanted values from our returns data

d<-dates[2:(n+1)]

#DESCRIPTIVE STATISTICS FROM RETURNS
library(pastecs)
library(moments)
des.b<-(stat.desc(ret.b)*100) #Mean, standard dev, max, min, etc
des.b<-round(des.b, digits=4)
skew.b<-skewness(ret.b) #Skewness
skew.b<-round(skew.b, digits=2) #Skewness
kurt.b<-kurtosis(ret.b) #Kurtosis
kurt.b<-round(kurt.b, digits=2) #Kurtosis
desc.b<-rbind(des.b[9], des.b[13], skew.b, kurt.b, des.b[4], des.b[5])

des.k<-(stat.desc(ret.k)*100) #Mean, standard dev, max, min, etc
des.k<-round(des.k, digits=4)
skew.k<-skewness(ret.k) #Skewness
skew.k<-round(skew.k, digits=2) #Skewness
kurt.k<-kurtosis(ret.k) #Kurtosis
kurt.k<-round(kurt.k, digits=2) #Kurtosis
desc.k<-rbind(des.k[9], des.k[13], skew.k, kurt.k, des.k[4], des.k[5])

des.f<-(stat.desc(ret.f)*100) #Mean, standard dev, max, min, etc
des.k<-round(des.k, digits=4)
skew.f<-skewness(ret.f) #Skewness
skew.f<-round(skew.f, digits=2) #Skewness
kurt.f<-kurtosis(ret.f) #Kurtosis
kurt.f<-round(kurt.f, digits=2) #Kurtosis
desc.f<-rbind(des.f[9], des.f[13], skew.f, kurt.f, des.f[4], des.f[5])

des<-cbind(desc.b, desc.k, desc.f) #Table for descript stat pr exchange
des<-round(des, digits=4)
colnames(des)<-c("Binance", "Kucoin", "FTX")
rownames(des)<-c("Mean, %", "Std, %", "Skew", "Kurt", "Min, %", "Max, %")
library("reactable")
reactable(des)



###STEP 4 - VOLUME
#CALCULATE DAILY VOLUME PR EXCHANGE
library(ggplot2)
day.vol.b<-Volume1day(binance, dates)/1000000 #Converting to per million USD
day.vol.k<-Volume1day(kucoin, dates)/1000000 #Converting to per million USD
day.vol.f<-Volume1day(ftx, dates)/1000000 #Converting to per million USD
```

```
#CREATE STACKED BARPLOT OF DAILY VOLUME
string.dates<-seq(as.Date("2021-01-01"), as.Date("2022-01-01"), by="days")
n.days<-1:365
vol.tot<-data.frame(day.vol.b, day.vol.f, day.vol.k) #Collection of daily volume
Exchange<-rep(c("3. Binance", "2. FTX", "1. Kucoin"), 365)
x<-rep(n.days, 3)
x<-sort(x, decreasing = FALSE)
y<-(as.vector(t(vol.tot)))
d<-data.frame(x, Exchange, y)
m<-c("1", "31", "59", "90", "120", "151", "181", "212", "243", "273", "304", "334", "365")
n<-c("Jan", "Feb", "Mar", "Apr", "May", "Jun", "Jul", "Aug", "Sep", "Oct", "Nov", "Dec",
"Jan")
ggplot(d, aes(fill=Exchange, y=y, x=factor(x)), xaxt='n') +
  theme_minimal() +
  geom_bar(position="stack", stat = "identity") +
  scale_fill_manual(values = c("darkgreen", "cyan3", "darkgoldenrod1")) +
  labs(x="Day", y="Volume - Per 1 mill USDT", title = "
Volume at Exchange per Day") +
  scale_x_discrete(breaks=m, labels=n)
```

```
###STEP 5 - PLOTTING ETH CLOSING PRICE ON BINANCE AS INDEX
plot(as.numeric(binance$Close), type="l", xlab="Dates", ylab="Ether price - USDT",
     main="ETHER PRICE 2021", col="gray12", cex=0.4, xaxt="n")
m<-c(1, 44640, 84849, 129336, 172099, 212671, 255871, 300511, 344881, 387957,
     432651, 475850, 520455)
n<-c("Jan", "Feb", "Mar", "Apr", "May", "Jun", "Jul", "Aug", "Sep", "Oct", "Nov", "Dec",
"Jan")
axis(1, at=m, labels=n) #X-AXIS TICKERS MARKED ON MONTHLY BASIS
x<-which(binance$Close==max(as.numeric(binance$Close)))
abline(v=x, lty=3, col="black")
legend(x="topleft", legend=c("Price", "Max Price - 4865 USD
10th November"),
       col=c("gray12", "black"), lty=c(1, 3), cex=0.75,
       box.lty=0, bty="n")
```

```
###STEP 6 - PLOTTING ETHEREUM NETWORK FEE FROM ETHERSCAN
Network<-read.csv("export-AverageDailyTransactionFee.csv", header=TRUE, sep=",",
dec=".")
s<-which(Network[,1]=="01-01-2021") #START OF DATAFRAME
e<-which(Network[,1]=="01-01-2022") #END OF DATAFRAME
Network<-Network[s:e,]
ind<-Network[,1]
Network<-data.frame(Network$Average.Txn.Fee..USD.)
rownames(Network)<-ind
colnames(Network)<-"Average tx fee USD"
```

```
plot(as.numeric(Network[,1]), type="l", xlab="Month", ylab="Transaction fee in USD",
    xaxt='n', main="Average Network Fee Per Day - Ethereum Blockchain", col="gray12")
m<-c(1, 31, 59, 90, 120, 151, 181, 212, 243, 273, 304, 334, 365)
n<-c("Jan", "Feb", "Mar", "Apr", "May", "Jun", "Jul", "Aug", "Sep", "Oct", "Nov", "Dec",
"Jan")
axis(1, at=m, labels=n) #X-AXIS TICKERS MARKED ON MONTHLY BASIS
mean.net<-mean(as.numeric(Network[,1])) #MEAN OF FEE
std.net<-sd(as.numeric(Network[,1])) #STANDARD DEVIATION OF FEE
abline(h=mean.net, lty=3)
legend(x="topleft", legend=c("Fee", "Average price - 9.88 USD"),
      col=c("gray12", "black"), lty=c(1, 3), cex=0.75,
      box.lty=0, bty="n")

des.net<-stat.desc(as.numeric(Network[,1])) #Descript stat fee
desc.net<-c(des.net[9], des.net[4], des.net[5]) #Descript stat fee



###STEP 7 - CREATING THE ARBITRAGE INDEX
one.binance<-AverageHLC(binance) #Create average HLC price
one.kucoin<-AverageHLC(kucoin) #Create average HLC price
one.ftx<-AverageHLC(ftx) #Create average HLC price
ones<-data.frame(one.binance, one.kucoin, one.ftx) #Data frame of average prices
ones<-as.zoo(ones)
d<-seq(from=1, to=(nrow(ones)*1), by=1)
index(ones)<-dates[d]
arb.index<-rep(0, nrow(ones)) #Empty variable to fill arbitrage index
for (i in 1:nrow(ones)) {
  arb.index[i]<-max(ones[i,])/min(ones[i,]) #Arbitrage calculation
}

##PLOT OF THE ARBITRAGE INDEX
plot(dates[d], arb.index, type="l", xlab="Dates", ylab="Relative Price Deviation",
    main="Arbitrage Index", col="blue", xaxt='n')
#TICKERS FOR LAST MINUTE OF EACH MONTH
ex<-c("2021-01-31 23:59:00 UTC", "2021-02-28 23:59:00 UTC", "2021-03-31 23:59:00
UTC", "2021-04-30 23:59:00 UTC",
     "2021-05-31 23:59:00 UTC", "2021-06-30 23:59:00 UTC", "2021-07-31 23:59:00 UTC",
"2021-08-31 23:59:00 UTC",
     "2021-09-30 23:59:00 UTC", "2021-10-31 23:59:00 UTC", "2021-11-30 23:59:00 UTC",
"2021-12-31 23:59:00 UTC")
xdates<-rep(0, length(ex))
for (i in 1:length(dates)) {
  xdates[i]<-which(dates==ex[i])
}
xdates<-c(1, xdates)
n<-c("Jan", "Feb", "Mar", "Apr", "May", "Jun", "Jul", "Aug", "Sep", "Oct", "Nov", "Dec",
"Jan")
axis(1, at=dates[xdates], labels=n) #MARKS TICKERS FOR EACH MONTH
```

```
##DESCRIPTIVE STATISTICS FOR ARBITRAGE INDEX
des.a<-stat.desc(arb.index) #Mean, std, max, min, etc.
skew.a<-skewness(arb.index) #Skewness
kurt.a<-kurtosis(arb.index) #Kurtosis
desc.a<-rbind(des.a[9], des.a[13], skew.a, kurt.a, des.a[4], des.a[5])
desc.a<-round(desc.a, digits=6)
colnames(desc.a)<-c("Arbitrage index")
rownames(desc.a)<-c("Mean", "Standard Devation", "Skewnewss", "Kurtosis", "Min",
"Max")
library("reactable")
reactable(desc.a) #Delivers a table from our dataframe


##OBSERVATION ANALYSIS OF THE ARBITRAGE INDEX
#WE WISH TO KNOW HOW MANY OBSERVATIONS ARE WITHIN THE GIVEN
INTERVALS
AboveFive<-length(which(arb.index>1.05))
AboveFour<-length(which(arb.index<1.05 & arb.index>1.04))
AboveThree<-length(which(arb.index<1.04 & arb.index>1.03))
AboveTwo<-length(which(arb.index<1.03 & arb.index>1.02))
AboveOne<-length(which(arb.index<1.02 & arb.index>1.01))
AbovePointfive<-length(which(arb.index<1.01 & arb.index>1.005))
AboveMoney<-length(which(arb.index<1.005 & arb.index>1.002))
BelowMoney<-length(which(arb.index<1.002 & arb.index>1.0002))
BelowAllMoney<-length(which(arb.index<1.0002))
NumberOb<-length(arb.index)
Money<-rbind(AboveFive, AboveFour, AboveThree, AboveTwo, AboveOne,
AbovePointfive, AboveMoney, BelowMoney, BelowAllMoney,NumberOb)
colnames(Money)<-c("Number of Observations")
rownames(Money)<-c("Profit, Above 5 %", "Profit, 4-5 %", "Profit, 3-4 %", "Profit, 2-3 %",
"Profit, 1-2 %", "Profit, 0.5-1 %", "Profit, 0.2-0.5 %", "Possible Profit, 0.02-0.2 %","No
Possible Profit, Below 0.02%", "Total observations")
reactable(Money)


##CALCULATE THE ARBITRAGE VOLUME
pos.max<-rep(0, nrow(ones)) #Creating a vector of zero's
pos.min<-rep(0, nrow(ones)) #Creating a vector of zero's
vol.max<-rep(0, nrow(ones)) #Creating a vector of zero's
vol.min<-rep(0, nrow(ones)) #Creating a vector of zero's
ones<-data.frame(as.numeric(one.binance), as.numeric(one.kucoin), as.numeric(one.ftx))

for (i in 1:nrow(ones)) {
  pos.max[i]<-which.max(ones[i,]) #Which column in every row contains the max price
  pos.min[i]<-which.min(ones[i,]) #Which column in every row contains the min price
}

volume<-data.frame(as.numeric(binance$Volume.USDT),
as.numeric(kucoin$Volume.USDT), as.numeric(ftx$Volume.USDT))
```

```
colnames(volume)<-c("Binance", "Kucoin", "FTX")
colnames(ones)<-c("Binance", "Kucoin", "FTX")

for (i in 1:nrow(ones)) {
  vol.max[i]<-volume[i,pos.max[i]] #Finds the volume at the exchange where price is max
  vol.min[i]<-volume[i,pos.min[i]] #Finds the volume at the exchange where price is min
}

vol<-data.frame(vol.max, vol.min) #Data frame with volume at max and min price in each
column


##USING ARBITRAGE VOLUME TO CALCULATE TOTAL PROFITS FOR SMALL
INVESTOR e profits for small investor
vol<-data.frame(as.numeric(vol.max), as.numeric(vol.min))
z<-which(arb.index>1.002) #Which arbitrage is over small investor fee

y<-rep(0, nrow(vol))
for (i in 1:nrow(vol)) {
  y[i]<-which.min((vol[i,]))
}

two<-which(y==2)
one<-which(y==1)

volmin<-rep(0, nrow(vol))
volmin[two]<-vol.min[two]
volmin[one]<-vol.max[one]

arb.profit<-arb.index-1.002 #Remove small investor fee from arb index
arb.profit[arb.profit<=0]<-0 #All calculations equal to or below zero become zero
realprof<-arb.profit*volmin #Arbitrage index after removal of fees times lowest volume

#PLOT OF TOTAL PROFITS FOR SMALL INVESTOR
plot(realprof, type="l", xlab="Arbitrage Opportunity Number",
     ylab="Arbitrage profit, USD", main="Arbitrage Profit, Small Investor",
     col="green", xaxt='n')
ex<-c("2021-01-31 23:59:00 UTC", "2021-02-28 23:59:00 UTC", "2021-03-31 23:59:00
UTC", "2021-04-30 23:59:00 UTC",
      "2021-05-31 23:59:00 UTC", "2021-06-30 23:59:00 UTC", "2021-07-31 23:59:00 UTC",
"2021-08-31 23:59:00 UTC",
      "2021-09-30 23:59:00 UTC", "2021-10-31 23:59:00 UTC", "2021-11-30 23:59:00 UTC",
"2021-12-31 23:59:00 UTC")
xdates<-rep(0, length(ex))
for (i in 1:length(dates)) {
  xdates[i]<-which(dates==ex[i])
}
xdates<-c(1, xdates)
n<-c("Jan", "Feb", "Mar", "Apr", "May", "Jun", "Jul", "Aug", "Sep", "Oct", "Nov", "Dec",
"Jan")
```

```
axis(1, at=xdates, labels=n) #TICKER FOR MONTHS ON X-AXIS

#TABLE FOR PROFITS WITHIN A GIVEN DOLLAR INTERVAL FOR SMALL
INVESTOR
AboveTwoHundred<-length(which(realprof>200000))
AboveHundred<-length(which(realprof<200000 & realprof>100000))
AboveFifty<-length(which(realprof<100000 & realprof>50000))
AboveTwentyFive<-length(which(realprof<50000 & realprof>25000))
AboveTen<-length(which(realprof<25000 & realprof>10000))
AboveOne<-length(which(realprof<10000 & realprof>1000))
AboveFiveHundred<-length(which(realprof<1000 & realprof>500))
AboveOneHundred<-length(which(realprof<500 & realprof>100))
BelowHundred<-length(which(realprof<100 & realprof>0))
Sumprof<-sum(realprof)
Profitsize<-rbind(AboveTwoHundred, AboveHundred, AboveFifty, AboveTwentyFive,
AboveTen, AboveOne, AboveFiveHundred, AboveOneHundred, BelowHundred, "-",
Sumprof)
colnames(Profitsize)<-c("Number of Arbitrage Opportunities")
rownames(Profitsize)<-c("Above 200 000 USD", "100 000 - 200 000 USD", "50 000 - 100
000 USD", "25 000 - 50 000 USD", "10 000 - 25 000 USD", "1 000 - 10 000 USD", "500 - 1
000 USD", "100 - 500 USD", "Below 100 USD", "-", "Total Arbitrage Profits")
reactable(Profitsize) #TABLE FOR GIVEN INTERVALS


##USING ARBITRAGE VOLUME TO CALCULATE TOTAL PROFITS FOR LARGE
INVESTOR
vol<-data.frame(as.numeric(vol.max), as.numeric(vol.min))
z<-which(arb.index>1.0002) #Which arbitrage is over large investor fee


y<-rep(0, nrow(vol))
for (i in 1:nrow(vol)) {
  y[i]<-which.min((vol[i,]))
}

two<-which(y==2)
one<-which(y==1)

volmin<-rep(0, nrow(vol))
volmin[two]<-vol.min[two]
volmin[one]<-vol.max[one]

arb.profit<-arb.index-1.0002 #Remove small investor fee from arb index
arb.profit[arb.profit<=0]<-0 #All calculations equal to or below zero become zero
realprof<-arb.profit*volmin #Arbitrage index after removal of fees times lowest volume

#PLOT OF TOTAL PROFITS FOR LARGE INVESTOR
plot(realprof, type="l", xlab="Arbitrage Opportunity Number", ylab="Arbitrage profit, USD",
     main="Arbitrage Profit, Large Investor", col="green", lwd=2.0,
     xaxt='n')
```

```
axis(1, at=xdates, labels=n) #Ticker for months on X-Axis

#TABLE FOR PROFITS WITHIN A GIVEN DOLLAR INTERVAL FOR LARGE
INVESTOR
AboveTwoHundred<-length(which(realprof>200000))
AboveHundred<-length(which(realprof<200000 & realprof>100000))
AboveFifty<-length(which(realprof<100000 & realprof>50000))
AboveTwentyFive<-length(which(realprof<50000 & realprof>25000))
AboveTen<-length(which(realprof<25000 & realprof>10000))
AboveOne<-length(which(realprof<10000 & realprof>1000))
AboveFiveHundred<-length(which(realprof<1000 & realprof>500))
AboveOneHundred<-length(which(realprof<500 & realprof>100))
BelowHundred<-length(which(realprof<100 & realprof>0))
Sumprof<-sum(realprof)
Profitsize<-rbind(AboveTwoHundred, AboveHundred, AboveFifty, AboveTwentyFive,
AboveTen, AboveOne, AboveFiveHundred, AboveOneHundred, BelowHundred, "-",
Sumprof)
colnames(Profitsize)<-c("Number of Arbitrage Opportunities")
rownames(Profitsize)<-c("Above 200 000 USD", "100 000 - 200 000 USD", "50 000 - 100
000 USD", "25 000 - 50 000 USD", "10 000 - 25 000 USD", "1 000 - 10 000 USD", "500 - 1
000 USD", "100 - 500 USD", "Below 100 USD", "-", "Total Arbitrage Profits")
reactable(Profitsize) #TABLE FOR GIVEN INTERVALS



###STEP 8 - CREATING ARBITRAGE INDEX ON EXCHANGE PAIRS
one.binance<-AverageHLC(binance) #Create average HLC price
one.kucoin<-AverageHLC(kucoin) #Create average HLC price
one.ftx<-AverageHLC(ftx) #Create average HLC price
ones<-data.frame(one.binance, one.kucoin, one.ftx)
#BK=BINANCE - KUCOIN
#KF=KUCOIN - FTX
#BF=BINANCE - FTX
arb.BK<-rep(0, nrow(ones)) #ARB INDEX Binance - Kucoin
BK<-data.frame(one.binance, one.kucoin)
arb.KF<-rep(0, nrow(ones)) #ARB INDEX Kucoin - FTX
KF<-data.frame(one.kucoin, one.ftx)
arb.BF<-rep(0, nrow(ones)) #ARB INDEX Binance - FTX
BF<-data.frame(one.binance, one.ftx)
for (i in 1:nrow(ones)) {
  arb.BK[i]<-max(BK[i,])/min(BK[i,])} #ARB INDEX CALCULATION
for (i in 1:nrow(ones)) {
  arb.KF[i]<-max(KF[i,])/min(KF[i,])} #ARB INDEX CALCULATION
for (i in 1:nrow(ones)) {
  arb.BF[i]<-max(BF[i,])/min(BF[i,])} #ARB INDEX CALCULATION

##Plot of arbitrage index on each pair of exchanges
plot(arb.BK, type="l", xlab="Month",
     ylab="Possible Arbitrage",
     main="Possible Arbitrage Between all pairs", col="black", lwd=2,
```

```
    xaxt="n")
lines(arb.BF, type="l", col="lawngreen", lwd=2)
lines(arb.KF, type="l", col="red1")
ex<-c("2021-01-31 23:59:00 UTC", "2021-02-28 23:59:00 UTC", "2021-03-31 23:59:00
UTC", "2021-04-30 23:59:00 UTC",
     "2021-05-31 23:59:00 UTC", "2021-06-30 23:59:00 UTC", "2021-07-31 23:59:00 UTC",
"2021-08-31 23:59:00 UTC",
     "2021-09-30 23:59:00 UTC", "2021-10-31 23:59:00 UTC", "2021-11-30 23:59:00 UTC",
"2021-12-31 23:59:00 UTC")
xdates<-rep(0, length(ex))
for (i in 1:length(dates)) {
  xdates[i]<-which(dates==ex[i])
}
xdates<-c(1, xdates)
n<-c("Jan", "Feb", "Mar", "Apr", "May", "Jun", "Jul", "Aug", "Sep", "Oct", "Nov", "Dec",
"Jan")
axis(1, at=xdates, labels=n) #Tickers for months on X-axis
legend(x="topleft", legend=c("Binance - Kucoin", "Kucoin - FTX", "Binance - FTX"),
       col=c("black", "red1", "lawngreen"), lty=c(1,1,1), cex=0.75,
       box.lty=0, bty="n")


###STEP 9 - CALCULATING PROFIT ON EACH EXCHANGE PAIR - SMALL
INVESTOR
afterfeeBK<-arb.BK-1.002 #Reducing for small investor fee
afterfeeKF<-arb.KF-1.002 #Reducing for small investor fee
afterfeeBF<-arb.BF-1.002 #Reducing for small investor fee

afterfeeBK[afterfeeBK<=0]<-0 #Where arbindex after fee is less than zero, return zero
afterfeeKF[afterfeeKF<=0]<-0 #Where arbindex after fee is less than zero, return zero
afterfeeBF[afterfeeBF<=0]<-0 #Where arbindex after fee is less than zero, return zero

#Trading volume within each exchange pair
BKvol<-data.frame(as.numeric(binance$Volume.USDT),
as.numeric(kucoin$Volume.USDT))
KFvol<-data.frame(as.numeric(kucoin$Volume.USDT), as.numeric(ftx$Volume.USDT))
BFvol<-data.frame(as.numeric(binance$Volume.USDT), as.numeric(ftx$Volume.USDT))

#Finding Minimum volume at each exchange
y1<-rep(0, nrow(BKvol))
y2<-rep(0, nrow(KFvol))
y3<-rep(0, nrow(BFvol))
for (i in 1:nrow(BKvol)) {
  y1[i]<-which.min((BKvol[i,])) #Which column of each row is the minimum observed
  y2[i]<-which.min((KFvol[i,])) #Which column of each row is the minimum observed
  y3[i]<-which.min((BFvol[i,])) #Which column of each row is the minimum observed
}

minvol1<-rep(0, nrow(BKvol))
minvol2<-rep(0, nrow(KFvol))
```

```
minvol3<-rep(0, nrow(BFvol))
for (i in 1:nrow(BKvol)) {
  minvol1[i]<-BKvol[i,y1[i]] #Which volume on each row is the lowest
  minvol2[i]<-KFvol[i,y2[i]] #Which volume on each row is the lowest
  minvol3[i]<-BFvol[i,y3[i]] #Which volume on each row is the lowest
}


profBK<-rep(0, length(afterfeeBK))
profKF<-rep(0, length(afterfeeKF))
profBF<-rep(0, length(afterfeeBF))
for (i in 1:length(afterfeeBK)) {
  profBK[i]<-afterfeeBK[i]*BKvol[i, y1[i]]} #Profit calcuation on the arb index
for (i in 1:length(afterfeeKF)) {
  profKF[i]<-afterfeeKF[i]*KFvol[i, y2[i]]} #Profit calcuation on the arb index
for (i in 1:length(afterfeeBF)) {
  profBF[i]<-afterfeeBF[i]*BFvol[i, y3[i]]} #Profit calcuation on the arb index

#Plot of possible profit on each pair of exchanges - SMALL INVESTOR
plot(profBK, type="l", xlab="Month",
     ylab="Possible Profit in USD",
     main="Possible Arbitrage Profit - Between exchange pairs for a small investor",
col="black", lwd=2,
     xaxt="n")
lines(profBF, type="l", col="lawngreen", lwd=2)
lines(profKF, type="l", col="red1")
n<-c("Jan", "Feb", "Mar", "Apr", "May", "Jun", "Jul", "Aug", "Sep", "Oct", "Nov", "Dec",
"Jan")
axis(1, at=xdates, labels=n) #Tickers for each month X-axis
legend(x="topleft", legend=c("Binance - Kucoin", "Kucoin - FTX", "Binance - FTX"),
       col=c("black", "red1", "lawngreen"), lty=c(1,1,1), cex=0.75,
       box.lty=0, bty="n")


#TABLES OF PROFIT BETWEEN PAIRS SMALL INVESTOR
table.BK<-proftable(profBK)
table.KF<-proftable(profKF)
table.BF<-proftable(profBF)



###STEP 10 - CALCULATING PROFIT ON EACH EXCHANGE PAIR - LARGE
INVESTOR
afterfeeBK<-arb.BK-1.0002  #Reducing for large investor fee
afterfeeKF<-arb.KF-1.0002  #Reducing for large investor fee
afterfeeBF<-arb.BF-1.0002  #Reducing for large investor fee

afterfeeBK[afterfeeBK<=0]<-0 #Where arbindex after fee is less than zero, return zero
afterfeeKF[afterfeeKF<=0]<-0 #Where arbindex after fee is less than zero, return zero
afterfeeBF[afterfeeBF<=0]<-0 #Where arbindex after fee is less than zero, return zero
```

```
BKvol<-data.frame(as.numeric(binance$Volume.USDT),
as.numeric(kucoin$Volume.USDT))
KFvol<-data.frame(as.numeric(kucoin$Volume.USDT), as.numeric(ftx$Volume.USDT))
BFvol<-data.frame(as.numeric(binance$Volume.USDT), as.numeric(ftx$Volume.USDT))

#Minimum volume at each exchange
y1<-rep(0, nrow(BKvol))
y2<-rep(0, nrow(KFvol))
y3<-rep(0, nrow(BFvol))

for (i in 1:nrow(BKvol)) {
  y1[i]<-which.min((BKvol[i,])) #Which column of each row is the minimum observed
  y2[i]<-which.min((KFvol[i,])) #Which column of each row is the minimum observed
  y3[i]<-which.min((BFvol[i,])) #Which column of each row is the minimum observed
}

minvol1<-rep(0, nrow(BKvol))
minvol2<-rep(0, nrow(KFvol))
minvol3<-rep(0, nrow(BFvol))
for (i in 1:nrow(BKvol)) {
  minvol1[i]<-BKvol[i,y1[i]] #Which volume on each row is the lowest
  minvol2[i]<-KFvol[i,y2[i]] #Which volume on each row is the lowest
  minvol3[i]<-BFvol[i,y3[i]] #Which volume on each row is the lowest
}

profBK<-rep(0, length(afterfeeBK))
profKF<-rep(0, length(afterfeeKF))
profBF<-rep(0, length(afterfeeBF))
for (i in 1:length(afterfeeBK)) {
  profBK[i]<-afterfeeBK[i]*BKvol[i, y1[i]]} #Profit calcuation on the arb index
for (i in 1:length(afterfeeKF)) {
  profKF[i]<-afterfeeKF[i]*KFvol[i, y2[i]]} #Profit calcuation on the arb index
for (i in 1:length(afterfeeBF)) {
  profBF[i]<-afterfeeBF[i]*BFvol[i, y3[i]]} #Profit calcuation on the arb index

#Plot of possible profit on each pair of exchanges - LARGE INVESTOR
plot(profBK, type="l", xlab="Month",
     ylab="Possible Profit in USD",
     main="Possible Arbitrage Profit - Between exchange pairs for large investor",
col="black", lwd=2,
     xaxt="n")
lines(profBF, type="l", col="lawngreen", lwd=2)
lines(profKF, type="l", col="red1")
n<-c("Jan", "Feb", "Mar", "Apr", "May", "Jun", "Jul", "Aug", "Sep", "Oct", "Nov", "Dec",
"Jan")
axis(1, at=xdates, labels=n) #Tickers for each month X-axis
legend(x="topleft", legend=c("Binance - Kucoin", "Kucoin - FTX", "Binance - FTX"),
       col=c("black", "red1", "lawngreen"), lty=c(1,1,1), cex=0.75,
       box.lty=0, bty="n")
```

```
#TABLES OF PROFIT BETWEEN PAIRS LARGE INVESTOR
table.BK<-proftable(profBK)
table.KF<-proftable(profKF)
table.BF<-proftable(profBF)



###STEP 11 - FINDING THE ARBITRAGE WINDOWS LENGTH
z<-which(arb.index>1.002)
windows<-split(z, cumsum(c(1, diff(z) != 1)))
Windowlengths <-rep(0, 704)

for (i in 1:length(Windowlengths)) {
  Windowlengths[i]<-length(unlist(windows[i]))
}

meanwindow<-mean(Windowlengths) #Average window length
maxwindow<-max(Windowlengths) #Maximum windows length
onewindow<-((length(which(Windowlengths==1))/704)*100)
threewindow<-(((length(which(Windowlengths<3 & Windowlengths>1)))/704)*100)
tenwindow<-(((length(which(Windowlengths<10 & Windowlengths>3)))/704)*100)
fiftywindow<-(((length(which(Windowlengths<50 & Windowlengths>10)))/704)*100)
abovefiftywindow<-(((length(which(Windowlengths>50)))/704)*100)

WindowAnalysis <- rbind(onewindow, threewindow, tenwindow, fiftywindow,
abovefiftywindow, meanwindow, maxwindow)
colnames(WindowAnalysis)<-c("How long until convergence? % of Arbitrage
Opportunities")
rownames(WindowAnalysis)<-c("1 Minute", "1-3 Minutes", "3-10 Minutes", "10-50
Minutes","Above 50 Minutes", "Mean", "Max")
WindowAnalysis<-round(WindowAnalysis, digits=2)
reactable(WindowAnalysis) #Returns table for analysis
```

A7 | Discussion paper – Patrick Klubben Lavik

International forces in the cryptocurrency market

In our thesis we looked at the viability of arbitrage opportunities in Ethereum markets. With this in mind our main objective was to look at the market efficiency and if there were possible ways to practically exploit the arbitrage opportunities. Findings suggest that there is in fact viable ways to exploit arbitrage in these markets. However, these arbitrage opportunities come during increased price volatility. This volatility has been shown to be affected by international forces such as government decisions and possibly also social trends.

Cryptocurrencies were first introduced in 2008 when Satoshi Nakamoto created Bitcoin (Nakamoto, 2008). Nakamoto introduced Bitcoin as a form of electronic cash which were built upon blockchain technology. The blockchain technology functions as a distributed and decentralized electronic ledger network where the decision-making and trust lies in the hands of the network rather than in the hands of a third-party. Although other cryptocurrencies have been introduced in recent years Bitcoin still remains as the largest in terms of market capitalization (Coinmarketcap, n.d.).

For a cryptocurrency to function they utilize the blockchain network structure, meaning that they can be transferred from anyone to anyone. These transactions can happen within a country or across borders, nonetheless they are efficient, low cost and can happen without limitations. In comparison if a user chose to make the transfer across borders through a bank the transfer often takes days, has a high minimum cost, and can be limited. However, users are required to have internet connection and needs to be connected to the blockchain network through a wallet on the blockchain. Such an infrastructure creates the opportunity for cryptocurrencies to become a globally used currencies for transactions and store of value. But for them to become globally used currencies, international forces such as governments, needs to establish a full set of frameworks and regulations in place. This has yet to be the case.
In comparison to the US dollar, which is backed by a government entity and a countries economy, the value of Bitcoin is not backed by any government or underlying asset. It is however regarded as legal tender in countries such as El Salvador and the Central African Republic (BBC News, 2022). Since the value is not fixed it obtains a speculative nature where the value of the asset arguably lies in which attributes it could adapt or represent for the future. With focus on international forces and the speculative value of cryptocurrencies it would be interesting to look at macro-factors and -decisions with regards to how they affect

the price of cryptocurrencies. Such factors and decisions could play a decisive role in the adoption of crypto and therefore create shocks in demand and supply, which again leads to arbitrage opportunities during the following price volatility. Since Bitcoin is the largest by market capitalization and the market seems to correlate with its movement, I use it as an example when identifying the factors (Coinmetrics, n.d.).

For such a task the PESTEL model is the natural tool of choice. This model seeks to identify Political, Economic, Social, Technological, Environmental and Legal factors that affects an industry (Yüksel, 2012, p. 1). Some of the factors identified in the model, made by international players, arguably gives the industry supply or demand shocks, which again affects the price formation.

PESTEL ANALYSIS	
Political	Bitcoin was regarded as legal tender in El Salvador (ES) in 2021, with Central African Republic (CAR) following in 2022.[4]
Economical	Interest rates were extremely low during 2021 on a global scale.[5] Inflation is on the rise worldwide.[6]
Social	Millennials, which grew up with technology, is reaching the age where one normally becomes more financially stable. [7]
Technological	Both smartphones and internet are becoming increasingly available for the global population.[8]
Environmental	Proof-of-work, which is the consensus mechanism behind Bitcoin, requires a significant amount of energy.[9]
Legal	China banned cryptocurrency mining in May 2021 and cryptocurrencies in general in in September 2021.[10]

While ES and the CAR are considered as small economies on the international stage, speculators could regard this as a positive change of perception in the world of politics. If two small economies are successful with introducing Bitcoin as legal tender, what is there to stop other countries from trying the same. If more countries were to follow the demand for Bitcoin would go up. In other words, while El Salvador and the CAR does not represent strong buying power, after the decision by the two countries to adopt Bitcoin. Investor started speculating on which other international players was next, which in theory would lead to a positive change in the demand cure and therefore a higher price.

[4] BBC News, 2022
[5] Global rates, n.d.
[6] Financial Times, n.d.
[7] Gibson & Sodeman,
[8] Bankmycell, n.d.
[9] New York Times, 2021
[10] Coindesk, 2022

Furthermore, when international interest rates decrease to the low-levels of 2021, investments in speculative assets rose. In this case where the international community as a whole introduces government relief checks and decreases interest rates one was bound to see a shock in the demand for speculative assets. This was due to the investor getting almost nothing in return on his saving in the bank, and rational investors would therefore seek returns on other investments. Now I am not saying that cryptocurrency speculation is a rational investment, but one could argue that 2021 led to an extremely speculative stock market as well. The backlash of the loosen monetary policy has become increasing inflation rates worldwide, which governments now try to manage through the increase of interest rates. Which again leads to less investment in speculative assets since the investor could get a higher guaranteed risk-free return on their savings. A perfect example of a country that could follow up on ES and the CAR with adopting cryptocurrencies is the nations of Venezuela or Lebanon, which are experiencing extreme inflation. If introducing Bitcoin as legal tender shows less fluctuation than their native currency, then the population could benefit from it.

With millennials, the generation born in and around the 90's, now growing into the age where one normally becomes financially stable there could become increases in investments into alternative technologies such as crypto. A reason for this is due to millennials having grown up with technology everywhere could be more likely to see a potential of new technologies compared to the older generation. Seeing that iPhones where somewhat ridiculed when they were introduced because of their touch screen, one could speculate that millennials might adapt to cryptocurrencies the same way they did with smartphones.

Cryptocurrencies exist on blockchain networks, a technology that utilizes the internet along with computers for its infrastructure. The increase in adoption of the internet and mobile electronics such as smartphones on a global scale could lead to more adoption. Today approximately 6.6 billion people have access to smartphones, while there are approximately around 5 billion that uses the internet. Being that internet and smartphones can be utilized in countries where financial systems are less stable an increase in demand could happen over time. Due to investors seeking more stable options and since one could easily just trade and store cryptocurrencies on their phone as long as they have access to the internet. This means that there are a lot of potential userbase across the world for cryptocurrencies.

The environmental impact of cryptocurrencies is quite controversial and is often advertised by international players as to why adoption of Bitcoin is bad. Seeing as just the mining of Bitcoin uses more energy than the whole of Finland there is no doubt that cryptocurrencies are impacting the environment negatively. If one were to look at what cryptocurrencies are trying to solve, being a type of electronic cash, one should compare the energy usage with that of regular government backed cash. Without going into the topic too deep, this could be regarded as a threat for the adoption of cryptocurrencies, as there is continuous focus on sustainable and efficient use of energy by international forces.

China introduced new legal framework banning mining of cryptocurrencies in May 2021 and further banning cryptocurrencies in general from September 2021. Since the Chinese had one of the leading mining industries and had quite a large userbase for cryptocurrency trading there was no doubt that this decision would lead to a more negative sentiment for cryptocurrency speculators. With such a legal framework, a global economy, and almost 15% of the world’s population were prohibited from trading or mining cryptocurrencies. After the mining ban in May 2021 the price of Bitcoin plummeted around 50% over the next coming months, possibly due to both the mining difficulty decreasing and that previous miners liquidated their holdings. However, after the trading ban in September 2021 the cryptocurrency market did not react to much, which could have been because of already negative sentiment about crypto in China.

In our paper we looked at the at the viability of arbitrage opportunities in Ethereum markets and found that such opportunities increase during periods with increased volatility in the markets. International forces and trends tend to play a huge part in these volatility spikes in the last year. Specifically, I would like to point out the decision made by ES and CAR to adapt Bitcoin as legal tender which leads to a positive sentiment for speculative investors as the possible future utility increases. However, such decisions made by small economies are nothing compared to the cryptocurrency ban in China of 2021. If frameworks and regulations were set in place one could speculate that the price volatility would decrease, since speculators then would see what the future holds for the currency instead of just speculating without any asset to back it up.

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Discussion Paper - Jørgen
International

This paper will discuss the concept of being international in light of the thesis that I am writing together with my colleague. I start with a brief presentation of our master thesis, before identifying international trends and forces. Then, I move on to discussing how these trends may affect the different aspects of our thesis. The paper continues with a discussion of the general relevance of the concept of being international to the thesis. Finally, I summarize the arguments that have been presented and conclude with my final thoughts.

Our thesis is an examination of cryptocurrency markets. Specifically, we are investigating the possibility for arbitrage exploitation with the cryptocurrency Ethereum on global centralized cryptocurrency exchanges. This gives us the research question: Do viable arbitrage opportunities exist in Ethereum markets? The research question entails that we are trying to identify deviations in price on Ethereum between the cryptocurrency exchanges. Given that we want to examine the viability of arbitrage opportunities, we look deeper into some of the factors that may hinder arbitrage exploitation. This includes the fees for trading on the platforms, the duration of price deviations, the volumes that are traded and the implementation of a practical strategy for arbitrage trading. We find significant price deviations between exchanges at times. We also find that the other factors do not take away the possibility of arbitrage exploitation, although they add complexity to the needed practical trading strategy, and lower the profitability somewhat. This gives us the conclusion that viable arbitrage opportunities do exist in Ethereum markets.

In this section of the paper I will identify some international trends and forces and discuss why they are relevant in regards to our thesis. Cryptocurrency can be argued to be very much a part of the world economy. Our thesis focuses on a large cryptocurrency traded on global exchanges. Our thesis is therefore very much connected to the world economy in general.

Peng & Meyer (2016, p. 18) say this about the world economy: “[...] the world economy may best be described as a combination of continuous technological advance and pendulum swings in government policies, resulting in waves of globalization”. This quote introduces two of the international forces that I want to discuss in this paper. The first one is technological advancements, and the second one is government policies. Neither of these forces have to be seen as inherently international, especially not government policies which are decided in large part in nation states. I would like to argue however, that these forces are important drivers of internationalization. Doing this, I assume to find my own road to a similar conclusion as Peng & Meyer (2016, p. 18), when they say that these forces end up “[...] resulting in waves of globalization”.

Firstly, I see the relationship between technological progress and government policy as something very similar to the relationship between chaos and order. Technological advance, which can be seen as chaos, is a process that breaks up the status quo and radically changes our environment. In doing this, we are catapulted into new and unknown territory which takes a while to figure out. Government policy, which can be seen as order, is a mechanism through which we can again establish order in our new and unknown environment. As we get familiar with a new technology, we learn more about the benefits and dangers of it. Then, government policy can be introduced to tame the technology and mitigate some of the dangers. Due to this, technological progress can be seen as an important international force because it breaks up the status quo. It makes the world more international by connecting people across national borders. It can let them communicate even though they do not speak the same language. And it can circumvent the legislative barriers that keep things national, as opposed to international.

Government policy can be seen as an important international force because it counteracts some of the effects of technological progress. It is important to note, however, that government policy can be argued to be constantly playing catch-up to technological progress. Given that it is the process that re-establishes order, it must happen after we have been sent into chaos by technological progress. It can therefore be thought to counteract the internationalization of technological progress. Even though this may be the case, it is still an important factor in the concept of international, because it does still have an effect on internationalization. Through this line of thinking, I can understand Peng & Meyer characterizing globalization as happening in waves. Technological progress suddenly makes the world more international, like a wave crashing onto land. Then, government policy takes the technology under control, like the ocean pulling back after the wave, slowly re-establishing some national order.

Now, I am going to discuss the relevance of these forces to our thesis. I start with technological progress, which is pretty straightforward to establish relevance for. Firstly, cryptocurrency is the result of very recent technological progress. Even though it would be possible to examine the effect of technological progress on numerous details about our thesis, like the technology used by the cryptocurrency exchanges, or the effect on future arbitrage possibilities, I would like to take a step back and start with the big picture. I would argue that technological progress is a key in deciding the fate of cryptocurrencies. I think it is going to have a strong effect on whether or not cryptocurrencies will be used at all some time into the future. I think this is due to a couple of different reasons. Firstly, it is possible to imagine new and better technology completely taking over as a form of currency. This way, cryptocurrency could be completely circumvented before it really takes off. Another possibility is that financial crime develops to be more effective at exploiting the weaknesses of cryptocurrency. Cryptocurrency, which might be regarded as a very safe form of currency today, could very much be affected by this. It is possible to imagine an arms-race between the makers of cryptocurrency and financial criminals. Should financial criminals gain the upper hand then it is not hard to imagine cryptocurrency completely falling out of favor. These are some of the ways that future technological progress could affect the standing of cryptocurrency in the world.

Government policy is also going to be crucial for the existence of cryptocurrency. It is something that I imagine can make or break the usefulness of cryptocurrency, or any other alternative form of currency. It is possible for government policy to put a straight out ban on cryptocurrency. This was the case in China in 2021, as the country's central bank announced that all transactions of cryptocurrencies are illegal (BBC, 2021). It can also be thought possible for governments to monitor transactions, freeze accounts and take away funds. All of this would contribute to removing some of the utility and security of cryptocurrency. However, I imagine that this type of government control is only possible in waves, as discussed in the previous part of this paper. That means that such bans are only really possible after a technology has been established and is somewhat well-known. Regulation is playing catch-up to the technology. It can also be imagined that as technological progress is accelerating massively, this type of government control will be increasingly difficult to exert. I imagine an arms-race between technology and regulation, where regulators will fall increasingly far behind. A counterpoint to this could be that currency needs to be well-known and trusted for people to have faith in its value. It could therefore be the case that cutting edge crypto technology, though able to circumvent regulation and government policy, might not be people's choice of asset to place their values in. It could be the case no matter how secure and theoretically perfect the technology might be for a currency, that people will still need a lot of time to trust it. Perhaps it could also be the case that governments could remove peoples trust in a currency, simply by voicing disapproval, even though they may not be able to hinder the technology yet. There are therefore many ways that government policy could affect the status of cryptocurrency. I would also like to note at this point, that I am not making a value judgment on whether or not currency having freedom from government regulation is a good thing. I would think that people having access to currency that cannot be meddled with in the case they live under a tyrannical government would be a good thing, but that there is also of course utility in regulation by well-functioning authorities. In this paper I am simply trying to imagine some of the outcomes that a continuous battle between technology, government regulation and crime might lead to in the future.

For the next part of this paper, I would like to take a deeper dive into the findings in our master thesis. I am going to discuss how the forces, technological progress and government policy affect the possibility for arbitrage trading and the efficiency of cryptocurrency markets. We start with the effect of technological progress on arbitrage opportunities. I imagine this is likely to reduce and remove arbitrage opportunities. As markets are tied together by better technology, price deviations are not as likely to appear. Information moves faster and therefore other players in the market can take action faster. Government policy however, can contribute to increasing the possibility for arbitrage opportunities. This is because regulation can create barriers between markets which in turn increase the likelihood of prices deviating.

In summary, even though there are no doubt many aspects of the concept international that could have an effect on different aspects of our master thesis, I have chosen to focus on technological progress and government policy. They are important international forces as they can be argued to affect the world economy in a process that is much like the struggle between chaos and order. For the discussion I wanted to take a step back and look at the big questions regarding cryptocurrency. One of those is; Is cryptocurrency going to be used as a currency on a large scale going into the future? The forces identified play a role in deciding the future fate of cryptocurrency. Technological progress does this perhaps through the empowerment of financial criminals or through the development of something superior that takes the place of cryptocurrency. Government policy can affect cryptocurrency directly through bans or by regulation of some of the features of cryptocurrency. It is also possible for government to de-legitimize cryptocurrency by voicing opposition to it. My thoughts on the subject can be summed up as a continuous competition between technology and government policy. In addition to this, I include a shorter discussion into the effects of these forces on the possibilities for arbitrage trading on cryptocurrencies. My thoughts are that technology is likely to reduce arbitrage opportunities, while government policy can increase the likelihood of them appearing.

Literature

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