Master Thesis U.S.E.

Non-fungible token and Cryptocurrency: Substitutes or Complements?*

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Abstract

On the 14th of March 2022, a vote was held by the European Commission, deciding on the future of half of the crypto market in Europe. This paper aims to investigate the relationship between non-fungible token and cryptocurrency. We want to know, weather non-fungible token and cryptocurrency are substitutes or complements. A review of the literature reveals, that this is not the first time that researchers attempt to analyse the relationship between NFTs and cryptocurrency however, this paper introduces a difference in difference methodology, which has never been used in this field before. Difference in difference is a statistical method used to establish solid cause and effect relationships. We can therefore say with confidence, that the results of this study depict a causal effect. The policy shock from the European Commission will show us, how the markets and in particular investors react to a changing sentiment in the crypto community. In previous studies, researchers believe to have found evidence of a complementary type of relationship between NFTs and cryptocurrency. The findings of this paper confirm these results and clearly show an increase in the number of buyers and an increase in sales volume, of selected non-fungible tokens after the shock.

Keywords: Non-fungible token, cryptocurrency, difference-in-difference, regulation

JEL-Codes: G18, C33, K24

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1.0 Introduction

It is often said that the first ever cryptocurrency is Bitcoin, which is created in 2009 by Satoshi Nakamoto and his famous whitepaper about blockchain technology. We still do not know the true identity of Nakamoto or the group that stands behind this pseudonym. Nevertheless, Bitcoin is actually not the first cryptocurrency. There have been various attempts and projects in the late 1980s and 90s to create a digital version of currency. One example is Blinded Cash. Blinded Cash is developed in 1989 by an American called David Chaum. Chaum gained a professional reputation for his comprehensive contribution to the field of cryptography. Cryptography is a scientific field, that strives to develop techniques that only enable the sender and receiver of a message to read its content (Kaspersky, n.d.). In his early experiments, he comes up with a system that encrypts data and enables the transfer of information, token, between individuals. At the same time, his encryption system guarantees safety and authenticity (Sharma, 2022). In today's terminology, such a system would be revered to as blockchain technology. As we can see, the idea of cryptocurrency has been around for more than 40 years, and new developments step into light constantly. Because of its long existence, extensive research has already been done in this field and we know quite a lot about this topic however, this is not the case for non-fungible token, short NFTs. Non-fungible token is a relatively new phenomena, that first appears in 2012, but only really takes off in 2017. The goal of this Master thesis is to explore the area of NFTs and add more insights to the growing literature.

1.1 Relevance of this paper

We all know someone who owns cryptocurrency or have heard the word NFT in a conversation. According to Fortunly, the non-fungible token market has seen transcations worth almost 41 billion USD in total in 2021 (Mitic, 2022). If we compare this number to an asset that has been around a little bit longer such as Gold, which humans use in trade and investment for more than 6522 years, we see that NFTs make up one sixth of global gold demand in 2021 (Gold.Info, n.d.). For an asset than has only been around for 10 years, this is an impressive number. The question we should ask ourselves is, how such a young innovation is able to achieve such tremendous success. We do not know what the future holds for us, but what we do know is, as is the case with cryptocurrency, non-fungible token will stick around, reach even new highs in the upcoming years and keep surprising us. The technology behind NFTs, but also the capabilities of it make non-fungible token so interesting to us. NFTs are at the forefront of innovation and technical development of the 21st century, and we are obliged to research this topic and foster our understanding of recent developments in this sector. Financial analysts are increasingly more sceptical of the non-fungible token market. If we look at the history of the older crypto market, since its creation in 2009, we have already witnessed 7 market crashes. Just to mention two of them, there is the crash of 2013, when China imposed more restrictions on its crypto market, which led to a depreciation of Bitcoin of 50%. In addition to that, a more recent crash is caused by the corona pandemic in early 2021, which led the currency to also drop by 50%, till it finally reached a new bottom line of 4000 USD (Lisa, 2021). Financial analysts claim to see parallels between cryptocurrency crashes in the past and the current situation of the non-fungible token market. Compared to August 2021 when more than 1 billion USD worth of NFTs were bought and sold, only 23 million USD worth of NFTs are sold in May 2022 (Irwin, 2022). People from all sorts of backgrounds, sex and age invest in both the NFT and cryptocurrency market or are planning to do so. There is even discussion among pension fund managers and companies if they should invest funds into the non-fungible token market. They have already done so with cryptocurrency, as reported by Forbes. One example for that is the Houston Firefighters Relief and Retirement Fund, that invested 25 million USD in Bitcoin (Wintermeyer, 2021). As pointed out by Lennart Ante in his research paper, in which the interrelationship between NFTs and cryptocurrency is investigated, the crypto market plays a crucial role in determining trends in the smaller non-fungible token market (Ante, 2021). These findings are confirmed by a later research paper, published by Michael Dowling, who examines co-movement between NFTs and cryptos (Dowling, 2022). The findings are in line with the first paper and suggest a complementary type of relationship between the two assets. Taking a step back from NFTs, the power of the crypto market as a dominant factor becomes apparent when we look at initial coin offerings. ICOs appear for the first time in 2013 next to the crypto market, and can therefore also be considered a smaller subset of the larger crypto market, as is the case with NFTs. Masiak et al. find evidence supporting the idea of ICOs and cryptocurrency being complements (Masiak et al., 2019). Considering the widespread use of NFTs and cryptocurrency, it would be dangerous, even foolish, to stay away from further research into NFTs. For the sake of retirees, pension managers, investors and wealth managers, this paper is of great relevance to them, because it explores the relationship between non-fungible token and cryptocurrency. The central question that this thesis attempts to answer is: Are NFTs and cryptocurrency complements or substitutes?

This question is designed to help us stay on the right path throughout this paper. An answer to this question will be provided in the final section of this thesis. There are two aspects that need further clarification, substitutability and complementarity. What does it mean if two goods are substitutes and what does it mean if two goods are complements? The two concepts originate from economics and are based on a demand and supply analysis. Two goods are generally described to be substitutes, if an increase in the price for one good, triggers the demand for the other good to rise. On the other hand, two goods are regarded complements, if an increase in price for one good leads to a likewise drop in demand for the other good (LivingEconomics, n.d.). These two concepts are explained in more detail later on in this thesis, please refer to the Theoretical Framework section for more details. What we want is to clarify the relationship in terms of complements and substitutes between NFTs and cryptocurrency through the application of a difference in difference strategy.

1.2 What is a non-fungible token?

Before we continue with this paper, it is important to clarify what a non-fungible token is and what distinguishes itself from cryptocurrency. The concept of NFTs dates back to 2012 however, back then the name given to a token with extended functionality is Colored Coin. In contrast to today's landscape, where most non-fungible token exist on the Ethereum blockchain, this is not the case for Colored Coins. A Colored Coin is essentially a token on the Bitcoin blockchain, that operates on additional code, that allows the token to save up to 40 bytes of data, also called metadata. In 2013, the founder and CEO of eToro, a popular investment platform, and Vitalik Buterin, the creator of Ethereum, publishe a whitepaper in which they expresse a need for a better/updated version of the Bitcoin blockchain, to deal with data storage limitations in Colored Coins. With initial success of tokenizing trading cards of famous players, Colored Coins eventually became obsolete with the introduction of ERC-721 special type token (eToro, 2022). The implication of the ERC-271 token compared to the format Colored Coins are based on, ERC-20, is that ERC-271 adds a whole new dimension to tokens. The new format adds the aspect of non-fungible to tokens, which are previously fungible and dividable. In contrast to non-fungible token, Colored Coins are not able to represent any kind of data, they can only represent limited types of data (Wirex Team, 2021). For instance, if we look at video games, Colored Coins have been used there to constitute in game currency. In addition to that, shares of companies can also be converted to these Coins. We mention the aspect of fungibility previously. One Colored Coins representing one share in Company A and can always be exchanged for another share in this company, which are both of equal value. On the contrary, non-fungible token cannot be exchanged for one another. Each individual NFT is unique and carries a different monetary value. One of the main use of NFTs is to tokenize real world assets. It has already found applications in the world of collectibles, art, real estate and law, in the form of smart contracts. A real life example of how non-fungible token can be put to use is shown by Ernst&Young, one of the worlds leading firms in assurance and consulting. In 2019, EY transformes one of its clients business model, WiV Technology, by introducing blockchain and the idea of NFTs to the business. The company is operating in the wine investment industry. One of the biggest hurdles in this industry is proving authenticity and transferring ownership rights. By transforming every wine bottle into a non- fungible token, the issue of provenance has been bypassed and investments are now able to take place in a much more timely and cost efficient manner (Makrygiannis, 2019). For the purpose of this paper, we will only consider NFTs in our datasets and regressions, not Colored Coins.

1.3 Expected results and structure of the paper

Oftentimes, it has been pointed out that non-fungible token and cryptocurrency are similar. A recent article from AnalyticsInsight point out a few interesting facts regarding their similarities. First of all, NFTs and cryptocurrency operate on the same blockchains. Most non-fungible token projects out there are based on the Ethereum blockchain, which also hosts the second most widely used cryptocurrency. In addition to that, because of common blockchains, both assets often attract the same group of investors, which is the reason why the NFT market is sometimes referred to as a subset of the larger cryptocurrency market. It is also mostly the case, that cryptocurrency has to be used in order to perform non-fungible token transactions. With more and more countries pushing for crypto regulations, this provides a unique opportunity for us to examine one of these regulatory changes and investigate its effect on the NFT market. As already pointed out by some of the relevant literature mentioned above, this thesis expects NFTs and cryptocurrency to be complements, because of their inherent similarities and the dependence of the NFT market on cryptocurrency. To investigate this predicted relationship, we are first going to elaborate more on the literature mentioned earlier, second of all we are going to talk about the relevant theories that this paper uses. Next, we will discuss what kind of data is required by this study and examine our key variables of interest and present the empirical strategy. With all the background information, we will continue with analysing the findings. The final section of this thesis provides some concluding remarks on the quality of the paper, its implications and finally as answer to the research question.

2.0 Literature Review

The idea behind non-fungible tokens has been around since 2012, but it only became known to the general public and mainstream media in 2021. Because the topic is still so new, which puts a constrain on the amount of available data, little is known about the relationship between non-fungible token and cryptocurrency. In contrast to that, a lot is known about cryptocurrencies, because they have been around for much longer. A recent study from a German based blockchain research lab by Lennart Ante, looks at the interrelationship between non-fungible token and two of the most prominent cryptocurrencies, Bitcoin and Ethereum (Ante, 2021). To measure the relationship between non-fungible token and cryptocurrency, the study employs a vector autoregressive model, targeting NFT sales volume and NFT active market wallets. The study finds that for larger currencies excluding Ethereum, for which no statistically significant effect is present, the cryptocurrency market influences the smaller non-fungible token market. Furthermore, the empirical findings suggest that Bitcoin leads to an increase in NFT sales volume. Therefore, we can conclude from this study that non-fungible tokens and cryptocurrencies are complements, not substitutes. The study goes further by suggesting that the reason why there is an interrelationship between non-fungible tokens and cryptocurrencies is because crypto is the most common currency used for buying and selling NFTs. When the price of Bitcoin rises, investors will be looking for other ways to invest their money and accordingly focus on non-fungible tokens. This line of reasoning also makes the author of this paper believe, that only those crypto investors who have mastered this discipline or feel satisfied with what they have achieved will eventually move on to the non-fungible token market. This comment is something that might have been true in 2021, but now one year later we get people showing interest in NFTs that have never traded with cryptocurrencies before. The idea of a secluded community of gamers and other frowned upon individuals investing in crypto is not true anymore. This is the reason why we believe that this paper, with data from 2022, might reveal different results.

A similar paper conducted by Michael Dowling, in the beginning of 2022. supports the view put forward by Lennart Ante, that the cryptocurrency market has an impact on the non-fungible token market (Dowling, 2022). This paper in turn makes use of a wavelet coherence methodology, to find traces of possible co-movement between NFTs and crypto. The central question Dowling tries to answer is, if the pricing of non-fungible tokens can be explained in terms of cryptocurrency pricing. He confirms the results of the first paper and finds that there in indeed co-movement between the NFT and crypto market, which means there must be factors affecting both markets universally. This paper also suggests that non-fungible tokens and cryptocurrencies are complements, not substitutes.

To get a broader understanding of the kind of forces that are present in the cryptocurrency market, another area of major interest is initial coin offerings, short ICOs. The connection between non-fungible token and initial coin offerings is that both involve cryptocurrencies as a form of payment. You purchase an NFT with Bitcoin for example and you can also participate in an initial coin offering by purchasing token, generated by the organization issuing the ICO, in exchange for a certain cryptocurrency. One of the first ICOs ia launched by the Ethereum blockchain, back in 2014, and raised a total of 31,000 Bitcoins, around 18 Million USD. Since the ICO market has been around for much longer, a lot more is known in this market about its interrelationship with the crypto market, helping us to gain important insights into the world of crypto, which is of relevance to this paper as well. Many prominent names in the industry have either participated in an ICO, launche their own NFT project or both. A paper published in 2020, talks about the relationship between initial coin offerings with Bitcoin and Ethereum (Masiak et al., 2019). Through the lens of a vector autoregressive model, this paper attempts to find evidence for market cycles in the ICO market and examine the relationship between initial coin offerings and cryptocurrencies. The paper finds evidence of a potential spill over effect, coming from the much larger crypto market onto the smaller ICO market and a positive relationship between ICOs and crypto. Shocks that occur to Ethereum and Bitcoin returns, positively influence ICO volume. What we can learn from this study is, that the two assets seem to be complementing each other.

A more practical paper for this study by Huan, about peer-to-peer lending versus bank lending (Tang, 2019). This paper is of central importance to this study, because it deals with the same kind of question surrounding substitutability and complementarity. In addition to that, Tangs paper uses a difference in difference approach, that is also used by this paper. A difference in difference methodology is ideally used in connection with a policy or regulation from a central authority, to study the effect on a treatment group, compared to a control group. The difference in difference approach is discussed in more detail in the empirical strategy section of this paper. Tang looks at the impact of a banking regulation, leading financial institutions to tighten their lending criteria, on peer-to-peer lending. The regulation helps Tang to accurately identify the size of the shock, which would have otherwise not been possible. A difference in difference approach removes the problem of causality.

3.0 Theoretical Framework

According to basic economic theory, two goods are considered to be substitutes if they can be consumed for the same purpose. Let the price of fictional good A rise, then this would encourage consumers to purchase more of good B, since good B is of equal value or in other words, good B is a substitute to good A so it can be consumed instead of good A, without loosing any utility. Such behavior is often described by the term cross elasticity of demand. Cross elasticity of demand measures the responsiveness of demand in relation to price. Substitutes are expected to exhibit positive cross elasticity of demand, meaning that if price of good A increases, demand for good B increases (EconomicsHelp, 2022). In addition to that, two goods are considered to be complements, if they are consumed together. Two typical examples of complementary goods would be fish&chips and pasta&pasta sauce. Complementary goods typically exhibit a negative cross elasticity of demand. As the price for good A rises, demand for good B falls (Tutor2u, 2019).

To analyse the effect of the exogenous shock described below, this study is going to test three dependent variables, buyers, salesusd and averageusd, through the application of a difference in difference framework. A difference in difference methodology is usually applied to analyse a policy change or regulatory rulings. In our case, we examine the relationship between non-fungible token and cryptocurrency through the lens of a regulation from the European Union, Markets in Crypto Assets, MiCA. To be more precise, the exogenous shock used in this paper is a vote on a proposed amendment to the regulation, by the European Commission. Since the vote is rejected, the exogenous shock is positive in nature, and perceived as good news by the crypto community. If we assume that non-fungible token and cryptocurrency are substitutes, then this means that they are competing with each other over who will get the upper hand for investors. After the vote on the proposed Markets in Crypto Assets amendment, the relief experienced by cryptocurrency investors would spill over to the non-fungible token market and draw away attention to the crypto market. We would expect to see a decline in the number of NFT buyers, a drop in total sales measured in USD and a decrease in the average transaction price. If non-fungible tokens and cryptocurrencies are complements, both investment assets add value to each other, and people will want to purchase them together. After a positive shock to the crypto market, we would expect to see an increase in the number of buyers in the NFT market, higher sales volume and an increase in the average transcation price for non-fungible token.

To provide the reader with a better understanding and information surrounding some of the key terminologies used above, we are going to continue with a detailed explanation of some of these terms. First of all, we are going to take a closer look at what exactly the exogenous shock mentioned above is and then we are going to discuss the hypothesis for the research question. The difference in difference strategy mentioned above is discussed in the Empirical Analysis section.

3.1 Exogenous Shock

This paper is interested in examining the relationship between cryptocurrency and non-fungible token investors. Previous research shows that certain elements of the crypto market such as Ethereum and Bitcoin, impact the non-fungible token market and can be considered to be a driving force in explaining NFT pricing. What we do not know is how investors in both markets interact. For the purpose of answering the research question stated in the introduction, the theoretical framework employed by this paper considers a positive shock to the crypto market, in the form of a vote by the European Union on a proposed regulation amendment to MiCA. MiCA stands for Markets in Crypto Assets. The Markets in Crypto Assets regulation finds its origin in 2018, when the European Commission acts in response to growing demand from stakeholders and national governments, but also in light of the growing acceptance of cryptocurrencies in the European Union. In recent years, terms such as platform economy, FinTech and distributed ledger technology find widespread support and increasing popularity. With such ground-breaking developments and innovations, the

European Commission sees a need to establish a better regulatory framework. As a result of this, in September 2020 the EU introduces the so-called Digital Finance Package. The Digital Finance Package is an assortment of regulations and strategies. In addition to the Markets in Crypto Assets regulation, it also includes a proposal for market infrastructure and an action plan mapping out the next five years in the European Union, regarding digital transformation. The purpose of the Digital Finance Package is consumer protection, safeguard the interests of the European Central Bank in terms of economic stability and lastly to guarantee fair competition among EU countries (KPMG, n.d.). Apart from that, the MiCA regulation also has its own reasons why it is necessary to be implemented. First of all, after the 2017 Bitcoin crash, where the digital currency lost more than 45% of its value, suddenly the downsides and dangers of cryptocurrency became apparent to policy makers as well (Gola, 2021). After the European Banking Authority and the European Securities and Markets Authority both agreed that current legislations do not cover most of the crypto assets in circulation, the idea for Markets in Crypto Assets is born. In addition to protecting consumers and safeguarding financial stability of the system, which is the overall aim of the Digital Financial Package, MiCA is also designed to put other assets such as stablecoins on the regulatory map, formulate common policies for CASP, short for Crypto Asset Service Providers, and finally to harmonise distributed ledger technology across all member states of the European Union (Vermaak, n.d.). In absence of policies, a lot of member countries already create their own rules and policies, which is of course counter productive to the idea of the EU, to have one set of applicable rules to abbey to. The actual exogenous shock that we use in this paper, the need for an exogenous shock is explained below in the empirical strategy section, is a proposed amendment on the MiCA regulation, which is put to vote by the European Commission but got rejected on the 14th of March 2022. The problem for the crypto community this proposed amendment excerpts is, that it contains language that could potentially lead to the ban of all proof-of-work related crypto activities in the European Union. "Crypto-asset service providers shall not provide services related in any way, shape, or form to crypto-assets that do not meet the environmental sustainability criteria" is among others one of the key phrases from the regulation (Wright, 2022). Proof-of-work cryptocurrencies would not meet environmental sustainability criteria, laid out by the EU. Ledger, an influential company operating in the crypto market, describes this proposed amendment as, if passed by parliament, a threat to the crypto economy in Europe (Wright, 2022). Since the amendment is rejected by the European Commission, the crypto community experiences this shock as good news. According to CoinNews, the crypto industry feels relieved about the outcome of the vote (Handagama, 2022). The weekend before the MiCA vote took place, many prominent cryptocurrencies relying on a proof-of-work consensus mechanism are in the red. The crypto market is down by 1.3% in terms of total market capitalization (Bank of Scotland, n.d.).

3.2 Hypothesis

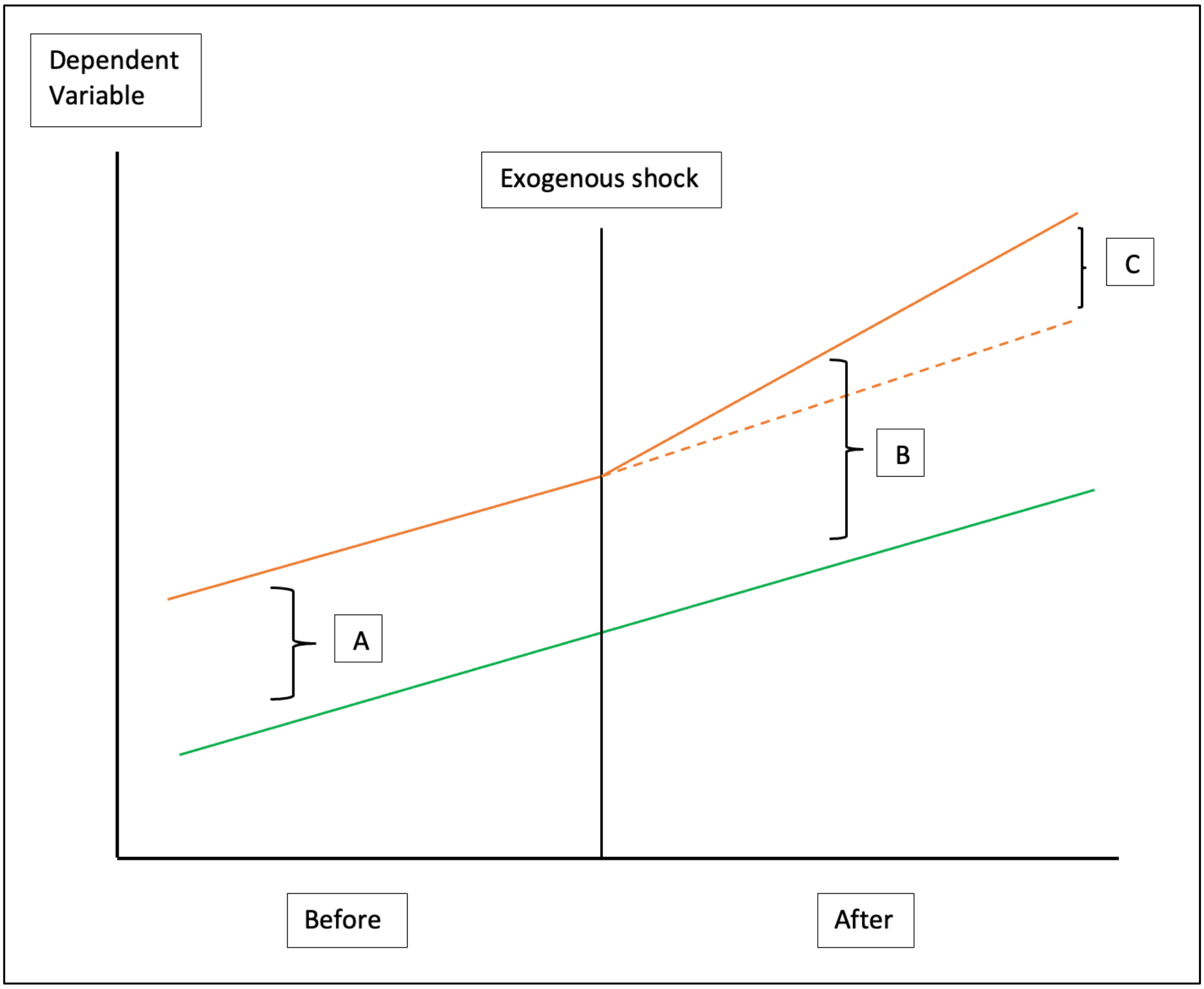
Now that we have explained all the relevant theories used in this paper, it is time to be clear on what we believe is going to happen and what we will actually test for empirically. This paper puts forward one hypothesis, in which we will test three dependent variables.

H1

1. With good news in the crypto market, there is an increase in the number of buyers in the non-fungible token market.
2. With good news in the crypto market, there is an increase in total sales (in USD?) in the non-fungible token market.
3. With good news in the crypto market, there is an increase in the average transaction in the non-fungible token marke.

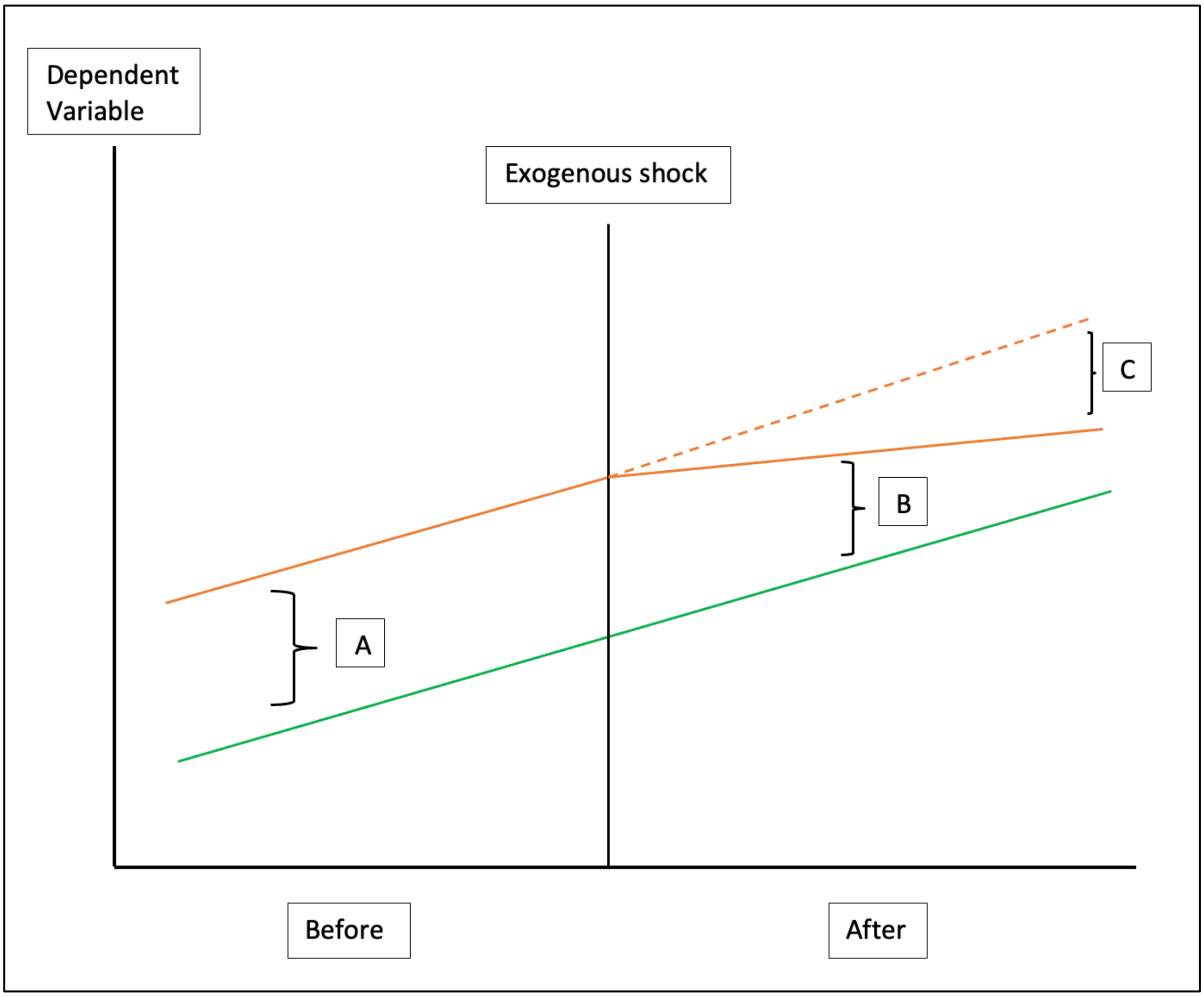
The average treatment effect on all three dependent variables is expected to be positive. This paper argues that non-fungible token and cryptocurrency are complements. As we can see in Graph 1, which is a graphical illustration of the difference in difference method employed in this paper, the orange line is steeper in the after-shock period than the green line, indicating that the MiCA regulation leads to positive effects in the NFT market. After computing the difference between A and B, we are left with the average treatment effect C, as described in the empirical strategy section. Other research papers analysed in the literature review section above, support the idea of a complementary relationship. Under the H0 hypothesis, we assume that for all three dependent variables, the exogenous shock in form of the MiCA regulation has no positive impact on the NFT market. Average treatment effects for all three variables would have to be either negative or statistically insignificant for us to reject the H0 hypothesis. In the case of negative treatment effects, we can also say that non-fungible token and cryptocurrency are substitutes. The case of non-fungible token and cryptocurrency being substitutes is illustrated in Graph 2.

Figure 1 – Difference in difference assuming NFTS and Crypto are complements



The graph above is a hypothetical illustration of how the difference in difference methodology that is used in this paper might look like, in the case that non-fungible token and cryptocurrency are complements. The Y axis, labelled dependent variable, will either be buyers, salesusd or averageusd. In addition to that, the line marked as exogenous shock, denotes the point in time when the vote on the proposed amendment to Markets in Crypto Assets was held, 14th of March 2022. Furthermore, the green line represents our control group, over which we will talk more in the empirical strategy section, the solid orange line is our treatment group and the orange dotted line represents the path of the treatment group theoretically.

Figure 2 - Difference in difference assuming NFTS and Crypto are substitutes



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4.0 Empirical Strategy

4.1 Data collection and description

In the previous section we discuss what kind of opinion this paper puts forward. To summarize, evidence from the literature review points us in a direction, where we believe that non-fungible token and cryptocurrency are complements. With respect to the positive nature of our exogenous shock, we expect to see a positive relationship between any of the dependent variables used in this study and TreatmentEffect. To test these predictions empirically, we will first talk about what sort of variables are necessary for a difference in difference framework, then we will continue the discussion by examining Group 1 variables and Group 2 variables as well. Finally, we will go through those variables that have not been mentioned at this point, our dependent variables. Table 6, which presents a summary of our variables based on five criteria, number of observations, mean and standard deviation and minimum and maximum value the specific variable can take. As we have already seen in the theoretical framework section, the empirical method chosen in this study is a difference in difference approach. Since we are going to include multiple non-fungible token collections that also vary across time, the data used in this paper can be described as panel data. All the variables summarized in Table 6 are reported in our data set as daily observations. The use of daily observations is not avoidable in this case, because of data availability issues. If the data format chosen was weekly data or monthly data, there would only be a handful of observations for the post shock period, which is not enough to establish statistical significance. From a technical standpoint, such an approach requires us to formulate two groups of variables, one that is typically referred to as control group and one that is usually named treatment group. In total, each group consists of four non-fungible token collections. As demonstrated in Table 1, our first variable individual, corresponds to the two groups mentioned above. Each individual non-fungible token collection gets a number assigned between 1 and 8, so we can always identify their individual observations as belonging to a specific non-fungible token collection. Solana monkey business, Degenerate ape academy, Zed run, Alien worlds, CryptoPunks, Bored ape yacht club, Art blocks and CryptoKitties, which are NFT collections, are part of the dataset and get a value of 1 to 8 assigned as previously mentioned. The first 4 collections form the control group, and the other four our treatment group. This can be seen by the first row of Table 6, where it says that individual has a minimum value of 1 and maximum value of 8. Information regarding mean and standard deviation are not relevant in this case, since this variable is only there so that we can identify NFT collections. A bit further down in Table 6, we see a variable called newtime. Together with the previously mentioned variable individual, they both form the skeleton for our panel data. Every outcome observation can be assigned to a specific individual and time period. There is a total of 4048 observations, the same applies to our first variable, individual. Before our time variable is of use to us, it first had to be converted into something that STATA can recognize. The original format in which newtime was, month-day-year, cannot be understood by STATA because it constitutes a string variable. This is the reason why we have a set of 5 numbers for our time variable in Table 1, regarding minimum and maximum value. The minimum value of 22281 and maximum value of 22787 refer to the 1st of January 2021 and 22nd of May 2022 respectively. Again, their mean and standard deviation do not reveal any meaningful insights. Every difference in difference analysis requires an interaction term, that represents the average treatment effect. In our case, this average treatment effect will tell us weather non-fungible token and cryptocurrency are substitutes or complements. TreatmentEffect, is a multiplication of two variables, t and post. These two variables are also shown in Table 1 at the very beginning. T is a dummy variable that can take a value between 0 and 1. T stands for treated and tells us weather the specific non-fungible token collection is part of the treatment group or not. Those NFT collections that are based on a proof-of-work consensus mechanism, get a value of 1 assigned, which explains the corresponding value for minimum and maximum in Table 1. Furthermore, post is another dummy variable, which we need to compute TreatmentEffect. Post takes a value of 1, if the individual observation from all 8 NFT collections take place after the 14th of March 2022. The 14th of March is the date, when the European Commission rejected a proposed amendment to MiCA, which would have practically led to a ban of Bitcoin and Ethereum. Since our 8 non-fungible token collections sum up to a total of 4048 observations, it makes sense that that all three variables, t, post and TreatmentEffect, also have the same number of observations. Next, we are going to focus our attention on Group 1 variables. Group 1 variables are those that are related to equity markets. Table 1 presents us with six variables, corresponding to Group 1. All six variables are derived from Yahoo Finance. Since all of those variables, except dax, are based on American metrices, this leaves the question of why we pay so much attention to America. The reason for this is simple. In terms of crypto acceptance and trade, the Unites States is first in the world (Brown, 2022). Data availability and trustworthiness is of course important, which is why American indices have been chosen. First in the list we have sp500. As the name already implies, it represents the American Standard & Poor’s stock market index, comprising a total of 500 companies from all over the United States. Considering the fact that stock markets are not open on the weekend and also have to adhere to public holidays, the number of observations only amounts to 2784. The individual observations for this variable are closing prices of the particular day. One of the first things we can say about sp500 is, that typically the closing price can be within 242 USD higher or lower than its mean of 2943 USD. The lowest closing price recorded in the dataset is 2237 USD and the highest closing price is 4088 USD. Another Group 1 variable reported in Table 1 is vix. Vix is a market volatility index and is based on future expectations regarding volatility. It has the same number of observations, the reason for that is given above, and takes values between 11,54 USD and 82,69 USD. On average, each observation should be within a range of 12,81 USD lower or higher than its mean of 20,37 USD. With one of the highest standard deviations among our variables, we will now look at DowJonesIndex. As the name implies, this variable represents the Down Jones Industrial Average market index, which reports a weighted average from 30 representative companies in the United States. This variable also has less than 4048 observations for reasons stated above, that represent market closing prices. Its mean closing price of 34,166 USD is allowed to vary between plus and minus 1492 USD. Between the 1st of January 2021 and 22nd of March, the Dow Jones Index had its lowest point at 29,982 USD and its highest point at 36,799 USD. Moving on to nasdaq, it has the same number of observations as the Dow Jones Index. Nasdaq is next to the New York stock exchange, the second exchange in New York City. During the time period of this paper for which data has been collected, its lowest value is 11.623 USD and its highest value is 16,057 USD. Nasdaq's mean of 14,210 USD can vary between plus and minus 899 USD. As with the previously discussed variable DowJonesIndex, its observations also represent closing prices. The last variable of Group 1 is bondindex. There are various types of bond indices out there, but the one used in this paper is the Vanguard Short Term Bond Index Fund and measures the performance of the bond market. We include a variable of such type in this paper, because of Kong, R. and Lin, T. contribution to the non-fungible token literature. They find evidence in their study, that bonds have an impact on NFTs (Kong & Lin, 2021). Their study also finds that NFTs show a standard deviation of 66,17%, which is similar to the standard deviation computed in Table 1, 59.24% for the NFTIndex variable. This leads us to Group 2 variables in the table below. Group 2 variables consist of the following variables, solana, polygon, wax, ethereum, bitcoin, CryptoIndex and NFTIndex. The first 5 variables are all cryptocurrencies and chosen for two reasons. First of all, bitcoin and ethereum are crucial elements in driving non-fungible token prices, as already discussed in the literature review section. Second of all, the remaining cryptocurrencies are native currencies for some of the most influential blockchains included in this study for our NFT dataset, and therefore it is important to have them in our regressions. All five cryptocurrencies have a total of 4048 observations and their lows and highs largely depend on the size of their respective blockchains. Please refer to Table 1 for more information. The smallest cryptocurrency is without doubt wax, which has a mean of smaller than 1 USD. The largest cryptocurrency in our sample is bitcoin, with a maximum value of 67,566 USD. The remaining two variables are CryptoIndex and NFTIndex. They are both chosen to be part of this paper, because they are representative of the two markets this study investigates. CryptoIndex is an index developed by Solacti, a financial analysis company based in Germany. The data is extrcated from Yahoo Finance and its proper name is CMC Crypto 200 Index. Furthermore, it is a collection of 200 most influential cryptocurrencies. Lastly, we have the NFTIndex. Even though the data is downloaded from Yahoo Finance as well, the data are provided by CoinMarketCap. CoinMarketCap, a website reporting real time data from the crypto market, created this index, tracking 8 outstanding non-fungible token collections in the market. It has reached an all-time high of 4325 USD and a low of 353 USD between 2021 and the 22nd of May 2022.

As already mentioned before, there are three dependent variables in this study, salesusd, buyers and averageusd. All three variables have 3688 observations each. Buyers refers to the number of buyers of a particular non-fungible token collection. In our dataset, this variable varies between 1 and 64,198. In addition to that, salesusd stands for total sales and summarized daily sales of a particular NFT collection. Averageusd is the average transaction price for all the NFTs in a particular collection, on a daily basis. All data concerning the three dependent variables are gathered from NonFungible, a website that tracks the NFT market since 2018. The reason why this study tests for three dependent variables, is to get more certainty over the results. If at least two of the variables point us in the same direction, we can form a more decisive conclusion weather NFTs and cryptocurrency are substitutes or complements.

Table 1 - Descriptive Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
individual	4048	4.5	2.292	1	8
t	4048	.5	.5	0	1
post	4048	.136	.343	0	1
buyers	3688	2283.607	7438.101	1	64198
salesusd	3688	3103700	8343374.2	0	2.484e+08
ethereum	4048	2806.342	894.516	730.37	4812.09
solana	4048	86.054	67.567	1.8	258.93
polygon	4048	1087979.7	799677.36	.018	2876757
wax	4048	.264	.163	.035	.936
sp500	2784	2943.838	242.283	2237.4	4088.85
vix	2784	20.369	12.811	11.54	82.69
CryptoIndex	2712	1068.388	234.642	601.29	1659.97
NFTIndex	3544	1519.588	900.513	353.56	4325.82
averageusd	3688	34130.72	99331.574	0	2201890.7
bitcoin	4048	45373.502	9231.547	28720.27	67566.828
newtime	4048	22533.543	146.16	22281	22787
TreatmentEffect	4048	.068	.252	0	1
dax	2736	15084.08	762.714	12831.51	16271.75
DowJonesIndex	2720	34166.927	1492.314	29982.619	36799.648
nasdaq	2720	14210.973	899.994	11623.25	16057.44
bondindex	2600	81.406	1.407	77.31	82.89

This table reports the summary statistics for the whole dataset used in this paper, including all 3 dependent variables and 14 independent variables. The data presented in the table above is extracted from STATA using the command asdoc sum, which requires the installation of a software extension to STATA. In addition to the already mentioned variables, Table 1 also includes 2 dummy variables, one called t and the other one called post. All observations are reported in USD apart from dax, which is the main German stock market index and is measured in Euro.

4.2 Data analysis

'Peer-to-Peer lenders versus banks: substitutes or complements?' by Huan Tang, is one of the key papers taken into consideration for this paper as inspiration. It is discussed in more detail in the literature review section. What we can take away from this study, is a good example of what a difference-in-difference method looks like and how it works. The reason why a DID method is used in this paper, is because of its unique characteristics. What we want is to measure how the non-fungible token market is affected by our exogenous shock described above. As with all empirical research, we are interested to find a cause-and-effect relationship to answer our research question however, saying that an increase in the number of non-fungible token buyers is because of the MiCA regulation, would lead us to the wrong conclusion. To confer causality to our results, we cannot simply use a standard regression model, the risk of unobserved variable bias is too great, and we would not be able to trust the estimators. A difference-in-difference methodology is one way to deal with the problem of causality. In the simplest words, in the case for buyers, we want to look at the number of buyers in the non-fungible token market after the proposed amendment to MiCA was rejected and compare it to the number of buyers in the non-fungible token market if there had been no regulation.

$$E[\text{Buyers1} \mid t = 1] - E[\text{Buyers0} \mid t = 1]$$

The equation above is an illustration of the kind of result we actually want to get in this paper, from empirical testing. T represents time in the equation and takes the value of 0 for all observations before the 14th of March, the date when the proposed amendment was rejected. Buyers1 stands for the number of buyers in the non-fungible token market with the vote and Buyers0 stand for the number of buyers without the vote. The problem with this is that the second part of the equation is not observable to us, because we cannot look at the number of buyers in the NFT market without the vote after the vote has occurred. This is the reason why the difference in difference method applied in this study, but also by Huan Tang and many others, takes a different form. Difference in difference makes use of two distinctive groups, a treatment group that experiences the exogenous shock and a control group that does not experience the exogenous shock. Through that, we are able to bypass the problem identified in the equation above. Generally speaking, DID is performed by computing two differences, hence the name difference-in-difference. The first difference is derived by calculating the difference in the mean between the treatment and control group in the period before the exogenous shock and in the period after the exogenous shock. The second difference is simply the difference between the two differences calculated in the previous step. From now on we may refer to this difference as the average treatment effect. The average treatment effect will provide us with the necessary information to decide whether non-fungible token and cryptocurrency are substitutes or complements. The average treatment effect is denoted by the variable TreatmentEffect.

$$(E[\text{Buyers1} \mid t = 1] - E[\text{Buyers0} \mid t = 0]) - (E[\text{BuyersC1} \mid t = 1] - E[\text{BuyersC0} \mid t = 1])$$

$$(E[\text{Salesusd1} \mid t = 1] - E[\text{Salesusd0} \mid t = 0]) - (E[\text{SalesusdC1} \mid t = 1] - E[\text{SalesusdC0} \mid t = 1])$$

$$E[\text{Averageusd1} \mid t = 1] - E[\text{Averageusd0} \mid t = 0]) - (E[\text{AverageusdC1} \mid t = 1] - E[\text{AverageusdC0} \mid t = 1])$$

The three equations above illustrate how the difference in difference approach looks like mathematically. In addition to the number of buyers, we also see total sales and average transcation price, which are the other two dependent variables used in this paper. In terms of regression models, we are now going to take a look at how the theory described above looks like in practice. Overall, there will be three regression models, one for each dependent variable. As we can see in Figure 3 below, instead of the usual regression command xtreg for time series and cross-sectional data, the one used in this paper is slightly different. Reghdfe is a regression command developed for Stata to deal with difference in difference regressions in particular. The fe part of the regression command stands for fixed effect and takes into account a time fixed effect and non-fungible token fixed effect, as denoted by t and post in brackets. In the next section of this paper, results and interpretation, we are first going to discuss the implementation of the regression models in Figure 1 and subsequently carry out a test for robustness. A unit root test will also be conducted, which can be found in the Appendix.

Figure 3 – Regression Models and STATA specification

1

$$Buyers_{it} = \beta_0 + \beta_1 T_{it} + \beta_2 Post_t + \beta_3 TreatmentEffect + \beta_4 Dax_{it} + \beta_5 Nasdaq_{it} + \beta_6 BondIndex_{it} + \beta_7 DowJonesIndex_{it} + \beta_8 SP500_{it} + \beta_9 Vix_{it} + \beta_{10} Ethereum_{it} + \beta_{11} Bitcoin_{it} + \beta_{12} Wax_{it} + \beta_{13} Polygon_{it} + \beta_{14} NFTIndex_{it} + \beta_{15} CryptoIndex_{it} + U_{it}$$

```
reghdfe buyers TreatmentEffect dax nasdaq bondindex DowJonesIndex sp500 vix ethereum
bitcoin wax polygon NFTIndex CryptoIndex, absorb(t post)
```

2

$$salesusd_{it} = \beta_0 + \beta_1 T_{it} + \beta_2 Post_t + \beta_3 TreatmentEffect + \beta_4 Dax_{it} + \beta_5 Nasdaq_{it} + \beta_6 BondIndex_{it} + \beta_7 DowJonesIndex_{it} + \beta_8 SP500_{it} + \beta_9 Vix_{it} + \beta_{10} Ethereum_{it} + \beta_{11} Bitcoin_{it} + \beta_{12} Wax_{it} + \beta_{13} Polygon_{it} + \beta_{14} NFTIndex_{it} + \beta_{15} CryptoIndex_{it} + U_{it}$$

```
reghdfe salesusd TreatmentEffect dax nasdaq bondindex DowJonesIndex sp500 vix ethereum
bitcoin wax polygon NFTIndex CryptoIndex, absorb(t post)
```

3

$$averageusd_{it} = \beta_0 + \beta_1 T_{it} + \beta_2 Post_t + \beta_3 TreatmentEffect + \beta_4 Dax_{it} + \beta_5 Nasdaq_{it} + \beta_6 BondIndex_{it} + \beta_7 DowJonesIndex_{it} + \beta_8 SP500_{it} + \beta_9 Vix_{it} + \beta_{10} Ethereum_{it} + \beta_{11} Bitcoin_{it} + \beta_{12} Wax_{it} + \beta_{13} Polygon_{it} + \beta_{14} NFTIndex_{it} + \beta_{15} CryptoIndex_{it} + U_{it}$$

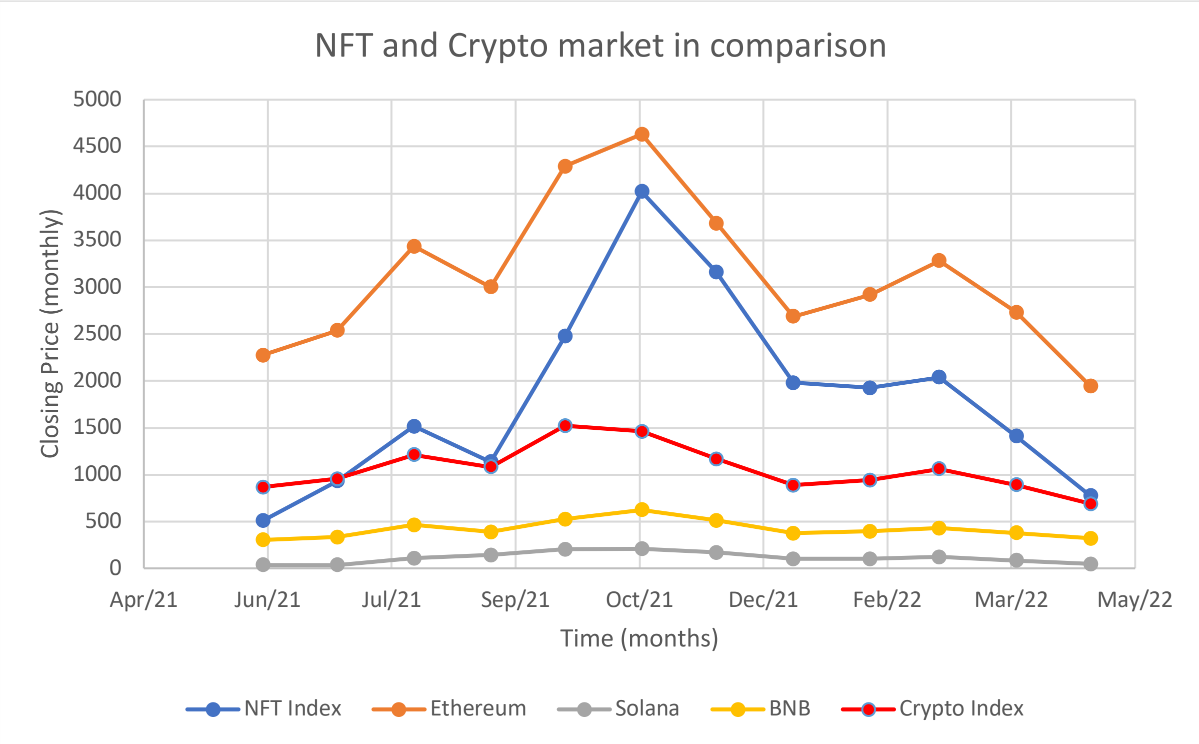
```
reghdfe averageusd TreatmentEffect dax nasdaq bondindex DowJonesIndex sp500 vix
ethereum bitcoin wax polygon NFTIndex CryptoIndex, absorb(t post)
```

The image above shows the three regression models that are used in this paper. The first regression has the number of buyers as its dependent variable, the second regression model has total sales as its dependent variable, and the third regression model has the average transaction price as its dependent variable. Regarding the Results and Interpretation section of this paper, the order presented above is also the order in which the regression results will be presented. To use the regression command reghdfe in Stata, a software extension first must be installed, using the following code, ssc install reghfde. In addition to that, each empirical specification in Figure 3 also included the corresponding code for STATA. Variables T and Post represent two dummy variables that are not present anymore in our STATA computations in their present form. A standard difference-in-difference model prescribes us to correct for NFT fixed effect and time fixed effect, which these two variables do respectively. In STATA however, the regression command reghdfe requires a different procedure to deal with fixed effect, as we can see in Figure 3 where it says absorb(t post). T takes a value of 1 for all observations that belong to non-fungible token based on PoW and Post takes a value of 1 for all observations after the exogenous shock.

5.0 Results and Interpretation

As mentioned before in the literature review, Bitcoin and Ethereum are good indicators for empirical models when it comes to the non-fungible token market. Before we start to look at the results of the empirical models introduced in the empirical strategy section, it is first important to assess the correlation between the crypto and NFT market from a visual standpoint, to get a basic idea of what is going on and to confirm what other papers say about the impact of Ethereum and Bitcoin. In addition to that, it is also crucial for us to understand how the nonfungible token market compares to the crypto market between 2021 till May 2022. Lastly, before we have gained enough insights into the two markets and can commence the analysis, we need to be aware of differences between NFTs in the control group and treatment group. Figure 4 is a graphical representation of the aforenamed points. As clearly visible in the graph below, the NFT market seems to have risen much more severely than the crypto market, who reached its peak in mid-October 2021 compared to the end of October, as is the case for the NFT market. Furthermore, what we can conclude from this first observation is that the Crypto Index, also used as an independent variable in all three regression models, will not be a key variables in terms of explanatory power, since the price development according to the crypto index is much more moderate compared to a sharp rise and drop in the NFT market. Moving on to the next point, where we want to focus on similarities between Ethereum and the NFT market, apart from a difference in size for Ethereum stemming from the fact that Ethereum is simply more valuable than the weighted average price of the overall non-fungible token market, the two are practically identical. What is to be derived from this second observation is that we can expect to see a strong correlation between Ethereum and the 8 NFT collections used in this paper. Continuing with the analysis of Figure 4, it is worth spending some time on Solana and BNB. Both are cryptocurrencies based on a proof-of-stake consensus mechanism, which are part of the control group of the difference-in-difference approach. The NFTs making up the control group are considerably smaller in size than their counterparts, proof-of-work NFTs. They also seem to have a weaker correlation with the NFT market than compared to Ethereum. They do move up and down in accordance with price movements visible in the graph, but their price development seems to be much more moderate. Only by carefully looking at Figure 4, we can spot a peak for both NFT collections at the end of October 2021, which is in line with what we can observe from Ethereum and the NFT market. Nevertheless, Solana and BNB are more closely in line with the crypto market, when comparing the price developments over time between the two currencies and the crypto index.

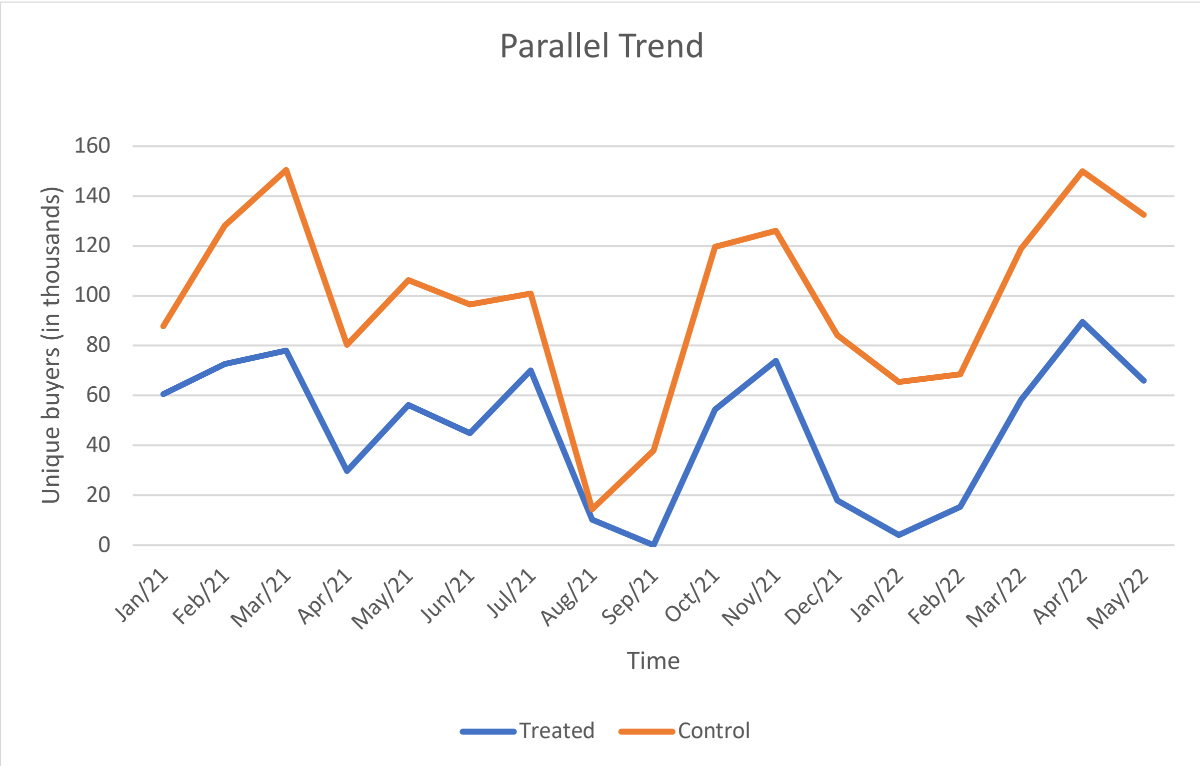
Figure 4 – NFT and Crypto market in comparison



This figure shows the price movements over time for indices in the Crypto and NFT market, as well as a selection of representative cryptocurrencies. The information provided in Figure 1 are all collected from Yahoo Finance. As a result of data availability issues mainly concerning the NFT Index, the time period begins on the 3^rd^ of May 2021 and ends on the 22^nd^ of May 2022. The blue line represents the NFT Index also used for empirical testing later on in this study, and comprises a collection of 8 tokens, based on proof-of-work and proof-of-stake consensus mechanism. Ethereum, the second largest cryptocurrency but the most influential currency used in the NFT market, is represented by the orange line. In contrast to Ethereum, Solana and BNB (Binance Coin) are both based on the proof-of-stake consensus mechanism, taking on grey and yellow respectively in Figure 1. The red line is a crypto index developed by Solactive AG, a German company constructing indices, comprising a total of 200 cryptocurrencies.

Since all three regression models used in this study are based on a difference-in-difference methodology, we have to make sure, before starting the analysis of the main results, that the dataset used for empirical testing actually fulfils the necessary criteria to be a possible and viable source for such an approach. Difference-in-difference requires internal validity in order to generate meaningful estimates of the treatment effect (Columbia Public Health, 2022). The treatment effect in this paper is based on a regulation from the European Union, discussed in more details in previous sections of this study. A graphical representation of the control group and treatment group is usually enough to confirm internal validity of the dataset. Before the introduction of the shock, the two groups must be parallel. As we can see in Figure 5, both control and treatment groups are fairly parallel before the shock occurs, which shows that the unobserved difference to be predicted between the two groups after the shock is an unbiased estimate.

Figure 5 – Parallel trend assumption



This figure shows the parallel trend between the control group and treatment group, both consisting of four non-fungible token collections respectively. The time period in Figure 2 spans from January 2021 till the 22nd of May 2022. Data for unique buyers for the corresponding NFT collections are recorded in monthly intervals. The data is collected from NonFungible, a company recording and presenting real time data surrounding transactions in the NFT marketplace. The blue line denoted by Treated, consists of four non-fungible tokens based on the proof-of-work consensus mechanism and the orange line, denoted by Control, consists of four NFTs based on the proof-of-stake consensus mechanism. Generating a graph showing the parallel trend in Figure 2 is not possible at the moment through STATA, the statistical software used in this paper, because software version of STATA available from Utrecht University does not support such a command.

5.1 First regression excl. independent variables

Now that we have gained an overview over the non-fungible token and crypto market and the difference between the control/treatment group, it is time to discuss the first findings of the empirical model of this paper. We will start our analysis by first examining the estimated treatment effect on buyers, salesusd and averageusd without any dependent variables. Next, we will add the independent variables to the model, to see how this will impact the significance and meaningfulness of the treatment effect. For the purpose of this division, the independent variables used in this study are split into two groups. Group 1 consists of variables that are related to the crypto and non-fungible token market and Group 2 consists of variables related to equity markets. As we can see in Table 2, the average treatment effect on buyers is 2.974, which is also statistically significant. In other words, compared to the control group a positive shock to the crypto community will lead to an upswing in the non-fungible token market in the form of an increase in the number of buyers by 2,974. Moving on to the next dependent variable in Table 2, the average treatment effect on total sales is 3.068,435 USD. In comparison with the control group used in this study, a positive shock to the crypto market increases sales by around 3 million USD. The estimated effect is statistically significant. On the other hand, the estimated average treatment effect on averageusd does not seem to be statistically significant. It will be interesting to see if that changes with the addition of independent variables later on. The explanatory power of this regression models amounts to 10%, 1.5% and 10% respectively.

Table 2 – Regression results excl. independent variables

	(1) buyers	(2) salesusd	(3) averageusd
TreatmentE~t	2974.3***	3068435.1***	90.03
	(4.56)	(4.01)	(0.01)
_cons	2061.0***	2874066.6***	34124.0***
	(16.34)	(19.43)	(20.27)
N	3688	3688	3688
R-sq	0.099	0.015	0.100
F	20.80	16.09	0.000107
p_value	0.000	0.000	0.992

t statistics in parentheses
* p<0.05, ** p<0.01, *** p<0.001

This table reports the effect of the rejected amendment of the European Union regulation MiCA, on 14th of March 2022, on number of buyers in the NFT market, total sales volume and average transaction price. Apart from TreatmentEffect, a dummy variable derived though the multiplication of two dummy variables (Post x Treatment), the regression output in Table 1 does not contain any other dependent variables. The variable gives us information on the casual relationship between the shock and the non-fungible token market and takes the value of 1 if the point in time is after the shock and the NFT is based on proof-of-work consensus mechanism (Treatment group). The table format and content are derived through STATA with help of a software extension, estout Package, which is developed to convert raw STATA regression output into a format typical for scientific publications. The statistic, p_value, at the bottom of the table represents the P values for TreatmentEffect.

5.2 Second regression excl. Group 2 variables

Table 3 reports the regression results for dependent variables buyers, salesusd and averageusd. Considering the fact that the regression in Table 3 includes a broader list of variables, the analysis has to be structured a bit different. We will start the analysis by first pointing out which variables are of statistical significance and why, next we will elaborate on their significance by explaining a logical reason behind their significance, after that we make an important distinction between statistical significance and economic significance and talk about what that means for the regression results and finally, we will briefly discuss those variables that are not statistically significant. This way of proceeding will be applied to all three dependent variables.

Buyers For the purpose of answering the question whether non-fungible tokens and cryptocurrency are substitutes or complements, the first variable named TreatmentEffect, at the very top of the table, is the most important indication for us. The variable is statistically significant since its P value is smaller than 0,01. The only other significant variable for the regression output on number of buyers is nasdaq. This variable also has a P value of smaller than 0.01, which makes is statistically significant.

The coefficient for TreatmentEffect is positive, indicating that a positive shock to the crypto market will result in a positive effect in the NFT market. Since the effect of the TreatmentEffect variable is significant, we can conclude that there is a noteworthy difference between the treatment and control group in this study. Looking at the history of nasdaq, it is no surprise that this variable positively influences the number of buyers in the non-fungible token market. As already mentioned before, indices from the Unites States are most likely to possess explanatory power in our regression models, because America is the biggest market in the world for cryptocurrency and its applications. Furthermore, nasdaq is the second largest stock exchange in the world, right after the New York stock exchange, and also includes seven exchanges from Europe. This variable does not only capture American semitism, but also European sentiment.

What is meant by economic significance is different to statistical significance. Economic significance goes beyond that and assesses how meaningful the relationship to the dependent variable actually is. In the case of the TreatmentEffect variable, we observe a positive correlation to buyers. Because TreatmentEffect is the product of multiplying two dummy variables, therefore not a quantitative variable, its interpretation looks a bit different from the rest. Non-fungible tokens based on a proof-of-work consensus mechanism receive more buying interest after the shock, 3.172 more buyers, than compared to non-fungible tokens based on proof-of-stake consensus mechanism. The number of 3.172 is economically significant, because it is large enough to actually have an impact. As depicted in Figure 6, an amount of 3.172 buyers is among the range of historic monthly buying activity for one of the most popular NFT collections, CryptoPunks. With the average monthly number of Buyers from CryptoPunks amounting to 8.090, 3.172 represents a significant portion of that amount. Based on those numbers, we can also conclude that the effect of nasdaq on number of buyers in the NFT market is also economically significant. A one unit increase of nasdaq leads to an increase in non-fungible token buyers of 1,219.

It turns out that variables based on equity markets have little to no explanatory power and excerpt no statistical significance, apart from nasdaq for reasons given above. Those insignificant variables are dax, DowJonesIndex, vix, bondindex and sp500. Compared to the regression output in Table 2, it is obvious that the average treatment effect on buyers has increased from 2.974 to 3.172 however, its significance dropped from P smaller than 0,001 to P smaller than 0,01. The only explanation for this increase lies in the effectiveness of the model in Table 3. According to Rsq statistic, the explanatory power of the regression model is higher in Table 3 than compared to Table 2, with 9% and 13% respectively. Adding Group 1 variables to our regression model is beneficial for predicting a good estimate for TreatmentEffect. The coefficient of the TreatmentEffect variable already helps us quite a lot in answering the research question. A positive correlation with buyers indicates, that non-fungible tokens and cryptocurrencies are complements. The vote on the MiCA regulation amendment has been perceived as positive news by investors, and lead to a jump in the crypto market. The same effect is present in the NFT market.

Salesusd TreatmentEffect, again the most critical variable to this paper, has a P value smaller than 0.01 or in other words, the relationship with salesusd is statistically significant. As opposed to the significant variables from the first regression on buyers, nasdaq does not seem to be statistically significant here, which is a surprise. Nevertheless, nasdaq has a T value of 1.80, which almost makes it significant. The regression output in Table 3 yields further surprises, namely dax, bondindex and vix. These three variables are statistically significant, which is not the case in the previous regression. All three variables have a P value smaller than 0,01.

A positive coefficient for the TreatmentEffect variable indicates that it moves in the same direction as salesusd, but of course we have to keep in mind that TreatmentEffect is a dummy variable. Statistically significance and positive correlation to salesusd can only mean that the shock in the form of the MiCA regulation has indeed an effect on NFT sales in the period after the shock compared to the period before. Since the dependent variable in this regression model is a monetary value, we expect variables based on traditional equity markets to correlate with sales in the non-fungible token market.

All of the variables identified above that are statistically significant turn out to be large enough to also be economically significant. When the German stock exchange index dax goes up by one unit, this will lead to an increase in sales of the NFT market of 1,934 USD. Taking a closer look at vix, a one-unit increase will be followed by an increase in sales of 82,985 USD. Furthermore, a one-unit increase will lead to an increase in sales of 1,134,667 USD.

If we compare the results obtained in Table 3 to the results obtained in Table 3, we again see an increase in the coefficient for TreatmentEffect. As observed for number of buyers, the significance drops slightly to P smaller than 0,01 but the explanatory power of the model makes a sharp jump, from merely 1% to almost 8%. With the TreatmentEffect variable being the most important variable to this study, it is a good sign that its coefficient turns out to be significant as discussed before. Non-fungible tokens based on PoW lead to an increase in sales after the shock of 3,152,115 million USD compared to NFTs based on PoS. The conclusion we can draw from this is that NFTs and cryptocurrencies are complements. This observation is in line with what we have seen in the other regression model.

Table 3 – Regression results excl. Group 2 variables

	(1) buyers	(2) salesusd	(3) averageusd
TreatmentE~t	3172.3**	3152115.0**	-8120.4
	(3.06)	(2.94)	(-0.69)
dax	0.580	1934.8**	0.952
	(0.93)	(2.98)	(0.13)
nasdaq	1.219**	776.3	20.67***
	(2.92)	(1.80)	(4.33)
bondindex	88.21	1134667.2**	-6594.2
	(0.22)	(2.71)	(-1.43)
DowJonesIn~x	0.0306	177.7	-1.977
	(0.09)	(0.48)	(-0.48)
sp500	1.072	1053.9	6.957
	(0.82)	(0.78)	(0.46)
vix	31.86	82985.4**	418.3
	(1.03)	(2.58)	(1.18)
_cons	-36092.3	-140468008.4***	299057.0
	(-0.97)	(-3.64)	(0.70)
N	1371	1371	1371
R-sq	0.133	0.077	0.155
F	8.454	13.27	8.639
p_value	0.002	0.003	0.493

t statistics in parentheses
* p<0.05, ** p<0.01, *** p<0.001

This table reports the effect of the rejected amendment of the European Union regulation MiCA, on 14th of March 2022, on number of buyers in the NFT market, total sales volume and average transaction price. In addition to variable TreatmentEffect as illustrated in Table 1, the regression output depicted above also include independent variables. These independent variables are part of Group 1 and make up variables related to equity markets. With America being the most influential country in the crypto community, five of the aforementioned variables concern the North American market (nasdaq, bondindex, DowJonesIndex, sp500 and vix) and one from Germany (dax).

Averageusd The final regression model has averageusd as its dependent variable. First of all, it is important to point out that the effect of the key dependent variable TreatmentEffect on averageusd is not statistically significant. For the remaining variables in Table 3, the analysis will be kept to a minimum, because of the insignificance of TreatmentEffect. The results only show one significant variable in the whole model, nasdaq, whose P value is smaller than 0,001. A one unit increase in nasdaq will lead to an increase in the average transaction size in the non-fungible token market of 20,67 USD. In conclusion, for the third regression model, the evidence does not tell us anything about the relationship between non-fungible tokens and cryptocurrencies. Since averageusd is similar to our other variable tested for in the previous regression, salesusd, a significant relationship was to be expected here. Nevertheless, as with previous findings we can see again the positive benefits associated with adding independent variables to the regression model. The explanatory power of the model has increased from 10% to 15,5%.

5.3 Third regression incl. Group 1+2 variables

As we can see in Table 4, adding variables related to the non-fungible token and crypto market to the regression model creates a better model with greater explanatory power than in Table 3 and Table 2. The regression model with dependent variable buyers has now an Rsq of 14,2% compared to 13,3% in the last regression. Apart from that, the regression model with dependent variable averageusd reports a value for Rsq of 17,3% which is a definite increase as illustrated in Table 2, 15,5%. Unfortunately, there is strong reason to believe that these rather promising empirical results are not accurate, they are biased. There is one variable in this regression, CryptoIndex, which comprises a collection of the 200 most influential cryptocurrencies world-wide. If any or all of the other crypto related variables are already included in this indix, than the empirical model used in Table 4 would suffer from multicollinearity. To test these suspicions, a correlation matrix for CryptoIndex, ethereum, bitcoin, wax and polygon is constructed. Table 5 in the Appendix reveals the results of this correlation matrix. It can be clearly seen that at least three cryptocurrencies are problematic to this study. Bitcoin, with a correlation of 0.91, can be classified as highly correlated to the variable CryptoIndex. Ethereum, with a correlation of 0.76, can be classified as being correlated to the variable CryptoIndex. Wax, with a correlation of 0.65, can be classified as being moderately correlated to the variable CryptoIndex, whilst polygon only shows a weak correlation. Therefore, the correct empirical model will not include all the Group 2 previously mentioned variables, but instead ethereum, bitcoin and wax are to be removed from the list.

Now that we have a regression model with all the independent variables discussed in previous sections of this paper, we can start to analyse the final regression outputs depicted in Table 6, which will determine whether non-fungible token and cryptocurrency are complements or substitutes. Overall, without the adverse effects of multicollinearity that influences the results in Table 4, the new regression model seems to be better suited to explain variations among our three dependent variables. For buyers, the explanatory power of the model has risen from 13,3% to 13,7%. For averageusd, the explanatory power of the model increases from 15,5% to 17,1% however, we do notice a slight drop for salesusd, from previously 7,7% to 6,7%.

Buyers As with previous regression models, our key variable TreatmentEffect has a statistically significant effect on the number of buyers in the non-fungible token market. Its P value is smaller than 0,001. Furthermore, there appear to be no other significant variables in Table 6, which is not the case in Table 4, where ethereum and CryptoIndex are both statistically significant. Nasdaq with a T value of 1,80 is not significant either, which comes as a surprise since it was significant in Table 3. With sufficient explanatory power in this model, it can be concluded that the variable TreatmentEffect accurately captures the effect of the European Union regulation MiCA, which explains why the coefficient of TreatmentEffect is positive. Crypto investors perceive the rejected amendment as positive news, which encourages investment in proof-of-work NFTs. Practically speaking, compared to the control group the number of buyers in the non-fungible token marketplace will go up by 3.766, which is also economically significant. This leads us to believe that NFTs and cryptocurrency are complements.

Salesusd In terms of sales volume, the variable TreatmentEffect is again statistically significant, which is also shown by previous regression models. Compared to Table 4, we notice a slight drop in the coefficient. Since this variable is statistically significant, P value is smaller than 0.01, and economically significant, it is right to say that this suggests a complementary relationship between non-fungible token and cryptocurrency. In contrast to the control group, sales will go up by 3,052,243 million USD. Other significant variables in this regression model are dax and vix, which both have a P value of smaller than 0.01 as well. A one unit increase in the German stock market index dax, leads to an increase in sales of

2,485 USD. When volatility in the market goes up by one unit, captured by variable vix, total sales in the NFT market rise by 101,642 USD. Commenting on the regression results for averageusd is pointless, because there is no statistically significant effect to be observed by variable TreatmentEffect.

Table 6 – Regression results with all the correct variables

	(1) buyers	(2) salesusd	(3) averageusd
TreatmentE~t	3766.9***	3052243.0**	-15332.7
	(3.45)	(2.69)	(-1.24)
dax	0.597	2485.5**	5.729
	(0.82)	(3.28)	(0.69)
nasdaq	1.252	375.8	19.22*
	(1.80)	(0.52)	(2.44)
bondindex	41.25	921712.5	-10347.6
	(0.08)	(1.67)	(-1.71)
DowJonesIn~x	-0.221	428.9	-10.45
	(-0.42)	(0.79)	(-1.76)
sp500	1.274	1406.4	16.71
	(0.91)	(0.97)	(1.05)
vix	29.13	101642.8**	343.5
	(0.83)	(2.77)	(0.86)
polygon	0.000157	-0.216	0.0109
	(0.28)	(-0.36)	(1.68)
NFTIndex	-0.0377	-174.9	-5.460
	(-0.06)	(-0.26)	(-0.74)
CryptoIndex	1.258	2603.5	60.10***
	(0.82)	(1.64)	(3.47)
_cons	-26439.4	-138279425.9**	746802.4
	(-0.56)	(-2.84)	(1.40)
N	1248	1248	1248
R-sq	0.137	0.067	0.171
F	4.324	6.585	6.481
p_value	0.001	0.007	0.216

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t statistics in parentheses
* p<0.05, ** p<0.01, *** p<0.001

This table reports the effect of the rejected amendment of the European Union regulation MiCA, on 14th of March 2022, on number of buyers in the NFT market, total sales volume and average transaction price. Compared to Table 1 and Table 2, Table 5 shows the complete regression results, including Group 1 and Group 2 variables.

5.4 Robustness Test

As every empirical analysis should include, to verify the accuracy of our preliminary regression results in Table 6, we check the regression models for heteroskedasticity. A presence of heteroskedasticity is an indication of the violation of the constant variance assumption. If this assumption is violated, we cannot consider the coefficients of our independent variables to be fully accurate. Furthermore, a violation of this assumption tampers standard errors and as an effect of that also important statistics, such as T and P values. The best way to test for heteroskedasticity is a visual representation of residuals against fitted values. Figure 7 in the Appendix shows the graphical representation of such a relationship, for all three dependent variables. As illustrated by the graph, there are two things we can immediately observe. First of all, the highlighted points in the graph are not equally spread for each level of fitted values. Second of all, the data points do not seem to be distributed randomly across the graph, they follow some kind of pattern and there are also a few significant outliers. These observations reveal that the constant variance assumption is indeed violated in all three cases, we therefore must correct the standard errors in our regression models. After successfully correcting for heteroskedasticity, we get new regression results as illustrated by Table 7. What Table 7 tells us, is that buyers and salesusd are still statistically significant, at a 0,1% and 1% level of significance respectively. On the other hand, what has changed are the test statistics, which we rely on to reject or not reject the null hypothesis for each of the listed variables. The T values, reported in brackets under the coefficients, are higher in most cases with the standard errors corrected for robustness. We have previously seen that for the regression on salesusd, variables dax and vix showed statistical significance. Both variables are still significant with robust standard errors however, the t value for vix has dropped to 2.27, which in turn made the variable significant at a level of significance of 5%, compared to 1% previously. In addition to that minor change, we now have a variable, bondindex, which was previously not significant. Through closer examination of the variable, we see that a one-unit increase will lead to an increase in total sales of 921,712 USD, which is also economically significant. Even with robust standard errors, no more additional variables turn out to be significant for buyers. Nevertheless, our computed average treatment effect on averageusd remains statistically insignificant. Through the addition of robust standard errors to the regression model of averageusd, two more variables turn out to be significant. Those two variables are bondindex and sp500. The updated regression results ultimately confirm what we have seen before, Group 1 variables pose greater explanatory power than Group 2 variables. Apart from a test for heteroskedasticity, we also carry out a test for autocorrelation and a unit root test. The test results can be viewed in the Appendix, under Table 9 and 8 respectively. The test results of our unit root test reveal, that we should reject the null hypothesis, which assumes a unit root in our models and instead assume that we have stationarity in our dataset. Furthermore, the test results of our autocorrelation test show no signs of autocorrelation. The null hypothesis assumes no first order autocorrelation, which we fail to reject based on the P values of the test.

Figure 7 – Regression with robust standard errors

	(1) buyers	(2) salesusd	(3) averageusd
TreatmentE~t	3766.9***	3052243.0**	-15332.7
	(5.94)	(3.10)	(-1.83)
dax	0.597	2485.5**	5.729
	(0.97)	(3.07)	(0.79)
nasdaq	1.252	375.8	19.22*
	(1.81)	(0.56)	(2.26)
bondindex	41.25	921712.5*	-10347.6*
	(0.11)	(2.01)	(-2.26)
DowJonesIn~x	-0.221	428.9	-10.45
	(-0.40)	(0.82)	(-1.51)
sp500	1.274*	1406.4	16.71*
	(2.21)	(1.55)	(1.98)
vix	29.13	101642.8*	343.5
	(1.53)	(2.27)	(1.33)
polygon	0.000157	-0.216	0.0109
	(0.25)	(-0.43)	(1.71)
NFTIndex	-0.0377	-174.9	-5.460
	(-0.05)	(-0.29)	(-0.64)
CryptoIndex	1.258	2603.5	60.10**
	(0.76)	(1.84)	(3.10)
_cons	-26439.4	-138279425.9**	746802.4
	(-0.76)	(-2.95)	(1.78)
N	1248	1248	1248
R-sq	0.137	0.067	0.171
F	5.996	9.378	5.941
p_value	0.000	0.002	0.068

t statistics in parentheses
* p<0.05, ** p<0.01, *** p<0.001

This table reports the regression results on buyers, salesusd and averageusd, taking into consideration robust standard errors. The implementation of robust standard errors to the regression models displayed in Figure 6, are based on a Stata command, vce(robust). Vce(robust) is the standard command in Stata for robust standard errors, when the dataset constitutes panel data. The statistical significance of variables is assessed by three different level of significance, which are 5%, 1% and 0,1% respectively. Most variables are significant on a 5% significance level.

6.0 Discussion and Conclusion

On the 14th of March 2022, a vote was held by the European Commission to decide on the future of the crypto community in Europe. The subject matter of this vote is the proposed amendment to a new regulation called Markets in Crypto Assets. One of the changes the amendment seeks to introduce to the main text of the regulation, is an additional clause that imposes strict sustainable measurements on all those that provide services in the crypto market. If passed, this amendment would have practically led to a ban of Bitcoin and many other cryptocurrencies in Europe. In a similar paper from Huan Tang, a regulation introduced in 2010 from the Financial Accounting Standards Board in the United States, forces banks to consolidate off-balance sheet assets, which in turn led banks to tighten their lending criteria for borrowers. As explained in Huan Tangs study, this paper draws inspiration from it and uses the same empirical strategy. A difference in difference method has never been used before in the field of non-fungible token and cryptocurrency. The most common empirical strategy employed by researchers in this field of study, is the so-called vector autoregressive model. Dowling, M. in his study from early 2022 also makes use of a vector autoregressive model, to investigate volatility spillovers between cryptocurrencies and NFTs. The papers mentioned in the literature review all point in the same direction. The suspicion is that non-fungible token and cryptocurrency are complements. It is therefore interesting to see if we can replicate their results, but using a different empirical strategy. Furthermore, Masiak, C. find evidence that there is a positive relationship between both Ethereum and Bitcoin to Initial Coin Offerings. The significance of this outcome is, that it shows that cryptocurrencies have an impact on smaller sub-markets, in this case ICOs. This paper looks at this phenomenon and focuses on the non-fungible token market, which is also a smaller market than the crypto market. There are two theories put forward in this paper. In the case of substitutability and complementarity, if we assume that NFTs and cryptocurrency are substitutes, then a positive shock to the crypto community would encourage less investments in the NFT market. On the other hand, if we assume that NFTs and cryptocurrency are complements, a positive shock to cryptocurrencies would also encourage investments in the non-fungible token market. The regression results in this study find a positive correlation with the number of buyers in the NFT market and total sales volume. It would be interesting to see if the same kind of theory and empirical strategy could be replicated and used in the case of initial coin offerings. Researchers looking forward to continuing the investigation of the MiCA regulation and its effects on the market must be patient, the regulation is only expected to be officially implemented into law in 2025. Till then we can expect to see more changes and more attempts to change the wording of the regulation as mentioned above. Further research could focus on the American market. One of the earlier drafts of a new infrastructure bill from 2021 seeks to impose a higher tax burden on proof-of-work crypto assets (Dore, 2021). A similar methodology as the one used in this paper could be applied.

The relevance of this thesis to other parties can be split into two broad groups. On the one side we could have policy makers and politicians, and on the other side we can have wealth managers, portfolio managers and investors. First of all, we learn that a shock to the crypto community also effects the non-fungible token market. They are both complementary in nature, as pointe out by the regression results, and therefore they both move in the same direction, regardless of the shock. If policy makers want to tackle the problem of high emissions and energy inefficiency, they should keep in mind that anything they do that effects cryptocurrency, will also affect the NFT market. Nevertheless, non-fungible token are much more than simple investment assets, as illustrated in the introduction, NFTs find very promising applications in other industries such as wine and real estate. The opinion put forward by this paper states with emphasiz, that policy makers should keep the world of cryptocurrency and NFTs separate. Regarding the second group of interested parties, if you are looking for investment opportunities or seek to diversify your investment portfolio, knowing that non-fungible token and cryptocurrency are complements is crucial. Suppose an investor who is investing money on behalf of a high net worth individual. His current portfolio of cryptocurrency is not doing so well because of recent development in Ukraine, Inflation, … . If he wrongfully decided to invest in NFTs, he might end up in a much worse position.

The regression models predict that, compared to the control group, the number of buyers in the non-fungible token market increase by 3767 investors and total sales go up by 3.052.243 USD. However, we encounter a few problems in this thesis, that might have an impact on the accuracy of the results. One issue is that all observations in the dataset are measured in daily prices, as a result of data availability issues. Future researchers are advised to wait some time, so that they can rely on weekly or even monthly data, which will yield better regression results. Furthermore, even though the crypto community in Europe only missed a ban of all PoW cryptocurrencies by only a little bit, this had only a small effect on the market, as suggested by Bloomberg. Reasons for that lie in other significant events, that happened at the same time such as the war in Ukraine and the FED in America raising interest rates (Nicolle & Pronina, 2022). In addition to that, the strength of the exogenous shock might also pose a problem to the effectiveness of this study. We are only talking about an amendment to the current version of the regulation, which will only become effective into law in 2025.

Putting it all together, we can argue that non-fungible token and cryptocurrency are complements. This relationship can be seen when we look at regulatory developments such as the MiCA regulation. Both types of assets move in the same direction, regardless of the shock. According to Jacob Cohen, the strength of a regression model in terms of Rsq can be classified according to four categories, very weak, weak, moderate and substantial (GitHub, n.d.). Based on his thresholds for each category, the regression models in this study on buyers and averageusd can be described as moderate, whilst the regression on salesusd would be weak. With this in mind, we can say that our results on the number of buyers are the most reliable ones.

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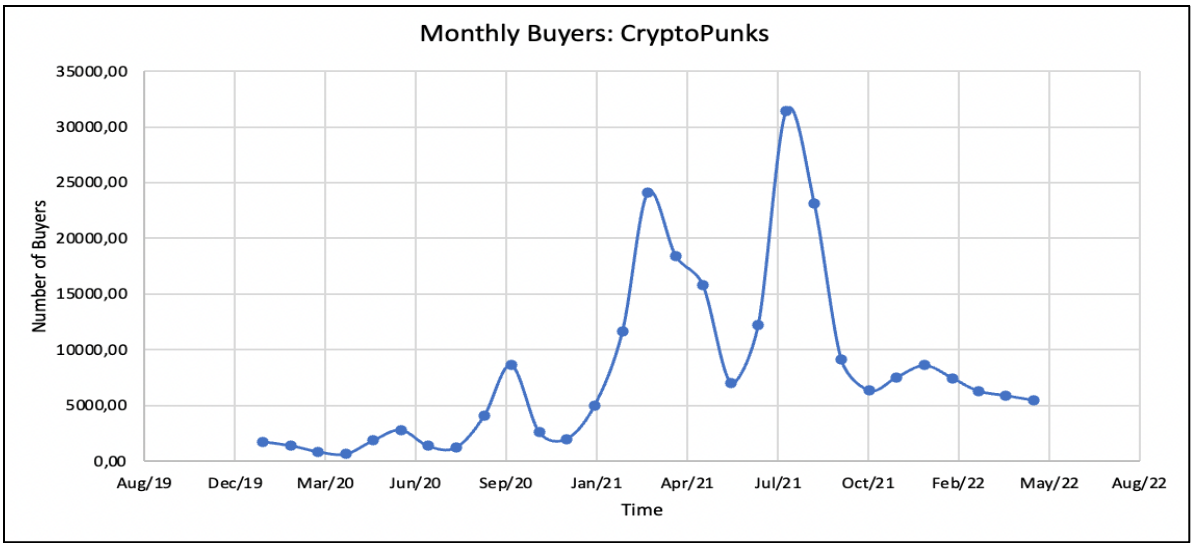
Appendix

Figure 6: Monthly buyers CryptoPunks



The figure above is a graphical illustration of monthly buying activity, measured by the number of buyers, for one of the most famous non-fungible token collections, CryptoPunks. CryptoPunks is a collection of 10,000 unique images, on the Ethereum Blockchain. Its significance in the NFT community is explained in the Introduction of this thesis. One crucial aspect of CryptoPunks is, that it is one of the oldest tokens around, and it decisively contributed to Ethereum's dominance over Bitcoin in the non-fungible token market. The data depicted in Figure 1 is collected from NonFungible.com and covers a time period of 3 years, from January 2020 till May 2022.

Table 4 – Regression results for Group 1 and 2

	(1) buyers	(2) salesusd	(3) averageusd
TreatmentE~t	3780.9*** (3.47)	3055132.1** (2.69)	-15308.0 (-1.24)
dax	0.388 (0.50)	2179.0** (2.69)	5.347 (0.60)
nasdaq	0.702 (0.95)	449.0 (0.59)	16.27 (1.95)
bondindex	761.5 (1.25)	1052369.6 (1.66)	-5268.2 (-0.76)
DowJonesIn~x	-0.180 (-0.33)	185.6 (0.33)	-10.40 (-1.69)
sp500	0.557 (0.39)	1474.0 (0.98)	14.16 (0.86)
vix	6.576 (0.18)	91897.8* (2.44)	194.9 (0.47)
ethereum	4.609** (2.68)	1651.4 (0.92)	31.47 (1.61)
bitcoin	0.255 (1.74)	43.80 (0.29)	2.262 (1.36)
wax	2810.8 (0.60)	9799343.8* (2.01)	43664.2 (0.82)
polygon	-0.000848 (-1.12)	-0.0126 (-0.02)	0.00698 (0.81)
NFTIndex	-0.677 (-0.61)	-2018.9 (-1.75)	-15.22 (-1.21)
CryptoIndex	-20.99* (-2.16)	-4618.2 (-0.46)	-114.9 (-1.04)
_cons	-72437.0 (-1.37)	-136233461.9* (-2.47)	391906.6 (0.65)
N	1248	1248	1248
R-sq	0.142	0.070	0.173
F	3.903	5.402	5.207
p_value	0.001	0.007	0.217

t statistics in parentheses
* p<0.05, ** p<0.01, *** p<0.001

This table reports the effect of the rejected amendment of the European Union regulation MiCA, on 14th of March 2022, on number of buyers in the NFT market, total sales volume and average transaction price. The difference to Table 2 is, that Table 3 includes in addition to Group 1 variables also Group 2 variables, which are related to the non-fungible token and crypto market. A total of six variables are added to our regression models (bitcoin, Ethereum, wax, polygon, NFTIndex and CryptoIndex)

Table 5 – Matrix of correlation

Variables	(1)	(2)	(3)	(4)	(5)
(1) CryptoIndex	1.000				
(2) bitcoin	0.913	1.000			
(3) ethereum	0.769	0.508	1.000		
(4) wax	0.659	0.523	0.805	1.000	
(5) polygon	0.336	0.061	0.768	0.632	1.000

This table reports the relationships between five of the Group 2 variables used in the regression model in Table 3. CryptoIndex is a variable consisting of 200 individual cryptocurrencies. Data concerning the five crypto variables are extracted from Yahoo Finance and cover a time span from 1st of January 2021 till 22nd of May 2022.

Table 8 - Unit Root Test

Buyers:		Statistic	p-value
Inverse chi-squared(16)	P	142.3555	0.0000
Inverse normal	Z	-8.5870	0.0000
Inverse logit t(44)	L*	-13.8017	0.0000
Modified inv. chi-squared	Pm	22.3367	0.0000

Salesusd:		Statistic	p-value
Inverse chi-squared(16)	P	191.4261	0.0000
Inverse normal	Z	10.3370	0.0000
Inverse logit t(44)	L*	18.7186	0.0000
Modified inv. chi-squared	Pm	31.0113	0.0000

Averageusd:		Statistic	p-value
Inverse chi-squared(16)	P	237.8026	0.0000
Inverse normal	Z	11.9681	0.0000
Inverse logit t(44)	L*	23.3323	0.0000
Modified inv. chi-squared	Pm	39.2095	0.0000

The data shown in Table 5 are the results for an Augmented Dickey Fuller unit root test, with a number of lags of 3. As we can see in the table above, for each dependent variable, the Dickey Fuller test reports four statistics. Every statistic also has a corresponding P value, as reported on the right hand side of the table.

Table 9 – Test for Autocorrelation

D.buyers	Coef.	Robust Std.Err.	t	P>t	[95%Cof.	Interval]
TreatmentEffect						
D1.		0		(omitted)		
dax						
D1.	0.065	0.157	0.420	0.690	-0.306	0.437
nasdaq						
D1.	-0.028	0.105	-0.260	0.800	-0.275	0.220
bondindex						
D1.	295.911	165.703	1.790	0.117	-95.915	687.736
DowJonesIndex						
D1.	0.061	0.097	0.640	0.545	-0.167	0.290
sp500						
D1.	-0.997	0.691	-1.440	0.193	-2.632	0.638
vix						
D1.	4.303	7.162	0.600	0.567	-12.632	21.239
polygon						
D1.	-0.000	0.000	-0.940	0.378	-0.001	0.000
NFTIndex						
D1.	0.172	0.181	0.950	0.373	-0.256	0.600
CryptoIndex						
D1.	2.976	2.842	1.050	0.330	-3.743	9.696

Wooldridge test for autocorrelation in panel data
H0: no first-order autocorrelation
F(1, 7) = 5.021
Prob > F = 0.0600 Prob > F = 0.4660 Prob > F = 0.1136

This table reports the outcomes of a test for autocorrelation. Since the methodology described in the Empirical Strategy section, is based on panel data, STATA requires a special command to test for autocorrelation, xtserial. This command must be installed to STATA, through an extension package called st0039. The most important results are reported at the bottom of Table 6. In the case of the dependent variable buyers, our P value is 0.06, for salesusd the P value is 0.4660 and in the case of averageusd the P value is 0,1136. A general rule of thumb is, we reject the null hypothesis if P is smaller than 0,05.

Figure 7 – Visual test for Heteroskedasticity

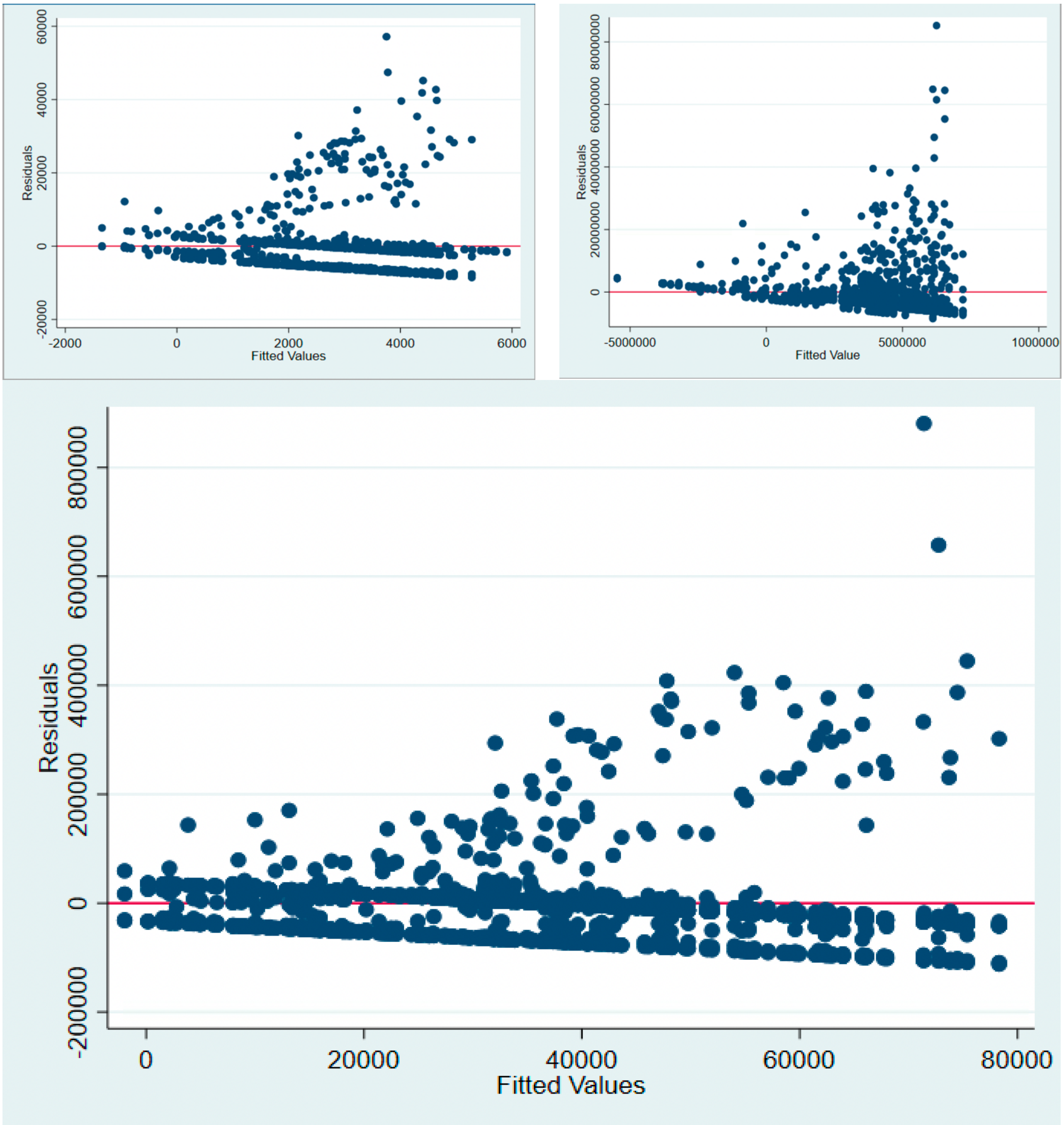


Figure 10 is a collection of three individual graphs, representing a visual test for heteroskedasticity, or in other words a method to test the constant variance assumption. All three graphs have as their x axis fitted values and as their y axis the residuals of those fitted values. The first graph in the top left-hand corner is based on the dependent variable buyer. The graph in the top right-hand corner is derived from salesusd and the bottom graph represents averageusd. STATA does not require the installation of any additional software for the computation of the three graphs above.