Better Than Ever? Analyzing The Impact of Change in Consensus Mechanism On Market Liquidity For Ethereum

Completed Research Paper

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Abstract

Recently, Ethereum, the second largest cryptocurrency, changed its consensus mechanism from Proof-of-Work to Proof-of-Stake. While this change has long been in the making to improve scalability and decrease energy consumption, it also impacts other factors that are incremental to cryptocurrency usage and adoption, such as market liquidity. We therefore utilize cryptocurrency price data to analyze the impact of change in consensus mechanism on market liquidity. By identifying cut-off dates and approximate measures for liquidity, various difference-in-difference and lagged-dependent-variable analyses are performed. We find that the change in consensus mechanism has a significant impact on price, suggesting a deterioration of market liquidity. However, tightened spreads suggest an increase in market liquidity, leading to the conclusion of a decrease in market breadth. This work provides a first step in the comprehensive analysis of change in consensus mechanisms. It thereby offers guidance for cryptocurrency developers and communities on whether to change consensus mechanisms.

Keywords: Consensus Mechanisms; Ethereum, Liquidity; Proof of Stake

Introduction

Ever since the introduction of Bitcoin, the sphere of cryptocurrency has been expanding rapidly, with currently over 22,000 different cryptocurrencies existing, according to CoinMarketCap (2023). Ethereum has emerged as one of the most influential and widely adopted blockchain-based platforms and currencies, revolutionizing the landscape of decentralized applications (Tikhomirov, 2018). Unlike Bitcoin, Ethereum enables developers to build and deploy decentralized applications on its blockchain, leading to use cases such as decentralized finance (DeFi), non-fungible tokens and smart contracts.

The consensus mechanism is the cornerstone of each cryptocurrency, as it ensures the validity of transactions and the consistent state of the network. As the name suggests, the consensus mechanism is the underlying mechanism used in the blockchain to reach joint agreement about its true state in real-time.

Since blockchains are (mostly) decentralized networks, there exists no party that can single-handedly validate pending transactions. Once joint agreement is reached and the legitimacy of a transaction is verified, the transaction is approved and engraved into the blockchain. The consensus mechanism further ensures security, immutability, and resistance against malicious attacks and is also the critical feature that establishes trust between two parties within the decentralized network.

The most common consensus mechanism is Proof-of-Work (PoW) as utilized in Bitcoin. PoW requires miners to solve complex mathematical algorithms, while only the first miner to decipher the puzzle is rewarded with the right to add the following block to the blockchain. Nowadays, there exist several other consensus mechanisms, with Proof-of-Stake (PoS) receiving the most attention (Nguyen et al., 2019). In contrast to PoW, this consensus mechanism chooses the validators in the network based on the number of staked coins they have. While both mechanisms possess advantages, it is argued that PoS is less energy-intensive and more scalable while keeping transaction costs low. Given these anticipated improvements, it was decided to change the consensus mechanism for Ethereum multiple years ago. On September 15, 2022, Ethereum successfully changed its underlying consensus mechanism from PoW to PoS in an event named “The Merge”, marking the transition from Ethereum 1.0 to Ethereum 2.0. With this change, Ethereum addressed scalability and energy-consumption concerns, reducing the power demand by more than 99% (De Vries, 2023). This change therefore prepared Ethereum for the future and ensured its competitiveness.

Following this substantial event in the second-largest cryptocurrency to date by market capitalization, this work aims to investigate the impact of this change in more detail by focusing on market liquidity.

Market liquidity determines an asset’s ability to be easily bought and sold, without impacting the price of that asset significantly. Illiquidity forces an individual to discount the price of an asset to sell it quickly (Keynes, 1930). Naturally, the change of consensus mechanism was expected to impact market liquidity as, under the PoS mechanism, validators need to stake part of their Ether, which means that those Ether are taken out of the free float in the market. In the cryptocurrency context, the free float refers to the number of tokens that are available to trade and not restricted due to e.g. staking or burned tokens that were sent to unspendable addresses. A reduction of free float has been found to negatively impact liquidity for other assets (Ding et al., 2016). Staked Ethereum cannot be bought or sold, which could therefore decrease liquidity in the Ethereum market. This process may be compared to stock buybacks of a major company, where some parts of the free-floating stocks are taken out of circulation, reducing market liquidity (Barclay & Smith Jr, 1988; Ben-Rephael et al., 2014).

Verifying the effect of change in consensus mechanism on market liquidity is incremental as illiquidity could impact the overall success and usability of cryptocurrencies such as Ethereum. Services and organizations that create applications around and within the Ethereum ecosystem rely on an efficient market, whereby efficiency is negatively affected by lack of liquidity (Al-Yahyaee et al., 2020). Liquidity shocks are, for instance, found to pose a challenge for investors in the Decentralized Finance (DeFi) market (Ante, 2022). Thus, a decrease in market liquidity needs to be seen as a negative side-effect of the change in consensus mechanism for the cryptocurrency itself but also for services and applications that are built around that cryptocurrency. A holistic analysis of the change of consensus mechanism for one cryptocurrency therefore provides value to other cryptocurrencies and their communities, where similar changes might also be considered. We therefore approach the topic from a blockchain design and investor decision-making perspective, with the objective to study the effects of a change in consensus mechanism on market liquidity. Thus, this work aims to answer the following research question:

RQ: How does the change in consensus mechanism from Proof-of-Work (PoW) to Proof-of-Stake (PoS) in Ethereum impact market liquidity?

The research question is addressed by observing two periods, namely pre-change and post-change, to compare differences and estimate the effect of the change on the underlying cryptocurrency Ethereum. Ethereum’s transition provides a rare and unique opportunity to examine those effects whilst having a counterfactual, Bitcoin, that has historically demonstrated bi-directional causality with Ethereum (Sifat et al., 2019). With our choice of counterfactual, we follow existing research (Tsuyuguchi & Wang, 2024), although future work could make use of other alternatives, such as Ethereum Classic. Different statistical methods are employed to analyze the impact on market liquidity. To our knowledge, no research exists that examines the effect of a change in consensus mechanism on a cryptocurrency that is performing this change using empirical data and statistical modeling. This work therefore aims to fill this gap and contribute to the ongoing debate on consensus mechanisms, helping developers, innovators and investors to understand the effects of such a substantial change. In light of rapid innovation and continuous advancements, it is crucial to understand how consensus mechanisms interact with the underlying cryptocurrency to foster the development of more efficient and usable cryptocurrencies.

Theoretical Background and Related Work

Consensus Mechanisms

Miners are at the heart of the PoW mechanism, competing for the right to add the following block to the blockchain and secure the corresponding reward, an amount of the underlying cryptocurrency, for their work. This work involves solving a complex mathematical puzzle by brute force, which requires high computational power. The computational power required to mine a new block serves as a critical security feature of the PoW mechanism. Blockchains operate on the premise that the longest chain is the valid one. Hence, a malicious actor creating fraudulent blocks would require the actor to consistently win the competition. However, an attack would require the malicious actor to have control over more than 51% of the network mining power, which, in the case of cryptocurrencies with a large market capitalization like Ethereum or Bitcoin, is unlikely due to the resources needed. While PoW is still the predominant consensus mechanism across the cryptocurrency industry, it comes with multiple disadvantages, the main one being its energy intensity (Platt et al., 2021). Zhou et al. (2020) note that with an increasing number of users, scalability problems become apparent and directly influence the further development of the blockchain. The authors note that PoW-based systems still fail to meet sufficient levels of critical metrics such as transaction throughput and transaction confirmation. To address these disadvantages, Ethereum switched its consensus mechanism from PoW to PoS in late 2022.

In PoS, miners get replaced by validators. Instead of solving a complex mathematical puzzle and mining the next block, validators randomly propose and vote on the next block by staking the underlying cryptocurrency, for example, ETH, on the blockchain. In the case of Ethereum, 32 Ether (ETH) are required to become a validator, which comes with the responsibility of attesting new proposed blocks and also proposing new blocks. The validators are incentivized to not act maliciously as the ETH staked act as collateral which can be destroyed in the case of misbehavior. While PoS-based systems are used less and therefore are less tested, they are expected to have significant advantages over PoW systems. Such advantages include improved decentralization as well as a massive reduction in energy consumption (De Vries, 2023). Furthermore, staking pools also allow users to participate while staking less than the required 32 ETH. Another obvious advantage is the reduced energy consumption since it is not necessary to solve complex mathematical puzzles that require high computational power. Other advantages are the increased scalability potential and the possibly negative net issuance of new ETH, as new block creation does not require miners to be compensated for hardware and energy costs.

According to CoinMarketCap, there exist only 54 cryptocurrencies that use PoS as their underlying consensus mechanism, while only six of those have a market capitalization of over $1Bn USD (CoinMarketCap, 2023). This demonstrates that PoS is still in its infancy, leading to the expectation that the current body of literature is, at best, limited. We therefore present the current academic work on consensus mechanisms in the following.

Lashkari and Musilek (2021) develop a taxonomy of blockchain consensus mechanisms based on a comprehensive review of academic journals as well as sources from industry. They classify consensus mechanisms as (1) either primitive, that is, Paxos-based, (2) extensions of either primitive, proof compliant, or Byzantine fault tolerance (BFT) compliant mechanisms, and finally (3) alternative mechanisms. Leewis et al. (2021) investigate decision rights and governance in blockchain and find that PoS can help alleviate the centralization issue of PoW systems caused by the concentration of mining power. The authors warn that PoS may itself allocate disproportionate power to deeply invested users at the cost of less wealthy ones. A great network of validators as well as large and frequent transactions are likely to foster decentralization (Mueller-Bloch et al., 2022). Researching the interconnectedness of PoW and PoS cryptocurrencies, Milunovich (2022) finds that PoW cryptocurrencies exhibit a stronger connection to other digital assets and tend to move more in tandem with them compared to their PoS counterparts. In line with these findings, Sadeghian et al. (2021) show that the time series of cryptocurrencies with similar underlying consensus mechanism exhibit similar behavior. The scalability potential of PoS is assessed by Gao et al.

(2019) and Li et al. (2023), demonstrating that the mechanism outperforms PoW. To our knowledge, only few studies have analyzed the Merge, that is the change of Ethereum from PoW to PoS so far. De Vries (2023) studied the impact of change on energy consumption, finding a reduction in power demand by more than 99%. Ampel (2023) study the impact of the change in consensus algorithm on Ethereum price and volume, finding a significant positive effect on price but a non-significant negative effect on transaction volume. Other work investigates DeFi lending during the Merge for two lending protocols on Ethereum (Heimbach et al., 2023). The authors identify high volatility but no mass liquidations or irretrievable loans during that timeframe. The study conceptually closest to this work was conducted in 2024 and analyzed the relationship between cryptocurrency returns and network factors (Tsuyuguchi & Wang, 2024). The authors follow a similar approach to this work by testing the time-series difference in differences (DiD) model and vector autoregression (VAR) models for the Ethereum merge, using Bitcoin as their comparison. While the authors focus on the Merge and use similar models (DiD), their work differs from ours in their focus of study, as our work focuses on market liquidity. Nevertheless, their approach and choice of Bitcoin as the counterfactual demonstrate the applicability of a comparison of Ethereum and Bitcoin for liquidity. This work goes beyond the existing work on consensus mechanisms as it analyzes the effects of changing a consensus mechanism hands-on with actual historical data on the factor of market liquidity. While other factors, such as scalability and decentralization, have already been analyzed in academia, the factor of market liquidity has largely been overlooked

Market Liquidity

As stated in the introduction, market liquidity describes the ease with which an asset can be bought or sold, without the sale causing a significant change in price (Keynes, 1930). A liquid market requires enough buyers and sellers who are willing to trade the asset in question during market hours. In an illiquid market, assets would need to be sold at a discount to facilitate transactions, thereby negatively impacting asset prices (Amihud and Mendelson, 1986). Moreover, low market liquidity signifies a market risk, with risk-averse actors demanding a higher expected return for the asset. The same holds true for potential liquidity shocks (Acharya and Pedersen, 2005), to which the change in consensus mechanism could be counted.

There exists a broad range of factors that interact with market liquidity. For instance, Nguyen et al. (2020) find that market liquidity explains volatility dynamics in the US treasury market, but not vice versa. Prior research already indicated that, in the long run, Ethereum is found to be a leading contributor to liquidity shocks in cryptocurrencies (Hasan et al., 2022). One factor commonly used to study liquidity is the bid-ask spread of an asset, that is the difference between the ask offer price and the bid offer price, reflecting the underlying liquidity of an asset (Plerou et al., 2015). The bid-ask spread has already been used in cryptocurrency research to study liquidity uncertainty (Koutmos, 2018). The author studied liquidity uncertainty in Bitcoin using bid-ask spread data from the Bitfinex cryptocurrency exchange and found that market microstructure variables explain liquidity behavior. Two further dimensions that impact liquidity are market depth and market breadth (Sarr and Lybek, 2002). Depth is defined as the abundance of orders above and below the current price of an asset, while marked breadth defines the existence of numerous orders, differing in order size, with a limited impact on price (Sarr and Lybek, 2002).

As for Ethereum transactions and the state of the network to be validated under PoS, validators must stake a part of their Ether, which consequently means that they get taken out of the free-floating Ether, comparable to stock buybacks for public companies. Existing research demonstrates the negative effect of stock buybacks on market liquidity (Barclay & Smith Jr, 1988; Ben-Rephael et al., 2014). While it could be argued that stock buybacks impact market liquidity through another mediator than the free float, abundant research examines the direct link between the free float and market liquidity, finding a positive relationship. For instance, Rezaei and Tahernia (2013) present evidence for Iran and El-Nader (2018) for the UK. The positive relationship between the free float and market liquidity is not limited to one geographical area, with Ding et al. (2016) demonstrating that this holds for a sample covering 55 countries. For cryptocurrencies, research demonstrated that both retail and institutional investors' attention boosts market liquidity (Ozdamar et al., 2022). The adoption of cryptocurrencies has routinely been studied in academia (see Xiong & Tang, 2020). In that context, liquidity and related financial risks have frequently been found to be of importance for the adoption of cryptocurrencies (Abooleet, 2023; Abramova & Böhme, 2016). Thus, we argue that a change in consensus mechanism may decrease market liquidity, which could ultimately negatively impact cryptocurrency adoption, calling for further investigation on the topic.

Methodology

Foucault et al. (2013) define market liquidity as "the ability to trade a security quickly at a price close to its consensus value" (p.8). Hence, market liquidity is usually measured by an approximation of the bid-ask spread, in line with the definition by Lehalle & Laruelle (2018), who state that "an asset is liquid if it is easy to buy and sell it" (p.1). The bid-ask spread directly represents the asset's liquidity and ability to buy or sell this asset as it enlarges when liquidity is low, thus making it expensive to buy or sell, and vice versa. Different measures exist to approximate the spread and market liquidity, broadly summarized in high-frequency measures and low-frequency measures. The available data often dictate the applicability of these measures. While there have been studies that use high-frequency data to study liquidity in cryptocurrencies (Brauneis et al., 2022; Makarov & Schoar, 2020), the research conducted in this article relies solely on low-frequency measures due to their availability.

The most frequently used measures for market liquidity are the Roll (1984) measure and the Amihud (2002) illiquidity ratio. Roll's measure utilizes the bid-ask bounce of an asset and the fact that price changes should be negatively serially correlated to estimate the bid-ask spread. While this approach was genuinely innovative, it is limited by its stringent assumptions and the fact that the covariance of price changes is not always strictly negative. Amihud (2002) proposed another low-frequency measure that relies on price impact, with the idea that with a fixed amount of trading volume, the price impact, approximated by returns, should be higher/lower if the stock experiences low/high liquidity. The main drawback of this method is that it attributes every price change to illiquidity, disregarding other possible sources. We refrain from using volume as a proxy for measuring liquidity, as existing research in bond and stock markets demonstrated that the two are unrelated over time (Johnson, 2008).

Brauneis et al. (2021) compare the performance of various low-liquidity measures as a way to estimate liquidity in cryptocurrency markets. The authors conclude that the Corwin and Schultz (2012) (CS) estimator and the Abdi and Ranaldo (2017) (AR) estimator perform best when modeling time series variation in liquidity. Following these results, both estimators are used in this work. Since both measures are High-Low estimators aimed at the spread that approximates liquidity using daily high and low prices, the Amihud (2002) (AMH) measure is used as well as a way to increase the robustness of our results.

The AR measure uses natural logarithms of high, low, and closing prices in each subinterval i to estimate liquidity. Further, the midpoint is defined as $\bar{p}_i = (h_i + l_i)/2$ with h_i being the natural logarithm of the highest price while l_i is the natural logarithm of the lowest price. Throughout this work, t is defined as a trading day which lasts from 00:00 UTC till 24:00 UTC with no trading halts while the subintervals i are the hourly periods within a day. The two-day corrected version of the estimator that uses two adjacent subintervals i is then defined as:

$$AR_i = \sqrt{max\{4 * (c_i - \bar{p}_i)(c_i - \bar{p}_{i+1}), 0\}}$$

with c_i being the natural logarithm of the closing price. The AR measure of interval t is then defined as the unweighted average of all subintervals i in t:

$$AR_t = \frac{1}{I-1}\sum_{i=1}^{I-1} AR_{t,i}$$

The Corwin and Schultz (2012) estimator is the second liquidity measure used in this study. It is calculated using high and low prices of two adjacent subintervals i and i+1 and is defined as follows:

$$CS_{i,i+1} = \frac{2(e^{\alpha}-1)}{1+e^{\alpha}}, \text{ with } \alpha = \frac{\sqrt{2\beta}-\sqrt{\beta}}{3-2\sqrt{2}} - \sqrt{\frac{\gamma}{3-2\sqrt{2}}}, \beta = \left[ln\left(\frac{H_i}{L_i}\right)\right]^2 + \left[ln\left(\frac{H_{i+1}}{L_{i+1}}\right)\right]^2,$$

$$\gamma = \left[ln\left(\frac{H_{i,i+1}}{L_{i,i+1}}\right)\right]^2$$

with H_i and L_i being the high and low prices in subinterval i, while $H_{i,i+1}$ and $L_{i,i+1}$ denote the high and low price of two adjacent subintervals i and i+1. Corwin and Schultz (2012) propose setting negative values of the estimator to zero which is followed in this study. As with the previous estimator, the daily measure is the unweighted average of all adjacent subintervals within that day.

The AMH illiquidity ratio is defined as the absolute return for each subinterval divided by the dollar trading volume in that subinterval. The absolute return is computed from the closing price of the previous subinterval to the current one. The Amihud (2002) illiquidity ratio is thus defined as follows:

$$Amihud_t = \frac{1}{I}\sum_i \frac{|return_{t,i}|}{volume_{t,i}}$$

The daily measure $Amihud_t$ is the unweighted average of the hourly subintervals i. The AMH illiquidity ratio is different from the CS and the AR measure as it is technically an estimator of the price impact and not the spread. However, AMH illiquidity ratio is commonly used as a proxy for market liquidity and thus included in this study. Although the measures approximate liquidity by different means, they are equivalent in direction, as a higher estimate corresponds to a lower level of liquidity across all measures.

Table 1 presents the descriptive statistics for these three liquidity measures for the data. The data is non-standardized at this point while the AMH measure is scaled by 10^3 for comparability. From Table 1, one can observe that the CS estimator and the AR estimator behave very similarly while the AMH measure is more sensitive and volatile, indicating that spreads are less volatile than the price impact.

Table 1. Descriptive Statistic of the three Liquidity Measures

	Ethereum			**Bitcoin**		
	CS	AR	AMH	CS	AR	AMH
Mean	0,0027	0,0023	0,0066	0,0024	0,0019	0,0053
Std	0,0015	0,0014	0,0040	0,0012	0,0011	0,0041
Min	0,0005	0,0004	0,0012	0,0005	0,0003	0,0006
25%	0,0017	0,0013	0,0041	0,0016	0,0012	0,0027
50%	0,0024	0,0020	0,0056	0,0022	0,0017	0,0043
75%	0,0034	0,0029	0,0075	0,0029	0,0023	0,0063
max	0,0131	0,0101	0,0292	0,0094	0,0087	0,0288

Data Used

To compute these three measures, hourly OHLCV data is obtained from Refinitiv for the ETH/USD currency pair and the BTC/USD currency pair while the sample period ranges from 16/05/2022 to 30/04/2023. Following the approach of Theiri et al. (2023), hourly data is aggregated to create daily liquidity estimates for each measure. It is important to note that Refinitiv does not provide actual volumes traded for the currency pairs ETH/USD and BTC/USD but only a "count" parameter which denotes the number of quotes received within that specific time interval. Thus, in this study the "count" parameter is used as it is the best proxy for market activity in the absence of the actual dollar volume traded. It can be observed that the estimators for Ethereum and Bitcoin move in tandem, already supporting the assumption of a parallel trend (Sifat et al., 2019). Further, it seems that the liquidity of Ethereum exhibits more volatility before The Merge compared to Bitcoin while it appears to exhibit less after the change to PoS.

As expected, the CS and AR estimator exhibit a high correlation (0.88), with both being high or low at the same time, which is not surprising since both measures aim at estimating the spread. Further, it appears that the AMH illiquidity ratio has a negative correlation with the other two measures, with the actual correlations being -0.2 for the CS estimator and -0.19 for the AR measure. It should be noted that the behavior of the AMH illiquidity ratio is distorted by using the "count" parameter as a proxy for the actual dollar volume.

This finding seems to be counterintuitive at first, since all three measures are used to proxy market liquidity in this study. At the same time, the three measures are inherently different, as AMH illiquidity ratio is a measure of price impact and does not aim at estimating the bid-ask spread. This is in line with the findings of Goyenko et al. (2009), who show that the different measures measure different components of market liquidity and that price-impact measures like the AMH illiquidity ratio do not perform well when estimating spreads and vice versa. In essence, both spread measures cover only the top of the order book, which is the electronic list of buy and sell orders in an exchange, and do not take into consideration the volumes at the top. The price impact measure, however, estimates liquidity in terms of volume at the top and potentially deeper levels of the order book. Hence it might be the case that the spreads are small while at the same time, the volumes at the top of the order book are extremely low, leading any incoming orders to sweep the order book and thus resulting in a huge price impact. Therefore, although counterintuitive, it is no contradiction that the two groups of estimators behave differently and even experience a slightly negative correlation.

Furthermore, the volatility of spreads and also the level of spreads seem to be lower after the merge. This trend seems to be particularly strong after the turn of the year. While this could be a possible effect of the change in the consensus mechanism, it could also be attributed to macroeconomic or other possible factors and thus lead to false conclusions. To overcome this, DiD and LDV models are employed, which, complemented by well thought-out covariates, aim at preventing false conclusions and facilitating correct statistical inference. The approach to use two different statistical methods to check the robustness of the findings is inspired by Angrist and Pischke (2009), who state that the usual way to validate one's results is "to find broadly similar results using plausible alternative models" (p. 245). This robustness check is further strengthened by using three distinct cut-off dates and explained in the following.

Statistical Methods Applied

Difference-in-Difference (DiD)

Card and Krueger (1993) developed the DiD approach by analyzing the effects of minimum wages on employment. The DiD method is a quasi-experimental approach that compares the differences between two-time series where one time series or group undergoes a treatment while the other does not. It assumes that if treatment had not occurred, both groups' outcomes would have continued to follow a parallel trend (Abadie, 2005). In this work, the change in consensus mechanism acts as treatment for Ethereum, while Bitcoin, acting as counterfactual, remains unchanged. Prior research verified the significant correlation of Bitcoin prices with other cryptocurrencies, including Ethereum (Nakagawa & Sakemoto, 2022), suggesting bi-directional causality between the two (Sifat et al., 2019). Both cryptocurrencies aim to act as money and/or an investment, with Ethereum possessing additional functionalities, including decentralized finance (DeFi) and the creation of non-fungible tokens and smart contracts.

Since cryptocurrencies historically experienced a lot of volatility and reacted sharply to many other factors, running a simple linear regression would inevitably run into an omitted variable bias where explanatory power is falsely attributed to the explanatory variables included in the regression while, in reality, the explanatory power is to be attributed to the omitted one. Even if one were to find an independent variable with real explanatory power, it would still only indicate correlation, which does not provide any proof for an underlying causal effect.

The change in the consensus mechanism of Ethereum provides a rare opportunity for a quasi-experimental approach that allows the identification of causal effects (O'Neill et al., 2016). However, the DiD approach relies on two major assumptions: the common shock assumption and the parallel trend assumption (Angrist & Pischke, 2009). The common shock assumption states that a shock, defined as an unpredictable exogenous event that influences the groups, affects both in the same way post-treatment. For example, an interest rate rise by the FED should have the same effect on Ethereum's and Bitcoin's liquidity after the consensus mechanism change. While the common shock assumption is crucial for employing the DiD model, it is also untestable since it involves unpredictable exogenous forces. We therefore assume that the common shock assumption is met since it is unlikely that a probable exogenous event affects the liquidity of Ethereum and Bitcoin in a significantly different way. The parallel trend assumption requires the trends of the two groups or time series to behave parallel before the treatment, hence making it reasonable to assume that they would follow that trend in the absence of treatment. This is the critical assumption the whole DiD setup is built on. While no definitive test of parallel trends exists, scholars still run different pre-treatment tests to find evidence supporting parallel trends and thus solidifying the DiD results. However, Kahn-Lang and Lang (2020) argue that these tests are neither necessary nor sufficient for the validity of the DiD setup to hold as "the purely statistical approach uses pre-testing and thus generates the wrong standard errors "(p. 5). Other authors also present strong arguments against the pre-testing of parallel trends (Roth, 2022). The author shows that pre-testing can significantly negatively impact the performance of the DiD setup and increase bias. Furthermore, he finds common pre-tests often to be underpowered against violations of the assumptions researchers aim to test. We therefore refrain from running any pre-tests but assume that the parallel trend assumption holds. The DiD regression estimated in this study is thus defined as follows:

$$DepVar_{i,t} = \alpha + \beta_1 Post_t + \beta_2 ETH_i + \beta_3 Post \times ETH_{i,t} + \delta_t + \varepsilon_{i,t}$$

where $Post_t$ is the time-specific dummy variable that is 0 before the treatment and 1 after the treatment, and ETH_i is the group-specific dummy variable which is 0 for Bitcoin and 1 for Ethereum. β_3 is the interaction of the two dummies and the value for our DiD model which resembles the effect the change in consensus mechanism had on the liquidity of Ethereum. $DepVar_{i,t}$ are the dependent variables, in our case the three liquidity measures, which consequently means that the above-mentioned regression will be estimated nine times in total since we examine three different dates as explained later on. δ_t are the time-specific covariates. While the above-outlined DiD approach allows for causal inference to be made (O'Neill et al., 2016), it is vulnerable to criticism about the underlying assumptions, especially the parallel-trend assumption. To counter these vulnerabilities and to increase the robustness of this study, a Lagged-Dependent-Variable regression is run additionally which relaxes the underlying parallel-trend assumption.

Lagged-Dependent-Variable (LDV)

Compared to the DiD setup, the LDV approach does not need the parallel trend assumption to be fulfilled (O'Neill et al., 2016). Instead, the LDV approach relies on the independence conditional on past outcomes assumption which O'Neill et al. (2016) define as "in the absence of treatment, the expected outcomes for the treated and control groups would have been the same, conditional on their past outcomes and covariates." (p.2). This is mathematically expressed with $Y(b)$ indicating potential outcomes in the b time periods before the treatment and $X(1)$ being observed covariates:

$$Y_o(1) \perp D(1) | [X(1), Y(b)]$$

In accordance with O'Neill et al. (2016), the parallel trend assumption defined by Abadie (2005):

$$E[Y_0(1) - Y_0(0) | X(1), D = 1] = E[Y_0(1) - Y_0(0) | X(1), D = 0]$$

is unlikely to hold in many settings as it is vulnerable to time-varying confounding factors that affect the outcome in the variable of interest. While the LDV approach performs better when the parallel trend assumption does not hold, it can lead to severe bias in case the parallel trend assumption is falsely rejected, which may be a reason for its low popularity amongst scholars (Angrist & Pischke, 2009).

LDV is not the only alternative to a DID setting where the parallel trend assumption does not hold. The synthetic control method is another approach which, compared to LDV, has received more attention from academics. In the synthetic control method, the outcome of the treatment group is compared to a weighted combination of control units (Abadie, 2021). Multivariate matching is yet another approach used when the parallel trend assumption is in doubt (Diamond & Sekhon, 2013). Here, the treatment and control groups are matched based on pre-treatment outcomes and other covariates.

While all three alternatives presented above are valid when the parallel trend assumption does not hold, O'Neill et al.(2016), using a Monte Carlo simulation, find that the LDV approach presents the least biased and most efficient estimates when the parallel trend assumption does not hold. Thus, it is implemented in this study to account for the possibility of the parallel trend assumption not being met and hence increase overall robustness of the results. Following O'Neill et al. (2016), the LDV regression estimated in this study is thus defined as follows:

$$DepVar_{i,t} = X_{i,t}\beta + \sum_{k=1}^{T_0} \theta_k Y_{i,t=k} + \tau D_i + \varepsilon_{i,t} \quad \forall t > T_0$$

where $X_{i,t}$ are the covariates or control variables described in the next subchapter and $D_i = 0$ indicates the counterfactual for the treated unit, essentially a dummy variable which is 0 for Bitcoin and 1 for Ethereum. As O'Neill et al. (2016) note, the introduction of past outcomes in the regression does not result in a dynamic model as the dependent variable is regressed on a fixed vector of pre-treatment outcomes as indicated by $\forall t > T_o$, where T_o indicates the specific point in time of the treatment. Similar to the DiD regression, $DepVar_{i,t}$ represent independent variables which, in our work, are the liquidity measures. The variable of interest in the LDV regression is τ, which represents the average treatment effect on the treated which is indicated as β_3 in the DiD regression. While some scholars have been arguing that the introduction of past outcomes as explanatory variables to the regression could bias the results, O'Neill et al. (2016) argue that this criticism does not apply to the estimation of average treatment effects on the treated as done in the LDV regression above.

Control Variables

The selection of control variables is based on Brauneis et al. (2022), who analyze the determinants of liquidity in Bitcoin, and Sovbetov (2018), who research factors that influence cryptocurrency prices. In this study, control variables are considered both with a lag of 0 and 1, as we assume that the liquidity of cryptocurrency markets does not always react instantly to changes in one of the control variables.

The control variables include general financial markets indices such as the daily return of the MSCI index, taken from MarketWatch, the source of all other variables unless otherwise specified, and the return of the SP500 index, sourced from the Wall Street Journal. The second group of control variables includes EUR/USD spot rate and daily change in DXY index, aiming to capture USD strength and general conditions of FX markets. VIX directly measures the stock market's expectation of volatility based on SP500 options. The daily return of gold acts as a proxy for inflation. The fifth component of the control variables includes the daily return of the CRIX index and the daily squared return of the CRIX index, sourced from S&P Global. The CRIX index (Trimborn & Härdle, 2018) aims to capture the general state of the cryptocurrency market. The last control variable is a Trading Day dummy which indicates whether financial markets are open at a current date. This is necessary as the cryptocurrency data used to construct the liquidity measures is available throughout the sample period, while traditional financial markets are closed on weekends and bank holidays. Control variables are depicted in Table 2.

Table 2. Control Variables

Variable	Description	lag
CRIX	Daily return of the CRIX index	0 & 1
CRIX_SQ	Daily squared return of the CRIX index	0 & 1
VIX	Daily change in the VIX index	0
MSCI	Daily return of the MSCI index	0
SP 500	Daily return of the SP500 index	0 & 1
EUR/USD	Daily return of the EUR/USD spot rate	0 & 1
DXY	Daily change in the DXY index	0
Gold	Daily return of gold	0 & 1
Trading Day	Trading day dummy (0 for non-trading days)	0

After sourcing the data and constructing the relevant control variables, the pairwise correlation between the control variables is calculated to address multicollinearity. While a regression is built on the correlation between the dependent variable and possibly multiple independent variables, having a high correlation between the independent variables themselves leads to the standard errors of the coefficients being magnified and thus can lead to potential false insignificance (Daoud, 2017). Thus, we exclude the daily change in the DXY from the control variables as it is highly correlated (-0.91) to the daily return of the EUR/USD spot rate. This is not surprising as both are indicators of USD strength. Further, the MSCI index's daily return and the VIX index's daily change are excluded as they both are highly correlated with other control variables depicted above.

Identification of Cut-Off Dates

As discussed previously, we expect the change in consensus mechanism to have a negative impact on market liquidity as Ether gets taken out of the free float to be staked and thus facilitates the verification of transactions and the state of the network under the PoS consensus mechanism. The staking of Ether, however, did not start with the change in the consensus mechanism but around two years earlier with the introduction of the Beacon Chain. The Beacon Chain is the original PoS blockchain which was merged with the Ethereum Mainnet on September 15th, 2022, in the event titled *The Merge*. The Beacon Chain was created to test the PoS mechanism and ensure that the new consensus mechanism is secure and working correctly before introducing it to the Mainnet. Before the merge with the Mainnet, the Beacon Chain was running side-by-side with it, already allowing cryptocurrency pioneers to stake their Ethereum in preparation for the coming merge. Thus, apart from the actual change in consensus mechanism, the LDV and DiD regressions discussed in previous chapters are also run using the percentage of total Ethereum staked as the factor for the cut-off date defining pre- and post-treatment. We title this cut-off date *Percentage-Staked*. Figure 1 shows the development of the percentage of total Ether staked, calculated by dividing the amount of staked Ether by the total supply. We refrain from using the date of the proposal of PoS for Ethereum in 2020, as the success of achieving PoS was not guaranteed at that time, making the announcement data unsuitable to act as a cut-off date. While the percentage of total Ether staked grew consistently throughout the sample period, it increased sharply after August 2022. Hence, August 1st is chosen as the cut-off date associated with the total *Percentage Staked* in Ether.

While the percentage staked grew throughout the sample period, it experienced another sharp increase after April 4th, 2023. This was a reaction to the *Shanghai Update*, which took place on that specific date. Since the launch of the Beacon Chain, cryptocurrency enthusiasts have begun to stake their Ether on the blockchain. However, this came with a caveat since the staked Ether were locked up on the blockchain and could not be withdrawn by the investor. Liquidity pools, such as Lido, saw this as an opportunity to introduce their own "staked ETH" (stETH) coin, which would be given out to the investors in their staking pool at a 1:1 ratio. This process, where third-party providers issue a liquid representation of the staked ETH, is called liquid staking. Investors in liquidity pools have a liquid asset that can be freely traded while still earning staking rewards. Creating this solution to unlock the staked Ether, Lido accumulated a significant market share and is currently responsible for staking around 31% of Ethereum as of July 2023, according to the cryptocurrency analytics platform Dune (Dune, 2023). The Shanghai Update introduced staking withdrawals, allowing users to withdraw their staked Ethereum from the Beacon Chain for the first time. While this is a possible explanation for the sharp 5% drop in Lido's market share, it also explains the increase of Ether staked in Figure 1. We hypothesize that the mere possibility of withdrawing staked Ether animated illiquidity-averse investors to start staking their Ether. Thus, the Shanghai Upgrade is the third cut-off date that will be used to define pre- and post-treatment in the above-outlined LDV and DiD regression.

Analyzing two different cut-off dates next to the actual change in the consensus mechanism may lead to allegations of deviating immoderately from the research question to analyze the effects of a change in the consensus mechanism. However, both the Percentage-Staked cut-off and the Shanghai cut-off are direct consequences of the change in consensus mechanism and are closely associated with the proposed cause for the change in liquidity, namely the staking of ETH.

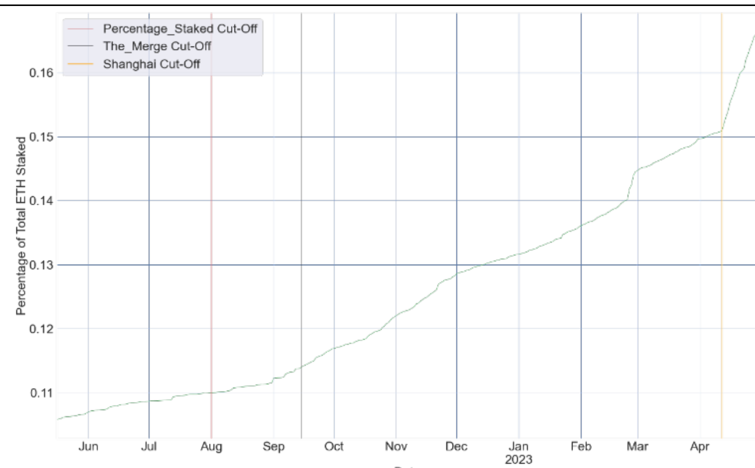

Figure 1. Percentage of Total Ether Staked and the Three Cut-Off Dates used.

Results

In total, 18 regressions are run: three regressions with different cut-off dates, namely, Percentage-Staked, The Merge, and Shanghai for each of the three liquidity estimators, obtained from, Abdi and Ranaldo (2017), Corwin and Schultz (2012) and Amihud (2002), for each of the two models, namely Lagged Dependent Variable, and Difference-in-Difference.

Results for Difference-in-Difference (DiD) Analysis

Table 3. presents the regression results for the DiD regression including all three cut-off dates. The first column, Ethereum_%_Staked, represents the estimated average treatment effects on the treated. It can be observed that, using the Percentage-Staked cut-off date the change in consensus mechanism did not have any significant effect on either spread estimator. At the same time, it seems to have significantly impacted the price impact estimator, AMH. The coefficient for the AMH estimator is highly significant at the 1% level, with an estimated coefficient of around 0.53. Since all liquidity measures are standardized, this translates to the change in consensus mechanism increasing the AMH estimator by 0.53 standard deviations, thus increasing price impact and reducing liquidity. It is also interesting to note that the correlation between any of the liquidity estimators and gold does not appear significant on any level.

For the Merge cut-off date, we observe that the price impact measure is significant at the 1% level and yields a coefficient of 0.48. Hence, the change in consensus mechanism increased the price impact, estimated by the AMH measure, by 0.48 standard deviations. The other two liquidity measures that approximate the spread both yield a negative coefficient of negative 0.22 and negative 0.24 for the CS and AR measure, respectively. While this indicates that the change in consensus mechanism led to smaller spreads, caution is advised, as both coefficients are only significant at the 10% level. Nevertheless, it is a recurring theme that the spread estimators behave opposite to the price impact estimator, which will be discussed in detail later on. All covariates, except for gold, are statistically significant.

While the percentage of total ETH staked rapidly increased after the Shanghai update, we cannot observe any significant effect of this event on the liquidity of Ethereum. The sample period of the data could be a possible explanation for the non-significance of the coefficients, as the post-treatment period only consists of roughly three weeks of data. Thus, it could be the case that if this study were to be repeated with a more extensive post-treatment, the coefficients would be significant.

Table 3. Percentage-Staked, The Merge and Shanghai Update DiD Regression Results on Market Liquidity

	Percentage-Staked DiD			**The Merge DiD**			**Shanghai Update**		
	CS	AR	AMH	CS	AR	AMH	CS	AR	AMH
ETH:%_Staked	-0.12	-0.19	0.53°	-0.22*	-0.24*	0.48°	-0.07	-0.18	0.03
R_CRIX	-4.36°	-2.59*	1.44	-3.99°	-2.28	1.49	-4.40°	-2.61	1.42
R_CRIX_SQ	87.30°	84.32°	3.69	84.55°	83.92°	5.70	101.37°	97.98°	7.50
R_CRIX _SQ_lag	158.95°	135.85°	-47.96^	151.65°	131.59°	-46.63^	172.49°	148.94°	-44.28^
R_CRIX_lag	-2.47*	0.04	-1.29	-2.33*	0.13	-1.30	-2.72*	-0.18	-1.37
R_Gold	-6.86	-2.50	1.48	-1.14	2.40	2.39	-6.55	-1.93	1.47
R_Gold_lag	-4.45	-6.24	-0.87	-0.28	-2.62	-0.16	-4.31	-5.79	-0.94
R_SP500	9.36°	6.43*	6.58	9.98°	7.18*	6.95	11.62°	8.50^	7.23*
R_SP500_lag	0.74	-5.74	7.05	1.38	-4.90	7.52*	3.29	-3.32	7.76*
R_eurusd	11.00	12.91	-16.06*	7.86	9.24	-17.77*	3.17	5.25	-18.16*

R_eurusd_lag	13.35*	19.88^	-3.50	11.98	17.78^	-4.87	7.28	13.67	-5.03
Trading_Day	0.43°	0.35°	-0.80°	0.41°	0.33°	-0.80°	0.41°	0.33°	-0.80°
Observations	700	700	700	700	700	700	700	700	700
R2	0.42	0.34	0.18	0.43	0.31	0.17	0.25	0.18	0.16
Adjusted R2	0.41	0.33	0.17	0.42	0.30	0.16	0.24	0.17	0.14
Residual Std. Error (df)	0.77 (685)	0.82 (685)	0.91 (685)	0.76 (685)	0.84 (685)	0.92 (685)	0.87 (685)	0.91 (685)	0.93 (685)
F Statistic (df)	35.46° (14;69)	25.66° (14;69)	10.98° (14;69)	36.90° (14;69)	22.04° (14;69)	10.25° (14;69)	16.42° (14;69)	11.05° (14;69)	9.27° (14;69)
Note: *p<0.1; ^p<0.05; °p<0.01, "R_ for return									

Lagged-Dependent-Variable Results

Table 4. presents the regression result estimating the above-outlined LDV regression using the Percentage-Staked, The Merge and Shanghai Update criteria as cut-off dates, defining pre- and post-treatment.

For the Percentage-Staked Cut-Off, similar to the DiD regression, only the price impact estimator, AMH, is significant. The coefficient of the price impact estimator is highly significant at the 1% level; however, the coefficient is smaller than before, yielding 0.00945. This means that the change in consensus mechanism, measured through the Percentage-Staked criteria, increased the price impact, respectively the AMH measure, by 1% of its standard deviation.

For The Merge, the results depict that both spread estimators, CS and AR, are significant at the 5% level and that both coefficients are negative. Thus, the change in the consensus mechanism seems to have tightened spreads by 28bps in terms of standard deviations of the estimator when spreads are approximated by the CS estimator. At the same time, spreads seem to have tightened by 29bps in terms of standard deviations of the estimator when spreads are approximated by the AR estimator. Meanwhile, the AMH measure continues to be negatively correlated to the spread estimators, as it indicates that market liquidity, approximated by the price impact, decreased as the price impact increased by around 90bps in terms of standard deviations of the estimator. Further, none of the covariates are significant when estimating the effect on the AMH measure which also yields a smaller R^2 compared to the explained variation of the spread estimators.

The regression results show that the Shanghai Update seems to have decreased spreads, while the Update did not affect the price impact. However, only the AR estimator can be described as significant as the coefficient of the CS estimator is only significant at the 10% level and thus fails to reach the typical 5% required to be deemed significant. The AR measure is significant at the 1% level and indicates that the Shanghai Update decreased spreads by 30 basis points, measured in standard deviations of the estimator. Interestingly, all the regressions seem to explain significantly more of the variation of the liquidity measures, as shown by the comparatively high R^2. One possible explanation for this could be that the time series of the liquidity measures have not experienced as much variation as previously since the LDV regression uses only post-treatment outcomes as dependent variables and regresses these on a fixed vector of pre-treatment outcomes. Hence, in the Shanghai case, the dependent variable, the liquidity estimators' time series, consists of less than 30 observations. Logically, the level of experienced variation in a time series should rise with an increasing number of observations in that time series.

Table 4. Percentage-Staked, The Merge and Shanghai Update LDV Regression Results on Market Liquidity									
	Percentage-Staked DiD			**The Merge DiD**			**Shanghai Update**		
	CS	AR	AMH	CS	AR	AMH	CS	AR	AMH
ETH:%_Staked	-0.00	-0.00	0.00°	-0.00^	-0.00^	0.01°	-0.00*	-0.00°	0.00
R_CRIX	-0.46	1.71	2.45	0.01	1.95	2.76	3.86	5.27	-4.25
R_CRIX_SQ	131.42°	136.92°	16.28	147.44°	163.92°	18.74	198.72	241.69*	-160.32
R_CRIX SQ_lag	181.57°	152.81°	-55.20^	177.13°	147.56°	-46.48	74.83	-141.59	-75.45
R_CRIX_lag	-1.87	0.47	-2.03	-2.31	0.75	-2.30	-5.94	1.70	-4.95
R_Gold	-2.91	1.80	1.78	0.49	4.96	0.14	12.12	-24.52^	27.81
R_Gold_lag	-3.06	-2.95	-1.78	3.85	0.74	-2.63	14.30	-17.24	50.42^
R_SP500	5.26	3.50	3.71	2.90	3.60	2.80	28.25	14.03	64.08
R_SP500_lag	2.87	-2.91	6.73	1.10	-4.83	7.15	-11.26	-1.72	-23.67
R_eurusd	-7.35	-4.14	-9.29	-9.65	-11.15	-7.64	-73.96	36.55	-111.82
R_eurusd_lag	2.97	4.46	1.28	-0.55	0.19	1.024	-59.37	-57.83	-95.19
Trading_Day	0.41°	0.36°	-0.86°	0.36°	0.32°	-0.92°	0.47^	0.67°	-1.29°
Observations	546	546	546	454	454	454	36	36	36
R2	0.38	0.34	0.197	0.42	0.38	0.20	0.69	0.78	0.72
Adjusted R2	0.36	0.33	0.18	0.41	0.365	0.18	0.52	0.67	0.58
Residual Std. Error	0.65 (533)	0.62 (533)	0.85(53)	0.62 (441)	0.62 (441)	0.92 (441)	0.33 (23)	0.310 (23)	0.49 (23)
F Statistic (df)	26.84° (12; 53)	23.11° (12; 53)	10.90° (12;53)	27.14° (12; 44)	22.68° (12; 44)	9.26° (12;44)	4.19° (12;23)	6.94° (12; 23)	5.00° (12;23)
Note: *p<0.1; ^p<0.05; °p<0.01, “R_” for return.									

Discussion

It can be seen that, throughout the regressions, covariates were mainly significant, indicating a good choice of covariates that demonstrate a significant correlation with our liquidity measures. Further, we observed that price impact and spreads generally correlate negatively as they move in opposite directions. This can be seen when looking at the results using The Merge as the cut-off date, where the coefficients of all measures are significant but comparing the spread estimators to the price impact estimator indicates different directions. However, an opposite direction in the liquidity estimators does not indicate any misspecification in the regression, as there are several explanations as to why it is plausible to have a market exchange where spreads and price impact do not move in tandem. The differences in the use cases of Ethereum and Bitcoin may also be an explanation for the observed behavior. Smart contract-based blockchains such as Ethereum can enable users to mint liquidized versions of tokens after staking or locking funds. Thus, the results might differ should cryptocurrencies like Bitcoin change their consensus algorithms in the future.

Trading in cryptocurrency markets is, or used to be, dominated by retail investors (Dyhrberg et al., 2018). A cryptocurrency exchange where many retail traders engage and submit bids leads to lower spreads than on comparable equity exchanges (Dyhrberg et al., 2018). As retail traders tend to trade much less volume than institutional investors, the highest levels of the order book consist only of small volumes, resulting in low market depth. With only small volumes at the top, the order book gets swept easily, resulting in a significant price impact when larger quantities of the cryptocurrency are traded.

Another plausible explanation backed by academic research is directly linked to the infinitesimal tick sizes: the price increment between the limits in the order book. Cryptocurrency exchanges generally allow orders to be submitted in infinitesimal tick sizes, which allows new traders to underbid the current best bid or best ask by bidding or asking just an infinitesimal amount more or less. Consequently, the top levels of the order book are filled with small orders, all just an infinitesimal amount apart. This aligns with the findings of Dyhrberg et al. (2020), who find that increasing tick sizes are associated with more market depth and, thus, less price impact. The work by Rindi and Werner (2019) further solidifies the above argument as they show that an increase in the tick size is associated with an increase in spreads and market depth or an increase in spreads and a decrease in price impact.

These two explanations show that it is not uncommon for spreads and market depth to behave differently and even exhibit negative correlation at the same time, the two presented explanations do not specifically explain the results of this work. The increase in price impact can be explained following the same logic as presented in our general assumption, namely that the change in consensus mechanism decreases the free float, which consequently should decrease market liquidity. This explanation is primarily supported by the LDV and DiD regression results that use the Percentage-Staked as the cut-off criteria. While these regressions show an increase in the price impact, the actual change in consensus mechanism has yet to happen. However, the free float has already decreased compared to the counterfactual level of the free float if no Ether was staked. Thus, assuming that the change in free-floating Ethereum had decreased market depth or reversely increased the price impact is reasonable.

While the increase in price impact is to be explained reasonably well with the assumptions and explanations provided so far, the reason for the decrease in spreads, as shown by the regression results, is less apparent. However, it is interesting to note that the decrease in spreads shows up only after the actual change in the consensus mechanism, which points to the fact that the origin of this effect is different from the effect influencing the price impact, as otherwise, the coefficients would yield significant also before the actual change in the consensus mechanism. While this does not provide a complete explanation for the regression results presented above, it points to a possible path for future research that digs deeper into the drivers of spreads and price impact in cryptocurrency exchanges.

Comparing the regression results between the LDV and DiD regressions, it is evident that the estimated coefficients are only partially congruent. This is unsurprising, as these models' underlying assumptions are different in nature: while the Lagged-Dependent-Variable approach does not assume parallel trends, the Difference-in-Difference regression does. However, the different results do not jeopardize the study's validity. The initial expectation was not to yield the same estimates using a different approach but "to find broadly similar results using plausible alternative models" (Angrist & Pischke, 2009). Hence, as the results point in a similar direction, including both approaches contributes significantly to the robustness of this study. Therefore, the LDV and the DiD approach provide evidence supporting the initial assumption that the change in consensus mechanism decreases the free float and thus impacts market liquidity negatively. However, it became apparent that liquidity estimates in cryptocurrency markets can deviate substantially from one another based on whether the approximation of liquidity is aimed at the spread or the price impact. Hence, while we find evidence supporting the initial assumption, we also find evidence that the change in consensus mechanism decreased spreads, which calls for further examination in future research. Finally, this work is not without limitations. The first limitation is the sample period which consists of only 350 days or 8400 hourly observations, due to the relatively recent change in consensus mechanism. A further limitation is the limited number of statistical methods applied in this work. A more extensive sample period combined with more advanced statistical methods could facilitate the construction of even more complex models, which may yield significant additional insights. Such models could also address the limitation of potential endogeneity in our models, which cannot easily be solved through LDV (Bellemare et al., 2015). Lastly, other possible counterfactuals, such as Ethereum Classic, could lead to different assessments, given the structural and functional differences between Ethereum and Bitcoin. While both have been compared in prior work (Tsuyuguchi & Wang, 2024), future research could use other Ethereum offspring to replicate this work and gain additional insights.

Conclusion

This work analyzes the impact of a change in consensus mechanism on the underlying cryptocurrency, from PoW to PoS in the second biggest cryptocurrency Ethereum, using Bitcoin as a counterfactual. While PoS has been introduced to address scalability and energy intensity issues, the staking of Ethereum is hypothesized to decrease market liquidity, as the free float is reduced if coins are staked. Liquidity has been overlooked in academic research, even though it remains a crucial factor that influences the overall success and usability of cryptocurrencies and their underlying ecosystems, such as DeFi applications.

Using cryptocurrency price data, we analyze implications on market liquidity of Ethereum in detail, using a Difference-in-Difference and an advanced Lagged-Dependent-Variable approach. Both of these methods are claimed to allow for the identification of real causal effects, compared to only correlative effects (O'Neill et al., 2016). Furthermore, three different cut-off dates were defined, all associated with the change in the consensus mechanism. For our analysis, we approximate market liquidity using three different measures: two spread measures, the CS, by Corwin and Schultz (2012) and the AR estimator, by Abdi and Ranaldo (2017), and one price impact measure, the AMH estimator, by Amihud (2002). The regression results presented by both approaches yield significant estimates and are mostly congruent, further solidifying the statistical validity of the approach. While we find a significant increase in the price impact, which suggests a deterioration of market liquidity, we also find that spreads have further tightened, which suggests an increase in market liquidity, answering our research question. However, these results do not pose a contradiction, as discussed in the prior chapter. Both liquidity measures estimate liquidity differently. Thus, we conclude that the change in consensus mechanism decreased market breadth, defined as the impact of trades on prices, while the effect on tightness, the difference between best-buy and best-sell, is opposite as both spread estimators yield significant negative coefficients, thus providing evidence of decreased spreads.

The contribution of this work is therefore the comprehensive analysis of the change from PoW to PoS consensus mechanism in Ethereum on market liquidity, a significant factor influencing cryptocurrency adoption. Future work should investigate this substantial technological change in cryptocurrency design in greater detail by also analyzing other potential effects, such as the impact on transaction cost, cryptocurrency interrelatedness, fairness and security. All these factors, including market liquidity, ultimately influence the performance of a cryptocurrency for a broad range of use cases, from payments and investments to more advanced business solutions and DeFi applications. Research that can draw from a more extensive time period will yield further significant results and reveal important information for practitioners and academics.

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