Essays on Blockchain: Trading Platforms, Stablecoins, and Cryptocurrency Price

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Chapter 1. Introduction.

This dissertation consists of three chapters that cover various facets of blockchain technology and its most notable application – cryptocurrency.

The first chapter explores the volatility of a specific cryptocurrency category – the stablecoin. Stablecoins are crucial to the functioning of crypto markets and exchanges. Their value is pegged to a fiat currency, usually the US dollar, and thus stablecoins provide a reliable way for users to trade in and out of Bitcoin and altcoins without converting back into fiat currency – potentially avoiding significant tax liabilities and transaction costs. The stablecoins' peg to the fiat currency is maintained via various mechanisms, thus creating subcategories of stablecoins based on peg mechanism/design. This chapter aims to find if there are any differences in the frequency of extreme volatility experienced by stablecoins based on design. The question is of interest in light of several major de-pegging events, which occur as a result of extreme volatility, that wiped out the market capitalization of prominent algorithmic stablecoins. To this end, a power law model is employed to fit the daily realized volatilities of stablecoins. Power law models have been shown to model and forecast volatility more accurately than GARCH models. They better account for risk of extreme events, which is crucial in data exhibiting fat tails. The majority of stablecoins' volatility analyzed exhibit extremely high kurtosis, higher than that of Bitcoin, which points to fat tails and a higher chance of extreme events occurring. Fitting the power law yields the alpha coefficient, and interpreting it allows us to judge frequency and scale of extreme events

and whether standard deviation and variance are meaningful statistics for volatilities of stablecoins. Then the stablecoin alpha coefficients are grouped based on the pegging mechanism and the groups are compared using non-parametric tests such as the Kruskal-Wallis test. They were also grouped into USD-pegged and non-USD-pegged groups, due to the prevalence of USD-pegged stablecoins. The results found a statistically significant difference between tokenized stablecoins and the two other major groups separated by design – crypto-backed and algorithmic. Surprisingly, no difference was found in the volatility of USD and non-USD pegged stablecoins. This study contributes to stablecoins literature by confirming the difference in terms of daily volatility between tokenized stablecoins and other subcategories of stablecoins is statistically significant, as well as presenting evidence that the former are on average less likely to exhibit extreme price movement, thus making them more reliable for wealth storage, and presenting a lower risk of de-pegging.

The second chapter is theoretical and attempts to model a hypothetical blockchain-based OTC derivative trading platform, using game-theoretic models and simple simulations in Python to visualize the predictions. The blockchain technology is best known for producing the phenomenon of cryptocurrencies – also known as decentralized currency. However, the promise of decentralization through blockchain is touted for many industries. One such area is OTC derivatives trading. It is a slow-paced market compared to equities, with clearing of trades taking up to three days and incurring significant back-office costs. Numerous authors in academic literature and in the industry believe the implementation of blockchain could significantly improve the speed of clearing and trade execution, with some success having been achieved in trials. Also, the opacity of this market is well-known, and some believe with better oversight the 2007-08 financial crisis could have been avoided. Some of the

expectations related to blockchain are: 1) reducing back-office costs, 2) reducing clearing time from days to minutes, 3) increasing transparency, thus allowing for better oversight by regulators. This chapter argues that the increased transparency could in fact allow the dealers in the OTC derivatives market to maintain a collusive equilibrium, decreasing the welfare of customers. The trading platform is modeled as a sealed bid first price auction. The existing Swap Execution Facilities for Index Credit Default Swaps are used as the baseline model, as they are fairly standardized and the trading process well-documented. By extrapolating from the primary features of permissioned blockchains and existing decentralized exchanges (DEXes), two versions of the blockchain platform are developed, distinguished by their transparency levels. This yielded two versions of the blockchain platform, the main distinction being their level of transparency. The simple auctions model shows the superior profits for dealers if they maintain collusion in an infinite game, and that GRIM trigger strategies are efficient at punishing deviators. This study relies on the concept of "naming" introduced in previous research, which allows the bidders to enforce the collusive equilibrium. This study's contribution is distinct in its focus on the OTC derivatives market, and the finding of the increase in collusive ability proportional to increase in transparency. It also effectively synthesizes models from game-theory and empirical studies about the behavior of dealers and customers in OTC derivatives markets, to forecast the perils of real-world application of this emerging technology. This study fills the gap in studying the possible detriment of application of blockchain in OTC derivatives market, where the literature is thin and mostly supportive of this shift. The conclusion is that the ability to maintain collusion increases with the level of transparency, with it being lowest in the

existing SEFs and highest at the fully transparent blockchain-based system, which is effectively an open auction.

The third chapter investigates the influence of ERC-20 token transfers on Ether price formation. It is done by utilizing a LASSO regression to measure the impact of change in daily transfers of ERC-20 tokens on Ether returns. The daily transfers of the ERC-20 tokens on the Ethereum network is blockchain level data which was not found to have been used in this context before. Previous research has used blockchain level data such as the number of crypto addresses to value cryptocurrencies and assess network effects, however none that used transfers data for this purpose. The existence of a consistent, significant, and positive impact would serve as a breakthrough in pricing Ether and imply the existence of network effects on the Ethereum network. Additionally, this study highlights the difference between cryptocurrencies with native blockchains and tokens that utilize those blockchains to execute their transactions. A LASSO regression is used, and additional variables were incorporated into the dataset to assess the explanatory power of ERC-20 tokens' daily transfers relative to the effects of a bull run in the crypto market and macroeconomic events that prompt investors to shift their portfolios toward cryptocurrencies for hedging purposes. The list of variables includes the price and volume data for the ERC-20 tokens chosen for the analysis. Also included are the price and volume for major cryptocurrencies like Bitcoin, ADA (Cardano), SOL (Solana), TRX (Tron) and macroeconomic variables like the EPU data for the US, the S&P500 index, NASDAQ, Google trends data etc. The LASSO regression shrinks the coefficients of variables that do not contribute to the model to zero, which allows us to compare the explanatory power of token transfers data to that of other variables. A post-

LASSO is performed after fitting the LASSO, which is an OLS fit with only the variables that the LASSO did not shrink to zero. The rationale behind it is that the LASSO selects the most relevant variables but produces biased results, and the post-LASSO uncovers the true coefficients. Additionally, different versions of the dataset are used. There are two versions of the dataset, the difference being the omission of certain variables in one of them. Considering that LASSO is a shrinkage method this step could be viewed as redundant, however, the different versions of the dataset were included for robustness. The first contribution of this chapter is showing daily change of ERC-20 token transfers do not impact Ether returns. In fact, out of the 9 variables that made it through the LASSO selection, no transfers variable was selected. The analysis yielded some interesting results, such as a statistically significant impact of the price/returns data of certain ERC-20 tokens on Ether returns. The transfers data, however, showed no impact on Ether returns. The second contribution is that based on this result the implication is that network effects are unlikely to be caused by ERC-20 activity and strengthens the belief that Ether price is driven mainly by speculation. This expands on the discussion in the literature about the existence of network effects in cryptocurrencies. The third contribution is to forecasting literature. A 100-step expanding window prediction of daily Ether returns is made using the LASSO regression and compared to the RIDGE regression, and post-LASSO. The benchmarks are the OLS and AR(1) models, compared in terms of Root Mean Squared Error (RMSE), Mean Directional Accuracy (MDA) and Mean Absolute Error (MAE). The results regarding forecasting with the regularization methods show that the best prediction were consistently obtained by the LASSO regression (with post-LASSO performing similarly), outperforming the OLS and

AR(1) predictions. The Diebold-Mariano test confirmed the statistical significance of the difference with the benchmark models.

Each chapter of this dissertation addresses a critical aspect of blockchain technology and cryptocurrencies, elucidating significant consequences for consumers and implications for policymakers. The first chapter underscores the systemic importance of stablecoins within the expanding crypto-markets, emphasizing how the collapse of major stablecoins like USDT or USDC could jeopardize trillions of USD in investments. The second chapter is theoretical and models the potential for increased collusive behavior among dealers on emerging blockchain-based trading platforms for OTC derivatives, an industry crucial to the global economy. The third chapter seeks to establish a clear, quantifiable metric for the price formation of Ether, the native cryptocurrency of the Ethereum network, while exploring network effects and the predictive capacity of a unique dataset. The findings reinforce the notion that cryptocurrency prices are largely driven by speculation. Collectively, these chapters investigate the potentially perilous issues associated with this technology and the asset class it has engendered, offering recommendations to safeguard investors and the general public.

Chapter 2. Comparative Analysis of Stablecoin Extreme Volatility Based on Pegging Mechanisms: Tokenized, Algorithmic, and Crypto-Backed.

Abstract

This chapter explores how stablecoin design affects the risk of extreme price volatility and potential de-pegging events. Daily realized volatilities are modeled using a power law to derive alpha coefficients, indicating the frequency and magnitude of extreme events. These coefficients are compared across design types and peg currencies (USD vs. non-USD) using the Kruskal-Wallis test, with data spanning 2015–2023 depending on each stablecoin's inception date. Findings suggest tokenized stablecoins are least susceptible to extreme volatility, algorithmic stablecoins are most susceptible, and crypto-backed stablecoins yield inconclusive results. Peg currency shows no significant effect on volatility risk. Based on these findings, we recommend regulating tokenized stablecoins along banking lines and requiring crypto-backed and algorithmic stablecoins to meet robust disclosure and operational standards.

Section 2.1. Introduction

Cryptocurrencies, initially introduced as a substitute for fiat currency that would not be controlled by a central authority, have faced challenges in mainstream adoption due to their inherent volatility. Replacing fiat currency was the original intention of Satoshi Nakamoto, the creator of Bitcoin - the first cryptocurrency (Nakamoto, 2008). However, as of 2023, their volatility has hindered widespread adoption. Cryptocurrencies became a speculative and volatile asset class which created fortunes but also lost billions of dollars of investors' money because of sudden price crashes.

Stablecoins were created as a remedy for the volatility issue. They claim to combine the best qualities of a decentralized, blockchain-based currency such as Bitcoin and the stability of fiat currency. The biggest stablecoin by market capitalization, Tether (USDT), states on its official website to espouse the "stability and simplicity of fiat currencies coupled with the innovative nature of blockchain technology". Stablecoins ordinarily peg their value to a fiat currency or stable commodity. The peg is maintained by using various mechanisms, of which there are currently four major ones (to be discussed below). As of January 2023, stablecoins' total market capitalization was around USD 138 billion (Lee, 2023), with the top three (USDT, USDC, and BUSD) accounting for USD 126 billion collectively.

Despite claims of offering a stable alternative, stablecoins are predominantly used to trade other cryptocurrencies. Coingecko data shows BTC/USDT as the highest-traded pair (USD 6 billion)

and BTC/BUSD as the second highest (USD 1.9 billion), with stablecoins dominating the top 10 trading pairs (confirmed by coinmarketcap.com). Rather than replacing fiat, they function as a crypto market medium of exchange.

Their importance to the crypto markets comes from stablecoins' high trading volume on exchanges, partly because they mimic fiat prices yet are taxed only upon redemption, allowing users to defer capital gains. They are central to DeFi applications, serving as primary transaction tools (e.g., the algorithmic stablecoin UST for the Terra project). Major fintech firms like PayPal plan to launch their own stablecoin, PayPal USD (Chipolina, 2023). Notably, cryptocurrencies—stablecoins included—contributed 17% of Robinhood's revenue in 2022 (Robinhood, 2021), indicating that shifts in the crypto market can significantly impact retail investors.

Stablecoins can create significant instability in crypto markets, as illustrated by multiple high-profile crashes despite their claimed stability. Heightened scrutiny followed the 2022 UST/LUNA collapse, amid concerns of mass withdrawals or "stablecoin runs" (Nicolle, 2022). Tether (USDT)—described as "practically quilted out of red flags" (Faux, 2021)—and USDC hold a combined 80% market share (Lee, 2023), so the loss of peg could render billions of dollars worthless. Their importance is widely acknowledged (Chipolina, 2023), and a general crypto crash could spill over into traditional finance (Liu, 2019). Though Park (2021) suggests Bitcoin fluctuations do not affect financial assets, extreme fluctuations or collapse of a major stablecoin would likely disrupt the wider crypto ecosystem, including Bitcoin trading and profitability.

Assets whose volatilities are artificially suppressed, such as stablecoin volatility suppressed by their peg, could lead to black swan events (Taleb, 2012). According to Taleb (2012), in cases where volatility is externally contained, latent risk is growing. As was shown in Grobys et al. (2021), the top stablecoins' daily volatility did in fact show a more erratic behavior compared to Bitcoin's, even though Bitcoin's daily volatility had a significantly higher standard deviation. Stablecoins tend to exhibit fat tails, which is a sign of higher chance of extreme price fluctuations that could cause a loss of peg.

As cryptocurrency markets evolve, new stablecoin designs—especially algorithmic stablecoins like UST-LUNA or TITAN—are emerging. The collapse of UST and its sister token LUNA, once valued at USD 139 billion, inflicted nearly USD 45 billion in losses (Davies, 2022). Stablecoins have become a vital part of the crypto market, yet they seem to lack the stability they claim is their primary utility. Some stablecoin types such as algorithmic ones appear to be more prone to crashes, evidenced by the recent demise of UST-LUNA and TITAN, or NUBITS before them. This type of crash happening to a stablecoin with the market share of USDT would be crippling to the crypto markets. As more innovative stablecoins appear, there have been attempts to group them based on their peg design (as per Bullmann et al. (2019).

Regulators have also taken notice. SEC Chairman Gary Gensler likened stablecoins to "casino chips" (Ligon, 2021), referencing tokenized designs. The U.S. Treasury deems top stablecoin issuers akin to unregulated banks and warns that their concentrated risk and economic power could spill into traditional finance (U.S. Department of the Treasury, 2021).

Amid regulatory scrutiny and the crypto market's reliance on stablecoins, it is crucial for investors and policymakers to differentiate stablecoin types and recognize their risks. The collapse of LUNA/UST demonstrates the potential scale of losses if a similarly designed coin gains widespread adoption ("What Happened to Luna?", 2022). If in future a coin with the same design characteristics appears and does succeed at capturing a large market share, its failure would impact a large share of investors. Stablecoins can be divided into four groups based on their design, and it could be beneficial to know which characteristics are indicative of higher risk of extreme events and fat-tails. Another major motivation for this study is that a significant number of researchers focus on standard deviation as the measure for stablecoin stability. According to Taleb (2020) and Grobys et al. (2021), fat-tailed data may render measures such as standard deviation ineffective.

Therefore, this chapter will be investigating whether there are any differences between stablecoin volatility and risk of de-pegging based on their design (pegging mechanism). It focuses on extreme volatility using the power law model as described in Clauset et al. (2009) and as implemented in Grobys et al. (2021) to model daily realized volatilities of stablecoins. The aim of the study is to use the power law model to measure the extreme volatility of realized volatilities of these assets and use that measure as a basis to investigate any differences based on stablecoin design. Frequency of extreme events in realized volatilities is chosen because it is a more meaningful measure for stablecoins' price movement and risk of de-pegging, considering the fat-tailedness of stablecoin daily volatility data. Fitting the daily realized volatilities to the power law model allows us to draw conclusions regarding the possibility of a price crash and de-pegging, as the alpha coefficient derived from the model indicates the frequency of extreme events and the "fatness" of

tails. Furthermore, an extreme rise in price of a stablecoin could be equally harmful, as stablecoins are primarily used as a medium of exchange on the crypto market.

The stablecoins are then compared as groups, based on the taxonomy by Bullmann et al. (2019) as well as based on the currency peg, using the non-parametric Kruskall-Wallis test and the Mann-Whitney U test. The results show that there is a statistically significant difference between the tokenized stablecoins and algorithmic ones in terms of frequency of extreme volatility, while no statistically significant connection was found in relation to crypto-backed ones. The tokenized stablecoins appear to be more stable and less prone to extreme events. Interestingly, no difference was found between USD pegged and non-USD pegged stablecoins, with USD pegged ones capturing the absolute majority of the market share. However, most of the daily realized volatilities of stablecoins analyzed were not found to have a theoretical variance, which implies that variance (and consequently standard deviation) is not a meaningful measure for these assets' daily volatilities. This has major risk implications for investors and policymakers. Frequency of extreme volatility appears high even in tokenized stablecoins, and considering their overwhelming share of the market it could be argued that audit requirements must be placed on their reserve assets. Simultaneously, algorithmic stablecoins could be treated as speculative assets considering their history of collapses, and investors must be aware of the risks these assets pose.

This study significantly broadens the scope of Grobys et al. (2021) by measuring stablecoin volatilities using the variation of the Clauset et al. (2009) they described for 63 stablecoins. It also attempts to group them based on pegging mechanism as was attempted in Jarno and Kołodziejczyk

(2021), however this study compares them based on frequency of extreme volatility estimated by fitting their daily volatilities to a power law model, rather than using the standard deviation of price. Additionally, this study contributes by partially ranking of the stablecoins based on their extreme volatility and pegging mechanism. The main contribution is the finding that tokenized stablecoins are less prone to extreme volatility - and consequently price movement - compared to crypto-backed and algorithmic stablecoins. It also contributes as the first study to use the power law model to compare the extreme volatility and consequently risk of de-pegging of stablecoins based on peg design.

The remainder of the chapter is organized as follows: Section 2.2 will discuss the taxonomy of stablecoin and the prior research. Section 2.3 will discuss the data, Section 2.4 will describe the methodology, Section 2.5 the empirical findings and Section 2.6 concludes and makes policy recommendations.

Section 2.2. Literature review.

On taxonomy of stablecoins.

According to Bullmann et al. (2019) the central banks define stablecoins as “digital units of value that are not a form of any specific currency (or basket thereof) but rely on a set of stabilization tools which are supposed to minimize fluctuations of their price in such currency(ies)”. In this study, peg-based taxonomy offered by Bullmann et al. (2019) will be followed. Below is a more detailed description of each stablecoin category.

Generally, there are four categories of stablecoins based on the mechanism they use:

1) Fiat-backed stablecoins. This is in essence tokenized fiat currency. Coins such as USDT and USDC are backed one-to-one by an equivalent amount of cash or cash equivalents. These are the least innovative and the most stable variation of stablecoins. The tradeoff is the centralization that goes along with it, which is contrary to the decentralization promise of crypto currencies. Also, coins such as USDT present considerable risk as they have not been audited by a reputable organization and there remain questions about their solvency. USDC is regarded to be the most trusted stablecoin as their reserves have been audited.
2) Collateralized off-chain. This follows the same logic as tokenized currency, but the collateral here could be any traditional asset, such as commodities or real estate. They are typically over-collateralized, with the ratio set by project rules. Also, such projects must operate within the rules of the jurisdiction they are in, as physical assets are involved. If the price of collateral falls too much a margin call occurs, and if not satisfied a compulsory liquidation may be triggered.
3) Collateralized on-chain. This type of stable coin is decentralized, unlike USDT or USDC, which are essentially tokenized currencies and rely on a trusted entity to hold the collateral. In on chain collateralized stablecoins there is a smart contract that governs coin issuance/burning. It automatically issues/burns coins based on the value of collateral sent to the crypto wallet of the project. There is no central authority. Redemption of coins has the same mechanism but in reverse. These types of coins, like off chain collateralized ones, have an overcollateralization ratio determined by the project governance. Their advantage is the transparency due to being fully decentralized – hence the level of collateral present is always known with certainty. Also, in case of a compulsory liquidation because of

insufficient collateral, the smart contract must purchase the remaining collateral and return the amount to the owner minus any punishment fees. This is an advantage to the user compared to using off chain collateralized coins, where forced liquidation could result in a dispossession of assets. Their main drawback is they are exposed to the volatility of the underlying collateral, which are other crypto assets. An example in this category is MakerDao's stablecoin DAI.

4) Algorithmic stablecoins. This type of stablecoin is viewed as the most innovative (Bullmann et al., 2019). No collateral is held to guarantee a coin's value, and they cannot be redeemed, only traded on an exchange. To stabilize the coins' value against the currency of reference, typically a dual-token system is used (examples: NuBits, LUNA/UST). One of those tokens is a stablecoin pegged to a reference fiat currency, and the second one is a token that may have other uses within the bounds of the project. The two tokens can be swapped for each other on chain for an equivalent dollar amount, so such projects rely on arbitrage from the stablecoin owners to correct the price if it deviates from the peg. Example: UST was the stablecoin pegged to the value of a fiat currency – USD - and could be swapped on the blockchain for LUNA. If the price of UST exceeds 1$ at 1.1$, then arbitrageurs could buy LUNA for 1$ and swap it for 1 UST. Then they sell the UST on an external exchange for 1.1$. If the price of UST fell below 1$, arbitrageurs could buy 1 UST for less than 1$, swap it for LUNA worth 1$ and sell it on an exchange. Thus, in both cases they would be making a riskless profit and maintaining the UST peg to USD through buying/selling pressure. These are attempts at innovation; however, they have so far been unsuccessful as many of these coins have collapsed, the most recent example being LUNA/UST.

The price of stablecoins is most commonly pegged to USD and allows its users to trade in and out of cryptocurrencies and not be subject to taxation and other regulations – since stablecoins are themselves issued on a blockchain. They can also be used to transfer money peer-to-peer quickly and cheaply. For a part of the market using them is an ideological choice of avoiding centralized institutions (Bullmann et al., 2019).

On volatility of stablecoins.

Because of their functions described above, stablecoins have become imbedded into the market. The growing literature on the stability of stablecoins has been mainly focusing on their volatility and its relationship with the wider crypto markets, rather than extreme volatility which occurs in the tails of the daily volatilities' distribution. Stablecoin trading has been linked to Bitcoin price fluctuations. Hoang and Baur (2021) linked Bitcoin price volatility and trading volume to that of major stablecoins, finding positive correlation between Bitcoin's volatility and that of the sample of stablecoins. Also, non-USD pegged stablecoins were found to be more volatile than USD pegged ones. This implies that stablecoins are not "stable", as their volatility is correlated with an unstable asset - Bitcoin - albeit to varying degrees for different stablecoins. In terms of relative stability, they were found to be less stable than fiat currencies. However, larger ones such as "USDT, USDC, TUSD and PAX" were found to have lower volatility compared to gold and stocks, while smaller ones were less stable in comparison to those asset classes.

The same paper finds that Bitcoin's daily trading volume is significantly correlated with that of major stablecoins, especially Tether (USDT). More importantly, a difference-in-differences

analysis found that after the introduction of Tether to major exchanges, Bitcoin trading volume increased significantly on the exchanges accepting Tether, and the opposite happening on the ones that did not accept Tether. This empirical analysis from Hoang and Baur (2021), which supports the claim made in Bullmann et al. (2019) regarding the primary usage of stablecoins, led to the conclusion that stablecoins are used as a medium of exchange for cryptocurrencies and Bitcoin in particular. Therefore, the collapse of a major stablecoin such as USDT, could lead to a crash of unpredictable magnitude in the crypto market.

Even highly regulated and trusted stablecoins such as USDC experience volatility. The main driving force of these coins' price and volume is the demand for other cryptocurrencies for which stablecoins are a medium of exchange and their role as safe-haven assets to keep the potential gains untaxed. There is no other major utility for stablecoins as of now. Their adoption for payments has been limited at best. So, it would be natural for their volatility to move contemporaneously with Bitcoin, as the primary purpose is trading cryptocurrencies. In the case of algorithmic stablecoins, however, there seems to be a significant opportunity for speculation because of the dual coin system meant to provide arbitrage opportunities that will keep the stablecoin's peg.

The issue of volatility has been long recognized, and different projects have attempted to innovate by creating different mechanisms to maintain the peg while remaining stable. Generally, the more innovative pegging mechanisms have been more volatile (Bullmann, 2019). Stablecoins generally regarded as the least volatile and innovative, such as USDT and USDC, are also the biggest by market capitalization.

As stablecoins are pegged to a fiat currency/commodity, their value proposition of being a stable alternative and the practical function of serving as medium of exchange depends on their ability to maintain the peg. Loss of peg not only undermines the purported aim of a stablecoin but could also lead to shocks in the wider market. As recently as 2022, UST - an algorithmic stable coin pegged to the dollar – lost its peg and led to the crash of LUNA. The project that created both is called Terra. Arbitrage in LUNA was part of how UST maintained its peg, as users could swap one for another. Due to a sudden and large volume of UST being sold in the market, the price of LUNA could not keep up and led to the crash of both. Algorithmic stablecoins are considered some of the least resilient, with LUNA being only the latest example. Thus, the ability to withstand such volatility and maintain its peg is crucial to a stablecoin.

The design and pegging mechanism of stablecoin types determine their vulnerabilities in terms of volatility sources. d'Avernas et al. (2022) points out the vulnerabilities of each type. Fiat backed coins are at a risk of misappropriation if the demand falls. Crypto collateralized on-chain coins risk early liquidation if asset value drops suddenly, and in general are exposed to the underlying assets fluctuations. They also are known for the need to overcollateralize and thus capital is used inefficiently. Lastly, algorithmic stablecoins require a constant increase in demand, therefore any decrease could trigger a death spiral. Catalini and Gortari (2021) and Chohan (2020) highlight the same issues. Catalini and Gortari (2021) additionally stress the importance of the relationship between the reserve asset and reference asset state that without a stable reserve asset stablecoins will not be adopted by the public as a medium of exchange.

From empirical studies the lagged volatility of Bitcoin was found to be Granger causal for the volatilities of stablecoins (Grobys et al, 2021). Grobys et al. (2021) claim that the reverse is not true – stablecoin volatilities do not Granger cause Bitcoin volatility. Therefore, volatilities of stablecoins do not spill over to Bitcoin while the reverse is true. This is in line with Kristoufek (2021), who found directional spillovers between stablecoins and other crypto assets, with stablecoin issuance increasing as crypto asset prices rose. Interestingly, Grobys et al. (2021) also find that the theoretical mean for stablecoin volatility processes exist but not the variance, which is infinite. This contrasts with Bitcoin whose volatility was found to be finite and well-behaved, despite having higher realized volatility.

Their paper stresses the importance of using power law models in measuring stablecoin volatility. They argue that GARCH models, which are commonly used as a benchmark when investigating volatility, underperform power law models based on the research done by Calvet and Fisher (2004) and Lux et al. (2014). Caporale and Zekokh (2019) conducted a study where they tested over 1000 GARCH models on the log-returns major cryptocurrencies (Bitcoin, Ethereum, Ripple, and Litecoin) and found they could be misleading with Value-at-Risk and Expected Shortfall forecasts due to high asymmetry in the data.

Instead of the standard GARCH model Grobys et al. (2021) employed a power law model. They base their choice of model on Taleb (2020), who claims that parameter estimations with GARCH-type models are sample specific if the fourth moment (kurtosis) is infinite or cannot be measured.

This is appropriate as Bitcoin itself was shown to have high kurtosis in Baur et al. (2018). Further justifying their choice of model, they point to Clauset et al. (2009) who demonstrated that power laws are followed in a wide range of disciplines. Based on this, they stress the better performance of power law based models compared to GARCH models, as the former better suit datasets with fat-tails (characterized by positive kurtosis), where extreme events are more likely.

As the Bullmann et al. (2019) report suggests, one of the usages of stablecoins is the ability to realize the gains from other cryptocurrencies without being exposed to regulations and the volatility of other crypto assets, effectively acting as safe-haven assets. Wang et al. (2020) found that stablecoins can exhibit safe-haven asset properties, though normally they act as diversifiers. They found that both gold-pegged and USD-pegged stablecoins performed better than their underlying assets in terms of being a safe-haven asset, and that the gold-pegged ones performed worse than USD-pegged ones. However, they underline that gold is a better hedge tool, but worse safe-haven asset compared to gold-pegged stablecoins. Similarly, USD-pegged algorithmic stablecoins were a better safe-haven but worse hedging tool than the underlying USD. Interestingly, USD is found to have a stronger connection to BTC, XRP, and LTC rather than USDT (Tether). This is confirmed in Baur and Hoang (2021), Wei (2018), and Grobys and Huynh (2021). Baur and Hoang (2021) show that USD-pegged stablecoins could be influenced by extreme downside in BTC. Wei (2018) finds that USDT (Tether) trading activity rises after negative BTC returns.

Additionally, Baur and Hoang (2021) highlight a trade-off between the 'stable' and 'safe haven' properties, where a strong safe-haven capacity lowers the stability of a stablecoin. This is supported by Wang et al. (2020), who found Bitcoin to have hedging capability but weak as a safe-haven asset.

Thanh et al. (2022) analyze fluctuations in major stablecoins and find they vary from coin to coin, and that volatilities of USDC and USDT (Tether) significantly impact those of other stablecoins analyzed. Evidence of impact of other stablecoins on USDC and USDT was weak. They also note that DAI exhibited more instability than other USD-pegged coins.

Jarno and Kołodziejczyk (2021) conducts a study of 20 stablecoins, comparing their volatilities based on their design (peg mechanism). They split the stablecoins into three groups and used standard deviation of log returns corrected for autocorrelation as a measure of volatility. Expectedly, they found tokenized stablecoins to be the most stable group. However, contrary to most other literature, their measures of individual coins appear to indicate PAX to have the least volatility and USDC - the most stable coin according to most other papers – to be the second. USDT (Tether), generally accepted to share the title of the most stable stablecoin with USDC, was 8th out of 20. This appears unusual and perhaps requires further investigation as most other authors posit USDT/Tether as being one of, if not the most stable one. A limitation of this study is also the small number of stablecoins tested, one of the categories only having one coin in them. In this chapter, 68 stablecoins are anaylzed.

Gadzinski et al. (2023) are the most recent study exploring coin design. They use the largest dataset among the papers covered in this literature review, covering 33 stablecoins, and propose their unique classification system different from Bullmann et al. (2019). By employing community detection analysis, they assess whether stablecoin price dynamics are influenced by their designs. The results indicate that the price dynamics of stablecoins do not appear to be dependent on protocol design, which is in contrast to Jarno and Kołodziejczyk (2021). Interestingly, certain non-custodial (algorithmic, crypto-collateralized, and partially collateralized) stablecoins, including algorithmic ones, exhibit similar dynamics to well-established custodial tokens (currency collateralized). For the sake of consistency only USD-pegged stablecoins are retained in the analysis. Some non-custodial stablecoins demonstrate similar statistical moments to the best custodial stablecoins, suggesting a potential shared dynamic between them.

Another study that attempted to evaluate stablecoins volatility based on their design is Jeger et al. (2020). He focuses on their ability to withstand the shocks of COVID-19 in 2020. The volatilities gold-pegged coins were found to not found have experienced a significant increase, which is in line with the previous research mentioned about the safe haven capacity of such coins (Wang et al., 2020). Also, USDT and USDC were found to be the most stable overall, in line will most other authors. They also mention the better ability of USDC of maintaining its peg, which the authors could not explain. It is possibly due to higher trust in USDC, which is well regulated and audited.

Bojaj (2022) measure the impact of stablecoin adoption on the economy of Montenegro and isolate country level macroeconomic effects this innovation would have. They find that stablecoins fail to maintain their peg in "crash times" but could be important for promoting growth.

This chapter focuses on the risk of extreme price volatility of stablecoins based on pegging mechanism (design). Specifically, the focus is on fitting the power law model and finding the alpha coefficient of these assets' daily realized volatility to gain insight as to the likelihood of a de-pegging and price crash which is preceded by extreme volatility, though a significant price rise could be harmful as well. The question is relevant as many stablecoins, especially the more innovative ones in terms of pegging mechanism, experienced de-peggings and sudden crashes in price. In the literature mentioned before, d'Avernas et al. (2022), Catalini and Gortari (2021) and Chohan (2020) discuss the risks of stablecoins, however, they conduct a mainly theoretical discussion. Hoang and Baur (2021), Thahn et al. (2022), Wei (2018), Kristoufek (2021) and Grobys and Huynh (2021) are empirical studies that focus on the volatility of major stablecoin price, however they mainly investigate directional volatility spillovers and correlation with bitcoin and/or between major stablecoins, while disregarding extreme volatility events. This chapter contributes by conducting an empirical study of extreme volatility events of stablecoins.

Gadzinski et al. (2023), Grobys et al. (2021) and Jarno and Kołodziejczyk (2021) are the closest in subject matter to this chapter. Gadzinski et al. (2023) use *only* USD pegged coins and attempt to find differences in price dynamics based on pegging design, however the method they used is unique in this literature – community detection analysis. In a sense, they do the reverse of Jarno

and Kołodziejczyk (2021) – they attempt to see if the pricing dynamics of the stablecoins are similar to a degree that they can be grouped together. This chapter will follow the latter and investigate the existing groups of stablecoins based on the taxonomy by Bullmann et al. (2019). However, Jarno and Kołodziejczyk (2021) investigate stablecoins' volatility based on standard deviation as the measure of volatility. This may not be a meaningful measure, as Grobys et al. (2021) and Taleb (2020) argue that standard statistical measures are not a valid for assets with extremely fat tails. Grobys et al. (2021) propose to use a modified power law model - originally described by Clauset et al. (2009) - to study the extreme volatilities of stablecoins, however they only investigate the top stablecoins and with no regard to the pegging mechanism. This chapter contributes by measuring the volatility as proposed by Grobys et al. (2021) to gain insight into the frequency of extreme volatility events while considering a significantly larger number of stablecoins. Furthermore, it contributes by comparing the frequency of extreme volatilities as groups based on peg design, using the Kruskal-Wallis test, and ranked based on the level of volatility. Lastly, this study contributes by comparing the volatility between groups of USD pegged coins and non-USD pegged coins.

Section 2.3. Methodological Framework.

The methodologies used to study stablecoin stability vary, however a literature review done by Ante et al. (2023) documents most of them to have used autoregression, OLS, VAR and GARCH models. None were found to have focused on extreme volatility based on peg design.

When comparing the stabilities of stablecoins as it pertains to their design the most relevant paper is Jarno and Kołodziejczyk (2021). They used standard deviation corrected for autocorrelation as a measure of volatility and the Kruskal-Wallis test to compare the volatilities of groups.

Gadzinski et al. (2023) used community clustering to find which stablecoins shared similarities based on their time series. The method used was Dynamic Time Warping proposed by Johnpaul et al. (2020), as cited in Gadzinski et al. (2023).

Jeger et al. (2020) also researched volatility of different stablecoin designs but in a more limited fashion, with fewer coins studied and mainly focusing on the impact COVID-19 shocks had. The method used to measure said volatility is Exponentially Weighted Moving Averages.

The methodology of Jarno and Kołodziejczyk (2021) relies on comparing the standard deviations of the stablecoins. This may lead to inaccurate results. As was noted in Taleb (2020), fat tailed data may not have a defined variance. In such cases all the estimation will be sample specific. Fitting a power law model will yield more reliable results considering the properties of stablecoin daily volatility data.

Standard deviation does not quantify the risk extreme events of an asset, such as a de-pegging of a stablecoin. Standard deviation is a measure of dispersion of a dataset around its mean, and it is the square root of the second moment, the variance. In fat tailed data that follows a power law

distribution, it is possible that the theoretical variance does not exist, therefore the variance is not informative of the actual behavior of the data. According to Taleb (2020), and described in Grobys et al. (2021), the exponent α of a power law model (which is a Pareto model), "captures via extrapolation the low probability deviations seen in the data". The power law model described by Clauset et al. (2009) and used by Grobys et al. (2021) for investigating stablecoin volatility is below:

$$p(x) = Cx^{-\alpha} \quad (1)$$

$p(x)$ is the probability density function (PDF) of observing a value $\boldsymbol{x}$ in the data. This function gives the probability per unit of $\boldsymbol{x}$ for a value to fall within a particular range. $\boldsymbol{C}$ is a normalization constant that ensures the total probability integrates to 1 over the range of $\boldsymbol{x}$. This constant makes sure that the PDF is properly scaled. Variable $\boldsymbol{x}$ is the size of the event or the variable of interest (e.g., the daily annualized realized volatility in our case). Lastly, $\boldsymbol{\alpha}$ is the power law exponent or scaling parameter, which determines the rate at which the probability of observing large values decreases with increasing $\boldsymbol{x}$.

It can also be demonstrated that the theoretical variance of the distribution only exists if $\alpha > 3$ and the mean exists only if $\alpha > 2$. We can observe this by deriving the mean and variance for $p(x)$:

First, we define the constant C,

$$\int_{x_{min}}^{\infty} Cx^{-\alpha}\, dx = 1$$

(2)

Solving for the integral and substituting,

$$C = (\alpha - 1)\, x_{\min}^{\alpha - 1}$$

(3)

$$f(x) = (\alpha - 1) x_{min}^{\alpha - 1} x^{-\alpha}$$

(4)

We can now solve for the expectation of $p(x)$,

$$E[X] = \int_{x_{min}}^{\infty} x \cdot f(x)\, dx = (\alpha - 1) x_{min}^{\alpha - 1} \int_{x_{min}}^{\infty} x^{1-\alpha}\, dx$$

(5)

$$E[X] = \frac{\alpha - 1}{\alpha - 2} x_{min}$$

(6)

We can also show the second moment $E[X^2]$,

$$E[X^2] = \int_{x_{min}}^{\infty} x^2 \cdot f(x)\, dx = (\alpha - 1) x_{min}^{\alpha - 1} \int_{x_{min}}^{\infty} x^{2-\alpha}\, dx$$

(7)

$$E[X^2] = \frac{\alpha - 1}{\alpha - 3} x_{min}^2$$

(8)

Therefore, the variance is

$$\mathrm{Var}(X) = E[X^2] - (E[X])^2$$

(9)

$$\mathrm{Var}(X) = x_{min}^2 \left(\frac{\alpha - 1}{\alpha - 3} - \frac{(\alpha - 2)^2}{(\alpha - 1)^2} \right)$$

(10)

As is evident from the derivations above, if $\alpha < 3$ the variance is undefined or infinite. Furthermore, if $\alpha < 2$ the mean is also undefined or infinite, which implies that these measures cannot be used to derive useful information about the data that exhibit this α.

As will be shown in the results section, a good fraction of stablecoin do not, in fact, have a theoretical variance, which implies that the standard deviation calculations are not informative. A few have no theoretical mean, which makes commonly used models for volatility forecasting such as GARCH completely sample specific (Taleb, 2020).

Crucially, the scalar α indicates how fat tailed the data is. Smaller values of α indicate fatter tails and more erratic behavior of the data. For these reasons, investigating the stability of stablecoins is more informative if we focus on tail behavior of its daily volatility employing the power law model.

This approach was taken by Grobys et al. (2021), where they looked at the daily volatilities of top stablecoins and Bitcoin. The method they proposed is a modified version of the power law model proposed by Clauset et al. (2009).

Another reason to choose a power law model over GARCH is that according to prior research by Lux et al. (2014), power law models tend to outperform GARCH models when applied to forecasting volatility.

Additionally, the power law model's has advantages over approaches such as the Extreme Value Theory, which also models on extreme events. The power law model's advantage is its flexibility. EVT requires data to be i.i.d. and stationary, whereas the power law model does not. More importantly, EVT requires significant amounts of data, as it samples only the extreme values to fit into the model. Considering the limited data for this analysis, the power law which requires at a minimum $n > 100$ based on Clauset et al. (2009) and fits all the data, is a better fit. Also, EVT helps understand the tail behavior and the likelihood and severity of extreme events in data, while the power law models the frequency and severity of extreme values across the entire dataset. A lower alpha signals a heavier tail, meaning that extreme events are more frequent and potentially more impactful.

The Clauset et al. (2009) approach to estimating the model above is as follows. First the x_{min} is estimated via the Kolmogorov-Smirnov approach. To calculate the Kolmogorov-Smirnov statistic D:

$$D = MAX_{x \geq x_{min}} |S(x) - P(x)|$$

(11)

The term $S(x)$ is the empirical CDF calculated from actual data and used to compare against the fitted model's CDF, represented by $P(x)$. $S(x)$ represents the observed cumulative distribution of the data. $P(x)$ is derived from the power law PDF by integration. It represents the cumulative probability according to the power law model. The D statistic is calculated for all the possible x_{min}, and the x_{min} that provides the minimum distance D is chosen for calculating the scalar α and fitting the model. The α is calculated via Maximum Likelihood Estimation (MLE), as it was shown in Clauset et al. (2009) to perform best in this estimation:

$$\hat{\alpha} = 1 + N(\sum_{i=1}^{N} \ln (\frac{x_i}{x_{min}}))^{-1}$$

(12)

The $\hat{\alpha}$ is the MLE estimator, N is the number of observations above the lowest cut-off point x_{min}.

After the model is fitted, a p-value can be generated via the goodness-of-fit test as outlined by Clauset et al. (2009). For the goodness-of-fit test from 1000 to 10000 synthetic datasets are generated, with the same x_{min} as the fitted model, and their D statistics are estimated. The fraction of the D statistics for the synthetic data that are above the D for the fitted model is the p-value. The null hypothesis is that the fitted model follows a power law relationship. If $p > 0.1$, we fail to reject the null, therefore the power law model is a possible fit for the data.

Grobys et al. (2021) proposes a different approach. They argue that the Kolmogorov-Smirnov test underperforms with extremely fat tailed data, as a result it tends to estimate α that will lead to the p-value of the model to be too low, which will reject the hypothesis that the data follows a power law model. Therefore, they propose an iterative approach: first they estimate the p-values for α/x_{min} combination where $\alpha = [2,\ 2.5,\ 3,\ 3.5]$. This is arbitrarily chosen, as it is expected to find a significant p-value in one of those instances. If it is found to be $p > 0.1$, for example for $\alpha = 3$ and $p < 0.1$ for $\alpha = 2.5$, the vector space of α between those combinations for α/x_{min} is searched, i.e. all combinations where the values of alpha fall in the vector space $\alpha = [2.501, 2502 \ldots 2.999]$, they determine the Kolmogorov-Smirnov statistic D and conduct the goodness-of-fit test outlined by Clauset et al. (2009), for each combination until the first p-value is found that does not reject the power law. This is a slower process that also requires more computing power, however, it is a more empirical approach and succeeds in the cases where the Clauset et al. (2009) approach of using the Kolmogorov-Smirnov statistic to find a robust α/x_{min} combination fails. In this study, the Grobys et al. (2021) was used as it is a more robust method for estimating α.

To normalize the data and obtain daily annualized realized volatilities the compounding as per Rogers and Satchell (1991), in line with Grobys et al. (2021) is used:

$$\sigma_{i,t} = \sqrt{T}\sqrt{\ln\left(\frac{HIGH_{i,t}}{CLOSE_{i,t}}\right)\cdot\ln\left(\frac{HIGH_{i,t}}{OPEN_{i,t}}\right) + \ln\left(\frac{LOW_{i,t}}{CLOSE_{i,t}}\right)\cdot\ln\left(\frac{LOW_{i,t}}{OPEN_{i,t}}\right)}$$

(13)

Section 2.4. Data.

The data was collected based on the stablecoins list on CoinMarketCap.com, which is a major cryptocurrency news website and data repository. The list included 140+ stablecoins, however only 63 of the projects were still active. The daily price data was downloaded from YahooFinance, which souces data from CoinMarketCap.com. The range of the dates vary, from 2015-2023 for the longest to 2022-2023 for the shortest.

The stablecoins were divided into four categories based on the taxonomy proposed by Bullmann et al. (2019): Tokenized, Crypto-Backed (Collateralized off-chain), Gold-backed (Collateralized off-chain, only examples found were gold-backed stablecoins), and Algorithmic stablecoins. Each category includes 21, 29, 3, and 10 crypto assets respectively. The gold backed category will be excluded from the analysis as it only has three stablecoins in it, developed by the same company, and having low volume. Also, it is preferable to have at least five data points for the non-parametric Kruskal-Wallis test to be conducted.

The categorization was done manually, by reading each stablecoin project's description. Some projects appeared to be distancing themselves from the "algorithmic" label, possibly to avoid association with the LUNA/UST collapse of last year, which was the biggest algorithmic

stablecoin crash to date. For example, FRAX claims to be a stablecoin that claims to be fractional-algorithmic. It essentially has some collateral but simultaneously uses the algorithmic dual coin structure. The FEI project uses a similar mechanism. These will be included in the algorithmic category for the purposes of this analysis.

Projects such as Rupiah Token also avoids clearly stating its pegging mechanism, simply stating that they work with third parties to ascertain their value and has low trading volume. Stablecoins such as these are also excluded since it is unclear which category they should belong to, based on the available information.

Other stablecoins, such as RSV (Reserve) use other tokenized stablecoins (USDC in this case) to maintain their value. It is ambiguous which category they should be included in, since in theory they must follow the price of the dollar, however USDC is itself a crypto-token whose peg fluctuates, therefore stablecoins such as RSV will be included in the crypto-backed category.

Importantly, the price data for stablecoins that are pegged to currencies other than USD were available only priced in USD, which means that the data reflected the exchange rate between USD and the respective currency such stablecoins were pegged to, such as EURO or YEN pegged stablecoins. In such cases to separate the fluctuations of the stablecoin around its peg and the exchange rate fluctuations, exchange rate data was the corresponding dates and peg currencies was subtracted from the stablecoins' daily prices. The exchange rate data for weekends was filled with linear extrapolation, as markets are closed on those days, unlike crypto markets, which operate

24/7. The data was converted using the 'Close' rate. Then 1 was added to the resulting number, to mimic the peg of the stablecoin.

Also, for this dataset, if the project claims it is backed by a physical asset it will be classified as off chain collateralized, since the physical asset must be audited even if it has been recorded on the blockchain. The only assets fitting this profile are Digix Dao (DGD) which claims on chain collateralized physical assets. The same project has the Digix Gold Token, which is backed by gold but somehow the project claims it is on chain collateralized. They will be excluded as they are created by one company and in total there are three assets in this category, which is too few for the Kruskal-Wallis test.

Below are the tables containing some descriptive statistics for daily realized volatilities for each of the stablecoin categories. The kurtosis numbers are of particular interest as higher kurtosis numbers (>3) are associated with fatter tails.

Table 2.1. Descriptive statistics for Tokenized stablecoins.

	Skew	Kurtosis	SD	Mean
BRZ (non-USD)	5.63942374	48.2866037	0.97842448	0.63644206
BUSD	6.56244215	79.9343491	0.15849662	0.09204073
EUROC (non-USD)	7.91470266	85.9910632	0.16357369	0.11969722
EURS (non-USD)	4.78865663	42.8412479	0.24563198	0.25651298
EURT (non-USD)	19.8473938	453.979294	0.26505762	0.14352579

GUSD	5.19089365	39.9651752	0.3603959	0.29118337
GYEN (non-USD)	24.1201139	634.921023	2.59033339	0.40409698
HUSD	15.7516903	372.915477	0.3430254	0.20145056
JPYC20648 (non-USD)	4.84815118	32.4325624	0.20303219	0.21634221
MXNT (non-USD)	4.41222043	39.0018583	0.15028676	0.34631269
TRYB (non-USD)	18.4028653	422.46851	1.43724515	0.47294282
TUSD	11.7567373	250.380022	0.22115876	0.1369532
USDC	31.7685655	1175.75326	0.43263436	0.11795232
USDD	6.82846639	64.1540851	0.09293537	0.07453715
USDK	3.88486435	22.5703065	0.23141777	0.24075351
USDP	24.9372123	678.395453	0.4812381	0.16085681
USDT	3.44690455	25.2316494	0.18640232	0.14219635
XCHF (non-USD)	13.6137204	235.181428	1.93856375	0.75307079
XIDR (non-USD)	1.76567665	5.383212	0.36494827	0.34298666
XSGD (non-USD)	8.82174547	103.275507	1.03255603	0.50241116
ZUSD8772	24.563383	628.711888	2.40516887	0.36854927

This table contains the descriptive statistics for the realized annualized daily volatilities of tokenized stablecoins, compounded as per Rogers and Satchell (1991).

The vast majority of the stablecoin volatilities across groups have high kurtosis. The lowest kurtosis is exhibited by one in the tokenized category is XIDR at 5.38, which is a non-USD pegged coin. However, it still classified as having fat tails. Interestingly, the second highest kurtosis across all categories (and highest in this category) is in the tokenized one, which is considered the most stable type of stablecoin on average. Furthermore, it belongs to USDC, with a kurtosis of 1175.75, which is extremely high. USDC is considered to be one of the most trusted stablecoins as their collateral has been audited thoroughly, so such a high number is unexpected. Standard deviation ranges from 9% to 259%.

Table 2.2. Descriptive statistics for crypto-backed stablecoins' realized volatilities.

	Skew	Kurtosis	SD	Mean
ANGLE	12.6152491	225.046554	1.89661013	1.14262918
BITCNY (non-USD)	37.2826297	1560.55734	1.19964111	0.39175509
CEUR (non-USD)	5.69934972	51.3579539	0.21010511	0.22440921
CUSD21871 (USDT-backed)	13.0882042	173.781897	1.52088187	0.2913336
CUSD21871(USDT-backed)	4.10626692	17.4506122	1.30662218	0.56141068
DAI	29.2948378	945.306469	0.74830368	0.1424941
DJED	6.44866717	48.8017419	1.6846488	0.9523042
DOLA	2.92025965	11.3737449	0.47449443	0.43433294
DUSD	12.8720309	196.510411	2.48215953	0.93882493
EOSDT	5.0113772	36.1895632	1.47371356	1.01546406
LUSD	20.3715802	490.991615	0.87739134	0.25331342
MCELO	9.30854686	131.853589	1.20634937	1.09303757
MCEUR (non-USD)	5.42136399	55.4088158	0.29275468	0.38747478
MIM	19.6434374	430.975796	0.58891422	0.19169351
MIMATIC	12.5128592	193.89163	0.60420305	0.24832684
MONEY18758	1.48078608	2.69762348	0.41792126	0.67701784
OUSD	14.7726652	264.769733	0.58904843	0.17792173
PAR8665	14.1998829	269.565708	1.58228512	0.50697258
RSV	15.8493023	288.512392	2.33182592	0.46060399
SUSD	9.98263987	139.370628	0.95410952	0.45059063

TOR18105	5.80234387	41.0597805	0.47762229	0.3057027
USDH	5.24242666	26.1137389	5.13109131	1.1686399
USDJ	7.26782253	102.114832	0.4382046	0.27974402
USDP8886	4.56181595	34.5018397	0.89068634	0.57023424
USDS17285	21.5883154	469.599714	6.42066429	0.77461715
USDX6651	14.5251204	264.480228	1.87019155	0.69136342
USX13080 (stablecoin-Backed)	21.9805288	506.12637	6.74119087	1.21419451
VAI	5.69174618	56.0867419	0.39892953	0.32194039
XDAI	14.3119675	224.58877	2.49184208	0.50717487

This table contains the descriptive statistics for the realized annualized daily volatilities of crypto-backed stablecoins, compounded as per Rogers and Satchell (1991).

Table 2.2 contains the descriptive statistics for crypto-backed stablecoins' volatilities. Standard deviation ranges from 21% to 674%. This category has the stablecoin with the highest kurtosis – BITCNY with a kurtosis of 1560.55. This category is also interesting for having the lowest kurtosis stablecoin across all categories - MONEY18758 with a kurtosis of 2.69. This number indicates that it may in fact have lighter tails. Its standard deviation is high at 41%. However, this may not be a valid indicator to analyse this asset, as was explained in Section 3.

Table 2.3. Descriptive statistics for algorithmic stablecoins' realized volatilities.

	Skew	**Kurtosis**	**SD**	**Mean**
CUSDT	10.5471246	122.790796	0.39870892	0.0820952
FEI	17.0822031	382.692335	0.7283881	0.37268356
FRAX (Hybrid)	17.3118448	397.138598	0.60665524	0.30921531
KRWTerra (non-USD)	12.7623245	214.193449	2.17412946	0.66913394
MUSD20025 (Hybrid)	8.04238036	80.042654	0.63725608	0.38265071

TRIBE	5.64237259	47.2752531	0.84301655	0.65809714
USDEX (USDC-peg)	5.37327377	38.5254895	0.60788236	0.42969797
USTC	10.1096133	137.172488	2.11964553	0.74637387
VUSDC	23.0706066	557.642531	0.4040644	0.04181073
XSTUSD	4.65327531	21.6772629	25.0697498	7.10194895

This table contains the descriptive statistics for the realized annualized daily volatilities of tokenized stablecoins, compounded as per Rogers and Satchell (1991).

Table 2.3 contains the algorithmic stablecoins. The standard deviation ranges from 39.8% to 250%. Kurtosis is high for all assets, ranging from 21.67 to 557.64.

Section 2.5. Empirical Findings.

As we can see from Table 2.4, all of the tokenized stablecoins' volatilities save one have can be said to follow the power law in equation (1). Out of the 20 tokenized coins, 14 do not have a theoretical variance, and 1 has neither variance nor theoretical mean. Unlike Grobys et al. (2021), who also estimated the a α-coefficient for USDT and USDC, it was found in this study that they in fact have a theoretical variance, which means that standard deviation is a meaningful statistic for their daily volatilities data in this case. It must be pointed out that 2 years passed since their study was published, so the difference could be due to more data being used in this study.

Table 2.4. The tokenized stablecoin alpha parameters and their p-values.

Coin	alpha	Xmin	p
BRZ (non-USD)	3.0076808	0.24764069	0.307
BUSD	3.22904828	0.32902511	0.282
EUROC (non-USD)	2.51782228	0.18041048	0.21
EURS (non-USD)	3.2590759	0.39709925	0.104
EURT (non-USD)	2.53601818	0.43802249	0.72
GUSD	2.75459758	0.32210636	0.101

GYEN (non-USD)	1.63297298	0.0541177	0.6
HUSD	2.52777432	1.18697317	0.32
JPYC20648 (non-USD)	2.5491495	0.00306609	0.288
MXNT (non-USD)	3.03355216	0.03135768	0.6
TRYB (non-USD)	2.01662977	2.32394399	0.421
TUSD	2.67566715	0.97149337	0.678
USDC	2.53963139	0.74043056	0.379
USDD	2.61087901	0.1077267	0.144
USDK	2.94586869	0.21479136	0.113
USDP	2.88051568	0.106126	0.133
USDT	3.33447123	0.26296263	0.102
XCHF (non-USD)	2.58339715	8.24190092	0.464
XIDR (non-USD)	3.22345542	3.00E-05	0.247
XSGD (non-USD)	2.32030761	0.28545492	0.103
ZUSD8772	2.67841213	4.27686281	0.3

These are the results derived from Clauset et al. (2009) power law model implemented by Grobys et al. (2021) on the tokenized stablecoins.

Table 2.5 below is the results for the crypto-backed coins. The ones with 'nan' values indicate that the power law was rejected. Out of 29 stablecoins, 6 could not be estimated to follow a power law using both methods. There are 2 stablecoins here that have $\alpha < 2$, indicating that their volatilities have neither a theoretical mean nor theoretical variance. Therefore, those parameters are not meaningful when assessing these crypto assets. Out the remaining ones only 3 have both a theoretical variance and mean ($\alpha > 3$). The rest only have a theoretical mean ($2 < \alpha < 3$). The lower α indicates fatter tails. Therefore, proportionally in this category the behavior could be said to be more erratic on average, with more tail events occurring. Intuitively, it is expected as these assets are backed by other crypto assets, which themselves are volatile. However, this category

also has the highest $\alpha = 3.83$, which is extreme compared to the median $\alpha = 2.5195$ in this category. Often the assets used as collateral for crypto-backed stablecoins are Bitcoin or Ethereum, which themselves have well-behaved variances.

Table 2.5. The crypto-backed stablecoin alpha parameters and their p-values.

Coin	alpha	Xmin	p
ANGLE	2.51389253	0.8452692	0.109
BITCNY (non-USD)	2.59843818	0.0614779	0.105
CEUR (non-USD)	2.76255187	0.35270901	0.279
CUSD	2.78143726	0.12712852	0.122
CUSD21871(USDT-backed)	1.82356817	0.40620019	0.104
DAI	2.0848565	1.66834279	0.8
DJED	2.30678516	3.27957123	0.5
DOLA	3.8381899	1.42702737	0.156
DUSD	2.51849996	7.0116684	0.431
EOSDT	2.38230919	0.79886966	0.104
LUSD	2.55778233	2.7816	0.7
MCELO	2.64505265	2.79900832	0.13
MCEUR (non-USD)	3.52030129	1.4887864	0.3
MIM	2.52068684	0.43724496	0.975
MIMATIC	2.51139199	0.56364636	0.677
MONEY18758	3.54410975	0.70677563	0.116
OUSD	2.00022845	0.05684893	0.113
PAR8665	2.16962636	0.39337366	0.103
RSV	2.00635807	3.40541292	0.704
SUSD	2.52073744	2.98342285	0.278
TOR18105	2.26447798	0.80717518	0.142
USDH	nan	nan	nan
USDJ	2.84811809	2.59270286	0.5
USDP8886	3.51159987	1.40814504	0.101
USDS17285	2.13875295	3.18746813	0.36

USDX6651	2.56172862	12.8685334	0.6
USX13080	2.04402147	3.75186415	0.527
VAI	2.51804172	0.2486895	0.107
XDAI	1.90094116	3.19561587	0.42

These are the results derived from Clauset et al. (2009) power law model implemented by Grobys et al. (2021) on the crypto-backed stablecoins. Nan values indicate that it could not be confirmed that the stablecoin follows a power law model as the p-value was < 0.1.

The last category examined are the algorithmic stablecoins, presented in Table 2.6. Two of them could not be estimated to follow a power law, while one had no theoretical mean or variance. None of them have a theoretical variance ($\alpha > 3$), which means standard deviation is not a meaningful parameter for them. Interestingly, the stablecoin with the highest α coefficient in this category – which makes it the best behaved one volatility wise - is a hybrid stablecoin, which has other cryptocurrencies backing it as well as an algorithm to stabilize its price.

Table 2.6. The algorithmic stablecoin alpha parameters and their p-values.

Coin	alpha	Xmin	p
CUSDT	1.87835141	0.50461516	0.352
FEI	2.50096772	0.24272649	0.108
FRAX (hybrid)	2.59750159	2.84771431	0.75
KRWTerra (non-USD)	2.15769842	0.000857	0.201
USTC	2.28344149	0.90365264	0.206
MUSD20025 (hybrid)	2.53508957	1.04869222	0.217
TRIBE	2.5071081	0.37356552	0.201
USDEX (USDC peg)	2.50326732	0.4386528	0.923
VUSDC	nan	nan	nan
XSTUSD	nan	nan	nan

These are the results derived from Clauset et al. (2009) power law model implemented by Grobys et al. (2021) on the crypto-backed stablecoins. Nan values indicate that it could not be confirmed that the stablecoin follows a power law model as the p-value was <0.1.

Comparing based on peg mechanism.

To compare the distributions of the α parameters of these categories the non-parametric Kruskal-Wallis test will be used. It is chosen over ANOVA since it requires the data in all the groups to be normally distributed. To check for normality, the Shapiro-Wilk test for normality is used. The table below shows the results for this test:

Table 2.7. Shapiro-Wilk test for normality.

Stablecoin Type	Test Statistic	p-value
Algorithmic	0.8257	0.0535
Crypto	0.8902	0.0068
Tokenized	0.9368	0.1881

The normality test implemented to check if ANOVA could be used, as it requires all groups to follow a normal distribution. Crypto-backed stablecoins do not follow the normal distribution.

As we can see from Table 2.7, for crypto-backed stablecoin group the null hypothesis of being normally distributed is rejected, hence ANOVA cannot be implemented. Instead, the non-parametric Kruskall-Wallis test is used, along with Dunn's post-hoc test for pairwise comparisons to find whether there is any significant difference between any two groups. The results are in the table below:

Table 2.8. Kruskal-Wallis test results.

	Test Statistic	p value
Alphas	9.08626	0.0106

This test confirms the statistically significant difference between groups. The Kruskal-Wallis test is a non-parametric test that determines if there are statistically significant differences between the medians of three or more independent groups. It assesses whether at least one group differs significantly from the others, without assuming a normal distribution.

The result of the Kruskal-Wallis test indicates that there is a significant difference in the distributions of the α coefficients within at least two of the groups. The null hypothesis for this test is that there is no significant difference. This null is rejected at a 5% significance level. To further investigate the pairwise relationship between the groups, the Dunn test is performed.

Table 2.9. Dunn's pairwise comparison.

		p-values
Algo	Crypto	0.239821
Crypto	Token	0.091522
Token	Algo	0.03499

The Dunn pairwise comparison allows for a more detailed look at the difference between groups as pairs. Dunn's pairwise comparison test is used following a Kruskal-Wallis test to determine exactly which groups differ from each other. It adjusts for multiple comparisons to maintain the specified level of significance and assesses differences between pairs of groups.

The results of the test indicate that Tokenized coins are distinct from algorithmic ones. The null hypothesis – that there is no difference – is rejected with a 5% significance level. No significant difference could be found between the algorithmic group and the crypto-backed one, or between crypto-backed and tokenized ones. However, this does not indicate that they are the same. We can only claim that the tokenized stablecoins are distinct to the algorithmic ones. To establish the nature of the difference (i.e. ranking) as it pertains to volatility distribution and tail event risk, we could look at the medians of the alpha values in each group:

Table 2.10. Medians of alpha coefficients of stablecoin groups.

Stablecoin Type	Median
Algo	2.5021
Crypto	2.5195
Token	2.6756

The tokenized stablecoins have a higher median alpha coefficient than the other two groups. They have a much closer alpha coefficient which could indicate a more similar volatility profile.

As the table above shows, tokenized stablecoins have a higher median alpha coefficient than the algorithmic or crypto-backed ones, therefore it could be claimed that they are on average more stable and less likely to experience extreme events, such as price crashes. The median is chosen over the mean as the former is a statistic more robust to outliers and if in cases when data is not normally distributed, which as mentioned before the alphas in the crypto-backed groups are not. It does confirm the public sentiment as well as the opinions of other authors regarding the higher stability of less innovative coins (Bullmann et al., 2019; d'Avernas et al., 2022).

Unlike Hoang and Baur (2021), Wei (2018), Grobys and Huynh (2021) and Thanh et al. (2022), which focused on the volatility of individual coins and the degree to which they are impacted by Bitcoin and major stablecoins such as USDT and USDC, this analysis focused on finding differences in possibility of extreme volatility levels based on the pegging mechanism. Also, the method used to model the frequency of extreme volatility is distinct as usual statistical measures

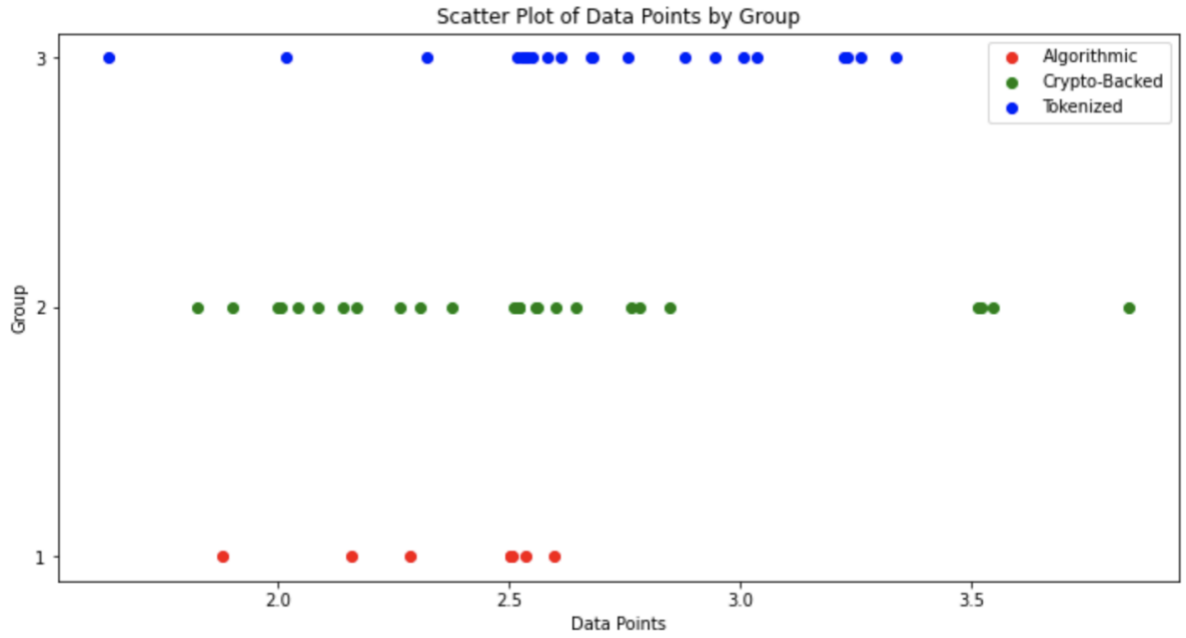
may be sample specific in case of stablecoins due to their extremely fat tails as was explained in more detail in Section 2 (Taleb, 2020).

The α coefficients presented in the above tables (Tables 4,5, and 6) were estimated based on the power law model proposed by Clauset et al. (2009) and modified by Grobys et al. (2021). However, Grobys et al. (2009) relaxed the significance criteria by making the $p>0.05$ for not rejecting the null hypothesis, unlike the original $p>0.1$ proposed by Clauset et al. (2009). This study followed the original stricter criteria, though the estimation process follows propositions of Grobys et al. (2021). Furthermore, the comparison based on peg mechanism was done using the Kruskal-Wallis test as in Jarno and Kołodziejczyk (2021) as well as the pairwise comparison using Dunn's pairwise test. However, in the latter paper, the measurement of autocorrelation corrected standard deviation that was applied directly to daily prices. As was argued in Section 2 to have potentially been sample specific for fat tailed data. Unlike Jarno and Kołodziejczyk (2021), who found a statistically significant difference between the Tokenized and Crypto-backed stablecoins but none with the Algorithmic ones, in this study the opposite was the case. Specifically, that there is a statistically significant difference between the Tokenized and Algorithmic coins but none with the Crypto-Backed ones. We must keep in mind, however, that they measured standard deviation while this analysis was focused on extreme volatility that could lead to a crash/de-pegging.

Interestingly, if we remove some outliers in the data, and perform the same tests, we find that the Crypto-backed stablecoins and Tokenized ones have a statistically significant difference as well.

To visualize the data for all three groups below is a chart containing the data for each of the stablecoin categories.

Figure 2.1. Scatter plot of stablecoin alpha coefficients, based on design groups.



Scatter-plot of the alpha coefficients of stablecoins based on their groups. The y-axis represents the groups number, while the x-axis the observed alpha value.

As is observable from Figure 2.1, there are outliers in all of the groups, with the crypto-backed groups containing the highest alpha stablecoin, which is two standard deviations above the mean. Using two standard deviations as the benchmark for removing outliers, we can remove one outlier from each group. The following stablecoins were removed: CUSDT from algorithmic, DOLA from the crypto-backed, and GYEN from the tokenized groups. Performing the Kruskal-Wallis test with groups without the outliers, we get the following results:

Table 2.11. Kruskal-Wallis test after removing outliers stablecoins in each group.

	Test Statistic	p value
Alphas	9.5069	0.0082

The Kruskal-Wallis test is a non-parametric test that determines if there are statistically significant differences between the medians of three or more independent groups. It assesses whether at least one group differs significantly from the others, without assuming a normal distribution.

The test repeated to confirm the differences between groups. However, outliers were removed from each group if they were above or below two standard deviations to see if it will impact the pairwise comparison.

Table 2.12. Dunn's pairwise comparison after removing outliers for each stablecoin group.

		p-values
Algo	Crypto	0.501824
Crypto	Token	0.022375
Token	Algo	0.028879

This table confirms that the removal of outliers yielded a statistically significant difference between the tokenized and crypto-backed stablecoin groups. Dunn's pairwise comparison test is used following a Kruskal-Wallis test to determine exactly which groups differ from each other. It adjusts for multiple comparisons to maintain the specified level of significance and assesses differences between pairs of groups.

With these modified results we could claim that Tokenized stablecoins carry a lower risk of a sudden extreme volatility event than both Crypto-backed and Algorithmic ones. This would be in line with the public perception. Though the Kruskal-Wallis test is non-parametric and more robust to outliers, there could be underlying reasons that are not immediately obvious to account this difference in result. One of them could be the assumption that the observations are independent, i.e. no correlation should exist between the member of each group as well as between groups.

For example, following Hoang and Baur (2021) results that found Bitcoin's and certain stablecoins' volatilities to be correlated the latter could not be stable as it is correlated with an unstable asset, Bitcoin. Likewise, on the surface it stands to reason that Crypto-backed stablecoins could not be as stable as Tokenized ones, as they basically share the same peg mechanism with the difference that Crypto-backed ones are collateralized by more volatile cryptocurrencies that are used to peg a stablecoin's price to a more stable fiat currency. Thanh et al. (2022) in their analysis of major

stablecoins found DAI (major Crypto-backed and USD pegged stablecoin) to be more unstable than USDT and USDC. Nevertheless, with the full dataset no statistically significant difference was found between those groups. Also, the highest α coefficient in the dataset belonged to a Crypto-backed stablecoin, which is contrary to the notion that they are less stable. The mean of Crypto-backed stablecoins is much closer to the Algorithmic ones than Tokenized, however. The major issue mentioned in Faux (2021) is the transparency of organizations behind USDT (the biggest stablecoin), which Crypto-backed coins do not have since their collateral is recorded on the blockchain and thus are transparent. This transparency could possibly impact the perception (making Tokenized stablecoins more volatile and Crypto-backed ones less) in the markets and thus the of these stablecoins may be similar, which would be contrary to the results in Jarno and Kołodziejczyk (2021) and in line with Gadzinski et al. (2023). As shown above, the elimination of outliers did lead to a result where Crypto-backed ones appeared significantly different, however not so with the full dataset. The difference in volatility between Tokenized and Crypto-backed stablecoins may require further research.

Comparing based on currency of the peg currency.

As can be observed from Table 2.4, Table 2.5, and Table 2.6, most of the stablecoins are pegged to USD, however 13 of them, independent of peg mechanism, are pegged to a different fiat currency, and some pegged to the price of USDT (which itself is pegged to USD). Since the previous test showed that pegging mechanism has an impact on how fat-tailed the data is, it is possible that the currency they are pegged to could have an impact on its stability. To investigate that the stablecoins are divided into two groups, based on whether they are pegged to USD or another fiat currency.

This is done because USD is predominantly chosen as the peg for a stablecoin. Then the two groups are compared using the Mann-Whitney test:

Table 2.13. Mann-Whitney U test.

	U-statistic	p-value
Result	383.0	0.2867

Statistics and p-value for Mann-Whitney U test which compares the USD-pegged and non-USD-pegged groups of stablecoins' alpha coefficients. It is a non-parametric test that determines if there are differences between two independent samples' distributions. It assesses whether one group consistently has higher or lower values than the other, without assuming a normal distribution.

According to the results above, no statistically significant difference was found between the USD and non-USD groups. This is contrary to the assertions made in Hoang and Baur (2021), who found their sample of non-USD pegged stablecoins to be more volatile than the USD-pegged ones. The difference is most likely due to the fact that Hoang and Baur (2021) focus on variance whereas this study assesses the extreme volatility via fitting realized daily volatilities to a power law model. As pointed out earlier, the only other paper that uses the power law model to measure stability of stablecoins is Grobys et al. (2021).

Table 2.14. Medians of USD and Non-USD pegged groups.

Group	Median
USD	2.520737437
Non-USD	2.583397147

Indeed, based on the medians of the groups the difference between the alpha coefficients is smaller than in the case of Tokenized and Algorithmic stablecoins in Table 2.10.

Robustness tests

To evaluate the robustness of the results provided by the Kruskal-Wallis test, a permutation test is conducted. In the literature this test has been used by Hübel et al. (2020) to study the impact of ESG indices on index performance. Romano and Tirlea (2020) who compare permutation tests to other tests of autocorrelation. Other examples include Cabrieto et al. (2018), who performed the test on multivariate time series and concluded that the permutation test is either equivalent to or outperforms the current leading significance tests in identifying changes in correlation, suggesting that it is generally recommended to use it.

By introducing random permutations to the data, we can quantify the likelihood that their findings could have occurred due to chance alone. In the case of alpha coefficients, this means assessing whether assets exhibit genuinely distinct power-law behavior or if the observed disparities in alphas could be attributed to random sampling variations.

Given the non-parametric nature of financial data, their use alongside the Kruskal-Wallis test is justified when testing the robustness of alpha coefficients obtained from power-law models.

The way the test is implemented is as follows:

1. **Pooling of data.** The observations from the three groups were aggregated into a single dataset.

2. **Calculation of the observed statistic.** The Kruskal-Wallis H-test statistic was calculated for the original groups of data, which will serve as our reference statistic against which permuted statistics will be compared.
3. **Permutation of data.** The combined dataset was randomly permuted (shuffled) a large number of times (10,000 iterations in this case) for the analysis. For each iteration:
    - The permuted data was split into three groups, maintaining the original group sizes.
    - The Kruskal-Wallis test statistic was computed for these permuted groups.
4. **Determining the empirical p-value.** The Kruskal-Wallis test statistic for each iteration is stored, and the proportion of the permuted test statistics that were as extreme or more extreme than our observed test statistic served as our empirical p-value. This p-value reflects the probability of observing a test statistic as extreme as the one computed from the original groups of data.
5. **Interpretation.** The hypotheses are formulated as follows:
    - H_0: There is no difference in the central locations of the distributions of the three groups.
    - H_1: At least one group's median is different from the others.

    If $p<0.05$, it means we reject the null within 5% significance.

The process above is sometimes described as a Monte Carlo permutation. Its difference from the full permutation test is that it is done a large number of randomly selected iterations, whereas in the full permutations test all of the possible permutations must be tested. The latter could get computationally difficult, and since this randomized sample of permutations provides a good

approximation it has been the version of the test used in some papers cited above (e.g. Hübel et al., 2020).

Additionally, for the purpose of comparing the differences between groups, the permutation test is more appropriate as it keeps the original data and tests whether the observed group structure could have arisen by chance. A bootstrap, for example, would be more effective for determining the variablity of a statistic within individual group, such as its mean or variance, but the permutation test is better suited to compare whether the group structure itself is accidental.

Permutation tests' main advantages are:

1. Robustness against outliers and extreme values
2. Good performance with small sample sizes
3. No assumption of equal variance

Performing 10000 permutations for the results of the comparison-based pegging mechanism (Tokenized, Algorithmic or Crypto-Backed), we get the result below:

Table 2.15. Permutations test for stablecoin groups based on peg mechanism (design).

Test Statistic	p-value
7.5392	0.0209

Table 2.16. Permutations test for stablecoin groups based on peg mechanism (design) without the outliers based on a two standard deviation benchmark.

Test Statistic	p-value
9.5069	0.0074

This mean that within a 5% significance level the results of the Kruskal-Wallis test were not due to randomness. After removing the outliers, the permutations robustness test was in fact within a 1% significant level.

For the robustness test of the USD and non-USD comparison the same permutation method is used, with the replacement of the repeated Kruskal-Wallis test with the Mann-Whitney U test used for comparing two groups. Performing this test we obtain:

Table 2.17. Permutations test for stablecoin groups based on currency peg (USD vs non-USD).

Test Statistic	p-value
262.0	0.6619

These results indicate that there is not sufficient evidence to reject the null, therefore we cannot claim a significant difference among the two groups. This is in line with the original result, which showed no significant difference between the two groups.

Section 2.6. Conclusion.

This chapter used the modified power law model described in Grobys et al. (2021), originally proposed in Clauset et al. (2009) to measure the probability of extreme price volatility of stablecoins based on their daily realized volatilities. Then their alpha coefficients were compared based on their pegging mechanism (design) using the non-parametric Kruskal-Wallis test and further analyzed using the Dunn pairwise comparison. This analysis of alpha coefficients revealed a statistically significant difference between tokenized stablecoins and the algorithmic ones, while the results for crypto-backed stablecoins were significant after removing outliers. An examination of Table 2.10 shows that the median for the alpha coefficients of realized volatilities for tokenized stablecoins is higher than for the other two categories, which implies a lower frequency of extreme volatility events for this category. Compared to the study by Grobys et al. (2021), it was found that some stablecoins, which overlapped with the five they examined, have higher alphas, implying a somewhat better-behaved variance. Also, the final Dunn's test showed a difference between tokenized and algorithmic stablecoins. This is in contrast to the Jarno and Kołodziejczyk (2021) study, who could not find a significant difference between those groups, though they based their analysis on standard deviation of price of stablecoins. Based on further tests, there appears to be no advantage to being pegged to the US dollar in terms of lower extreme volatility occurence, as no difference was found in terms of the alpha coefficients when split into groups based on the currency peg.

The purpose of this study was to find the impact that stablecoin design may have on their stability and risk of extreme price volatility, which would make stablecoins unreliable as a medium of

exchange and store of value, and could lead to de-pegging events. This could be of value to the regulators, as finding any characteristics of stablecoin design that inform of their future performance and risk they pose on the customers may aid in the implementation of regulation. As recently as this month the SEC has increased the pressure on the major crypto exchanges that account for over 50% of global trading volume (SEC, 2023). The political pressure has also been mounting, since the collapse of FTX, and authorities in the US are expected to push to regulate these assets. Earnest discussions around tokenized stablecoins started at least since the treasury report on stablecoins (U.S. Department of the Treasury, 2021). However, the stablecoin market is not limited to tokenized coins, and each pose their unique risks. In the pursuit of more innovative ways to maintain their pegs new mechanisms are created, however they were shown in this chapter to not be as effective, on average, as simple tokenization. Based on the findings in this chapter, it is safest to use tokenized funds as they exhibit the lowest propensity for extreme events, as shown by their larger alpha coefficient derived from the power law model. Conversely, algorithmic stablecoins could be said to be more volatile on average and the riskiest.

Regarding policy making, algorithmic stablecoins and in general more innovative peg designs should be scrutinized more carefully. The Tokenized stablecoins are more stable and less prone to extreme price volatility based on the results of this study, however, most still have high kurtosis and an α coefficient lower than 3, which implies fat tails and a higher probability of price crashes/de-pegging. As Faux (2021) stated, there are significant concerns about transparency of firms such as Tether, which are deeply imbedded not only in the stablecoins market but in the crypto space in general. Also, a recent report claims the companies behind these coins operate as unregulated banks (U.S. Department of the Treasury, 2021). Based on this, and the concerns of

‘stablecoin runs’, it would be sensible to regulate tokenized stablecoins. The most obvious first step would be to require regular audits, such as ones voluntarily undertaken by USDC. Though it must be pointed out that USDC still does have extremely high kurtosis and a low α coefficient, implying higher frequency of extreme volatility. Nevertheless, making sure that it does have the collateral required to cover its minted coins in case of a ‘run’ is vital, perhaps even more so considering its risk of crashing.

In the case of crypto-backed and algorithmic stablecoins, it must be assumed these assets are speculative and treated as such, based on the information at hand. Though the results regarding crypto-backed stablecoins were inconclusive, their collateral are volatile cryptocurrencies. Therefore, customers must develop a clear understanding about the risks of buying such assets. This is even more valid for algorithmic stablecoins, which were conclusively more volatile than tokenized ones and have a history of major crashes in the recent past. Audits in this case may not be meaningful as the crypto-backed ones have presumably transparency since all transactions are recorded on the blockchain, while algorithmic ones claim to base the value of their stablecoin on their arbitrage system and its utility in the ecosystem. Possibly certain limitations in marketing of these assets must be introduced, to prevent claims about stability and reliability.

The currency to which the stablecoins are pegged (USD or non-USD), however, do not appear to impact their stability and no immediate requirement in policymaking is in sight with regards to this.

One of the limitations of this study is the smaller number of observations for some of the stablecoins. All of them have a number of observations n>100, which is the smallest recommended number by Clauset et al. (2009). According to him a smaller number will always yield a p>0.1, which would make the results meaningless. However, the power law model he proposes is data sensitive, and the small number of observations limited the robustness test that could have been performed. This limitation possibly contributed to inconclusive results with regards to crypto-backed stablecoins, where no clear difference could be established with the tokenized ones.

Further investigating the crypto-backed stablecoins' volatility and comparing it to that of the tokenized stablecoins could be revealing. Crypto-backed stablecoins possess transparency due to the public nature of the records on the blockchain but are backed by volatile assets yet are pegged to a fiat currency. Conversely, tokenized stablecoins are backed by the same fiat currency they are pegged to yet lack the transparency. In this environment, the tokenized stablecoins have the higher median alpha coefficient thus lower extreme event risk, however the highest alpha coefficient belongs to a crypto-backed stablecoin. The question of the cause or combination of features more specific than simply peg design for a higher/lower power law alpha coefficient could be addressed by future research.

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Chapter 3. Impact of blockchain on OTC derivatives trading: A Game-Theoretic Analysis.

Abstract

This chapter investigates how blockchain-based decentralized ledgers could heighten collusion risks in Over-the-Counter (OTC) derivatives trading, specifically for Index Credit Default Swaps (CDS). The research models the trading process on a decentralized ledger using a game theoretic framework, assessing how different levels of transparency facilitated affect market participants' ability to collude. A game-theoretic model treats trading as an auction whose transparency depends on how winner history is displayed. Three platform models are analyzed, with increasing levels of transparency. The analysis shows that tacit collusion could be a significant issue in OTC trading, and be more efficient on a fully decentralized platform, proportional to the level of transparency. If caution is not exercised by regulators, this technology could facilitate tacit collusion and harm the end customers in this systemically important industry.

Section 3.1. Introduction.

Satoshi Nakomoto in his 2008 whitepaper outlined a way to use Decentralized Ledgers Technology (DLT) to conduct transactions without the need for a central authority to validate said transaction. The transactions were going to be peer-to-peer and they were going to be validated by a pool of decentralized nodes, also known as miners (Nakomoto, 2008). This became known as the blockchain technology and since the introduction of Bitcoin – the first cryptocurrency - its applications have grown beyond simple monetary transactions. Blockchain was first envisioned in 1991 by Stuart Haber and W. Scott Stornetta to cryptographically secure timestamps on documents to make them tamper-proof. Satoshi Nakamoto took it a step further and created a decentralized system that uses blockchains to secure the transaction history. The technology was expanded with the emergence of Ethereum, with its native coin Ether, which is the second largest cryptocurrency by market capitalization, by adding the functionality of smart contracts. These are in essence contracts written in code and stored on a blockchain. Therefore, smart contracts share the immutability of cryptocurrency transactions. They have the potential to automate business processes such as back-office costs, simultaneously decentralizing industries and avoiding single points of failure and achieving more transparency. Combined with the currency functionality the benefits of a decentralized ledger system extend to areas such as logistics, trade finance, stock exchanges, fund raising through ICOs, among others. For example, the Hyperledger project has several tools allowing businesses to build their application to share information and conduct transactions. IBM, Intel, and notably the Depository Trust & Clearing Corporation (DTCC) have supported this project (Hyperledger, 2022). Corda – a system initially created by banks as an attempt to test blockchain systems on the ability to improve the efficiency of their operations is another notable example.

In the past few years, the number of blockchain based projects and investments in them have soared – in 2022 alone VCs invested 33 billion USD in blockchain start-ups. The average valuation of crypto/blockchain start-ups was 70m compared to the average of 29m for non-crypto projects (Galaxy Digital Research, 2022). Based on this, the enthusiasm on crypto projects is not waning. There are countless forums and articles claiming that decentralized technologies are the future and will change most industries. Marc Andreesen, the co-founder of Netscape (the first internet browser) and major VC investor went so far as to claim this is what the internet has needed since its inception (Fung, 2014). In finance specifically, the advent of smart contracts promises that blockchain based DLTs will revolutionize not only monetary transactions but also clearing and settlement of securities.

An example of how the blockchain technology proponents believe it will disrupt finance is the rapidly growing industry of decentralized exchanges (DEX), such as Uniswap and 1Inch. Their selling point is the absence of a single point of failure and the difficulty speculators would face if they attempted to manipulate the market on a DEX. However, these DEXes have been plagued by issues of front-running and liquidity (Daian et al., 2020). A systemically important industry that many believe could be improved by switching from legacy systems to a blockchain-based one is the OTC derivatives industry (Jayeola, 2019; Patsinaridis, 2020; Surujnath, 2017). This industry is mostly unregulated, despite the attempts after the 2007-08 crisis. Also, discriminatory pricing was found to be exercised against the non-financial customers (Hau et al., 2017). It is believed effective regulation of this market could be done through use of the blockchain technology because it would increase the transparency of transactions, which would be beneficial for the end

customers. It would also be cost-efficient, and in fact, this technology has already been implemented by Paxos, shortening contract settlement to a few hours (Stafford, 2021). Symbiont, a private company is developing a solution for the OTC derivatives trading. Also, NASDAQ has been rolling out a solution for OTC derivatives in the Tallin Stock Exchange, which NASDAQ owns. The biggest financial organization to try to implement this solution is the Australian Stock Exchange (AUX). The system was originally going to be operational in 2021, but the roll out got postponed.

However, despite the enthusiasm of investors and the public alike, some have questioned not only the viability but also the benefits of decentralizing certain processes. The central issue that bitcoin solved was The Byzantine Generals problem, which is a game theoretic problem highlighting the difficulty of reaching consensus without a central authority. Bitcoin solves this by using its Proof-of-Work protocol (Nakomoto, 2008). The key point here is that after the transaction has occurred it is broadcast publicly to be verified by the nodes (miners). After verification occurs, anyone can access the ledger and check if a specific transaction happened, provided they have the necessary information such as the wallet addresses the sender and receiver. Otherwise, the ledger will simply show all the transactions that have occurred up to that minute. In the case of Bitcoin, the public addresses are anonymized and randomly changed with every transaction. Thus, in theory, though the transactions are publicly visible, the identities are not traceable. The second biggest blockchain, Ethereum, similarly anonymizes addresses of transactions, however they are not changed with each new transaction. This is crucial because the smart contract functionality is based around Ethereum's systems. In a private blockchain (also known as a permissioned blockchain) with a limited number of participants - application of which are being attempted derivatives trading – this

public nature of transactions and contracts changes the informational environment. It is highly relevant for the financial systems they are intended to replace, as the impact may be detrimental to the consumer. As mentioned above, there have been attempts at introducing decentralized blockchain clearing and trading for derivatives. Most authors focus on the benefits of this transition (Jayeola, 2019; Surujnath, 2017; Priem, 2020; Kumar, 2022). This chapter studies the possible harm the implementation of this technology may cause by increasing the ability of participants to maintain tacit collusion.

The aim is to demonstrate that the benefits of applying this technology in OTC derivatives trading are not without tradeoffs. The current consensus in the literature is that back office and reconciliation costs will be lowered, more transparency provided to regulators and clients, which will increase welfare for the customers and society at large. This chapter aims to show that it is not clear that this will be the case. It may create opportunities for tacit collusion among the dominant actors, thus increasing their control of the market instead of democratizing it. A game theoretic framework is used to demonstrate the mechanics of this scenario, modelling OTC derivatives trading as a simple auctions game that depends on information available to players, which determines the discount factor. Previous research done by Blume and Heidhues (2008) shows that collusion could be maintained in second price auction if the process of naming the participants could be conducted. Cong and He (2019) also point out the challenges that the blockchain's transparency could cause, and they likewise use a game-theoretic model to model these issues. This chapter follows the approach of Cong and He (2019) in attempting model the proposed trading platforms using well-known game-theoretic models and demonstrate the increased ability of bidders to maintain collusion under a transparent blockchain based system. It also creates trading

simulations based on the parameters identified for the current and blockchain-based systems and records the change in the profit margins to visualize the effectiveness of collusion, especially on a fully transparent platform.

The conclusions made based on the analysis of the game-theoretic model chosen to express the trading environment and the trading simulation is that the average profit margins maintained through collusion and the ability to maintain it increase as the level of transparency increases. This implies that policy makers must be vigilant and cautious about allowing a large-scale implementation of this technology.

This chapter contributes to the literature by analyzing the impact decentralization would have on the OTC derivatives trading process. This is done by applying game theory to model three auctions which serve as models to the existing trading process and the one expected a blockchain-based system would entail: 1) first auction model demonstrates the bidding equilibrium for the existing trading process of Credit Default Swaps, 2) second auction model modifies the ruleset to account for some transparency a blockchain would provide but maintains some aspects of the current system, 3) the third model demonstrates the results to be expected from a fully transparent trading process conducted on a blockchain. The results show that the growing transparency of transaction history - which is expected to occur on a blockchain-based trading platform - would allow more efficient collusion to be maintained than is currently possible on Swap Execution Facilities. In other words, the ability to collude is proportional to the level of transparency. The results also highlight that introducing blockchain-based trading is an issue policy makers must remain cautious

about. This chapter also contributes by running a rule-based simulation to demonstrate the profit margins this hypothetical trading platform would have for the dealers, based on the conception of the trading rules such a platform we currently imagine would have, which we derive from the literature.

Section 2 will be a literature review on the discussions about implementing these systems in derivatives trading and existing research about the possible dangers related to increased collusion. Section 3 describes possible ways to implement a trading platform for OTC derivatives trading; Section 4 describes the game theoretic model to analyze the trading platforms, the rule-based simulations, and states the results; Section 5 Concludes.

Section 3.2. Literature Review

Derivatives as an instrument have been surrounded by controversy. The latest major example is the role OTC derivatives, Credit Default Swaps (CDS) and Collateralized Debt Obligations (CDO) specifically, in the 2008 financial crisis. The opacity of this market was such that regulators had an incomplete picture about the concentration of risk (Jayeola, 2019). Paolini (2020) puts CDS trading at the center of the 2007/08 crisis. As a reaction to this, attempts to regulate this market have been made. According to Deloitte (n.d.), European Market Infrastructure Regulation (EMIR)

requires all standardized OTC derivatives in Europe to be cleared through a Central Counter Party (CCP). Central Clearing Counterparty or Central Counter Party (CCP) is the financial institution that acts as a buyer to the seller and seller to the buyer and provides clearing and settlement services (Rehlon & Nixon, 2013). CCPs are integral to managing counterparty risk, which they achieve by putting themselves in the middle of the trade and ensuring the counterparties hold their end of the trade. CCPs also set the collateral requirements for each trade. This implies higher margin requirements and capital charges for exposure. In fact, the initial margin requirement was not present in bilateral trading previously. However, the biggest cost is expected to be the more thorough reporting requirements for the dealers, thus increased back-office and compliance costs (Patsinaridis, 2020).

Paolini (2020) states that despite the tightening of regulation and a push towards central clearing the OTC market is expected to remain largely the same. The new regulations, Paolini (2020) agrees, introduced considerable costs because of the increased compliance measures. Using smart contracts to lower said costs is an attractive alternative, as this will help keep prices lower for the clients. The emergence of decentralized technologies which promise to make transactional information both public and anonymous appears ideal for alleviating the shortcomings of derivatives trading – namely the opacity which makes it difficult to regulate and the back-office costs regulation may incur.

According to Jayeola (2019), efficiencies blockchain could introduce are in record-keeping and reporting. The process of reconciliation incurs significant costs, due to the duplication of the

records of transactions/contracts through multiple organizations and jurisdictions, because of the global nature of OTC derivatives (Paech, 2016). Jayeola (2019) further states that regulators could gain real-time view of the market if a blockchain system would be implemented – though a huge standardization effort must be undertaken for the type of data to be reported. Also, the presence of a regulator and a CCP in the trade means the valuation will be ongoing and thus capital requirement may be more accurate and risk management superior. This could increase the participants' liquidity and the disintermediation could reduce systemic risk by allowing new players into the market (Patsinaridis, 2020).

The key amelioration that proponents of blockchain technology claim is the anonymity it provides while allowing for public consensus. Because of this set up, the regulators may have a bird's eye view of the market while the participants maintain their anonymity in relation to other buyers/sellers. It has been argued that the anonymity attribute of decentralized ledgers like Bitcoin provide is redundant in financial markets, as it is important to maintain transparency and accountability to regulators. To improve accountability to regulators it has been stated that the creation of a global CCP would promote transparency, integrity and reduce costs (Gregory, 2014). Also, it would lead to an immense concentration of risk in one organization and would constitute a single point of failure. However, if decentralized technologies were implemented, the latter issue could be overcome, yet in turn lead to new issues being introduced in the form of tacit collusion – the risk of which this chapter attempts to show is enhanced under a decentralized system.

This introduces the issue of information dissemination – sensitive financial information cannot become public. Thus, decentralized consensus - the center of blockchain technology – must take into account the sensitivity of information and regulate information distribution. Cong and He (2019) state this is a "fundamental tension", as decentralization in this case could be detrimental if the sensitivity of the information being distributed is not considered. Cong and He (2019) claim public visibility of data would improve the ability of sellers - in their trade finance model - to maintain collusive equilibria. Regulators would have a full view of the market and of market participants, but not the public. However, even within the permissioned blockchain the visibility of transactions data to all participants could be harmful to the buyers as it could help sustain collusion - which Cong and He (2019) argue in their study.

Among other attractive qualities of blockchain cleared smart contracts is the speed of execution of contracts – it takes up to three days to settle a contract. By using a DLT this process could be shortened to a few minutes.

In summary, the promises of blockchain as it pertains to OTC derivatives trading are:

- Lowering of operation costs
- Preventing a single party exercising overwhelming power over the financial system
- Increasing efficiency and lowering the trading spreads
- Provide real-time data to regulators and make the industry less opaque

- Benefit the end customer by eliminating discriminatory pricing through increased transparency

Expanding on the last point above - an issue with OTC derivatives trading is financially unsophisticated clients in the OTC markets are at a disadvantage. EMIR data shows discriminatory pricing is being exercised against non-financial clients on a regular basis (Hau et al., 2017). It is not clear that there is any collusion occurring. However, on average these customers are charged 25% above the spread. Hau et al. (2017) have also shown that by trading on a centralized multi-asset platform the discriminatory spreads were eliminated. The expectation is that decentralizing the system by using a blockchain will achieve the same effect with the benefits summarized above and will avoid having a single point of failure.

However, the transparency that a blockchain-based system would introduce could in fact make the issue of practicing discriminatory pricing worse. Cong and He (2019) highlighted the fundamental tension of informational dissemination in the case of trade finance and how increased transparency could allow for tacit collusion among dealers, which could keep prices non-competitive. Therefore, discriminatory pricing exercised against financially unsophisticated actors could morph into non-competitive, collusive pricing which affects all customers. In fact, depending on the way the blockchain is organized, it may be even more detrimental to the welfare of customers than shown in Cong and He (2019), which this chapter argues.

The relevance of collusion in OTC derivatives dealing increases due to the structure of the market. According to an ISDA report in 2010, 82% of the notional amount was issued by 14 major dealers. The four-firm and eight-firm concentration ratios – used for measuring market power of participants – were 40% and 63% respectively (ISDA, 2010). A more recent ESMA report, focusing on the European market specifically showed only a few dealers – mostly credit institutions and investment banks - held 90% of the outstanding notional amounts in Credit Default Swaps (CDS). It must be noted that based on ISDA's analysis the concentration levels are not high enough to facilitate collusion. According to ISDA it is a "loose oligopoly", where effective collusion is unlikely. Market concentration is important from a game theoretic standpoint, which this chapter uses to model trading on a blockchain. Punishments exercised to maintain collusive equilibria depend on the level of market concentration. As such, grim trigger strategies are more effective when concentration levels are high, which has been argued is high for OTC derivatives markets (Hatfield et al., 2018; ISDA, 2010).

Kaminska (2015) argues that it is within the interest of major banks to implement this technology precisely to exercise cartel-like control over the market. The Corda blockchain solution, major investors of which are names such as Wells Fargo, Barclays Corporate Banking, NatWest Group etc., is stated as a possible candidate to solve the opacity issue in the OTC derivatives market (Jayeola, 2020). However, R3 – the company developing Corda – has itself been vocal about the issues with data privacy it could create. Combining the role of information dissemination for maintaining collusion established by Cong and He (2019) and the parties interested in the development of systems such as Corda it is easy to speculate about the capacity of such systems to facilitate collusion.

It is shown in Hau et al. (2017) that multi-asset trading platforms were able to improve the position of clients, however, other factors hinder progress. Clients depend on dealers who are also their clearing members to access the market. The superior bargaining power of dealers relative to clients is also emphasized by the fact that 50% of clients have one clearing member, and 30% have two. The clearing members can cease to serve the customer with 1-3 month notice, while it would take much longer for the client to replace the clearing member (Joint FSB-BCBS-CPMI-IOSCO report, 2018). This asymmetry could be alleviated with the usage of a decentralized marketplace where regulators are present. The extent of this issue has not been thoroughly researched, but there have been lawsuits against dealers who attempted to use their power to avoid using trading platforms.

It is also alarming that tacit collusion in Decentralized Exchanges (DEX) for cryptocurrencies has already been observed empirically. It has been observed in conjecture to another issue – frontrunning. In currently existing decentralized crypto exchanges frontrunning is a major issue. They were expected to solve the issues centralized crypto exchanges possessed, which were outlined above, and potentially replace regular stock exchanges. However, just like the regular exchanges suffer from frontrunning as described in Flash Boys by Michael Lewis, so do decentralized exchanges (Lewis, 2015). The expectation was that the lack of trust in central cryptocurrency exchanges caused by high-profile thefts and price manipulation can be remedied with a peer-to-peer solution. This did not come to pass, as trading even relatively small sums on these platforms comes with a huge risk of slippage (loss of value) caused by frontrunning (Daian et al., 2020). In fact, it is so ubiquitous that up to 90% of the transaction's value could slip. This is done mainly through trading bots which offer higher gas (pseudo currency within Ethereum

blockchain) prices for the transaction and get in front of it, which in turn is possible because of slow execution of these transactions on chain. Different bots compete for every transaction, which in theory would suggest it would be a race to the bottom for these bots, and they would not make any profit. In practice, the opposite takes place - Daian et al. (2020) demonstrated that these bots effectively engage in uncoordinated cooperation, decreasing the welfare for miners.

One more major change is that the Dodd-Frank Act was the requirement to execute all trades for "a subset of liquid, standardized interest rate swaps (IRS) and credit default swaps (CDS)" on a Swap Execution Facility (SEF), as an attempt to make the markets more transparent (Riggs et al., 2020). This trading could be done on a blockchain which will perform the trade and act as a CCP simultaneously. ESMA (2016) point out that the clearing and settlement done by the CCPs can be combined into a single step. As mentioned before, the Tallin and Australian Stock Exchanges have already started moving in the direction of a blockchain based exchange. It is the logical next step that OTC derivatives could be traded and cleared in one step, since the blockchain technology's speed of execution in clearing would allow it. Kumar (2022), Shär (2021), and Morini (2017) detail how a decentralized, blockchain based system could be implement for managing all processes related to derivatives trades.

OTC trading platform models are modelled as auctions in this chapter. The main proposition is that the ability and incentives to collude are higher as the transparency increases through the use of blockchain. In auction games literature collusion is a possible equilibrium. Blume and Heidhues (2008) show that in a standard second price auction collusion is sustainable, conditional on the

ability of participants to conduct naming (identifying individual bidders by a label) and having a public history. Dutta and Madhavan (1997) posit that implicit collusion is different from price fixing in the pricing pattern exhibited. Hatfield et al. (2017) do not use an auctions model; however, they demonstrate through their game theoretic model that collusion is highly likely in the US IPO underwriting market.

This study uses the standard first price sealed bid auction model to demonstrate how the ability of dealers to maintain collusion increases with the level of transparency on the hypothetical blockchain-based trading platform. This question is relevant for two reasons. Firstly, due to the attempt to implements this technology in the industry and discussions in academia about the benefits of this technology (Stafford, 2021; Jayeola, 2019; Surujnath, 2017). Secondly, the question is relevant because of the existing issues regarding OTC derivatives trading: discriminatory pricing exercised against non-financial clients; market concentration in OTC derivatives trading; the ability to use GRIM trigger strategies to maintain collusion in high concentration markets and existing signs of collusion in the US IPO underwriting market; uncoordinated collusion of trading bots on DEXes; sustaining of collusion if bidders are able to perform the naming of other bidders, which the blockchain could allow (respectively: Hau et al., 2017; ISDA, 2010; Hatfield et al., 2017; Daian et al., 2020; Blume and Heidhues, 2008). Considering these points, it is important to evaluate whether increasing the transparency of trading could allow for effective tacit collusion and thus diminish the welfare of clients to the benefit of the dealers.

This chapter shows that the currently discussed improvements the blockchain technology would make to the OTC derivatives trading - which have been implemented in practice by a few companies (notably by Paxos) – could take in fact improve the ability of dealers to collude. It is in line with the Cong and He (2019) who concluded collusive equilibria could be sustained on a permissioned blockchain. However, this study focuses on OTC derivatives market, specifically basing the model on the descriptions of Index CDS trading given by Riggs et al. (2020) and the types of decentralized exchanges described in Daian et al. (2020). This chapter also draws on the research of Blume and Heidhues (2008) and uses history of winners (bidder memory) as key element that allows sustained collusion. The results show that increasing levels of transparency in winner history and the bidding process allow for collusive equilibria to be maintained more easily. More specifically, the collusive ability is proportional to the level of transparency. This is another contribution that distinguishes this study.

Section 3.3. Blockchain trading platform design.

Currently OTC deals are initiated by the clients who contact the dealer-brokers, who may in turn forward the request to a different dealer or to its internal department. This has led to a sprawling network of interconnected organizations. Based on new regulations introduced by the Dodd-Frank act, once the details are finalized the certain types of standardized OTC derivatives contracts must get through the Central Counter Party (CCP) and obtain regulatory approval (Riggs et al., 2020). Nevertheless, bilateral transactions without central clearing are still common, and even in standardized Index CDS trading this remain the most common trading method (Riggs et al., 2020).

According to Surujnath (2017) this in fact, is the biggest opportunity for blockchain. It could become the CCP for the OTC markets. However, instead of being a CCP in the ordinary sense and becoming a single point of failure, it would be a Decentralized Clearing Network (DCN). The only parties aware of the transaction would be those involved and the regulator. The ledger could be publicly visible or hidden. This is the approach taken by consortium blockchains. The most famous example is Corda by R3, which was backed by a consortium of major financial institutions, among which are names like JP Morgan and Barclays. The Corda ledger is considered to be more suitable for financial institutions due to its closed nature. Members of this DLT must be permitted to join, therefore there will be a gatekeeping node or group of nodes (member-organizations on the DLT are known as nodes). The uniqueness of the Corda blockchain is in its verification method to prevent double spending. It is achieved through on-chain notaries. Unlike permissionless blockchains like Bitcoin, which relies on public broadcasts of all transaction to verify them and prevent double spending, Corda took a different approach. The notaries could be a single node or a group of nodes representing different organizations. Notaries could be validating or non-validating. The former would have access to all the details of a transaction while the latter would only have limited access. The validating notaries, transacting parties, and potentially the regulator would be the only ones with access to transaction details. This is Corda's attempt at solving the privacy issue that a public blockchain would present for financial institutions, as trading data is proprietary information.

It will not necessarily be one single organization doing the validation, but since they will be entrusted with full visibility of transaction data, they must be a known and trusted entity by both buyers and sellers. Additionally, since there will be a limited number of validating nodes neither

the buyer nor the sellers could be in the pool of nodes being chosen for this role. This is to avoid informational advantage the chosen entities would gain as they are also involved in trading. Therefore, the validating notaries will be known and trusted third parties not involved in the transactions itself. Let us assume that the validating notary is the blockchain equivalent of a CCP. There is, however, a fundamental flaw with such a design. This would not achieve decentralization as we would simply be shifting the single point of failure onto the validating notaries - the blockchain equivalent of a CCP. To achieve true decentralization in the sense of the Nakomoto Blockchain, we would have to broadcast the transactions to all the participating nodes. It is unclear if this will ever be a solution that will be adopted. In fact, to achieve better consensus while maintaining privacy, zero-knowledge validation algorithms are in the works, where the data would be broadcast to all nodes but encrypted, therefore unreadable to the nodes. The value of this concept as far as decentralization is concerned is likewise debatable. However, for setting up the model this chapter is considering the case of true decentralization, where all participating nodes could see the transaction data and validate it. Therefore, we would have the client and seller agreeing on a contract and recording it on a blockchain. Then the CCP on the node would act as the buyer to the seller and seller to the buyer, thus mitigating counter party risk. Lastly, the transaction is globally (i.e. visible to all members of the permissioned blockchain) broadcast and verified by all the nodes.

Surujnath (2017) suggested that for this purpose decentralized organizations are suitable, known as DAOs. This would be the basis of a DCN. In its current form, however, this could only serve to exacerbate the possibility of collusion. DAOs are governed by the smart contract that establishes it and agreed upon the founding organizations. The members can vote to amend the smart contract,

but the results will depend on who has more voting power within the DAO. If it is done in the manner which Corda was created, where the major banks are clearly the main contributors, the power they wield may be a source for concern. Simple regulation could prevent this, however DAOs being part of the crypto world are still largely unregulated. If private entities join a DAO they cannot be stopped under current regulation. It could be possible to balance the influence of all the players. The buyers and sellers of contracts could make a payment to join the platform and then renew the membership continually, like the fees for CCPs. Those that joined the system would be awarded voting power in a manner that would balance the influence within the system. Also, this could cover the costs of keeping the system, keeping it independent.

Further considerations:

1) The CCP on the chain would act as the gatekeeper. Following the business model from the current system, where the CCP charges membership fees, they would do the same on the blockchain. They would screen the members as well as check for compliance. They would, in principle, have monopoly over who gets to participate in this system. Their other function would be assessing the risk of the contracts and calculating collateral necessary to offset some of the risk. This will be the main source of uncertainty and systemic risk, as these instruments are difficult to analyze and informational asymmetries are significant. CCPs and regulators simply cannot most of the time accurately assess the risk profile of these contracts, which eventually leads to the build-up of systemic risk. Considering the inter-connectedness of this market, the potential domino effect could be catastrophic. Case in point is the 2008 financial crisis, where most participants were unaware of the actual riskiness of CDOs.

2) Once the ledger is publicly broadcast (within the ledger), the informational deficiency of the non-financial clients will be somewhat alleviated. Assuming they have the capacity to extract useful information about the pricing and spreads, the discriminatory pricing issue should disappear. However, according to Akerlof (1970) – "The prices will keep going up or the quality will go down until the market disappears". In the build-up of the 2007-08 crisis, this indeed happened – the quality of the assets that went into the CDO kept going down until the whole market crumbled. Akerlof (1970) in his paper notes that accessibility of information helped this issue. The blockchain is attempting to do exactly that. This intuitively will help with discriminatory pricing. However, the dealer will still have a better understanding of the riskiness of the asset.
3) Also, the inter-connectedness of this market could lead to tacit collusion on the pricing. The publicly broadcast ledger ensures that anyone that deviates will be immediately recognized.

As an example of a fairly standardized instrument that is traded over-the-counter, we can look at the trading process of Index Credit Default Swaps (CDS). After a request for an Index CDS is made, the buyer is forwarded to a Swap Execution Facility (SEF). According to Riggs et al. (2020), the buyer has three options in the SEF:

1) Use the Central Limit Order Book (CLOB) - an order book similar to a regular order book on an exchange. The requests are visible to all the dealers. This is the least popular method of trading Index CDSs (Riggs et al., 2020).
2) Request-for-Quote (RFQ) – customers request quotes from dealers bilaterally. The dealers do not know the quotes provided by other dealers but do know the number of dealers contacted.

3) Request-for-Streaming (RFS) – customers observe quotes by dealers and can choose to respond to one deemed suitable. Customer identity is revealed upon revealing interest in the quote.

If we compare the existing stock exchanges to decentralized ones, we can observe a crucial difference. In a centralized exchange, the order book is centrally run and matched based on best prices offered by participants. In decentralized exchanges it is not necessarily the case. Three main types of order matching systems have been identified in Daian et al. (2020):

1) The order book is kept off-chain, and the customers can themselves select the most attractive offer and clear it on the chain.
2) The order book is kept off-chain, but the matching is done by the system and then submitted to the smart contract to be cleared on chain.
3) The most hardline approach where the DEX itself performs the matching and serves as the counterparty to all trades. This allows for anonymity as the counterparties are not discovered. Depending on which tokens are bought/sold, the chain's own reserves will fluctuate and thus affect prices. Consequently, this approach requires constant arbitrage on part of the chain in order to keep the price of tokens constant.

Using the examples of DEXes for token trading and the structure of the current Index CDS trading, we can envision a system for trading products such as Index CDSs on a blockchain.

For the purpose of modeling a decentralized trading platform, focusing on Index CDS trading is appropriate following reasons:

1) These are standardized assets that were traded OTC before, but after Dodd-Frank are now traded on Swap Execution Facilities and centrally cleared.
2) The observations reported in Riggs et al. (2020) show that CLOB usage has declined and is the least used type of trading on the SEFs. This is believed to have been encouraged by the practice name give-up which occurs post-trade when trading swaps. Here we can observe how the informational environment is affecting the trading process.

In the third method of matching trades, if it were to be applied to trading derivatives the anonymity of the counterparties cannot be preserved if we are to copy the existing system onto the blockchain. The CCP acts like the DEX matching engine, both acting like the buyer to the seller and vice versa. However, in the case of CCPs it is done after all the details have been agreed upon by the counterparties. The CCP takes on the function of a regulator and assumes the counterparty risk, but the counterparties do not remain anonymous. For this reason, if the matching of buyers were to be done on-chain it would resemble an open auction, where all the bids of dealers would be observable by other dealers. This represents the most radical scenario analyzed. Both the trading and clearing could be done on the DCN as the clearing time would also be down to minutes. This is assumed in the rest of the chapter when referred to a DCN or blockchain based trading platform, the terms are interchangeable in this context and mean a decentralized platform where the trading of an OTC derivative occurs and rapidly clears afterwards.

It could be a platform where the trading and clearing occurs. The prevailing opinion in the literature is that a DCN would likely be a permissioned system. Therefore, the number of participants will be limited. The orders would be submitted in one of the three ways described above. Unlike the

SEF, where in the RFQ and RFS methods the trade details are only known to the two counterparties, on a DCN they would be known to all the participants as it would be cleared on-chain. This would only happen after the clearing in case of method 2 and 3, as the matching would be done off-chain. There is also the option to have both the matching and clearing on-chain. Therefore, the informational environment would be different on DCNs i.e. decentralized trading and clearing platforms for OTC derivatives. Below is a table summarizing the distribution of information on transactions on different types of trading platforms:

Table 3.1. Informational environment post-trade.

	Buyer (trading)	Buyer (rest)	Dealers(winner)	Dealers(rest)
CLOB	+	-	+	-
RFQ	+	-	+	-
RFS	+	-	+	-
DCN (off-chain)	+	+	+	+
DCN (on-chain)	+	+	+	+

This table shows which participants can see the identities of the parties of the trades that were agreed. There are multiple separate trades happening simultaneously hence the division into "trading" and "rest".

Section 3.4. Model and Results.

According to Riggs et al (2020), the most commonly used trading system used is the RFQ (request-for-quote). Hence, it is used as the baseline against which hypothetical blockchain-based platforms are compared.

1) Firstly, the case of currently existing Request-for-Quote (RFQ) systems used on Swap Execution facilities is analyzed – this is the basic model of the trading platform currently used in practice.
2) Secondly, a blockchain-based model with *off-chain* matching – meaning that only the winner of the auction is observed – is analyzed.

3) Thirdly, a blockchain-based model with *on-chain* matching is analyzed. The differentiating factor from the previous model that the whole auction process is observable, including the names of all the participants and their bids. This is essentially a blockchain powered open auction.

In an RFQ auction, customers make a request, and a finite number of bidders show up with offers. Based on Riggs et al (2020), the average number of dealers contacted by a customer is 4.1. This subset of B is the reason why increasing levels of transparency by using blockchain-based trading platform is more conducive to collusion. On a currently used RFQ system the anonymity is maintained, so the bidders have no way of **naming** the other bidders or knowing how many bidders are there. Naming is the process by which bidders gradually identify and attach bids to individual bidders.

Meanwhile on a decentralized platform, based on the trading models proposed in this study one of the following methods could take place: 1) the quotes could be requested and matched off-chain, like in the currently existing DEXes, 2) the quotes request and matching to bidders could be done on-chain, the most radical and transparent way of trading. The requests occurring on-chain would mean that the dealers within one deal are essentially participating in an open auction. It follows that they will know how many dealers are participating and have the ability to name them. This is a reasonable assumption to make because as mentioned above, the addresses on the Ethereum blockchain - which is popular precisely because of the smart contracts that would allow clearing

OTC traded assets - do not change with each transaction. This distinction in transparency levels is viewed in more detail when the decentralized systems are analyzed below.

This requires the concept of transaction history to be defined. It is denoted by $h(t)$, and is dependent on time t. In this study it will be defined as a function storing all the publicly available information. Three types of auctions will be viewed, therefore, three types of history h will be defined as $H \in [h_1, h_2, h_3]$. The first type $h_1$does not have memory and corresponds to the existing RFQ or RFS systems, as the information about winning bids is kept confidential. The second, h_2 will denote the history collected in a permissioned blockchain with matching done off-chain. This means a full history of bid winners will be available but not what other losing players bid, neither will the identities of losing bidders be recorded.

To conduct the analysis of decentralized trading platforms for derivatives a simple auctions model is used. The set of dealers is finite and long-lived. They are referred to as bidders and denoted as B. The bids are denoted b_i. They discount future at the rate $\delta \in (0,1)$.

Other general assumptions for the model are listed below:

1) Bidders *i: 1,2…..n.*
2) Bidder *i* observes his own valuation v ~ F(.), which takes on values of v ∈ [$\underline{v}$, $\overline{v}$].
3) Assume F(.) is continuous and the distribution is uniform.

4) All bidders draw their valuations from some distribution F(.).
5) All v_i are independent.
6) Bidders are risk-neutral.

These assumptions are standard for a first price sealed bid auction. Bayesian Nash Equilibrium will be used as the equilibrium concept. Also, this is a game of *incomplete information* as player i only observes his own valuation and therefore does not know other players' payoff. Crucially, *only the winner's bid* is made public. This applies perfectly to the case of derivative trading on RFQ or RFS, as they are bilateral, and the winner is not observed. In essence, every trade on the RFQ is a separate static game. They can be referred to as "stage games". This is a key difference from on chain matching. The assumption that v $\in$ [$\underline{v}$, $\overline{v}$] is also realistic, as the OTC dealers largely consists of firms who will use model-based approaches to valuation to achieve better margins (Deloitte, n.d).

Also, this is a standard auction, meaning the following conditions are satisfied:

1) Buyers can make any non-negative bid.
2) The highest bid wins the good.
3) The expectation from a zero bid is zero.
4) Participants are treated symmetrically.
5) There exists a unique and common equilibrium strategy for increasing v (Blume and Heidhues, 2008).

First model - Auction on an RFQ

First, we build a model of trading on RFQ and show that trading on it is competitive. As mentioned before, the identities on an RFQ are revealed to the trader b_i and client a_i **only**, and only after the trade is agreed upon. A similar model for second price sealed bid auctions was studied in Blume and Heidhues (2008) where they called this property *name-freenes*. This means that the repeated auction has no memory, also called history. In case of RFQs $h(t) = 0$, as neither the winning bid nor bidder b_i's identity are made public. This is the key difference that this study argues is the reason a blockchain based system will be less beneficial for the clients. The history function $h(t)$ will determine how large the discount factor $\delta \in (0,1)$ is, i.e. the level of patience of the bidders.

Also, we assume that the bidders are symmetric i.e., they have the same bidding function $b_i(\,.\,) = b(\,.\,) \; \forall \; i = 1,2 \ldots n$.

Below is the formal utility function of any bidder b_i. In this case the expected payoff to be maximized would be:

$$U_i(b_i, b_{-i,} h) = \; [v_i - \; b_i(v)]\Pr\,(\; b_j = b(v_j) \leq b_i)$$

(2)

$$\Pr\left(b(v_j) \leq b_i\right) = [F(b^{-1}(b))]^{n-1}$$

(3)

Therefore,

$$U_i(b_i, b_{-i,}h) = \ max[v_i - \ b_i(v)]\ [F(b^{-1}(b_i))]^{n-1}$$

(4)

Since this is an infinitely repeated game, it can be formally expressed as

$$\pi_1 \ = E\left\{\sum_{n=1}^{\infty} \delta\ _{h_1}(\max[v_i - \ b_i(v)])\right\} = \frac{1}{1-\delta}\left(\max[v_i - \ b_i(v)]\left[F\left(b^{-1}(b_i)\right)\right]^{n-1}\right)$$

(5)

In this game the lack of history of winning bids and identities of bidders is the crucial factor that determines the bidding strategy and consumer welfare. Intuitively, since a b_i is not affecting history in any way, every stage game is treated like a one-shot game. Therefore, he will choose to bid competitively in every round of the game. Since $b_i(.) = b(.)$ by assumption, it is the equilibrium bid of the game, which means that the winning bid will depend on the signal v. This equilibrium is calculated below by differentiating the utility function with respect to v_i and equating to 0, which yields:

$$[v_i - \ b_i(v)](n-1)F\left(b^{-1}(b_i)\right)^{n-2} f\left(b^{-1}(b_i)\right)\frac{1}{b'\left(b^{-1}(b_i)\right)} - \ F\left(b^{-1}(b_i)\right)^{n-1} = 0$$

(6)

Solving for $b_i(v)$ will yield the Bayesian Nash Equilibrium for this game in competitive bidding:

$$b(v) = v - \frac{\int_{\underline{v}}^{v} F(v)^{n-1} dv}{F^{n-1}(v)}$$

(7)

We can see from the formula above that the bid will be lower than the private valuation of the bidder. This is the common solution to the general case of a first price sealed bid auction, and the full derivation can be found in the Appendix to this chapter.

In an auction where the names of the winners are not made public, which is the case for the existing RFQ and RFS systems, the superior anonymity means collusion is not sustainable. This claim is shown to be valid in Blume and Heidhues (2008). The model they present shows that in an auction where history of winners is not public payoffs are maximized by competitive bidding. Dealers from in every auction will choose competitive bidding because of the inability to coordinate.

In Cong and He (2019) it is suggested that not receiving customers within sufficiently large $T - t$ could be treated as a sign that a bidder has deviated and thus the punishment phase would be triggered where the dealers engage in Bertrand competition. However, on an RFQ the collusion phase will be skipped altogether or be unsustainable early on, and the bidding will be competitive from the start. The knowledge of the existence of other bidders in absence of communication (because of anonymity) motivates each b_i to bid lower. This argument has empirical evidence

behind it. In Hau et al. (2017) shows that the discriminatory pricing exercised against certain customers disappears in RFQs. Here δ (measure of patience) is close to 0 and the only scenario, based on this model that collusion would be possible is if δ is approaching 1 (it cannot be 1 since $\delta \in (0,1)$). However, if a bidder does not win for any arbitrarily extended $h_i(t)$, then his δ will be decreasing as there is no way to confirm other bidders are not deviating. Thus, the only possible equilibrium in this informational environment is competitive bidding.

Figure 3.1 and Figure 3.2 below are the results of the rule-based simulation run to visualize the evolution of profit margins of bidders on this trading platform. The simulation has six parameters:

Table 3.2. Parameters of the simulation.

Parameters	Value
Number of bidders	5
Number of rounds	100
Valuation range	0.95;1.05
Collusive margin **X**	5
Patience	10
Discount factor	conditional

The discount factor bound depends on the type of platform.

The purpose of this simulation is to visualize the movement of the profit margin under simplified conditions. The parameters of the simulation are as follows:

- **Number of Bidders**: 5, mirroring the close-knit competitive landscape of SEFs. Based on Riggs et al. (2020), 90% of customers using RFQ auctions request quotes from three to five dealers.

- **Number of Rounds**: 100, to adequately capture the trends and strategic adjustments over time.
- **Valuation Range**: 0.95 to 1.05, representing the private, yet closely clustered, valuations of each bidder.
- **Collusive Margin (X)**: Set at 5 initially, signifying the profit margin target under collusive behavior. This is an assumed number. More formally: The collusive margin in this context is defined as the difference between the price that would result from competitive bidding and the lower price achieved when bidders coordinate to suppress competition, thereby increasing their collective surplus.
- **Patience**: Each bidder starts with a patience level of 10, decrementing with each round lost, simulating the thinning tolerance for non-winning outcomes for dealers.
- **Discount Factor**: Conditionally applied, reflecting the speed with which the bid of the bidder is going to decrease.

This is a Python simulation, where the parameters do not reflect the auction model one-to-one, but rather attempt to reflect the bidding process of the infinite game. The "discount factor" parameter reflects the patience of dealers in maintaining a higher profit margin in the game theoretic model, i.e. the value assigned by players to future payoffs. In the simulation it reflects is related to two factors. Firstly, it reflects how fast the bids decrease, once competitive bidding starts. Secondly, a separate parameter for patience is assigned to bidders, equal for all bidders. Every round a bidder loses, their patience decreases by an amount dependent on the discount factor. The discount factor determines the rate at which patience decreases, indicating how quickly losing bidders are driven to deviate. Additionally, the "collusive margin x" is set to 5, this number is also assumed, its

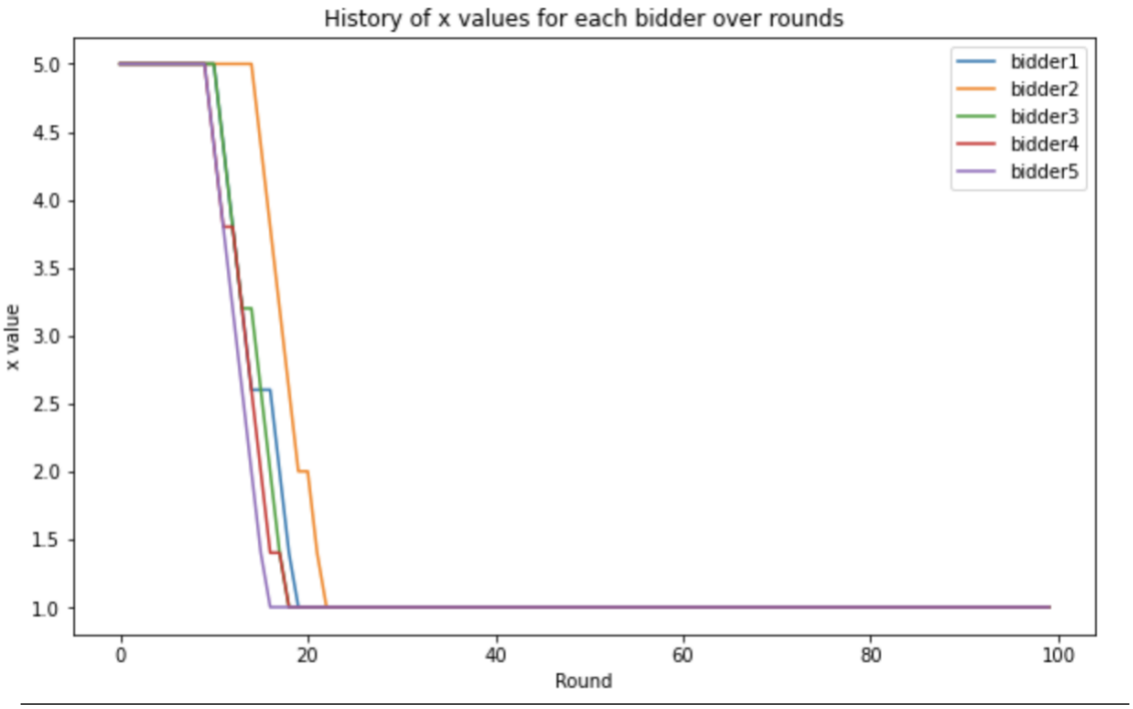
purpose being simply to demonstrate how quicky the collusion between dealer breaks down compared to the other two platforms, changing only the discount factor while maintaining all else equal. Similar simulations are often conducted in information technology literature to simulate electronic auctions (e.g. Mizuta and Steiglitz, 2000)

These choices for simulation design were made for practicality, to visualise how the profit margins for dealers as a group are impacted. Figure 3.1 shows the impact on profit margins within one constant group dealers.

In the simulated Request for Quote (RFQ) trading platform, patience plays a key role. The discount factor in this case is assumed to be below 0.5, as this is the RFQ and the dealers cannot verify that no one deviated. Every round a dealer loses, his "patience" goes down slightly. Upon patience reaching zero, bidders adjust their strategy by incrementally lowering their bids in subsequent rounds, until reaching the lower bound for X, set at 1 in this simulation.

As we can see in the Figure 3.1 below, which shows the bidding process of the same group of 5 bidders, they start rapidly lowering their bids.

Figure 3.2. This chart shows the profit margin x of bidders as they deviate.

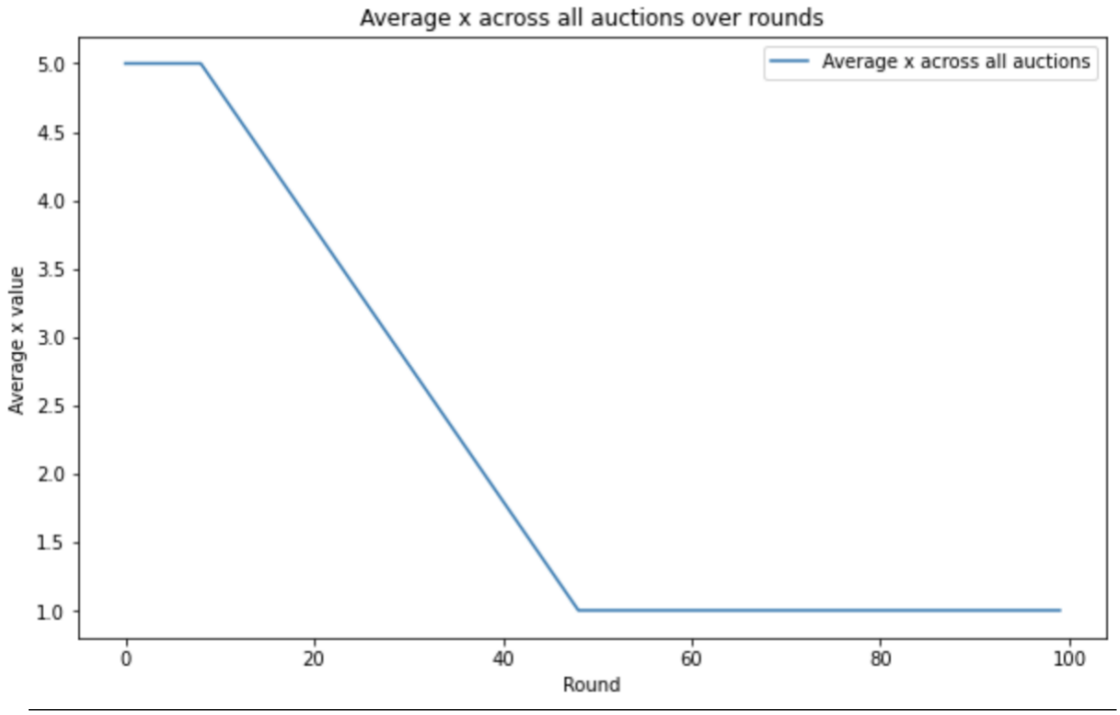


This figure contains the result of a Python simulation of a single bidding group where the bidders attempt to maintain collusion and start lowering their bids after a deviation occurs.

In the real-world market, there would multiple auctions happening simultaneously, and even if within one group no one deviates, there will eventually be a reshuffling of the auction groups, and the deviators will win more consistently.

This dynamic ensures that even if a single group maintains collusion temporarily, the market-wide equilibrium gradually shifts, leading to a universal reduction in the collusive margin (X), eventually stabilizing at the lower bound, as depicted in Figure 3.2.

Figure 3.3. This chart shows the profit margin x of bidders across all auctions as they deviate.



This figure visualizes the profit margin across all the auctions on an SEF. It is in essence the market wide collusive margin X.

Second model - Blockchain auction with off-chain matching (DCN off-chain)

The key difference decentralized clearing will make is the informational environment. In this system the trade and clearing is moved to a decentralized system but the matching of counterparties would be done off-chain, as in the RFQ. However, the results of the auction would be publicly broadcast for verification, thus the winner (and only the winner) of every round of the stage game would be known. This could allow for coordination among bidders, as the deviators are known immediately; thus, allowing for the bidders to condition their actions based on the history (Blume and Heidhues, 2008). The bids will depend on history h_2, and after a deviation has occurred in $h_2(t-1)$ the players will move into a punishment phase where they engage in Bertrand competition, which will lower the payoffs for bidders in the infinite game. Thus,

$$\pi_2 = E\left\{\sum_{n=1}^{\infty} \delta_{h2}(\max[v_i - b_i(v)a])\right\} = \frac{1}{1-\delta}(\max[v_i - b_i(v)a]\left[F\left(b^{-1}(b_i)\right)\right]^{n-1})$$

(8)

Let us assume in this case that $a \in (0,1)$ is a constant factor by which the bidders have agreed to lower their respective bids. This may have happened without any need for explicit communication. As is shown in Daian et al (2020), trading bots made by individual traders have come to a collusive mark up through repeated bidding rounds. Also, Hatfield *et al.* (2017) shows that in the underwriting industry there is an unspoken mark-up applied to most transactions that is the equal for most firms. Based on these observations it is reasonable to assume bidders could collude in such a fashion. Using the same derivation as in the previous case, we get an equilibrium bid:

$$b(v) = v - \frac{\int_{\underline{v}}^{v} F(v)^{n-1} dv}{F^{n-1}(v)} \frac{1}{a}$$

(9)

Which is expectedly lower than in the case of RFQ trading:

$$v - \frac{\int_{\underline{v}}^{v} F(v)^{n-1} dv}{F^{n-1}(v)} \; \frac{1}{a} < \; v - \frac{\int_{\underline{v}}^{v} F(v)^{n-1} dv}{F^{n-1}(v)}$$

(10)

Here the addition of the $a \in (0,1)$ term to model the collusive bid and using the same derivation as in the standard first price sealed bid auction we get the left hand side of the inequality above. We can observe that with any value of a the collusive bid (left hand side) is going to be lower than the competitive one, thus benefiting the bidders.

The discount factor will necessarily be $\delta_{h_2} > \delta_{h_1}$, which will allow to sustain collusive equilibrium for a longer period. The dependence of equilibria in dynamic repeated games on the discount factor is well documented starting with the Folk Theorems, which state that with a high enough δ any equilibrium can be sustained. Also, to enforce collusion a variety of strategies could be used. In the blockchain trading platform, once a deviation has been recognized a punishment phase will commence which will last k periods. In this instance we are looking at a simple GRIM Trigger strategy to show that competitive bidding yields lower profits for the bidders. To verify this, we can model the payoff of the infinite game as follows:

$$(1-\delta)\left[\sum_{t=0}^{k-1}(v_i - b(v_i)a)\delta^t \; + \big(v_i - b(v_i)\big)\delta^k + \sum_{t=k+1}^{\infty}\big(v_i - b(v_i)\big)\delta^t\right]$$

(11)

In the equation above the first term within the square brackets is the collusive phase. The second term is the deviation, where player i makes a competitive bid. We assume that the deviation guarantees the win. The third term within the brackets is the punishment phase, where all players

engage in Bertrand competition and bid competitively. The $(1-\delta)$ is the normalization factor. Expanding the equation, we get:

$$(1-\delta)\left[(v_i - b(v_i)a)\frac{1-\delta^k}{1-\delta} + \big(v_i - b(v_i)\big)\delta^k + \frac{\big(v_i - b(v_i)\big)\delta^{k+1}}{1-\delta}\right]$$

(12)

Next, we simplify this expression and compare it against competitive bidding $\sum_{t=0}^{\infty}\big(v_i - b(v_i)\big)\delta^t = (1-\delta)\frac{(v_i - b(v_i))}{1-\delta}$, thus:

$$v_i - b(v_i)a - b(v_i)\delta^k + b(v_i)a\delta^k > v_i - b(v_i)$$

(13)

$$v_i - b(v_i)\,(a - a\delta^k + \delta^k) > v_i - b(v_i)$$

(14)

Simplifying this

$$(a - a\delta^k + \delta^k) < 1$$

(15)

$$\delta^k(1-a) < (1-a)$$

(16)

$$\delta^k < 1$$

(17)

The discount factor is $\delta \in (0,1)$, which this derivation confirms and implies that under any δ withing the assumed bound the payoff for the collusive game followed by the GRIM Trigger strategy is higher than competitive bidding. However, it does not show the lower bound for δ, merely that the condition for $\delta \in (0,1)$ holds. The lower bound for δ in GRIM Trigger strategies is usually $\delta \approx \frac{1}{2}$, i.e., the minimum patience value to sustain any cooperation among players. Under this condition, competitive bidding will yield a lower payoff in the infinite game, assuming the minimum payoff is 0. Thus, there is no profitable deviation in the infinite game. This result's value is in the comparison with competitive bidding, which it demonstrates will yield lower payoffs in the infinite game, and we are assuming a lower bound for patience of $\delta \approx \frac{1}{2}$ in this case, which is commonly accepted for GRIM Trigger strategies. These strategies have been argued to be effective in maintaining collusion in markets with high concentration, which was argued in the literature review the OTC derivatives market is (Hatfield et al., 2017; ISDA, 2010).

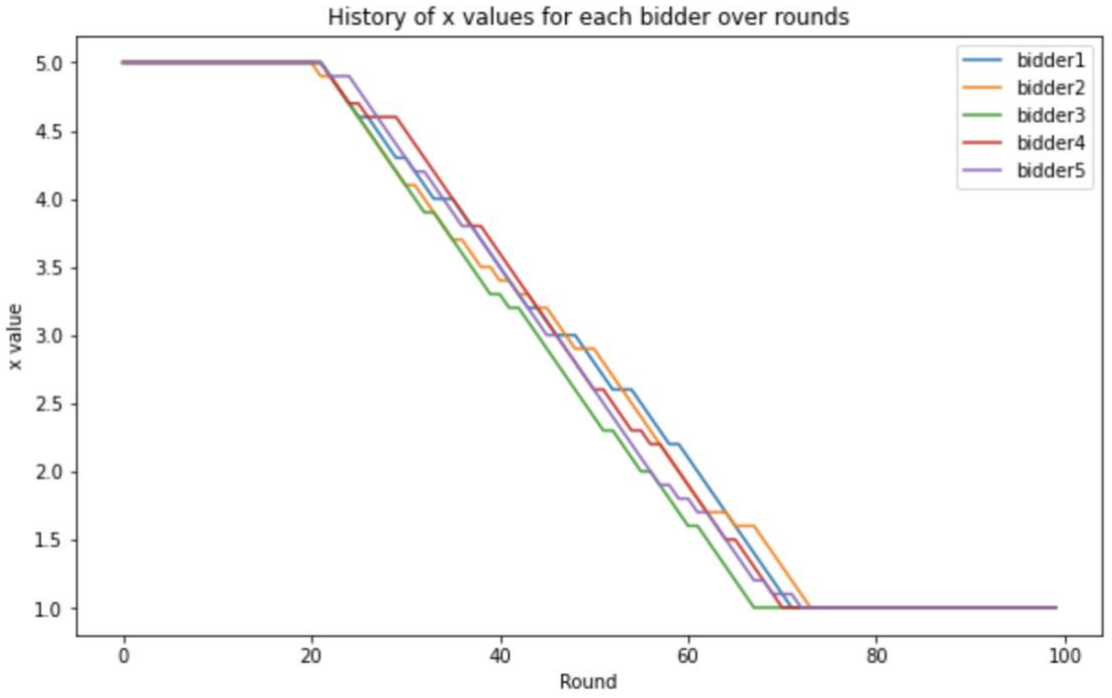
The names of winners provide a way for the bidders to communicate and assign roles. They could collude through a simple rotation mechanism, which could be followed by observing the winners of each round (Blume and Heidhues, 2008). If a bidder deviates from his assigned role, it will be

the signal to engage in Bertrand competition to punish the deviator. Thus, the long-term gains of the deviator will be washed out by the punishment phase.

The presence of a public history is going to be the defining factor as it provides the dealers the ability to track any deviators. The certainty of knowing whether there was a deviant in period $t = k - 1$ and that punishment will only be executed in that case will motivate dealers to cooperate. Thus, there is a dependence of discount factor δ – which represents patience of dealers - on $h(t)$.

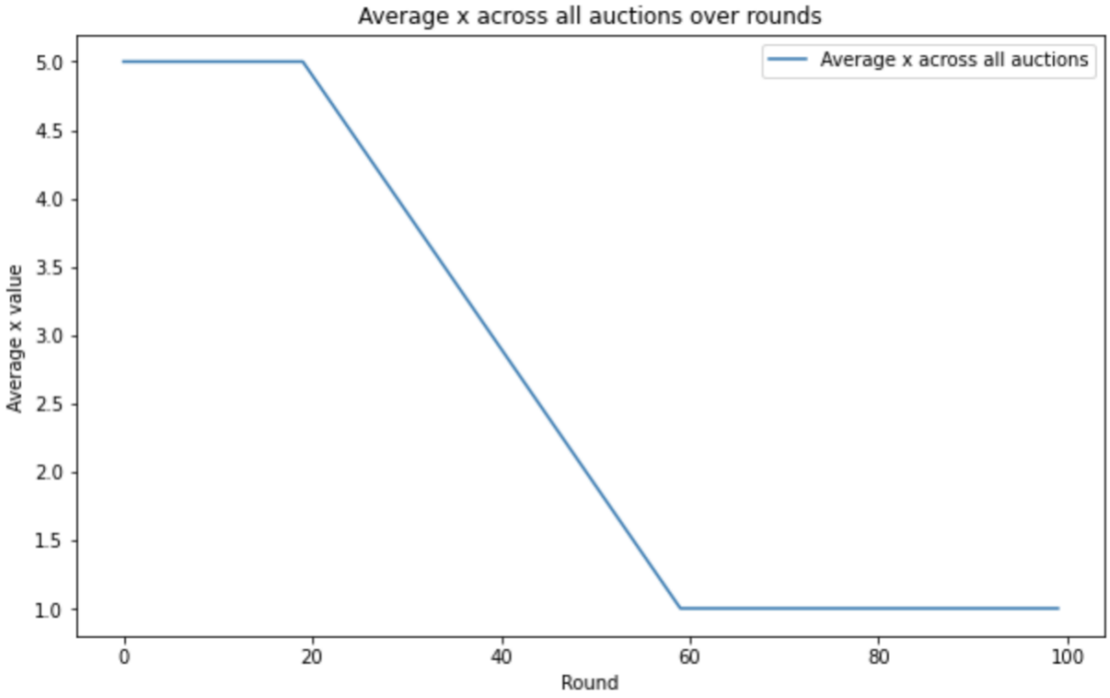
The Figures 3.3 and 3.4 below visualize this process in a simulation of 100 rounds, as was done in the previous section. The discount factor here is assumed to be above $\delta > 0.5$, which is the lower bound to maintain the collusion based on the GRIM trigger strategy. The second figure, which summarizes the profit margin over all the simultaneous auctions, is likewise starts decreasing at a later point. In this set up, the simplicity of the visualization does not account for the possibly temporary nature of the punishment phase. Since naming is possible here, it is known with higher precision whether there was a deviation, or it was simply streak of losses caused by randomness. In the real world, however, we could expect the collusion to be resumed if the game is played infinitely.

Figure 3.4. This plot shows the profit margin x of bidders as they deviate on an off-chain matched platform.



This figure contains the result of a Python simulation of a single bidding group where the bidders attempt to maintain collusion and start lowering their bids after a deviation occurs. The auction is on a blockchain-based platform, with off chain matching and the corresponding history visibility.

Figure 3.5. This plot shows the profit margin x of bidders across all auctions as they deviate.



This figure visualizes the profit margin drop across all the auctions on the blockchain-based trading platform with off-chain matching. It is in essence the market wide collusive margin X for this platform.

Third model - Blockchain auction with on-chain matching (DCN on-chain)

This is the case where the individual auctions are also public, and all bids as well as the winner of each bid are observable. In this case it must be specified that each auction has a set of bidders show up which is a subset of the whole pool of bidders. This subset is randomly drawn from B. A fraction of these auctions, which we will denote as x will end up with b_i deviating. Therefore,

$$\pi_3 = (\sum_{t=0}^{\infty}(v_i - b(v_i)a)\delta^t)x + \Big[\big(v_i - b(v_i)\big) + \sum_{t=1}^{k}\big(v_i - b(v_i)\big)\delta^t + \sum_{t=k+1}^{\infty}(v_i - b(v_i)a)\delta^t\Big](1-x)$$

(17)

The first term represents the payoff of all the auctions if they were cooperating for the entirety of the game, multiplied by factor x. The factor represents the percentage of auctions where all bidders cooperated. Adding to it equation *11* multiplied by $1 - x$, representing the payoffs of the auctions with deviators, we get the payoff in this auctions platform which has the most transparency. Simplifying and normalizing the equation above we get

$$\pi_3 = (v_i - b(v_i)a)x + [v_i - b(v_i)a - b(v_i)\delta^k + b(v_i)a\delta^k](1-x)$$

(18)

In this case, there is a fraction of auctions where a bidder b_i deviates. Previously, once a deviation occurred all b_i would revert to Bertrand competition in period $t = 1$ for duration k to punish the deviator. This is because in h_2 only the winner is observed, and not the participants of individual auctions – they would still be anonymous. However, in the case where matching is done on-chain, participants of individual auctions, b_i are observable during the auction. Therefore, not all b_i revert to Bertrand competition, instead only the auction participants that end up with the deviator do. The proposition is that:

$$(v_i - b(v_i)a)x + [v_i - b(v_i)a - b(v_i)\delta^k + b(v_i)a\delta^k](1 - x)$$
$$> \qquad v_i - b(v_i)a - b(v_i)\delta^k + b(v_i)a\delta^k$$

(189)

We can simplify the inequality to

$$(v_i - b(v_i)a)x > [v_i - b(v_i)a - b(v_i)\delta^k + b(v_i)a\delta^k](1 - 1 + \mathrm{x})$$

(20)

To find the minimum bound for δ:

$$v_i - b(v_i)a > v_i - b(v_i)a - b(v_i)\delta^k + b(v_i)a\delta^k$$

(21)

$$b(v_i)\delta^k - b(v_i)a\delta^k > 0$$

(22)

The lower bound for δ is

$$\delta > 0$$

(23)

This means that the payoffs for auctions on this type of platform will be higher to one with off chain, off-chain matching with h_2. This will be the case since in the case of off-chain matching discount factor is assumed $\delta > \frac{1}{2}$, corresponding to the GRIM trigger bound, whereas with full transparency with any level of patience higher payoffs than on the off-chain platform could be achieved utilizing a simple GRIM Trigger strategy only on auctions with deviators present.

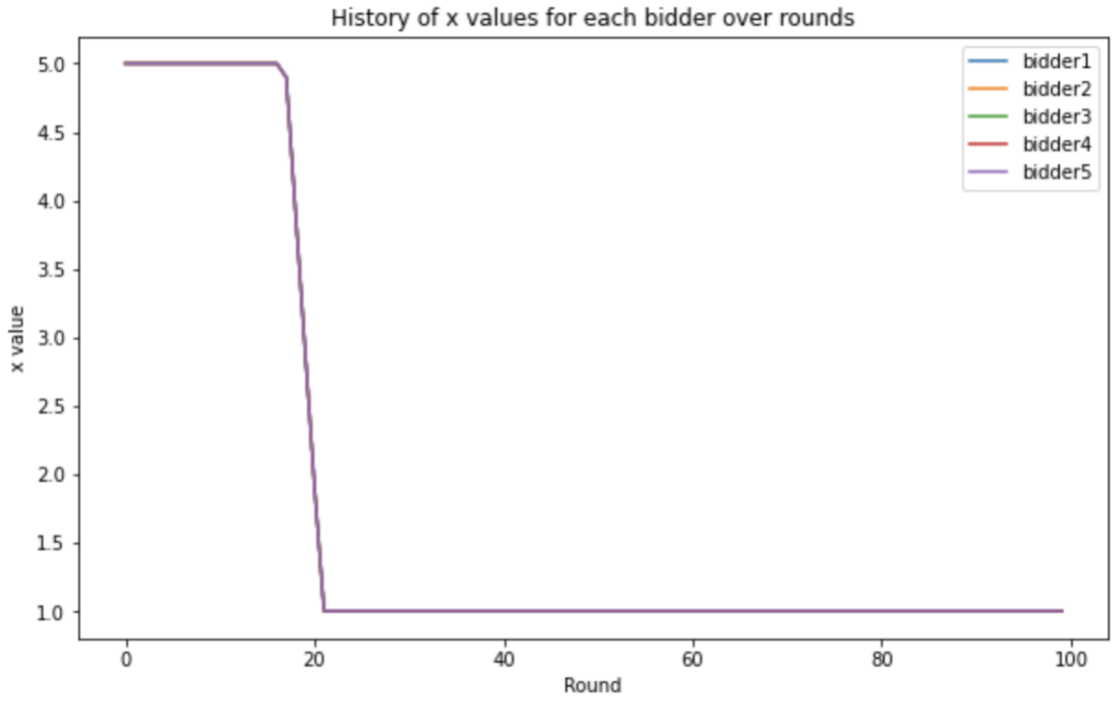
Thus, the case will always be that $\pi_3 > \pi_2$. This type of platform will allow for a more effective way to maintain the collusion.

Also, there is the possibility of the punishment phase starting immediately, since the bids would be immediately observable. In other words, the deviant would not have the opportunity to lock in the profit as the punishment phase could start before the current auction is finalized. In this case the incentive to deviate is even lower as even if the deviator wins the bidding the payoff would be equal to the competitive one.

The distinctive nature of this platform is reflected in the charts below. Figure 3.5 shows a steep drop off, which would occur because the punishment phase would start as soon as the deviation occurs, during that particular auction. Because the bids would be visible during the auction, unlike in the case of off-chain matching, where only the winner was revealed and only *after* the bidding was over. However, bidders in this case can observe the bids at the time of their occurrence. This allows them to punish the deviator immediately, even without the naming process. However, the

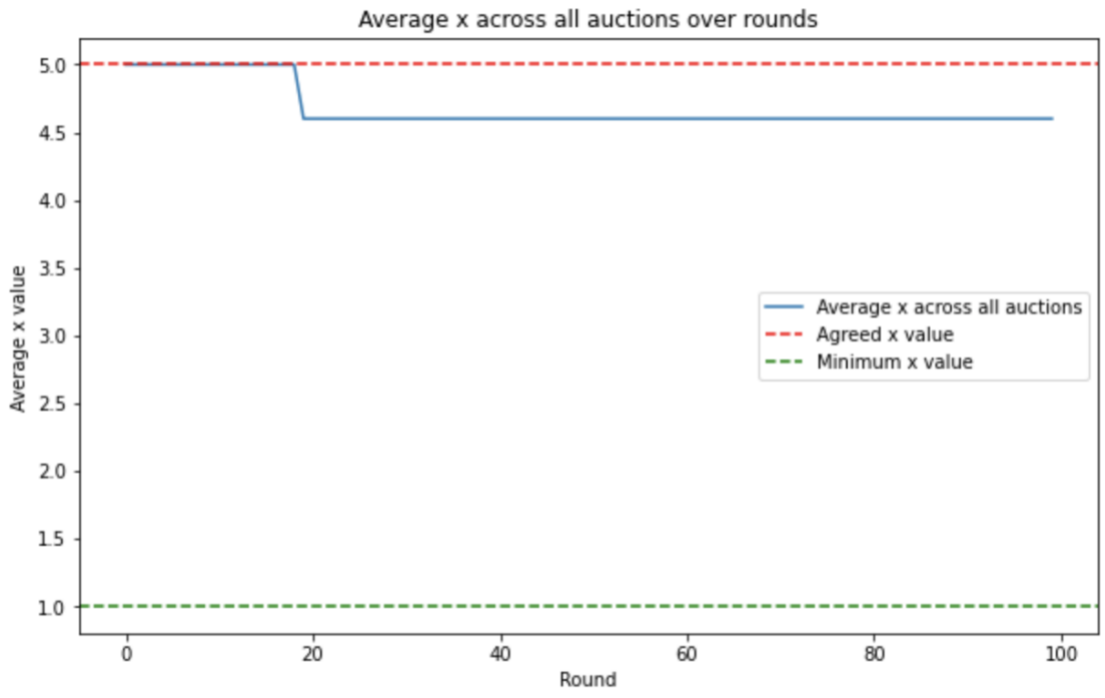
naming would also allow the deviator to be continuously punished, even if there is a re-shuffling of groups. The plot in Figure 3.6 demonstrates the key efficiency this platform would allow the colluders – since the deviator is visible during the auction process, the auction groups that do not have any known deviators can maintain their collusive margin. Therefore, the overall collusive margin of the platform would decrease less than in the previous case of off-chain matching. Assuming that the punishment phases are temporary (which is not reflected in these plots) and the game is infinite the profit for dealers/bidders on this platform are higher, and the temporary punishment phases do not spill over to the whole platform but are limited to auctions that currently have deviators. In terms of the game-theoretic model, this platform allows for collusion to be maintained with any level of patience above 0, i.e. the lower bound for achieving higher payoffs than on the other platforms is $\delta > 0$.

Figure 3.6. This plot shows the profit margin x of bidders as they deviate on an on-chain matched platform.



This is the visualization for the on-chain matched auction, effectively an open auction. Here the bidders have the ability to punish immediately, while the bids are occurring, hence the steep drop.

Figure 3.7. This plot shows the profit margin x of bidders across all auctions.



This plot is distinct from its counterparts because in the on-chain matched platform, the punishment phase occurs immediately and only impact auctions that have deviators present, therefore the margin of most players is not affected.

Section 3.5. Discussion.

The models above propose that increased transparency provided by blockchain technology may in fact increase the possibility of collusion and negatively impact the end consumers. This is in line with research on auctions done by Blume and Heidhues (2008) and Dutta and Madhavan (1997). In Blume and Heidhues (2008) the impact of an observable history is attributed to making collusion possible.

It must be highlighted that the anonymity provided by Bitcoin's ledger is different than those of Ethereum. We look at Ethereum because it is the second largest cryptocurrency and many of the most popular crypto-tokens and services are based on Ethereum's blockchain. Also, for the purpose

of creating a DCN, Ethereum is more appropriate as it was the first blockchain that implemented smart contracts, which are central for DCNs. The difference is that when a transaction is recorded on Bitcoin's ledger, the anonymized public address changes for every new transaction. It is not the case for Ethereum. Therefore, in a permissioned blockchain with a limited pool of participants it could be possible to attach identities to addresses. In fact, the real-world identity of the participant is irrelevant, as long as there is a traceable history of his transactions for a constant address. This adds further realism to the models described above, and supports the possibility of *naming* described in In Blume and Heidhues (2008).

The results are also in line with Bloomfield and O'Hara (1999), who found in an experimental setting that increased transparency increases the spreads and trading costs as the market makers' need to compete for order flow is reduced. Kwarsica and Sherstyuk (2007) show that in repeated setting bidders are able to coordinate better payoffs for themselves. This problem of observability has been pointed out early by Stigler (1964). These studies support the conclusion of this chapter that a fully transparent, blockchain-based platform could increase collusion among dealers. The results of this chapter take it one step further by positing that any level of patience above 0 will result in superior payoffs in the repeated game.

Outside of financial markets, research by Jap (2018) points out that greater price transparency in online auctions facilitates opportunism suspicion. Gupta et al. (2008) in B2B procurement reverse auctions winning bid are higher (thus lower payoff for the seller, as this is a reverse auction) if the same bidders engage regularly. This is relevant in the case of OTC derivatives as personal ties with

dealers are a factor for the buyers when it comes to requesting quotes. It is in line with the result of this chapter regarding on-chain matched bids as it was shown that the collusive payoff would be higher at any non-negative level of patience.

Also, a successful DCN cannot simply be limited to being a platform where transactions occur. A crucial part of clearing is netting. Derivatives have long life cycles and netting is seen as essential by both regulators and market participants (Bliss and Stiegerwals, 2006). Netting is important also because its abolishment would increase systemic risk and thus higher collateral requirements would have to be instituted (ESMA, 2017).

Pinna and Ruttenberg (2016) mention another possibility – the fragmentation of the market. If some institutions or groups of institutions decide to create separate decentralized clearing networks, this will lead to a fragmented marketplace where regulatory oversight will be more complex. There will be more transparency compared to the current system, due to the clearing process. However, different networks may have different frameworks which will be difficult for the regulator to keep track of. This is currently the case, where Commodity Futures Trading Commission (CFTC) has four different Swap Data Repositories (SDR) in use, each using unique software. It is a time-consuming endeavour for the CFTC to aggregate all this data. Thus, while DCNs could be a solution to the record keeping problem if the market goes in the opposite direction – towards more fragmentation – the situation for the regulators will hardly become less burdensome.

Additionally, if fragmentation occurs but the DCNs are established by independent organizations, this could spark a pricing competition on fees to attract new members. In this scenario the organizations could also feel pressure to skew the environment in favor of certain groups. Ultimately, shifting the paradigm in this industry will be a compromise to solve some existing issues while tolerating the possibility of new ones.

Section 3.5. Conclusion.

The main point this chapter attempted to make is that the implementation of decentralized ledgers in the systemically important OTC derivatives industry must be approached with caution. The technology may bring improvements in the form of lower back office and reconciliation costs and provide full information to the regulators. Yet its main selling point – being transparent yet anonymous - could cause changes in the informational environment which may lead to collusion and lower welfare for the end customer. The main finding is that with each increase in the level of transparency the dealers may find it easier to adhere to a collusive strategy without the need for overt communication and can do so with lower levels of patience. This will be the case because their ability to punish deviators will be superior in the context of OTC derivatives trading when transparency is maximized, as they will not need to engage the whole population of dealers to punish the deviator, making the punishment phase less costly.

There are major challenges with policy making if transparent, blockchain based platforms are to become the norm. Potential for collusion will still be present as the dealers will represent a more cohesive block. The design of a blockchain - based transparent platform must be given careful

thought as in case this gains mainstream acceptance, it will impact a significant portion of the economy. If proven effective at cost cutting, the interested parties will pursue this opportunity, but the customers will be at a disadvantage. In fact, consortiums (like Corda) have been shown unable to prevent collusion (Gomes, 2016). Transparency is normally considered to be a net positive, especially in the post Sub-Prime mortgage crisis world, however it could lead to more effective collusion as discussed in this chapter. At the moment, the SEFs seem to have improved the pricing issue faced by the clients (Hau et al., 2017). The recommendation would be to focus on zero-knowledge validation systems in development. These systems will presumably maintain full anonymity during the validation process, which currently - as outlined before - broadcasts transactions to all miners for validation.

The limitation of this study is the lack of empirical data, which is due to the novelty of this technology – it has simply not been applied at scale yet. Also, there are other dimensions to consider, such as personal relationships between the dealers and customers, as well as the number of dealers involved and levels of market concentration (Hatfield, 2017). In markets with high concentration, grim trigger strategies can be used to maintain a desired price, as any deviant will be punished by the rest engaging in Bertrand competition which will bring the profits down to 0. Conversely, if market concentration is too low, syndication strategies could be used to maintain collusive equilibria. At intermediate levels there are no subgame perfect Nash Equilibria to maintain this equilibrium (Hatfield et al., 2018). The level of concentration in the OTC derivatives market is not clear, but even ISDA itself has pointed to some level of concentration (ISDA, 2010; Patsinaridis, 2020).

It is important to consider the possible pitfalls of this technology before applying it to an industry so crucial. Regulators must take a cautious approach as tacit collusion is difficult to prove in practice. As it currently stands, attempts to regulate the industry have been unsuccessful. Implementing a blockchain based trading platform, presented in this chapter as a Decentralized Clearing Network, could solve the issue of a lack of oversight as information will readily be available, yet it may cause tacit collusion to occur. Perhaps changes in market structure along an improvement in technology could be the answer to this, which is an area for further research. For future study it would be of interest to analyze data from a blockchain clearing platform such as Paxos, once it is more widely adopted.

Appendix

Equation for π_1:

$$\max[v_i - b_i(v)]\left[F\left(b^{-1}(b_i)\right)\right]^{n-1}$$

Here $b(v_n) < b_i$ is equivalent to its inverse $v_n < b^{-1}(b_i)$. Taking the derivative and equating to 0

$$[v_i - b_i(v)](n-1)F\left(b^{-1}(b_i)\right)^{n-2} f\left(b^{-1}(b_i)\right)\frac{1}{b'\left(b^{-1}(b_i)\right)} - F\left(b^{-1}(b_i)\right)^{n-1} = 0$$

Since we are looking for a symmetric equilibrium, $b_i = b(v)$, so we can replace all b_i with $b(v_i)$

$$[v_i - b_i(v)](n-1)F\left(b^{-1}(b(v))\right)^{n-2} f\left(b^{-1}(b_i(v))\right)\frac{1}{b'\left(b^{-1}(b_i(v))\right)} - F\left(b^{-1}(b_i(v))\right)^{n-1}$$

$$= 0$$

Since $v_n < b^{-1}(b_i)$ is the inverse of $b(v_n) < b_i$, $b^{-1}(b_i(v)) = v$, therefore

$$[v_i - b_i(v)](n-1)F(v)^{n-2}f(v)\frac{1}{b'(v)} - F(v)^{n-1} = 0$$

Rearranging this equation we get

$$b'(v) = (v_i - b_i(v))(n-1)\frac{f(v)}{F(v)}$$

Rearranging again

$$F(v)b'(v) + b(v)(n-1)f(v) = v(n-1)f(v)$$

The left-hand side of the equation is the derivative of $F(v)^{n-1}b(v)$ if we multiply both sides of the equation by $F(v)^{n-2}$. So,

$$F(v)^{n-1}b'(v) + b(v)(n-1)f(v)F(v)^{n-2} = v(n-1)f(v)F(v)^{n-2}$$

$$\frac{d}{dx}F(v)^{n-1}b(v) = v(n-1)f(v)F(v)^{n-2}$$

Taking the integral of the left-side we have

$$\int_{\underline{v}}^{v} \frac{d}{dx} F(v)^{n-1} b(v) = F(v)^{n-1} b(v)$$

Taking the integral of the right-hand side

$$\int_{\underline{v}}^{v} u dv = uv - \int_{\underline{v}}^{v} v du = vF(v)^{n-1} - \int_{\underline{v}}^{v} F(v)^{n-1}\, dv$$

Equating both sides we get

$$b(v) = v - \frac{\int_{\underline{v}}^{v} F(v)^{n-1} dv}{F^{n-1}(v)}$$

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Chapter 4. The Role of ERC-20 Token Activity in Daily Ether Returns: An Empirical Analysis via LASSO Regression.

Abstract

This study investigates whether ERC-20 token activity influences Ether's price, potentially indicating network effects on the Ethereum blockchain. Ether returns serve as a proxy for changes in Ethereum's value, while daily on-chain transfers of major ERC-20 tokens capture network usage. Using a LASSO regression with macroeconomic and cryptocurrency data from August 20, 2020, to October 20, 2023, we find no significant impact of token activity on Ether returns, suggesting the absence of network effects. However, LASSO outperforms benchmark models in forecasting Ether returns. These results reinforce the speculative nature of cryptocurrency markets and highlight the policy challenge of promoting fintech innovation while mitigating systemic risks.

Section 4.1. Introduction.

As of March 2024, the global cryptocurrency market is valued at USD 2.58 trillion (Digital Assets, 2024), with Bitcoin and Ethereum dominating by market cap. However, there is little consensus on how to price these assets; some argue they lack intrinsic value (Browne, 2023; Silverman, 2021) or dismiss blockchain as "a solution looking for a problem" (von Zanten, 2021). Despite such skepticism, the market's size has prompted debate over whether accurate valuation is possible—or if cryptocurrencies remain purely speculative.

A key but often overlooked factor is whether a cryptocurrency has its own blockchain. 'Cryptocurrency' is an umbrella term applicable to assets running on a blockchain, however, they can be divided into native coins and tokens. Bitcoin and Ethereum are blockchains that have native coins – BTC and Ether, respectively. Thus, they have infrastructure in place to run the transactions of their native coins. Tokens, on the other hand, do not have a native blockchain, they are created on the infrastructure of an existing one, most commonly Ethereum. Ethereum with its native coin Ether is the second biggest blockchain by market capitalization and remains so as of this writing.

Ethereum launched in 2015 with the novel capability to deploy smart contracts, enabling third parties to create their own tokens (effectively new cryptocurrencies) on the Ethereum blockchain. The ERC-20 protocol standardizes token creation, so most "cryptocurrencies" are actually tokens hosted on blockchains like Ethereum, Solana (SOL), Cardano (ADA), or Tron (TRX). As the pioneer of this functionality, Ethereum hosts thousands of ERC-20 tokens—such as MATIC,

LINK, and WETH—each with a market cap exceeding USD 5 billion (CoinMarketCap, 2024; accessed January 10, 2024). Ethereum also introduced the ERC-721 standard for NFTs, and all transactions incur a gas fee (in GWEI) to incentivize miners. Transactions on the Ethereum blockchain use resources of the miners, and to incentivize them the network makes pays a “gas price “ for each transaction measured in GWEI, a unit created for the Ethereum blockchain’s transaction cost.

This study examines whether ERC-20 token activity influences Ether’s price. Specifically, it asks whether daily on-chain transfers or token prices affect Ether returns. A significant impact would indicate potential network effects and offer a new metric for Ether valuation. Using a LASSO regression, we incorporate variables from ERC-20 tokens, other leading cryptocurrencies (as proxies for overall market conditions), and macroeconomic indicators. The inclusion of economic variables is informed by discussions about the crypto bull run during the pandemic being partly driven by shifts toward cryptocurrencies as a hedge in turbulent times (Popper, 2020). As current literature frequently connects macro trends and on-chain activity to crypto pricing—particularly for Bitcoin—examining ERC-20 activity’s effect on Ether is timely and relevant.

If there is a significant effect, and the activity of ERC-20 tokens on the Ethereum blockchain does impact Ether returns, the LASSO regression will assign a non-zero and positive coefficient to the on-chain transfers variables, as their increase would be expected to raise Ether price and consequently returns. However, crypto trading is considered highly speculative, in which case the prices and returns would be more affected by unpredictable events/factors than by an easily

quantifiable metric such as number of token transfers. Therefore, if there is no connection found between token activity and Ethereum's native coin's price, it strengthens the argument that cryptocurrency prices are mostly speculative.

The logic of transaction costs described below applies to other blockchains as well, such as Cardano or Solana, albeit their fee structure may be different. Ethereum is chosen to study this effect because it has consistently been the second biggest cryptocurrency and it hosts the largest number of tokens as of this writing.

High demand for ERC-20 tokens potentially raises the number of on-chain transactions, increasing the congestion on the Ethereum blockchain and raising the gas price, since gas price on this blockchain fluctuates depending on the level of congestion. The blockchain as of now can process 30 transactions per second, which is low compared to traditional credit card companies Visa and MasterCard, which can process 24000 and 5000 transactions per second respectively. Rival blockchains such as Solana, which started operating in March of 2020, claims to be capable of processing 65000 transaction per second. The objectively low bandwidth of Ethereum has led to high transactions costs (for a blockchain) in 2021, during one of the bull runs of the crypto markets. This was when Ether's own price peaked at 4,891.70$.

Undoubtedly, the general crypto optimism and the bull run had a huge impact, perhaps even a definitive one in Ether's price fluctuations. However, due to Ethereum's role as an infrastructure provider, there could potentially be a connection between its own native coin Ether and the ERC-

20 tokens' activity. This is akin to network effects observed in other businesses, such as smartphones or computer operating systems.

While comparing Ethereum's ecosystem to typical "network effects" can be informative, it is not a perfect analogy. The interplay between ERC-20 token activity, network congestion, and gas fees reflects scalability and resource utilization concerns rather than direct value enhancement for end users. Indeed, higher transaction volume can raise gas fees—paid in Ether (ETH)—potentially worsening user experience due to increased costs. Nevertheless, daily transfers of ERC-20 tokens still influence Ether's demand, since every on-chain transaction requires payment in ETH. As network congestion grows and further raises fees, Ether's demand may increase accordingly, potentially affecting its market price. Thus, ERC-20 token activity can partially explain Ether's price dynamics, even if it does not constitute a pure network effect.

Figure 4.8. Ether price, supply, and daily transfers.

To illustrate the potential for network effects on Ether's price, consider a plot (normalized for scale) showing Ether's price, its circulating supply, and daily transfers on the Ethereum network over the study period. The supply expanded until mid-2022, yet Ether's price often rose beyond that growth. Meanwhile, daily on-chain transfers of Ether remained within a tighter range, suggesting demand may have stemmed more from trading on exchanges than from using Ether to

buy goods or services. This demand could arise from Ether's appeal as an investment or speculative asset—or from its necessity as gas for ERC-20 token transfers. If gas fees are the primary driver, that would strongly support a network-effect argument. Cryptocurrencies may be among the most significant financial innovations of the past two decades, but it remains unclear whether they will transcend speculation. Demonstrating a direct link between ERC-20 token activity and Ether's price would enhance our understanding of crypto valuation; conversely, finding no relationship would reinforce the idea that speculation dominates these markets. Thus, it is crucial to determine whether ERC-20 tokens meaningfully influence Ether returns or remain irrelevant to its price formation.

The results show that on-chain token activity does not affect Ether returns, and daily average transaction costs (GWEI) also lack significance. While certain ERC-20 tokens' *returns* exhibit predictive power, their *on-chain activity* does not. This challenges the network-effect arguments of Cong, Li, and Wang (2020) and aligns more with Stylianou, Spiegelberg, Herlihy, and Carter (2021). Major cryptocurrency returns do significantly influence Ether's price, whereas macroeconomic variables and Google Trends data display minimal or no predictive value. Robustness tests further confirm that token activity provides no explanatory power beyond a minor influence on Ether volume. Additionally, the LASSO model outperforms benchmark regressions, but network effects remain difficult to validate.

A key takeaway from this study is that the lack of connection between on-chain activity and Ether price – which could have served as evidence for network effects and a basis for pricing - further

strengthens the argument that cryptocurrency price is speculative. This has challenging implications for policymakers. The public must be protected from potential huge losses and the unfounded exuberance of the crypto markets, where scams are common. Simultaneously, regulations too stringent could stifle innovation. Satisfying these competing needs will require an uneasy balance to be struck.

This chapter makes three contributions: firstly, to the understanding of cryptocurrency price formation by viewing Ethereum as an infrastructure provider and thus emphasizing the differences between native coins and tokens. To this end, the daily change ERC-20 token transfers serve as a proxy for network usage and Ether returns as a proxy for value of the Ethereum network. In pricing cryptocurrencies, the existing literature focuses on the link between macroeconomic variables and/or major cryptocurrencies' price moves (e.g., Sovbetov (2018); Panagiotidis, Stengos, and Vravosinos (2018); Ciner, Lucey and Yarovaya (2022)). Some authors focus on blockchain-level information and attempt to use it to value and price cryptocurrencies (e.g., Liu, Tsyvinski, and Wu (2021)). This study is unique in its approach to use the blockchain-level information attributed to individual tokens and draw a connection between their activity on the blockchain and its native coin's returns. The second contribution is made to the study of network effects on the Ethereum network. The approach taken in this study makes implications about the existence of network effects on the Ethereum network, caused by ERC-20 token usage, which is the second contribution of this chapter. The studies done in the stream of literature concerned with network effects in cryptocurrencies, such as Cong, Li, and Wang (2020), Stylianou, Spiegelberg, Herlihy, and Carter (2021) did not consider the on-chain activity of tokens in determining if network effects are present in cryptocurrencies that possess a native blockchain, which distinguishes this study. Thirdly, a

contribution is made to price forecasting literature via testing the effectiveness of different regularization methods and benchmarking it against robust models, as well as revealing which predictors are more powerful and strengthening/weakening the argument for using indicators such as Google Trends data and macro-economic data. On this question, previous authors focused on the factors mentioned – such as macroeconomic variables and Google Trends, and used the LASSO regression, machine learning, and explored the presence of momentum (Jang and Lee (2018); Grobys and Sapkota (2019); D'Amario and Ciganovic (2022)). This chapter focuses on evaluating the effectiveness of the LASSO regression compared to benchmark models - OLS and AR(1) – which, combined with the dataset that includes blockchain-level information makes it a unique approach in crypto returns forecasting literature.

The rest of the chapter is organized as follows. Section 2 provides a review of existing literature on crypto valuation and forecasting. Section 3 provides a detailed description of the data used. Section 4 describes the methodological framework, Section 5 discussed the results and Section 6 concludes.

Section 4.2. Literature review.

This chapter is attempting to find a connection between the daily change in ERC-20 token transfers and Ether returns, which would also indicate presence of network effects. However, the expectation is that cryptocurrency pricing is highly speculative, therefore no strong effect will be found. The role of cryptocurrencies as either speculative investments or viable alternatives to

traditional currencies remains a subject of debate in the literature. Baur, Hong, and Lee (2018) and Kristoufek (2015) both acknowledge the speculative nature of Bitcoin, noting its lack of correlation with traditional asset classes. Yermack (2015) further reinforces the notion of Bitcoin being purely speculative, arguing that it fails to meet the criteria of a *bona fide* currency and instead parallels the speculative internet stocks of the late 1990s. In his analysis, Bitcoin also fails to a demonstrate any value as a hedging tool in business as it appears untethered from major fiat currency values. Kristoufek (2015) supports this sentiment by adding that Bitcoin does not exhibit safe-haven properties expected based on its instability of prices. Contrary to these views, Blau (2018) challenges the presumption that speculative trading is a major contributor to Bitcoin's volatility, suggesting that Bitcoin might be more viable as a currency than commonly perceived. Despite these varying perspectives, all authors seem to agree on the high volatility and speculative nature of cryptocurrencies. However, Kristoufek (2015) and Biais et al. (2023) introduce a nuanced view. The former suggests that factors such as usage in trade and money supply do have a long-term impact on Bitcoin's price, although much of its price variation remains unexplained by those. Biais et al. (2023) state that, based on their theoretical model, fundamentals play a significant role in Bitcoin price formation; however, they do not explain a large part of the variation in its price. These studies collectively highlight the complex nature of cryptocurrency valuation – by extension Ether valuation - oscillating between speculative asset and emerging currency, with fundamental factors playing a role amidst prevalent market speculation.

There is a growing literature focusing on cryptocurrency price formation and factors influencing their price. Macroeconomic indicators are commonly used to this end, and this chapter incorporates relevant ones into the dataset to control for the impact of ERC-20 token data. One indicator that is

widely used is the US Economic Policy Uncertainty (EPU). Bouri, Gupta, and Roubaud (2019) and Demir et al. (2018a) identify a significant relationship between EPU and cryptocurrency behavior, with the former noting time-varying herding behavior in cryptocurrencies driven by EPU. Wang, Sarker, and Bouri (2022) also use EPU as an explanatory variable for Bitcoin prices, along with other economic variables such as CPI and the money supply, showing a dynamic inter-shock with Bitcoin prices. They found EPU and money supply to affect Bitcoin price negatively, whereas CPI affected it positively in the short term, in line with claims of Bitcoin being a hedging asset. Likewise, Panagiotidis, Stengos, and Vravosinos (2018), using a LASSO regression for their analysis, find a negative impact of EPU on Bitcoin returns.

Wang, Ma, Bouri, and Guo (2022) offer a broader perspective, asserting the dominance of macroeconomic indicators over technical factors in forecasting Bitcoin volatility, with EPU being one of the key macroeconomic factors. They focused on forecasting Bitcoin volatility using a LASSO regression and found the S&P 500 realized volatility to have the highest selection rate by the LASSO, along with global real economic activity index, and trade-weighted USD index returns. Technical indicators performed significantly worse, except when Bitcoin volatility was lower, where they outperformed macroeconomic ones. The LASSO regression was also used in Panagiotidis, Stengos, and Vravosinos (2018); Ciner, Lucey and Yarovaya (2022); and D'Amario and Ciganovic (2022). Panagiotidis, Stengos, and Vravosinos (2018) find a negative relationship with uncertainty indicators such as the Chinese Economic Uncertainty Index (CEPU), European Economic Uncertainty Index (EEPU), and the US Economic Uncertainty Index (US-EPU). Another macroeconomic factor was studied in Gopana (2019), who finds shocks from the LIBOR

interest rate affect Bitcoin price and are statistically significant, yet Bitcoin price shocks do not affect the LIBOR rate.

Google Trends data is widely used among other predictors of crypto returns and/or volatility. It is used as a proxy of investor attention and shows at least some predictive power in most studies cited above. Zhang and Wang (2020) expand on the subject of Uruquhart (2018) and Panagiotidis, Stengos, and Vravosinos (2018), who also used Google Trends data as a proxy for attention to Bitcoin, by testing a dataset of 20 cryptocurrencies. However, Uruquhart (2018) found no significant connection between realized volatility and return for Bitcoin, but the reverse was observed – realized volatility had an impact on next day's attention. Google Trends will be further mentioned as part of datasets in studies described below.

Sovbetov (2018) examines the factors influencing the prices of five major cryptocurrencies - Bitcoin, Ethereum, Dash, Litecoin, and Monero over 2010-2018, identifying crypto market factors such as market beta, trading volume, volatility, and the perceived attractiveness of cryptocurrencies as significant determinants, particularly in the long run. The study also notes a weak positive long-term impact of the S&P 500 index on certain cryptocurrencies.

Polasik et al. (2015), contrary to most of the studies described above, indicate weak associations between Bitcoin returns and fluctuations in major currencies or global macroeconomic aggregates, and find them statistically insignificant. Their findings suggest that company characteristics,

alternative payment methods, customer knowledge, and the size of both official and unofficial economies play crucial roles.

Cheung, Wai-K, Roca, and Su (2015) conduct an econometric investigation into the existence of bubbles in the Bitcoin market. Their findings indicate several short-lived bubbles during this period, with three significant bubbles identified between 2011 and 2013, each lasting between 66 to 106 days. This study underscores the presence of substantial volatility and speculative behavior in the Bitcoin market during its early years. Gronwald (2021), on the other hand, explores the explosiveness in the prices of Ether, XRP, and Litecoin, including pricing data expressed in units of Bitcoin. The study draws parallels between the discussion on the intrinsic value of cryptocurrencies and money. Gronwald (2021) emphasizes the difficulty in determining the value of cryptocurrencies, suggesting that the use of the term "bubble" should be approached with caution until there is a better understanding of their underlying value. His paper highlights the challenges in categorizing rapid price increases in cryptocurrencies as bubbles due to the current lack of clarity on what constitutes their intrinsic value.

Valuation and pricing of cryptocurrency are central to this study. Though it must be noted that these terms, while close, are slightly different. Valuation in the sense of traditional financial markets often means using discounted cash flows or fundamentals of the companies/assets, concepts that are yet unclear in cryptocurrency. Pricing is market driven, and in this sense in both traditional finance and crypto finance share the term.

Regarding crypto valuation, the relative cost of production has been proposed as the main determinant of Bitcoin price in Hayes (2017). Hayes (2017) also states that altcoin (all cryptocurrencies besides Bitcoin are referred to as altcoins) production is an intermediary to Bitcoin production. Also, in Hayes (2015) it is found that the difficulty of mining, the rate of unit production, and the cryptologic algorithm employed were the main drivers of cryptocurrency value.

Another popular metric proposed for cryptocurrency valuation is through measuring the network effects of cryptocurrencies. Liu, Tsyvinski, and Wu (2021) discover that this information explains a significant portion of cryptocurrency returns, and its explanatory power remains robust even when controlling for changes in transaction volume and Google searches. They also introduce the concept of the price-to-new address ratio, which they find to be a negative predictor of future cryptocurrency returns, suggesting a valuation effect based on network growth. Furthermore, they claim that network effects have a significant impact on cryptocurrency value and the speed user adoption.

Cong, Li, and Wang (2020) agree with the importance of network effects and develop a dynamic asset pricing model that accounts for the network effects in token valuation. They identify a feedback loop between platform adoption and token price, which accelerates adoption and stabilizes the user base. Their approach emphasizes that the equilibrium price of tokens is driven by transactional demand rather than traditional cash flow discounting, highlighting the unique nature of cryptocurrency valuation.

However, the extent to which network effects can be used for cryptocurrency valuation has been questioned. Pagnotta and Buraschi (2018) point out that Bitcoin and other decentralized network assets (DNAs) are traded, unlike other protocols with network effects protocols.

Stylianou, Spiegelberg, Herlihy, and Carter (2021) observe that the loss of a user in networks with strong effects can lead to a disproportionate loss of value, potentially causing rapid depreciation. They call this a *reverse network effect*. Their study challenges the conclusions in Liu, Tsyvinski, and Wu (2021) and Cong, Li, and Wang (2020). In contrast to the former, they do not use the number of wallet addresses as a proxy for network value and user base, claiming that most addresses are dormant and thus this measure cannot be considered reliable. Instead, they use proxies such as token price and transaction value. They also question the conclusion of Cong, Li, and Wang (2020) regarding the importance of network effects - Stylianou, Spiegelberg, Herlihy, and Carter (2021) find that network effects do affect cryptocurrencies, but not to the degree it is associated with on the market.

Gandal and Halaburda (2016) also scrutinize the perceived impact of network effects. They they find no evidence of winner-take-all dynamics, even though Bitcoin dominates the crypto market. However, later data suggest a shift towards strong network effects and winner-take-all outcomes, particularly favoring Bitcoin, which appreciated against USD while other cryptocurrencies depreciated.

There have also been attempts to use machine learning to predict the price of cryptocurrencies. Jang and Lee (2018) evaluate the effectiveness of Bayesian Neural Networks (BNN) in modeling and predicting Bitcoin's log prices and log volatility, using support vector regression (SVR) and linear regression as benchmark methods. Their study used blockchain level information as well as macroeconomic variables. They found the BNN to perform exceptionally well compared to the benchmark models, based on the evaluation criteria of root mean square error (RMSE) and mean absolute percentage error (MAPE). Patel, Tanwar, Gupta, and Kumar (2020) introduce a deep learning-based cryptocurrency price prediction scheme, focusing on Litecoin and Monero. They employ Long short-term memory (LSTM) and Gated Recurrent Unit (GRU)-based hybrid models. They evaluate the results based on using mean absolute error (MAE), mean squared error (MSE), mean absolute percentage error (MAPE) and root mean squared error (RMSE), finding the models to be more accurate than the baseline LSTM model.

Grobys and Sapkota (2019) explore the existence of momentum in cryptocurrency markets between 2014 and 2018. Contrary to earlier findings, they conclude that momentum is insignificant in this period, suggesting increased market efficiency in more recent years.

Shen, Urquhart, and Wang (2020) propose a three-factor pricing model for cryptocurrencies, considering over 1700 cryptocurrencies. Their model, which incorporates factors like SMB, HML, RMW, CMA, and WML, significantly outperforms the cryptocurrency-CAPM model, especially for smaller cryptocurrencies.

This chapter is attempting to use on-chain data of the Ethereum network to attempt to find a connection between Ether's returns and ERC-20 token activity on its blockchain. In this sense, it is in the same line of thought described in Liu, Tsyvinski, and Wu (2021), who used the number of addresses on the Bitcoin blockchain as the explanatory variable for their model. However, as Stylianou, Spiegelberg, Herlihy, and Carter (2021) point out, most user addresses are dormant and thus this metric is not a reliable measure of current blockchain value. Instead, they use token price and transaction value. This study uses on-chain information, like Liu, Tsyvinski, and Wu (2021), however it is also in agreement with Stylianou, Spiegelberg, Herlihy, and Carter (2021) as to the reliability of new addresses as measure of blockchain growth. Therefore, the number of transfers for the most popular ERC-20 tokens and their daily returns are going to be used as the proxies for change in value of the blockchain studied – which is Ethereum. Token price is used as a proxy in Stylianou, Spiegelberg, Herlihy, and Carter (2021) as well, however their second proxy - transaction value – is of questionable value for the case of Ethereum, as outlined in this chapter. To reiterate, the congestion on the blockchain network is caused by the number of transactions being requested at any given second, not the transaction value. The level of congestion determines the transaction cost and ultimately the feasibility of using Ethereum for a given transaction and its value to the users, therefore the on-chain activity measured by the number of transfers appears a more logical proxy for Ethereum's value and price. The analysis utilizes daily returns rather than prices to ensure stationarity. To this end, all data, including token transfers, are transformed into returns. This methodological choice does not detract from the study's objective to assess the significance of token transfers in influencing daily Ether returns. By focusing on returns, this analysis aims to capture the short-term effects of network activity on Ether's value, thereby

providing insights into the dynamics of price formation on the Ethereum blockchain. This is the first contribution of this chapter.

Also, this chapter contributes to the discussion of network effects in cryptocurrencies and Ethereum in particular. Liu, Tsyvinski, and Wu (2021) and Cong, Li, and Wang (2020) agree that network effects are a valuable measure of user adoption and cryptocurrency value, whereas Pagnotta and Buraschi (2018) and Stylianou, Spiegelberg, Herlihy, and Carter (2021) question the existence of network effects in crypto and their impact on value. This chapter relies on the logic of Ethereum's utility to the organizations that use its network and to the end users who are required to own Ether to make transactions on-chain. Thus, the growing ERC-20 token activity on the Ethereum network must increase the demand for its native coin Ether, as its utility will grow for the end user who would want to take advantage of the Ethereum network. This increase in value could be viewed as a network effect. In this case, we would expect to observe a positive impact of token activity on Ether returns. This author believes that such an effect on Ether price and returns cannot be observed, as crypto pricing is mostly speculative. This also implies a contribution to the discussion on the speculative nature of cryptocurrencies.

Lastly, a contribution to forecasting of cryptocurrency returns is made by using the LASSO regression to predict Ether returns. Other papers described in this literature review have used the LASSO regression to study cryptocurrency price, and authors such as Jang and Lee (2018) and Patel, Tanwar, Gupta, and Kumar (2020) have used machine learning methods to this end. However, most have focused on using macroeconomic factors and Google trends data as

independent variables. This chapter explores a new angle – the relationship of the activity of tokens on a blockchain and its native coin's returns and its predictive power. A wide range of predictors are added, including Google Trends data and macroeconomic factors. Thus, the LASSO regression will reveal which data is more valuable in crypto pricing. To the best of my knowledge, this relationship has not been studied before.

Section 4.3. Data.

This study utilizes a comprehensive dataset with daily frequency comprised of ERC-20 token blockchain-level data, historical data on major cryptocurrencies, global economic indicators, and Google Trends analytics. All variables are converted into returns (percentage change for transfers data) in the pre-processing, in order to achieve stationarity and for more meaningful analysis. The Augmented Dickey-Fuller was done to confirm the stationarity of all variables after converting them into returns – all were stationary.

The LASSO regularization is expected to shrink the coefficients of the less relevant predictors and assign a coefficient of 0 to the ones deemed irrelevant. Thus, this approach allows us to compare some of the indicators used in similar research such as Panagiotidis et al. (2018) and Cenir et al. (2022) which focused on the economic and conventional finance indicators. The economic variables included in this dataset are meant to be a proxy for the state of global economy.

The ERC-20 tokens were chosen on the basis of their activity on the Ethereum blockchain, i.e. the daily number of transfers. The number of transfers were chosen as the criteria for selecting the tokens for this analysis as this better indicates the strain posed on the network by that token rather than the volume measured in USD. The reasoning behind this choice is that a single large transaction will have an outsized impact on volume measured in USD but would not indicate how much strain transactions of a particular token are causing on the Ethereum blockchain. Also, the number of transfers rather than their total USD volume better indicates the blockchain's popularity with the public as well as the impact on current GWEI (transaction fees).

The raw data on transactions numbers was extracted from the BigQuery dataset on the Ethereum blockchain. BigQuery is a data warehouse platform provided by Google. It copies the data stored on the Ethereum blockchain on a daily basis, keeping it up to date. The tokens were ordered based on the number of transfers in September of 2023 (last month as of this writing). Analyzing the full history of transactions on the blockchain and deriving the historically most active tokens proved to be computationally intensive, as there are a total of over 500,000 tokens on Ethereum as of now,

and each had multiple transactions daily since the inception of the platform. Therefore, a sample of one month was taken to determine the most popular ERC-20 tokens. Of those, only the ones that have data going to at least 2020 were chosen, which led to the current dataset. The analysis of raw blockchain data in BigQuery revealed that among the top 30 unique addresses used for transfers were the following ERC-20 tokens:

Table 4.1. List of top 8 ERC-20 tokens by number of transfers in September.

Token	Average Transfers
WETH	168107.89
USDT	139026.65
USDC	60487.39
DAI	12972.37
SHIB	9566.34
LINK	8407.16
MATIC	5470.94
WBTC	4472.77

This table contains the average monthly transfers for September 2023 of major tokens ERC-20 tokens.

The rest of the top 30 addresses were NFT addresses, which are not used for this analysis. GWEI, which is also known as the measure of Gas Price (transaction cost) on the Ethereum blockchain is also added as a relevant measure, as the level of GWEI depends on the congestion of the network in any given moment, which depends on the number of transfers and hence the activity on the blockchain of the ERC-20 tokens. Furthermore, aside from WBTC, all selected tokens consistently rank among the top 30 in market capitalization according to CoinMarketCap, reinforcing their relevance and impact within the Ethereum ecosystem. This focused approach allows for a more manageable and meaningful analysis of the influence of token activity on Ethereum's network and its native currency, Ether.

The BigQuery data also allowed to extract the USD volume of each ERC-20 token on the Ethereum blockchain specifically. Popular data sources such as CoinMarketCap.com and CoinGecko.com include volume data for tokens, however it is aggregate data from exchanges and does not indicate the level of activity on the blockchain specifically. Most tokens, including all used in this analysis (except Bitcoin) can be transferred using several blockchains, such as BNB Smart Chain or Solana. In this chapter the focus is on the impact of ERC-20 tokens on the price of Ether, the Ethereum blockchain's native coin, therefore the isolated data of volume on the blockchain itself is valuable. The on-chain volume of a token is denoted as such in the data used for this analysis. Besides blockchain-level data, the exchange traded price and total volume of each token was included in the dataset. This was downloaded from Yahoo Finance, which uses CoinMarketCap.com as its source. The latter is a popular source for cryptocurrency data used in the industry and academically as well.

Major cryptocurrencies' price and volume information were added to the dataset alongside the ERC-20 tokens'. This inclusion is motivated by the existence of correlations and interdependencies among the returns of dominant cryptocurrencies, especially Bitcoin which often acts as an unofficial benchmark for the cryptocurrency market by virtue of being the first and biggest cryptocurrency by market capitalization (Zhang & Mani, 2021).

By integrating data from major cryptocurrencies, the aim is to account for potential externalities and spill-over effects that may occur with Ether prices and to discern whether ERC-20 tokens

independently possess sufficient explanatory power for predicting Ether's price. The cryptocurrencies added are: ADA (Cardano), DOT (Polkadot), TRX (Tron), BNB, SOL (Solana), XRP (Ripple), DOGE.

The start date was determined based on the token that has the shortest length of data – Polkadot (DOT). Based on its creation date, the start date was determined to be 20/08/2020, and the end date is 20/10/2023.

Global economic indicators may also be a factor in forming Ether's price. In 2020, the year of the COVID-19 pandemic the price of Bitcoin started surging dramatically and reached its all-time peak of 68,789.63 USD. The cryptocurrency market in general experienced a bull run. It was proposed that this happened due to the pessimism of investors regarding the state of the economy, thus many fled to cryptocurrencies viewing it as an alternative asset class to hedge against possible inflation (Inman (2020); Popper (2020)). Thus, economic indicators included are: NASDAQ (daily close price), NASDAQ (daily volume), 10-year Treasure Notes (daily close price), US EPU Index (daily values), NIKKEI225 index (daily close price), Brent Oil EU (daily price), SP500 index (daily values).

Google Trends data has often been used in cryptocurrency research, including a paper that used the LASSO regression for predicting Ether's price (Panagiotidis, 2018). The full list of variables is summarized in the table below. The frequency in which each variable was available is indicated in the table.

Table 4.2. Full list of predictors.

Variable	Description	Source
LINK_on_chain_transfers	ERC-20 tokens daily transfers and volume on the Ethereum blockchain only	BigQuery Ethereum Data
LINK_on_chain_volume		
WBTC_on_chain_transfers		
WBTC_on_chain_volume		
USDT_on_chain_transfers		
USDT_on_chain_volume		
USDC_on_chain_transfers		
USDC_on_chain_volume		
MATIC_on_chain_transfers		
MATIC_on_chain_volume		
SHIB_on_chain_transfers		
SHIB_on_chain_volume		
WETH_on_chain_transfers		
WETH_on_chain_volume		
DAI_on_chain_transfers		
DAI_on_chain_volume		
GWEI_average_daily	Gas price (transaction cost) on the Ethereum blockchain	
ETH_Volume	Ether daily total volume	Yahoo Finance (CCC)
BTC_Price	Bitcoin daily price and volume	
BTC_Volume		
LINK_Price	Daily price and total volume for each of the ERC-20 tokens	
LINK_Volume		
WBTC_Price		
WBTC_Volume		
USDT_Price		
USDT_Volume		
USDC_Price		Yahoo Finance (CCC)

USDC_Volume MATIC_Price MATIC_Volume SHIB_Price SHIB_Volume WETH_Price WETH_Volume DAI_Price DAI_Volume		
NASDAQ_Close NASDAQ_Volume	NASDAQ Composite daily close price and volume	Yahoo Finance (Nasdaq GIDS)
TNX_Close	CBOE Interest Rate 10 Year Treasury Notes	Yahoo Finance (ICE Futures)
USEPUINDXD	Economic Policy Uncertainty Index for United States (daily)	Federal Reserve Economic Data (St. Louis FED)
NIKKEI225	Nikkei Stock Average (daily, close)	
DCOILBRENTEU	Crude Oil Prices: Brent – Europe (daily)	
SP500	S&P 500 Index	
GOOGTREND	Google searches of "Ethereum"	GoogleTrends
TRX_Close TRX_Volume XRP_Close XRP_Volume DOT_Close DOT_Volume ADA_Close ADA_Volume BNB_Close BNB_Volume SOL_Close SOL_Volume DOGE_Close DOGE_Volume	Daily price and total volume for major cryptocurrencies	Yahoo Finance (CCC)

This table contains all the variable included in the LASSO regression. The middle column describes the variable, and the rightmost column indicates its source.

Section 4.4. Methodology.

The LASSO regression is used to estimate coefficients of predictors and observe which ones have more impact on Ether price. This method was originally proposed by Tibshirani (1996), and the acronym stands for Least Absolute Shrinkage and Selection Operator. Shrinkage refers to data regularization, which involves adding a penalty to different parameters of the model to prevent overfitting and enhance prediction accuracy. Below is the quadratic equation solved when fitting the model:

$$\hat{\beta} = argmin\left\{\sum_{i=1}^{n}\left(y_i - \beta_0 - \sum_{j=1}^{p} x_{ij}\beta_j\right)^2\right\} \text{ subject to } \sum_{j=1}^{p}|\beta_j| \leq t$$

It is often written in Lagrangian form as:

$$\hat{\beta} = argmin\left\{\frac{1}{2n}\sum_{i=1}^{n}\left(y_i - \beta_0 - \sum_{j=1}^{p} x_{ij}\beta_j\right)^2 + \lambda\sum_{j=1}^{p}|\beta_j|\right\}$$

where y_i represents the response variable, x_{ij} are the predictor variables, β_j are the coefficients, n is the number of observations, p is the number of predictors, and λ is the regularization parameter that controls the strength of the penalty applied. The data is normalized before being used as inputs for the model, as LASSO is sensitive to scale.

The LASSO regression results in some coefficients becoming exactly 0, thus dropping the variable from the list of predictors. This method's advantage over Ordinary Least Squares (OLS) is that it addresses overfitting by the penalisation, which could result in a better out-of-sample performance. It drops the variables that do not contribute to the model, which is especially important in cases of high dimensional data. In the case of this study, there are 63 predictors. Using OLS will likely result in overfitting, therefore LASSO is preferred. Additionally, LASSO can be effective in dealing with multicollinearity.

This regression method is a logical choice for purposes of this study. Firstly, there is a large number of independent variables, where LASSO will be effective in punishing the ones that do not contribute to explaining the returns for Ether. Secondly, the aim of the chapter is to compare the regressors based on their impact on Ether returns. The LASSO will allow us to isolate the most effective predictors and then compare their impact based on their coefficients. It also allows us to make one step predictions based on the model, thus the model's and the regressors' forecasting power is tested.

A crucial part of the LASSO is choosing the λ parameter – a large λ will penelise more variables than needed and potentially create higher standard errors, and a small one will lead to bias. To select the regularization parameter the Cross-Validation (CV) method is typically used. In the CV method, a parameter k must be selected, which is the number of random samples that are taken from the data to calculate the λ that minimizes the mean squared error (MSE) of the morel. $k = 5$

and $k = 10$ have been found empirically to perform most consistently, neither suffering from excessively high bias nor variance. In this analysis $k = 5$ is used as it is computationally easier and the alternative did not provide radically different results.

After the LASSO selects the relevant variables, a Post-LASSO estimation is done. Post-LASSO is simply an OLS done with *only* the variables that have non-zero coefficients based on the LASSO. This is done because the LASSO shrinks all variable towards 0, including the relevant ones, thus creating bias. Therefore, the Post-LASSO is done to potentially uncover the true coefficients.

The last 100 daily returns of Ether are predicted based on an expanding window of training data and one step predictions. Then the RMSE, Mean Directional Accuracy (MDA) and Mean Absolute Error (MAE) are calculated as a measure of the model's efficacy. These are commonly used measures for evaluating predictive accuracy. In the literature, RMSE and MDA were used in D'Amario and Ciganovic (2022), who used a LASSO-VAR model to forecast cryptocurrency log returns and the MAE was used alongside other measures in Patel, Tanwar, Gupta, and Kumar (2020), a GRU-based hybrid model they used for their forecasts.

The forecasting performance of the LASSO with two datasets that have varying numbers of regressors are compared to the OLS, Post-LASSO and RIDGE, the latter of which is also a regularization technique. The dataset with smaller number of regressors contains ERC-20 tokens variables and the macroeconomic ones. The other dataset includes price and volume data of major cryptocurrencies on top of the rest. The LASSO is a shrinkage method so it should select only the

ones with the highest contribution and have a similar RMSE in both datasets. If the results are drastically different, it would indicate that either in that dataset there is a variable with a much higher explanatory power, or that the LASSO is not stable or robust. The RMSE, MAE, and MDA are used to evaluate the accuracy across models. This serves as a comparison of the accuracy of LASSO and as a robustness test.

Wang, Ma, Bouri, and Guo (2022), who also used LASSO in their study, used the AR model as a benchmark, basing it on the work of Paye (2012). The OLS is also a common benchmark model and was used as such in Jang and Lee (2018). The Auto-Regressive (AR) and OLS models are used as benchmarks in this study, with the baseline dataset being the one that includes ERC-20 tokens variables and major cryptocurrency variables (their aggregated price and volume), macroeconomic indicators.

Other papers that have used the LASSO and its variations are Wang, Ma, Bouri, and Guo (2022); Panagiotidis, Stengos, and Vravosinos (2018); Ciner, Lucey and Yarovaya (2022); and D'Amario and Ciganovic (2022).

Section 4.5. Empirical Findings.

Results.

The table below contains the non-zero β-coefficients of the explanatory variables resulting from the LASSO regression. In other words, the variables that were found to have an impact on returns of Ether (ETH). The coefficients are in descending order based on their absolute value.

Table 4.3. LASSO-regression results.

Explanatory Variable	β-coefficient (LASSO)
BTC_Price	0.33982022
LINK_Price	0.24193903
SOL_Close	0.07350412
DOT_Close	0.06258402
ADA_Close	0.05070248
MATIC_Price	0.04952827
WBTC_Price	0.02912834
TRX_Close	0.01589501
BNB_Close	0.00309568

This table contains the results for the LASSO selection. The results appear more in line with expectations.

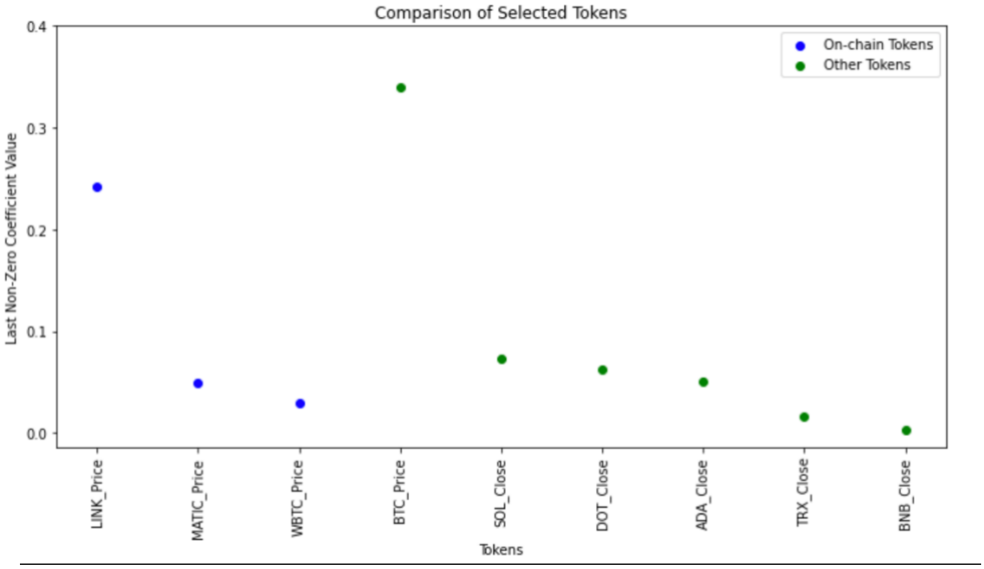
Based on these results, out of the 63 variables, only 9 have explanatory power over Ether returns. All of them represent ERC-20 token and cryptocurrency returns data. Of the 8 ERC-20 tokens chosen for this regression, with each having four variables associated with them (number of on-chain transfers, on-chain volume, price, and total volume), no transfers variable was found to have an impact on Ether returns. From the selected predictors, 3 of the ERC-20 token related predictors appeared – albeit it was their returns rather than transfers data. The second most impactful predictor

in particular, the returns of LINK (LINK_Price in the table), is substantially ahead in terms of its predictive power based on its coefficient. MATIC and WTBC returns, which are also ERC-20 tokens, were also selected, though markedly less powerful than LINK. The strongest predictor of Ether returns is Bitcoin returns.

The central question of this study is whether ERC-20 tokens' activity impact the price formation of Ether, as they are using Ethereum infrastructure and the more popular an ERC-20 token is the more transfers will be made on-chain, which will lead to more congestion and higher transaction costs on the Ethereum blockchain. Out of 8 predictors that were on-chain transfers data none made it to this list. All predictors selected are price related (transformed into returns), though interestingly out of the 9 selected 3 are ERC-20 token returns, with the second strongest being Bitcoin and ERC-20 token's returns (LINK).

To visualise the relative size of each predictor below is a scatter plot which contains all the non-zero coefficients.

Figure 4.9. Scatter plot of LASSO coefficients.



This scatter plot shows the ERC-20 tokens data in blue and the rest in green.

These results, however, may be biased. As mentioned in the previous section, the LASSO shrinks all the coefficients, which may create bias. Therefore, a Post-LASSO is done, which is an OLS done with only the variables selected by LASSO. This allows us to uncover the "true" coefficients and to get their statistical significance. Table 4.5 below contains the results for the Post-LASSO.

Table 4.4. Post-LASSO coefficients and p-values.

Explanatory Variable	β-coefficient	p-value
BTC_Price	0.3259	0.001
LINK_Price	0.2406	0.000
SOL_Close	0.1214	0.000

DOT_Close	0.0826	0.000
MATIC_Price	0.0790	0.000
ADA_Close	0.0685	0.001
WBTC_Price	0.0605	0.524
TRX_Close	0.0599	0.001
BNB_Close	0.0265	0.184

This table contains the results for the Post-LASSO, which is an OLS done with only the LASSO selected variables. This is meant to give us the unbiased coefficients.

We observe a difference here – starting from the third predictor (SOL_Price), the coefficients are larger. However, the first two are close the results of the LASSO. The Post-LASSO has somewhat different results, though the relative impact is almost the same – only MATIC_Price and ADA_Price have swapped positions. Additionally, WBTC_Price and BNB_Close are not statistically significant. SOL_Close is the third strongest predictor, and it would be of interest to see whether there is any correlation with Ether returns, given that SOL also a network provider, as well as ADA and TRX. These could be connected in unexpected ways since they often host the same tokens.

The Post-LASSO results indicate most of the regressors to be more impactful. The main conclusion, however, remains the same: token activity does not appear to influence Ether returns and price. The hypothesis in this case is that cryptocurrency pricing is mainly speculative, so the

results indirectly confirm this notion, while also demonstrating that token activity has no impact on Ether returns.

Based on the results described above, the activity of most ERC-20 tokens in this dataset appears to have no explanatory power. The majority of literature appears to focus on the interplay between cryptocurrencies, mostly Bitcoin, and macroeconomic factors (Zhang and Wang (2020)**;** Uruquhart (2018); Panagiotidis, Stengos, and Vravosinos (2018); Wang, Ma, Bouri, and Guo (2022)). In this study, based on the size of the coefficients we can see that Bitcoin returns is dominant in terms of explanatory power on Ether returns. However, the second cryptocurrency in terms of explanatory power - LINK is one with a smaller market capitalisation than others on the list like SOL (Solana), which is roughly ten times larger in terms of market capitasation. This could suggest that the impact is not merely due to dominance on the crypto markets like in case of Bitcoin, LINK is an ERC-20 token. The macroeconomic factors found significant by previous research also did not get selected by the model used in this chapter. For example, US EPU, which was found to be a predictor of Bitcoin price in Bouri, Gupta, and Roubaud (2019); Demir et al. (2018a) and Wang, Sarker, and Bouri (2022). The latter highlighted the importance of both EPU and CPI, none of which were selected as having an impact on Ether returns. S&P500 returns likewise did not get selected by the model, unlike in Wang, Ma, Bouri, and Guo (2022) who also used a LASSO regression, where it was found to be a powerful indicator. This difference could have been caused by the presence of more powerful predictors in the dataset used in this study, which could have made the S&P500 returns and other macroeconomic factors' coefficient shrink to 0 because it did not contribute to the model. The bigger role of cryptocurrency variable in predicting Ether price is also in line with D'Amario and Ciganovic (2022), who found "Granger causality between all cryptocurrencies

except Bitcoin, Tether, and Feathercoin and from returns to the bitcoin sentiment extracted from Twitter".

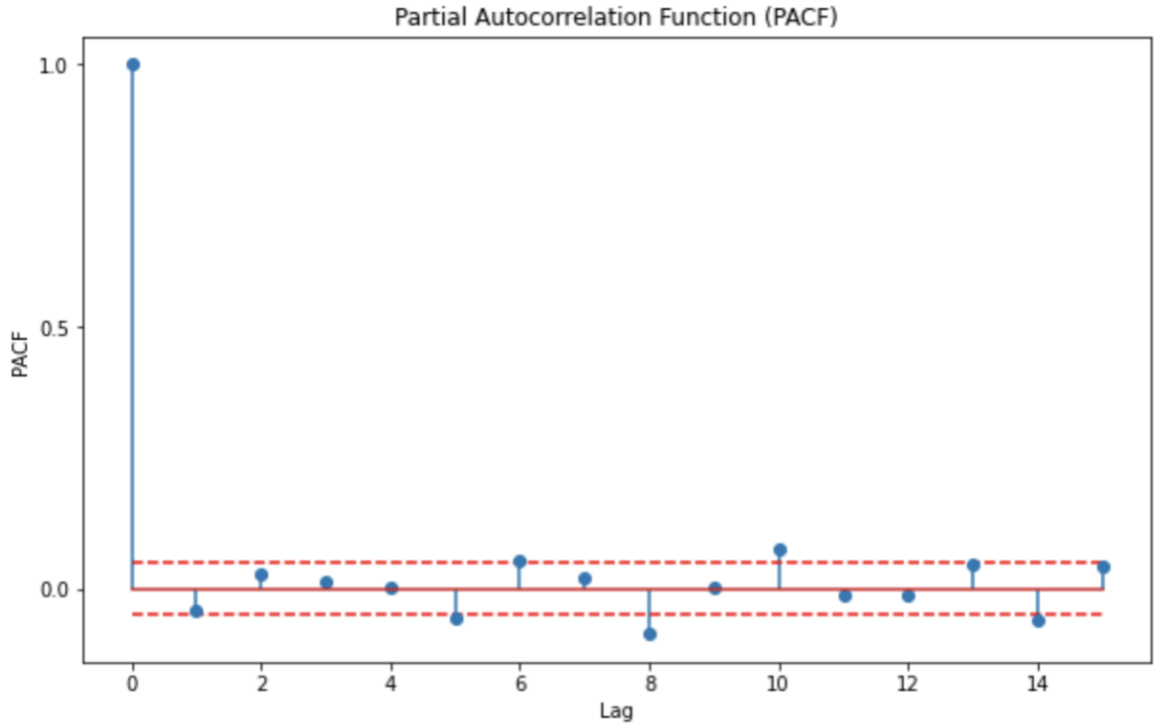
Lastly, among the commonly used variable to explain crypto price/returns is a proxy for investor attention – Google Trends data. It was not selected by the LASSO, implying it does not possess explanatory power or that it is far weaker than the ones presented in the table above. This is contrary to the literature that included this variable in their analysis (Sovbetov (2018); Zhang and Wang (2020); Panagiotidis, Stengos, and Vravosinos (2018)). The slight differences were in the papers by D'Amario and Ciganovic (2022) where they found that the Google Trends data was a predictor but was not Granger causal, and in Uruquhart (2018), which found the attention to Bitcoin to be influenced by the previous day's return, and not vice versa. This variable, however, requires more analysis and is further discussed after robustness checks below.

In regard to network effects that ERC-20 tokens cause in Ether, there is no evidence to suggest there are any. If there was an increase in price/returns associated with the increased activity of tokens on the Ethereum network, it could be viewed as a network effect since an increase in price of Ether would indicate higher demand and value to the user. Instead, we observe that from on-chain activity proxies none have been selected. In this regard, the conclusion of this study is that there are no network effects on Ethereum caused by ERC-20 tokens. This is in line with the broader conclusion by Pagnotta and Buraschi (2018) and Stylianou, Spiegelberg, Herlihy, and Carter (2021) that network effects are much weaker than believed, and contrary to the conclusions of Liu,

Tsyvinski, and Wu (2021) and Cong, Li, and Wang (2020), who conclude network effects are a valuable determinant of cryptocurrency value and price.

To evaluate the efficacy of the LASSO and the predictors in terms of their predictive accuracy, it is being compared to the benchmark OLS and AR(1) models, the Post-LASSO, and the RIDGE regression. Two slightly different datasets (as described in Section 4.3) will be used to conduct the same regressions, except for the AR(1) as it only takes the dependent variable as input. The order of lag for the AR model was chosen using the PACF plot:

Figure 4.10. PACF plot for the dependent variable (ETH_returns).



As we can observe from the plot, the 14th lag is the highest one that crosses the significance lines and 8th is the strongest. However, upon running the regression there was no significant difference

in the RMSE of the AR(1), AR(8) and AR(14) models, in fact the AR(1) outperformed slightly. Therefore, the more commonly used AR(1) was chosen to proceed with the analysis. As explained in Section 4.4, the metrics are calculated based on the one step out of sample predictions made on an expanding window. In total there are 100 predictions made using each model.

Table 4.5. RMSE calculated various regressions and datasets.

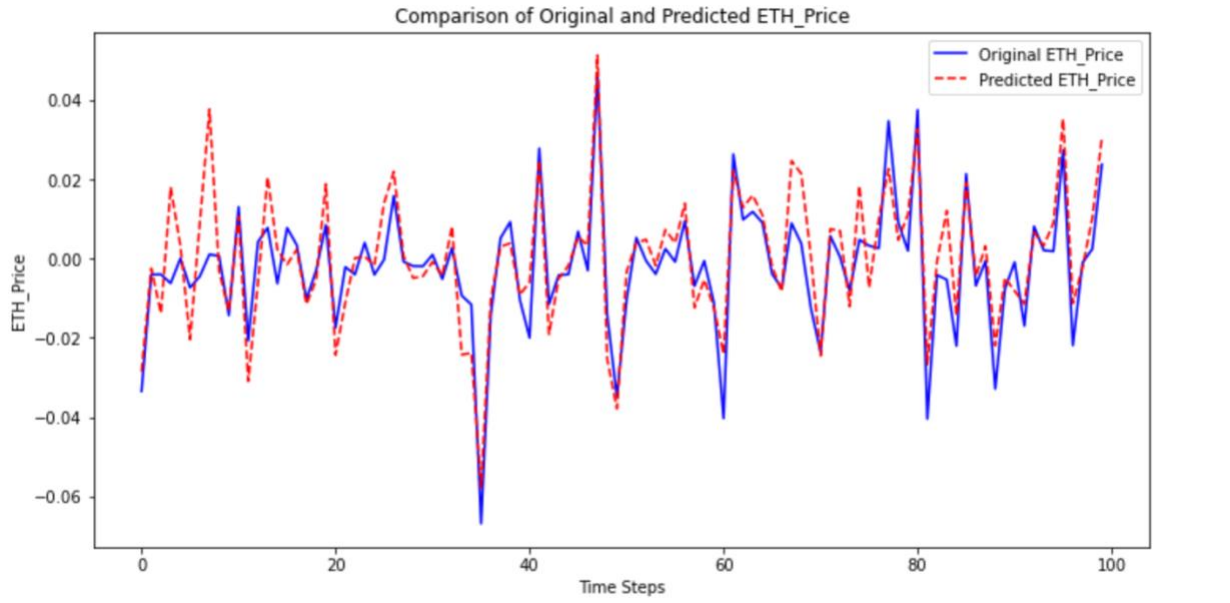
Data set	Regression method	RMSE	MAE	MDA
ERC-20 Tokens	**LASSO**	**0.2155**	**0.1485**	**86**
	RIDGE	0.2573	0.207	76
	Post-LASSO	0.2191	0.1591	85
	OLS	0.3325	0.2616	68
ERC-20 Tokens + Major Cryptocurrencies	**LASSO**	**0.1955**	**0.149**	**84**
	RIDGE	0.2603	0.1998	76
	Post-LASSO	0.1891	0.1416	86
	OLS	0.3203	0.256	69
Dependent variable ETH_Price	AR(1)	0.3734	0.257	67

This is a comparison of the RMSE, MAE, and MDA measures of forecasting accuracy. It compares the LASSO results to other models, using two datasets, which include the same base variables, but one lacks major crypto variables. This allows to see if the LASSO is consistent.

The results above suggest that the predictions made by the LASSO are stable, as it performed similarly with both datasets. The LASSO predictions were slightly better in terms of RMSE with the dataset that included the major cryptocurrencies, confirming that they have explanatory power. However, the RIDGE regression performed worse in the larger dataset, and worse than the LASSO. The LASSO and post-LASSO show similar accuracy, and their higher accuracy is more pronounced when compared with the benchmark models of OLS and AR(1). To interpret the

RMSE in this context, we must account for the fact that the data was normalized prior to fitting the models and making the predictions, and the values were bounded between 0 and 1. Therefore, the RMSE of 0.1955, for example, means that the predictions were wrong on average within 19.55% of the original data prior to normalization. Figure 4.4 below visualizes the LASSO predictions with the full dataset including major cryptocurrencies and the actual returns.

Figure 11.4. LASSO prediction compared to actual values.



This chart overlays the original path of Ether returns with the LASSO predictions based on the full dataset including major cryptocurrency price and volume (transformed into returns).

D'Amario and Ciganovic (2022) use RMSE and MDA to compare LASSO-VAR models to their benchmarks Large Bayesian VAR (LBVAR) and find the LASSO-VAR to perform slightly better in terms of MDA and comparably in terms of RMSE, though it was slightly worse. Wang, Ma, Bouri, and Guo (2022) employ different measures for their forecasting results, and only includes macroeconomic data and technical indicators to predict Bitcoin volatility. The results presented in this chapter show that at least for the case of Ethereum returns, macroeconomic variables did not have enough predictive ability to be selected when compared to other cryptocurrency returns. This

could be expected since other major cryptocurrencies are part of the same market as Ether. However, most of the literature covered focuses on the predictive power of macroeconomic factors and attention indicators on cryptocurrency prices, most commonly that of Bitcoin.

Jang and Lee (2018) use Bayesian Neural Networks incorporating blockchain information to predict Bitcoin prices. Similar to this study, they utilized macroeconomic data along with blockchain-level information, though they focused on Bitcoin and information like hash rates, mining difficulty, and block size. They also included transaction costs on the Bitcoin network, while this chapter's dataset included its equivalent for Ethereum. Additionally, they used the RMSE to compare the results to benchmark models of OLS and support vector autoregression (SVR), and found their model to be extremely performant. Unfortunately, they do not specify the scale of data so a one-to-one comparison with the RMSE results of this study would not be accurate. However, it is worth mentioning that their model and dataset that included blockchain-level information outperformed the benchmarks in all metrics, unlike in D'Amario and Ciganovic (2022). Yet again, a direct comparison cannot be made due to the difference in methodologies.

In terms of MDA, which simply measures the frequency at which the model predicted the direction of returns movement, the LASSO and the dataset appears to have performed well. The MDA is measured in percentages, therefore, the lowest result for the LASSO was 84%, much higher than the 67% of the benchmark AR(1) model. The worst performance in terms of MDA was recorded for AR(1) and for OLS using the restricted dataset (ERC-20 tokens no other cryptocurrencies), at 67% and 68% respectively. The LASSO outperformed other regressions here, the best result being

the Post-LASSO with the full dataset. D'Amario and Ciganovic (2022) also found in their study that the LASSO-VAR models performed better in terms of the MDA than their benchmark, though it cannot be directly compared to this model.

In terms of MAE, again the LASSO and Post-LASSO regressions performed similarly and outperformed both the benchmarks and the RIDGE regression.

Also, this study employed a comprehensive dataset that includes macroeconomic indicators, on-chain data, and major cryptocurrencies' prices and volume. There is evidence for impact on Ether returns by ERC-20 tokens' returns that the Ethereum network hosts. There has been discussion about the speculative nature of cryptocurrency pricing, and this study was not able to establish a connection between the daily number of transfers and Ether price/returns, which would be a quantifiable metric. Price of other tokens does have an impact, and it could be expected to be bigger than on-chain activity as price is readily observable and such information travels faster. However, these are indicative of a more speculative nature of Ether price, rather than on user adoption and network usage as measured by daily transfers. Based on this fact, this study cannot claim Ether price/returns to be less speculative, as was done in Blau (2018) for Bitcoin, which found Bitcoin speculative trading not to be excessively high.

Robustness tests.

To assess the robustness of the LASSO results, bootstrapping is used. The main advantage of the LASSO is variable selection. This depends heavily on the regularization term λ. In order to select an appropriate λ, 5-fold cross-validation is done when fitting the model, which is the first step to ensuring the robustness of the model. To further analyse the reliability of the selections, we can perform bootstrapping with 10000 resamples, and count the proportion of times each variable was not selected, i.e. its coefficient was zero. The resamples are done randomly with replacement for every variable. Then the model is fit and cross validation is done for every resample. A similar approach was taken in Wang, Ma, Bouri, and Guo (2022). The advantage of a bootstrap is that it also allows us to measure a confidence interval for the coefficients. The closer the "Zero Proportion" to 0, the more robust the predictor is as it indicates being selected in a higher number of resamples.

Table 4.7. Results of the bootstrap of the original LASSO results.

Token Name	Zero Proportion	95% Confidence Interval
ETH_Volume	**0.0285**	**(0.00000, 0.33937)**
BTC_Price	**0.0248**	**(0.00169, 0.40475)**
BTC_Volume	**0.0688**	**(-0.17972, 0.00000)**
LINK_number_of_transfers	0.8051	(-0.00707, 0.00797)
LINK_on_chain_volume	0.8522	(-0.00493, 0.00581)
LINK_Price	**0**	**(0.15666, 0.27313)**
LINK_Volume	0.7656	(0.00000, 0.03795)
GWEI_average_daily_gas_price_gwei	0.5096	(-0.00729, 0.02314)
WBTC_number_of_transfers	0.2977	(-0.06620, 0.00000)
WBTC_on_chain_volume	0.8236	(0.00000, 0.01071)
WBTC_Price	0.3648	(0.00000, 0.34269)
WBTC_Volume	0.4748	(0.00000, 0.05790)
USDT_number_of_transfers	0.8514	(-0.00276, 0.01247)
USDT_on_chain_volume	0.8628	(-0.00881, 0.01417)

USDT_Price	0.6839	(-0.01098, 0.02009)
USDT_Volume	0.947	(-0.01176, 0.00000)
USDC_number_of_transfers	0.6497	(-0.03105, 0.00000)
USDC_on_chain_volume	0.6099	(-0.01886, 0.00000)
USDC_Price	0.2778	(-0.04696, 0.00000)
USDC_Volume	0.8191	(0.00000, 0.00441)
MATIC_number_of_transfers	0.7322	(-0.01398, 0.01767)
MATIC_on_chain_volume	0.934	(-0.00223, 0.00000)
MATIC_Price	**0.003**	**(0.02324, 0.14613)**
MATIC_Volume	0.3827	(-0.05296, 0.00000)
SHIB_number_of_transfers	0.544	(-0.01758, 0.00000)
SHIB_on_chain_volume	0.7322	(0.00000, 0.00764)
SHIB_Price	0.6194	(-0.01797, 0.00098)
SHIB_Volume	0.748	(-0.01277, 0.00000)
WETH_number_of_transfers	0.593	(-0.00641, 0.02964)
WETH_on_chain_volume	0.5115	(-0.03620, 0.00000)
WETH_Volume	0.7732	(-0.00638, 0.00000)
DAI_number_of_transfers	0.2361	(-0.06066, 0.00000)
DAI_on_chain_volume	0.4795	(-0.02557, 0.00000)
DAI_Price	0.4606	(0.00000, 0.03687)
DAI_Volume	0.7966	(-0.01950, 0.01090)
new_tokens_monthly_x	0.3326	(0.00000, 0.03669)
CPILFESL	0.5868	(-0.00151, 0.02205)
EUEPUINDXM	0.7066	(-0.01834, 0.01382)
CHNMAINLANDEPU	0.6188	(0.00000, 0.02173)
NASDAQ_Close	0.4927	(0.00000, 0.03223)
NASDAQ_Volume	0.7361	(-0.01248, 0.00733)
TNX_Close	0.6309	(-0.02002, 0.00624)
USEPUINDXD	0.7025	(-0.01547, 0.00455)
FFR	0.3829	(0.00000, 0.02592)
NIKKEI225	0.4537	(0.00000, 0.02743)
DCOILBRENTEU	0.5671	(-0.00095, 0.02162)

SP500	0.8097	(0.00000, 0.02142)
GOOGTREND	**0.0405**	**(0.00000, 0.11640)**
TRX_Close	**0.085**	**(0.00000, 0.07351)**
TRX_Volume	0.8268	(-0.01061, 0.00792)
XRP_Close	0.1495	(0.00000, 0.06730)
XRP_Volume	0.7026	(-0.02704, 0.00000)
DOT_Close	**0.0003**	**(0.04646, 0.17522)**
DOT_Volume	**0.085**	**(-0.09663, 0.00000)**
ADA_Close	**0.0212**	**(0.00196, 0.12802)**
ADA_Volume	0.2384	(-0.07232, 0.00000)
BNB_Close	0.2275	(0.00000, 0.13990)
BNB_Volume	0.5552	(-0.03434, 0.00000)
SOL_Close	**0**	**(0.07631, 0.18218)**
SOL_Volume	**0.0375**	**(-0.10113, 0.00000)**
DOGE_Close	0.6924	(0.00000, 0.05901)
DOGE_Volume	0.8533	(-0.00659, 0.00000)

This table contains the results for the bootstrap of the LASSO, with 1000 resamples. The LASSO does not provide p- values, therefore the Post-LASSO and this bootstrap allow us to see the most consistently selected variables.

In the table above the variables that had a proportion of 0 lower than 10% are highlighted in bold. The confidence intervals of the coefficients are calculated at the 95%, meaning 95% of coefficients from the 10000 iterations fall within that interval. This allows us to judge the impact the variable would have. By the criteria outlined above, 7 of the predictors selected in the original LASSO were consistently selected across iterations – BTC_Price, LINK_Price, MATIC_Price, BNB_Close, SOL_Close, TRX_Close and ADA_Close. Out of these, LINK_Price and MATIC_Price are tokens using the Ethereum network, but the variables are price related rather than on-chain activity. Interestingly, WBTC_Price and BNB_Close, which were selected by the LASSO but found to be statistically insignificant in the post-LASSO have zero proportions much higher than 10%, further indicating their unreliability as predictors of Ether returns. On the other

hand, variables like ETH_Volume, BTC_Volume, DOT_Close, DOT_Volume, SOL_Volume have low zero proportions, though they were not selected by the LASSO.

Another noteworthy observation is that the confidence interval for coefficients of BTC_Price, the strongest regressor, is wide and the lower bound close to 0. With other regressors, namely with LINK_Price, MATIC_Price, and SOL_Close, however, the zero proportion is 0 (or nearly 0 for MATIC_Price), meaning they are always selected, and the confidence interval has a much higher floor especially for LINK_Price.

Google Trends data also has a low zero proportion, though was not selected by the LASSO in the original full dataset. This is a popular regressor in the literature and was found to be a significant predictor in most studies covered in the literature review (Sovbetov (2018); Zhang and Wang (2020); Panagiotidis, Stengos, and Vravosinos (2018)). All of the on-chain activity proxies have a zero proportion of above 10%, which further contributes to the notion that on-chain activity is not a strong predictor of Ether returns.

This also indirectly contributes to the discussion of the importance of network effects and quantifiable measures in crypto valuation. The activity of the biggest tokens on the Ethereum network directly impact the network congestion and transaction costs. However, the results of this study show that token activity has no impact on Ether returns, which would be expected if positive network effects were present. To further test this the dependent variable is changed from ETH_Price to ETH_Volume and ETH_transfers and the LASSO regression is fitted again, while conducting the 100-step prediction of volume and daily transfers to measure their RMSE. Table 4.8 and Table 4.9 summarize the results.

Table 4.8. Coefficients for the dependent variable Y = Eth_Volume.

Independent variable	Coefficient
USDT_Volume	0.3571
BTC_Volume	0.2921
ETH_Price	0.1859
WBTC_Volume	0.1152
LINK_Volume	-0.1069
BTC_Price	-0.1068
BNB_Close	-0.0611
BNB_Volume	0.0535
DAI_number_of_transfers	0.0518
SOL_Volume	0.0514
WBTC_number_of_transfers	0.0477
GOOGTREND	0.0431
ADA_Volume	0.0407
DOT_Volume	0.0407
WETH_number_of_transfers	0.0310
XRP_Close	-0.0303
WETH_on_chain_volume	0.0254
DOT_Close	-0.0208
DOGE_Close	-0.0172
TNX_Close	-0.0124

GWEI_average_daily_gas_price_gwei	-0.0091
USDC_Price	0.0085
USEPUINDXD	0.0053
MATIC_Price	-0.0048
USDC_on_chain_volume	-0.0018
TRX_Volume	0.0006
MATIC_number_of_transfers	-0.0004
RMSE	**0.7627**

These are the results for the case when the dependent variable is switched to Ether volume instead of price, with all variables transformed into percentage changes. In this case, volume replaces price returns as the dependent variable.

In Table 4.8, which contains the coefficients for the variables selected by the LASSO as predictive of ETH_Volume, we can see that there are noticeably more variables than for the case of ETH_Price as the dependent variable. Four on-chain activity metrics were included in the selection, though one (MATIC) has almost no effect. This model shows that transfers have weak predictive power, with the biggest one being number 9 in the list. The aggregate exchange volumes for USDT , BTC and ETH itself were far more effective. However, the RMSE for the 100-step prediction is much lower than in the case for the ETH_Price with the same data and prediction model (complete data including major cryptocurrencies).

Table 4.9. Coefficients for the dependent variable Y=Ether_daily_transfers.

Independent variable	Coefficient
USDT_transfers	0.134228318
RMSE	**1.1763**

This is the result for the case when the dependent variable is switched to Ether transfers on the blockchain. It further shows that transfers are not impactful regressors. This one has the lowest RMSE, drastically worse than the previous two.

In Table 4.9, the results are worse compared to Table 4.8. Here, the dependent variable is set to ETH_daily_transfers. The model selected one on-chain activity variables, out of 63 total. It selected only one variable, but it does not explain the data well, based on coefficient size, and neither does it have good predictive capacity – the RMSE is significantly higher than in the case for Price and Volume. This test is not definitive, as there are other tokens, especially NFTs that could have been impacting the number of transfers. Also, these are tokens that were chosen based on the September of 2023, but the test was conducted for 2020-2023. However, the token selected is a major cryptocurrency in its own right – USDT - a stablecoin, and a systemically important one. Its weak impact on Ethereum transfers does not add confidence in the presence of a network effect.

The Diebold-Mariano test is conducted to check for the significance of the difference between the LASSO predictions with the full dataset without the lags and the benchmark models, OLS and AR(1). For the details about the test the reader can refer to the original paper Diebold and Mariano (1995). This is a well-known test for predicting forecast accuracy, however it has its limitations. The main assumption is that the difference in squared forecast errors of the models – which is what

is being tested - is covariance stationary. Also, it must be homoscedastic and there must be no autocorrelation. In practice these assumptions, especially the main assumption of covariance stationarity, is difficult to satisfy. The Diebold-Mariano test still serves as an important approximation, but the results must be interpreted having the test's limitation in mind. It was developed to analyse differences using metrics like MSE and MAE, and both are tested. Table 4.10 summarizes the results for the assumption tests and the Diebold-Mariano test itself.

Table 4.10. Results for statistical significance (p-values) for the Diebold-Mariano (DM) test and the test for assumptions of DM.

	LASSO vs. OLS		**LASSO vs. AR(1)**	
	MSE	MAE	MSE	MAE
Ljung-Box	0.9173	0.3086	0.4826	0.1383
ADF	0.000	0.000	0.000	0.000
Breusch-Pagan	0.000	0.000	0.000	0.000
Diebold-Mariano	**0.0002**	**0.000**	**0.0023**	**0.0002**

These are the results for the Diebold-Mariano test, and the tests for its assumptions. The DM test is commonly used to compare the predictive accuracy of models, however its assumptions are rarely fully met so it must be interpreted with caution. It is important to note that it is best for comparing the particular predictions, not the models as a whole.

Table 4.10 contains the p-values for the tests done. The Ljung-Box test checks for autocorrelation, the Augmented Dickey Fuller test for stationarity, and the Breusch-Pagan test checks for homoscedasticity. The null hypothesis for the tests are:

1. **Ljung-Box:** There is no autocorrelation up to a specified lag. A $p<0.05$ rejects the null hypothesis and suggests significant autocorrelation.
2. **Augmented Dickey-Fuller (ADF) Test**: The series has a unit root (is non-stationary). A $p<0.05$ Indicates stationarity, rejecting the null hypothesis of a unit root.
3. **Breusch-Pagan Test**: Homoscedasticity (constant variance). A $p<0.05$ implies heteroscedasticity, rejecting the null hypothesis.
4. **Diebold-Mariano (DM) Test**: Two forecasting methods have the same forecast accuracy. A $p<0.05$ suggests a significant difference in forecast accuracy, rejecting the null hypothesis.

We can see from Table 4.10 that for the difference in squared errors the assumption of no autocorrelation always holds. The main assumption is covariance stationarity, which as mentioned often does not hold when conducting this test. However, this assumption for stationarity holds in this case. The Breusch-Pagan test for homoskedasticity is rejected, meaning there is evidence for heteroskedasticity. Nevertheless, the DM test is a useful approximation, and the main assumption of stationarity holds, so the results are still of interest. In every case examined, the p-value for the DM test is extremely low, which suggests that the differences between LASSO and the benchmark models is statistically significant for both MSE and MDA.

Section 4.6. Conclusion.

This chapter examined whether token activity is a good predictor of Ether returns. If it were, this could have been considered an indicator of value for the Ethereum network and an important

pricing metric. Also, it could have supported the argument of a network effect existing between tokens and their host network. A LASSO regression was used to compare the impact of proxies of token activity to other predictors such as commonly used macroeconomic indicators and other cryptocurrencies' price and volume. The predictive accuracy of the LASSO with this dataset was measured through RMSE, MAE, and MDA, using OLS and AR (1) as benchmark models, as well as comparing them to the RIDGE regression and Post-LASSO OLS.

The results of the LASSO regression show that from the 9 selected predictors of Ether returns out of 63, none were ERC-20 token transfers variables. The biggest statistically significant impact was by price of LINK and Bitcoin. The aim of this research is to find if ERC-20 tokens' activity impacts Ether price, and based on the results some token activity has no influence, whereas the price of some tokens does, namely LINK and MATIC. Additionally, 4 of the selected were the returns of network providers like Ethereum - SOL, TRX, ADA and BNB. Bitcoin was the strongest in terms of explanatory power. Regarding selection rates in the LASSO, the bootstrap of the LASSO showed that most predictors selected by the original model were robust, except WBTC and BNB, which were statistically insignificant in the post-LASSO and likewise had high zero proportions in the bootstrap. One ERC-20 token's price data – LINK – and one cryptocurrency with its own blockchain – SOL -– were always selected by the model, with a perfect score of 100% (zero proportion equal to 0). Also, it was found in the robustness test that some indicators like Google Trends, though not selected in the original model, could be useful in explaining Ether returns, though weaker than other cryptocurrencies price and volume data. Other variables that were not selected in the original model but had good selection rates in the bootstrap were volumes data, such as ETH volume.

On-chain activity data was found to have a no impact on Ether returns. This supports the claims made in the strain of literature that questions the strength of network effects in crypto adoption. In this study, the price of some ERC-20 tokens had a strong impact on Ether returns, which could be of interest for future research. However, there is no evidence for the transfers' data impact, there no network effects could be observed.

In terms of predictive accuracy the dataset and the LASSO model performed better than the benchmark OLS with the same dataset and the AR(1) model. Based on the metrics of RMSE and MAE it performed reasonably and based on the MDA – which predicts the direction of the dependent variable – it performed well, better than the comparable model and dataset in D'Amario and Ciganovic (2022).

The approach this study takes is to look at the valuation of cryptocurrencies from a new angle – that of certain major blockchain being providers of infrastructure. The results imply that there is no connection between the native coin's price/returns and token activity therefore the cryptocurrency's price cannot be anchored to it. This fails to dispel the notion that cryptocurrency prices are mostly speculative. The fact that Bitcoin returns were the strongest predictor of Ether returns and that Bitcoin's price is viewed as a gauge for the general state of the cryptocurrency market further adds to this belief that crypto price is mainly influenced by the state of the market. However, the fact that LINK_Price – an ERC-20 token's returns variable was a close second to Bitcoin could be of interest. It could be of value to explore this further with a fuller dataset

involving more blockchain-level transactions data, including NFT transfers. The fact that almost half of the variables selected were also infrastructure providers like Ethereum could be of interest as well – they often host the same tokens, meaning the same token could be on several blockchains.

Also, there are implications for crypto returns forecasting – crypto related indicators clearly outperformed macroeconomic ones – in this study none were selected by the model. A dataset involving blockchain-level data was also used in Jang and Lee (2017), where the prediction accuracy was high. This is a possible indication that this type of data should be more of a focus, rather than macroeconomic data.

The main policy implications of the results discussed in this chapter are related to the speculative nature of cryptocurrencies. Based on the results, there was no connection found between the ERC-20 token activity and Ether price. If such a connection existed, it could have served as a grounding for the value of the Ethereum ecosystem, similar to how a performance of a business serves as a basis for its stock price. While not a definitive rejection of the possibility of the existence of a quantifiable measure for the intrinsic value of Ethereum, it is yet another failure to rationally justify its price and price swings with anything other than investor sentiment and speculation. This argument applies to other major cryptocurrencies with their own blockchains too, as they are structured similarly to Ethereum and it being arguably the second-best known cryptocurrency. The argument that cryptocurrency pricing is mainly speculative is even more potent in case of lesser-known coins, especially in light of the high failure rate of cryptocurrencies and rampant fraud in this industry.

The ample opportunity for speculation is the main concern and challenge for the regulator. In fact, the pump and dump schemes, which are common in the crypto markets, are well documented in Dhawan & Putniņš (2022). These schemes exploit the tendency for gambling of retail investors engaged in crypto trading. Their scale is not big enough to cause a shock that would spill over into traditional financial markets. However, considering the mounting evidence – including the conclusions of this chapter – that even major cryptocurrencies like Ether lack a justification for their price creates a dangerous situation. Also, it must be noted that most of the pump and dump coins are created on an existing blockchain. Regulating the crypto market more stringently would serve to protect the customers from the explicitly speculative pump and schemes and help prevent possible future speculation in major cryptocurrencies like Bitcoin or Ether. To clarify and conclude something akin to the 1933 Securities Act must be in discussion for cryptocurrencies. Specifically:

1) **Implement and Enforce Market Manipulation Rules:** Adapt existing market manipulation regulations to the cryptocurrency markets to explicitly outlaw pump and dump schemes, insider trading, and other fraudulent practices.
2) **Risk Disclosure Requirements**: Mandate clear, comprehensible disclosures by crypto exchanges and investment platforms regarding the risks of speculative trading and potential for sudden price crashes.
3) **Mandatory Disclosure Requirements:** Require cryptocurrency projects and exchanges to disclose information transparently. This includes project ownership, financial health, technological robustness, and any potential conflicts of interest. Transparency can help investors make more informed decisions.

The main limitation is that the full history of token activity could not be extracted from the BigQuery repository of Ethereum data, due to computational intensity it required. The full data could have provided a more accurate picture. Instead, the data for recently most active coins was used. Another limitation is that the same hypothesis should be tested with other blockchain that can host tokens, such as Solana, Tron or BNB, to name a few. This would provide better understanding of the robustness of the results. Finally, the LASSO does not provide statistical significance measures, so a bootstrap was done as a compromise to check for the stability of the model. Also, the Diebold-Mariano test for predictive accuracy has limitations and must be interpreted with caution, though it is widely used as a good approximation to understand the difference between predictions' accuracy. For future research recommendations I believe it would be beneficial to explore the subject of price formation based on blockchain-level data for Ethereum with a richer dataset and compare them by performing the same analysis with other infrastructure providers like Solana, Tron, and BNB, to name a few. Lastly, further research into forecasting using blockchain-level data would be of interest.

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Chapter 5. Conclusion.

This thesis explored various aspects of the potential application of blockchain technology and the attributes of the cryptocurrency market it has spawned. The findings across the three studies underscore the complex dynamics influencing blockchain related markets.

Chapter 2 explored stablecoins' frequency of extreme volatility conditional on their peg design. Stablecoins are a key element of crypto trading, being the medium of exchange for most trades across exchanges. The risks they pose are due to the extreme volatility and fat tails they exhibit in the distribution of their daily volatilities. The probability of extreme volatility events could lead to a de-pegging of their value and wipe out billions in investments. The ripple effects of such an event, if experienced by a major stablecoin, would be felt across all crypto markets, and possibly spill over into traditional financial markets to some degree. Therefore, it is essential to consider the degree to which stablecoins were exposed to extreme volatility events, i.e. risk of extreme events, conditional on their peg design. The results showed that the more innovative stablecoins were more exposed to extreme volatility and exhibit fatter tails in their volatility distributions, while the tokenized stablecoins – considered to be the least innovative in terms of their peg design – were less likely to experience extreme volatility and consequently to crash. Additionally, by comparing USD-pegged (majority of stablecoins) and non-USD pegged stablecoins' volatility measures derived from the power law model, it was found that the peg does not impact the distribution of daily volatilities. This chapter makes contributions to the literature on stablecoin stability, which has mostly focused on volatility measured by variance, Granger causality, and the relationship of stablecoins with the volatility of major cryptocurrencies. By specifically analyzing how different peg designs affect the frequency of extreme volatility, this study provides insights

that distinguish it from existing research. It extends the understanding of risk factors in stablecoin design and offers valuable implications for the design and regulation of these digital assets.

Chapter 3 addressed the potential risks associated with applying blockchain technology to Over-the-Counter (OTC) derivatives trading—a topic often heralded positively in academic literature and finance-related media. Utilizing auction theory and game-theoretic models, including strategies for simple collusion enforcement derived from the game theory literature, this chapter argued that increased transparency, which is expected to be facilitated in OTC derivatives by blockchain technology, might in fact harm customers. This arises because the delicate balance between anonymity and transparency, which is central to blockchain technology, can inadvertently facilitate collusion among dealers. The analysis in this chapter contributes by demonstrating that the increase in transparency proportionally increases ability of dealers to collude. This chapter contributes to the sparse literature regarding the applications of blockchain technology in the derivatives market and highlights the perils of it in terms of diminishing the welfare for customers. The conclusion is important as it is contrary to the purported benefits of blockchain technology – which is touted to be the key to democratizing markets and reducing the concentration of power in the hands of governments and corporations.

Chapter 4 examined whether the Ethereum network's value could be impacted by the activity of tokens that it hosts through the ERC-20 protocol, hence they are known as ERC-20 tokens. Many of the stablecoins studied in the 2nd chapter are also hosted on the Ethereum network, though most tokens now have several hosting blockchains. Ethereum, however, being the pioneer of this technology, remains the dominant one in terms of the sheer number of tokens it hosts. The specific question studied was whether the activity of ERC-20 tokens had any impact on Ether returns, as the transactions costs on the Ethereum network depend on the level of congestion caused by the

transactions activity on it. The proxy for activity is the daily change in the number of transfers for the biggest ERC-20 tokens in terms of market capitaliztion and number of daily transfers, and proxy for change in the Ethereum's value is Ether price returns, Ether being the native coin of this network which is used among other functions to cover the transaction costs for ERC-20 tokens on this network. The dataset includes variables such as price and volume data (all variables were differenced) for major cryptocurrencies and macroeconoomic data, to compare the magnitude of their impact to that of token activity. A positive and significant impact would have indicated a quantifiable metric for Ether price and the existence of network effects on the Ethereum network. The findings contribute firstly to the strain of literature that deals with crypto price and returns, finding that the activity of tokens have no impact on Ether returns. This study is the first to view Ethereum as an infrastructure provider for other tokens and attempts to establish a connection between them and Ether price/returns. The results in this chapter indicate a no impact of ERC-20 token transfers on Ether returns. The second contribution is extrapolated from the previous result, which indicates that network effects are unlikely. These findings strengthen the argument of cryptocurrency price being mostly speculative. Third contrbution of this chapter is testing the efficacy of the the dataset in forecasting Ether return, likewise employing the LASSO regression. The LASSO regression was found to outperform the benchmark models in terms of the metrics established.

All three chapters study blockchain and crypto related questions that are potentially systemically important. Chapter 3 delves into the implications of applying blockchain technology to the systemically important OTC derivatives trading market. It contributes to the rather thin literature on the application of blockchain technology in the area of OTC derivatives clearing and trading.

This chapter extends the implications of a blockchain facilitated clearing process to trading and shows its negative implications, in contrast to the current literature in this subcategory focusing the benefits of blockchain. It also effectively synthesizes concepts and methods from game-theory and from studies in applications of blockchains in trade finance.

In contrast to Chapter 3, Chapters 2 and 4 focus on the empirically observable elements of the crypto economy spawned by the blockchain technology, assessing their implications in broader financial contexts. Chapter 2 assesses the extreme stablecoin volatility, while Chapter 4 studies the pricing of Ether from a novel perspective and makes several contributions.

Each chapter of this study highlights specific areas for policymakers to focus on. Chapter 2 emphasizes the importance of raising awareness about the extreme events in stablecoins, which can be attributed to vulnerabilites in their peg design. Chapter 3 recommends exercising caution when implementing blockchain technology in areas such as derivatives clearing and trading, as it could adversely affect the welfare of customers. Lastly, Chapter 4 discusses the speculative nature of cryptocurrency pricing and notes that the lack of a connection between the activity on the network and the pricing further underscores the role of speculation in cryptocurrency markets.

The limitations and recommendations for future research across the chapters are varied and highlight specific areas for further investigation. In Chapter 2, although the power law model used was appropriate for the available data, the accuracy of the study could be improved with access to more comprehensive data on stablecoins, as some had limited datasets. Chapter 3 faced challenges due to a lack of empirical data, which restricted a closer examination of the predictions made by the analysis; hence, an empirical study following the implementation of the technology would provide more robust insights. For Chapter 4, while the analysis focused on Ether and data from tokens on the Ethereum blockchain, exploring comparisons with other blockchain networks and

their token transfer numbers would provide a broader perspective. Additionally, more granular data collection from Ethereum itself was constrained by computational power when filtering and extracting data from the Ethereum blockchain data repository on BigQuery, suggesting that enhancements in this area could yield more detailed insights in future studies.

These chapters collectively underscore the critical need for balanced, informed approaches to integrating blockchain technologies within financial systems, advocating for nuanced regulatory frameworks that accommodate both the innovations and the challenges posed by these technologies.