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Decentralized Finance and the Crypto Market: Indicators and Correlations

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Decentraliserad Finans och Kryptomarknaden: Indikatorer och Korrelationer

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Title

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Abstract

Background:
Within the emerging field of cryptocurrencies, the sub-sector DeFi (decentralized finance) has experienced explosive growth over the last year, and its importance for crypto as a whole has grown with it. The currencies have developed from simple peer-to-peer transactions to complex applications such as lending and exchanges. Several studies have researched determinants of cryptocurrency prices, and a few have focused on metrics central to DeFi, such as total value locked (TVL). However, academia has aimed sparse attention to the relationships between these metrics, which this article seeks to amend.

Aim:
The purpose of this essay is to research the relationship between total value locked (TVL) in DeFi, the prices of native tokens on related platforms, and the price of ether, which is the dominant currency across DeFi.

Methodology:
This study is deductive and quantitative and categorized as a causal-comparative thesis. The purpose of causal-comparative research is to find relationships between variables, independent and dependent, over a certain period.

The authors used deductive reasoning to form the hypotheses and collect the data necessary to investigate the hypothesis. Additionally, the structure of the paper and the epistemological process is quantitative and based on the scientific method.

The sources used for data gathering have primarily been DefiPulse and their API:s, retrieved using simple python coding and different applications that parse JSON code into the excel format. The transparent nature of blockchain has provided easy access to data needed for this study. Once the data was collected, it was categorized and compiled into an Excel sheet.

Conclusions:
It is a considerable result that the ratio of locked ETH to total supply lacks significance for the price of ether, as it is counterintuitive to the macroeconomic theory of demand and supply. Presumably, the locked eth is not to be considered as a corresponding decrease in supply. However, if that was the case, the locked ratio of 10% is considerable and should affect the price as there is less supply available to the market.

In accordance with hypotheses two, three, and four, changes in the price of ether, TVL, and utilization rate affect the price of the native token. A notable distinction between the three different platforms lies in what metrics correlate more strongly with price changes. It for Compound and Aave was TVL, but utilization rate for MakerDAO. What causes these differences between seemingly similar platforms is a subject for further study.

Keywords:
DeFi, Decentralized finance, Peer-to-Peer, Bitcoin, Ethereum, Lending protocols, Total Value Locked, TVL, Cryptocurrency, Blockchain

Sammanfattning

Bakgrund
Inom den växande kryptovalutamarknaden har delsektorn DeFi (för "decentralized finance") vuxit explosionsartat det senaste året, och utgör en allt mer relevant del av den övergripande marknaden. Sedan Bitcoins skapande 2008 har kryptovalutor och blockchain gått från medel för enkla transaktioner till plattformar för komplexa tjänster såsom låneförmedling och handelsplatser. Flera studier undersöker determinanter för priser på kryptovalutor och några få fokuserar på viktiga parametrar för DeFi specifik, såsom "total value locked". Det är dock en sparsam skara artiklar som producerats på relationerna mellan dessa parametrar, vilket denna uppsats ämnar åtgärda

Syfte
Målet för denna uppsats är att undersöka relationerna mellan det totala fastlåsta värdet (TVL) av Ethereum inom DeFi, priserna på de inhemska valutorna för de relaterade plattformarna Aave, Compound och MakerDAO och priset på ether, vilket är den dominerande valutan inom DeFi.

Metod
Studien är deduktiv och kvantitativ och kategoriseras som kausal-komparativ, då syftet med kausal-komparativa studier är att hitta relationer mellan variabler, beroende och oberoende, över en viss tidsperiod. Författarna har använt deduktivt resonerande för att forma hypoteserna, och samlat datan nödvändig för att undersöka hypoteserna. Utöver det är uppsatsens struktur och epistemologiska process kvantitativ i sin natur, och baserad på den vetenskapliga metoden.

Källorna för datan har i huvudsak varit DeFiPulse och deras API:er, insamlade tack vare enkel python-kod och olika applikationer som kan läsa in data genom JSON-kod. Detta har sedan lagts in i Excel. Den inneboende transparenta kvalitéen hos blockkedjor har bidragit till en smidig datainsamlingsprocess.

Slutsatser
I enlighet med hypoteser indikerar en tillväxt i TVL eller utilization rate en tillväxt i priset, vilket tyder på att plattformar som Aave, MakerDAO och Compound har lyckats skapa bra incitament för användare att låsa fast sitt kapital, vilket i sin tur gör att vardera plattforms inhemska tokens blir mer värdefullt då de ofta är genom att äga plattformens token som en användare kan ta del av plattformens tjänst. Det är intressant att korrelationerna för TVL och utilization rates skiljer sig åt mellan plattformar, då de till ytan är så pass lika. Vad detta beror på är ett ämne för vidare studier, men sannolikt ligger i det i vardera plattforms incitamentsstruktur.

Vad gäller priset på ether och dess relation till hur mycket av ETH som är fastlåst var resultatet i motsats till förväntningarna. I enlighet med utbud och efterfrågan borde det finnas ett samband mellan hur mycket ether som är tillgängligt, vilket minskas ju mer som är fastlåst, och priset. Givet den höga graden av TVL i ether så borde det därför ha en effekt på priset, men så är inte fallet enligt beräkningarna. Huruvida detta beror på författarnas modeller eller de faktiska sambanden kvarstår att avgöra.

Acknowledgments

First and foremost, we cannot extend enough gratitude to Gazi Salah Uddin, without whom this article would not have been much of a contribution to society.

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Finally, we wish to show appreciation for Campushallen and their extended opening hours, the local gym, for keeping us sane throughout the process of writing this thesis.

"*I think that the Internet is going to be one of the major forces for reducing the role of government. The one thing that's missing, but that will soon be developed, is a reliable e-cash - a method whereby on the Internet you can transfer funds from A to B without A knowing B or B knowing A*."
- Milton Friedman, 1999

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1. Introduction

This chapter introduces the cryptocurrency market and Decentralized Finance (DeFi). DeFi is a subsector within crypto comprised of decentralized and permissionless financial applications built on top of a distributed ledger technology (DLT), of which blockchains are an example. An apt but rudimentary analogy being that cryptocurrencies are to blockchains what email is to the internet. DeFi services include - but are not limited to - decentralized exchanges (DEX:es), lending and borrowing, and decentralized trading derivatives (Voshmgir 2020).

The decentralized finance market saw explosive growth during the last year, growing from $677 million to $16.5 billion during 2020 and reaching an all-time high of $88.5 billion in May 2021 (DeFiPulse, 2021). As the DeFi subsector continues to grow, its influence will as well.

Therefore, it is vital to research the relationships between DeFi and the general crypto market to estimate the implications of this growth, and to achieve that this paper builds on the original research of, among others, Hegardt and Wieslander (2018), Stepanova and Eriņš (2021), and Gudgeon et al. (2020). The authors aim to contribute to an increased understanding of the cryptocurrency market by examining how central parameters within DeFi correlate and their relationships with the broader market. Additionally, the authors hope to provide a stepping-stone for further research, as the cryptocurrency market is yet to be adequately explored by academia.

Lastly, the authors approached this article with the scientific method, producing the hypotheses by deductive reasoning, and the research is causal-comparative and based on quantitative design.

1.1. Background

With the publishing of the Bitcoin whitepaper "*Bitcoin: A Peer-to-Peer Electronic Cash System*" (2008) by the pseudonymous figure or group Satoshi Nakamoto, on October 31, 2008, blockchain technology and the first cryptocurrency came into being. As quantitative easing permeated the global economy (IMF, 2009; Caldentey, 2017), Satoshi introduced a new payment processing system through distributed networks. It eliminated the need for intermediaries, central authorities, and trust, with peer-to-peer non-reversible transactions verified through decentralized consensus facilitated by the digital currency called Bitcoin (Nakamoto, 2008). In addition, through a combination of previously existing technologies and research, Nakamoto solved the Byzantine Generals Problem, a set of problems in computer science relating to malicious actors (nodes) in a decentralized network.

Through its consensus mechanism Proof-of-Work (PoW), it mitigated the influence of these malicious actors as participants instead gain from being a productive part of the network. Additionally, since a distributed consensus verifies the network and transactions submitted to it, attackers need to control more than 50% of the network to manipulate transactions, which would mean corrupting independent nodes located in various parts of the world by token of the distributed structure. As such, it consumes less power and yields greater returns to provide computational power (the “work” in PoW) to maintain the integrity of the blockchain, as active nodes receive rewards for their participation with newly minted bitcoins (Nakamoto, 2008). Other currencies appeared shortly, with early movers such as Litecoin, Ripple, and Dogecoin (dedicated to the famous meme Doge) entering the space. However, while new, they did not bring much innovation compared to the original Bitcoin protocol.

That changed in 2013 as Vitalik Buterin, a Canadian-Russian student, released the whitepaper of Ethereum, “*A Next-Generation Smart Contract and Decentralized Application Platform”* (Buterin, 2014), with a Turing-complete coding language called Solidity, adding additional functionality to the blockchain: smart contracts. While not new in theory, the combination of cryptographically ensured digital contracts launched and executed on a distributed, decentralized network allowed for far more complex structures on the platform than on earlier blockchains. Facilitated by the programmable quality of smart contracts and Solidity being Turing-complete, any service can be built on Ethereum, stretching from simple transactions to decentralized exchanges and database management systems. This opened up building services and platforms seen in traditional finance in a decentralized, trust-minimizing manner, where third-party actors or central authorities were no longer needed (Voshmgir, 2020).

As the market evolved, innovation grew with it, going beyond simply emulating what already exists in traditional finance (TradFi), with NFT:s being a good example. With a market share of 20% and over half of all cryptocurrency projects built on it, Ethereum is the dominant platform for DeFi projects, including - among others - derivatives, decentralized exchanges, perpetual swaps, indices, payment and asset management systems, automated market makers, insurance and lending. (Coingecko, 2021)

With the Ethereum blockchain as the base layer, smart contracts to build the decentralized applications on and economic incentives for liquidity provision, users get increased utility from their holdings through incentivized programs such as liquidity provision, staking, and other yield-bearing activities, to make their capital active. (defiprime, 2021). This is how DeFi services - like those mentioned above - attract capital to fund their project and service. All completely peer-to-peer. As an example, in DeFi lending, lenders can provide liquidity to borrowing pools. Borrowers - who provide collateral as security - can then borrow funds, paying an interest rate (“borrowing rate”) in return to the lenders, based on the ratio between total liquidity and outstanding loans (the utilization rate) (Voshmgir, 2020; Xu & Vadgama, 2021).
Currently, there are numerous DeFi platforms like Ethereum, such as NEAR Protocol, Avalanche, and Polygon, all of which have experienced considerable growth since the start of 2021 with market caps of $1,3B, $2.35B, and $11.5B, respectively (CoinGecko, 2021). Just as on Ethereum, a multitude of dApps exist on each of the platforms, often with their own token.

However, the dynamics between the platforms, their native projects, and token prices are not well understood by academia, including how the usage of the platform token across the platform's projects affects the price. To better understand the price determinants and financial flows within DeFi, further research is required.

1.2. Aim

The purpose of this thesis is to investigate the relationships between the total value locked (TVL) in DeFi, Ethereum, and the native tokens of major DeFi platforms, as well as the utilization rate across DeFi. The research focuses on relationships between factors central to DeFi and the crypto market and their relation to prices on related assets. The findings should help build an understanding of this emerging market, why large portions of liquidity and investor attention are attracted to DeFi, and the effect this has on prices for Ethereum and the native tokens on the platforms.

This article is the first step towards a greater understanding of how the growth of the DeFi market affects its surroundings and expands on earlier research on price determinants for cryptocurrencies.

Whether the hypotheses hold true or not, the results should provide insights on price determinants for platform tokens such as ether and if they gain value from the use of the platform and the adoption of the native token. In that sense, a comparison can be made to a common argument regarding what makes gold valuable, as it is used for jewelry and in technological hardware in addition to being a store of value.

1.3. Problem

Decentralized finance has developed from a peripheral part of the cryptomarket to an emerging subsector over the last year, attracting considerable liquidity and experiencing a high level of innovation. Since the latter part of last summer (colloquially known as "DeFi Summer"), the DeFi sector market capitalization has grown by 1500% (See figure 1. 800% for the cryptomarket as a whole), with a 545% growth since the start of this year (Coingecko, 2021).

Figure 1. DeFi market growth since May 18, 2020 (Source: CoinGecko, 2021)

Furthermore, the total value locked in DeFi protocols has grown from $15.8 billion at the start of 2021 to $84 billion at the time of writing (May 9, 2021, DefiPulse). Besides providing an overview of the market, it is interesting to research what implications this sub-sector growth has on the cryptocurrency market and how it correlates with related assets. As DeFi continues to attract investments and liquidity, the role of parameters fundamental to it as determinants of associated assets will likely grow. Consequently, as more users and investors flock to DeFi (see figure 2) and the more the rest of the crypto market connects to the DeFi subsector, the impact of the relationships investigated here will likely grow in relevance. Additionally, the research should provide insights on determinants of the price of ether.

Whether the hypotheses hold true or not, it should speak to some degree about what creates value for a token, and if how entrenched the token is across crypto, and how well used the token's native platform is, are determinants of price.

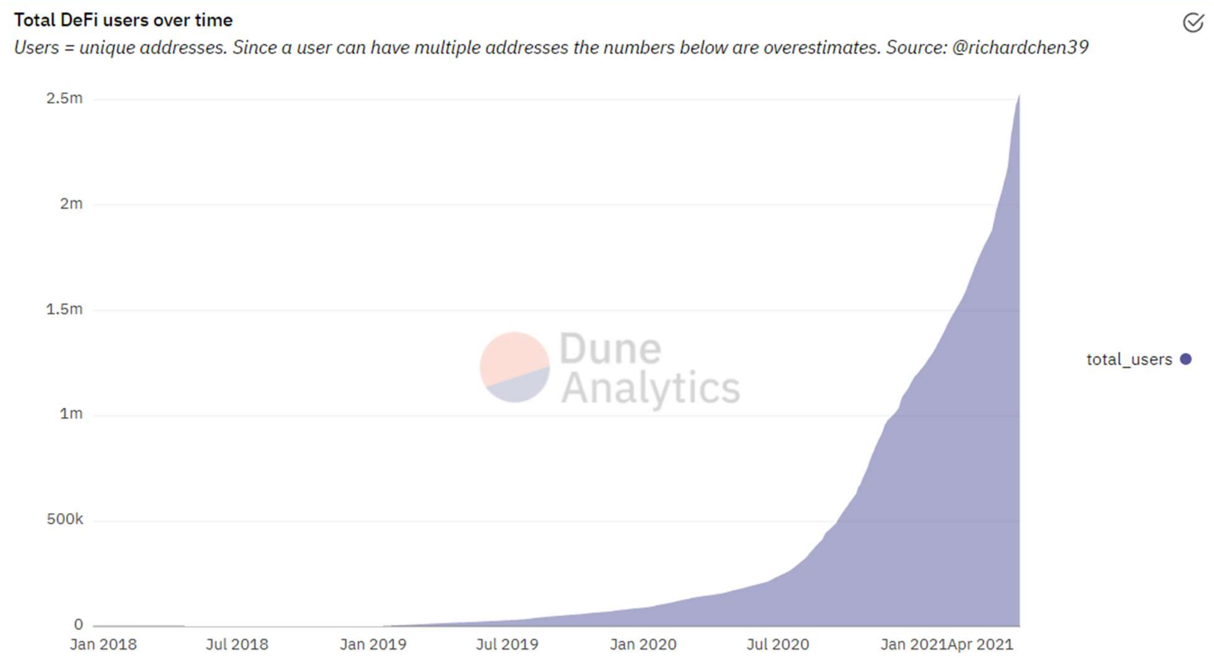

Figure 2. Growth in the number of DeFi users (Dune Analytics, 2021)

In *DeFi Protocols for Loanable Funds: Interest Rates, Liquidity, and Market Efficiency*, Gudgeon et al. research interest rates, the utilization rate of liquidity and provide a study of the markets for major currencies within DeFi lending, namely DAI, ETH, and USDC (USDC and DAI both being stablecoins). Following the research produced by Ciaian and Rajcaniova (2018), they find interdependence between interest rates across protocols for loanable funds (a term they coin in the article, referring to protocols that establish distributed ledger-based markets for loanable funds). Additionally, they find that ETH, USDC, and DAI comprise most loanable funds for Compound, Aave, and dydx (the same goes for MakerDAO, included in this article). Finally, together with Stepanova and Eriņš (2021), they provide insights on the development and dynamics of the DeFi market, its liquidity and interest rates, and why funds flow their way. While they are excellent papers that provide interesting insights into how DeFi has developed, its impact on the market and asset pricing is yet to be explored by academia.

1.4. Hypotheses

Based on the problem identified and accounted for above, the authors have produced a set of hypotheses to clarify the issues mentioned above. Subsequently, the thesis is based on the following hypotheses:

H1: The ratio of total ETH locked in DeFi services affects the Ethereum price
H2: Ethereum price, TVL, and utilization rate changes affect the MKR price
H3: Ethereum price, TVL, and utilization rate changes affect the COMP price
H4: Ethereum price, TVL, and utilization rate changes affect the AAVE price

1.5. Delimitations

To provide relevant research for the decentralized finance market and its relationship with the crypto market within the timeframe, limitations in scope were necessary.

The article's focus lies solely on DeFi platforms on the Ethereum blockchain. The top three services MakerDAO, Compound, and Aave, and their respective native tokens, represent the DeFi market. Given their market share (50% as of May 2021), the results produced should provide a general picture of TVL-prices dynamics. Additionally, our models and measurements should suffice as analytical tools for the broader crypto market and a stepping stone for future research.

With a market share of 31% as of May 8, 2021, and being the dominant non-stable coin within DeFi (DefiPulse, 2021), ETH should be a reliable proxy for the DeFi market's effect on other currencies.

We are aware that several potentially significant cryptocurrencies and various platforms are excluded but appreciate that the correlation between utilization rates, TVL, and the prices of assets readily available for trade on the selected platforms, should be stronger and indicative of a general relationship. Furthermore, centralized cryptocurrency platforms are not included.

1.6. Conclusions

It is a considerable result that the ratio of locked ETH to total supply lacks significance for the price of ether, as it is counterintuitive to the macroeconomic theory of demand and supply. Presumably, the locked eth is not to be considered as a corresponding decrease in supply. However, if that was the case, the locked ratio of 10% is considerable and should affect the price as there is less supply available to the market.

In accordance with hypotheses two, three, and four, changes in the price of ether, TVL, and utilization rate affect the price of the native token. A notable distinction between the three different platforms lies in what metrics correlate more strongly with price changes. It for Compound and Aave was TVL, but utilization rate for MakerDAO. What causes these differences between seemingly similar platforms is a subject for further study.

2.0. Literature review

Identifying determinants of an asset's price is one of the essential questions in finance, but a question whose answer for cryptocurrencies is yet to be adequately explored by academia. Traditional assets derive their prices from economic fundamentals such as earnings, with quantifiable metrics such as EBITDA (Campbell & Shiller 1988). Cryptocurrencies and related valuation models, on the other hand, are fields still in their infancy. Hayes (2017) argues, in opposition to Yermack (2013), that there is a fundamental value of Bitcoin (and, by extension, of other cryptocurrencies as well), although it is computational rather than physical. At the time of writing for Hayes, Bitcoin's market capitalization was approximately \$7 billion. As of May 9, 2021, it stands at \$1.1 trillion (Coingecko, 2021). Presumably, he was on to something. Playing to the same tune, (Bhambhwani et al. 2019) examines the relationship between computational power dedicated to a set of mineable cryptocurrencies (Bitcoin, Ethereum, Monero, Litecoin, and Dash) and prices. He finds that the hash rate (measuring how much computational power the network receives) and network are long-term determinants of price.

From fundamental analysis to forecasting, (Nasir et al. 2019) try to predict cryptocurrency returns and volume from search engine trends. While results were surprisingly accurate, it speaks little to the internal dynamics of the cryptocurrency market and how prices are determined. On the same note, (Cheah, E. and Fry, J. 2015) research the speculative quality of cryptocurrency investments, concluding that the cryptocurrency market is vulnerable to speculative bubbles and argue that the fundamental value of Bitcoin is zero.

On correlations, (Deniz, 2020) concludes that after analyzing the price determinants for Bitcoin, Ethereum, and Ripple, there are relatively few correlations or causal relationships between the selected cryptocurrencies, commodities, and precious metals. An exception is Bitcoin, found to be a Granger cause of Gold. Similar results were found by Ciaian and Rajcaniova (2018), as the cryptocurrency market showed to be independent of exogenous factors. However, coin prices (of those selected) are interdependent (although Angela & Sun (2020) showed the EUR/USD exchange rate to have a significant positive effect on the price of ether).

Unsurprisingly - considering its just until recently inconsequential share of the cryptocurrency market -, decentralized finance has received scarce attention by academia. Notable studies being Stepanova and Eriņš (2021). who researched DeFi protocols and their TVL. Gudgeon et al. (2020) coined a new terminology with "Protocols for Loanable Funds" (PLFs) to refer to protocols for loanable funds on distributed ledger technology. Muzzy et al. continued on that path with their report, *An analysis of Ethereum's decentralized finance ecosystem in Q3 2020,* written for ConsenSys.

Regarding interest rates Hegardt & Wieslander (2019) show - following the results produced by Ciaian and Rajcaniova -, that the effect of central bank interest rates on the crypto market has decreased over time, comparing with studies by (Corbet et al. (2017), Fama et al. (2019), Li & Wang, (2017), Gustafsson & Bengtsson, (2019), indicating a resilience against exogenous factors.

As such, this article constitutes an essential piece of the puzzle, as it expands on this field of research and examines yet unexplored relationships between cryptocurrency asset prices, total value locked, and utilization rates.

On cointegration, most of the relevant research underlines the importance of adequately testing for cointegration and for long-term relationships in the models as not to have spurious regressions. Stock & Watson (2014) defines two or more cointegrated variables as having a common stochastic trend, meaning that they share a long-term relationship where they tend to have a similar random walk. The most central papers on this subject are Granger (1981), in which the term was coined, and Engle & Granger (1987), where the econometric and mathematical foundations were expanded on. Granger and Newbold (1974) describe the importance of ensuring the stationarity of variables as not as previously mentioned to create spurious regressions where some variables seem to be causally correlated when they are not. Integrated variables are non-stationary that are differenced over time. This, in turn, simulates stationarity and stochastic processes.

3.0. Basics of blockchain and cryptocurrencies

The following chapter aims to provide an overall understanding of the most fundamental definitions and aspects of blockchain and cryptocurrency. In addition, it will explain and detail the building blocks and the concepts necessary to provide the reader with sufficient information to fully grasp the subject matter.

A blockchain is a public, open, peer-to-peer, distributed, secure and reliable network, functioning as a permanent, continuously updated ledger - a registry of the growing chain of transactions since genesis (the chain's first recorded block. See figure 3) - accessible and verifiable by anyone with an internet connection. (Nakamoto, 2008; Voshmgir 2020)

Each transaction has a unique fingerprint (called a hash) and is stored together with other transactions verified in the same batch (the block).

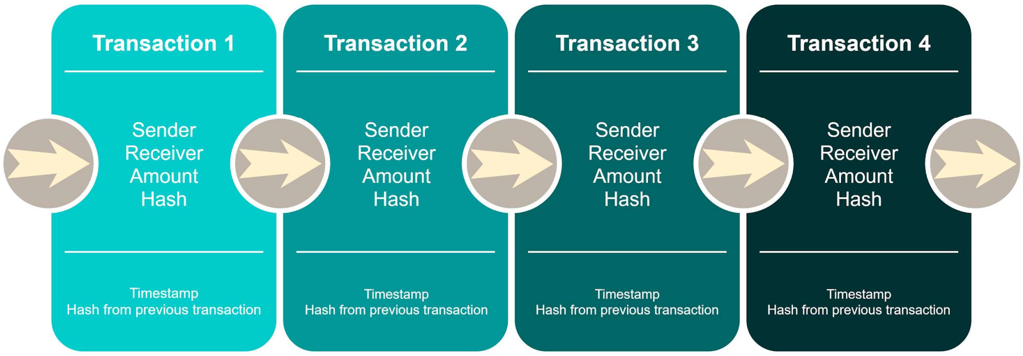

Figure 3. Simplified illustration of the blockchain transactional mechanics (Own illustration, 2021)

The blockchain is formed in the same manner, as the information of every block is encrypted into a hash and added to the "header" of the next block in line, creating a chain. Then, the network participants perform the verification of transactions and maintenance of the blockchain by dedicating hash power to it, ensuring that everything follows the protocol (the rules of the blockchain). This verification process is determined by the consensus mechanisms - the process of reaching consensus on a blockchain. (Nakamoto, 2008).

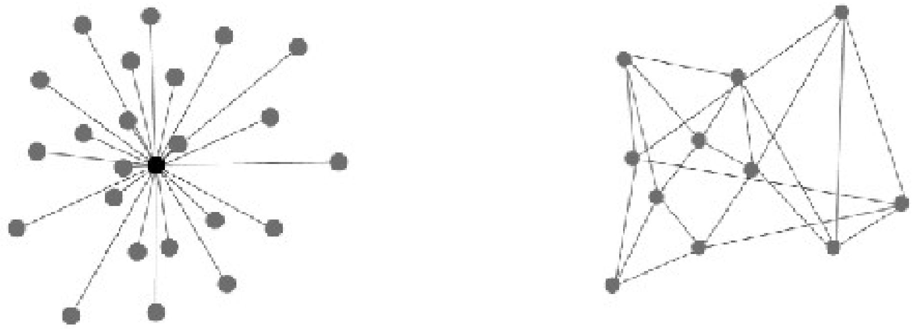

Figure 4. Centralized contra distributed networks (Voshmgir, 2020)

Once verified, nodes then broadcast this new information to other nodes to achieve complete synchronization of the ledger (see figure 4). One significant contribution is that it enables digital scarcity, as it solves the double-spending problem of digital items. Furthermore, since the balance of each account on the blockchain is public and verified by the network, no account can send more than they have access to (determined by the history of transactions to and from that account) (Voshmgir, 2020). As such, an account cannot copy a Bitcoin or any other asset, as that would require the approval of the network, as opposed to an email that can be reproduced indefinitely. Therefore, a value can be determined for the digital item, and markets with fully digital assets can develop. One example of these digital items is cryptocurrencies, which represent ownership on the blockchain.

The original cryptocurrencies (Bitcoin and - among others -, Ripple, Litecoin, and Dogecoin) are examples. However, while their use as digital currencies - available anywhere in the world, requiring only an Internet connection - garnered interest, the blockchain concept was still primitive, allowing for little else than simple transactions between users. This changed with the launch of Ethereum in 2015.

4.0. Ethereum and decentralized finance

Decentralized finance (DeFi) came with the launch of Ethereum, in 2015, two years after the release of the whitepaper, *A Next-Generation Smart Contract, and Decentralized Application Platform*, in 2013. As mentioned above, it expands on the blockchain concept with smart contracts, allowing for more complex services to be built on decentralized, distributed networks as decentralized applications. With the blockchain as the settlement layer and with the help of interoperable, transparent smart contracts, it allows peer-to-peer interactions, removing the necessity for third parties or central authorities, such as banks or clearinghouses.

Smart contracts are digital, self-enforcing agreements used to encode rules of engagement on the blockchain for any interaction, such as a transaction, or the creation of new assets with certain functionalities on the same blockchain, or even entire financial services such as a decentralized exchange. (Voshmgir, 2020).

Services typically seen in traditional finance could now be built in a decentralized manner, and exchanging assets between users could be automated in a trustless, decentralized system. A system where users can enter and exit at will and protocols can connect seamlessly without permission in a financial ecosystem akin to open-source financial legos (see figure 5 for an overview of how different bricks fit together, from blockchain to decentralzied applications). This composability is one of the significant benefits of DeFi and is a by-product of the open-source, permissionless nature of crypto.

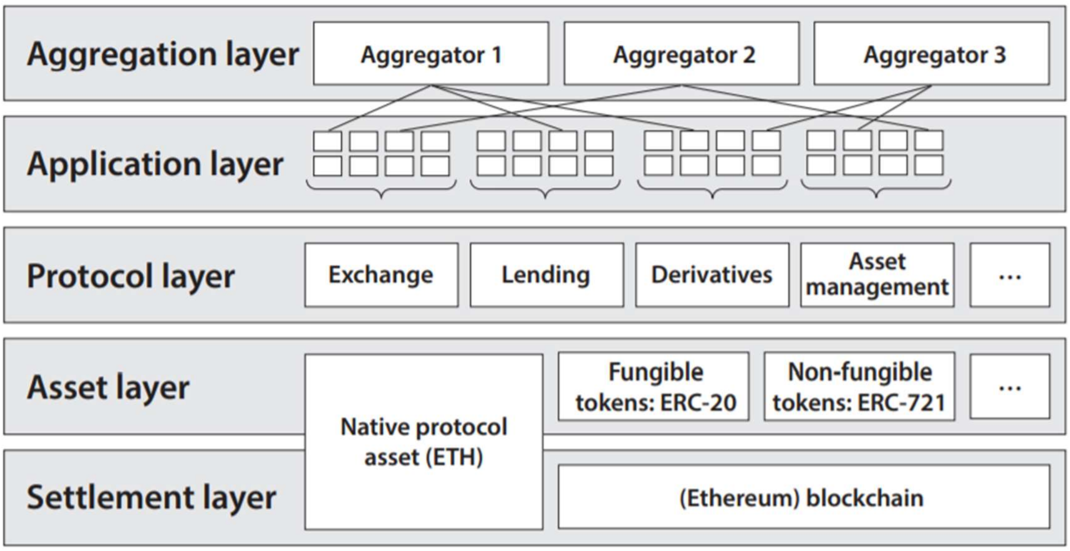

Figure 5. "The DeFi Stack", (St Louis Federal Reserve, 2021)

Further, entire organizations can be structured in the same manner. Known as Decentralized Autonomous Organizations (DAO:s), these decentralized organizations are entirely governed by the collective of network nodes (users), facilitated through tokens used for voting on proposals made by users to the network. One benefit of this distributed structure is that it tackles the principal-agent dilemma (the misalignment of priorities between shareholders and management), (Voshmgir, 2020).

4.1. The DeFi Market

The decentralized finance sub-sector currently comprises a small part of the total cryptocurrency market (5,6%) but has experienced explosive growth since DeFi Summer. The major platforms are MakerDAO, Compound, and Aave, all of which are lending platforms where users can stake liquidity that other users can borrow from, if they provide collateral (often >150% of the amount borrowed, to cover against fluctuations in price (defirate, 2021)) and for a given interest rate.

In contrast to how lending works in traditional finance, with financial institutions as the trusted third parties that mediate between lenders and borrowers, there is no mediator in DeFi as users interact directly via the smart contracts on the platform. Another contrast lies in banks' unique position as money creators. Through the system of fractional reserves, they can issue loans larger than the amount they hold in reserve. The issues originating from such a system are not the subject of this article, but worth mentioning is the risk of bank runs in times of economic hardship. If a sudden wave of depositors were to withdraw their funds, the banks would quickly run out of the reserves used to finance their loans, leading to defaults. A similar dynamic caused banks' default in 2008, as financial institutions' holdings became nearly worthless as the housing market collapsed (Reinhardt and Roghoff, 2011). In comparison, the over-collateralization on DeFi platforms average at 258% (defirate, 2021), meaning that in order for someone to borrow $100, they usually provide $258 in collateral. The resulting system is, in theory, more stable than fractional reserve banking despite the heavy fluctuation in asset prices, as the norm is over-collateralization from the borrowers' side rather than leveraging from the lender side.

A second major part of DeFi is decentralized exchanges (DEX:es), with Uniswap, Curve Finance, Sushiswap, and Balancer being the dominant actors (joint market share of 25,9/XX, DeFiPulse, 2021). The major difference compared to centralized exchanges is that DEXes is decentralized, open, peer-to-peer applications running on distributed ledger technology (DLT), allowing users to trade digital assets (such as tokens or NFTs) without the need for an institution clearing the settlements. Instead, it is settled peer-to-peer through the ledger (the seller's balance account is lowered, and the buyer's balance is increased). It also means that anyone can list their assets on the exchange without permission (Voshmgir, 2020). An apt comparison is the processes of an IPO on Nasdaq and that of listing your token on a DEX. The latter requires an hour of work and can be done by anyone - regardless of how long the token has existed or how established it is.

5.0. Data and Methodology

The following chapter presents the methodology and the data retrieval process used to test the hypotheses presented earlier in the paper. It will also explain how the data were categorized and compiled and the authors' approach through the study.

The nature of this study is deductive and quantitative, and as such, it can be categorized as a Causal-Comparative design. The purpose of causal-comparative research is to find relationships between variables, independent and dependent, over a certain period. This process can determine whether the independent variables have a causal relationship with the dependent variable. For this paper, the aim is to investigate the effect of one or more variables on selected dependent variables, and as such, a causal-comparative approach has been chosen.

Throughout the study, the authors have used deductive reasoning. First, to form the hypotheses and collect data necessary to investigate the problem according to them. The hypotheses that lay the groundwork for this thesis aim to explore what relationships are present and central to DeFi dynamics.

The significant amount of locked Ethereum gives the background for the first hypothesis in DeFi services and earlier research (Stepanova & Eriņš and Deniz & Teker, particularly) DeFi TL and price determinants. The hypothesis aims to continue their work and investigate whether changes in the locked ratio (the amount of ETH locked compared to the total supply of ETH) affect the price. The assumption being those changes in the amount of ETH locked correlate with price.

Hypotheses two through four aim to expand that same research on DeFi-specific platforms and their native tokens. As the protocols in question run on the Ethereum blockchain and many loans are denominated in ether, this paper aims to study the relationship between the ether price and the price of the tokens of the protocols above. The assumptions being that Ethereum and ether have a significant effect on the native tokens of the protocols. It will also delve deeper into the relationship between changes in utilization rate, total value locked, and the prices of the native tokens.

To answer these hypotheses, the structure of the paper and the epistemological process is quantitative and based on the scientific method.

Additionally, the basic quantitative design procedure can be described as making your observations about something unknown and then hypothesizing an explanation for these observations. The authors identified these potential relationships within DeFi and produced a group of hypotheses that should help explain the phenomena observed (Salkind, 2010). The sources used for data gathering have primarily been DefiPulse and their API:s, retrieved using simple python coding and different applications that parse JSON code into the excel format. All time-series data is daily given the volatile nature of the assets in question and the custom practice when investigating price determinants in cryptocurrencies. The service "Cryptosheets" has also been used to gather data. The service allows the retrieval of data to Google Sheets/Excel through an add-on using the previously mentioned DefiPulse API. The transparent nature of blockchain has provided easy access to data needed for this study. Once the data was collected, it was categorized and compiled into an Excel sheet. This Excel sheet has been used to construct econometric models in EViews as well as RStudio.

Lastly, logarithmic variables were chosen to control for outliers in the price movements.

5.1. Variables Definitions

Table 1. Variable definition of all variables used in the models.

Variable	Definition
ETH	Ethereum price
BTC	Bitcoin price
LockedRatio	Ratio of locked ETH in Defi services compared to total ETH supply
MKR	MakerDAO token price
MKRTVL	Total Value Locked in all MakerDAO Defi services
COMP	Compound token price
COMPTVL	Total Value Locked in all Compound Defi services
AAVE	Aave token price
AAVETVL	Total Value Locked in all AAVE services
UTILRATE	Utilization Rate, Debt outstanding in Lending Services divided by Total Value Locked in Lending

5.2. Process of Empirical Testing

The following process has been conducted for each model to get the best possible model fits and to observe the effect of the independent variables on the dependent variable:

Stationarity: Given the prerequisite of stationarity for the utilization of autoregressive models, stationarity will be tested using the Augmented Dickey-Fuller (ADF) Test. The ADF test is used as it is the best available test for determining the order of integration, that is I(0), I(1), or even I(2) in some cases. Furthermore, stationarity is necessary to ensure the stability of the statistical properties of the time series (constant mean and standard deviation as well as accounting for seasonality) and as not to get spurious relationships, where multiple variables are associated but not necessarily causally related (Box et al., 2015; Dolado et al., 1990; Hubler & Frohn, 2006). This will be done through the normal unit root function with Akaike's information criteria (AIC) in EViews, displaying the ADF test statistic and p-value for the level of difference.

Autoregressive Distributed Lag Model (ARDL) Test: The primary function of the ARDL is for dynamic regressions, in which an independent variable can be tested for correlations over time for both itself, and it is the independent variables to see what orders of lags affect the dependent variable at period t, that is the observed period (Hubler & Frohn, 2006; Stock & Watson, 2014).
Once all previous steps are done, an ARDL test can be executed to test for the best lag structure and best model fit. Using the ARDL estimation function in EViews, this is done with Akaike Info Criterion (AIC) as the model selection method. After that, a bound's test is conducted to test for cointegration to check whether the variables are bound together in the long term. Finally, the

ARDL model fit process is done as indicated by Bo Sjö (2015), in which the lags are gradually increased in a fixed and not automatic matter until the best model is found.

Diagnostics Test (Serial Correlation): Stock & Watson (2014) defines autocorrelation as a pervasive feature of time series, in which previous years tend to correlate with what happens in later years. To test for the autocorrelation of residuals and their lagged values but also between the dependent and independent variables, the function "Serial Correlation LM Test" is used. This is to ensure the unbiasedness of the coefficients in the models.

An example of a simple autoregressive model distributed lag model ARDL(p, q) would be as following:

$$\Delta lnY_t = \alpha + \sum_{i=0}^{p} \beta_i \Delta lny_{t-i} + \sum_{i=1}^{q} \delta_i \Delta lnx_{t-i} + \varphi_1 \Delta lnx_{t-i} + \mu_t \tag{1}$$

Where:
ΔlnY_t *is the logarithmic change in the dependent variable*
$\sum_{i=0}^{p} \beta_i \Delta lny_{t-i}$ *is the sum of lagged dependent variable* (y) *where* p *is the optimal number of lags*
$\sum_{i=0}^{q} \delta_i \Delta lnx_{t-i}$ *is the sum of lagged independent variable* (x) *where* q *is the optimal number of lags*
$\varphi_1 \Delta lnx_t$ *is the effect of* x *at period* t & μ_t *is the error term*

5.3. Data Periods

Given the infancy of the subject matter, the data is restricted to the following dates:

Table 2. Periods and number of observations for each of the time series.

Series	Start	End	N
H1	2017-09-02	2021-05-10	1347
H2	2019-11-18	2021-05-17	547
H3	2020-06-18	2021-05-17	334
H4	2020-01-07	2021-05-17	497

The periods and number of observations vary as different protocols have different launch dates and available data. This should, however, be sufficient to conduct proper empirical testing.

5.4. Descriptive Statistics

Table 3. Descriptive statistics for all variables and their logarithmic first differences.

	SERIES	MEAN	MEDIAN	MAX	MIN	STD. DEV.	SKEW NESS	KURTOS IS	N
H1	Ethereum	478.64	275.21	3954.28	82.83	537.39	2.84	12.62	1347
	Bitcoin	12509.73	8660.45	63445.64	3185.07	12797.1	2.62	8.92	1347
	LockedRatio	0.0265	0.0203	0.0961	8.72E-06	0.0262	1.162	3.26	1347
	Δ Ln (ETH)	2.678442	0.234610	478.1715	-235.1286	39.40857	2.46	34.04	1346
	Δ Ln (BTH)	38.11880	15.41911	7118.922	-5391.664	735.6882	0.97	21.47	1346
	Δ Ln (LR)	0.026457	0.020329	0.096057	8,72E-06	0.026209	1.16	3.26	1346
H2	Maker	1013.693	542.9320	6066.121	201.0659	1095.280	2.322787	8.120757	546
	Ethereum	709.6943	353.8957	4155.772	110.3282	826.0711	1.913050	6.340093	546
	Ln (Maker TVL)	20.79595	20.89573	23.34406	16.96641	1.323077	0.040955	2.153911	546
	Utilisation Rate	0.370579	0.348763	0.601132	0.225933	0.088382	0.783694	2.903508	546
	Δ Ln (MKR)	0.003456	0.001280	0.409505	-0.840156	0.074946	-1.477380	36.54585	546
	Δ Ln (ETH)	0.0053	0.004293	0.244828	-0.565614	0.053896	-2.017850	26.67261	546
	Δ Ln (MKRVL)	0.013897	0.008806	1.435361	-0.241153	0.078499	11.28124	200.7294	546
	Δ Ln (UtilRate)	0.000490	-0.000831	0.113862	-0.123554	0.036270	0.166695	4.120569	546
H3	Compound	272.2486	179.8354	859.1714	87.17034	186.6023	1.207567	3.519366	333
	Ethereum	1047	574.2141	4155.772	220.6994	908.8903	1.320231	4.221152	333
	Compound TVL	22.03037	21.90649	23.54787	20.23550	0.847914	0.276513	1.807913	333
	Utilisation Rate	0.500804	0.511627	0.594705	0.296312	0.055729	0.074265	0.048607	333
	Δ Ln (COMP)	0.004668	-0.000930	0.425460	-0.186875	0.074265	0.688940	6.025207	333
	Δ Ln (ETH)	0.007963	0.007514	0.244828	-0.188621	0.048607	-0.037488	5.539970	333
	Δ Ln (CompTVL)	0.010229	0.010584	0.357233	-0.255581	0.049145	0.967672	17.02064	333
	Δ Ln (UtilRate)	0.001626	0.000440	0.293163	-0.121340	0.029413	0.029413	2.812886	333
H4	Aave	121.1868	46.35548	597.7807	1.618930	162.2293	1.283422	3.071319	496
	Ethereum	767.0007	379.8965	4155.772	110.3282	845.7975	1.789467	5.819093	496
	Aave TVL	20.07594	21.04460	23.55603	12.68088	2.378136	-0.576057	2.357670	496
	Utilisation Rate	0.208039	0.206463	0.381624	0.004210	0.042277	0.530005	5.377978	496
	Δ Ln (AAVE)	0.011386	0.008165	0.577416	-0.644731	0.093287	-0155685	10.53000	496
	Δ Ln (ETH)	0.006313	0.005482	0.244828	-0.565614	0.055379	-2.076930	26.42729	496
	Δ Ln (AaveTVL)	0.029848	0.013930	3.987249	-0.607791	0.200795	15.70444	306.6799	496
	Δ Ln (UtilRate)	0.007274	-0.000583	3.399643	-0.805359	0.180886	13.25738	253.1701	496

6.0. Results

In this chapter, we will provide an in-depth analysis of the results that were fetched through the data analysis. As well as present the finding from the empirical process detailed in the previous chapter.

6.1. Stationarity Test

Table 4. Results from the ADF-test with the Akaike Information Criterion.

	Series	Level - I(0)		1st Difference – I(1)		
		t-Stat	Prob.	t-Stat	Prob.	N
H1	ETH	4.6344	1.0000	-4.0502	0.0012 ***	1324
	BTC	2.0329	0.9999	-8.5273	0.0000 ***	1325
	LockedRatio	0.8219	0.9944	-7.9662	0.0000 ***	1325
H2	MKR	0.668432	0.8600	-4.234208	0.0000 ***	528
	ETH	3.963114	1.0000	-5.625955	0.0000 ***	529
	Ln(MKRTVL)	3.821546	1.0000	-16.11141	0.0000 ***	545
	UtilRate	-0.090895	0.6520	-22.79509	0.0000 ***	546
H3	COMP	-0.177022	0.9383	-18.92369	0.0000 ***	333
	ETH	1.355019	0.9989	-5.107612	0.0000 ***	319
	Ln (COMPTVL)	-0.635752	0.8593	-12.03939	0.0000 ***	330
	UtilRate	-3.780746	0.0034 **	-	-	332
H4	Aave	0.493932	0.9864	-4.237368	0.0006 ***	480
	ETH	2.985136	1.0000	-5.772201	0.0000 ***	479
	Ln (AAVETVL)	-4.641063	0.0001 ***	-	-	496
	UtilRate	-4.736103	0.0001 ***	-	-	495

Note: * indicates significance at 10%, ** at 5% and *** at 1%

Table 4 details the results from the ADF tests with the Akaike Information Criterion conducted to evaluate the most proper order of integration for the variables, both dependent and independent. The results can be read as the following, the probabilities presented indicate the p-value of the test, any result above the significance level of 5% means the rejection of the null hypothesis of stationarity at the tested order of integration.

As for hypothesis 1, in which the effects of bitcoin and the locked ratio on Ethereum are investigated, the results indicate that the first difference is most suitable for all variables in the model. As shown in the table, all variables had p-values way above the significance level and were significant at the first order of integration. Hypothesis 2, where the determinants of the Maker token price are probed, shows similar results as in the model for the first hypothesis, meaning the optimal order of integration for the variables is the first difference.

The models for hypotheses 3 and 4 evaluate the effects of the determinants on the price of Compound and Aave respectively, the results from the ADF tests vary from that of the previous models as the UtilRate variable in the third model and both the logarithmic TVL and UtilRate in the fourth model show stationarity at level and need therefore no differencing.

6.2. ARDL Test Results

H1: The ratio of total ETH locked in DeFi services affects the Ethereum price.

Table 5. Results from the ARDL short-term test for the model related to the first hypothesis.

	Series	Coefficient	Std. Error	t-Stat	Prob.	R^2	AIC
	Dependent variable: $\Delta\, ln\, \mathrm{ETH}_t$						
H1	$\Delta\, ln\, \mathrm{ETH}_{t-1}$	0,102595	0,027252	3,764683	0,0002 ***		
	$\Delta\, ln\, BTC_t$	0,952562	0,021895	43,50535	0,0000 ***		
	$\Delta\, ln\, BTC_{t-1}$	-0,133687	0,033792	-3,956174	0,0001 ***		
	$\Delta\, ln\, BTC_{t-2}$	0,045986	0,021819	2,107652	0,0352 **		
	$\Delta\, ln\, LockedRatio_t$	-0,005760	0,006929	-0,831281	0,4060		
	C	9.27E-05	0,000931	0,099635	0,9206	0,5898	-3,921370
	Note: * indicates significance at 10%, ** at 5% and *** at 1%						

Table 5 shows the results from the ARDL test for the model in hypothesis 1. The ARDL model brought forward, through the fixed method previously mentioned in chapter 5, was an ARDL (1, 2, 0) in which the dependent variable is lagged once, the independent variable BTC is lagged twice, and no lags were implemented for the Locked Ratio variable.

The lagged logarithmic change in the price of ETH, the logarithmic difference in the price of BTC as well as the first two lagged values in BTC show a significant effect on the logarithmic change in the price of ETH at period t, given that their p-values (Prob.) are below the significance level of 5%. Locked Ratio shows no statistically significant effect on the dependent variable with a p-value of 0,4060, meaning that the changes in the locked ratio do not affect the changes in the price of Ethereum. The model shows a high level of R-squared, at around 58.98%.

H2: Ethereum price, TVL, and utilization rate changes affect the MKR price.

Table 6. Results from the ARDL short-term test for the model related to the second hypothesis.

	Series	Coefficient	Std. Error	t-Stat	Prob.	R^2	AIC
	Dependent variable: $\Delta\, ln\, \mathrm{MKR}_t$						
H2	$\Delta\, ln\, \mathrm{MKR}_{t-1}$	-0,109896	0,033636	-3,267250	0,0012 ***		
	$\Delta\, ln\, \mathrm{MKR}_{t-2}$	0,024321	0,031337	0,776126	0,4380		
	$\Delta\, ln\, \mathrm{MKR}_{t-3}$	0,122001	0,030755	3,966826	0,0001 ***		
	$\Delta\, ln\, ETH_t$	0,978216	0,047313	20,67531	0,0000 ***		
	$\Delta\, ln\, MKRTVL_t$	0,061444	0,065799	0,933813	0,3508		
	$\Delta\, ln\, UtilRate_t$	0,206008	0,083054	2,480420	0,0134 **		
	C	-0,002452	0,002353	-1,041885	0,2979	0.5177	-3.049857
	Note: * indicates significance at 10%, ** at 5% and *** at 1%						

Similarly, table 6 shows the results from the ARDL test for the model in the second hypothesis, in which the best ARDL structure turned out to be an ARDL (3, 0, 0, 0) model, meaning that the dependent variable is lagged thrice and no lags were implemented on the independent variables. Here, it can be observed that the first and third lagged variables of MKR are statistically significant, meaning that they assumably influence the price at period t, the observed period. On the other hand, the second lagged variable of MKR and the TVL seems not to affect the changes in price for the MKR native token. Finally, the changes in Ethereum price and the changes in the utilization rate significantly influence the price changes in MKR, as can be seen under "Prob." where they both have p-values lower than the significance level of 5%, indicating significance.

H3: Ethereum price, TVL, and utilization rate changes affect the COMP price.

Table 7. Results from the ARDL short-term test for the model related to the third hypothesis.

	Series	Coefficient	Std. Error	t-Stat	Prob.	R^2	AIC
	Dependent variable: $\Delta\, ln\, \mathrm{COMP}_t$						
H3	$\Delta\, ln\, \mathrm{COMP}_{t-1}$	0,053003	0,051431	1,030571	0,3035		
	$\Delta\, ln\, ETH_t$	0,711460	0,068988	10,31282	0,0000 ***		
	$\Delta\, ln\, ETH_{t-1}$	-0,247056	0,078255	-3,157067	0,0017 ***		
	$\Delta\, ln\, COMPTVL_t$	0,169212	0,073271	2,309386	0,0215 **		
	$ln\, UtilRate_t$	-0,031950	0,029165	-1,095511	0,2741		
	C	-0,024385	0,020528	-1,187863	0,2358	0.2987	-2.783008
Note: * indicates significance at 10%, ** at 5% and *** at 1%							

The results from the ARDL test for the third hypothesis are presented in Table 7. The results indicate an ARDL model of (1, 1, 0, 0), meaning that 1 level of lag was implemented on both the dependent variable, COMP, and the independent variable, ETH.

A significant effect can also be seen from the table. Both the logarithmic change in ETH and the one period lagged ETH have p-values below the significance level of 5% (0,0000 & 0,0017, respectively). Similarly, the logarithmic change in COMPTVL also seems to be significantly correlated with the logarithmic change in the price of the MKR token. The first lagged value of COMP and the independent variable UtilRate seem to not affect the price, however, given their p-values above 5%. The R-squared value for this model is 29.87%, a somewhat low R-squared but one good enough to perform time-series data with.

H4: Ethereum price, TVL, and utilization rate changes affect the AAVE price.

Table 8. Results from the ARDL short-term test for the model related to the fourth hypothesis.

	Series	Coefficient	Std. Error	t-Stat	Prob.	R^2	AIC
	Dependent variable: $\Delta\, ln\, \mathrm{AAVE}_t$						
H4	$\Delta\, ln\, \mathrm{AAVE}_{t-1}$	-0,055999	0,040361	-1,381747	0,1659		
	$\Delta\, ln\, ETH_t$	0,809313	0,067304	12,02481	0,0000 ***		
	$ln\, AAVETVL_t$	0,089883	0,041437	2,169148	0,0306 **		
	$ln\, AAVETVL_{t-1}$	-0,090332	0,041111	-2,197272	0,0285 **		
	$ln\, UtilRate_t$	-0,014262	0,018956	-0,752361	0,4522		
	C	-0,008508	0,042915	-0,198245	0,8429	0,2589	-2,184378
Note: * indicates significance at 10%, ** at 5% and *** at 1%							

Lastly, the output of the ARDL test for the fourth hypothesis can be seen in Table 8. The most optimal ARDL structure turned out to be an ARDL (1, 0, 1, 0) model, in which both the lagged version of AAVE and AAVETVL are implemented into the models and no lags for ETH and UtilRate. The variables with significant effects on the logarithmic change in price for the AAVE protocol token turned out the following: ETH, AAVETVL, and the one period lagged version of AAVETVL (p-values of 0.0000, 0.0306, and 0,0285, respectively), all other variables seemed not to influence the price. For this model, the R-squared value amounted to 25,89%, quite like the previous model.

6.3. Diagnostics Test (Serial Correlation)

Table 9. Results from the LM Serial Correlation test for each of the constructed models.

	Lags	F-statistic	Prob. F	Prob. Chi Square	Serial Correlation
H1	2	0,479122	0,6194	0,6178	No
H2	3	1,47588	0,2201	0,2147	No
H3	1	0,026467	0,8709	0,8694	No
H4	1	0,324568	0,5691	0,5662	No

The LM Serial Correlation tests investigated whether there is any serial- or autocorrelation between the independent variables. The results from the test show no serial correlations at the 5% significance level, meaning that there is no autocorrelation nor serial correlation between the variables in all models. This can be observed through the Prob. Chi-Square in which all values above 5% (0.05) cannot reject the null hypothesis of no serial correlation. The test was done on the different number of lag orders to fit with the specific nature of each model.

6.4. ARDL Bounds Test (Cointegration test)

Table 10. Results from the ARDL F-bounds Cointegration test for each of the models.

	F-statistic	k	Sign. level	N	I(0)	I(1)
H1	273,9611	2	5%	1344	3,1	3,87
H2	165,7283	3	5%	543	2,79	3,67
H3	68,62274	3	5%	332	2,79	3,67
H4	200,7883	3	5%	495	2,79	3,67

The ARDL Bounds test was used to determine the long-term cointegration relationship between the dependent and independent variables. The test results indicate long-term cointegration if the F-statistic, given the k (number of independent variables) and depending on the levels of integration, is outside the bounds at the specified significance level. All hypothesis models returned values way above the bounds meaning that all variables have a long-term cointegration relationship between the dependent and independent variables. Engle & Granger (1987) proves this removes the risk for spurious regressions and allows for proper time series analysis.

6.5. Model Construction

The following chapter will present a snapshot of the models that were used throughout the empirical process. This only aim is to provide a simplified understanding of the models behind the results. These models were built with model 1 (see sub-chapter 5.2.) in mind. In turn, the model was inspired by Bo Sjö (2019), in which the author provides a detailed guide on how to test for ARDL and cointegration.

1. **The ratio of total ETH locked in DeFi services affects the Ethereum price. ARDL (1,2,0)**

The following model was constructed for hypothesis one given the results from the tests from the previous sub-chapters:

$$\Delta lnETH_t = \alpha + \sum_{i=0}^{p} \beta_i \Delta lnETH_{t-i} + \sum_{i=1}^{q} \delta_i \Delta lnBTC_{t-i} + \pi \Delta lnLockedRatio_t + \varphi_1 lnETH_{t-i} + \varphi_2 lnBTC_{t-i} + \mu_t \qquad (2)$$

Where:

$\Delta lnETH_t$ *is the logarithmic change in the Ethereum price at period t*

$\sum_{i=0}^{p} \beta_i \Delta lnETH_{t-i}$ *is the sum of lagged dependent variable* (ETH) *where p is equal to* 1

$\sum_{i=0}^{q} \delta_i \Delta lnBTC_{t-i}$ *is the sum of lagged independent variable* (BTC) *where q is equal to* 2

$\pi \Delta lnLockedRatio_t$ *is the effect of the logaritmic change in LockedRatio on the change in price at period t*

$\varphi_1 lnETH_{t-i} + \varphi_2 lnBTC_{t-i}$ *is the long − term effect &* μ_t *is the error term*

2. **Ethereum price, TVL, and utilization rate changes affect the MKR price. ARDL (3,0,0,0)**

The following model was constructed for hypothesis two given the results from the tests from the previous sub-chapters:

$$\Delta lnMKR_t = \alpha + \sum_{i=0}^{p} \beta_i \Delta lnMKR_{t-i} + \delta_i \Delta lnETH_t + \pi \Delta lnMKRTVL_t + \omega \Delta lnUtilRate_t + \varphi_1 lnMKR_{t-i} + \mu_t \qquad (3)$$

Where:

$\Delta lnMKR_t$ *is the logarithmic change in the Maker price at period t*

$\sum_{i=0}^{p} \beta_i \Delta lnMKR_{t-i}$ *is the sum of lagged dependent variable* (MKR) *where p is equal to* 3

$\pi \Delta lnMKRTVL_t$ *is the effect of the logaritmic change in MKRTVL on the change in price at period t*

$\omega \Delta lnUtilRate_t$ *is the effect of the UtilRate on the change in price at period t*

$\varphi_1 lnETH_{t-i}$ *is the long − term effect &* μ_t *is the error term*

3. **Ethereum price, TVL, and utilization rate changes affect the COMP price. ARDL (1,1,0,0)**

The following model was constructed for hypothesis three given the results from the tests from the previous sub-chapters:

$$\Delta lnCOMP_t = \alpha + \sum_{i=0}^{p} \beta_i \Delta lnCOMP_{t-i} + \sum_{i=1}^{q} \delta_i \Delta lnETH_{t-i} + \pi \Delta lnCOMPTVL_t + \omega lnUtilRate_t + \varphi_1 lnCOMP_{t-i} + \varphi_2 lnETH_{t-i} + \mu_t \qquad (4)$$

Where:

$\Delta lnCOMP_t$ *is the logarithmic change in the Compound price at period t*

$\sum_{i=0}^{p} \beta_i \Delta lnCOMP_{t-i}$ *is the sum of lagged dependent variable* $(COMP)$ *where p is equal to* 1

$\sum_{i=0}^{q} \beta_i \delta_i \Delta lnETH_{t-i}$ *is the sum of lagged independent variable* (ETH) *where q is equal to* 1
$\pi \Delta lnCOMPTVL_t$ *is the effect of the logaritmic change in COMPTVL on the change in price at period t*
$\omega lnUtilRate_t$ *is the effect of UtilRate on the change in price at period t*
$\varphi_1 lnCOMP_{t-i} + \varphi_2 lnETH_{t-i}$ *is the long − term effect &* μ_t *is the error term*

4. Ethereum price, TVL, and utilization rate changes affect the AAVE price. ARDL (1,0,1,0)

The following model was constructed for hypothesis four given the results from the tests from the previous sub-chapters:

$$\Delta lnAAVE_t = \alpha + \sum_{i=0}^{p} \beta_i \Delta lnAAVE_{t-i} + \sum_{i=1}^{q} \delta_i\, lnAAVETVL_{t-i} + \pi \Delta lnETH_t + \omega lnUtilRate_t + \varphi_1 lnAAVE_{t-i} + \varphi_2 lnAAVETVL_{t-i} + \mu_t \quad (5)$$

Where:
$\Delta lnAAVVE_t$ *is the logarithmic change in the Compound price at period t*
$\sum_{i=0}^{p} \beta_i \Delta lnAAVE_{t-i}$ *is the sum of lagged dependent variable* $(AAVE)$ *where p is equal to* 1
$\sum_{i=1}^{q} \delta_i\, lnAAVETVL_{t-i}$ *is the sum of lagged independent variable* $(AAVETVL)$ *where q is equal to* 1
$\pi \Delta lnETH_t$ *is the effect of the logaritmic change in ETH on the change in price at period t*
$\omega lnUtilRate_t$ *is the effect of UtilRate on the change in price at period t*
$\varphi_1 lnAAVE_{t-i} + \varphi_2 lnAAVETVL_{t-i}$ *is the long − term effect &* μ_t *is the error term*

7.0. Discussion

This chapter will discuss the results as they are presented throughout chapter 6, the implication these results might uphold, and the essential aspects extrapolated from the empirical process. In addition, a mix of the literature review from chapter 2 and the results will help explain the factors behind the changes in asset prices. Finally, to better understand the discussed models, we reference the equations from the previous chapter, where sub-chapter 6.5 provides detailed information about the construction of each of the models and the variables included.

The empirical process used through the fifth chapter and the results produced in the sixth gives us a clear indication of the health of our models. Given the validity of all steps of the process and that all requirements are fulfilled (no serial correlation, stationarity, and especially the cointegration and long-term relationships between the variables), it can be concluded that the results are valid and can be used for empirical analysis to test whether the hypotheses in question are to be rejected or not.

As shown in Chapter 6.5 equation 2, the model for the first hypothesis, Ethereum price movement, is the dependent variable, and both Bitcoin price movement and locked ratio are the independent variables. The results for the first hypothesis provide a clear-cut refusal and lack of evidence for the correlations between the total Ethereum locked in DeFi services compared to the total supply and the price changes in Ethereum. The initial aim of the hypothesis was to test for the determinants of the asset Ethereum (as argued for in Chapter 2) and whether the locked Ethereum could have limited the total supply and, in turn, increased the price through the supply-demand mechanisms from classical macroeconomics. This could, however, clearly be rebuffed given the lack of empirical evidence to support the claim.

The main ambition behind the second, third and fourth hypotheses was to test for the determinants of the dependent variable, that is, the token price for each of the protocols (mainly Aave, Compound, and Maker) as they constitute a considerable share of the DeFi market. The independent variables analyzed for each of the tokens were the following: The price of Ethereum, the total value locked in each of the protocols, and the utilization rate (the ratio between debt outstanding and liquidity locked). Additionally, the effect of lagged variables (both dependent and independent) on the price of the native tokens was tested through an ARDL process. These models can be observed in chapter 6.5 as the equations numbered 3, 4, and 5, respectively.

The results for the three models were quite surprising, mainly due to their inconsistency. First to be analyzed was the maker native token MKR. The outcome revealed a clear correlation between changes in the price of the native token and the Ethereum price changes. Changes in utilization rate influence the price changes in MKR. Lastly, the lagged variables for MKR and ETH influenced the price. This corresponds to earlier research, such as Ciaian and Rajcaniova (2018), showing evident interdependence between cryptocurrencies.
However, there was no indication that the total value locked in MakerDAO (MKRTVL) had any effect on the price, as the p-value was far higher than 5%. Consequently, it can be derived that both the utilization rate and the price of Ethereum can be used as determinants for the price of

MKR. As for the hypothesis, the conclusion is that only certain parts of the hypothesis could be verified where the rest must be rejected, mainly the influence of the TVL on the price of MKR.

After that, the price determinants for COMP were analyzed similarly to MKR; these were ETH, Utilization Rate, and the total value locked in the Compound DeFi services. As expected, there is a correlation between the changes in price for Ethereum and that of COMP. This can be seen in the regressions where ETH and the first lagged order of ETH have a p-value lower than that of the significance level. Furthermore, and contradictory to the results from the previous hypothesis, the total value locked in the Compound seems to influence the price of COMP while the utilization rate does not. This is a clear divergence from the results previously observed and paves the way for further research.

Finally, the price determinants for AAVE were put through the empirical process with similar variables as those for the second and third hypothesis, meaning ETH, AAVETVL, and UTILRATE. Analogous to the previous hypotheses, changes in the price of Ethereum seem to influence the price movement in AAVE, confirming that part of the hypothesis. Regarding TVL and UtilRate, however, the results here seem to be like those of COMP and contrary to those of MKR, where both AAVETVL and its first lagged order seem to affect the price changes in AAVE. The utilization rate seems not to have any influence on the price.

In relation to earlier research these results are quite interesting. As shown by Ciaian and Rajcaniova (2018), there are similarities between cryptocurrencies and how their prices move (high interdependency within crypto), but the results in this article clearly identify differences between price determinants of similar tokens, as Aave, Compound and MakerDAO are all lending platforms, but differ in correlations and causal relationships for prices. Additionally, the lack of influence from utilization rate for Compound is quite interesting, especially in relation to Hegardt and Wieslander (2019); If exogenous prices on capital are not influential (disregarding the results produced by Angela and Sun), endogenous factors would presumably take their place. In this case, it appears to be otherwise.

Given the scarcity of research regarding this topic, it is difficult to explain the reasons behind these divergences. However, as previously mentioned, this sets up for future research in which the specific reasons can be delved into more detail.

7.1. Methodological critique

The methodology used throughout this paper can be held for much scrutiny. However, whether it is the way the models were constructed or how the empirical process was performed, many improvements and even different techniques can be implemented further to progress the accuracy and authenticity of the paper.

The authors find the following areas to be most lacking in the paper:

- The empirical process could have been improved upon significantly in the case of data processing and ARDL testing. A more proper and thorough approach, with additional types of tests (for example, VARMA, DCC-GARCH, ARIMA, etc.), could have presented better results than those found in this paper.

- A deeper look into other determinants of the prices could have been highly relevant, in which a closer look at the mechanics and code behind the protocols could have been a better approach.
- Further linking the subject matter to aspects of traditional finance would have possibly increased the relevance and made the study more approachable and easily understood.
- Other price determinants of Ethereum should have been implemented but were omitted as not to overcomplicate the study and limit it to a specific area.
- The recent crash in the price of Ethereum and the substantial decrease in total value locked in DeFi services are not included in this study, as they occurred after the data was tested. This could have played a significant role in the testing and might have presented a more nuanced picture of the nature of the correlations.
- One of the misses of this research is to investigate the directionality of correlations in the regression; here, we believe in having committed Simultaneous Causality Bias. That is that we did not investigate the direction of the correlation between the variables in the hypotheses.
- The results from the empirical process could have been presented more legibly.
- More relevant aspects of the DeFi market should have studied, i.e., interest rates.

7.2. Further research

As the cryptocurrency market in general and DeFi are relatively unexplored research areas, the venues for continued research are plenty. Additionally, the relevance of the markets and related research will likely grow as they garner increased interest from traditional finance. While there are many more related and interesting topics to research than what can be included here, there have surfaced several points of interest during writing this thesis, but the including of which the short timespan did not allow for. From the delimitations alone, there can be derived topics for further research: A similar study includes centralized platforms, as their interest rates and TVL indeed influence asset prices (primarily provided the interdependencies in the cryptocurrency market shown by cited research), would be interesting.

Further, closer studies on different parts of DeFi, as correlations likely differ between, among others, lending, DEX:es and AMM:s. A greater understanding of how they differ could be of great interest to the sector for many reasons. One of them is to help mechanism designers build applications with better-calibrated incentives.

Another point of interest in which proper research needs to be conducted relates to the interest rates in DeFi lending services. The previous aim of this paper was to investigate the relationship between interest rate changes and the price of native tokens. Unfortunately, the lack of time and resources restricted the scope of the research, and delimitations were introduced not to bloat the aim of the thesis.

Research on price determinants for platform tokens such as ETH will likely grow together with the sector, with projects such as Avalanche, Polygon, and Near Protocol experiencing considerable growth in users during 2021. This article provides a glimpse into the implications this has for their respective tokens, TVL, connected platforms and projects, and other relevant metrics. Still, a vast area of unexplored dynamics remains unexplored.

Finally, given the results of this thesis, further research can be conducted on why there is a correlation between MakerDAO token price and utilization rate but not for the TVL, and vice versa for the Compound and Aave tokens.

8.0. Conclusion

It is a considerable result that the ratio of locked ETH and total supply lacks significance for the price of ether, as it is counterintuitive to the macroeconomic theory of demand and supply. It follows that the amount of locked ETH is not considered a corresponding decrease in supply. If that was the case, the considerable locked ratio of 10% should affect the price as there is less supply available to the market. Additional research is needed to explore that dynamic and determine more relevant metrics of value-creating usage for platform tokens, as - provided our research holds - the ratio between locked supply and total supply does not affect the token price. Whether this is generally applicable to platforms similar to Ethereum, such as Near Protocol, Polygon, and Binance Smart Chain, is a subject for future research. Still, the authors would be surprised if there are considerable differences. Although, there is some credence to the argument that this is a dynamic unique to ETH, provided by how established it is across the entire cryptocurrency market - DeFi being no exception. Other platforms will likely not enjoy the same position for some time, which should affect their pricing. As Bhambhwani et al. (2019) showed, the network effect is one factor in price determination.

In accordance with hypotheses two, three, and four, changes in the price of ETH, TVL, and utilization rate affect the price of the native tokens. However, a notable distinction between the three different platforms lies in what metrics correlate more strongly with price changes, as for Compound and Aave was TVL, but utilization rate for MakerDAO. What causes these differences between seemingly similar platforms is also a subject for further study.
In relation to the results on price determination for ETH, we find some credence to the argument made for ETH above regarding its position in the market.

Delving into this unexplored topic carried a heavy weight, the uncertainty of not coming to a proper and relevant conclusion was a looming thought throughout writing this thesis. However, we believe that we have managed to create something highly relevant, if not for the substance of the paper itself, for it to be a guide for future research and discussion. Furthermore, both Blockchain and DeFi have shown their antifragility throughout the last years, constantly adapting and adjusting for black swans and the turbulence in the markets. With that in mind, we believe that this topic will bear great relevance in the upcoming years.

9.0. List of References

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10.0. Glossary

- **Decentralized Finance (DeFi)**
  Financial services that are built on blockchain technology, with no central authority or third party.
- **Lending Pools**
  Liquidity provided by users to DeFi lending protocols, where different pools allow for different assets to be
- **Cryptocurrency**
  Digital cryptographically ensured currencies, built on a blockchain.
- **Total Value Locked (TVL)**
  The total value of assets locked in a protocol. Used in this paper for lending protocols lending pools.
- **Timestamp**
  Used for the measurement of date and time. Symbolizes the number of seconds since Unix Epoch (01/01/1970).
- **Collateralized Debt Positions** Collateral deposited into a lending pool in exchange for the protocol currencies of choice.
- **Stablecoins**
  Cryptocurrencies with stable values, ensured either by reserve or by algorithms.
- **Peer-to-Peer (P2P)**
  Trading is executed between seller and buyer directly, without intermediaries.
- **Tokens**
  A digital representation of an asset, tradable between users in a peer-to-peer manner.
- **Smart contracts**
  A smart contract is a self-executing contract with the terms of the agreement between buyer and seller being directly written into lines of code.
- **Whitepaper**
  A document outlining the purpose and structure of a service or product.
- **Collateral ratio**
  The ratio between collateral deposited and loan supplied.
- **TradFi**
  Traditional finance
- **Utilization rate**
  The ratio between outstanding loans and total value locked. An important metric within DeFi lending as it measures available liquidity.
- **Byzantine Generals Problem**
  A problem related to decentralized networks, on how to ensure that the network makes correct decisions even if some nodes in the network go rogue (malicious actors).
- **Mining**
  The process of verifying and recording transactions and maintaining protocol integrity.
- **Consensus Mechanism**
  The mechanism through which consensus is reached in a decentralized, distributed network.
- **Proof-of-Work**
  A kind of consensus mechanism, where nodes who provide work to the network, can vote.
- **Validator**
  A role within the proof-of-stake consensus mechanism, which validates transactions. Corresponds to the Miner role in Proof-of-Work.
- **Proof of stake**
  A consensus mechanism in which nodes gain voting rights by staking the native token of the protocol.
- **Granger Causality**
  a hypothesis test in statistics for determining whether one time series is useful in forecasting another.
- **Turing-complete**
  A thing (such as a programming language) is Turing-complete when it can be used to solve any computational problem.