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Price Dynamics in Centralized and Decentralized Exchanges

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Price Dynamics in Centralized and Decentralized Exchanges

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Statement of Authorship

I hereby declare that the thesis submitted is my own work. All direct or indirect sources used are acknowledged as references. I further declare that I have not submitted this thesis at any other institution in order to obtain a degree.

To my family.

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"Whereas most technologies tend to automate workers on the periphery doing menial tasks, blockchains automate away the center. Instead of putting the taxi driver out of a job, blockchain puts Uber out of a job and lets the taxi drivers work with the customer directly."

Vitalik Buterin

Resumo

Esta dissertação investiga a dinâmica de preços do Ethereum em corretoras centralizadas e descentralizadas para contribuir com a sistematização do conhecimento de criptomoedas e Finanças Descentralizadas (DeFi). Este estudo segue Alexander et al. (2020) usando modelos autorregressivos, incluindo VECM, e de cointegração para investigar a dinâmica de descoberta de preços entre os mercados. Usamos Diebold and Yilmaz (2012) para estimar a magnitude dos spillovers entre a Uniswap V2 (corretora descentralizada) e três outras corretoras centralizadas, Binance, Gemini e Bitstamp, comparando os preços de ETH/USDC em todas as corretoras. Nossa análise revela que a Binance desempenha um papel central no processo de descoberta de preços entre mercados, pois demonstra um nível mais alto de spillover bruto para outras corretoras em comparação com Uniswap, Bitstamp e Gemini. Por outro lado, o Uniswap oferece significativamente menos spillover para outras corretoras do que as outras corretoras centralizadas e é influenciado pelas outras corretoras centralizadas significativamente mais do que as influencia. Além disso, o estudo mostra que a Binance responde mais rapidamente a desvios de preços em outras corretoras em comparação com as outras corretoras do estudo, enfatizando o papel crucial da Binance no processo de descoberta de preços. Por fim, observamos que o ruído da microestrutura nos mercados estudados se dissipa à medida que a frequência das observações diminui, a curva do gráfico de assinatura de volatilidade torna-se mais suave e começa a filtrar o ruído, com o Uniswap convergindo com as trocas spot por volta da marca de 40 minutos. No geral, as descobertas deste estudo fornecem uma melhor compreensão da dinâmica de preços do Ethereum em corretoras centralizadas e descentralizadas e contribuem para o crescente corpo de conhecimento sobre criptomoedas e DeFi.

Palavras-chave: *blockchain*, finanças, finanças descentralizadas, corretora, corretora descentralizada

Resumo Expandido

Introdução

O white paper de Nakamoto (2008) introduziu o Bitcoin, uma moeda digital peer-to-peer baseada no blockchain proof-of-work. Posteriormente, Buterin et al. (2014) identificou limitações no Bitcoin e criou o Ethereum, uma blockchain Turing-completa de propósito geral, possibilitando o desenvolvimento de contratos inteligentes, retomando ideias de Szabo et al. (1994). Com Ethereum, introduziu-se a criptomoeda Ether, utilizada para pagar pela execução dos contratos inteligentes (gas fees). Os contratos inteligentes permitiram a criação de tokens interoperáveis, como o ERC-20, e dentre eles, as stablecoins, que possuem valor atrelado a moedas fiduciárias ou ativos. Um exemplo é a USD Coin (USDC), considerada uma das mais transparentes stablecoins lastreadas off-chain.As Finanças Descentralizadas (DeFi) fornecem serviços financeiros automatizados por meio de contratos inteligentes. Chain Analysis (2021) destaca o crescimento de DeFi liderado por investidores institucionais e profissionais e o predomínio de corretoras descentralizadas (DEXs) nesse ecossistema.As DEXs permitem transações diretas entre compradores e vendedores sem intermediários confiáveis e reduzem riscos associados às plataformas centralizadas. Em comparação às corretoras centralizadas (CEXs), as DEXs têm velocidade de transação dependente da taxa de "gas"paga e do par de negociação.As DEXs baseadas em livros de oferta enfrentaram dificuldades devido a ineficiências, enquanto os modelos de formação automática de mercado (AMM) obtiveram sucesso. Uniswap V2 é um exemplo de DEX que utiliza o protocolo AMM e segue uma função constante para as reservas de ativos antes e depois das trocas.

Objetivos

O objetivo é aprofundar a pesquisa em um nicho específico das Finanças Descentralizadas, as Corretoras Descentralizadas (DEXs). Essas plataformas operam com modelos automatizados, sem intermediação centralizada. Com a crescente popularidade e adoção das DEXs como alternativa às Corretoras Centralizadas (CEXs), torna-se relevante analisar as diferenças entre elas em termos de liquidez, segurança e velocidade de transação, o que pode impactar a dinâmica de preços, volatilidade, oportunidades de arbitragem e eficiência de mercado.

Metodologia

Neste estudo, foram analisados dados de diferentes origens para investigar a dinâmica de preços do token Ether (ETH) em relação à stablecoin USDC. Utilizando o Dune Analytics, uma ferramenta de pesquisa de blockchain, foram extraídos dados minuto a minuto do par de negociação UniswapV2 ETH/USDC. A escolha do Uniswap V2 foi motivada pela simplicidade em comparação com o V3 e pela possibilidade de determinar facilmente o preço de um par específico. Os dados brutos foram coletados diretamente das APIs das bolsas, evitando o uso de agregadores de classificação, que podem alimentar dados incorretos. Os dados da Binance, Bitstamp e Gemini foram extraídos de seus respectivos bancos de dados. A análise compreendeu o período de setembro de 2021 a setembro de 2022. Para investigar a descoberta de preços em praças centralizadas e descentralizadas, foram seguidos modelos VAR, VECM e de cointegração propostos por Alexander et al. (2020). Além disso, adotou-se a abordagem de Diebold and Yilmaz (2012) para computar medidas de spillover, quantificando os spillovers entre a corretora descentralizada Uniswap e corretoras centralizadas Binance, Bitstamp e Gemini. Calculou-se o índice de spillover de volatilidade e replicou-se a tabela de conectividade, permitindo entender e quantificar a direção dos spillovers de volatilidade entre as classes de ativos. O estudo baseou-se na suposição de cointegração, testando a relação de cointegração através do teste de Johansen. A análise incluiu uma avaliação da correlação de retornos do par de negociação ETH/USDC e um gráfico de assinatura de volatilidade para visualizar melhor a descoberta de preço entre os diferentes mercados.

Resultados e discussão

Analisamos a descoberta de preços entre a corretora descentralizada Uniswap V2 e as corretoras centralizadas Binance, Bitstamp e Gemini. Descobrimos que, em média, o spillover total não varia significativamente e se mantém próximo a 61,03%, indicando alta conexão entre os mercados. Os spillovers líquidos mostram que Bitstamp e Gemini têm pouca influência, enquanto Binance afeta mais os outros mercados. Em contraste, Uniswap é mais afetada pelos outros. A dinâmica de descoberta de preços apresenta distinções claras entre corretoras. Uniswap tem menos spillover para outras corretoras (6,04%) do que é influenciada por elas (35,9%). Binance, por outro lado, influencia mais os outros mercados (82,47%) do que é influenciada por eles (62,74%). Os coeficientes de correção de erro mostram que a Binance é a mais rápida em responder a desvios de preço em outras corretoras. A análise destaca o papel central da Binance na descoberta de preços, com maior spillover direcional total e resposta rápida a desvios. Em contrapartida, Uniswap é mais influenciado pelas outras corretoras centralizadas e tem menor impacto no mercado.

Considerações Finais

Investigamos a dinâmica de preços do ETH/USDC em exchanges centralizadas e descentralizadas, utilizando índice de spillover, tabela de cointegração e gráfico de assinatura de volatilidade. Os resultados apontam a Binance como protagonista na descoberta de preços, respondendo rapidamente aos desvios e causando maior spillover. Em contrapartida, a Uniswap não apresenta spillover significativo nem resposta ágil a choques de preços. Ademais, não foi identificada maior interconexão entre Uniswap e exchanges centralizadas ao longo do tempo, e o ruído da microestrutura tende a dissipar conforme a frequência das observações diminui.

Palavras-chave: *blockchain*, finanças, finanças descentralizadas, corretora, corretora descentralizada

Abstract

This thesis investigates the price dynamics of Ethereum across centralized and decentralized exchanges to contribute to the knowledge systematization of cryptocurrencies and Decentralized Finance (DeFi). This study follows Alexander et al. (2020) using autoregressive, including VECM, and cointegration models to investigate the price discovery dinamics between markets. We use Diebold and Yilmaz (2012) to estimate the magnitude of spillovers between the Uniswap V2 (decentralized exchange) and three other centralized exchanges, Binance, Gemini, and Bitstamp, comparing the prices of ETH/USDC in all of the exchanges. Our analysis reveals that Binance plays a central role in the inter-market price discovery process, as it demonstrates a higher level of gross spillover to other exchanges compared to Uniswap, Bitstamp, and Gemini. On the other hand, Uniswap gives significantly less spillover to other exchanges than the other centralized exchanges, and it is influenced by the other centralized exchanges significantly more than it influences them. Furthermore, the study shows that Binance responds more quickly to price deviations in other exchanges compared to the other exchanges in the study, emphasizing the crucial role of Binance in the price discovery process. Finally, we observed that microstructure noise in the studied markets dissipates as the frequency of observations decreases, the volatility signature plot curve becomes smoother and start to filter out the noise, with Uniswap converging with spot exchanges at around the 40 minute mark. Overall, the findings of this study provide a better understanding of the price dynamics of Ethereum across centralized and decentralized exchanges and contribute to the growing body of knowledge on cryptocurrencies and DeFi.

Keywords: *blockchain*, finance, decentralized finance, exchange, decentralized exchange

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1 Introduction

Cryptocurrencies have rapidly gained popularity and have been widely discussed and adopted over the past few years. With the emergence of blockchain technology, the financial landscape has undergone a transformation, and Decentralized Finance (DeFi) has emerged as a new paradigm in finance. DeFi refers to a system of financial applications built on blockchain technology that operate in a decentralized, peer-to-peer manner, without the need for intermediaries such as banks or financial institutions. Despite the growing interest and adoption of cryptocurrencies and DeFi, there is still a lack of knowledge systematization about these new financial instruments. As the speed of innovations in the blockchain space is challenging to follow, it is necessary to explore their particularities.

Our goal is to deepen the research in a specific niche of Decentralized Finance, which are Decentralized Exchanges. These exchanges operate using unique, automated models in which there is no centralized escrow or trusted third parties. With the increasing popularity and adoption of decentralized exchanges (DEXs) as an alternative to traditional centralized exchanges (CEXs) it is relevant to explore the differences between these two types of exchanges in terms of liquidity, security, and transaction speed may have implications for price dynamics, including volatility, arbitrage opportunities, and market efficiency.

The motivation for this study stems from the lack of research in the literature regarding the uniqueness of DEXs compared to CEXs and how they relate in terms of price discovery and efficiency. Some argue that DEXs may lead to more efficient and fair prices, due to their decentralized nature, while others contend that CEXs have advantages in terms of liquidity and speed (Capponi; Jia, 2021). Therefore, this study aims to contribute to the ongoing debate by examining the spillover effects and price dynamics of ETH/USDC across different types of exchanges.

We conduct a comprehensive examination of the price dynamics in both centralized and decentralized cryptocurrency exchanges, with a focus on the largest players in each category. By comparing the trading volume, number of trades, and volume per trade of the biggest centralized exchange (Binance) and the biggest decentralized exchange (Uniswap), we aim to shed light on the differences and similarities between these marketplaces and their implications for price discovery in the digital asset ecosystem.

Our study follows Alexander et al. (2020) which used autoregressive models, including VECM, and cointegration models to investigate the price discovery dynamics between markets. This thesis utilizes the connectedness framework developed by Diebold and Yilmaz (2009) and Diebold and Yilmaz (2012) to examine the relationship between Ether (ETH) prices in the decentralized exchange Uniswap and cryptocurrency prices in centralized exchanges. The primary objective of this study is to investigate the dynamics of price discovery between these two markets. To achieve this, we employ a cointegrated vector autoregressive (VAR) model based on Alexander et al. (2020).

Utilizing the cointegrated VAR model, we calculate the spillover measures as proposed by Diebold and Yilmaz (2012) in order to quantitatively assess the extent of connectedness between the two markets under study. Our analysis, grounded in empirical data, reveals that Uniswap predominantly functions as a net receiver of price spillovers, thereby indicating that price information primarily flows from centralized to decentralized exchanges. Moreover, our findings underscore the pivotal role that Binance, as a leading centralized exchange, plays in the process of inter-market price discovery. This evidence contributes to a more nuanced understanding of the interaction between centralized and decentralized cryptocurrency markets and their respective influences on the overall price formation process.

Furthermore, following Hansen and Lunde (2006), we conduct an additional exercise to compare the returns and volatility of Ether negotiated in Uniswap to those negotiated in a centralized exchange. We created a volatility signature plot, which helped us to understand how the process of price discovery occurs across various markets as it displays the relationship between the observed volatility and the sampling frequency of the data. We find that microstructure noise in the studied markets dissipates as the frequency of observations decreases; the volatility signature plot curve becomes smoother and starts to filter out the noise, with Uniswap converging with spot exchanges at around the 40-minute mark. Overall, our findings provide insights into the dynamics of interconnectedness between decentralized and centralized markets and their implications for price discovery and market efficiency in the cryptocurrency ecosystem.

2 Literature Review

2.1 Blockchain

Nakamoto (2008)'s white paper created a purely peer-to-peer digital currency for the first time, which does not require trusted third parties, financial institutions, or central banks. The primary technology, introduced by Nakamoto, behind Bitcoin, is the proof-of-work[1] blockchain. A public, immutable ledger shared by all nodes on that system (maintained by miners, each node maintains a complete copy of the blockchain). For the first time, in a public, decentralized network, participants did not need to know and trust each other to verify electronic transactions — which are done through cryptographic algorithms that can be verified and corrected, even if attacked by malicious nodes.

Buterin et al. (2014) describes several limitations of the Bitcoin scripting language, such as the lack of not supporting all types of computation (Turing-completeness). Leading the movement to use blockchain technology for other purposes beyond simply being a cryptocurrency, without all these limitations of the Bitcoin blockchain, alongside his peers, Ethereum was created - a new general-purpose Turing-complete blockchain (Ethereum can compute any program of any complexity).

Ethereum, often described as a 'global computer,' is a decentralized computing infrastructure that uses its blockchain to synchronize and store all system state changes. In addition, it runs programs called smart contracts.

2.1.1 Smart Contracts

The term smart contract was created by Szabo et al. (1994) to designate computerized transaction protocols that execute the terms of a contract. The design goals of these smart contracts are to satisfy common contractual conditions, minimize malicious and accidental exceptions, and eliminate the need for trusted intermediaries.

Buterin et al. (2014) formalizes and introduces smart contracts into the Ethereum blockchain. Within this context, Smart Contracts are programs (scripts) that run on blockchain and have their correct execution guaranteed by a consensus protocol. These programs can, for example, automatically move digital assets according to pre-specified arbitrary rules (Zheng et al., 2020).

The cryptocurrency Ether, the native token of the Ethereum blockchain, is used to pay for the execution of smart contracts on this blockchain. This cost is called gas

[1] A decentralized consensus mechanism that requires members of a network to solve an arbitrary mathematical puzzle to prevent someone else from manipulating the system.

fee, and it depends as much on the complexity of the code as on the computational work required to run it as on the general usage of the Ethereum network. This vision that Ethereum would be a blockchain that could be programmed for different use cases was quickly adopted and expanded. It increasingly became a platform for developing and programming Decentralized Applications - dApps - which are automatic programs written with smart contracts with a web interface. (Antonopoulos; Wood, 2018)

Ethereum's smart contracts have allowed other projects to create their own tokens, which can have different uses and could represent just about anything. These tokens, issued on the Ethereum network, have robust standards that keep all tokens issued interoperable. This is because they follow standards. For example, the ERC-721 refers to the non-fungible token standard, and the ERC-20 standard refers to fungible tokens. Most cryptocurrencies issued follow the latter; the advantage of using it is that there is no need to create a new blockchain for that case, all these tokens are part of the Ethereum blockchain.

The Swiss Financial Market Supervisory Authority - FINMA - guidelines FINMA (2018) categorizes tokens issued on blockchains into three categories based on their respective economic functions. Payment tokens (cryptocurrencies): tokens intended for use, present or future, as a means of payment to purchase goods or services or as a means of payment or transfer of value. Utility Tokens: Tokens intended to provide digital access to an application or service through a blockchain-based infrastructure. Asset Tokens: represent assets such as a debt or equity claim on the issuer. Asset tokens promise, for example, a share in the company's future profits or future capital flows. In terms of their economic function, therefore, these tokens are analogous to stocks, bonds, or derivatives. Tokens that allow physical assets to be traded on the blockchain also fall into this category. It is worth mentioning that these classifications are not mutually exclusive; the tokens can perform the three functions described — in this case, FINMA refers to them as hybrid tokens.

2.1.2 Stablecoins

The prices of crypto assets such as Bitcoin or Ethereum are primarily determined by the supply and demand dynamics in the market. The value of these assets is not backed by any physical commodity or government guarantee, which means that their prices can fluctuate rapidly based on market sentiment, news, and regulatory developments. Unlike traditional financial markets where central authorities control monetary policy, crypto markets are decentralized and operate based on a consensus algorithm, which allows for peer-to-peer trading and transactions.

In contrast, tokenized fiat currencies such as the tokenized US dollar are designed to be stablecoins and are pegged to a fiat currency or a basket of assets. This means that the value of one tokenized USD must always be equal to one fiat USD. The price stability of these tokens is achieved through various mechanisms, such as over-collateralization, algorithmic adjustments, and governance protocols that ensure the proper functioning of the stablecoin. The pegging mechanism allows that tokenized fiat currencies can be used as a medium of exchange and a store of value, which is critical for the growth and adoption of blockchain-based applications.

According to Berentsen and Schär (2019) this makes stable tokens useful for fiat connectivity and for hedging for cryptocurrency exchanges, especially in those that do not provide a fiat currency ramp. A hypothetical investor may choose to hedge the fluctuating value of bitcoin by trading their bitcoin for US dollar tokens in one transaction and make sure that the value of those tokens in US dollars will not fluctuate against the fiat dollar. This protection will exist as long as the price is truly stable and as long as protections such as minting and redeeming tokens are still in place. When transforming assets into tokens, a process known as tokenization, the issuer risk is one of the factors of most concern. Digital assets like Bitcoin and Ether will not natively suffer this moment in trouble, but the issuance of a token with a promise, depends significantly on the issuer's credibility. stablecoins are o particular case. They are tokens whose purpose is to keep a peg against another asset and are commonly found in the US dollar or Euro. The big advantage is bridging assets outside the blockchain (off-chain) into the blockchain (on-chain) .

There are three types of stablecoins: those with off-chain collateral, those without on-chain collateral and those with no collateral. Off-chain collateral stablecoins: These stablecoins are backed by real-world assets (such as US dollar or gold) held by a trusted third-party custodian. The issuer of the stablecoin then creates and distributes tokens on the blockchain that represent the value of the collateral. On-chain collateral stablecoins: These stablecoins are backed by other cryptocurrencies held in a smart contract on the blockchain. The value of the stablecoin is maintained by ensuring the value of the collateral always exceeds the value of the stablecoin issued. Algorithmic stablecoins: These stablecoins use a combination of algorithms and incentives to maintain their value. The supply of the stablecoin expands or contracts depending on market demand, with the goal of keeping the stablecoin price stable. Algorithmic stablecoins do not have collateral backing them up and rely entirely on market mechanisms. (Berentsen; Schär, 2019)

The first successful stablecoin - Tether (USDT) - was launched in late 2014 by a group called Tether Lmtd. Tether Foundation created an off-chain colleteral type of cryptocurrency that stays stable: for every USDT offered, the reserve holds $1. This keeps the USDT price stabilized around $1, as each unit of USDT can be redeemed for one US dollar in reserve. This was a solution to the limited use of cryptocurrencies at the time. (Tether, 2015)

According to data extracted from Coingecko (2022), with the increase in volume in the cryptocurrency market in 2017 and the appreciation of Bitcoin at the time, the demand for Tether increased significantly. Total Tether in circulation surpassed $1 million for the first time in January 2016. A year later, in January 2017, it was just below 10 million. As early as January 2018, with the price of Bitcoin approaching $20,000, the amount of Tether in circulation grew to over $1.4 billion. Today, the total market capitalization of stablecoins is $136.31 billion U.S. dollars. The Tether token has a capitalization of $70 billion U.S. dollars, making it the most dominant stablecoin.

Despite being the most stable and liquid cryptocurrencies, Tether (USDT) has been the subject of several controversies, with many questioning the company's transparency and whether there would really be a 1:1 ratio between Tether and the US dollar. (Lopatto, 2021)

USD Coin (USDC) is the second-largest stablecoin by market capitalization and volume. It is considered by many to be the most transparent alternative of off-chain stablecoins, as its audits prove the existence of underlying assets every month, much more regularly than Tether's. (Tether, 2022)

The stablecoin Dai, created by MakerDAO, was the basis of what would come to be called DeFi. This protocol allows individuals to issue a stablecoin, pegged to the US dollar price, using other tokens as collateral - on-chain. This stablecoin was the first that would not need an equivalent reserve of dollars in a bank to maintain its peg. (MakerDAO, 2017)

2.1.3 Decentralized Finance

According to Evans (2021), Decentralized Finance — DeFi — can be described as the set of protocols and dApps that provide automated financial services through smart contracts.

Werner et al. (2021) draws a scenario of what would be DeFi for optimists: a revolutionary technological advance that offers a new architecture for a non-custodial, permissionless financial system), public and fully auditable, pseudo-anonymous, and potentially bringing new capital efficiencies. This view believes that DeFi takes up the original ideas of non-custodial transactions from the Nakamoto (2008) whitepaper, expanding them to financial applications.

A metric commonly used to measure the adoption of DeFi protocols is the Total Value Locked - TVL - which is precisely the sum of the value, in dollars, of all assets (Ether and ERC-20) deposited in smart contracts actively receiving yield. This amount has increased from 2 billion dollars in August 2018 to 180 billion dollars in December, 2021 to 48 billion dollars at February 2023. (DefiLlama, 2023)

According to Chainanalysis (2021) there is a distinction between the growth of DeFi and the general cryptocurrency ecosystem. While emerging markets are at the forefront of cryptocurrency adoption, institutional and professional investors are driving the growth of DeFi.When analyzing transaction volume, it was noticed that between July 2020 and July 2021, nine out of twenty-five of the cryptocurrency services in North America were DeFi protocols, the most popular being Uniswap, dydx and Compound. Each of these services has different uses: the first is a DEX, the second has a greater focus on derivatives and the third on loans.

Examining the interrelatedness of NFTs, DeFi tokens and cryptocurrencies Karim et al. (2022) examined the connectedness and transmission of extreme risk in blockchain markets using (Diebold; Yilmaz, 2012) spillover indices and Quantile VAR estimates at different levels of volatility. The study found significant risk spillovers among blockchain markets, with a strong disconnection of non-fungible tokens (NFTs).

Decentralized Exchanges

Among all existing DeFi applications, Decentralized Exchanges (DEXs) stand out — they use different protocols to perform non-custodial swaps on the Ethereum network (on-chain); this way, all trades are public and verifiable. Furthermore, DEXs are free markets connecting buyers and sellers directly without needing a trusted third party to guarantee the funds during the transaction (Ethereum, 2023). By allowing individuals to trade without having to trust others and delegating the burden of security to the individual user, DEXs eliminate the inherent risks of a centralized exchange, such as being hacked and fleeing with the funds in their custody or some sudden government regulation. The demand for a secure decentralized exchange from users has been around since the advent of blockchain, as centralized exchanges like Mt. Gox, Bitfinex, and Quadriga have already caused billions of dollars in losses to their users (Warren; Bandeali, 2017).

According to Lin (2019) the trends of regulations and the industry can be mentioned as factors that lead individuals to use DEXs. Among these, the rapid increase in the number of new tokens that would make listing on exchanges impractical, regulatory risks of the listing of these tokens in centralized exchanges, and the desire of users to avoid registration processes (know-your-customer) in exchanges, aiming at more private transactions, without the risk of censorship.

Decentralized Exchanges DEXs based on order books developed on the Ethereum blockchain did not gain traction and did not generate large volume due to inefficiencies in their designs, which impose a high friction cost on market makers as they must pay gas fees each time they send, modify and cancel an order (Warren; Bandeali, 2017).

An alternative to protocols based on on-chain order books is Automated Market Makers (AMM) smart contracts. Unlike solutions based on supply books, where the market price is given by the last coincident order between supply and demand, each AMM uses a 'conservation function', which prices the assets algorithmically, letting prices move along pre-defined paths. In these price adjustment models, the price of an asset responds deterministically to market forces; moreover, market participants on both sides of the market trade with the AMM itself instead of trading with each other (Xu et al., 2023).

Among the existing AMM designs used in DEXs, the most common is the so-called geometric mean market makers. In these, liquidity providers (Liquidity Providers) deposit assets in the reserves of a smart contract known as Liquidity Pool. These contracts allow third parties to send trades against offered reserves, executing an exchange only if the geometric weighted average of the reserves after the exchange is equal to the previous average. In most protocols, two assets are deposited in a proportion of 50%-50%, as with Uniswap V2, while another DEX called Balancer allows deposits in different proportions. When Liquidity Providers offers its reserves for the contract, shares are issued in the liquidity pool in proportion to their contributions. These shares can be redeemed at any time, along with the proportional fees accrued by the Liquidity Pool (Evans, 2021).

According to Aspris et al. (2021), DEXs, do not need an intermediary to hold cryptocurrencies. DEXs facilitate exchanges, which leads to a greater diversity of tokens and greater participation in the cryptocurrency ecosystem. It should be noted that tokens can be exchanged in a DEX, in a CEX, or in both; however, the process of listing a token in a CEX is a major barrier to entry. It is a costly process, depends on several legal approvals, and is time-consuming. Especially when compared to a DEX, where the token simply needs to follow the blockchain standard used by DEX itself, which facilitates capital raising by project founders and almost instantaneous access to secondary markets. An increased growth of DEXs can be seen when measuring the total amount deposited (TVL), from \$20 million dollars in August 2018 to \$19.3 billion February 2023.

How a DEX works

To illustrate how a DEX works and all the actors involved, we will use documents from Uniswap V2 Uniswap (2020), the DEX with the biggest daily volume and the biggest amount of tokens listed.

Furthermore, Uniswap V2 is an automated market making - AMM - protocol that follows a constant product formula (CFMM) and ensures that the asset reserves before and after a swap (without considering fees) follow the following function described by Lo and Medda (2020) as:

$$R_x * R_y = k \tag{2.1}$$

In this case, R_x refers to the amount of the asset x's reserves. R_y is the number of reserves for asset y, and k is a constant. Exchanges do not change the proportion between booking prices $p_{xy} = R_y/R_x$. Given a purchase of x the reserves follow ($R_x - \Delta R_x$)($R_y + \Delta R_y$) = k . The marginal price of a new transaction will equal the relative change in the quantity of the two reserves $p_{xy} = \Delta R_y/\Delta R_x$.

Liquidity Pool

It refers to each Uniswap V2 smart contract, or simply - a trading pair, as the name suggests, consists of a pair of ERC-20/ERC-20 type tokens. By interacting with this AMM contract, users can execute their exchanges.

An advancement of Uniswap V2 over Uniswap V1 is precisely the introduction of pools of any pair of ERC20 tokens. In the previous version, only pairs between ETH and other ERC20 tokens could be formed. This makes for greater diversity for liquidity provider positions without having direct exposure to ETH.

Direct pairs facilitate trades as they reduce fees and slippages; in many cases, both fees and slippages would be added to each pair involved in the transaction. Even if two ERC20 tokens do not form direct pairs and do not have pairs in common, it is still possible to trade these two tokens, as long as there is a path between these two ERC20 tokens.

Liquidity Provider

A liquidity provider is a participant in a decentralized exchange (DEX) who contributes funds to the exchange's liquidity pool, which enables traders to buy and sell assets without needing a counterparty. By adding the equivalent monetary values of two different ERC-20 tokens, and in exchange receive Pool Tokens. These represent the proportion of the position in relation to the assets deposited in the Pool, which can be redeemed at any time. The liquidity provider earns a portion of the trading fees as a reward.

The more tokens deposited in the smart contract, the greater the liquidity, and this reduces slippage in exchanges between the two assets. According to **??**) this slippage would be one of the costs of using a DEX (low liquidity). Unlike a market where there is a coincidence of supply and demand at a given price, in an AMM, there is always slippage, and its impact will depend on the size of the exchange made in relation to the total assets deposited in the Pool.

Another risk, commonly called Impermanent Loss, in the literature is called divergence loss - which is the fact that each exchange changes the composition of the Liquidity Pool - following the price conservation function, as well as changing its value as a whole. Since arbitrageurs capture part of the value of price changes, the assets of a Liquidity Provider (excluding fees) will under perform a fixed portfolio of the original assets unless prices are reversed to the original prices before the exchange. Even if prices reverse, LPs underperform a portfolio that actively rebalances (Lo; Medda, 2020).

Therefore, compared with simply holding the two tokens instead of depositing in the Pool, it can result in a relative loss, and this loss can be zeroed if the relative price of the assets changes again. In other words, Liquidity Providers benefit from fees that are a function of volatility but suffer from the volatility of price changes. One of the main drivers of growth in the use of decentralized exchanges in 2020 was Yield Farming. Yield Farming, similar to discounts given to borrowers in the traditional market, that is, it involves subsidizing the provision of liquidity for a newly issued cryptocurrency. In this way, losses related to Divergence Loss are mitigated, and there is a greater incentive for individuals to become Liquidity Providers (Angeris et al., 2021).

Xu et al. (2023) mentions that there is significant competition between protocols to capture more liquidity; for this, they give additional incentives in addition to the 0.3% fee charged for each exchange carried out in the Pool. These incentives are usually in the form of ERC-20 tokens. DEXs commonly distribute Governance Tokens (each token gives the right to one vote in protocol decisions); other projects (dApps, for example) that wish to have greater liquidity award their ERC-20 tokens utilities for liquidity providers that deposit their LP tokens - received by providing liquidity - into another smart contract, this is called a staking deposit. This purpose is to encourage individuals to keep their assets deposited in a contract.

Swap

It is the trade itself, for the user of a DEX, the ERC-20 token that the individual wants to sell is chosen (enter the Pool), and the other ERC-20 token that they want to buy (withdraw from Pool). By entering the quantity of the first token, the protocol calculates, based on the current price, the quantity of the second token that can be withdrawn. The agent can then accept and execute the exchange, paying the 0.3% Uniswap V2 fee and gas fees for interacting with the smart contract on the Ethereum network.

Comparing CEXs and DEXs

According to Gould et al. (2013), most traditional markets in the world use the Order Books Limit system to facilitate trades. This type of market is characterized by its flexibility because any individual participating in the market can place buy or sell orders. The authors describe how a Limit Order Book works as follows: when a buy (or sell) order x is sent, a Limit Order Book exchange matching algorithm checks if it is possible to match x to some other previously submitted sell (or buy) order. In this case, the correspondence takes place immediately. Otherwise, order x becomes active and remains active until it is combined with a sent sell (or buy) order or until the original order is canceled. Cancellation usually occurs because the owner of an order no longer wants to make a trade at the stated price. However, the rules governing a market can also lead to the cancellation of an active order, for example, due to market closing.

According to Schnaubelt, Rende and Krauss (2019) cryptocurrency exchanges use Limit Order Book systems and replicate several features common to traditional markets. Users of these exchanges can send buy and sell offers with price and quantity limits; these orders are matched by orders for transactions to take place; otherwise, they are transferred to the Limit Order Book. Most exchanges have a system of fees depending on the total volume traded, and they are different for givers and takers when orders are executed, and they usually have fees for deposits and withdrawals of fiat currencies. A significant difference between cryptocurrency exchanges and traditional exchanges is that they operate continuously, there is no opening or closing auction as with these exchanges.

On a traditional exchange, the price of an asset is given by the supply and demand of that asset, but this does not apply to a DEX. Market Makers contribute to price discovery, and liquidity providers are price takers. Liquidity providers do not have any price protection other than the constant product function, which treats the price as a product. (Lo; Medda, 2020)

Lehar and Parlour (2021) cites two critical differences between the AMM market used by decentralized exchanges and order books used by traditional exchanges. First, in decentralized exchanges, both the benefits and costs of providing liquidity are mutualized, that is, liquidity providers do not compete with each other. On the other hand, in markets that use the order book, strategic liquidity providers actively compete with each other, so the costs and benefits of promoting liquidity are individual to each liquidity provider. Second, in a DEX, the price impact is deterministic. In particular, the transaction price is determined by the AMM model curve and is perfectly predictable, given the size of the liquidity pool and the bid order received. In contrast, at centralized exchanges, liquidity providers choose to position themselves at a price that maximizes their profits and may even strategically withdraw liquidity.

In the study Angeris et al. (2021), the most significant tradeoff faced by an individual when choosing between using a DEX and CEX is described, which would be the choice between the anonymity and security that a DEX offers and the greater liquidity of a CEX.

On centralized exchanges, orders are executed in millisecond scales[2] , using the exchange's own infrastructure to manage all orders. While on decentralized exchanges, exchanges are made and confirmed using the blockchain, the confirmation speed of a transaction will depend on the gas fee paid to the blockchain and the pair in which it is being carried out. the exchange. (Capponi; Jia, 2021)

[2] https://news.bitcoin.com/order-speed-analysis-reveals-the-fastest-cryptocurrency-exchanges/

Amler et al. (2021) describes centralized exchanges as based on trust in an intermediary (the exchange itself), requiring authentication via Know Your Customer - KYC practices, having limited scalability (transactions per second), suffering from security issues, processing transactions outside the blockchain and charging significant fees.

According to Qin et al. (2021), unlike traditional centralized finance, decentralized exchanges have three distinguishing characteristics: transparency, control and accessibility. A user of a DEX can inspect the precise rules by which financial assets and products operate. Decentralized finance avoids private agreements, back-deals, and centralization, which are factors that limit the transparency of Traditional Finance. DeFi users have custody of their assets in their wallets, i.e., no one can censor, move or destroy user assets without their consent. Ultimately, anyone with a moderate computer, internet connection and know-how can build and deploy DeFi products, as long as the blockchain and its distributed network of miners continue to effectively operate the DeFi application - dApp.

Therefore, while in Centralized Exchanges, individuals are identified by a KYC process, they do not have custody of their assets and use the exchanges' infrastructure to execute trades. On the other hand, in a decentralized exchange, individuals have full custody of their assets in their cryptographic wallets. These have a hexadecimal address, with a 0x prefix, which represents them; through these wallets, individuals interact directly with the autonomous smart contracts of the Decentralized Exchanges without contacting third parties or the need for any kind of trust or guarantee (other than in smart contract codes).

Barbon and Ranaldo (2021) shows that Uniswap and the other decentralized exchanges experienced a sharp increase in adoption and trading volume during the year 2020, accompanied by a significant increase in available liquidity. However, they provide evidence showing that DEX would still not be competitive with the largest centralized exchange in terms of transaction costs and pricing efficiency - mainly due to the level of transaction fees and amounts of capital invested in liquidity pools. Despite this, it is observed that decentralized exchanges offer several advantages over centralized exchanges, particularly in terms of security, resistance to censorship, and accessibility. According to the authors, it is reasonable to speculate that end users value these features and are willing to pay a premium for using decentralized rather than centralized locations.

3 Methodology

We have analyzed the period between January 2022 and September 2022. The data used in the exercises explored by this thesis come from different origins, given the characteristics of each market explored and the underlying technological framework. Decentralized exchanges data was extracted from the Ethereum blockchain itself; data in blockchain are kept in a distributed ledger (in logs, calls and transactions) in a bytedata form. (Guo; Yu, 2022)

We used Dune Analytics, a tool for blockchain research, to decode the bytedata, make it human readable, and using SQL queries we extracted the minute data from the UniswapV2 ETH/USDC trading pair. The prices data in the ETH/USDC trading pair was obtained by dividing the average total amount of ETH in the pool by the average total amount of USDC in the pool at a minute time frame. If there wasn't any trades, or changes in the total amount of the assets at a certain minute, the imediate previous minute price was considered.

We have decided to use Uniswap's V2 trading pair because of its simplicity compared to Uniswap V3, and more importantly, the price table from Dune Analytics is constructed from an average of the market, pulled from coin paprika API as described on Dune (2023). A price table that is calculated by the average of the market does not fit in our proposed exercise, this way, using Uniswap V2, and dividing assets the form the pool, is an easy way to determine the price of an specific trading pair at the specific time the data is being pulled. To do that, we query the amount of reserves in each pool of the trading pair and extrapolate all of our analysis at any point of the price bonding curve from it. In Uniswap V3, liquidity is concentrated in bands in the price bonding curve, these positions are represented by an NFT help by the liquidity provider; in the V3 there are also multiple trading pairs with different fees, this would mean that we would have to analyize three different smart contracts for the ETH/USDC trading pair.

Alexander and Dakos (2020) illustrates how some cryptocurrency data sources could feed incorrect data. In our study the inputs do not come from ranking aggregators, we extract it directly through the exchange's APIs, this way, we collect the raw proper data for our exercise.

Data from Binance, the centralized exchange with the biggest volume and currently the most used exchange was extracted using the exchanges' own databases through their API. All the Data collected from Bitstamp and Gemini come from their databases, we have used the CryptoData (2023) API aggregator to extract it. We have used minute data from January 2022 to September 2022.

Based on the data presented by the two types exchanges, we have made a comparison of the dynamics of the prices of the Ether token (ETH) in relation to the USDC stablecoin, for this we have applied tools from modern finance theory to better understand how trading dynamics on decentralized exchanges compare to what is observed in the traditional financial system.

This thesis methodology follows Alexander et al. (2020) using vector autoregressive models, including VECM and cointegration models to investigate the price discovery dynamics between these markets.

We follow Diebold and Yilmaz (2012) to compute spillover measures, since they provide a comprehensive approach by using a vector autoregression (VAR) framework. This method allows us to estimate the magnitude of spillovers. In our analysis, we have used it to quantify the spillovers between a Decentralized Exchange, Uniswap, and Centralized Exchanges, Binance, Bitstamp and Gemini. This has enabled us to provide a more comprehensive assessment of the spillovers and their effects on the two types of markets.

According to Tsay (2005) a VECM can be described as an error correction model for a k-dimensional VAR(p) time series x_t, and given as

$$\Delta x_t = \mu_t + \Pi x_{t-1} + \Phi_1^* \Delta x_{t-1} + ... + \Phi_{p-1}^* \Delta x_{t-p+1} + a_t \tag{3.1}$$

Where $\Pi = \alpha\beta' = -\Phi(1)$, and Φ_i^* are defined below, as AR coefficient matrices and functions of the original coeficient matrix Φ_j^*

$$\Phi_j^* = -\sum_{i=j+1}^{p} \Phi x_i, \qquad j = 1, ..., p-1 \tag{3.2}$$

$$\alpha\beta' = \Phi_p + \Phi_{p-1} + ... + \Phi_1 - I = -\Phi(1). \tag{3.3}$$

The term Πx_{t-1} is called error correction term. The rank of Π in the ECM of equation 3.1 is the number of cointegrated vectors and to test for cointegration, one can examine the rank of Π, that's the approach used by (Johansen, 1991). We followed the study to define the rank of the matrix and estimate the cointegration vectors.

Diebold and Yilmaz (2009) introduce a volatility interconectivity index based on the variance decomposition associated with an N-variable vector autorregressive model (VAR) separating measures in return spill overs and volatility spill overs. Diebold and Yilmaz (2012) describe that the Diebold and Yilmaz (2009) framework has several limitations, such as relying on the Cholesky-factor identification of VARs can cause the variance decomposition to be dependent on the variable ordering. Another crucial difference is that the older framework only addresses the total spillovers, while the new one introduces directional spillovers.

To address these limitations, Diebold and Yilmaz (2012) revise the original DY spillover index, by measuring the directional spillovers in a generalized VAR framework. Orthogonal innovations are necessary to calculate variance decompositions; However, the innovations in the VAR model presented by the authors are usually correlated with each other at the same time. Identification methods such as the Cholesky factorization can create orthogonality, but the resulting variance decompositions will depend on the order of the variables. The authors avoit this problem by utilizing the generalized VAR framework developed by Koop, Pesaran and Potter (1996) and Pesaran and Shin (1998), referred to as KPPS, producing variance decompositions which are invariant to the ordering.

The total volatility spill over index is described by Diebold and Yilmaz (2012) as

$$S^g(H) = \frac{\sum_{ij=1, i \neq j}^{N} \Theta_{ij}^g(H)}{\sum_{ij=1}^{N} \Theta_{ij}^g(H)} \cdot 100 = \frac{\sum_{ij=1, i \neq j}^{N} \Theta_{ij}^g(H)}{N} \cdot 100 \tag{3.4}$$

A directional volatility index is introduced by the authors, which allows to understand and quantify the direction of the volatility spillovers accross asset classes, for example, the directional volatility spillovers received by the market i from all markets j can be measured as

$$S^g(H) = \frac{\sum_{j=1, j \neq i}^{N} \Theta_{ij}^g(H)}{\sum_{ij=1}^{N} \Theta_{ij}^g(H)} \cdot 100 = \frac{\sum_{j=1, j \neq i}^{N} \Theta_{ij}^g(H)}{N} \cdot 100 \tag{3.5}$$

Similarly the directional volatility spillovers from market i to all other markets j can be measured as

$$S^g(H) = \frac{\sum_{j=1, j \neq i}^{N} \Theta_{ji}^g(H)}{\sum_{ij=1}^{N} \Theta_{ji}^g(H)} \cdot 100 = \frac{\sum_{j=1, j \neq i}^{N} \Theta_{ji}^g(H)}{N} \cdot 100 \tag{3.6}$$

Finally, in our robustness analysis we also used a volatility signature plot, following Hansen and Lunde (2006) to better visualize how the price discovery takes place between all the different markets.

4 Data Description

Since 2020 there has been a significant increase in the amount of money deposited in smart contracts on decentralized exchanges. The vast majority of these deposits are in exchanges on the Ethereum blockchain. Figure 1 shows the total value locked in all decentralized exchanges.

There has been a significant increase since 2020 in the weekly volume traded on decentralized exchanges. In the last year, there has been a consolidation of the total volume between ten and twenty billion dollars weekly.

We can also see an increase in the dominance of the Uniswap exchange in relation to the other DEX. At the time this thesis was written, its market share was 77%. This dominance was maintained after several improvements in AMM models, in the release of 3 versions over the years. In 2, with each release of a new AMM model, we can see a considerable increase in volume in the new model over the previous one.

One explanation for Uniswap's increased dominance is that in its V3 model, liquidity concentrated in price bands with different rates is beneficial for stablecoins liquidity. Individuals can provide liquidity in very concentrated bands around the $1 peg. This made Uniswap competitive with Curve's AMM, stablecoins DEX with the highest amount of capital deposited in their smart contracts. This AMM called 'stableswap' has no slippage and low fees. In Figure 3 we can see the dominance gain of Uniswap over Curve considering exchanges between all pairs of stablecoins.

Presented the significant differences between centralized and decentralized exchanges. Next, we will briefly analyze the data related to the trading of a pair of assets, the Ether (ETH) tokens, and the stablecoin USDC. We will make a comparison between the two types of exchangeage and their market making models.

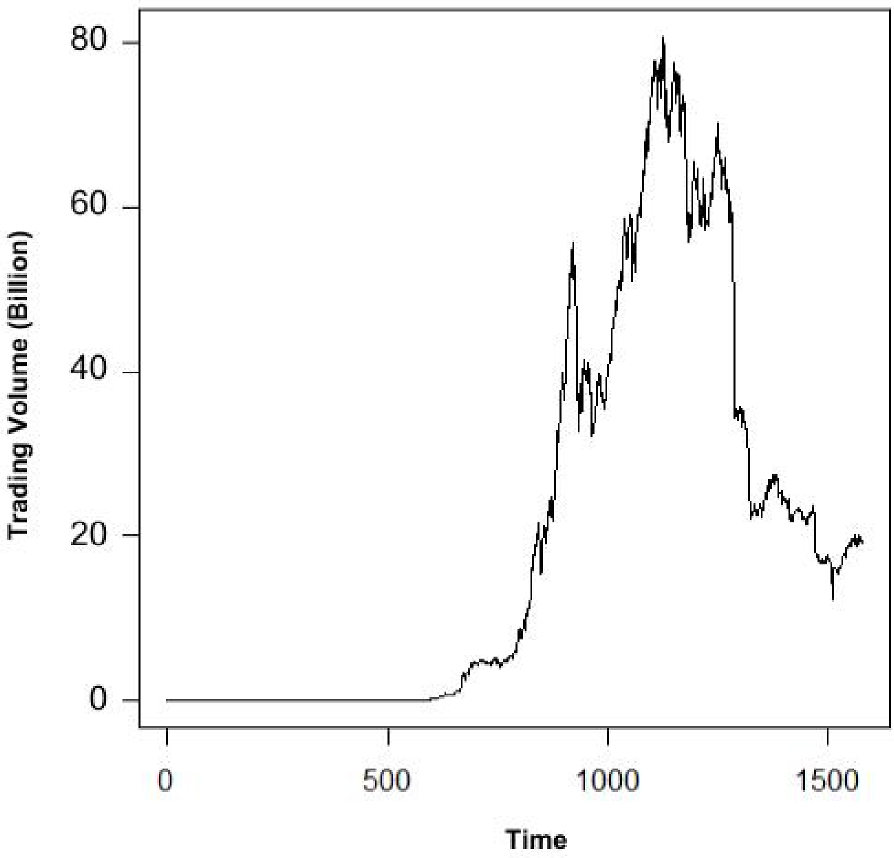
Ether, the native token of Ethereum blockchain, is the second largest token by market capitalization, at the time this thesis was written, U$198 billion. stablecoin USDC is the second stablecoin with the largest market capitalization, U$42 billion. Both assets are traded on the majority of cryptocurrency exchanges around the world.

First in Figure 4. we compare the volume of the ETH/USDC trading pairs in both Uniswap V2 and Binance. It is noticed that the volumes in both exchanges are similar.

Adding the total daily volume of all versions of Uniswap and comparing it with Binance in the ETH/USDC pair, we find that there is a significantly more volume traded on the decentralized exchange Uniswap than on Binance (Figure 5) .

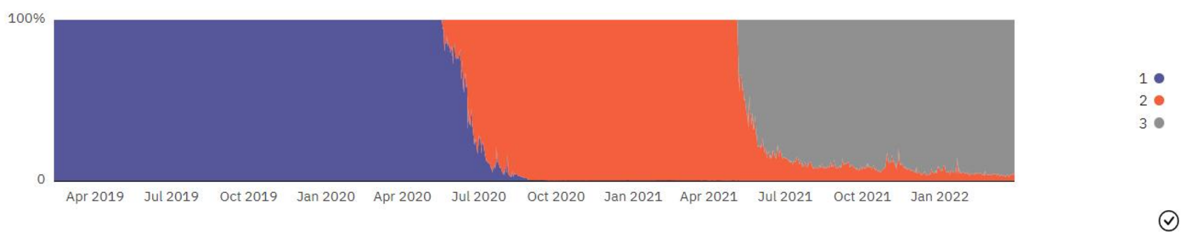
Although there is a larger trading volume on Uniswap than on Binance, when

Figure 1 – Total Value Locked in all decentralized exchanges.



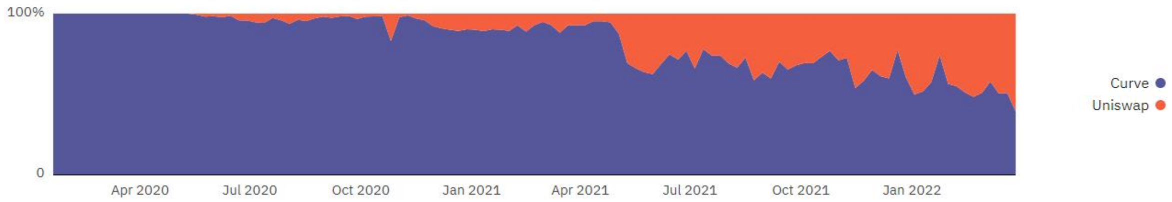
Total Value Locked, value deposited in smart contracts, in all decentralized exchanges, in all chains. Daily data extracted from DefiLlama (2023).

Figure 2 – Dominance of Uniswap V1, V2 and V3.



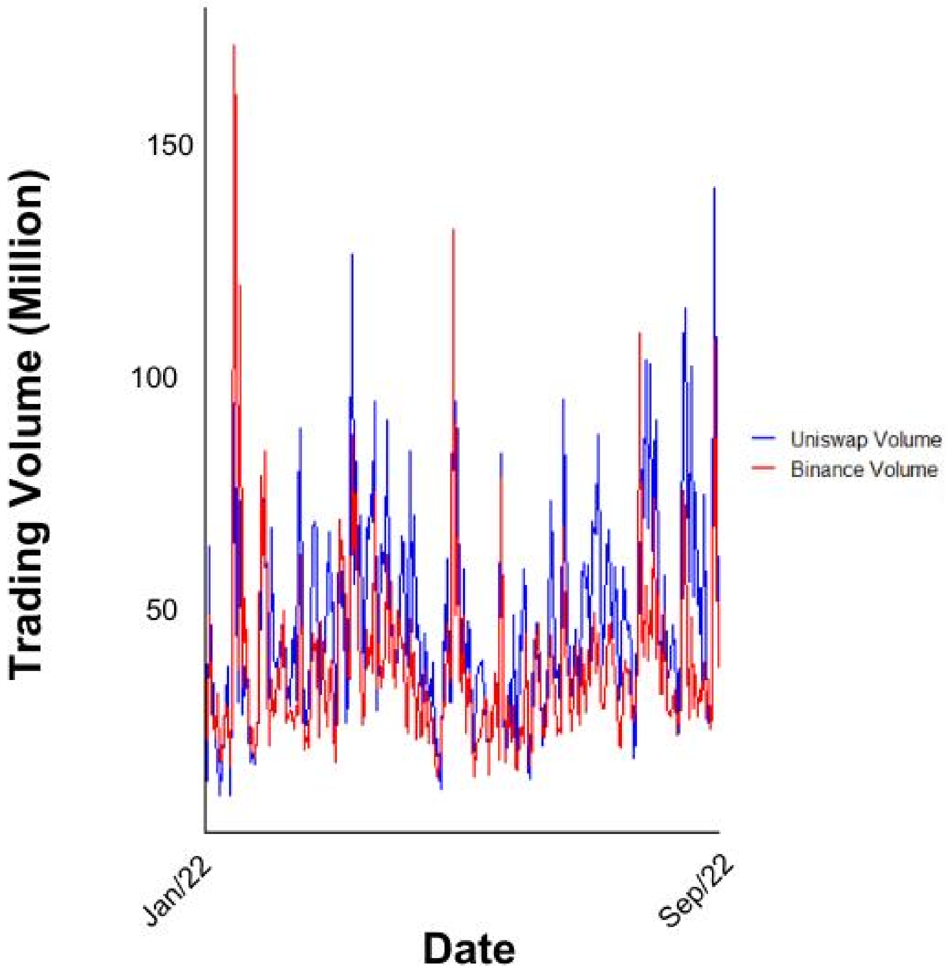
Data extracted from Dune Analytics. Figure 2 shows the volume traded in all of the versions of Uniswap: V1, V2 and V3. It portrays the adoption of a new technological framework over time.

Figure 3 – Dominance of Uniswap versus Curve Finance.



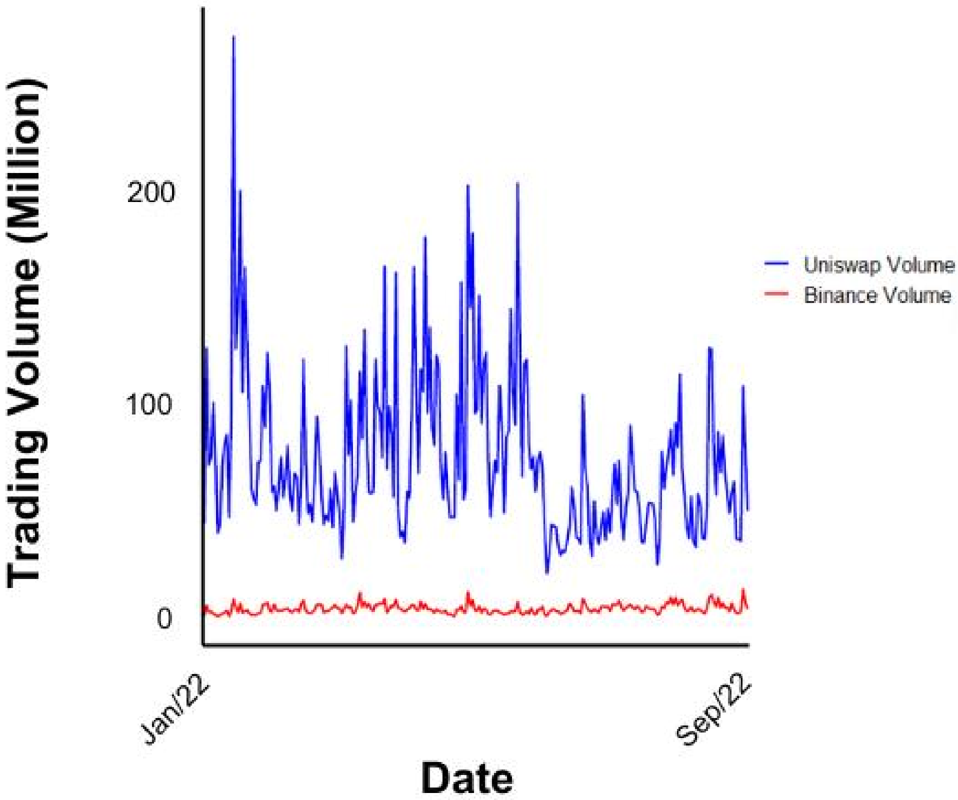
Note: Data extracted from Dune Analytics. This chart shows the volume of Uniswap compared against the volume Curve Finance, it shows Uniswap V3 stablecoin adoption.

Figure 4 – Daily volume on the ETH/USDC trading pair on Uniswap V2 and Binance.



Note: Data extracted from Dune Analytics. This chart shows the daily volume of the ETH/USDC trading pair on the Uniswap V2 exchange compared to the Binance exchange.

Figure 5 – Daily volume on the ETH/USDC trading pair on Uniswap and Binance.



Note: Data extracted from Dune Analytics. This chart shows the daily volume of the ETH/USDC trading pair on the Uniswap (all versions summed) exchange, compared to the Binance exchange.

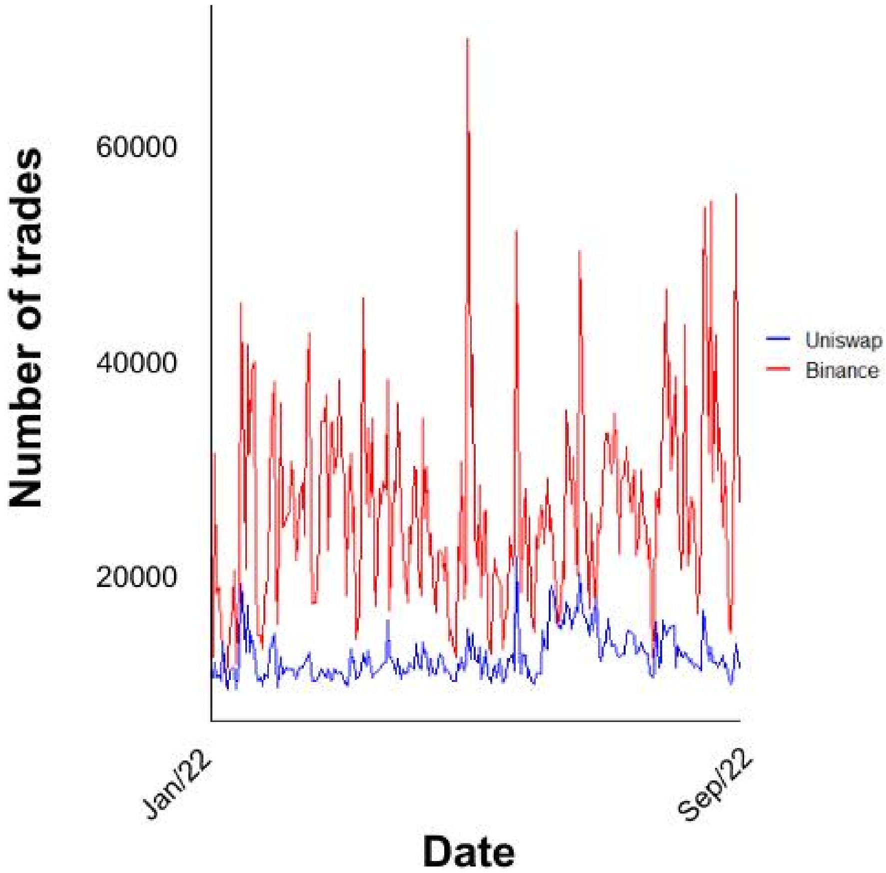
comparing the number of trades on both exchanges, we see that there are more trades on the Binance exchange than on Uniswap (Figure 6).

Therefore, when considering volume per transaction, the difference between the two exchanges and protocols is quite significant, with an average of approximately U$114.000 per trade on Uniswap and U$1.800 on Binance (Figure 7).

This is consistent with the analysis by Chainanalysis (2021) that high-value transactions are much more common in DeFi when compared to the cryptocurrency market in general, which indicates that institutional and professional investors are among those who, for the time being, show a greater use of decentralized finance. Gas fees are necessary to execute transactions on a decentralized exchange (on average U$38, but can reach more than U$100) could be an explanation for why smaller transactions are less frequent in these protocols.

The great dominance of professional and institutional investors in DeFi protocols

Figure 6 – Number of trades on the ETH/USDC trading pair on Uniswap V2 and Binance.



Note: Data extracted from Dune Analytics. This chart describes the number of trades on the ETH/USDC pair on the Uniswap V2 and Binance exchanges.

can be explained by the high yields that DeFi protocols offer, commonly exceeding 8% per year[1] in stablecoins.

4.1 Correlation

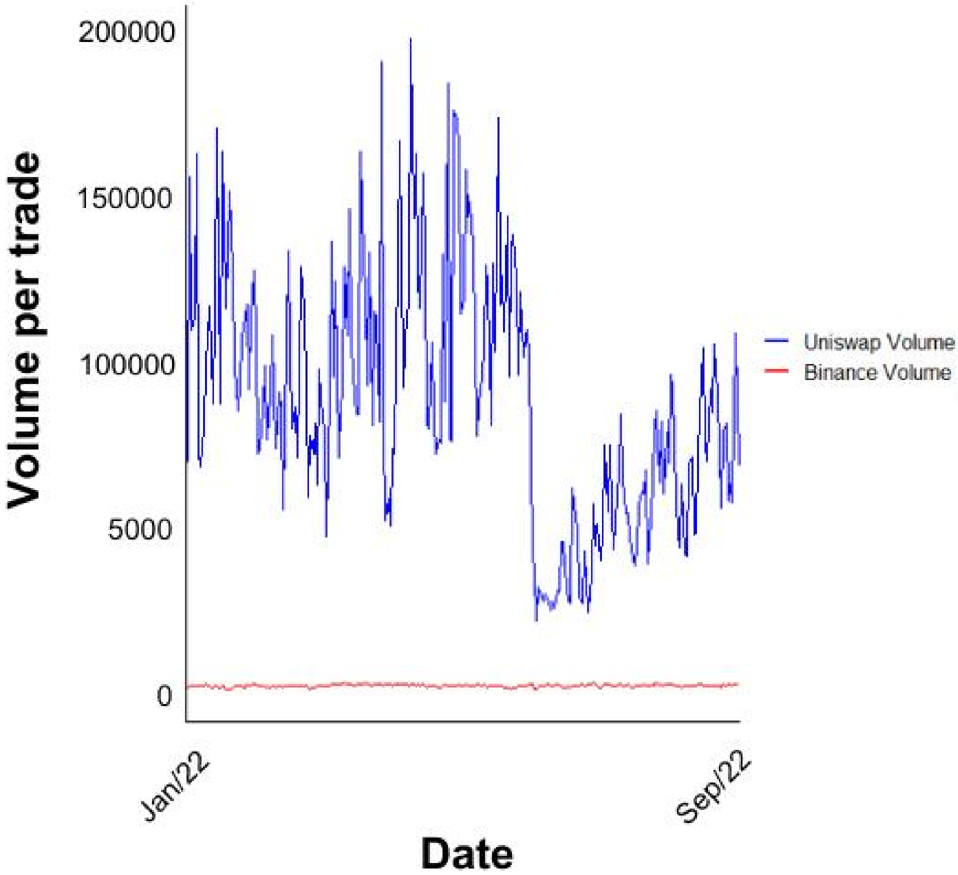
The correlation coefficient is defined by Tsay (2005) as

$$\rho_{x,y} = \frac{\text{Cov}(X,Y)}{\sqrt{Var(X)Var(Y)}} = \frac{E[(X-\mu_x)(X-\mu_y)]}{\sqrt{E(X-\mu_x)^2 E(X-\mu_y)^2}} \tag{4.1}$$

where the mean of X and Y are represented by μ_x and μ_y, respectively. The degree of linear association between X and Y can be quantified by this coefficient, and it can be

[1] https://defirate.com/lend/

Figure 7 – Volume per trades on the ETH/USDC trading pair on Uniswap V2 and Binance.



Note: Data extracted from Dune Analytics. This chart describes the volume per trades, calculated by dividing the volume by the number of trades on the ETH/USDC trading pair of Uniswap V2 and Binance.

Table 1 – Correlation of the returns of ETH/USDC trading pair across all exchanges studied.

	Uniswap	Binance	Bitstamp	Gemini
Uniswap	1.000	0.324	0.333	0.332
Binance	0.324	1.000	0.832	0.859
Bitstamp	0.333	0.832	1.000	0.829
Gemini	0.332	0.859	0.829	1.000

Note: table results of correlation of the returns of ETH/USDC trading pair across all exchanges studied.

demonstrated that $-1 \leq \rho_{x,y} \leq 1$ and $\rho_{x,y} = \rho_{y,x}$. If $\rho_{x,y} = 0$ the two random variables are uncorrelated.

In Table 1, we present an analysis of the correlation of returns of the ETH/USDC trading pair across four popular cryptocurrency exchanges: Uniswap, Binance, Bitstamp, and Gemini. The focus of this analysis is to assess the degree of correlation between

Table 2 – Johansen test results, assessing the cointegration rank of the price dynamics of the ETH/USDC trading pair in all exchanges studied.

	$r = 0$	$r \leq 1$	$r \leq 2$	$r \leq 3$
Test statistic	511.75	426.39	80.76	4.13
% of rejecting H_0	100%	100%	99.17%	16.60%

Note: table displays results from Johansen cointegration tests and the H_0 rejection % for each rank.

decentralized and centralized exchanges. The results indicate that there is a high degree of correlation among the centralized exchanges, with Binance and Bitstamp showing the strongest correlation coefficient of 0.83. Similarly, Binance and Gemini also displayed a high correlation coefficient of 0.86. On the other hand, Uniswap, the only decentralized exchange included in the study, showed a significantly lower level of correlation with the other markets. The correlation coefficients between Uniswap and the centralized exchanges were 0.32 with Binance, 0.33 with Bitstamp, and 0.33 with Gemini. These results suggest that the market dynamics on decentralized exchanges like Uniswap may be quite distinct from those on centralized exchanges, which may have implications for trading and investment strategies.

4.2 Cointegration test

As we follow (Alexander et al., 2020), most of their analysis are based on the assumption of cointegration, because of that, cointegration relationship over their study full-sample and subsample periods are tested. We follow the same procedure, we use Johansen (1991) test to assesses the cointegration rank of the price dynamics of the ETH/USDC pair in the different exchanges studied against the alternative of higher ranks.

The test was conducted using minute, high-frequency, data, and the average test statistic was calculated for each day. The results were then presented in Table 2, which included the test statistic and the H_0 rejection % for each rank. The null hypothesis of the cointegration rank being equal to 0 or 1 is rejected for 100% days of the sample. Additionally, the null hypothesis of a cointegration rank equal to 2 was rejected in 99.2% of the trading days. However, the cointegration rank equal to 3 could not be rejected in 83.4% of the trading days. Therefore, based on these findings, we can assume in this thesis that there is a strong likelihood of a cointegration relationship between the variables under analysis, and this relationship is likely to have a cointegration rank of 3. For that, this study assumes a cointegration rank of 3.

5 Results

Following Alexander et al. (2020) we explore the contribution to the price discovery by a decentralized exchange, Uniswap V2, and three centralized orderbook exchanges, Binance, Bitstamp and Gemini.

Price discovery can be described, according to Karabiyik, Westerlund and Narayan (2022), as the process where cointegrated trading prices are adjusted given shocks that cause deviations from the law of one price. Given an asset traded in multiple markets, and considering transaction costs, information asymmetry and regulations exist, a new information is not incorporated instantaneously into the price, but in a gradual fashion.

Hasbrouck (1995) introduces the concept of Information shares — IS — to measure a market's contribution to the process of price discovery in different markets. In the same article, the author also introduces the use of VECM for the prices of the same asset in different markets.

In Figure 8 we portray a 24 hour long-horizon (60 min) net spillovers from centralized and decentralized exchanges, in four markets: Uniswap (panel A); Binance (panel B); Bitstamp (panel C) and Gemini (panel D). Uniswap is the only decentralized AMM market, while the other three are spot, orderbook markets.

The net spillover effect from market i refers to the gross spillover impact from market i on all other markets, minus the spillover influence that other markets have on market i. The spillovers are estimated on a daily basis from a VECM using minute-by-minute log prices. VECM, vector error-correction model (Diebold; Yilmaz, 2012).

Diebold and Yılmaz (2015) introduce the connectdness table, replicated on Table 3 as it is useful for understating the conenctedness measures and their relationships with each other. The table, called by the authors a 'variance decomposition matrix' is denoted by $D = [d_{ij}]$. This table portrays the forecast-error variance decompositions (d_{ij}), they measure the pairwise directional connectdness, from a connectdness point of view. The authors show that the pairwise connectdness measure from j to i is

$$C_{i \leftarrow j} = d_{ij}, \tag{5.1}$$

and the total directional connectdness from others to i is despicted by

$$C_{i \leftarrow \bullet} = \sum_{j=1, j \neq 1}^{N} d_{ij}. \tag{5.2}$$

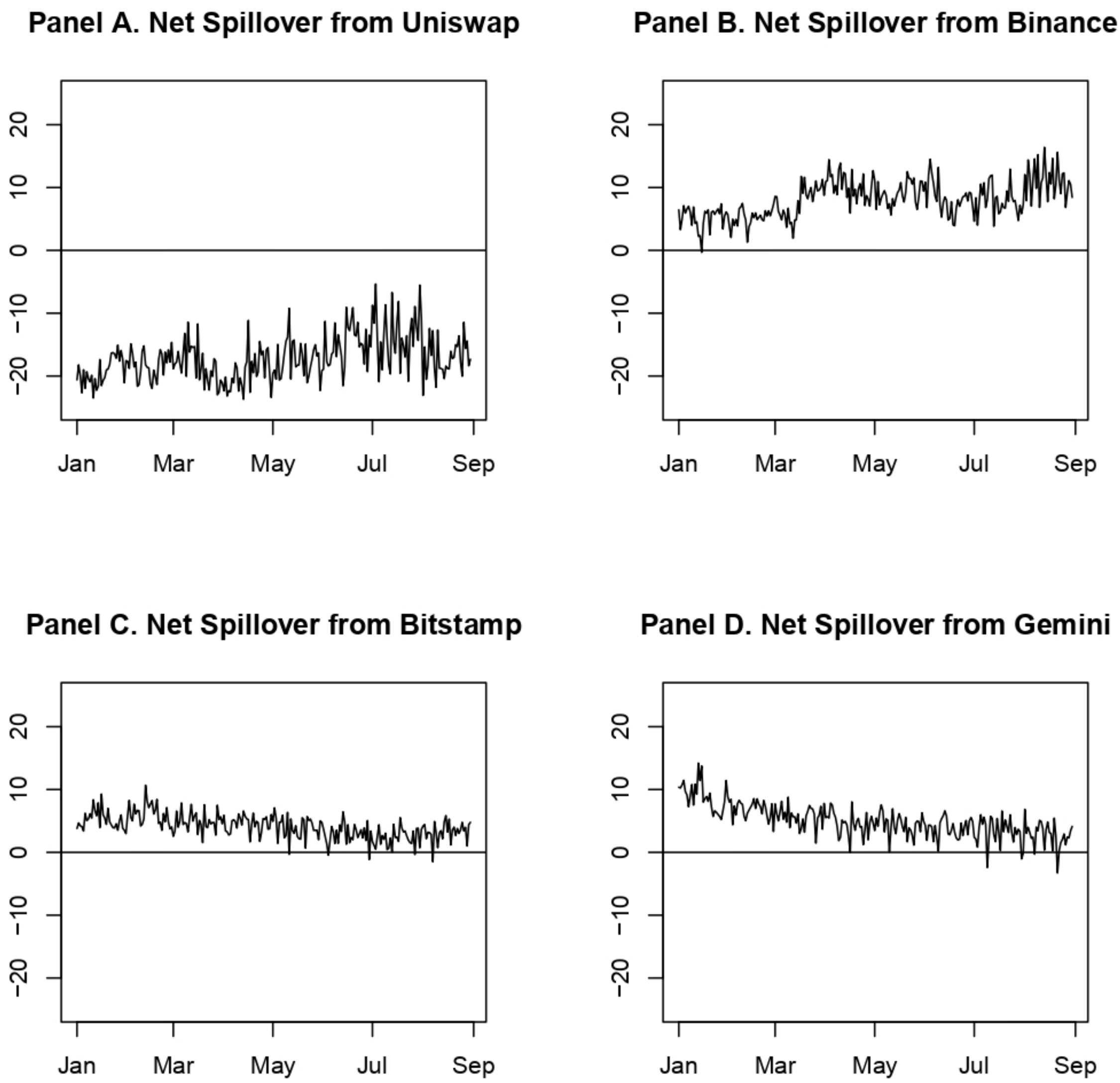


Figure 8 – Net spillover panel for all exchanges studied.

Finally the authors show that to calculate the net total directional connectdness, the net spillover, we use

$$C_i = C_{\bullet \leftarrow i} - C_{i \leftarrow \bullet}. \tag{5.3}$$

In Figure 8 we can see that the net spillover is smaller on Bitstamp and Gemini, which indicates that these exchanges don't influence other markets significantly. In Binance, innovations increasingly affect other markets more than other markets influence Binance. Uniswap on the other hand, innovations consistently are more affected by other markets than it influences them.

Table 3 gives an overview of the inter market price discovery dynamics. The

Table 3 – Results of the Gross and Netspillover estimated for each day, in all of the exchanges studied.

		From			
	To	UNISWAP(%)	BINANCE(%)	BITSTAMP(%)	GEMINI(%)
Gross Spillover	UNISWAP	64.11	12.31	10.79	12.80
	BINANCE	2.05	37.27	27.41	33.28
	BITSTAMP	2.00	32.21	40.54	25.25
	GEMINI	1.99	37.95	24.98	35.07
Net Spillover		-29.86	19.73	3.72	6.41

Note: table portrays four forecast-error variance decompositions. Results of the spillovers estimated on a daily basis from a VECM using minute-frequency log prices. The Gross Spillover and Net spillover are listed for all of the exchanges studied.

Table 4 – Error-correction coefficients table, for all of the exchanges studied.

	With respect to deviation from			
Response of	**UNISWAP**	**BINANCE**	**BITSTAMP**	**GEMINI**
UNISWAP		0.0187	0.0015	0.0040
		(0.0013)***	(0,0013)	(0.0013)**
BINANCE	-0.1531		0.1964	0.1835
	(0.0009)***		(0.0045)***	(0.0046)***
BITSTAMP	0.1175	-0.1198		0.0502
	(0.0033)***	(0.0046)***		(0.0042)***
GEMINI	0.0066	0.0432	-0.2791	
	(0.0030)*	(0.0042)***	(0.0042)***	

Note: Table shows the average of the error-correction coefficients calculated by the daily estimation of the VECM. The response of all of the exchanges studied given an deviation of others are listed.

spillovers are estimated for each day, and the values in the table are the average of the daily estimates. We find that there is a clear distinction between the spillovers from a Decentralized Exchange and Centralized Exchanges, Uniswap gives significantly less spillover to other exchanges than the other centralized exchanges give spillovers to other exchanges. In our study, the full sample period being from January 2022 to September 2022, the gross spillovers from a specific market to itself are the following: 64.11% for Uniswap, 37.27% for Binance, 40.54% for Bitstamp and 35.07% for Gemini.

The spillover from Uniswap to the three other centralized exchanges is 6.04% while the spillover to Uniswap coming from the other exchanges is 91.59%. As such, Uniswap influences the other centralized exchanges significantly less than it is influenced by them. This is reflected in its negative, and, biggest in module, net spillover, -29.86%.

The spillover from Binance to the other exchanges is 82.47% while the spillover to Binance coming from the other exchanges is 62.74%. With a net spillover of 19.73%, Binance influences all other exchanges in the market significantly more than it is influenced by all of them.

The error-correction coefficients measure the response that a given exchange will respond given a shock in the price of the same particular asset in a different exchange. Table 4 gives the error-correction coefficients for Uniswap, Binance, Bitstamp and Gemini. It is noticeable that Binance is the faster to respond to price deviations in other exchanges; given an 1% increase in the price in Uniswap, the price in Binance moves by 0.1531%, while Bitstamp changes 0.1175%, Gemini barely reacts, with 0.0066% change.

Given an 1% increase in the price in Binance, the price in Uniswap changes by 0.0187%, 0.1198% in Bitstamp and 0.0432% in Gemini. Given a 1% shock in the prices of Bitstamp, we see that prices in Uniswap change by 0.00155, while Binance changes 0.1964% and Gemini changes 0.2791%. A shock of 1% of the price in Gemini, results in a 0.0040% price reaction in Uniswap, a 0.1835% reaction in Binance and a 0.0502% reaction in Bitstamp.

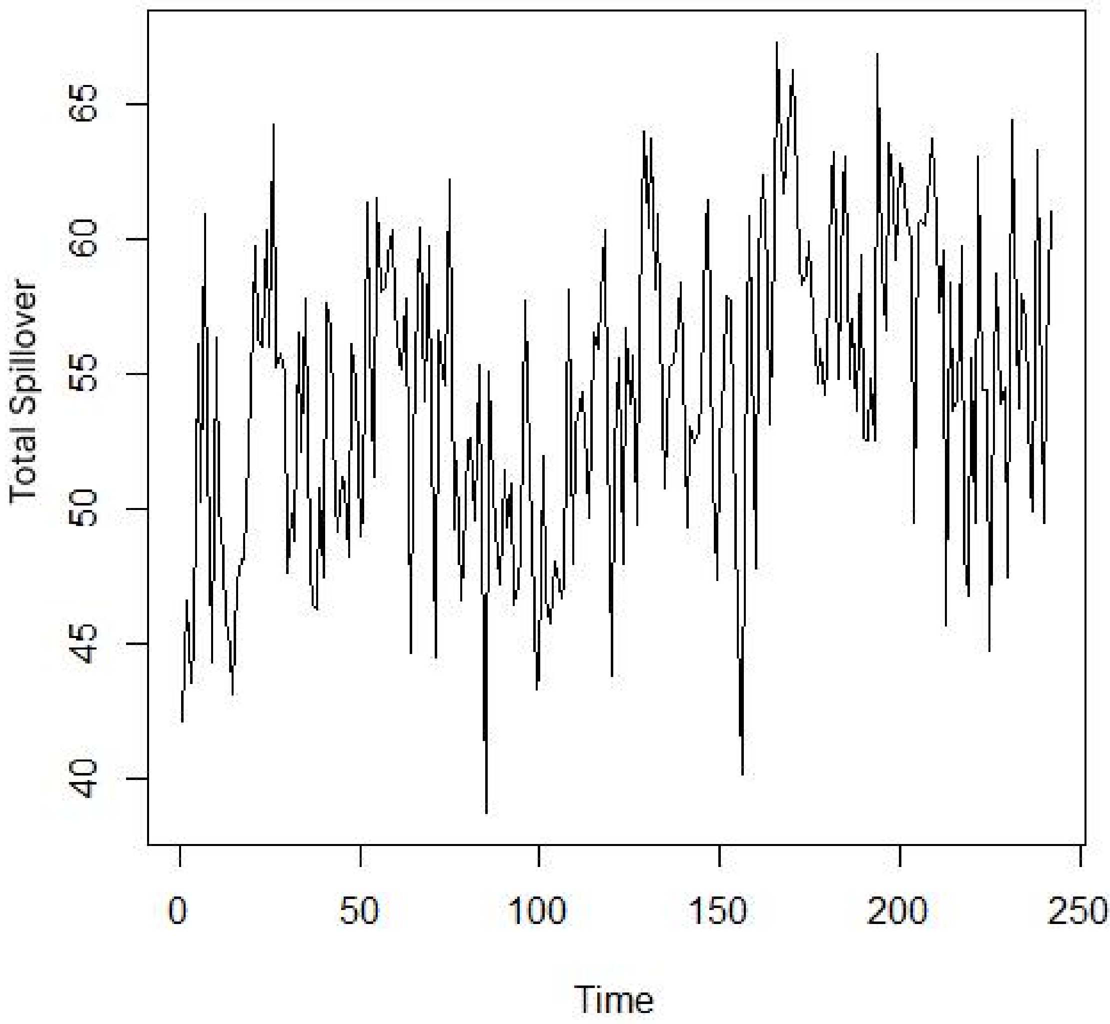
The analysis reveals that Binance plays a central role in the inter-market price discovery process, as it demonstrates a higher level of gross spillover to other exchanges compared to Uniswap, Bitstamp, and Gemini. Specifically, Binance has a gross spillover value of 82.47% and a net spillover of 19.73%. These findings highlight the importance of Binance in the price discovery process, as it responds more rapidly to price deviations in other exchanges and influences the prices of other exchanges more significantly than it is influenced by them. In contrast, Uniswap gives significantly less spillover to other exchanges than the other centralized exchanges, with gross spillovers from Uniswap to itself at 64.11%. The net spillover of Uniswap is -29.86%, indicating that it is influenced by the other centralized exchanges significantly more than it influences them. Our analysis reveals that Uniswap does not react significantly given shocks in all of the other exchanges.

Furthermore, our study shows that Binance responds more quickly to price deviations in other exchanges compared to the other exchanges in the study. Binance has the highest error-correction coefficient, with an increase of 1% in the price of Uniswap resulting in a price change of 0.1531% in Binance. This finding emphasizes the crucial role of Binance in the price discovery process, as it serves as a critical player in the market and influences the prices of other exchanges significantly. In contrast, Uniswap shows a lower error-correction coefficient, suggesting that it responds less rapidly to price shocks in the market. Taken together, our results demonstrate that Binance is a key player in the inter-market price discovery process, while Uniswap plays a less significant role compared to the other centralized exchanges.

In our analysis we have calculated the Total Spillover in Figure 9, we have observed that there is no evidence to suggest that the decentralized exchange Uniswap and the orderbook exchanges have become more interconnected over time. The total spillovers are estimated for a 24 hour period with the values being averages of that period estimates.

On average, the total spillover doesn't change significantly in magnitude and it is

Figure 9 – Total spillover



Note: Figure 9 shows 60 minute frequency 24 hour horizon, total spillover estimated for each day from a VECM that used minute-frequency prices of the ETH/USDC trading pair, for the four exchanges studied.

maintained close to 61.03%, over the time period studied. This indicates that a notable part of the error variance is explained by shocks in different markets, this could indicate that the markets are highly connected.

6 Robustness Analysis

There are significant noises in the 1 minute observations of the Uniswap V2 trading pair. Since that are gaps in data where the state of the trading pool doesn't change, that is, the proportion of the sum of the amount of USDC and ETH (in value) is the same. This maybe explained by the amount of volume to change the proportions between the pools of both assets, or the higher fees, making arbitrageurs act at a longer time frame.

According to Hansen and Lunde (2006) microstructure noise is high-frequency financial data, like the one we have explored in this article, makes it difficult to estimate financial volatility and realized variance. These microstructure noises make us to consider that we can't take the values explored in our previous exercises at face value.

The authors describe that the volatility displays the sample average as a function of the sampling frequencies m, with the average taken over multiple periods, usually trading days. Let $\overline{RV}_t^{(m)}$ denote the RV (realized volatility) based on m intraday returns on day t

$$\overline{RV}_t^{(m)} \equiv n^{-1} \sum_{t=1}^{n} RV_t^{(m)} \tag{6.1}$$

McAleer and Medeiros (2008) demonstrates the adverse effects of microstructure noise on the consistent estimation of the daily realized volatility estimator. The authors cite that the market microstrucuture noise could come from several different sources, including the properties of trading mechanisms as Amihud and Mendelson (1987) finds that the trading mechanism has a significant effect on stock price behavior.

We utilized Equation 6.1 to create a volatility signature plot, which helped us gain a better understanding of how the process of price discovery occurs across various markets as it it displays the relationship between the observed volatility and the sampling frequency of the data.

As illustrated in Figure 10, our analysis included an examination of realized volatilities in all of the exchanges under investigation. We observe how the microstructure noise in the studied markets dissipates as the frequency of observations decreases, the volatility signature plot curve becomes smoother, indicating that the microstructure noise has been filtered out.

Specifically, we observed that spot exchanges such as Binance, Bitstamp, and Gemini exhibited a relatively narrow band of realized volatilities and did not deviate significantly from one another. Conversely, Uniswap demonstrated to have more microstrucutre noise, ultimately appeared to filter out most of the microstructure noise at the same 40 minute mark as the frequency of observations decreased, as all the other spot exchanges, converging

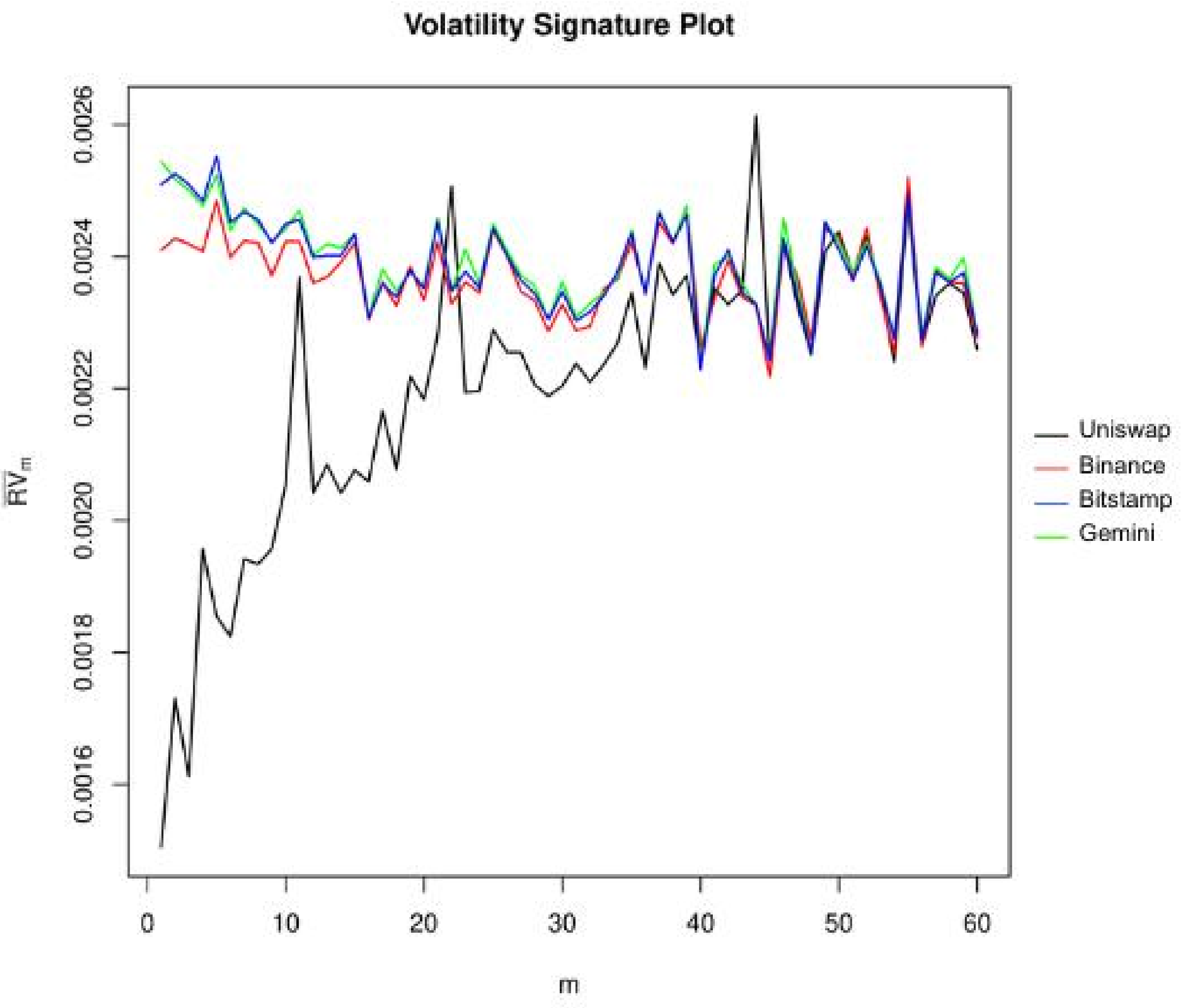


Figure 10 – Volatility signature plot

with spot exchanges at that mark. Overall, the volatility signature plots has provided us with a more comprehensive understanding of the dynamics of price discovery across multiple markets, and exchanges.

7 Conclusion

Our study aimed to investigate the price dynamics of ETH/USDC in both centralized and decentralized exchanges, with a focus on the degree of interconnectedness and transmission of price movements between them. Our use of the Diebold and Yilmaz (2012) spillover index, cointegration table and Hansen and Lunde (2006) volatility signature plot provided us with a comprehensive understanding of the dynamics of price discovery across multiple markets.

Our results suggest that Binance, one of the largest centralized exchanges, plays a central role in the inter-market price discovery process, as it demonstrates a higher level of gross spillover to other exchanges compared to Uniswap, Bitstamp, and Gemini. Binance responds more quickly to price deviations in other exchanges compared to the other exchanges in the study, emphasizing its crucial role in the price discovery process. In contrast, our analysis reveals that Uniswap, a popular decentralized exchange, does not give significant spillover to other exchanges compared to the other centralized exchanges, and it responds less rapidly to price shocks in the market. Furthermore, we found that there is no evidence to suggest that the decentralized exchange Uniswap and the orderbook exchanges have become more interconnected over time. We followed Hansen and Lunde (2006) to create a volatility signature plot and observed that microstructure noise in the studied markets dissipates as the frequency of observations decreases, the volatility signature plot curve becomes smoother and start to filter out the noise, with Uniswap converging with spot exchanges at around the 40 minute mark.

Overall, our findings contribute to the literature regarding the comparison of centralized versus decentralized exchanges in terms of price dynamics and efficiency. Our analysis highlights the importance of Binance in the inter-market price discovery process and emphasizes the need for further research to understand the evolving dynamics of the cryptocurrency market.

In addition to our main findings, our study has several implications for the cryptocurrency market and future research. The results suggest that Binance's dominant position in the market may be due to its volume added to its centralized and faster reaction nature compared to the decentralized exchanges.

Our study has some limitations that should be considered in future research. Our analysis considers one cryptocurrency pair (ETH/USDC) and four exchanges, the way the minute prices are calculated in for Uniswap V2 maybe the main cause of microstructure, small trades might be not enough to change the state of the proportion of the two asset pools. This doesn't happen on the orderbook centralized exchanges, where prices at the convergence between the bid and ask. Other trading pairs could be considered, and other exchanges considered in future studies.

Future research could examine a broader range of cryptocurrency pairs and exchanges to provide a more comprehensive understanding of the interdependence of prices across different markets. Additionally, Uniswap V3 could be used in the future, with data being pulled directly from the blockchain, the concentrated liquidity could cause less microstrucuture noise.

In conclusion, our study contributes to the growing body of literature on the price dynamics of centralized and decentralized exchanges. Our findings suggest that Binance plays a central role in the inter-market price discovery process, while Uniswap plays a less significant role compared to the other centralized exchanges. Our results can inform investors and traders in their decision-making processes and can also provide guidance to policymakers in regulating and overseeing the cryptocurrency market. Furthermore, our study highlights the need for further research to understand the evolving dynamics of the cryptocurrency market, particularly in the context of the growing popularity of decentralized exchanges.

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