Design of Blockchain Applications and Its Impact on User Behaviors

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Statement of Originality

I hereby certify that the work embodied in this thesis is the result of original research, is free of plagiarised materials, and has not been submitted for a higher degree to any other University or Institution.

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Authorship Attribution Statement

This thesis contains material from three papers, in which I am designated as one of the primary authors, that have been submitted or published to peer-reviewed journals or peer-reviewed conferences.

Chapter 3 is submitted as Erdong Chen, Mengzhong Ma, and Zixin Nie. VValue Blockchain Networks: Modelling the Growth of EVM-compatible Blockchains and Decentralized Applications. Financial Cryptography 2025: FC'25.

- I provided the research problem and project direction. I drafted the papers. I co-designed the study and experiments with Mengzhong Ma. I analyzed the data.
- Mengzhong Ma edited the manuscript drafts, and analyzed the data.
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- I provided the research problem and project direction. I drafted the papers. I co-designed the the study and experiments with Mengzhong Ma. I also analyzed the data.
- Mengzhong Ma edited the manuscript drafts, and analyzed the data.
- Zixin Nie assisted in the collection of the data.

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“Code is law; it provides the rules and regulations that govern blockchain networks.”

—Vitalik Buterin

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Abstract

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Abstract

Network structure is essential for understanding the interactions and overall behavior of complex systems. Over the past decade, blockchain networks have attracted over 3 trillion dollars in assets, with hundreds of millions of users worldwide. This research seeks to explore the factors driving such widespread adoption, particularly in the context of decentralized applications. It addresses key questions: What motivates users to adopt blockchain technology? How does trust propagate through these networks? And how can we better understand and predict the value dynamics within these rapidly evolving ecosystems? Additionally, the study examines how decentralized systems influence user behavior across various platforms.

Initially, the study investigates user trust in blockchain by analyzing Daily Active Users (DAU) and Monthly Active Users (MAU) of Ethereum applications, finding similar usage patterns in Stablecoins and Lending applications. By applying Metcalfe's Law, a comprehensive analysis of various EVM-compatible blockchain networks reveals that while the Ethereum mainnet exhibits exponential growth, many layer-2 networks and sidechains follow linear or sublinear growth patterns.

This finding further supports that Metcalfe's Law provides a better fit for networks such as Facebook, Tencent, Bitcoin, and Ethereum, compared to other network effect models, offering strong empirical validation of the law's applicability in these cases.

The thesis also investigates trader behavior in perpetual futures contracts through a Systematization of Knowledge (SoK) approach. In 2023, the 24-hour trading volume of perpetual futures contracts across all exchanges exceeded 100 billion dollars, accounting for more than half of total trading volume across blockchain products and exchanges. This raises an important question: Why do users trust decentralized applications with such significant sums of money? The research examines trader dynamics on centralized (CEXs) and decentralized exchanges (DEXs), proposing four models to classify exchange operations. Empirical analysis shows that the relationship between market volatility and trader activity varies significantly based on the exchange's mechanical design. Moreover, it reveals that in Virtual Automated Market Making (VAMM) models, open interest impacts price volatility differently for long and short positions.

Symbols and Acronyms

Acronyms

AMM	Automated Market Maker.
CeFi	Centralized Finance.
CEX	Centralized Exchange.
DeFi	Decentralized Finance
DEX	Decentralized Exchange
LP	Liquidity Provider
MEV	Maximal Extractable Value
PNL or P&L	Profit and Loss
TPS	Transaction Processing Capacity Per Second
VAMM	Virtual Automated Market Maker
ZK	Zero Knowledge

Symbols

EX	Perpetual contract trading exchange.
$O_i = (U, C)$	An order that provides asset C as collateral to trade the asset U.
$Und(O_i)$	Amount of asset in O_i
$Coll(O_i)$	Amount of collateral asset in O_i.
$P^{U \to C}(O_i)$	Price of U in the unit of C in O_i.
$TF(O_i)$	Transaction fees of O_i.
$P_j = (U, C)$	A position providing asset C as collateral to hold asset U.
$Coll_t(P_j)$	Amount of collateral in P_j at time t.
$\bar{P}_t^{U \to C}(P_j)$	Avg price of U in the unit of C in P_j at time t.
$MR_t(P_j)$	Margin ratio of P_j at time t.
$PnL_t(P_j)$	PnL in P_j at time t
$\mathrm{LP}(P_{Liq_{\mathrm{j}}})$	Liquidation penalty of P_j.
$\mathrm{FF}_{t_0 \to \mathrm{t}_1}(P_{\mathrm{j}})$	Funding fees of P_j from t_0 to t_1.

$\mathrm{BF}_{t_0\to \mathrm{t}_1}(P_\mathrm{j})$	Borrowing fees of P_j from t_0 to t_1.
$MR_{min}(U)$	Maintenance margin ratio of underlying asset U.
FR_t	Funding fees rate at time t.
BR_t	Borrowing fees rate at time t.
TR_{id}	Transaction fees rate of a trader.
$P_t^{U\to C}$	Price of underlying asset in the unit of collateral at time t.
$\mathrm{WV}_t(T_\mathrm{id})$	Withdrawable value in USD of a trader.
$VL_t(LP_{id})$	USD value of the liquidity that a LP provides time t.
$V_{id} = (VA, VD, C)$	A vault.
$VA_t(V_{id})$	token asset sheet of V_{id} at time t.
$VD_t(V_{id})$	token asset debt sheet of V_{id} at time t.
$Coll_t(V_{id})$	Amount of collateral in V_{id} at time t.
$\mathrm{LP}(V_{id})$	Liquidation penalty of V_{id}.
$IL_t(V_{id}^{LP})$	Impermanent loss from providing liquidity of V_{id} at time t.
$TF_t(V_{id}^{LP})$	Transaction fees earned by providing liquidity of V_{id} at time t.

Chapter 1

Introduction

1.1 Background and Motivation

The past ten years have witnessed the rapid development of blockchain technology, with more than 200 million users worldwide. Nowadays, blockchain has become a new computing platform, and a decentralized data-driven self-organization network. This research seeks to explore the factors driving such widespread adoption, particularly in the context of decentralized applications. It addresses key questions: What motivates users to adopt blockchain technology? How does trust propagate through these networks? And how can we better understand and predict the value dynamics within these rapidly evolving ecosystems? Additionally, the study examines how decentralized systems influence user behavior across various platforms.

Similar to the Blockchain network, the Internet was invented as an open platform which anyone could participate equally. In 1962, several M.I.T. scientists invented ARPAnet, which is a “galactic network” of computers that could send information to each other. By 1970s, Vinton Cerf invented the handshake protocols TCP/IP (“Transmission Control Protocol/Internet Protocol”), which allow any computer to participate into the network.

The openness of internet and its underlying permission-less technologies allowed internet to grow significantly in 1990s, especially after Tim Berners-Lee introduced the World Wide Web standard which helped created many browsers. Dixon [1] summarizes this period as this early Read era of internet, where most of the content are free. The network structure of the internet and its growth is mainly driven by the read traffic.

Since "read-write" Web 2.0 became popular in 2000s, user interaction shifted significantly on many web 2.0 internet websites. The rise of user-generated content (UGC) contribute to exponential growth of websites for social networking and collaborative platforms. In addition to read content, Internet users became active writers: contributing content, sharing information, and engaging in online social networks to reach massive audiences. All successful online platforms have unique social graphs which allow them to survive intensified competition among these for-profit Big Tech companies.

Network effects play a critical role for the growth of these digital networks, where the utilization and retention of users is decided by the size of the network. Network effects can be categorized based on the number of distinct sides involved in the network ecosystem. The classification of network effects as two-sided, three-sided, four-sided, which is derived from the economic theory of multi-sided platforms.

The Facebook social graph in 2004 comprises hundreds of millions of users and their relationships with each other. Since Facebook launched its open platform and Pages product, Facebook social graph has a three-sided Network effects: Facebook individual users, app developers, and businesses (advertisers, merchants, etc). The data analysis of these multi-sided network effects are crucial in understanding value creation and network dynamics, and especially among competitive products and services.

With the invention of smartphones in middle 2000s, the mobile internet accelerated the growth of the internet. The write v.s. read ratio increased significantly because mobile phones allow users to write or update more quickly. Due to the dominance of Apple and Google Android operating systems, the restricted "Corporate networks" became the dominant players. Dixon [1] estimated that users spent about three hours per day in the apps of these two stores (App Store and Google Play store).

To overcome the limitation and restriction imposed by the Big Tech (Apple, Google, Meta, Amazon, etc), a group of open source developers started to build a decentralized computing platform. This is aligned with the original mission of the permission-less internet in 1960s - 1980s. Two most famous decentralized networks Bitcoin network and Ethereum network started to attract many developers to build on these decentralized computing platform. Unlike corporate networks like Facebook/Google, network participants gain governance and economic power. All participants of the decentralized networks benefit from its growth, while only a small number of stakeholders, employees, and partners benefit from the growth of these "corporate networks". Dixon [1] summarized this era as "read-write-own" era.

This thesis is to analyze and formulate the value, dynamics, and growth of networks. The goal is to provide mathematical formula and explanation to understand the fundamental problems of social graphs. The transparency and availability of several mature Blockchain social graphs provide the ideal data for us to study and for other researchers to continue their studies on the publicly available data set.

1.2 Contribution

Firstly, This thesis is the first known attempt to undertake a comprehensive analysis of a diverse set of blockchain networks, encompassing layer-1, layer-2, and decentralized finance (DeFi) applications. Leveraging the proposed analytical framework, these networks are categorized into distinct classes, providing a theoretical basis for understanding and predicting their behavior. Despite the importance of networks across various economic and social domains, a comprehensive and consolidated analysis of network growth and value remains scarce. Decentralized blockchain networks present a unique opportunity, providing transparent and detailed transaction data from their inception.

Secondly, this study presents an in-depth Systematic Survey of Knowledge (SoK) that effectively contrasts the operational dynamics of Centralized Exchanges (CEXs) and Decentralized Exchanges (DEXs) in the realm of perpetual futures trading.

Last not the least, the thesis also includes an empirical analysis of traders' behavior in exchanges of the 4 types of models. This study sheds light on the potential risks and advantages of using perpetual future contracts within the DeFi space while provides mathematical basis and empirical insights based on which future theoretical works can be configured, offering crucial insights into the rapidly evolving world of blockchain-based financial instruments.

1.3 Outline of the Thesis

The Chapter 2 reviews the related work of this thesis and provides the background knowledge.

The Chapter 3 is a comprehensive analysis of a diverse set of blockchain networks, encompassing layer-1, layer-2, and decentralized finance (DeFi) applications. The investigation examines these networks from multiple perspectives, including their network design , and the underlying laws governing their growth (monthly active users and daily active users) and value creation. The research findings indicate that among all the EVM-compatible blockchains and decentralized applications (DApps), only the Ethereum mainnet exhibits predominantly nonlinear dynamics. In contrast, the majority of layer-2 networks and sidechains have demonstrated either linear or sublinear growth trajectories to date. So far, these layer-2 and sidechains failed to achieve the initial roadmap of the Ethereum ecosystem to develop more applications outside DeFi. However, all these layer-2 and sidechains are fighting with the dominant Ethereum mainnet for DeFi market share and liquidity. We believe that this dynamic explains why layer-2 and sidechain networks do not yet have exponential growth. Existing studies have examined the relevance of Metcalfe's Law, a fundamental principle in network theory, for assessing the value of digital blockchain networks. Alabi [2] performed a comparative study on three major blockchain networks: Bitcoin, Ethereum, and Dash. Alabi's research found that the value dynamics of these networks are consistent with Metcalfe's Law. My finding further supports that Metcalfe's Law provides a better fit for mature networks such as Facebook, Tencent, Bitcoin, and Ethereum.

In 2023, the 24-hour trading volume of perpetual futures contracts across all exchanges exceeded 100 billion dollars, accounting for more than half of total trading volume across blockchain products and exchanges. This raises an important question: Why do users trust decentralized applications with such significant sums of money? The Chapter 4 presents the first in-depth Systematic Survey of Knowledge (SoK) that effectively contrasts the operational dynamics of Centralized Exchanges (CEXs) and Decentralized Exchanges (DEXs) in the realm of perpetual futures trading. The chapter discusses the different models of perpetual futures exchanges, classified based on their level of centralization and reliance on blockchain technology. The Centralized Exchange (CEX) model closely resembles traditional financial practices with limited use of blockchain, while the Decentralized Exchange (DEX) models, including the Hybrid, Oracle Pricing, and Virtual Auto Market Making (VAMM) models, leverage smart contracts and decentralized components to varying degrees. As the level of decentralization increases, there is a trade-off with transaction processing capacity per second (TPS) due to the limitations of the underlying blockchain network. Additionally, the passage highlights the transparency of Miner Extractable Value (MEV) extraction and allocation in different models, with CEX and Hybrid models being opaque, while Oracle Pricing and VAMM models offer more transparency due to the execution of trades through smart contracts on the blockchain.

The Chapter 5 includes an empirical analysis of traders' behavior in exchanges of the 4 types of models. Empirical analysis shows that the relationship between market volatility and trader activity varies significantly based on the exchange's mechanical design. Perpetual trading exchanges experience growth primarily driven by network effects, with market depth being closely tied to the expansion of network effects. More than half of the liquidity and trading volume is concentrated in the BTC/USD trading pair and associated liquidity pools.

In the Automated Market Maker (AMM) model, network effects become apparent when Bitcoin's price rises due to an increase in short position liquidations. This price movement attracts additional liquidity providers, whose participation helps mitigate price volatility. The dampening effect of this influx of liquidity often outweighs the volatility amplification caused by the liquidations themselves. In Centralized Exchanges (CEXs), the effects of trading activity on price volatility reflect market depth, which can be explained by Kyle's model (1985) [3].

The Virtual Automated Market Making (VAMM) model introduces a nuanced dynamic in how open interest impacts long and short positions. This asymmetry arises from VAMM's price formation mechanism, where the rate of change in an asset's price is inversely related to its abundance in the liquidity pool. As a result, market depth increases with rising open interest in short positions, as the underlying asset accumulates in the liquidity pool, and the reverse holds true for long positions.

In Decentralized Exchanges (DEXs) using the Oracle Pricing Model, I observed a distinct asymmetry in trader behavior between buyers and sellers. Such asymmetry might stem from uninformed traders reacting more strongly to positive news than to negative, leading to a tendency to accumulate long positions. This study sheds light on the potential risks and advantages of using perpetual future contracts within the DeFi space while provides mathematical basis and empirical insights based on which future theoretical works can be done.

The Chapter 6 includes a series of future work should be conducted to fully understand how the trust and user behaviors are established towards the blockchain and why people within the blockchain can trust each other.

Chapter 2

Literature Review and Background

This chapter reviews the related work of this thesis and provides the background knowledge. I first provide detailed explanation of all the related concepts and background knowledge in various Blockchain applications in order for readers to understand this thesis. After that, Metcalfe's Law is introduced with the Literature Review of it. At the end of this chapter, I present the Literature Review of Perpetual Future Contracts.

2.1 Background of Blockchain Ecosystems

In this section I explain the foundational principles of perpetual trading in both Decentralized Finance (DeFi) and Centralized Finance (CeFi), indispensable for comprehending the innovations discussed in this thesis.

2.1.1 Ethereum

Ethereum, conceptualized by Vitalik Buterin [4], epitomizes a blockchain furnished with an integral Turing-complete programming language and has subsequently ascended as the preeminent widely utilized public chain. Ethereum endeavors to instantiate an alternative protocol for the development of decentralized applications, as delineated in its whitepaper [4]. It facilitates users to instantiate and run smart contracts on its decentralized framework. Through the agency of these smart contracts, developers are empowered to devise multifarious programs to articulate varied application logic, thereby proliferating a vast spectrum of internet-based applications.

2.1.2 Decentralized Finance (DeFi)

Decentralized Finance, abbreviated as DeFi, characterizes a financial paradigm anchored in the robustness and immutability of distributed ledger technology [5]. In terms of capital, a preponderance of DeFi DApps are architectured on Ethereum's infrastructure. As of December 2021, the aggregated value locked in DeFi reached a peak of over $178 billion, primarily concentrated on the Ethereum blockchain. These DeFi DApps enable users to fulfill many financial objectives, like Spot trading, Lending, Liquidity Staking, and Derivative trading, simultaneously proffering features not present in CeFi instruments, notably trustless asset custody and complete transparency.

2.1.3 Decentralized Exchange (DEX) and Centralized Exchange (CEX)

There are two primary categories of trading platforms that facilitate the exchange of blockchain assets: Centralized Exchanges (CEX) and Decentralized Exchanges (DEX). CEXs operate similarly to traditional electronic securities exchanges, wherein a centralized entity facilitates trades. Users are typically required to deposit their assets into wallets controlled by the exchange, and transactions are executed on a centralized server. From the participants' perspective, CEXs may be viewed as a "black box," as operators have direct control over customer assets, which raises potential risks, including mismanagement or misuse of funds.

In contrast, DEXs function without centralized intermediaries, allowing users to retain control over their assets. The code governing fund custody and trade facilitation is deployed on a blockchain through smart contracts. Users engage directly with these smart contracts to trade assets, significantly reducing the reliance on intermediaries and mitigating the moral hazards associated with the potential misuse of customer funds by exchange operators.

A significant number of DEXs originated on the Ethereum network, designed to eliminate single-entity ownership and operational control. Among these, Uniswap stands out for its innovative automatic liquidity protocol, which revolutionized trading practices. Launched in 2018, Uniswap supports a wide array of ERC-20 tokens and integrates seamlessly with decentralized wallet services such as MetaMask and WalletConnect.

On the other hand, Binance operates as a CEX and does not control or administer PancakeSwap, a DEX that mirrors Uniswap's operational framework. PancakeSwap is specifically designed for BEP-20 tokens on the Binance Smart Chain, benefiting from enhanced transaction speeds and significantly lower fees.

2.1.4 Perpetual Futures

Perpetual futures, a brainchild proposed by Robert J. Shiller in [6], found their foray into the cryptocurrency trading market via BitMEX in 2016 (https://bitmex.com/). These futures, a distinctive variant of the traditional futures contract, eschew a fixed delivery date, thereby allowing for an indefinite tenure without necessitating contract rollovers as expiration looms.

In traditional futures contracts, the basis, or the price differential between the futures and the spot price, progressively narrows as the contract nears its expiration date, a phenomenon predominantly influenced by arbitrage activities. In contrast, perpetual futures contracts, which lack a predetermined expiration date, implement a mechanism known as funding fees to align their trading prices with the underlying spot prices. This mechanism operates within a specified interval, wherein the exchange imposes funding fees on either long or short positions, redistributing these fees to the counterpart.

Traders' funding fees over a given period are calculated by multiplying their position size by the funding rate for that period. The funding rate, determined by the premium or discount between the perpetual futures and spot markets, dictates both the amount and direction of the payment. For example, a scenario where the perpetual futures price exceeds the spot market price results in a positive funding rate, necessitating long positions to compensate short positions through funding fees. The extent of the price discrepancy directly influences the funding rate, thereby determining the proportional funding fees imposed on long positions [7].

Another significant characteristic of perpetual futures is the provision of higher leverage. For BTC-USD perpetual contract trading pairs, BitMEX supports a maximum leverage of up to 100×, while some smaller exchanges even offer leverage of up to 1001×[1]. In contrast, for BTC delivery futures, major exchanges typically offer a maximum leverage of only 25×.

As of recent, perpetual futures have burgeoned as the most coveted financial derivative in the cryptocurrency market. In the years 2021 and 2022, the nominal trading volume for Bitcoin perpetual futures achieved $51,989 billion and $39,806 billion, respectively [7], significantly surpassing other derivative transactions, including options[2].

Notwithstanding, a sizable fraction of perpetual futures trading is on centralized platforms, leading many traders to harbor reservations regarding the inherent risks of centralized trading. However, courtesy of DeFi, traders can now participate in perpetual futures trading on decentralized platforms. While CEXs substantially eclipse DEXs in terms of nominal trading volume, the growth rate of DEX trading volume significantly outpaces that of CEX. Prevalent perpetual DEX frameworks encompass the Hybrid Model, Oracle Pricing Model, and VAMM Model.

2.1.5 Stablecoins

Stablecoins represent a distinct category of cryptocurrency that typically exist as tokens on blockchain networks. They employ various mechanisms to peg their value to fiat currencies, effectively addressing the demand for stable digital assets within the blockchain ecosystem. This stability is essential for users seeking to mitigate the excessive price volatility commonly associated with digital currencies.

[1] On ApolloX DEX (https://www.apollox.finance/en), users can use leverage up to 1001× in Degen Mode.

[2] https://www.theblock.co/data/crypto-markets/options.

Stablecoins can be classified into two primary issuance mechanisms: centralized and decentralized. Centralized stablecoins, such as USDT and USDC, are issued and managed by centralized entities that ensure value stability through backing assets, typically at a 1:1 ratio with the U.S. dollar. Conversely, decentralized stablecoins, like DAI, are created through the over-collateralization of other cryptocurrencies, particularly Ether (ETH). DAI utilizes transparent liquidation and arbitrage mechanisms to maintain its value stability, while its decentralized nature enhances its appeal among users, despite its relatively lower liquidity compared to centralized options.

The emergence of stablecoins can be traced back to the excessive volatility in the digital currency market, which highlighted the need for a more stable digital asset to facilitate liquidity and serve as a benchmark for other funds. USDT, the first stablecoin issued by Tether, effectively bridged real-world assets with the digital currency market, providing a safe haven during periods of significant capital outflows. Currently, USDT is the largest stablecoin in circulation, while USDC is issued by Circle, and DAI is a decentralized stablecoin operating on the Ethereum blockchain. While USDT and USDC are backed by traditional fiat reserves, DAI is backed by over-collateralized ETH to account for its volatility, ensuring its issuance remains fully transparent and not controlled by any single entity.

2.1.6 Price Oracles

Given the constraints of blockchains in accessing off-chain data, DeFi DApps invariably require certain centralized mechanisms, colloquially termed 'Oracles'. Price Oracles predominantly extract recent transactional data from preeminent exchanges, calculate a weighted average price governed by certain criteria, and subsequently dispatch this data to smart contracts, serving as a conduit between DeFi and the external environment.

2.1.7 Liquidity Provider

Liquidity Providers, pivotal constituents in the DeFi ecosystem, possessing specific assets, contribute them to Liquidity Pools orchestrated by smart contracts. This facilitates catering to the liquidity requisites of diverse traders in scenarios including lending, spot trading, and derivatives trading. Simultaneously, these Liquidity Providers levy various fees from traders.

2.1.8 Automated Market Maker (AMM)

Centralized exchanges predominantly utilize the limit order-book model (LOB) for the processes of price discovery and order matching, harmonizing buyers' propositions with sellers' offerings. Conversely, decentralized exchanges have gravitated towards the Automated Market Maker (AMM) owing to its congruence with blockchains of lower throughput. The AMM smart contract, dictated by a prespecified algorithm, ascertains particular trading prices and taps into the reserves of liquidity providers to accommodate traders' transactional needs.

Uniswap, the most prominent spot decentralized exchange on the Ethereum network, employs the constant product market maker (CPMM) [8]. CPMMs are based on the function $x \times y = k$, x and y denote the quantities of two distinct tokens in the liquidity pool, and their product, k, represents the pool's liquidity depth. In this model, a transaction results in an increase in one token's quantity and a corresponding decrease in the other, maintaining the constancy of their product. This mechanism ensures liquidity equilibrium within the pool during trading activities.

2.1.9 Maximal Extractable Value (MEV)

Maximal (or Miner) Extractable Value (MEV), refers to revenue obtained beyond transaction fees and block rewards by manipulating transaction order on blockchain networks. MEV was originally introduced in the context of proof-of-work (PoW) systems, where it was referred to as "miner extractable value." In PoW networks, miners possess the authority to control the inclusion, exclusion, and ordering of transactions within a block. However, following Ethereum's transition to a proof-of-stake (PoS) consensus mechanism, the responsibilities previously held by miners have shifted to validators, rendering mining obsolete within the Ethereum protocol. Despite this change, the methods for value extraction persist; thus, the terminology has evolved to "Maximal Extractable Value" to reflect the broader scope of value that can be captured in both PoW and PoS environments.

MEV extraction often occurs through front-running attacks, where parties observe transactions in the public mempool to exploit profitable opportunities like arbitrages, liquidations, and mis-priced NFTs. To ensure execution of their profitable transactions at a high priority, adversaries offer high transaction fees to the block proposer or sequencing party via public mempool or private channels. Since 15th September, 2022 (Ethereum Merge[3]), more than 421K ETH has been distributed through MEV-Boost[4], which is a MEV auction channel.

2.1.10 Sidechain and Layer2

With the development of the blockchain over the years, the current predominance public chain Ethereum still has a broad consensus, but with the rapid development of DeFi, the shortcomings of Ethereum are becoming more and more obvious. For example, the old problems that have appeared: slow transfers, high handling fees and difficulties in Cross-chain.

For example, transfers can be slow. During peak congestion, if a transaction's priority fee is set too low, it might remain unprocessed for days. On Ethereum, submitting a request does not guarantee immediate processing, as validators prioritize transactions based on fees. The highest transfer fees can reach up to 2 ETH (around 8,000 USD), making it prohibitively expensive for simple transactions. As a result, Ethereum is widely criticized for its high transaction fees.

There is widespread anticipation that Ethereum's upcoming ETH 2.0 upgrade will address these issues. Meanwhile, the competition among permissionless DeFi public chains has intensified. Networks like Polkadot, Solana, Avalanche, and BNB Chain[5] have gained significant attention, with Avalanche and BNB Chain emerging as leaders due to their rapid ecosystem growth.

Avalanche protocol was invented by researchers at Cornell University. Avalanche combines the most popular classic consensus and the Nakamoto consensus. The classic consensus: has the advantages of high speed, scale and energy saving. Nakamoto Consensus: It has the advantages of decentralization and robustness.

[3]https://ethereum.org/roadmap/merge.

[4]https://mevboost.pics/.

[5]It was named Binance Smart Chain (BSC) that time. https://www.binance.com/en/blog/ecosystem/introducing-bnb-chain-the-evolution-of-binance-smart-chain-421499824684903436

The Avalanche protocol is a fusion consensus mechanism of both. Avalanche can support 6000 transactions per second. With the popularity of DeFi, high-performance and low-fee transactions have gradually become a rigid demand for users.

The Avalanche protocol implements the merger of the classic consensus and the Nakamoto consensus. In the process of verifying information, there is no need to compare with the nodes of the entire network, as long as the majority of the N nodes are randomly selected, and then the nodes of the entire network repeat this process. . This form of verification between nodes, like a snowball on a mountain, will roll bigger and faster, so it is more scaled, safer and faster on the basis of a decentralized network.

Avalanche is a new public chain driven by consensus. In fact, compared to other public chains such as Bitcoin, Ethereum, Polkadot, Avalanche can also achieve higher performance, security and efficiency. Avalanche can clear thousands of transactions per second, which is beyond the reach of Bitcoin and Ethereum. High TPS is not the biggest advantage, and the most powerful place is that the delay in the protocol is very small. For example, the delay of Bitcoin has reached at least 10 minutes, and according to the test, even in a highly decentralized network environment, the delay of the protocol itself can reach the order of 1.35 seconds for a single transaction.

After Avalanche, February 19, 2021, is definitely a turning point in the history of DeFi. Who would have thought that BNB Chain, which has always been low-key, suddenly became the number one DeFi public chain. BNB Chain's surpassing of Ethereum is reflected in the data: the transaction volume of BNB Chain DEX PancakeSwap surpassed ETH DEX Uniswap, and BNB Chain TVL (Total Value Locked) also surpassed ETH TVL. BNB Chain achieves very high performance through centralized means. BNB Chain's account addresses have exceeded 70 million, and the 24-hour transactions are over 10 million.

2.2 Valuation of Blockchain Network and Metcalfe's Law

Metcalfe's Law, articulated by Robert Metcalfe (1973) [9], asserts that the value of a network is proportional to the square of the number of its users. Specifically, if n represents the number of users in a network, then the value of the network can be expressed as $V \propto n^2$. This relationship underscores the exponential increase in potential connections and interactions as user participation grows, illustrating that each additional user not only enhances the value of existing connections but also facilitates the creation of new ones.

The implications of Metcalfe's Law are particularly relevant in the context of digital networks, such as social media platforms and communication technologies, where the utility of the service escalates with each new user. This phenomenon, known as the network effect, leads to a reinforcing cycle where increased user participation attracts further users, thereby amplifying the network's overall value.

For social networks like Facebook and Tencent, Zhang et al. [10] concluded that the actual data from these social networks fit Metcalfe's Law better than other network effect laws, indicating a strong validation of Metcalfe's Law through empirical evidence.

Initial studies, as exemplified by Hayes (2017) [11] and Pagnotta [12], aimed at valuing Bitcoin and analogous Proof-of-Work (PoW) Blockchain Networks, predominantly anchor their valuation models on production-related costs, such as the hashrate. However, the applicability of these models is largely confined to the Bitcoin network. In contrast, contemporary energy efficiency Blockchain networks, frequently adopt alternative consensus mechanisms, notably Proof-of-Stake (PoS), rendering the aforementioned valuation frameworks less relevant.

Existing studies have examined the relevance of Metcalfe's Law, a fundamental principle in network theory, for assessing the value of digital blockchain networks. Alabi [2] performed a comparative study on three major blockchain networks: Bitcoin, Ethereum, and Dash. This research found that the value dynamics of these networks are consistent with Metcalfe's Law, which posits that a network's value increases proportionally with the square of the number of its active users.

Peterson [13] validated Metcalfe's Law's effectiveness in predicting the medium- to long-term price trends of Bitcoin. Additionally, Wheatley et al. [14] explored the predictability of price bubbles within the Bitcoin network. Their study incorporated a modified Metcalfe's Law and a Log-Periodic Power Law Singularity (LPPLS) model, designed to understand the complex relationship between network effects and speculative behavior in cryptocurrency valuations.

2.3 DeFi & Perpetual Future Contracts

In board terms, the Chapter 4 and 5 relate to three types of literature: those examining DeFi, cryptocurrency future contracts, and Automated Market Making (AMM). The literature on DeFi includes works discussing the fragility and inefficiency of the DeFi lending platforms (e.g., [15–17]), those examining the liquidation and leverage risks (e.g., [18–24]), and those comparing DeFi and CeFi platforms (e.g., [25, 26]). Qin et al. [22] investigated four major DeFi protocols involving lending (MakerDAO[6], dYdX[7], Aave[8], and Compound[9]), revealing that liquidators can optimize strategies to maximize profits, potentially increasing borrowers' losses during liquidations. It underscores the inherent risks and instabilities in DeFi markets, particularly through the lens of liquidation mechanics and their impact on market dynamics. Later, Wang et al. [27] analyzed the risks associated with on-chain leverage in the DeFi sector by formalising a model for under-collateralized DeFi lending platforms. They provide evidence that high levels of leverage can lead to significant risks and instabilities. Since liquidation risk is also considered as one of the major risks of perpetual futures, this study evaluates the differences in traders' behavior in CEXs and DEXs revealed by liquidation. Gramlich et al. [28] conducted the systematic literature review on decentralized finance.

Existing literature evaluates cryptocurrency future contracts mainly in terms of their relationship with the spot market. Akyildirim et al. [29] studied the impact of Bitcoin futures on the cryptocurrency market, particularly the introduction of CME and CBOE futures contracts in December 2017. Alexander et al. [30] found that BitMEX derivatives lead the price discovery process over major Bitcoin spot

[6]https://makerdao.com/.
[7]https://dydx.exchange/.
[8]https://aave.com/.
[9]https://compound.finance/.

exchanges. Hung et al. [31] identifies substantial pricing effects and breakpoints in market efficiency, indicating the dominant role of Bitcoin futures in price discovery compared to spot markets. As a special case of future contracts, perpetual future contracts are scarcely investigated, although with much higher trading volume. Besides the theoretical discussion on the arbitrage between perpetual future markets and spot markets [7], there lacks enough empirical works examining perpetual future traders' behavior, especially in DEXs. After the pioneering work by Soska et al. [32], which conducted the first analysis on the investor profile for perpetual future contracts in BitMEX, i.e., a CEX, Alexander et al. [33] constructed the optimal hedging strategy with empirical corroboration.

Since some DEXs of perpetual futures adopt VAMM Model, which utilize AMM as the core, the study also shed lights on the effect of traders specifically derived by AMM. There is an emerging sort of research on the economic implications of AMM, most of which, however, focuses on the incentives of liquidity provision, driven by the relationship between transaction fee and impermanent loss (e.g., [34–37]). While the limited existing empirical studies are based on the spot market [36, 38], i.e., Uniswap, the study contribute to the understanding of AMM by conducting the first analysis on the future market supported by AMM from the perspective of traders, enlightening the effect driven by AMM in a new context. As Uniswap and its AMM only consists of a subset of DEXs while other forms of DEXs, i.e., the Hybrid and Oracle Model in this work, have not been reached by the current studies, the study also contribute by clearly defining and examining the implication of decentralization to different extent in exchanges.

Chapter 3

Value Blockchain networks: Modelling the growth of EVM-compatible blockchains and decentralized applications

Networks serve as the foundational structure across numerous fields such as economics, biology, physics, mathematics, computer science, sociology, and beyond. Blockchain technology, an emergent distributed computational paradigm, plays a pivotal role in supporting the infrastructure of decentralized applications. This technology facilitates interactions akin to those in online social networks, where participants form a complex social graph within blockchain ecosystems. The anonymous nature of transactions on the blockchain calls for a detailed exploration of trust dynamics.

Despite the importance of networks across various economic and social domains, a comprehensive and consolidated analysis of network growth and value remains scarce. Decentralized blockchain networks present a unique opportunity, providing transparent and detailed transaction data from their inception. In this study, I comprehensively analyze a diverse set of blockchain networks, encompassing layer-1, layer-2, and decentralized finance (DeFi) applications. My research findings indicate that among all the EVM-compatible blockchains and decentralized applications (DApps), only the Ethereum mainnet exhibits predominantly nonlinear dynamics. In contrast, the majority of layer-2 networks and sidechains have demonstrated either linear or sublinear growth trajectories to date.

The rest of the chapter is summarized as follows. In Section 2.1, I explain foundational principles of layer-1, layer-2 blockchains and different DeFi applications, lending, spot trading and derivative trading. Section 3.1 delineates the foundational principles and my research objectives. In Section 3.2 and Section 3.3, I offer a empirical analysis on their user network growth, delineating their characteristics and distinctions. Finally, Section 3.5 provides the concluding remarks.

3.1 Research Objective Description

This paper focuses on three main categories: blockchains, decentralized applications, and tokens.

A blockchain functions as a public ledger that documents the balances of various non-zero accounts (public key addresses). I propose that active non-zero addresses on the blockchain be regarded as users within the blockchain's user network, and that an increase in the number of these users will correspondingly enhance the value of the user network. In addition to measuring the value of the blockchain's user network, considering that one of the primary purposes of user interaction within this network is through smart contract interactions, I also sequentially measure the value of DApps and their contribution to the user network's overall value.

3.1.1 Blockchain

For the analysis of blockchain networks, I have selected Ethereum as the largest Proof of Stake (PoS) Layer 1 user network by market capitalization. Additionally, I examine the most active Layer 2 networks built on Ethereum, including Optimism, Arbitrum, and Base, as well as prominent sidechain user networks such as BNB Chain, Polygon, and AVAX. These user networks share a common feature: they all utilize the Ethereum Virtual Machine (EVM) for smart contract execution.

The adoption of the EVM ensures consistency in account systems and transaction structures across these user networks, providing a foundation for my analysis of active users. The EVM consists of two types of accounts: Externally Owned Accounts (EOAs), controlled by private keys, and Smart Contract Accounts (SCAs), controlled by other EOAs or smart contracts without private keys. Activity within the EVM is recorded as transactions on the blockchain, with each transaction containing "from" and "to" data structures. The "from" field stores the sender's address, while the "to" field stores the recipient's address. My approach to identifying active users within these user networks considers each EOA and SCA as an independent user. I analyze all transactions within a statistical period, counting any user whose address appears in the "from" field of a transaction as an active user.

3.1.2 Decentralized Application

Decentralized Applications (DApps) leverage blockchain technology to offer decentralized functionality, eliminating the need for centralized servers or authorities. They execute operations transparently and reliably through smart contracts deployed on the blockchain.

DApp developers avoid reliance on centralized servers by using the blockchain's decentralized infrastructure as a public ledger. Users interact with DApps by sending transactions to smart contracts, which process the requests and return responses as the blockchain executes these transactions.

DApps are designed to facilitate direct user interactions, removing intermediaries to create a more autonomous and decentralized user experience. They span various domains such as finance, gaming, and social networks, emphasizing user control and privacy.

In essence, DApps are applications built on blockchain technology that prioritize decentralization, transparency, and security. They aim to reshape how traditional applications operate, pushing the digital world towards a more open and autonomous model.

Decentralized exchanges (DEXs) are among the most common types of DApps. For this study, I have selected Uniswap, the leading Spot DEX by market capitalization, along with representative native Spot DEXs from the previously mentioned blockchain user networks.

These Spot DEXs follow similar business models. Through their smart contracts, users can swap any ERC20 token for another ERC20 token or ETH (Ethereum's native token).

To identify active users within DEXs, I analyze transactions involving the DEXs' smart contracts over a given statistical period. Any user whose address appears in the "from" field of a transaction is counted as an active user.

3.1.3 Token

A token embodies an abstraction, representing ownership or entitlement to a specific asset or utility within a decentralized environment. Tokens serve as abstract entities facilitating ownership and control, enabling users to assert rights over assets or functionalities without reliance on centralized authorities, thereby emphasizing the principles of abstraction and ownership in a distributed and secure manner. They can represent various forms of value such as currency, art, music, text, code, and even physical assets like real estate or funds in a bank account. By wrapping various assets in the form of Tokens, these assets can be bought, sold, used, stored, transferred, etc., giving users control and ownership over these assets.

In traditional systems, digital assets are often controlled by centralized entities and can be altered or revoked, limiting user autonomy. Tokens based on blockchain technology, however, ensure asset ownership in a more transparent and secure manner through decentralization. Through mechanisms like smart contracts, blockchain technology ensures that ownership and transactions of Tokens adhere to predefined rules, giving users greater control and security.

In summary, as a core concept of blockchain technology, Tokens emphasize the abstraction and ownership of digital assets. Through the decentralized nature of blockchain, Tokens empower users with greater control and autonomy, driving innovation and development in the digital economy.

This research further explores the role and impact of tokens within blockchain user networks. It examines the design and application of different token types and their influence on user behavior and network development. By analyzing the characteristics and functions of tokens, this study seeks to understand the economic models and user participation mechanisms of blockchain networks, providing a foundation for future research and analysis.

3.2 Data Description

In this section, I elucidate the logic, methods, and preliminary findings of blockchain networks, DEXs and tokens.

3.2.1 Blockchain Activity

I conducted a statistical analysis of the Daily Active Users (DAU) and Monthly Active Users (MAU) across Ethereum Mainnet, prominent Ethereum Rollups, and major EVM Sidechains. Each unique address is considered as an individual user. If a transaction originating from an address is confirmed on the chain, it is counted as an active user.

I classified users based on nonce, which represents "number used once" and stores the state of an address. The nonce starts from zero and increments by one with each confirmed transaction from that address. Addresses with lower nonce values can be considered new users or addresses temporarily used by existing users for specific purposes. After comparing the results of filtering based on different nonce thresholds, I found that using a threshold of nonce greater than 10 was sufficient to filter out some suspicious accounts.

There are a couple of interesting insights:

1. BNB Chain (BSC) is the blockchain network that boasts the highest number of active users, reaching a peak of more than 1.4 million daily active users and over 6 million monthly active users in November 2021. Even during subsequent bear markets, it maintained over 400,000 daily active users and more than 3.5 million monthly active users. Ethereum's mainnet ranks second, followed by Polygon.

2. Ethereum's active user count consistently exceeds that of its Layer 2 networks for most of the time. While the daily active counts of Arbitrum and Base

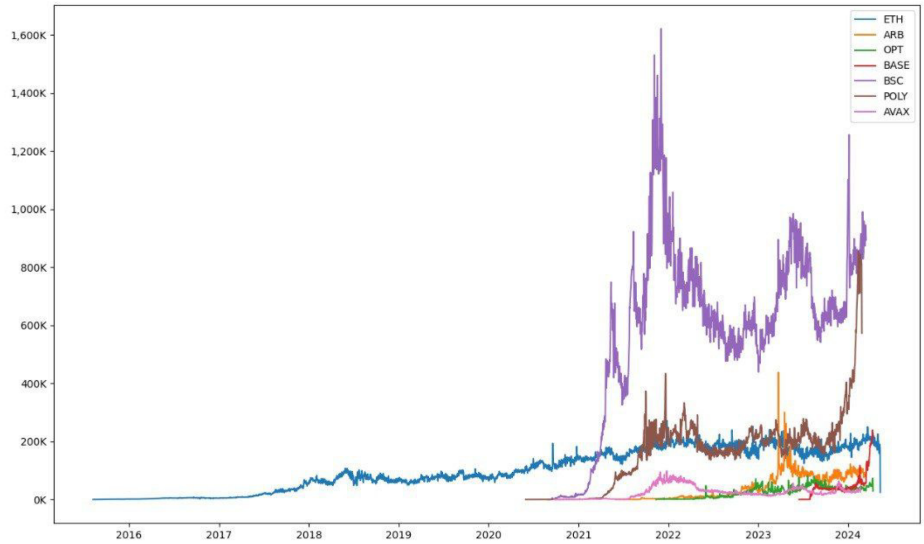

FIGURE 3.1: Daily Active User on different blockchain networks

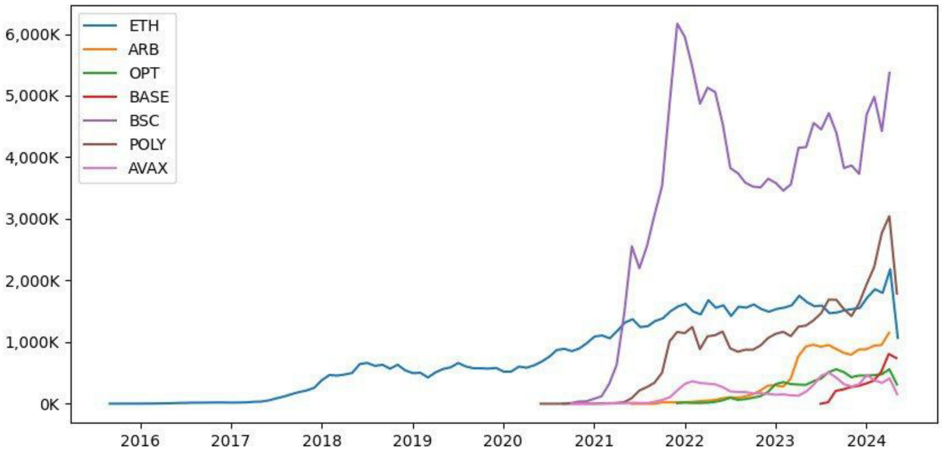

FIGURE 3.2: Monthly Active User on different blockchain networks

briefly surpassed those of the Ethereum mainnet, there remains a significant difference in monthly active counts.

3. The number of DAU on blockchain networks exhibits a clear correlation with the bull and bear cycles of the cryptocurrency market. Generally, bull markets witness an influx of active users, while bear markets see a gradual decline in the number of active users. Ethereum serves as a typical example. Its

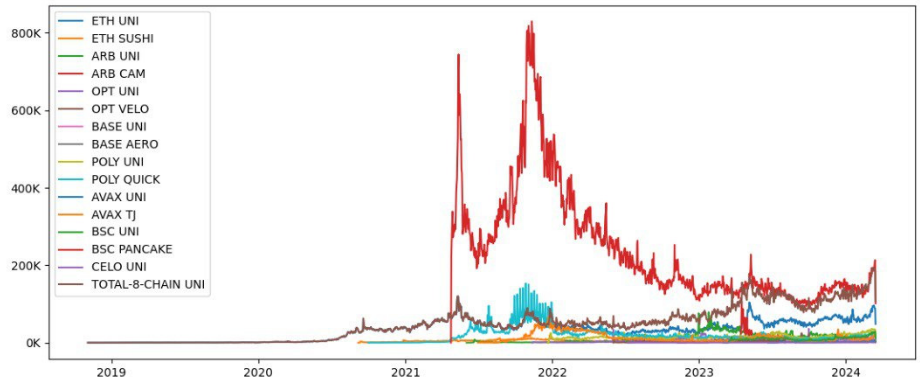

FIGURE 3.3: Daily Active User for DEX

growth in active users experienced two surges, from April 2017 to January 2018 and from January 2020 to August 2022.

4. Polygon exhibited slightly different performance. During the bull market cycle, Polygon experienced its first surge from March 2021 to September 2021 and maintained a high level for the following six months. After a brief decline from May 2022 to September 2022, it rapidly recovered to historical highs, even surpassing them in early 2024, establishing a significant lead over other blockchain networks.

3.2.2 DEX Activity

I examined the activity levels of Uniswap across eight deployed blockchains and compared them with the most representative native DEX on each chain. When an address engages in token swapping on a DEX, it is counted as an active user.

There are a couple of interesting insights:

1. Pancake Swap, on BNB Chain (BSC), boasts the highest number of active users, consistent with the situation on the BNB Chain network, as trading tokens is one of the primary motivations for users to engage with blockchain networks.

2. Overall, Uniswap is the preferred DEX for users on Ethereum and Layer 2 networks, while users on sidechains tend to favor native DEXs. This is

because the Uniswap team often deploys contracts early in the development of Layer 2, but support for sidechains is relatively delayed.

3. Similar to blockchain, the number of active users on DEX platforms also follows bull and bear cycles, although the time frames may not necessarily align. Consider Uniswap as an illustration: since its launch in November 2018, it took until January 2020 to gradually stabilize its daily active users at over 1,000. Subsequently, from January 2020 to May 2021, the DAU surged rapidly to over 70,000. From June 2021 to January 2023, the lowest point was around 33,000 in September 2021, stabilizing around 50,000 thereafter. Starting from February 2023, it entered a new growth cycle, continuously setting new historical highs.

3.2.3 Token Activity

3.2.3.1 Stablecoins

Stablecoins are designed to be anchored to 1 unit of fiat currency. I have selected the top three stablecoins by market capitalization, including USDT, USDC, and DAI. Without exception, they are all pegged to the US dollar and backed by other assets. When a stablecoin is transferred from one address to another, or when an address uses stablecoins to purchase another token on a DEX or sells other tokens to acquire stablecoins, the sender's address is logged as an active user.

USDT is a stable currency issued by the Tether company and is currently the largest stable currency in circulation. USDC is a stable currency issued by Circle. DAI is a decentralized stable currency issued on the Ethereum mainnet. USDT and USDC operate by collateralizing a basket of assets, mostly U.S. treasury bills, and guaranteeing 1:1 payment.[1] DAI is backed by over-collateralized ETH (due to the high volatility of ETH, it must be over-collateralized to ensure payment). Its issuance is also completely public and not controlled by anyone. DAI's decentralization makes it an attractive choice. However, DAI's current liquidity is relatively small.

I analyzed the daily active and monthly users of these stablecoins. The DAU/-MAU numbers in Figure 3.4 are around 5 percent. The ratio of DAU to MAU is

[1] https://tether.to/en/transparency/?tab=reports

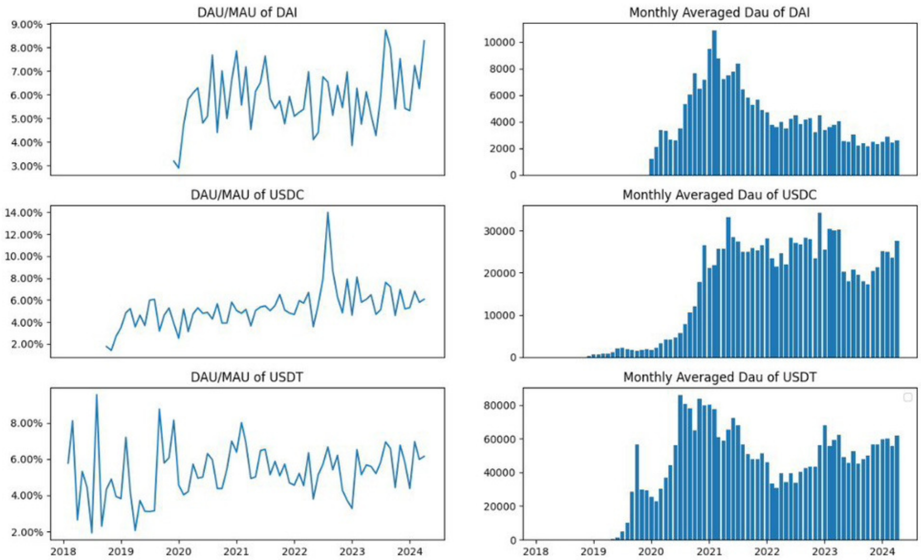

FIGURE 3.4: Avg Daily Active User each month for Stablecoins on Ethereum network.

the proportion of monthly active users who have transactions with the particular stablecoin in a single day window. The application scenarios here mainly include Swapping tokens, Providing liquidity, Lending/Borrowing, and Transfer. Today, the application scenarios of stablecoins are enough to attract monthly active users to use them more actively daily. Given that the application scenarios of various stablecoins are similar, it is normal to have a similar daily active/monthly active ratio. It also shows that DAU/MAU is a good indicator of user engagement similar to how Facebook and Twitter use engagement.

3.2.3.2 Lending DApps' Governance Token

After stablecoins, I analyze the user patterns of several lending DApps' governance token. Compound, Aave, and MakerDAO are decentralized, blockchain-based protocols that allow users to lend and borrow crypto. The interest rates paid and charged by borrowers and lenders are determined by the supply and demand of each encrypted asset. Interest rates are generated for each block mined. Loans can be returned at any time and locked assets can be withdrawn at any time. There are a couple of interesting insights:

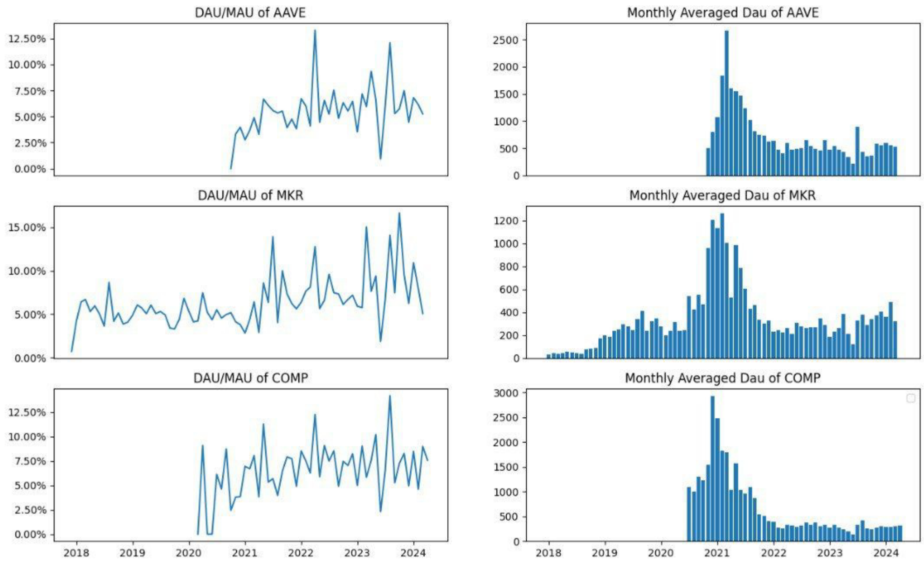

FIGURE 3.5: Avg Daily Active User each month for Lending Protocols' governance token on Ethereum network.

The DAU/MAU numbers in Figure 3.5 are around 5 - 8 percent, which is similar to the usage pattern of stablecoins. There are several reasons for that. People use stablecoins as frequently as Lending because stablecoins are used as collateral assets and borrowing assets. In addition, most of these loans are short-term loans that users need to renew monthly or weekly. DAU numbers and the DAU/MAU trends are quite different for these lending protocols, which essentially shows the importance of trust. Essentially users treat these protocols as their banks to lend and borrow assets. The level of trust in these protocols is similar to the level of trust in banks, and the online protocol provides more transparency.

3.3 Empirical Approaches: Valuing Blockchain Networks

Essentially, I have adapted and modified the methodology suggested in [14], which utilizes Metcalfe's Law to characterize the growth of the active user base. Metcalfe's Law posits that the value, in this context the market capitalization, of a network is

$$P = e^{\alpha_0} u^{\beta_0}, \tag{3.1}$$

where u denotes the count of active users, which is approximated by a proxy measure, typically the number of active addresses.

Wheatley et al. (2019) [14] rewrite Eq.(4.1) in a logged form to find the estimated value of β for bitcoin as follows:

$$\ln(p) = \alpha + \beta \ln(u) + y\epsilon. \tag{3.2}$$

However, since how to define effective nodes in a network is different between physical networks, e.g., telephony, and blockchain, I need to reconsider the approaches to capture the estimation of β.

Metcalfe's law assumes the value of a network proportional to the sum of all possible edges between nodes, which equals to $\frac{(n)(n-1)}{2}$ for a network in size of n and this value can be simplified to n^2 when n gets large. A node is considered excluded from the network only if it is physically disconnected from the network. However, for the network formed by a blockchain, the connectedness of a node, e.g., address, will not be affected even if this node has been abandoned. In contrast, although still connected to the blockchain network, the node abandoned becomes valueless and the network can be overvalued based on Metcalfe's law. As a result, how to estimate the number of effective addresses, i.e., *Total number of addresses − The number of abandoned addresses*, is critical in valuing the blockchain network.

In [14], this discount in the number of effective addresses is revealed by a estimation of β smaller than 2, while a small β may indicate a large proportion of abandoned addresses. As Wheatley et al. (2019) [14] estimate β by regression with data pooled together, this estimation assumes β to be static across time. However, the market condition actually changes overtime, which has been broadly examined and corroborated by literature on traditional finance [39–41], participants' behavior also evolves across time, resulting in probable dynamic proportion of abandoned address rather than a static one. The estimated β in [14] is actually a averaged value across the sampling time window but the real value of β may change overtime. Therefore, in this study I conjecture that β will change depending on different market conditions and higher when the market is bullish, as addresses are less likely to be abandoned during bullish market.

To examine the dynamic effects of the effective addresses on the valuation of the blockchain networks, I employ the Fixed Transition Probabilities Markov-Switching model (FTP-MS) by Diebold & Rudebusch (1999) [42]. I propose two regimes of the market, one in bearish and another in bullish, and the basic specification is as follows:

$$
\begin{aligned}
&\ln(p_t) = \begin{cases} \alpha + \beta_{1,1}\ln(u_t) + \epsilon & \text{if } s_t = 1 \\ \alpha + \beta_{1,2}\ln(u_t) + \epsilon & \text{if } s_t = 2 \end{cases} \\
&P\left(s_{t+1} = i \mid s_t = j\right) = p_{ij}, \quad i,j \in \{1,2\}
\end{aligned}
\tag{3.3}
$$

where I set β as parameter switching between $\beta_{1,1}$ and $\beta_{1,2}$ while p_{ij} indicates the transition probability between two states (1 and 2). The unobservable state variable, s_t, evolves according to the first-order Markov-switching process:

$$
P = \begin{pmatrix} P_{1,1} & 1 - P_{2,2} \\ 1 - P_{1,1} & P_{2,2} \end{pmatrix}
$$

where $P_{(s_{t+1}} = i_{|}s_t = j\big) = p_{ij}$ and $0 < P_{i,i} < 1; 0 < P_{j,j} < 1$. If I set regime 1 $(s_t = 1)$ as the regime when addresses are less likely to be abandoned and regime 2 $(s_t = 2)$ as the regime when addresses are more likely to be abandoned, $1 - P_{2,2}$ denotes the probability the market would switch from regime 2 to regime 1.

Moreover, as a robustness-check, I also run FTP-MS model in three regimes with other settings the same with Eq.(4.3). The first two regimes are defined in the same manner as in Eq.(4.3), while the third regime amounts to a redundant one containing any unexpected circumstances. The specification is as follows:

$$
\begin{aligned}
&\ln(p_t) = \begin{cases} \alpha + \beta_{1,1}\ln(u_t) + \epsilon & \text{if } s_t = 1 \\ \alpha + \beta_{1,2}\ln(u_t) + \epsilon & \text{if } s_t = 2 \\ \alpha + \beta_{1,3}\ln(u_t) + \epsilon & \text{if } s_t = 3 \end{cases} \\
&P\left(s_{t+1} = i \mid s_t = j\right) = p_{ij}, \quad i,j \in \{1,2,3\}
\end{aligned}
\tag{3.4}
$$

where the state variable s_t evolves in the following process:

$$P = \begin{pmatrix} P_{1,1} & P_{1,2} & P_{1,3} \\ P_{2,1} & P_{2,2} & P_{2,3} \\ P_{3,1} & P_{3,2} & P_{3,3} \end{pmatrix}.$$

3.4 Empirical Results

Before estimating parameters in Eq.(4.3), I set some conditions to filter the addresses under each blockchain or project so that abandoned addresses could be filtered out as much as possible. For the five blockchains I examine in this study, i.e., Ethereum, Optimism, BNB Smart Chain, Polygon, and Avalanche, I filter the addresses on those chains using the number of nonce[2], as a count of transactions, for each address. As shown in the second column of Table 5.6, the filtering conditions include: nonce ≥ 5, nonce ≥ 10, nonce ≥ 50, and nonce ≥ 100. For the on-chain projects I examine, i.e., Uniswap and SushiSwap, I filter the addresses using the dollar value of tokens in the address, while the thresholds are 10, 50, 100, and 1000 USD. Although here I try to filter addresses, it is unnecessary that there are more effective addresses left in the case of stricter conditions.

Table 5.6 illustrates the parameter estimations of Eq.(4.3). $P_{1,1}$ and $P_{1,2}$ represent the estimated probability that the blockchain or project will remain at regime 1 or 2, respectively, so zero value in one of those two probabilities implies that the model reduce to just one state, the other regime. It is shown that the FTP-MS model successfully split conditions into two regime for Ethereum, BNB Smart Chain, Polygon, Uniswap, and SushiSwap, since I can find at least one line of result with positive estimations for both βs ($\beta_{1,1}$ and $\beta_{1,2}$) and both P ($P_{1,1}$ and $P_{1,2}$) far larger than zero. For illustration, fitted value, as well as the real value, of the market capitalization are plotted in Fig.3.6 to Fig.3.12 for the estimation with smallest value of Akaike Information Criterions (AIC) in Table 5.6. All the fitted values of market capitalization are calculated with smoothed daily number of addresses, which is the trend decomposed using Locally Estimated Scatterplot Smoothing (LOESS).

[2]In Ethereum, the nonce represents the count of transactions sent from a specific address. With each transaction dispatched, the nonce value increments by one.

For the estimation on Ethereum with filtering condition $nonce \geq 5$, in regime 1 β ($\beta_{1,1}$) is estimated to be 1.31 while larger than that in regimes 2 ($\beta_{1,2}$ is estimated to be 1.19). As shown in Fig.3.6, periods of regime 1 are indicated by the shaded area, which coincides with the 2017 ICO boom and 2021 Defi summer, two most recent periods of bullish market of crypto. Since how regime change is determined endogenously in my model, this coincidence highlights a potential relation between the market condition and the proportion of addresses abandoned, which affect the determination of β. Prominent in Defi summer, Uniswap and SushiSwap surged and drawed a lot of attention, followed by a sudden drop as signal of the end of this round in bullish. This clear dichotomy in market condition is also revealed by a clear decomposition in regimes using my model. As shown in Fig.3.11 and Fig.3.12, regime 1, which is indicated by the shaded area, coincident with the period of 2021 Defi summer, further substantiating my conjecture that β would be larger during bullish market as addresses are less likely to be abandoned.

The patterns in other blockchains, i.e., Optimism, BNB Smart Chain, Polygon, and avalanche, do not exhibit clear dichotomy in the setting of two regimes. However, in the setting of three regimes, results in some filtering conditions shed lights on this dichotomy. Table 3.2 reports the estimated parameters in the setting of Eq.(4.4). For most of the circumstances, AIC of Eq.(4.4) is larger than that of Eq.(4.3), suggesting Eq.(4.4) as robust and its better fitting. Meanwhile, for some cases, i.e., Optimism of $nonce \geq 50$, BNB Smart Chain of $nonce \geq 5$, and Polygon of $nonce \geq 50$, AIC under Eq.(4.4) is significantly lower than that for Eq.(4.3), suggesting Eq.(4.4) as the better choice. The estimated periods of different regimes for these three cases, as well as the fitted market capitalization, are plotted in Fig.3.13 to Fig.3.15. Unlike the case of 2-regime setting, the dichotomy of regimes appears for Optimism, BNB Smart Chain, and Ploygon, while regime 1 and regime 2 in Eq.(4.4) dominate (indicated by gray and orange color in shade), further confirming the existence of 2-regime switching in reality. The introducing of regime 3 allows the very extreme cases, so the first 2 regimes can be effectively modeled.

In summary, FTP-MS model gives us a solution to differentiating periods when the proportion of effective address is higher and thus the value of β. My empirical results on Ethereum blockchain suggest evidence supporting my conjecture on the relationship between the magnitude of β and market conditions, while some layer-2 chains do not exhibit the same regime switching patterns as Ethereum. This

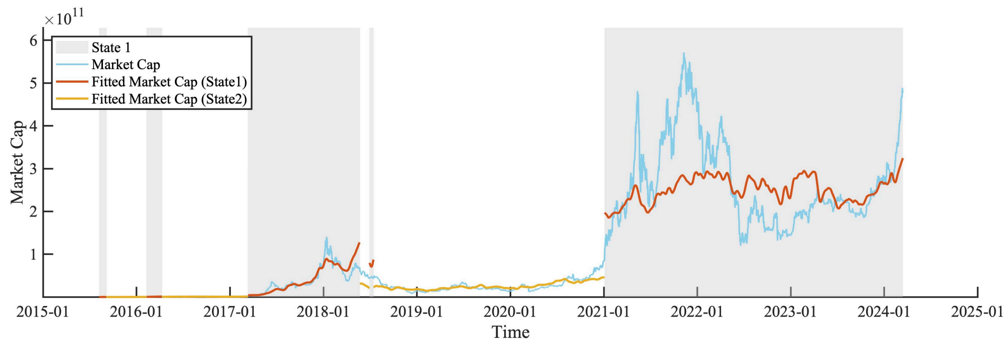

FIGURE 3.6: Ethereum (2-regimes, *nonce* ≥ 5)

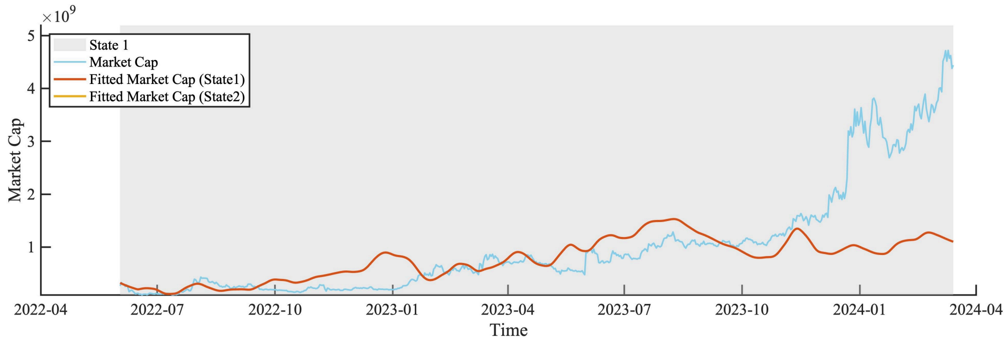

FIGURE 3.7: Optimism (2-regimes, All)

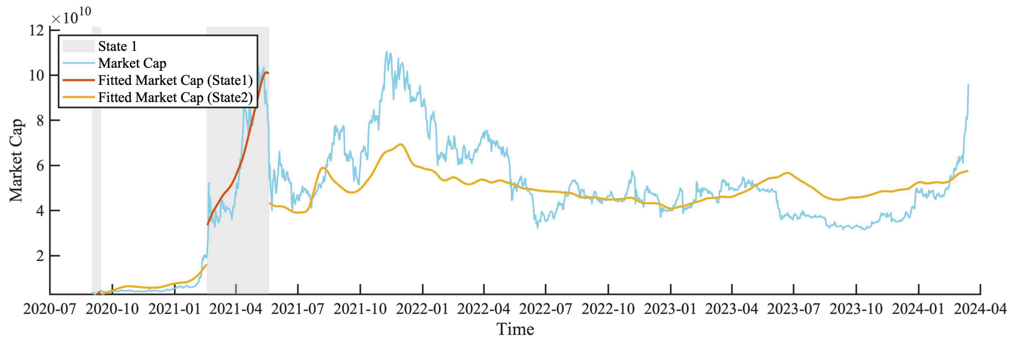

FIGURE 3.8: BNB Smart Chain (2-regimes, *nonce* ≥ 50)

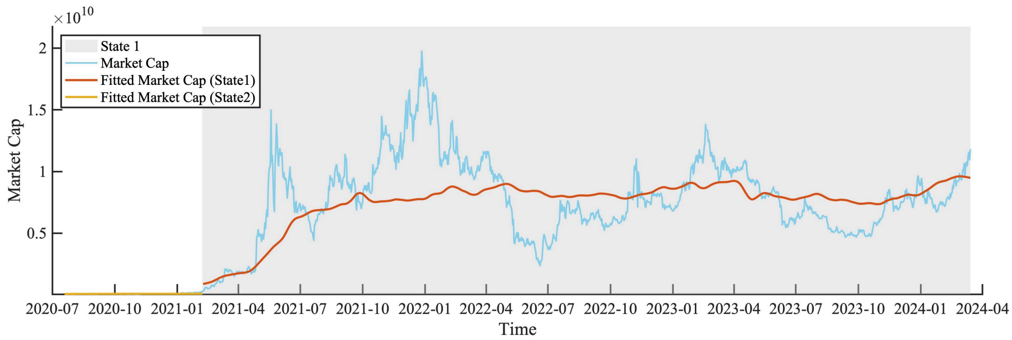

FIGURE 3.9: Polygon (2-regimes, *nonce* ≥ 100)

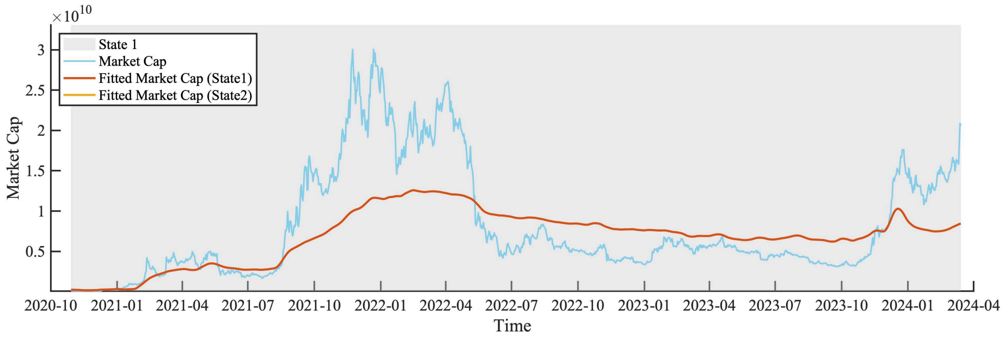

FIGURE 3.10: Avalanche (2-regimes, $nonce \geq 50$)

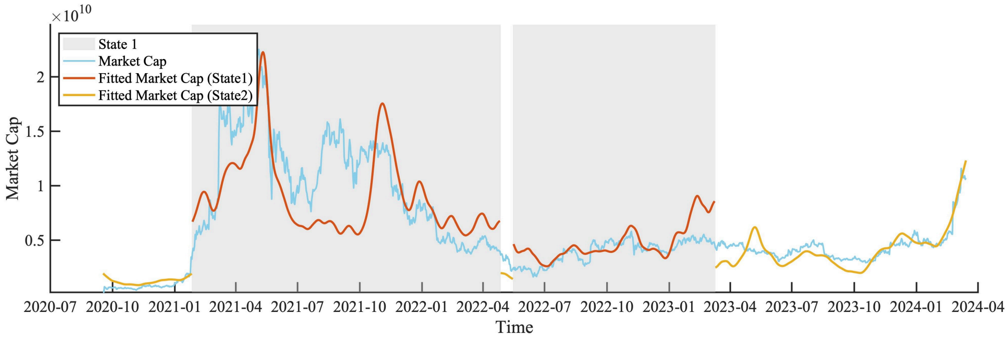

FIGURE 3.11: Uniswap (2-regimes, $USD \geq 100$)

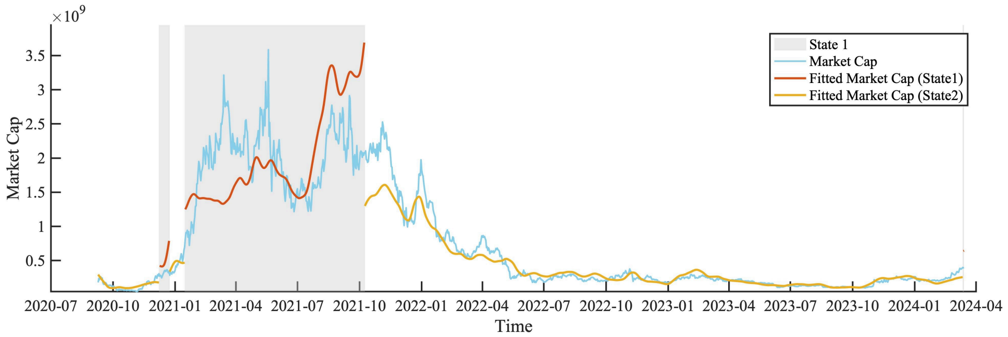

FIGURE 3.12: SushiSwap (2-regimes, $USD \geq 100$)

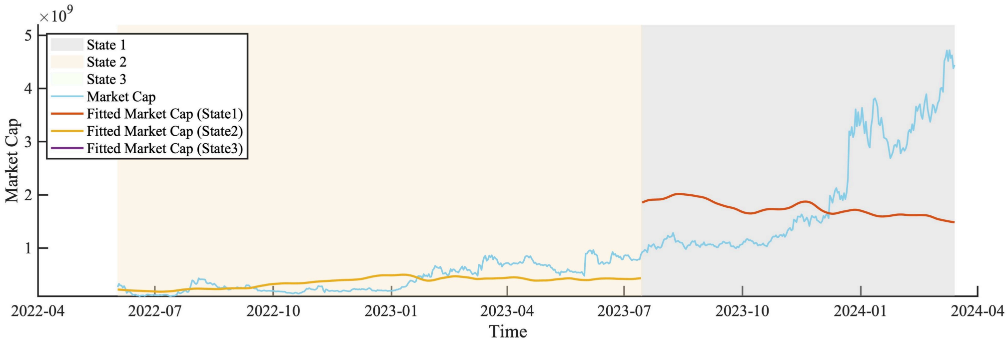

FIGURE 3.13: Optimism (3-regimes, $nonce \geq 50$)

TABLE 3.1: Parameter estimation results of Eq.(4.3)

Blockchain /project	**Filtering condition**	α	$\beta_{1,1}$	$\beta_{1,2}$	$P_{1,1}$	$P_{2,2}$	**AIC**
Ethereum	All	9.91***	**1.27*** **	**1.15*** **	1.00	0.98	2753
	$nonce \geq 5$	10.15***	**1.31*** **	**1.19*** **	0.99	0.99	2108
	$nonce \geq 10$	10.43***	**1.31*** **	**1.18*** **	1.00	0.99	2704
	$nonce \geq 50$	12.05***	**1.24*** **	**1.09*** **	0.99	0.99	5006
	$nonce \geq 100$	11.44***	**1.29*** **	0.95***	1.00	0.00	8424
Optimism	All	9.65***	**0.98*** **	-12.57***	1.00	0.00	1379
	$nonce \geq 5$	9.97***	**0.99*** **	-3.96***	1.00	0.01	1484
	$nonce \geq 10$	10.31***	**0.97*** **	-6.97***	1.00	0.00	1533
	$nonce \geq 50$	12.89***	**0.76*** **	0.02***	1.00	0.19	1656
	$nonce \geq 100$	11.75***	**0.92*** **	-0.45***	1.00	0.02	1533
BNB Smart Chain	All	17.97***	**0.48*** **	0.23***	1.00	0.02	1137
	$nonce \geq 5$	18.21***	**0.48*** **	**0.23*** **	1.00	0.91	1001
	$nonce \geq 10$	17.51***	**1.12*** **	**0.53*** **	1.00	1.00	646
	$nonce \geq 50$	18.29***	**0.56*** **	**0.49*** **	1.00	1.00	601
	$nonce \geq 100$	18.03***	**1.10*** **	**0.53*** **	0.97	1.00	630
Polygon	All	15.18***	**0.60*** **	-3.51***	1.00	0.00	2286
	$nonce \geq 5$	14.48***	**0.81*** **	**0.67*** **	0.99	1.00	1389
	$nonce \geq 10$	15.16***	**0.67*** **	**0.60*** **	0.99	1.00	1311
	$nonce \geq 50$	15.36***	**0.70*** **	**0.62*** **	0.99	1.00	1429
	$nonce \geq 100$	18.16***	**0.41*** **	**0.04*** **	1.00	0.97	1088
Avalanche	All	18.89***	**0.37*** **	**-0.55*** **	1.00	0.96	1903
	$nonce \geq 5$	19.00***	**0.37*** **	**-0.79*** **	1.00	0.95	1897
	$nonce \geq 10$	19.01***	**0.37*** **	**-0.88*** **	1.00	0.95	1868
	$nonce \geq 50$	19.08***	**0.39*** **	-0.99***	1.00	0.00	1849
	$nonce \geq 100$	19.24***	0.41***	**0.38*** **	0.03	1.00	1940
Uniswap	All	26.23***	**-0.33*** **	**-0.51*** **	0.99	1.00	2046
	$usd \geq 10$	14.12***	**0.74*** **	-23.04***	1.00	0.00	2926
	$usd \geq 50$	4.06***	**1.74*** **	**1.61*** **	1.00	1.00	1406
	$usd \geq 100$	5.26***	**1.64*** **	**1.52*** **	1.00	0.99	1379
	$usd \geq 1000$	11.90***	**1.06*** **	-1.79***	1.00	0.00	2511
SushiSwap	All	13.18***	**0.92*** **	**0.76*** **	0.99	1.00	1070
	$usd \geq 10$	9.13***	**1.43*** **	**1.30*** **	1.00	1.00	900
	$usd \geq 50$	9.82***	**1.35*** **	**1.23*** **	0.96	1.00	722
	$usd \geq 100$	10.68***	**1.26*** **	**1.14*** **	1.00	1.00	636
	$usd \geq 1000$	11.73***	8.06***	**1.12*** **	0.00	1.00	1614

Notes: This table summarizes the results based on the FTP-MS model in Eq. (4.3). I select effective addresses based on some filtering conditions, for which blockchains I adopt nonce while the projects I adopt the minimum value of tokens (in USD) in the addresses. Akaike Information Criterions (AIC) are reported in the mostly right column to show the model explanatory power. In the columns reporting the estimated value of $\beta_{1,1}$ and $\beta_{1,2}$, the estimations with probability to be retained in that regime larger than 0.5 are emphasised by bold and blue font. $*$, $**$, and $***$ denote significance at 0.1, 0.05, and 0.01 level, respectively.

difference could be attributed to the existence of extreme periods on these chains, which can be controlled under the 3-regime setting, or their state of being relatively isolated from the general market oscillation. Therefore, in practice, I can select between models with setting of 2-regimes and 3-regimes according to some selection criteria, e.g., AIC here I use.

TABLE 3.2: Parameter estimation results of Eq. (4.4)

Blockchain /project	Filtering condition	α	$\beta_{1,1}$	$\beta_{1,2}$	$\beta_{1,3}$	$P_{1,1}$	$P_{2,2}$	$P_{3,3}$	AIC
Ethereum	All	8.03***	**1.41*****	1.29***	**4.14*****	1.00	0.32	0.77	4882
	$nonce \geq 5$	10.15***	**1.31*****	**1.19*****	**14.62*****	1.00	1.00	0.97	2108
	$nonce \geq 10$	10.43***	**1.31*****	**1.18*****	-1.29***	0.99	0.99	0.00	2829
	$nonce \geq 50$	9.47***	**1.43*****	2.70***	2.66***	1.00	0.00	0.00	7586
	$nonce \geq 100$	12.42***	**1.26*****	**1.12*****	-1.78***	1.00	1.00	0.07	5673
Optimism	All	9.65***	**0.98*****	9.70***	5.99***	1.00	0.00	0.00	1389
	$nonce \geq 5$	9.97***	**0.99*****	5.38***	10.40***	1.00	0.00	0.00	1494
	$nonce \geq 10$	17.41***	**0.33*****	**0.18*****	**265.55*****	1.00	1.00	1.00	1060
	$nonce \geq 50$	15.78***	**0.55*****	**0.41*****	-11.28***	1.00	1.00	0.00	1114
	$nonce \geq 100$	11.75***	**0.92*****	**21.00*****	-1.28***	1.00	1.00	0.00	1543
BNB Smart Chain	All	17.97***	**0.48*****	20.73***	-6.13***	1.00	0.00	0.00	1147
	$nonce \geq 5$	20.73***	**0.29*****	**0.17*****	-2.29***	1.00	0.95	0.00	372
	$nonce \geq 10$	18.29***	**0.47*****	6.07***	-0.15***	1.00	0.02	0.42	998
	$nonce \geq 50$	18.56***	**0.47*****	**107.74*****	-13.88***	1.00	1.00	0.00	982
	$nonce \geq 100$	18.51***	**0.49*****	3.15***	5.75***	1.00	0.00	0.30	872
Polygon	All	15.18***	**0.60*****	**-26.57*****	-10.30***	1.00	0.99	0.00	2296
	$nonce \geq 5$	18.15***	**0.38*****	0.38***	**0.03*****	0.92	0.00	1.00	1142
	$nonce \geq 10$	15.15***	**0.60*****	0.61***	**0.67*****	0.85	0.12	0.99	1319
	$nonce \geq 50$	17.87***	**0.45*****	**0.40*****	**0.09*****	0.87	0.96	0.82	475
	$nonce \geq 100$	15.67***	**0.70*****	**0.61*****	7.03***	0.99	1.00	0.00	1407
Avalanche	All	18.71***	**0.38*****	**207.26*****	-179.70***	1.00	1.00	0.00	1942
	$nonce \geq 5$	18.88***	**0.38*****	**13.33*****	-5.54***	1.00	1.00	0.00	1931
	$nonce \geq 10$	18.89***	**0.38*****	**39.44*****	-20.85***	1.00	1.00	0.00	1902
	$nonce \geq 50$	19.08***	**0.36*****	25.81***	7.85***	1.00	0.00	0.00	1859
	$nonce \geq 100$	19.24***	**0.38*****	**19.20*****	-182.72***	1.00	1.00	0.00	1951
Uniswap	All	11.93***	**1.03*****	**0.89*****	12.66***	1.00	0.99	0.38	1718
	$usd \geq 10$	5.80***	**1.56*****	**1.44*****	**3.44*****	0.97	0.95	0.99	1700
	$usd \geq 50$	5.85***	**1.57*****	**1.45*****	**4.69*****	0.94	0.98	1.00	1529
	$usd \geq 100$	6.05***	**1.57*****	**1.45*****	**2.32*****	0.99	0.87	0.93	1506
	$usd \geq 1000$	14.91***	**0.77*****	**0.59*****	6.87***	1.00	0.99	0.00	1473
SushiSwap	All	7.08***	**1.73*****	**1.58*****	5.64***	1.00	0.98	0.00	2200
	$usd \geq 10$	9.15***	**1.43*****	**1.30*****	**5.80*****	0.83	0.99	0.74	1003
	$usd \geq 50$	12.01***	**1.11*****	**1.01*****	**0.93*****	0.78	0.84	0.99	345
	$usd \geq 100$	10.69***	**1.25*****	**1.14*****	2.52***	1.00	0.99	0.01	658
	$usd \geq 1000$	12.77***	**1.07*****	**0.96*****	12.62***	0.42	0.94	0.07	1319

Notes: This table summarizes the results based on the FTP-MS model in Eq. (4.4). I select effective addresses based on some filtering conditions, for which blockchains I adopt nonce while the projects I adopt the minimum value of tokens (in USD) in the addresses. In the columns reporting the estimated value of $\beta_{1,1}$, $\beta_{1,2}$, and $\beta_{1,3}$ the estimations with probability to be retained in that regime larger than 0.5 are emphasised by bold and blue font. $*$, $**$, and $***$ denote significance at 0.1, 0.05, and 0.01 level, respectively.

3.5 Key Findings

In this study, I conducted a comprehensive analysis of various blockchain networks, including layer-1, layer-2, and decentralized finance (DeFi) applications. My investigation examined these networks from multiple perspectives, focusing on their design and the underlying principles governing their growth—measured by monthly and daily active users—and their capacity for value creation.

One key finding is that among all EVM-compatible blockchains and decentralized applications (DApps), only the Ethereum mainnet exhibits predominantly

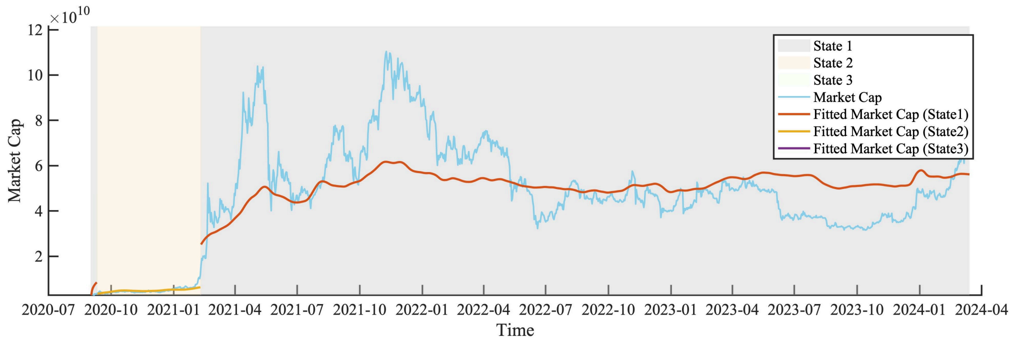

FIGURE 3.14: BNB Smart Chain (3-regimes, *nonce* ≥ 5)

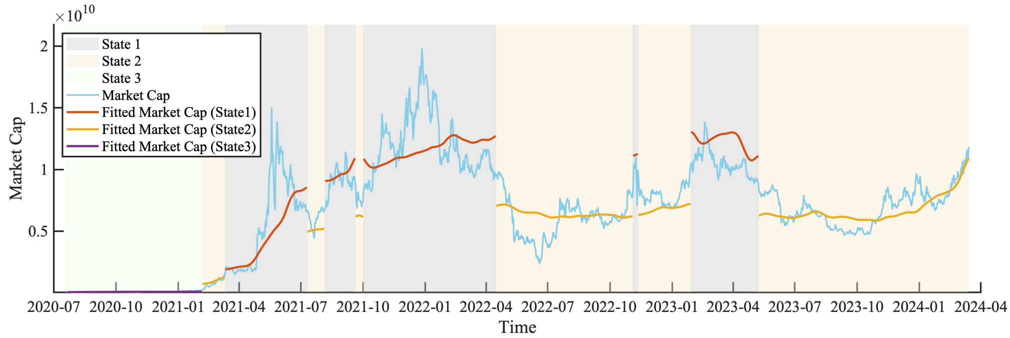

FIGURE 3.15: Polygon (3-regimes, *nonce* ≥ 50)

exponential growth dynamics. In contrast, most layer-2 networks and sidechains have displayed linear or sub-linear growth trajectories. These layer-2 networks and sidechains have so far fallen short of achieving Ethereum's original vision of fostering a broader range of applications beyond DeFi. However, they continue to compete with the Ethereum mainnet for DeFi market share and liquidity. This competition likely explains the absence of exponential growth in these networks. Previous research has explored the applicability of Metcalfe's Law, a key principle in network theory, for evaluating the value of digital blockchain networks. Alabi (2017) [2] conducted a comparative study of three major blockchain networks (Bitcoin, Ethereum, and Dash) and concluded that the value dynamics of these networks align with Metcalfe's Law. My findings further support that Metcalfe's Law is a better fit for mature networks such as Facebook, Tencent, Bitcoin, and Ethereum, reinforcing its empirical validity.

To examine the dynamic effects of active addresses on the valuation of blockchain networks, I employed the Fixed Transition Probabilities Markov-Switching (FTP-MS) model by Diebold & Rudebusch (1999) [42]). My empirical analysis of certain EVM-compatible chains provides evidence supporting my hypothesis regarding the relationship between the magnitude of the parameter β and market conditions, though some networks did not exhibit similar regime-switching patterns.

Chapter 4

Systematization of Knowledge: Perpetual Trading Exchanges and on-chain Protocols

[1]

Among all these DeFi applications, cryptocurrency derivative trading applications are implemented among exchanges organized in both centralized and decentralized manner, within which perpetual futures came to the most prominence with daily trading volume of more than 100 billion[2]. Investors prefer perpetual future contracts to future contracts, reflected by the far less 24H volume of future contracts ($1.1 billion), mainly because of the efficiency of perpetuals in hedging and speculation with high leverage while without the need of delivery and rollover. Before 2022, investors trade perpetual futures on centralized exchanges (CEXs), but following the collapse of FTX[3] there emerged many decentralized exchanges (DEXs) carrying perpetual futures, which are operated with more elements on-chain. Since the DEXs are constructed with smart contracts involved, more transparency can be ensured, helping guard against the fraudulence incurred in CEXs.

[1]The work in this chapter has been published in [Erdong Chen, Mengzhong Ma, and Zixin Nie. Perpetual Future Contracts in Centralized and Decentralized Exchanges: Mechanism and Traders' Behavior. Electronic Markets 2024.]

[2]At the time of writing, 22 November 2023, the 24H trading volume of perpetual future contracts among all the exchanges is $109.9 billion (Source: https://coinalyze.net).

[3]FTX misappropriated client funds for risky investments while failed in a run and collapsed after exposure. Source: https://www.investopedia.com/what-went-wrong-with-ftx-6828447.

In this Chapter, the study illustrates designs of the perpetual future contracts trading system for DEXs and CEXs, with emphasis on their differences and similarities. In Section 4.1, the study delineates the key stakeholders and elements of perpetual exchange systems, as illustrated in Fig. 4.1. I formalize the perpetual exchange model using the notations in Table. 5. Secondly, I summarized the differences between various models in Section 4.2. Subsequently, in Sections 4.3 to 4.6, I present the distinct architectures of each model through system diagrams. Then the study characterizes the unique properties of each model using mathematical formulations. Furthermore, utilizing a specific case, I elaborate on the operational processes of each model.

4.1 Fundamental Terminology and Concepts

The key stakeholders and elements are as follows:

- Traders: Individuals or entities engaged in the purchase and sale of perpetual contracts. These traders furnish collateral to maintain and manage their positions through the trading of such contracts.
- Custody Module: This module is responsible for ensuring the security of assets across all trader accounts. It consistently updates and retains the latest balance details and facilitates both deposit and withdrawal operations initiated by traders.
- Matching Module: This module is entrusted with storing, correlating, and executing purchase and sale orders of contracts.
- Risk Control Module: This module is vital for assessing and supervising the position of every trader account, contingent on the orders that have been executed. Its role is pivotal in ascertaining that the provided collateral is sufficient to offset potential deficits. Furthermore, in specific scenarios, it assumes control of a trader's position and proceeds with its liquidation.

I delineate a formalized model of perpetual contract trading. Additionally, Table. 5 is presented to encapsulate and summarize the notations employed throughout this thesis.

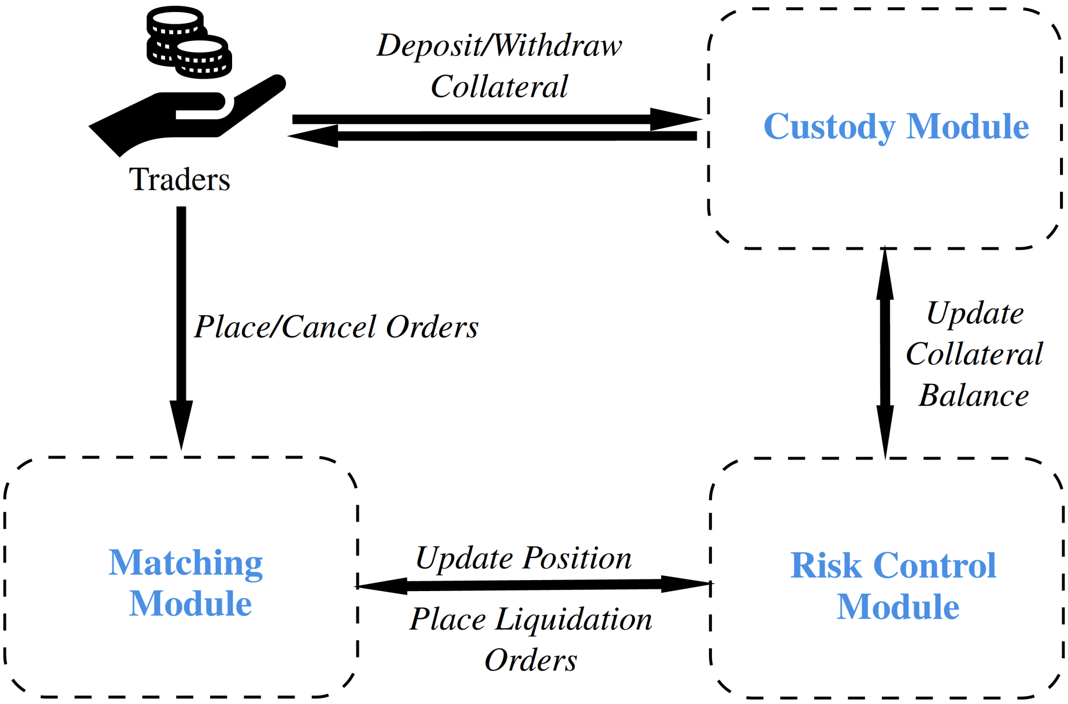

FIGURE 4.1: Elements of Exchange Systems

I denote a perpetual contract trading exchange as $EX = (\mathbb{U}, \mathbb{C}, \mathbb{T}, \mathbb{P})$, where $\mathbb{U}$ denotes the set of underlying assets; $\mathbb{C}$ denotes the set of collateral assets; $\mathbb{T}$ denotes the set of traders; $\mathbb{P}$ denotes the set of positions.

Next, I define the most fundamental element in trading, the order, as $O_i = (U, C)$, where the i-th order is based on U in $\mathbb{U}$ and C in $\mathbb{C}$. For each order, three key variables are considered: $Und(O_i)$ indicates the underlying asset and quantity of the i-th order, with positive values indicating long and negative values indicating short; $Coll(O_i)$ represents the amount of collateral provided by the trader for the order; $P^{U \to C}(O_i)$ denotes the execution price of the order. The j-th position, denoted as P_j, is a compilation of a set of k executed orders. Therefore, the net exposure of the j-th position at time t can be represented as:

$$\mathrm{E}_t(P_{\mathrm{j}}) = \sum_{\mathrm{i}=1}^{k} \mathrm{Und}(O_{\mathrm{i}}). \tag{4.1}$$

The margin ratio $MR_t(P_j)$ of the j-th position at time t can be represented as:

$$MR_t(P_j) = \frac{P_t^{U \to C} \times |\mathrm{E}_t(P_{\mathrm{j}})|}{Coll_t(P_j)} \times 100\%. \tag{4.2}$$

When $MR_t(P_j)$ is less than $MR_{min}(U_{P_j})$, which is the maintenance margin ratio required by the exchange, P_j will be taken over by the exchange and liquidated at an appropriate time.

When P_j is liquidated, the collateral is not only used to cover losses but also incurs a liquidation penalty charged by the exchange[4]. This fee is also referred to as the Insurance Clearance fee in some exchanges[5]. As different exchanges have diverse methods for calculating the liquidation penalty, I do not provide a unified formula, rather denoting it simply as $\mathrm{LP}(P_{Liq_\mathrm{j}})$.

In addition, the average holding price $\bar{P}_t^{U\to C}$ of the j-th position at time t can be represented as:

$$\bar{P}_t^{U\to C}(P_j) = \frac{\sum_{\mathrm{i}=1}^{k}\left(Und(O_\mathrm{i}) \times P^{U\to C}(O_\mathrm{i})\right)}{\sum_{\mathrm{i}=1}^{k} Und(O_\mathrm{i})}. \tag{4.3}$$

The profit and loss (P&L) of the j-th position at time t can be represented as:

$$\mathrm{PnL}_t(P_\mathrm{j}) = (P_t^{U\to C} - \bar{P}_t^{U\to C}(P_j)) \times \mathrm{E}_t(P_\mathrm{j}). \tag{4.4}$$

From t_0 to t_1, the funding fee paid or received by a trader for their held positions P_j can be represented as:

$$\mathrm{FF}_{t_0\to \mathrm{t}_1}(P_\mathrm{j}) = \sum_{\mathrm{t}=t_0}^{t_1}(FR_t \times \mathrm{E}_t(P_\mathrm{j}) \times P_t^{U\to C}), \tag{4.5}$$

where FR_t denotes the funding rate.

The trading fees paid by a trader for the orders O_i can be represented as:

$$\mathrm{TF}(O_\mathrm{i}) = TR_{id} \times |Und(O_\mathrm{i})| \times P^{U\to C}(O_i), \tag{4.6}$$

where TR_{id} is the transaction fee rate for the id-th trader.

At time t, for the id-th Trader who executed k orders to open n positions, where m positions $(Liq_1, ..., Liq_m)$ were liquidated and $(n-m)$ positions were closed actively,

[4] https://help.dydx.exchange/en/articles/4797401-perpetual-contract-liquidations.
[5] https://www.binance.com/en/support/faq/liquidation-protocols-360033525271.

TABLE 4.1: Comparison of different exchange models

Type	Custody	Matching	Risk Control	Counterparty	Pricing
CEX	Hot & Cold Wallet	Off-chain Server	Off-chain Server	Traders	Traders
Hybrid	Smart contract	Off-chain Server	Off-chain Server	Traders	Traders
Oracle Pricing	Smart contract	Smart contract	Off-chain Keepers	Liquidity Providers	Oracle
VAMM	Smart contract	Smart contract	Off-chain Keepers	Liquidity Providers	AMM Algorithm

then the withdrawable value he can ultimately access at time t can be represented as:

$$\begin{aligned} \mathrm{WV}_t(T_{\mathrm{id}}) = & \sum_{\mathrm{j=1}}^{n} Coll(P_j) + \sum_{\mathrm{j=1}}^{n} \mathrm{PnL}_t(P_{\mathrm{j}}) - \sum_{\mathrm{j=1}}^{m} \mathrm{LP}(P_{Liq_{\mathrm{j}}}) - \\ & \sum_{\mathrm{j=1}}^{n} \mathrm{FF}_{t_0 \to \mathrm{t}}(P_{\mathrm{j}}) - \sum_{\mathrm{i=1}}^{k} \mathrm{TF}(O_{\mathrm{i}}). \end{aligned} \tag{4.7}$$

4.2 Model of Exchange Systems

The modules employed by different trading systems (models) vary significantly. In Table. 4.1, I provide a horizontal comparison across five dimensions: Custody, Matching, Risk Control, Counterparty, and Pricing. In Fig. 4.2 I compare the efficiency and centrality of transaction processing among different models. In addition, the study compared MEV transparency among these models.

The Custody Module assumes a central role in demarcating the distinct classifications within the realm of perpetual futures exchanges. Those that employ centralized custody solutions are classified as Centralized Exchanges (CEX), whereas those that abstain from such practices fall under the rubric of Decentralized Exchanges (DEX). Within the domain of DEX, further subdivisions emerge contingent upon factors encompassing order matching, price determination, and counterpart matching, resulting in to the Hybrid Model, Oracle Pricing Model, and Virtual Auto Market Making (VAMM) Model.

The CEX Model closely resembles traditional financial practices. Apart from deposits and withdrawals, it makes limited use of blockchain technology. The technology stack used for custody of client funds, order matching, settlement, risk

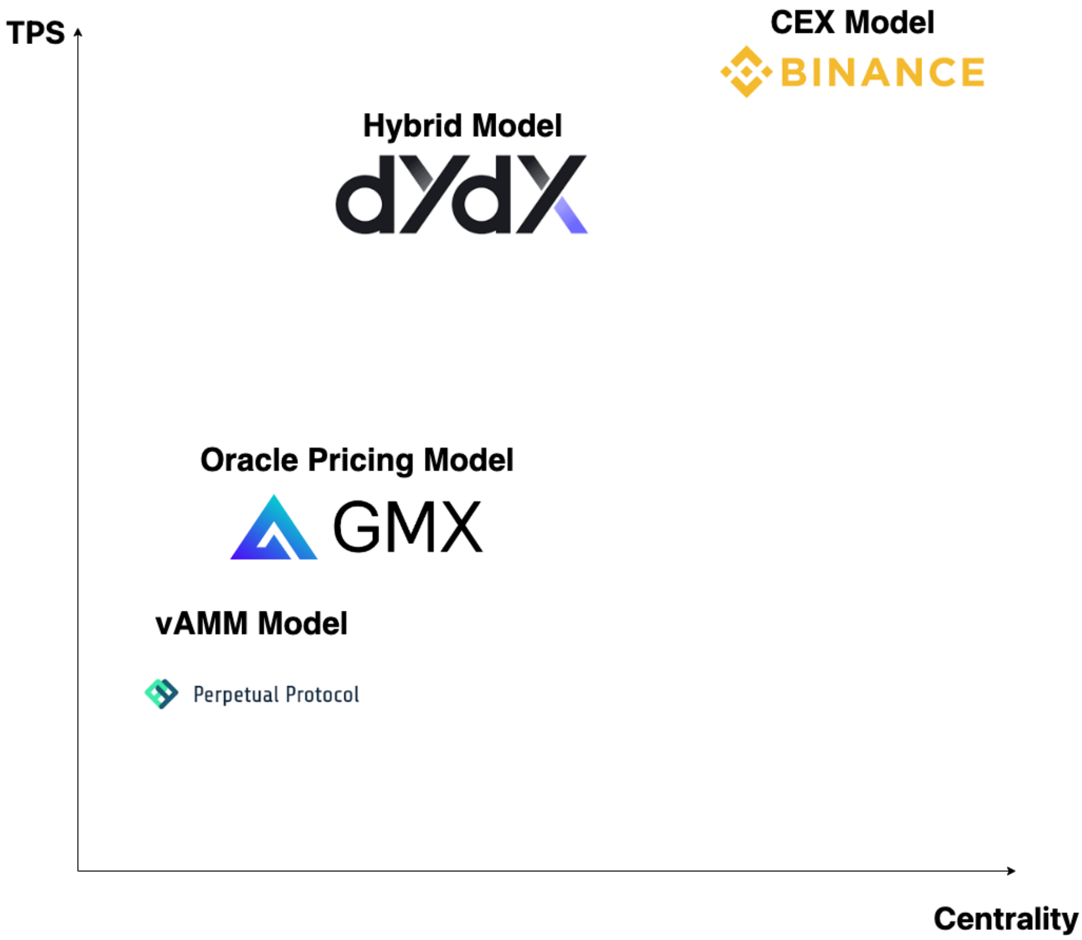

FIGURE 4.2: Transaction Per Section (TPS) and Centrality Comparison. In this figure, under each model there exemplifies a corresponding exchange. CEX Model: Binance; Hybrid Model: dYdX (https://dydx.exchange); Oracle Pricing Model: GMX (https://gmx.io); and VAMM Model: Perpetual Protocol V2 (https://perp.com).

assessment, and control closely aligns with traditional financial practices. Due to the imperfect state of infrastructure and regulatory rules in the cryptocurrency trading industry, CEX often combines the functions of custody banks, traditional exchanges, clearinghouses, and brokerages entities.

In contrast, the Hybrid Model harnesses smart contracts for custody and settlement processes, while retaining certain centralized elements. Notably, off-chain servers persist in facilitating order matching and counterparty matching functions.

The Oracle Pricing Model and VAMM Model gravitate toward a greater degree of decentralization. Both models leverage smart contracts for order matching, with Liquidity Providers assuming the role of direct counterparties to traders, engendering an indirect mode of trade execution among traders. Nevertheless, it is imperative to acknowledge that both models still rely upon centralized constituents. The involvement of Oracles and Keepers in the Risk Control Module remains a requisite for effecting the liquidation process. Moreover, the Oracle Pricing Model hinges upon Oracles for the determination of precise trade prices.

The augmentation of decentralization engenders certain trade-offs. While diminishing reliance on centralized components can mitigate specific security vulnerabilities and fortify resistance against censorship, it concurrently imposes constraints on the exchange's transaction processing capacity per second (TPS). As one progresses from the CEX Model to the Hybrid Model, Oracle Pricing Model, and VAMM Model, the degrees of centralization diminish. However, correspondingly, the ability to handle transactions experiences a commensurate decline due to the TPS limitations inherent in the underlying blockchain network, as shown in Fig. 4.2. Consequently, blockchain developers have embarked upon the development of diverse technologies aimed at enhancing throughput and efficiency. For instance, Scroll[6] constitutes a zero-knowledge scaling solution tailored for Ethereum (zkEVM), characterized by diminished costs, accelerated transaction speeds, and infinite scalability, all without compromising the twin tenets of security and decentralization.

In CEX, MEV extraction and allocation are opaque. In contrast, except for the Hybrid Model, MEV extraction and allocation are relatively transparent in DEX. For the CEX Model and the Hybrid Model, since trades are matched within centralized servers and original trade data is not publicly disclosed, exchanges have significant autonomy in determining which orders to prioritize. In theory, exchanges can arbitrage from this, or even prioritize trades from deeply collaborating market makers.[7]

For the Oracle Pricing Model and the VAMM Model, since trades are executed by smart contracts on the blockchain, the operations of traders extracting MEV are often traceable. For example, a trader in GMX once exploit a vulnerability in the Oracle Pricing Model mechanism and low liquidity in the AVAX-USDT trading pair on Binance to extract MEV across exchanges.[8]

[6] https://scroll.io/.

[7] The CFTC's lawsuit against FTX reveals FTX's alleged preferential treatment of Alameda, providing evidence of how MEV exists in CEXs. (source: https://assets.bwbx.io/documents/users/iqjWHBFdfxIU/rMZxB_xGUGQY/v0)

[8] Transaction records: https://dune.com/adamzjw/gmx-trader-dashboard?user$_{a}ddress_{t}86d10 = 0x10ddb60960fe619ee9ff62056bcec9bc330d9c8e$

4.3 Centralized Exchange Model

Considering that the CEX Model closely resembles traditional commodity futures exchanges, the study will prioritize its introduction. Building upon the CEX Model as a foundation, the study will emphasize the differences among CEX Model and other models.

4.3.1 Architectures

In accordance with Fig. 4.1, the study provides an enhanced delineation and representation of the constituents and stakeholders in the Centralized Exchange Model, as depicted in Fig. 4.3, where diamonds represent on-chain smart contracts, rectangles represent off-chain databases, and ellipses represent off-chain servers.

Within a Centralized Exchange, traders can be bifurcated into two primary categories:

1. Retail Traders: These are users who interact via the front-end interface provisioned by the exchange.
2. API Traders: Engaging through the API interface extended by the exchange, these users are conventionally known as Pro Traders, Institutional Traders, or Market Makers. While the essence of the orders remains invariant regardless of the interaction medium, API Traders possess the capability to initiate or terminate orders at an augmented velocity, thereby enabling sophisticated trading methodologies such as high-frequency quantitative trading. Given that API traders often engage in higher-frequency trading, resulting in significantly higher trading volumes compared to retail traders, their TR_{id} tend to be much lower than those of the latter. This opaque fee structure provides API traders with a significant advantage over their counterparty.

Custody module predominantly functions off-chain, with the sole exception of the on-chain hot wallet. Notably, private keys are stored off-chain.

1. Hot Wallet: This digital wallet is designed to cater to the routine deposit and withdrawal requirements of traders. Functioning under the auspices of the

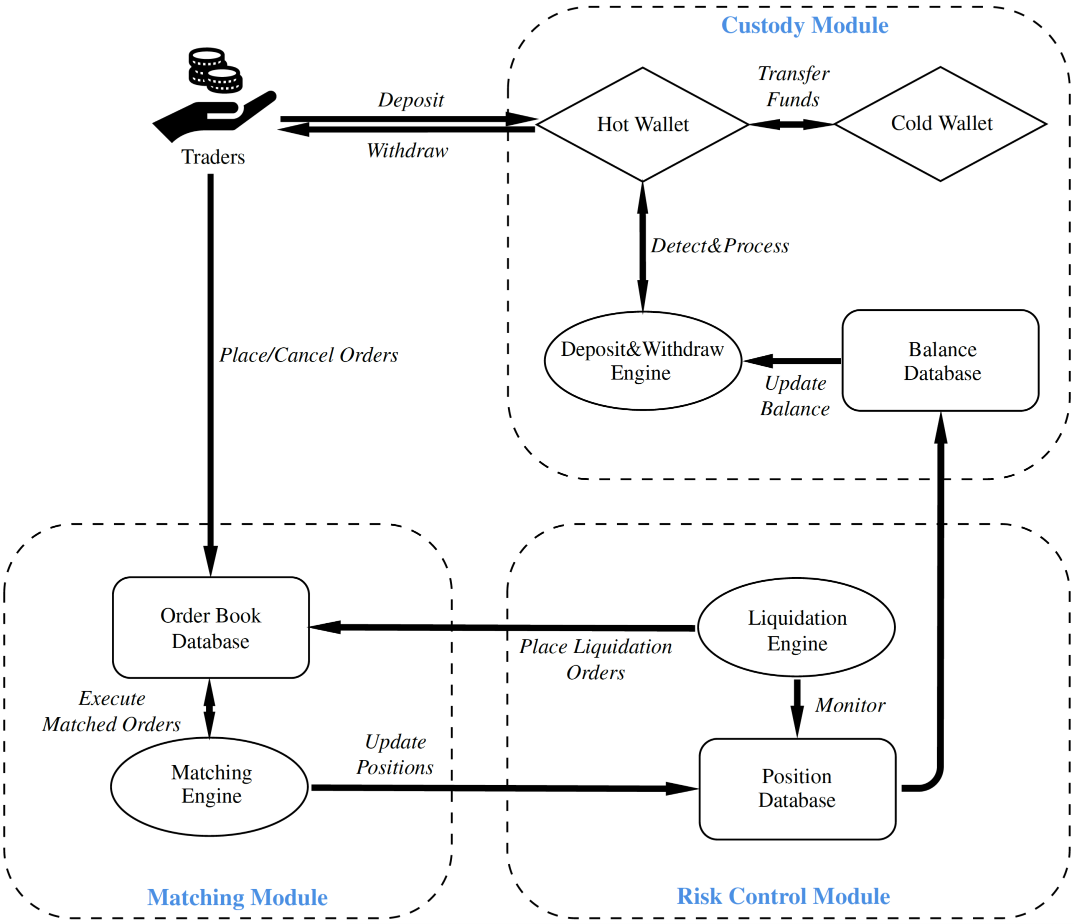

FIGURE 4.3: CEX Model. In this diagram, diamonds represent on-chain smart contracts, rectangles represent off-chain databases, and ellipses represent off-chain servers.

exchange, it maintains a specified percentage of the exchange's total assets, sufficient to accommodate the peak daily withdrawal demands.

2. Cold Wallet: Acting as the primary repository for the exchange's assets, this wallet is entirely offline. This segregation between the Hot and Cold Wallets amalgamates efficient user transactions with fortified security.

3. Deposit & Withdrawal Engine: Comprising both the blockchain's complete nodes and off-chain servers, this engine supervises on-chain deposits, operationalizes user withdrawal directives, and refreshes the off-chain Balance Database post on-chain transaction validation.

4. Balance Database: An off-chain server database accountable for documenting the balance of every trader's account.

Matching module consists of two off-chain components.

1. Order Book Database: An off-chain server database responsible for logging various types of orders.
2. Matching Engine: Operating off-chain, this server application is designated for order matching and execution, subsequently conveying the execution outcomes to the Position Database.

Risk control module consists of two off-chain components.

1. Position Database: This off-chain server database is mandated to record the margin balance and P&L (Profit & Loss, aka PNL) for each position, communicating account balance modifications to the Balance Database.
2. Liquidation Engine: An off-chain server program that monitors the Position Database and takes over positions that meet liquidation criteria, closing them under appropriate conditions.

4.3.2 Properties

In the CEX Model, three equivalent relationships exist, as follows:

Firstly, traders act as counterparts to each other. Whenever one trader sells contract, there is another trader matched to buy this contract. Therefore, while it may not always be possible to find two traders with exactly opposite but equally sized positions, the absolute value of the net exposure for all long positions always equals the absolute value of the net exposure for all short positions. So, assuming a CEX has p long positions and q short positions, I can derive:

$$\sum_{\mathrm{j}=1}^{p} \mathrm{E}_t^{\mathrm{Long}}(P_{\mathrm{j}}) = -\sum_{\mathrm{j}=1}^{q} \mathrm{E}_t^{\mathrm{Short}}(P_{\mathrm{j}}). \tag{4.8}$$

Furthermore, from t_0 to t_1, the total funding fees paid by all long positions must equal the total funding fees received by all short positions, and the total profit of all long positions equals the total loss of all short positions. This leads to:

$$\sum_{\mathrm{j}=1}^{p} \mathrm{FF}_{t_0 \to \mathrm{t}_1}^{\mathrm{Long}}(P_{\mathrm{j}}) = -\sum_{\mathrm{j}=1}^{q} \mathrm{FF}_{t_0 \to \mathrm{t}_1}^{\mathrm{Short}}(P_{\mathrm{j}}), and \tag{4.9}$$

$$\sum_{\mathrm{j}=1}^{p} \mathrm{PnL}_{t_0 \to \mathrm{t}_1}^{\mathrm{Long}}(P_{\mathrm{j}}) = -\sum_{\mathrm{j}=1}^{q} \mathrm{PnL}_{t_0 \to \mathrm{t}_1}^{\mathrm{Short}}(P_{\mathrm{j}}). \tag{4.10}$$

4.3.3 Case Study

The life cycle of a position on a CEX can be described as follows:

1. Deposit Funds: Funds are deposited by traders into the exchange's specified on-chain address. Following on-chain transaction validation, traders are enabled to designate a portion or entirety of the funds as collateral for derivative trading.

2. Create and Place Order: Traders opt for order types and input the pertinent parameters to craft an order tailored to their trading objectives. Post order validation, it is transmitted to the exchange's servers.

3. Execute Order and Initiate Position: Successful order matching and its execution influence the trader's position. If the trader did not hold any position in the underlying asset before the trade, the order is considered an opening position operation.

4. Add or Reduce Position: Traders can revisit Steps 2 and 3, executing additional orders to modify the size or direction of their positions.

5. Close Position: Traders can manually close positions or might be forced to close due failing to meet the maintenance margin requirement.

   (a) Voluntary Closure: Employing Step 2, traders can dispatch orders opposing to their current position, to close their positions and settle actual profits and losses.

   (b) Forced Closure (Liquidation): During the tenure of a position, if collateral adequacy falters below the maintenance margin threshold, the liquidation engine intercedes. It compulsorily concludes the position, contingent on market liquidity parameters, and imposes a certain percentage of penalty. Residual collateral post loss and penalty settlement is reimbursed to the trader. If there's a deficit, the trader must cover it before continuing to trade.

6. Withdraw Funds: Concurrently with position holding, traders are empowered to retract unutilized funds. Upon position closure, residual collateral can be withdrawn post the reconciliation of profits and losses.

4.4 Hybrid Model

4.4.1 Architectures

The Hybrid Model is a DEX Model that bears the closest resemblance to the CEX Model. Based on Fig. 4.3, the study further delineates and illustrate the actors and components of the Hybrid Model in Fig. 4.4. In each figure illustrating the DEX models, the study uses blue background to indicate elements differentiating from the CEX Model, while diamonds represent on-chain smart contracts, rectangles represent off-chain databases, and ellipses represent off-chain servers.

The hybrid nature of the Hybrid Model lies in its use of off-chain components, running on centralized servers, for trade matching and risk control against liquidation. Simultaneously, it utilizes smart contracts and a valid proof system, e.g., Zero Knowledge (ZK) proof[9], to manage fund custody and verify that off-chain transaction results are genuine and valid.

This approach addresses the issues of non-transparency and centralization in the CEX Model, ensuring that exchange operators cannot scrutinize trader withdrawals, fabricate trader transactions, or misappropriate trader funds, thus mitigating risks similar to those witnessed in incidents such as FTX[10].

In terms of key stakeholders and elements, the Hybrid Model shares similarities with the CEX Model regarding the composition of traders and the Matching Module. The distinctions lie in the Custody Module and the Risk Control Module.

[9] https://ethereum.org/en/zero-knowledge-proofs/.
[10] https://www.investopedia.com/what-went-wrong-with-ftx-6828447.

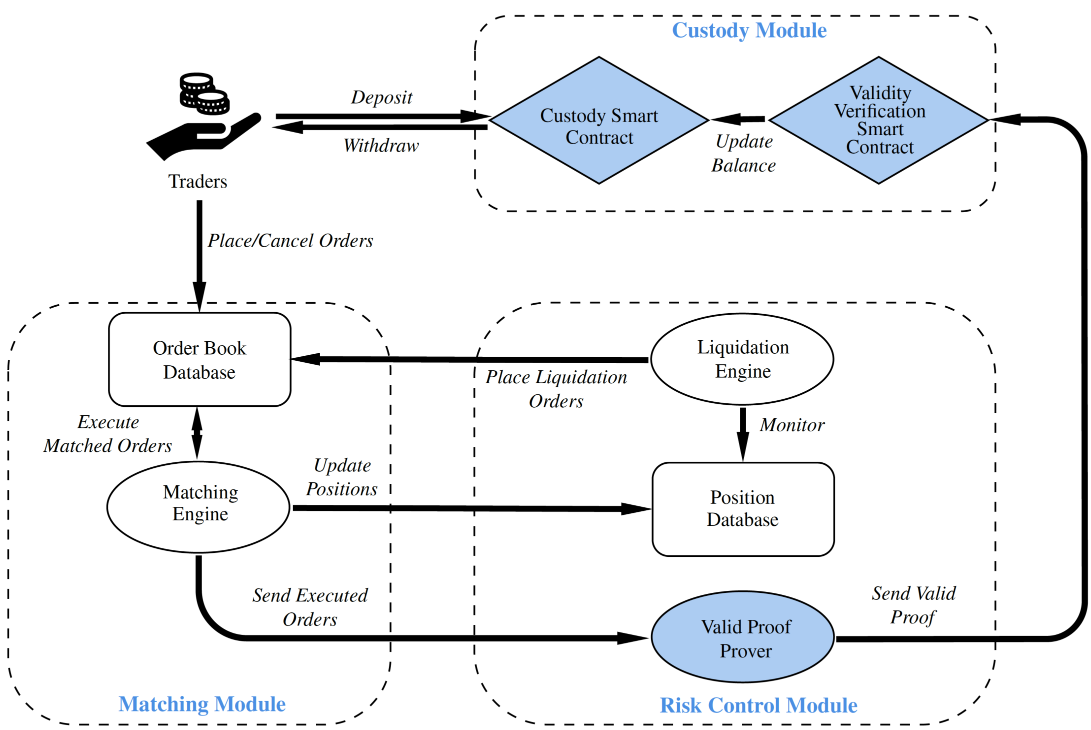

FIGURE 4.4: Hybrid Model. In this diagram, diamonds represent on-chain smart contracts, rectangles represent off-chain databases, and ellipses represent off-chain servers. The diagram use blue background to indicate elements differentiating Hybrid Model from the CEX Model.

Custody Module is composed of two on-chain smart contracts.

1. Custody Smart Contract: An on-chain smart contract responsible for safeguarding funds deposited by traders, storing the balance status of each trader account, and handling traders' deposit and withdrawal needs.
2. Validity Verification Smart Contract: An on-chain smart contract tasked with verifying the valid proof corresponding to off-chain transactions to confirm the correctness and reliability of transaction results. It updates the balance status of each trader account in the Custody Smart Contract based on valid transactions.

Risk Control Module is comprised of three off-chain components.

1. Position Database: An off-chain server database responsible for recording the margin balance and P&L of each position, and relaying changes in trader account balances to the Balance Database.

2. Liquidation Engine: An off-chain server program that monitors the Position Database and takes over positions that meet liquidation criteria, closing them under appropriate conditions.

3. Valid Proof Prover: An off-chain server program responsible for packaging successfully executed orders into batches, compressing them, and generating the corresponding valid proof, such as Zero Knowledge Proof. Subsequently, these proofs are transmitted to the on-chain Validity Verification Smart Contract for validation.

4.4.2 Properties

The Hybrid Model shares the same mathematical properties with CEX, as expressed in Eq. (4.8) to (4.10), albeit with different technological implementations.

4.4.3 Case Study

The life cycle of a position on a DEX with Hybrid Model can be described as follows:

1. Deposit Funds: Traders deposit funds into the custody smart contract. Once confirmed by the exchange, traders can allocate a portion or the entirety of the funds as collateral for perpetual trading.

2. Create and Place Order: Same as in the Centralized Exchange Model.

3. Execute Order and Initiate Position: When an order is successfully matched and executed, the trader's position is affected. To ensure trading responsiveness, the executed orders are not immediately confirmed on-chain. Instead, the exchange server provides a pre-confirmation, also known as "soft confirm". All pre-confirmed orders are batched and valid proofs are generated offline by the Prover. At predefined intervals, proofs are uploaded to the on-chain Validation Verification Smart Contract. Subsequently, traders' balances are updated, pre-confirmed orders receive their final confirmation, or "hard confirm." In practice, whether the original order data are also stored on-chain

is flexible. Not storing them on-chain reduces gas costs, while storing them enhances data availability, thereby increasing security.

4. Add or Reduce Position: Same as in the Centralized Exchange Model.

5. Close Position: Same as the Centralized Exchange Model.

6. Withdraw Funds: Unlike the Centralized Exchange Model, the Hybrid Model includes three mechanisms for withdrawal: Slow Withdrawal, Fast Withdrawal, and Forced Withdrawal[11] [12]:

   (a) Slow Withdrawal: In Slow Withdrawal, traders' withdrawals may require a longer waiting period compared to the Centralized Exchange Model. Regardless of holding positions, traders need to wait until all pre-confirmed orders under their account are verified before the Custody Smart Contract executes the withdrawal. Generally, the waiting duration is determined by the Valid Proof Prover's upload cycle and the Valid Proof Verifier's verification speed.

   (b) Fast Withdrawal: If traders have an urgent withdrawal requirement, they can pay a fee to access funds in advance from the withdrawal liquidity provider. The withdrawal liquidity provider waits for the entire verification process and eventually receives the funds that would have been returned to the trader.

   (c) Forced Withdrawal: The emergency withdrawal mechanism significantly distinguishes the Hybrid Model from the Centralized Exchange Model. If the exchange's off-chain servers go offline or deliberately ignore traders' withdrawal requests, traders can initiate the *forcedWithdrawal* function in the Custody Smart Contract. When a *forcedWithdrawal* request is made, the Hybrid Exchange must either process the withdrawal or prove that the request is illegitimate. If the Hybrid Exchange fails to do so within a time limit, traders can invoke the "freeze" function. This function prevents any further changes to the contract's state, activating the "escape mode." In this mode, traders can exit their assets based on the total value of their position in the last accepted on-chain batch. This

[11] https://help.dydx.exchange/en/articles/5108558-withdrawing-funds-from-layer-2.

[12] https://help.dydx.exchange/en/articles/4797365-what-is-promising-me-that-my-money-can-be-transferred-back-to-l1-what-prevents-dydx-from-ignoring-my-withdrawal-requests.

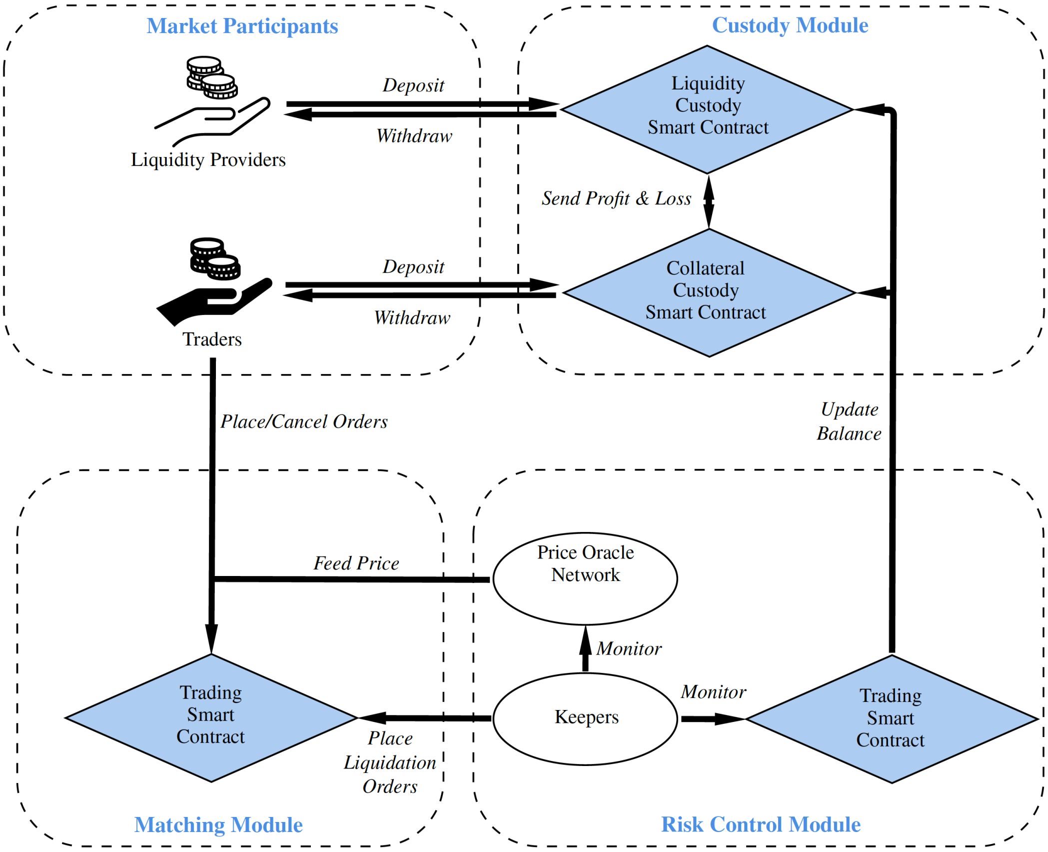

FIGURE 4.5: Oracle Pricing Model. In this diagram, diamonds represent on-chain smart contracts, rectangles represent off-chain databases, and ellipses represent off-chain servers. Blue background is used to indicate elements differentiating Oracle Pricing Model from the CEX Model.

mechanism ensures that traders' funds cannot be frozen or misappropriated by the exchange. They remain under the custody of the smart contract, promoting "self-custody" or "non-custody" principles.

4.5 Oracle Pricing Model

4.5.1 Architectures

Based on Fig. 4.3, the study further refines and illustrates the actors and components of the Oracle Pricing Model in Fig. 4.5.

Compared to the Hybrid Model, the Oracle Pricing Model relies less on centralized components but mainly on decentralized ones (labeled as blue diamonds in

Fig. 4.5). The custody of funds, the storage, and execution of trades are all undertaken by on-chain smart contracts. Only risk control and trade price confirmation still require some centralized components (labeled as blue ellipses in Fig. 4.5).

Under the Oracle Pricing Model, traders can be divided into two categories. The first category includes active traders, who are similar to the traders in the Centralized Exchange Model and Hybrid Model. Traders in the second category accept trades passively, acting as the counterparties to traders in the first category, and are therefore referred to as Liquidity Providers.

1. Traders: Users who actively place various orders, either using the exchange's front-end interface or by directly calling the on-chain smart contracts.
2. Liquidity Providers: Users who passively accept orders from Traders. They act as the direct counterparty to all Traders. Liquidity Providers deposit their funds into the on-chain Liquidity Pool, providing liquidity for the Traders' orders.

Custody Module is composed of two on-chain smart contracts.

1. Collateral Custody Smart Contract: An on-chain smart contract responsible for safeguarding the collateral of Traders, storing the balance status of each trader's position, and ultimately settling profits and losses.
2. Liquidity Custody Smart Contract: An on-chain smart contract responsible for safeguarding the funds of Liquidity Providers and calculating and storing the balance of each Liquidity Provider.

Matching Module is composed of one on-chain smart contracts.

1. Trading Smart Contract: An on-chain smart contract responsible for executing trades and updating the status of each position.

Risk Control Module still relies on three off-chain components.

1. Price Oracle Network: An off-chain network responsible for providing the Trading Smart Contract with the prices of underlying assets.

2. Keepers: Off-chain servers responsible for monitoring the status of each position and taking over positions that meet liquidation criteria, closing them under appropriate conditions.

3. Trading Smart Contract: The Trading Smart Contract also holds data for each position, encompassing collateral quantity and position volume. As such, it is also a constituent of the Risk Control Module.

4.5.2 Properties

In the Oracle Pricing Model, all traders directly trade to liquidity providers (LP) rather than other traders. Consequently, whenever a trader holds a long position, there is an LP holding an equally sized short position, and vice versa. Thus, the sum of the net exposure of all traders equals the sum of the net exposure of all LPs in the opposite direction. Assuming a total of p long positions and q short positions held by all traders in an exchange, the net exposure of all LPs can be derived as follows:

$$\mathrm{E}_t(P^{LP}_{total}) = -(\sum_{\mathrm{j=1}}^{p} \mathrm{E}^{Long}_t(P^T_j) + \sum_{\mathrm{j=1}}^{q} \mathrm{E}^{Short}_t(P^T_j)), \tag{4.11}$$

where P^{LP}_{total} denotes the aggregated position passively held by all LPs while P^T_j denotes the j-th position held by a Trader. The positions passively held by LP are referred to as *impermanent positions*. In Oracle Pricing model, LP proportionally share the size of the *impermanent positions* based on the provided liquidity. The exposure of the *impermanent positions* assumed by the id-th LP can be determined as follows:

$$\mathrm{E}^{Net}_t(LP_{id}) = \frac{\mathrm{E}^{Net}_t(P^{LP}_{total}) \times VL_t(LP_{id})}{\sum_{\mathrm{i=1}}^{l} \mathrm{VL}_t(LP_i)}, \tag{4.12}$$

where $\mathrm{VL}_t(LP_{id})$ denotes the dollar value of liquidity that the id-th liquidity provider provides at time t. Furthermore, the profit and loss incurred by all l LPs due to the *impermanent positions* and the profit and loss borne by id-th individual LP can be calculated as :

$$\mathrm{PnL}_t^{\mathrm{Net}}(P_{total}^{LP}) = -(\sum_{\mathrm{j=1}}^{p} \mathrm{PnL}_t^{\mathrm{Long}}(P_{\mathrm{j}}) + \sum_{\mathrm{j=1}}^{q} \mathrm{PnL}_t^{\mathrm{Short}}(P_{\mathrm{j}})), \tag{4.13}$$

$$\mathrm{PnL}_t^{Net}(LP_{id}) = \frac{\mathrm{PnL}_t^{Net}(P_{total}^{LP}) \times VL_t(LP_{id})}{\sum_{\mathrm{i=1}}^{l} \mathrm{VL}_t(LP_i)}. \tag{4.14}$$

In addition to *funding fees* and *transaction fees*, traders in the Oracle Pricing Model also incur two other specific costs, namely, *borrowing fees* and *gas fees*.

As Traders' profits and losses are ultimately redeemed by LP, the exchange locks funds in the liquidity pool for possible redemption during the holding period. Consequently, Traders are obliged to pay interest, referred to as *borrowing fees*. The value of *borrowing feesrate* at time t, denoted as BR_t, is typically determined by the proportion of funds occupied in the liquidity pool, with higher proportions resulting in increased BR_t.

From t_0 to t_1, the *borrowing fees* paid by a Trader for his/her held position P_j can be represented as:

$$\mathrm{BF}_{t_0 \to \mathrm{t}_1}(P_{\mathrm{j}}) = \sum_{\mathrm{t}=t_0}^{t_1} (BR_t \times |\mathrm{E}_t(P_{\mathrm{j}})| \times P_t^{U \to C}), \tag{4.15}$$

The distinct feature of the Oracle Pricing Model, setting it apart from the CEX Model and Hybrid Model, is the inclusion of *gas fees*. This divergence arises from the fact that the Oracle Pricing Model executes each order within smart contracts on the blockchain, while the CEX Model and Hybrid Model execute orders exclusively within off-chain servers. Consequently, traders in the Oracle Pricing Model bear the responsibility of covering *gas fees* for every order, a obligation not shared by traders in the CEX Model and Hybrid Model. The specific amount of *gas fees* paid by a trade depends on the mechanism set by the blockchain network. This chapter refrains from presenting specific formulas but simply denotes the *gas fees* for the i-th order as $GF(O_i)$.

As a result, for the id-th Trader who opened and closed n positions with k orders, where m positions $(Liq_1, ..., Liq_m)$ were liquidated, the withdrawable value he can ultimately access at time t can be represented as:

$$\begin{aligned}\mathrm{WV}_t(T_{\mathrm{id}}) = &\sum_{\mathrm{j}=1}^{n} Coll(P_j) + \sum_{\mathrm{j}=1}^{n} \mathrm{PnL}_t(P_{\mathrm{j}}) - \sum_{\mathrm{j}=1}^{m} \mathrm{LP}(P_{Liq_{\mathrm{j}}}) - \\ &\sum_{\mathrm{j}=1}^{n} \mathrm{BF}_{t_0 \to \mathrm{t}}(P_{\mathrm{j}}) - \sum_{\mathrm{j}=1}^{n} \mathrm{FF}_{t_0 \to \mathrm{t}}(P_{\mathrm{j}}) - \sum_{\mathrm{i}=1}^{k} \mathrm{TF}(O_{\mathrm{i}}) - \sum_{\mathrm{i}=1}^{k} \mathrm{GF}(O_{\mathrm{i}}).\end{aligned} \tag{4.16}$$

4.5.3 Case Study

The life cycle of a position on a oracle pricing exchange can be described as follows:

1. Provide Liquidity: Before Traders can engage in trading, Liquidity Providers must offer liquidity to the Liquidity Pool. Liquidity Providers deposit funds into the Liquidity Custody Smart Contract and receive corresponding deposit certificates (LP Tokens).

2. Create and Place Order: Unlike the previous two models, Traders on DEX with Oracle Pricng Model do not need to deposit funds into the Custody Smart Contract before initiating trades. In the Oracle Pricing Model, traders encapsulate orders as Ethereum transactions off-chain, sign them with their private keys, and then broadcast them to the blockchain. This transaction also includes an "Approve" action, authorizing the Custody Smart Contract to debit the corresponding collateral from their Ethereum address.

3. Execute Order and Initiate Position: When the price offered by the Oracle matches the conditions of an order, the order is executed, resulting in a change to the trader's position. As the order's execution occurs entirely on-chain, there are no pre-confirmations as in the Hybrid Model. The execution is always a hard confirmation.

4. Add or Reduce Position: Traders can repeat step 3 by executing additional orders to adjust the size or direction of their positions.

5. Close Position: Traders can initiate a voluntary position closure, or their position might be forcibly closed if they fail to meet the maintenance margin requirements.

(a) Voluntary Position Closure: Traders can repeat step 3 and 4 by executing orders in the opposite direction of their existing position to close it and settle realized gains or losses.

(b) Forced Position Closure: While holding a position, if a Trader's provided collateral fails to meet the maintenance margin requirement, their position becomes liquidatable. Off-chain Keepers continuously monitor all Traders' positions. When a liquidatable position is detected, a liquidation transaction is sent to the on-chain contract by keepers. Similarly, the contract imposes a penalty on the liquidated position, and any surplus collateral is returned to the liquidated Trader.

6. Withdraw Funds: After reducing or closing a position, Traders automatically receive released collateral from settled gains and losses. There is no need for manual extraction of collateral. As for Liquidity Providers, they can burn their LP Tokens and exchange them for funds as long as their capital is not tied up by Traders' positions.

4.6 Virtual Auto Market Making (VAMM) Model

4.6.1 Architectures

Based on Fig. 4.3, the study further refines and illustrates the actors and components of the Virtual Auto Market Making (VAMM) Model in Fig. 4.6.

The VAMM Model shares many similarities with the Oracle Pricing Model: traders can also be categorized into liquidity providers and active traders. However, apart from this, even though both employ smart contracts for user fund custody, trade order management, and off-chain Keepers to control risk, there are differences in the specific implementation details.

Unlike the Oracle Pricing Model, where the collateral provided by Traders and the funds offered by Liquidity Providers are kept separately, in this model, both Trader's collateral and Liquidity Providers' funds are stored within the same smart contract:

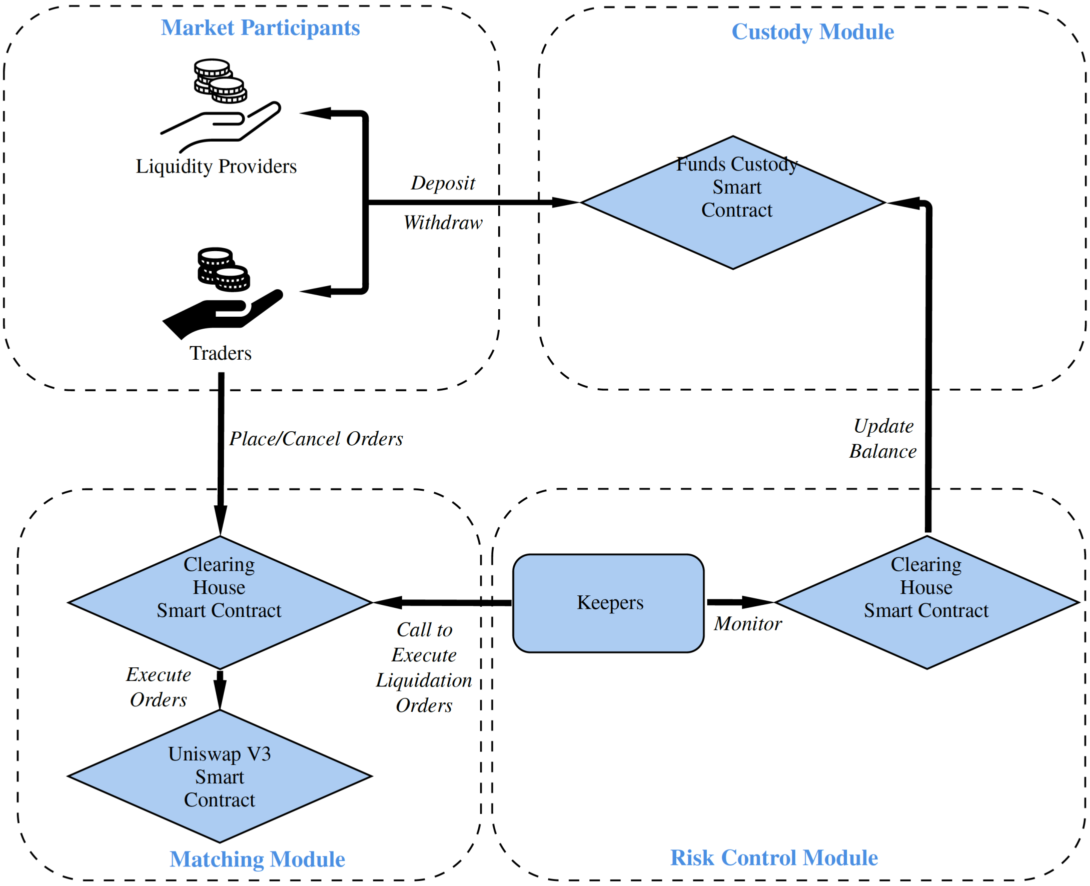

FIGURE 4.6: VAMM Model. In this diagram, diamonds represent on-chain smart contracts, rectangles represent off-chain databases, and ellipses represent off-chain servers. Blue background is used to indicate elements differentiating VAMM Model from the CEX Model.

1. Funds Custody Smart Contract: This on-chain smart contract is responsible for safeguarding both the collateral of Traders and the funds of Liquidity Providers.

The distinctive characteristic of the VAMM Model resides within its Matching Module. Under this model, Liquidity Providers opt to allocate funds for specific trading pairs, prompting the Clearing House Smart Contract to generate virtual tokens that serve the purpose of augmenting leverage. Each virtual token is endowed with a nominal valuation equivalent to that of an underlying token, denoted as follows: 1 vUSDC = 1 USDC, 1 vETH = 1 ETH, and so forth. These virtual tokens are subsequently injected into the AMM Smart Contract, where they undergo trading activities akin to those of actual underlying tokens. However, it is imperative to underscore that exclusive authority for the minting of vTokens, management of Add/Remove Liquidity operations, and facilitation of vToken exchanges resides solely within the purview of the Clearing House Smart Contract. In essence, vTokens assume a role confined to accounting tools exclusively operational within the ecosystem of the VAMM Exchange, without circulation beyond its ecosystem.

1. Clearing House Smart Contract: The Clearing House Smart Contract serves as the central component within the VAMM Model, responsible for executing all transactions and maintaining records of all Traders' and Liquidity Providers' positions.

2. Spot DEX Smart Contract: For the VAMM Model, the AMM Smart Contract functions as an external contract, acting as a repository for holding and swapping virtual tokens.

Risk Control Module still relies on off-chain components.

1. Keepers: These are off-chain servers tasked with monitoring position statuses and intervening in positions that meet liquidation criteria. They execute closure actions under appropriate circumstances.

2. Clearing House Smart Contract: Given its comprehensive record-keeping of all Traders' and Liquidity Providers' positions, the Clearing House Smart Contract also functions akin to a "Position Database." Thus, it constitutes an integral part of the Risk Control Module.

4.6.2 Properties

In the Virtual Auto Market Making (VAMM) Model, the exchange utilizes virtual tokens as trading intermediaries and accounting tools, while actual trading occurs within a Spot DEX.

The specific process involves LP's providing funds as collateral, allowing the ClearingHouse contract to mint two types of virtual tokens for a specific trading pair. These tokens are then injected into the liquidity pool to provide liquidity for traders. E.g. by offering USDC as collateral, LP mint vBTC and vUSDC, depositing them into the AMM liquidity pool.

Subsequently, Traders provide funds as collateral to the ClearingHouse contract, and mints a specific virtual token. Traders then swap this token from the liquidity pool for another virtual token. E.g. by using USDC as collateral, traders mint vUSDC and swap it for vBTC from the vBTC-vUSDC liquidity pool, effectively going long on vBTC.

In essence, the VAMM Model employs virtual tokens as leverage tools, amplifying the purchasing power of traders and LPs. It utilizes the ClearingHouse contract and other on-chain Spot AMM DEX to create a perpetual contract trading DEX.

In practice, each user's address corresponds to a Vault in the ClearingHouse contract, documenting the user's debts and assets. The virtual tokens minted by users represent their debts, while the collateral provided and the purchased virtual tokens or liquidity provided constitute their assets. The user's net position is equal to the actual virtual tokens held minus the virtual tokens minted. The deposited assets serve as the collateral for this position. This conclusion holds true whether the user acts as a trader, an LP, or both simultaneously.

For any user, their net exposure is equal to the quantity of virtual tokens held in the Vault minus the accumulated quantity of virtual tokens in debt. Positive values represent a long position in the corresponding virtual token, while negative values indicate a short position. An example vault balance sheet is illustrated in Fig. 4.7. Thus, this relationship can be expressed as follows:

$$\mathrm{E}_t^{Net}(V_{\mathrm{id}}) = \mathrm{VA}_t(V_{\mathrm{id}}) - \mathrm{VD}_t(V_{\mathrm{id}}), \tag{4.17}$$

where V_{id} denotes the Vault corresponding to the address of id-th user, $\mathrm{E}_t^{Net}(V_{\mathrm{id}})$ represents the aggregated net exposure of the vault for the id-th user that might hold multiple positions at time t, $\mathrm{VA}_t(V_{\mathrm{id}})$ represents the amount of virtual token as asset in the balance sheet of the vault for the id-th user at time t, and $\mathrm{VD}_t(V_{\mathrm{id}})$ denotes the the amount of virtual token as debt in the balance sheet of the vault for the id-th user at time t.

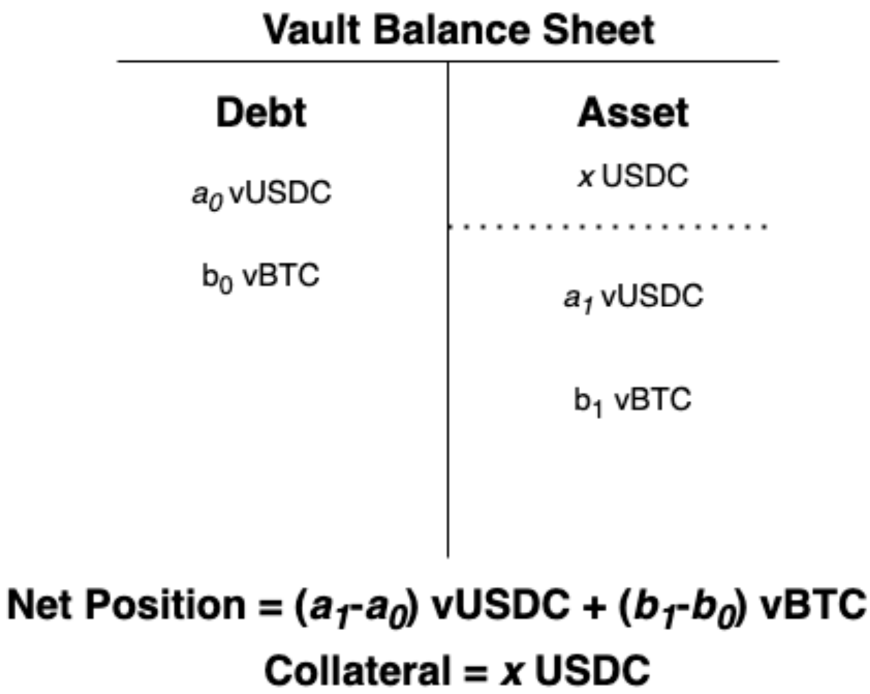

FIGURE 4.7: VAMM Vault Balance Sheet

Therefore, the PnL of the vault belonging to the *id*-th user is equal to the current USD value of its net exposure:

$$\mathrm{PnL}_t^{Net}(V_{\mathrm{id}}) = \mathrm{E}_t^{Net}(V_{\mathrm{id}}) \times P^{VT \rightarrow USD}, \tag{4.18}$$

where $\mathrm{PnL}_t^{Net}(V_{\mathrm{id}})$ represents the aggregated profit and loss of the vault for the *id*-th user at time t and $P^{VT \rightarrow USD}$ denotes the the dollar value of virtual tokens.

Similar to the Oracle Pricing Model, the sum of the net positions of all traders equals the sum of the net positions of all LP in the opposite direction. However, unlike the Oracle Pricing Model, the size of the *impermanent position* passively assumed by each LP is not evenly distributed based on the quantity of liquidity provided. Instead, it is determined by the quantity of virtual tokens provided, the price range at which liquidity was provided, the initial liquidity-providing price, and the current price. Thus, the properties represented by Eq. (4.11) and Eq. (4.13) still hold and can be expressed as follows:

$$\sum_{\mathrm{id}=1}^{l} \mathrm{E}_t^{Net}(V_{id}^{LP}) = -(\sum_{\mathrm{id}=1}^{p} \mathrm{E}_t^{Long}(V_{id}^{T}) + \sum_{\mathrm{id}=1}^{q} \mathrm{E}_t^{Short}(V_{id}^{T})), \tag{4.19}$$

$$\sum_{\mathrm{id}=1}^{l} \mathrm{PnL}_t^{Net}(V_{id}^{LP}) = -(\sum_{\mathrm{id}=1}^{p} \mathrm{PnL}_t^{Long}(V_{id}^{T}) + \sum_{\mathrm{id}=1}^{q} \mathrm{PnL}_t^{Short}(V_{id}^{T})). \tag{4.20}$$

However, the property represented by Eq. (4.12) does not hold in the VAMM Model. In VAMM, to calculate the *impermanent position* borne by a LP, it is necessary to isolate the virtual tokens related to providing liquidity in their Vault and apply Eq. (4.17). This can be expressed as:

$$\mathrm{E}_t^{Net}(V_{id}^{LP}) = \mathrm{VA}_t(V_{id}^{LP}) - \mathrm{VD}_t(V_{id}^{LP}), \tag{4.21}$$

where V_{id}^{LP} denotes the Vault corresponding to the address of *id*-th Liquidity Provider.

Moreover, the *impermanent loss* resulting from the price change on the *impermanent position* can be calculated using Eq. (4.18), expressed as:

$$\mathrm{IL}_t(V_{id}^{LP}) = \mathrm{E}_t^{Net}(V_{id}^{LP}) \times P^{VT \to USD}. \tag{4.22}$$

The transaction fees earned by the *id*-th LP for providing liquidity from t_0 to t_1 can be expressed as:

$$\sum_{\mathrm{t}=t_0}^{t_1} \mathrm{TF}_t(V_{id}^{LP}) = \sum_{\mathrm{t}=t_0}^{t_1} \frac{\sum_{\mathrm{i}=1}^{k} \mathrm{TF}(O_i) \times VL_t(LP_{id})}{\sum_{\mathrm{id}=1}^{l} \mathrm{VL}_t(LP_{id})}. \tag{4.23}$$

Unlike the Oracle Pricing Model, in the VAMM Model, traders are essentially trading spot virtual tokens. During the holding period, there is no need to lock funds in the liquidity pool, and as a result, no borrowing fees are incurred. However, since transactions are still executed through smart contracts, traders are still required to pay $gas\ fees$.

The value of assets that each vault can withdraw is represented as:

$$\begin{aligned}\mathrm{WV}_t(V_{\mathrm{id}}) =& Coll(V_{id}) + \mathrm{PnL}_t^{Net}(V_{\mathrm{id}}) - \mathrm{LP}(V_{\mathrm{id}}) - \mathrm{FF}_{t_0\to \mathrm{t}}(V_{\mathrm{id}}) - \\ &\sum_{\mathrm{i}=1}^{k} \mathrm{TF}(O_{\mathrm{i}}) + \mathrm{TF}_t(V_{id}^{LP}) - \sum_{\mathrm{i}=1}^{k} \mathrm{GF}(O_{\mathrm{i}}).\end{aligned} \tag{4.24}$$

4.6.3 Case Study

The life cycle of a position on a VAMM exchange can be described as follows:

1. Provide Liquidity: Similar to the Oracle Pricing Model, before traders can engage in trading, Liquidity Providers must offer liquidity to the Liquidity Pool. However, unlike the Oracle Pricing Model, Liquidity Providers have the option to use leverage to amplify the liquidity they provide. The process involves Liquidity Providers depositing funds into the Funds Custody Smart Contract, selecting the trading pairs for which they wish to provide liquidity and the desired leverage ratio. They then encapsulate this operation into an Ethereum transaction, sign it with their private key, and broadcast it to the blockchain. When the blockchain executes this transaction, the Clearing House Smart Contract creates corresponding virtual tokens and injects them into the AMM Liquidity Pool. Liquidity Providers' positions are calculated based on the virtual tokens they hold, using their deposited funds as collateral. If the collateral provided by Liquidity Providers fails to meet the required maintenance margin for their positions, they may also face liquidation.

2. Deposit Funds: Similarly, Traders need to deposit funds into the Funds Custody Smart Contract to initiate trading.

3. Create and Place Order: Similar to the Oracle Pricing Model, traders encapsulate orders into Ethereum transactions off-chain, sign them with their private keys, and then broadcast them to the blockchain.

4. Execute Order and Initiate Position: When the blockchain executes the aforementioned transaction, the Clearing House Smart Contract mints the virtual tokens that traders wish to sell and performs a Swap operation within the

AMM Liquidity Pool, converting them into the virtual tokens that traders wish to buy.

5. Add or Reduce Position: Traders can repeat step 3 by executing additional orders to adjust the size or direction of their positions.

6. Close Position: Traders can voluntarily close positions or might be forcibly closed if they fail to meet the maintenance margin requirement.

   (a) Voluntary Position Closure: Traders can repeat steps 3 and 4 by executing orders in the opposite direction of their existing position to close it and settle realized gains or losses.

   (b) Forced Position Closure: The liquidation process is similar to the Oracle Pricing Model, and will not be reiterated. Notably, unlike the Oracle Pricing Model, not only traders' positions but also Liquidity Providers' positions subject to liquidation.

7. Withdraw Funds: Traders and Liquidity Providers can withdraw funds that have not been used to mint virtual tokens at any time. For funds used as collateral, they need to close positions and settle gains and losses before withdrawal is possible.

4.7 Key Findings

In 2023, the 24-hour trading volume of perpetual futures contracts across all exchanges surpassed 100 billion dollars, representing more than half of the total trading volume across blockchain products and exchanges. This raises a critical question: Why do users place such significant trust in decentralized applications for managing vast sums of money? This chapter presented the first comprehensive Systematization of Knowledge (SoK) that systematically contrasts the operational dynamics of Centralized Exchanges (CEXs) and Decentralized Exchanges (DEXs) within the context of perpetual futures trading. Through mathematical formulations, it highlighted the distinct properties of each model, laying a solid foundation for further research in this domain. We believe that perpetual futures contracts have the potential for widespread adoption across various financial markets.

Chapter 5

Empirical Analysis of Traders' Behavior of Perpetual Future Contracts

[1]

Although both running perpetual futures, CEXs and DEXs are considerably different in terms of the order matching, price discovering, and custody of investors' fund, leading to different traders' behavior and implications on the market micro-structure. Unlike the case of CEXs, which adopt the limit-order book to form prices, orders submitted by traders in DEXs are matched with liquidity providers and the prices are formed based on the relative abundance of assets in the liquidity pool. The great difference in the design of market making and price discovering discourages us from using traditional micro-structure model, e.g., Kyle's model (1985) [3], to understand DEXs. Therefore, this chapter asks, what are the fundamental differences of the design among DEXs and CEXs carrying perpetual futures, how those differences affect price formation and investors' behavior, and what kinds of empirical implications can be provided to the potential theoretical models for the micro-structure of DEXs? To this end, the previous chapter delineates a detailed Systematization of Knowledge (SoK) contrasting the operational paradigms of Centralized Exchanges (CEXs) and Decentralized Exchanges (DEXs) in the context of

[1]The work in this chapter has been published in [Erdong Chen, Mengzhong Ma, and Zixin Nie. Exploring the Impact: How Decentralized Exchange Designs Shape Traders' Behavior on Perpetual Future Contracts. ChainScience 2024.]

perpetual futures trading. The previous chapter summarizes the features of CEXs and DEXs and propose 4 exchange models that govern the operations of exchanges in different type, allowing for the classification of any exchange into one of these predefined models. The chapter examines traders' behavior in exchanges under different exchange models with data from August 2020 to September 2023, revealing distinctive relationship between price formation and trader behavior derived from the fundamental design differences among different exchange models. This study contributes to the literature by providing a classification standard for the design of DEXs and CEXs on which perpetual future contracts are traded, while elaborating the distinctive features of each exchange model. The trading process and participants' payoffs are formalized separately for each exchange model, offering basis on which future works can be constructed. The pattern revealed by the empirical study corroborates the differences implied by different exchange model, constituting the first sort of empirical research on how traders behave on DEXs and shading lights on potential theoretical frameworks for DEXs.

CEXs and DEXs are categorized based on their Custody Module, with CEXs (CEX Model) managing traders' funds off-chain and DEXs (DEX models) recording and managing funds on-chain via smart contracts. DEXs are further classified into three exchange models: Hybrid, Oracle Pricing, and Virtual Market Making (VAMM). The Hybrid Model, straddling CEX Model and the other DEX models, still employs limit-order books for trade matching, while the Oracle Pricing Model and VAMM Models utilize smart contracts. In the latter two, participants are categorized into active traders (Traders) and passive liquidity providers (Liquidity Providers), the latter accepting orders and earning transaction fees for their liquidity provision. The decentralized, transparent nature of DEXs, underpinned by smart contracts, mitigates risks of misconduct and fraud, highlighting their advantages.

The study investigates the distinct behaviors of traders on exchanges within different models by examining the relationship between the price volatility of the underlying asset, i.e., Bitcoin, and various trading activities, i.e., trading volume, open interest, liquidation, and leverage. the study adopts the measure of intra-day price volatility by Garman and Klass (1980) [43] and modify the method proposed by Wang and Yau (2002) [44] to examine traders' behavior while fitting the context of perpetual future contract trading. Besides, variables relating to traders' behavior are decomposed into the expected and unexpected portion using ARIMA(p, k, q)

model according to Bessembinder and Seguin (1993) [45]. The study encompasses prominent CEXs such as Binance and Bybit, alongside DEXs like GMX, GNS, and Perpetual Protocol V2, with the latter two operating under the Oracle Pricing Model and Perpetual Protocol V2 employing the Virtual Automated Market Making (VAMM) Model. The empirical evidence shows that, for CEXs, price volatility is positively related with trading volumes but negatively related with open interests, consistent with findings in the traditional future markets. While the effects of trading activity on price volatility in CEXs reflect the market depth and can be explained by Kyle's model [3], the VAMM Model introduces a nuanced dynamic in the impact of open interest, varying between long and short positions. This asymmetry is attributable to the VAMM's price formation mechanism, where the rate of change in an asset's relative price inversely correlates with its abundance in the liquidity pool. Consequently, market depth increases with rising open interests in short positions, as the underlying asset accumulates in the liquidity pool, and the reverse holds true for long positions. While in CEXs and exchange of VAMM Model traders' trading activity help form the price, traders in exchanges of Oracle Pricing Model (GMX and GNS) accept the price offered by the Oracle and thus act as pure price takers. Therefore, trading activity should be interpreted as purely traders' reaction to the price change of the underlying asset. When the price become more volatile, trading volumes increase while open interests decrease, with change in long and short positions different. These empirical estimations can be explained by the predictions based on Shalen's dispersion of beliefs model (1993) [46], which address the asymmetry of information traders can access. Uninformed traders tend to overreact more to positive news than negative, evidenced by more of the long positions accumulated.

This study not only delineates the distinct behavioral patterns of traders across exchanges of different design (CEXs and DEXs) but also provides a deeper understanding of the underlying mechanisms driving these behaviors, offering valuable insights for future research and practical applications in the evolving landscape of digital asset trading. While the primary focus of the research is on Decentralized Exchanges (DEXs) operating with perpetual contracts, the findings and theoretical frameworks developed herein have broader applicability, extending to other trading paradigms within DEXs that exhibit the fundamental bifurcation between Traders and Liquidity Providers. This is exemplified in platforms such as PancakeSwap (https://pancakeswap.finance) and Uniswap (https://uniswap.org). Furthermore, as the Decentralized Finance (DeFi) ecosystem evolves, the proliferation of synthetic assets is anticipated to enhance the diversification of portfolios managed on DEXs. The insights gleaned from this study are thus of paramount importance to both academic researchers and industry practitioners.

This chapter is organized into distinct sections for clarity and depth of exploration. At first, the chapter embarks on an empirical investigation into the trading behaviors exhibited on five prominent perpetual futures platforms: GMX, GNS, Perpetual Protocol V2, Binance, and Bybit. The chapter culminates with Section 5.4, which offers concluding observations and reflections on the implications of the findings for the broader field of blockchain-based financial instruments and their role in the evolving landscape of finance.

Soska et al. [32] presents the initial foray into the examination of liquidation processes within the realm of perpetual futures, with BitMEX serving as the focal point of investigation. The researchers observed a correlation between the escalation in the daily volume of liquidated contracts and the heightened price volatility of the underlying asset, specifically Bitcoin, within this particular context. However, it is imperative to acknowledge a notable constraint inherent to BitMEX's operational framework, namely its status as a centralized exchange (CEX). In consequence, the transactions executed on BitMEX are not subject to on-chain recording, thereby engendering a notable degree of scepticism concerning the chapter's data accuracy and precision. In contrast, transactions involving perpetual contracts within decentralized exchanges (DEXs) are on-chain, ensuring a verifiable level of data accuracy. This inherent characteristic affords a heightened level of confidence when analyzing trader behavior within the DEX milieu.

Diverse configurations of the liquidation process engender varying degrees of credit risk exposure for investors holding different categories of perpetual futures contracts. The consequent divergence in credit risk profiles, stemming from the disparate liquidation mechanisms, significantly influences the decision-making process of investors when confronted with a choice among multiple types of perpetual futures contracts linked to the same underlying asset. Theoretical assessment of credit risk, often synonymous with default risk, within the context of futures contracts presents inherent complexities, primarily attributed to the mutual risk-sharing dynamics between the two contracting parties [47]. However, in the case of perpetual futures contracts operational within decentralized exchanges (DEXs), exemplified by platforms such as GMX and GNS, orders are meticulously matched between individual traders and the liquidity pool. Consequently, credit risk is predominantly contingent upon the risk of traders facing liquidation, given that liquidity providers can always cover their loss.

This section of the study undertakes an examination of trader behavior through an analysis of their activities and the corresponding volumes subject to liquidation in response to fluctuations in price volatility. The scope of the analysis encompasses perpetual futures contracts linked to Bitcoin, spanning five exchanges, categorized into two distinct classifications: (1) GMX[2], GNS[3], and Perpetual Protocol V2[4], representing decentralized exchanges (DEXs), and (2) Binance[5] and Bybit[6], constituting centralized exchanges (CEXs). In addition, GMX and GNS adopt Oracel pricing model, which is elaborated in Section 4.5, while Perpetual Protocol V2 adopts VAMM pricing model, which is discussed in Section 4.6. Traders' behavior implied by different designs of the exchange with different pricing mechanisms are compared.

You can refer to the Section 2.1, which delineates the foundational principles underpinning perpetual trading within both the realms of Decentralized Finance (DeFi) and Centralized Finance (CeFi). You can refer Section 4 for Systematization of Knowledge (SoK) approach of the various models associated with perpetual futures.

5.1 Data

In this section, as a case study, GMX, GNS, and Perpetual Protocol V2 are selected as the representatives for DEXs, while Binance and Bybit as the representatives for CEXs. Specifically, the study focuses on perpetual futures on Bitcoin listed on the five exchanges.

[2]https://gmx.io.
[3]https://gains.trade.
[4]https://perp.com.
[5]https://www.binance.com/en.
[6]https://www.bybit.com.

GMX constructs its trading system on Arbitrum and Avalanche[7], and users can trade perpetual futures on both of the two layer-2 networks. This study focuses on trading on Arbitrum from 31 August 2021 to 26 September 2023, the data of which are retrieved from Dune (https://dune.com/queries/3110823). Similarly, GNS is based on Arbitrum and Polygon[8], and the study chooses the perpetual futures on Polygon from 20 December 2021 to 26 September 2023 to examine, the data of which are retrieved by the constructed queries on Dune (https://dune.com/queries/2829105 and https://dune.com/queries/2825251).
The study also retrieves data for Perpetual Protocol V2 (based on Etherum mainnet) from 27 November 2021 to 26 September 2023 by constructing the query on Dune (https://dune.com/queries/3039245). All the above data for DEXs are at transaction level and with length from launches of the instruments to the time of writing this work.

The study retrieves data on Binance and Bybit at the daily-level frequency using API provided by Coinalyze (https://coinalyze.net/). Data for these two CEXs are at market-level rather than transaction-level. BTC Perpetual data for Binance and Bybit are available from 05 August 2020. Data of BTC pricing at the daily-level are collected from CryptoCompare with API (https://cryptocompare.com/). The time frames of data vary across exchanges because they are launched on different dates. However, this would not harm the validity of the analysis, as the time frames largely overlap and traders' behavior in different exchanges separately are examined.

5.2 Empirical Approaches

Drawing inspiration from previous research conducted in the realm of traditional futures markets [44, 45], this study introduces methodological approaches tailored to the investigation of trader behavior within the perpetual futures market. These methodologies, subsequently applied in Section 5.3, facilitate an in-depth exploration of leverage dynamics and liquidation processes.

[7]Arbitrum and Avalanche are two chains to address scalability of Ethereum (https://vitalik.eth.limo/general/2023/10/31/l2types.html), while detailed explanation can be found at: arbitrum.io and www.avax.network.

[8]Information about Polygon can be found at: polygon.technology.

It is paramount to recognize that the pricing mechanisms governing perpetual futures contracts are intentionally designed to approximate the spot price of the underlying asset. Consequently, traders engaged in the trading of perpetual futures are confronted with prices inherently tethered to the underlying asset's market valuation. This inherent convergence between the price of perpetual futures and the spot price signifies that perpetual futures contracts endow traders with an efficient means of exposure to fluctuations in the spot price of the underlying asset [7]. For the purpose of the analysis, and without loss of generality, the focus is directed toward an examination of how traders operating within the perpetual futures market respond to variations in the price of the underlying asset, specifically Bitcoin.

5.2.1 Speculation metrics.

Perpetual futures contracts, characterized by their provision of exceedingly high leverage, create an environment conducive to speculative activities. The presence of speculators assumes considerable significance within the market ecosystem, as they assume the role of risk bearers, thereby effectively absorbing risk transferred by hedgers. Conversely, arbitragers capitalize on market inefficiencies to generate gains with very limited risk exposure.

Hedgers, in contrast, adopt a risk-mitigation strategy by retaining their futures positions for relatively longer durations. Their decision-making process remains relatively impervious to short-term price fluctuations, as it predominantly hinges upon non-pricing determinants, encompassing factors such as the quantity of spot goods at their disposal and the designated delivery timelines. Consequently, transient shifts in prices are frequently instigated by speculators, who exhibit responsiveness to short-term price oscillations [48].

In light of the substantial risk assumed by speculators within this framework, this study takes an initial step by proposing a set of speculation metrics. These metrics, encompassing trading volumes and liquidations standardized by open interests, are instrumental in shedding light on speculative activities within the market.

The standard speculative index ($\mathcal{SI}$) proposed by [49] is defined as:

$$\mathcal{SI} := \frac{\text{Trading Volume}}{\text{Open Interest}}, \tag{5.1}$$

in which speculators drive up trading volume while having little impact on open interest in the short-run. So, large $\mathcal{SI}$ indicates plenty of speculation.

Another measure of speculation is proposed by [48], defined as the ratio of liquidation volume to open interest. The only difference in this study is that, since traders trade with liquidity pools rather than other matched traders in DEXs, the aggregate position of sellers does not necessarily equal to that of the buyers, different from the case of CEXs where there are always a buyer and a seller for any contract. Therefore, the definition of *liquidation index* ($\mathcal{LIQ}$) to fit the features of perpetual in DEXs can be modified as :

$$\begin{aligned} \mathcal{LIQ}_{\text{short}} &= \frac{\text{Short Liquidation Volume}}{\text{Open Interest for Short}}, \quad \text{and} \\ \mathcal{LIQ}_{\text{long}} &= \frac{\text{Long Liquidation Volume}}{\text{Open Interest for Long}}. \end{aligned} \tag{5.2}$$

As Eq. (5.2) measures the liquidation as a proportion of open interest, the expected value of $\mathcal{LIQ}$ is the probability of being liquidated in a certain day. In addition to measuring speculation, the standardization of trading volumes and liquidations by dividing them with open interests makes those metrics comparable among different exchanges, as exchanges vary considerably in size.

5.2.2 Traders' behavior examination.

To analyze the response of perpetual traders to Bitcoin price fluctuations, it is imperative to first establish an estimation for the daily volatility of Bitcoin's price. This study employs the extreme-value volatility estimator, as proposed by Garman and Klass (1980) [43] (on P.74), which incorporates intra-day price volatility. The simplified expression of this estimator is represented as follows:

$$\hat{\sigma}_t = \left\{0.5 \times \left(\ln\left(P_{t,H}/P_{t,L}\right)\right)^2 - \left(2\ln(2) - 1\right)\left(\ln\left(P_{t,O}/P_{t,C}\right)\right)^2\right\}^{1/2}, \tag{5.3}$$

where $P_{t,H}, P_{t,L}, P_{t,O}$, and $P_{t,C}$ are the high, low, opening, and closing prices of Bitcoin on date t, respectively.

Previous research has consistently shown that variables related to traders' activities, such as trading volumes and open interests, exhibit significant correlation [45], suggesting their predictability based on the previous values. Consequently, these variables are often analyzed by dividing them into expected and unexpected components. The expected component, constructed from lagged variables, encompasses information about current trends, while the unexpected component captures unforeseen changes in traders' behavior. This concept is illustrated in the following equation:

$$\hat{\varepsilon}_t = \text{ Activity }_t - E\left\{ \text{ Activity }_t \mid \text{ Activity }_{t-\tau}, \tau = 1, \ldots 10 \right\}, \tag{5.4}$$

traders' activity at date t can be predicted using their activities in previous 10 days, i.e., $E\left\{ \text{ Activity }_t \mid \text{ Activity }_{t-\tau} \right\}$, while the unexpected portion $\hat{\varepsilon}_t$ equals to the different between the realized value Activity _t. Hedgers, who adjust positions infrequently with a long-term focus, exhibit predictable behavior captured in the expected component. In contrast, speculators, who frequently adjust positions to manage risk, are represented by the unpredictable, unexpected component of activity.

Beyond traditional trading activity variables like trading volumes and open interests, this study also assesses the conditional effects of leverage and liquidation on price volatility. These four types of variables are decomposed into expected and unexpected components to differentiate the effects of hedgers and speculators, who vary in their trading willingness. Following the methodology of Bessembinder and Seguin (1993) [45], trading volume, open interest, volume of liquidated positions, and daily average leverage are partitioned using the Autoregressive Integrated Moving Average (ARIMA(p, k, q)) model. The ARIMA(p, k, q) model, which predicts future values based on past data smoothed by lagged moving averages, allows us to designate the model's fitted values as the expected component and its residuals as the unexpected component. For the ARIMA(p, k, q) model, the existence of a unit root determines k, in which case a variable without a unit root is decomposed using ARIMA$(p, 0, q)$, while a non-stationary variable is decomposed using

ARIMA$(p,1,q)$[9]. The corresponding series is differenced k times as an Autoregressive Moving Average (ARMA(p,q)) process. The values of p and q are selected based on the Akaike Information Criterion. The existence of unit roots in each time series is tested using the Augmented Dickey–Fuller (ADF) test, with results detailed in Section 5.2.2.1.

To explore how investors' behavior vary with volatility, the study adapts the model proposed by Wang and Yau (2002) [44] to include daily volumes of liquidated short and long positions separately:

$$\begin{aligned}\hat{\sigma}_t =& \mu + \sum_{i=1}^{m} \phi_i \hat{\sigma}_{t-i} + \sum_{j=1}^{3} \alpha_j EA_{j,t} + \sum_{j=1}^{3} \beta_j UA_{j,t} + \\ & \sum_{k=1}^{2} \gamma_k EL_{k,t} + \sum_{k=1}^{2} \lambda_j UL_{k,t} + \varepsilon_t,\end{aligned} \tag{5.5}$$

where $\hat{\sigma}_t$ is the estimated volatility on day t. $EA_{j,t}$ and $UA_{j,t}$ denote the expected and unexpected trading activity respectively, with j represents different trading activity when assigned different values: $j = 1$ for open interest on long positions, $j = 2$ for open interest on short positions, and $j = 3$ for trading volumes. $EL_{k,t}$ and $UL_{k,t}$ denote represent the expected and unexpected daily liquidated volumes for long ($k = 1$) and short ($k = 2$) positions. The model accounts for volatility persistence through lagged volatility estimates, with the lag structure (m) determined by the Akaike Information Criterion. Given the established correlation between trading activities and volatility [44], these variables are included as controls. This analysis using Eq. (5.5) is applied to perpetual futures from all three DEXs and two CEXs, given the availability of trading volume, open interest, and liquidation data.

In addition to assessing how traders' activities and liquidations respond to price volatility, speculation can be examined, as indicated by Eq. (5.1) and Eq. (5.2), using the following specification:

$$\begin{aligned}\hat{\sigma}_t =& \mu + \sum_{i=1}^{m} \phi_i \hat{\sigma}_{t-i} + \sum_{j=1}^{3} \alpha_j TA_{j,t} + \beta_{SI} \mathcal{SI}_t + \\ & \beta_{LIQS} \mathcal{LIQ}_{\text{short},t} + \beta_{LIQL} \mathcal{LIQ}_{\text{long},t} + \varepsilon_t,\end{aligned} \tag{5.6}$$

[9]Readers can refer to [50] for details about ARIMA(p,k,q) model.

where β_{SI}, β_{LIQS}, and β_{LIQL} measure whether speculation is stronger in respond to the more volatile change in price. Among those, β_{LIQS} and β_{LIQL} indicate whether a short or long position is more likely to be liquidated than usual when the market become more volatile. $TA_{j,t}$ represent trading activities, i.e., j represents trading volume, open interest on short positions, and open interest on long positions. Considering the considerable correlation between trading activities and price volatility, trading activities are included in Eq. (5.6) but do not decompose them as those are not the variables of interest.

Anticipating that traders are inclined to modify their leverage strategies in response to heightened liquidation risks under increased volatility of the underlying asset, this study incorporates an analysis of leverage adjustments. Research focusing on centralized exchanges (CEXs) often omits leverage considerations due to the general unavailability of such data [32, 48]. However, leveraging transaction-level data from GMX and GNS, this investigation calculates and integrates the daily average leverages for both long and short positions into the analytical framework. This is achieved by adapting the existing volatility estimation model, as delineated in Equation (5.5):

$$\begin{aligned}\hat{\sigma}_t =& \mu + \sum_{i=1}^{m} \phi_i \hat{\sigma}_{t-i} + \sum_{j=1}^{3} \alpha_j EA_{j,t} + \sum_{j=1}^{3} \beta_j UA_{j,t} + \sum_{k=1}^{2} \gamma_k EL_{k,t} + \\ & \sum_{j=k}^{2} \lambda_j UL_{k,t} + \sum_{k=1}^{2} \rho_k ELV_{k,t} + \sum_{k=1}^{2} \omega_k ULV_{k,t} + \varepsilon_t,\end{aligned} \tag{5.7}$$

where $ELV_{k,t}$ and $ULV_{k,t}$ denote expected and unexpected average leverage for long ($k = 1$) and short positions ($k = 2$), respectively, on day t. Notably, due to the cross-margining feature in Perpetual Protocol v2, where a collective pool of funds backs each position[10], the specific leverage level for each position remains undefined. Consequently, the leverage analysis using Equation (5.7) is confined to perpetual futures from GMX and GNS.

In addition to exploring how average leverage changes with price volatility, how

[10]Documents of Leverage and Margin Ratio for Perpetual Protocol v2: support.perp.com/hc/en-us/articles/5257393633945-Leverage-Margin-Ratio.

trading volume in different leverage level contribute to the change in average leverage level? To this end, following specification is proposed:

$$\begin{aligned}\hat{\sigma}_t =& \mu + \sum_{i=1}^{m} \phi_i \hat{\sigma}_{t-i} + \sum_{j=1}^{2} \alpha_j EA_{j,t} + \sum_{j=1}^{2} \beta_j UA_{j,t} + \sum_{k=1}^{2} \gamma_k EL_{k,t} + \\ & \sum_{j=1}^{2} \lambda_j UL_{k,t} + \sum_{k=1}^{10} \psi_k ELC_{k,t} + \sum_{j=k}^{10} \kappa_j ULC_{k,t} + \varepsilon_t,\end{aligned} \tag{5.8}$$

In this equation, trading volumes are categorized into ten distinct groups based on their leverage levels: less than 1X, 1X to 5X, 5X to 10X, 10X to 15X, 15X to 20X, 20X to 25X, 25X to 30X, 30X to 35, 35X to 40X, 40X to 45X, 45X to 50X, and more than 50X. $ELC_{k,t}$ and $ULC_{k,t}$ denote the expected and unexpected portions of trading volume within each leverage category k To avoid issues of multicollinearity, total trading volume is not included as a separate variable in $EA_{j,t}$ and $UA_{j,t}$, , given that the aggregated trading volume across all leverage categories equates to the total trading volume.

5.2.2.1 Augmented Dickey–Fuller test

Table. 5.1 reports the results of the Augmented Dickey–Fuller (ADF) test, which is used to check whether the time series examined are stationary. According to Section 5.2, when decomposing the series into expected and unexpected portions, the series for which the study fails to reject the hypotheses of the existence of a unit root are differenced, i.e., the series with insignificant statistics in Table. 5.1.

TABLE 5.1: Augmented Dickey–Fuller (ADF) test statistics

Variables	Perpetual Contracts on Bitcoin				
	GMX	***GNS***	***Perpetual Protocol V2***	***Binance***	***Bybit***
Trading Volume	-4.850***	-4.178***	-3.680***	-3.725***	-2.609*
OI on Short	-2.896**	-1.868	-1.621	-2.930*	-1.428
OI on Long	-3.556***	-1.559	-2.179	-	-
Liquidation on Short	-13.712***	-16.172***	-24.228***	-2.115	-2.886**
Liquidation on Long	-26.746***	-8.175***	-8.540***	-2.787*	-3.430***
Leverage on Short	-6.769***	-5.844***	-	-	-
Leverage on Long	-4.110***	-4.204***	-	-	-
$\mathcal{SI}$	-3.388**	-2.542	-4.375***	-3.044**	-3.836***
$\mathcal{LIQ}_{short}$	-26.480***	-8.453***	-23.066***	-1.799	-2.982**
$\mathcal{LIQ}_{long}$	-27.120***	-2.872**	-15.664***	-2.764*	-2.260
Leverage (in categories):					
less than 1×	-6.106***	-	-	-	-
1× to 5×	-5.149***	-6.247***	-	-	-
5× to 10×	-5.194***	-4.790***	-	-	-
10× to 15×	-3.846***	-8.132***	-	-	-
15× to 20×	-9.448***	-8.472***	-	-	-
20× to 25×	-4.339***	-24.221***	-	-	-
25× to 30×	-4.614***	-7.505***	-	-	-
35× to 40×	-2.338	-15.250***	-	-	-
40× to 45×	-3.139**	-3.196***	-	-	-
45× to 50×	-2.245	-14.365***	-	-	-
More than 50×	-4.361***	-4.145***	-	-	-

Notes. This table reports the statistics for Augmented Dickey–Fuller (ADF) test, which is used to test whether a time series is stationary. ADF test statistics are for the hypothesis that a series contains a unit root. $*$, $**$, and $***$ denote significance at 0.1, 0.05, and 0.01 level, respectively.

5.3 Empirical Results and Discussion

5.3.1 Descriptive statistics and dynamics of metrics.

Table. 5.2 delineates the descriptive statistics for trading volumes, open interests, liquidations, and leverage of the five perpetual future platforms under examination, while Fig. 5.1 graphically depicts these metrics on a weekly basis. Centralized exchanges (CEXs) have historically exhibited preeminence in trading volume and open interest, yet decentralized exchanges (DEXs) have demonstrated a notable ascension since 2023, as detailed in Fig. 5.2 [11]. An analysis of average daily liquidation volumes reveals a predilection for higher liquidations in long positions over short positions, with the exception of Perpetual Protocol V2. In the cases of GMX and GNS, the open interest for long positions surpasses that for short positions, and the leverages for both orientations (long & short) are relatively equivalent (15.57 & 15.80 for GMX and 72.33 & 75.28 for GNS), logically inferring a higher liquidation volume for long positions. With liquidation standardized, the close proximate values of $\mathcal{LIQ}_{short}$ and $\mathcal{LIQ}_{long}$ for GMX (0.016 and 0.016) and GNS (0.035 and 0.032) suggest a comparable probability of liquidation for both long and short positions. A symmetrical pattern in liquidation is anticipated between long and short positions with similar leverage levels and volumes. This symmetry is observed for Perpetual Protocol V2 and Bybit, but not for Binance. A two-sample t-test indicates that the discrepancy between $\mathcal{LIQ}_{short}$ and $\mathcal{LIQ}_{long}$ is statistically significant exclusively for Binance (p-value = 0.001), whereas it remains statistically insignificant for the other platforms, namely GMX (p-value = 0.997), GNS (p-value = 0.813), Perpetual Protocol V2 (p-value = 0.883), and Bybit (p-value = 0.184). Despite the absence of leverage data for Binance, the order book matching mechanism posits an equivalent leverage distribution between sellers and buyers, yet empirical observations contradict this equilibrium. This discrepancy remains inconclusive pending further data.

Additionally, Fig. 5.1 reveals an anomaly for Binance, where liquidation volumes for both long and short positions were concentrated during the bullish period in

[11] Fig. 5.2 shows the dynamics of trading volumes, open interests, and liquidations solely for DEXs. GMX dominated across time with the highest trading volumes. Although the trading volumes on GNS are far less than those on GMX, it has open interest comparable to GMX. In addition, liquidations on long positions are more frequent and higher in value than those on short positions along the time.

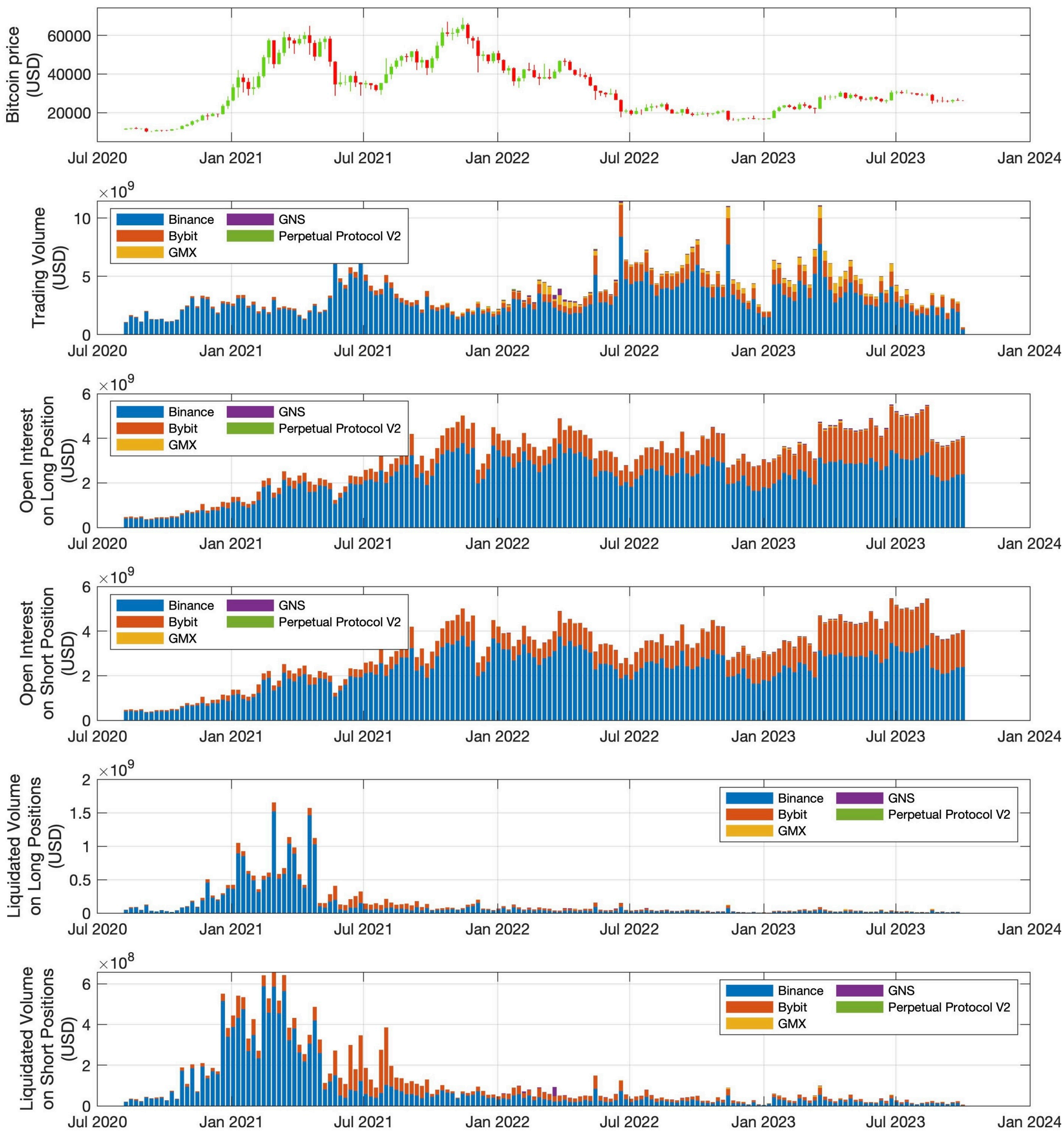

FIGURE 5.1: Trading Volumes, Open Interest, and Liquidated Volumes of Perpetual Futures on all the Five DEXs and CEXs. As CEXs dominate the market, the figure is created for solely illustrating DEXs, which is in Fig. 5.2.

the first half of 2021, peaking in March and declining post-June, yet maintaining a consistently low level throughout the cryptocurrency market downturn in 2022. This trend may be attributable to Binance's historical allowance of up to 125× leverage, which was reduced to a maximum of 20× on July 26, 2021[12] [51], significantly diminishing the likelihood of liquidation events.

[12]For further details, refer to Binance's announcement on July 27, 2021: https://www.binance.com/en/support/announcement/updates-on-rules-of-binance-futures-leverage-for-new-accounts-2021-07-27-d6457e23eb2e42f2b9c3ce44f46f9a6d.

TABLE 5.2: Descriptive Statistics of Trading Volumes, Open Interest, Liquidation, and Leverage of Perpetual Futures

Statistics		Perpetual Contracts on Bitcoin				
		GMX	***GNS***	***Perpetual Protocol V2***	***Binance***	***Bybit***
Mean	Trading Volume (M)	40.46	7.62	2.65	411.55	92.18
	OI on Short (M)	10.43	20.29	6.51	2235.61	831.39
	OI on Long (M)	18.31	26.38	4.13	2235.61	831.39
	Liquidation on Short (K)	62.68	197.30	4.53	11875.03	4527.90
	Liquidation on Long (K)	124.09	248.76	3.54	17128.46	4753.27
	Leverage on Short (K)	15.57	72.33	-	-	-
	Leverage on Long (K)	15.80	75.28	-	-	-
	$\mathcal{SI}$	5.74	0.93	1.40	0.24	0.13
	$\mathcal{LIQ}_{short}$	0.016	0.035	0.002	0.009	0.012
	$\mathcal{LIQ}_{long}$	0.016	0.032	0.002	0.013	0.013
Std. Dev.	Trading Volume (M)	50.82	12.40	2.75	249.56	84.57
	OI on Short (M)	10.88	11.45	3.31	898.54	519.86
	OI on Long (M)	19.37	16.87	1.36	898.54	519.86
	Liquidation on Short (K)	459.08	1406.25	27.11	24231.71	7933.40
	Liquidation on Long (K)	947.45	609.53	18.11	49440.90	7263.63
	Leverage on Short (K)	6.89	14.32	-	-	-
	Leverage on Long (K)	6.89	21.34	-	-	-
	$\mathcal{SI}$	14.71	2.28	5.51	0.19	0.10
	$\mathcal{LIQ}_{short}$	0.173	0.359	0.017	0.022	0.024
	$\mathcal{LIQ}_{long}$	0.173	0.101	0.029	0.040	0.026
No. of observations		747	628	668	1147	1147

Note. This table reports the daily mean and standard deviation of trading volumes (in million USD), open interest (O.I. in million USD), short liquidations (in thousand USD), long liquidations (in thousand USD), $\mathcal{SI}$, $\mathcal{LIQ}_{\text{short}}$, $\mathcal{LIQ}_{\text{long}}$ of USD or USDT bitcoin perpetuals across GMX, GNS, Perpetual Protocol V2, Binance, and Bybit. Daily mean and standard deviation of average leverage on short and long positions (in thousand USD) are reported for perpetuals on GMX and GNS. The measure of daily average leverage is calculated by dividing the sum of daily transaction volume by the total amount of collateral supporting those transactions, which is the weighted average leverage of transactions in a day. The study also conducts ADF test for each of the series, the results of which can be found in Section 5.2.2.1.

Upon examination of the mean values for $\mathcal{SI}$ and $\mathcal{LIQ}$ delineated in Table. 5.2 across various trading platforms, it is discernible that GMX exhibits the highest mean value for $\mathcal{SI}$ at 5.74, while GNS registers the maximal values for both $\mathcal{LIQ}_{short}$ (0.035) and $\mathcal{LIQ}_{long}$ (0.032) respectively. This suggests a relatively heightened level of speculative trading activity on GMX and GNS compared to

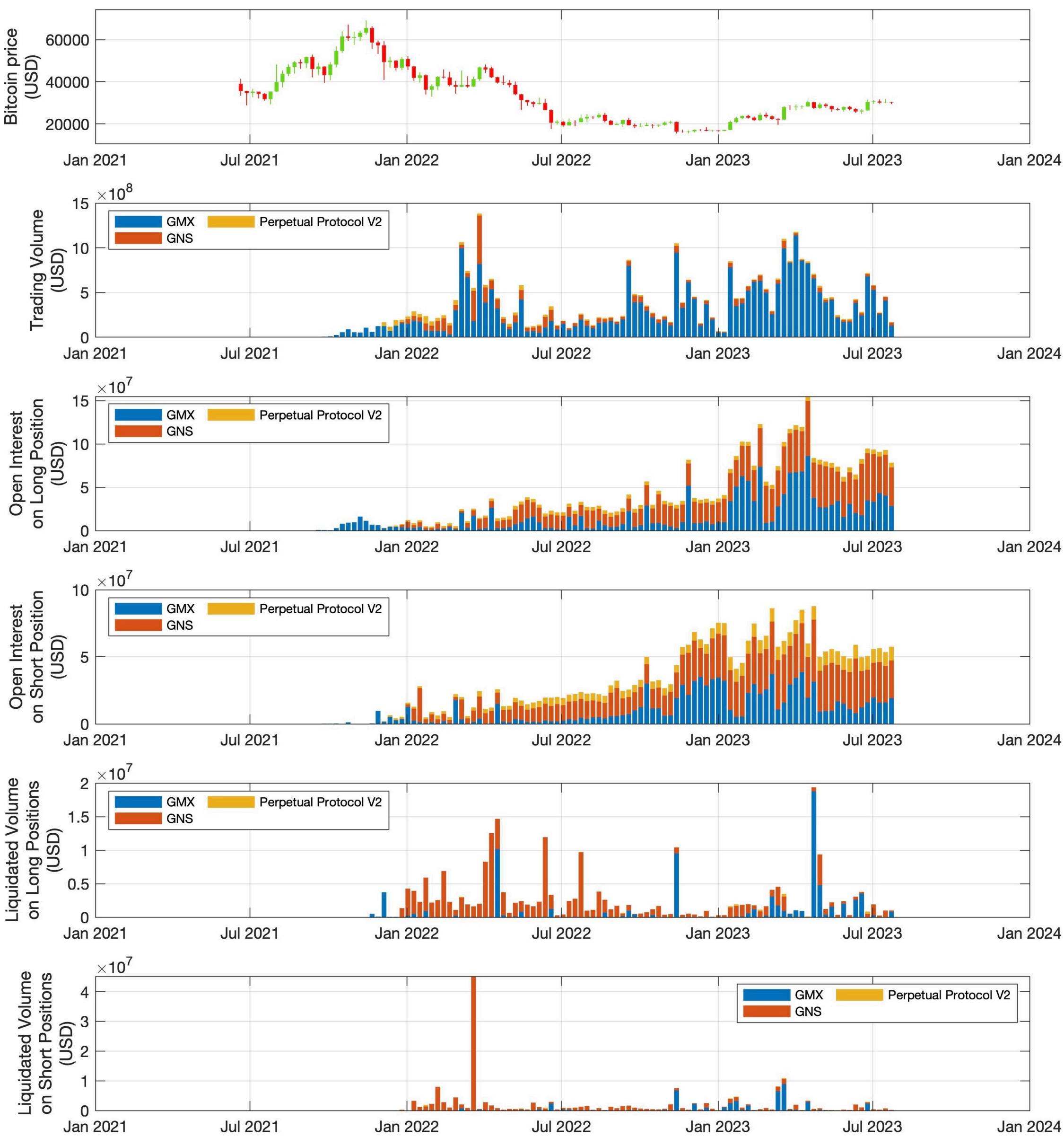

FIGURE 5.2: Trading Volumes, Open Interest, and Liquidated Volumes of Perpetual Futures on the Three DEXs.

other exchanges. Such a trend aligns with the operational parameters of GMX and GNS, which afford traders the opportunity to engage with higher leverage options and impose a lower threshold for maintenance margins relative to their counterparts. Specifically, GMX and GNS extend maximum leverage ratios of 100× and 150× respectively, in contrast to centralized exchanges (CEXs) like Binance and Bybit, which implement a tiered leverage system that inversely correlates the maximum allowable leverage with the size of the position[13]. The maintenance margin

[13]For maximum leverages allowed in each tier of position size on Binance and Bybit, readers can refer to https://www.binance.com/en-IN/futures/trading-rules/perpetual/leverage-margin and

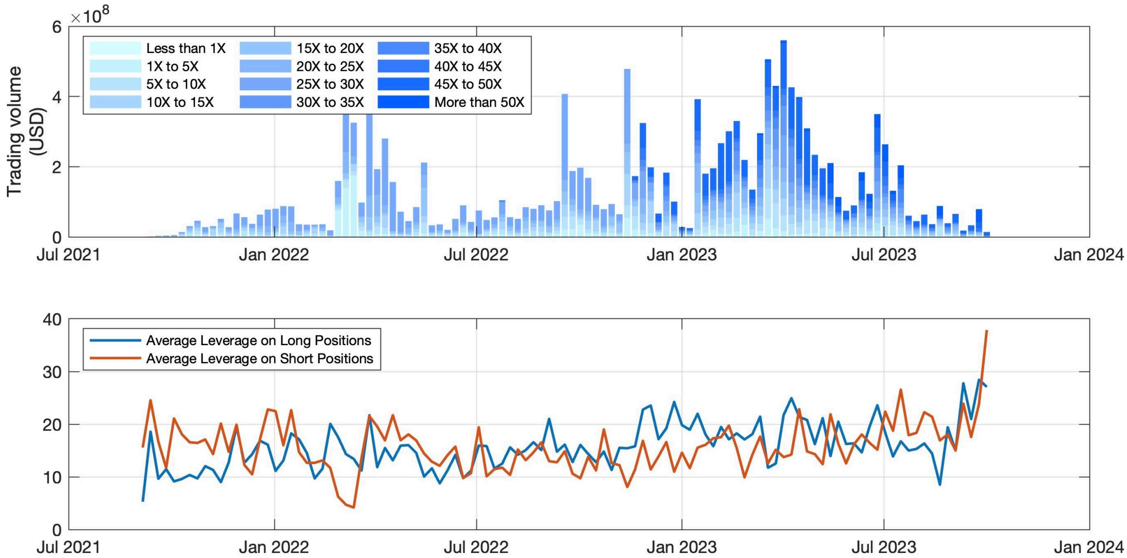

FIGURE 5.3: Trading Volume in Leverage Categories and Average Leverage of Daily Transactions (GMX). The upper panel shows the dynamics of the daily trading volume in each of the 12 leverage categories defined in Section 5.2.2, while the lower panel shows the daily average leverage for long and short positions.

required by GMX is 1%, and the liquidation price on GNS is calculated by:

$$\begin{aligned} &Liquidation\ Price = Open\ Price - Liquidation\ Price\ Distance, if\ long, and \\ &Liquidation\ Price = Open\ Price + Liquidation\ Price\ Distance, if\ short,\ where \\ &Liquidation\ Price\ Distance = \frac{Open\ Price \times Leverage}{Collateral} \times (Collateral \times 0.9 \\ &\qquad - Borrowing\ Fees). \end{aligned} \tag{5.9}$$

Effectively, traders on GNS trade with the lowest maintenance margin ratio among the five exchanges, where Perpetual Protocol V2 adopts the maintenance margin ratio of 6.25% and 0.4% for both Binance and Bybit in the tier of the smallest position[14].

Fig. 5.3 and Fig. 5.4 illustrate the dynamics of the daily trading volume in different leverage categories defined in Section 5.2.2 as well as the daily average leverage level for long and short positions respectively. GMX announced to rise its maximum

https://www.bybit.com/en-US/help-center/article/Risk-Limit-USDC-Contract. Since Perpetual Protocol V2 adopts cross-margining, the leverage for individual position is undefined.

[14]With Eq. (5.9), if a trader opens a long position with collateral of 50 USD and open price of 20,000 USD, he/she would be liquidated when the price drops to 19,824 USD, liquidated with a maintenance margin ratio of 0.1% equivalently.

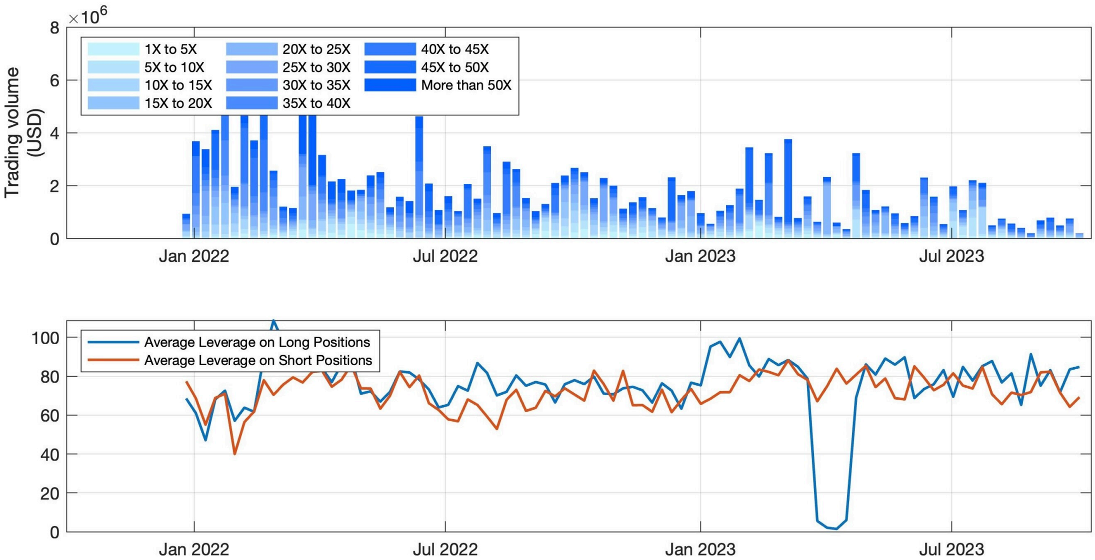

FIGURE 5.4: Trading Volume in Leverage Categories and Average Leverage of Daily Transactions (GNS).The upper panel shows the dynamics of the daily trading volume in each of the 11 leverage categories defined in Section 5.2.2, i.e., there does not exist transaction with less than 1× leverage in the dataset on GNS, while the lower panel shows the daily average leverage for long and short positions.

leverage on 8 November 2021 [52], followed with significant trading volumes in leverages more than 35× after November 2021, as shown in the upper panel of Fig. 5.3. It shows that although trading volumes with different leverages vary across time, the level of daily average leverage oscillates within a narrow range. The two-sample t-test indicates the insignificant difference of leverage between long and short positions for GMX, with p-value of 0.515, while the difference is significant for GNS, with p-value of 0.004, in which case long positions are with higher leverages than short positions averagely for GNS. This finding is consistent with the record by BitMEX CEO Arthur Hayes [53], in which the average effective leverage for long positions is on average higher than that for short positions. Around April 2023, there was a sudden drop in average leverage on long positions for GNS, shown in Fig. 5.4. This change could be attributed to the huge drop in the daily value of collateral used for transactions on long positions during this period, as the average leverage is calculated with dividing the aggregated value of collateral by the aggregated transaction value each day.

Fig. 5.5 shows the fraction of liquidations over total trading volume across time for DEXs, which is the liquidations standardized by trading volumes and also a proxy for evaluating the risk of an instrument [32]. As expected, GNS acts as

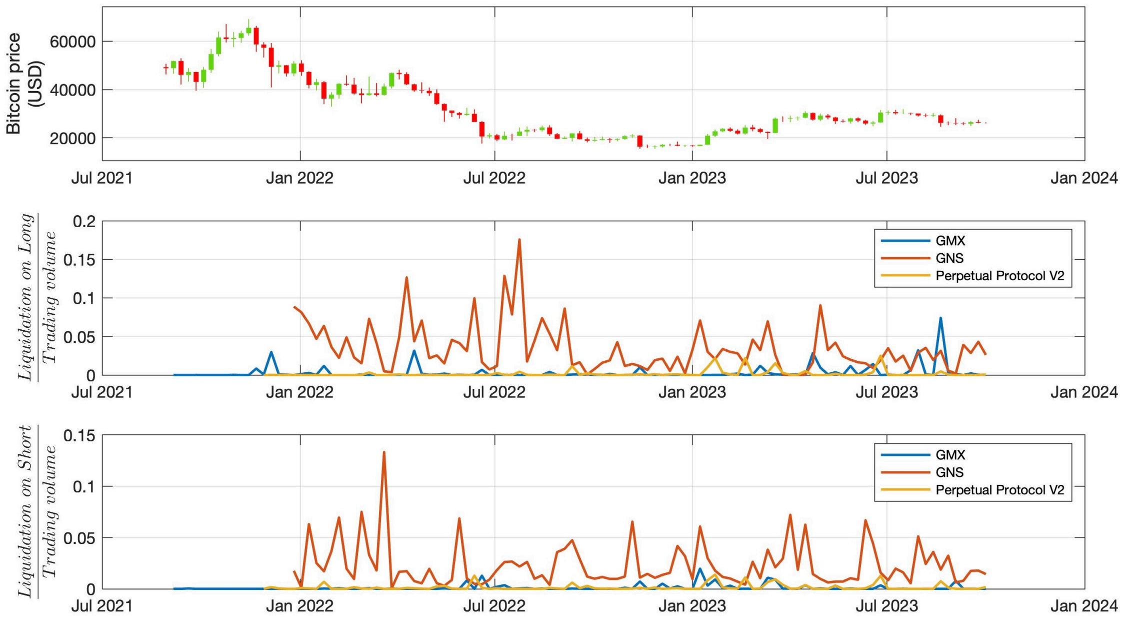

FIGURE 5.5: Volume-normalized Liquidations for DEXs. The middle and bottom panel depict the fraction of liquidations on long and short positions over total trading volume across time respectively.

the most risky DEX across time, for its liquidations standardized by trading volumes for both long and short positions consistently higher than that for GMX and Perpetual Protocol V2 overtime. The standardized liquidation of long (short) positions increases even when the Bitcoin price trended up (down), however, short after July 2022, a counter-intuitive pattern also noted by [32]. [32] mentions the increased volatility accompanied by the uptrend of Bitcoin price, which presents as high intra-day price volatility due to price expansion, as a potential explanation but without empirical evidence. In the rest of this section, the study systematically examines the association between liquidation the price volatility of Bitcoin, explaining the pattern of liquidation as well as the asymmetry between long and short positions.

5.3.2 Empirical results and analysis for CEXs.

Table. 5.3 aggregates regression results on Eq. (5.5) and Eq. (5.6). Coefficient estimates for expected and unexpected trading volume are positive across all the five exchanges, and are statistically significant except the one for expected trading volume on GNS. Estimated coefficients for the unexpected volume (the shocks) are uniformly higher than those for the unexpected volume, suggesting that one unit change in the unexpected portion of trading volumes has higher effect on the price volatility of Bitcoin than one unit change in the expected volume, consistent with the findings in the previous studies on traditional futures market [44, 45].

For CEXs, i.e., Binance and Bybit, all the estimated coefficients measuring the marginal effects of expected and unexpected open interest are negative and significant, while the estimated coefficients for the unexpected portion are also larger in magnitude than those for the expected portion. Since in CEXs each seller is matched with a buyer of the perpetual futures, aggregated value of long positions equals to that of short positions, so do the open interests. Eq. (5.5) includes open interests on short, as open interests on long are of the same value. Since CEXs adopt the mechanism with order books, it relates to the determinants of market depth, which [3] defines as the volume of unanticipated order flow required to move price by one unit. When capital inflows into the market, the liquidity increases, which is reflected by higher level of open interests, making the price less volatile in response to new orders. Consequently, it is expected that when open interest is large the price volatility conditional on contemporaneous trading volume, which proxies market depth, would be lower. Therefore, those negative estimated coefficients imply that an increase in unexpected open interest, e.g., inflow of speculative capital, lessens the impact of trading volume shock (unexpected volume) on price volatility. In the case, for Binance, when a trader increase his/her position by 1 USD, the marginal effect of the 1 USD increase in trading volume on price volatility is 5.943×10^{-8}, while mitigated by the effect of 1 USD increase in open interest (-2.365×10^{-11}), resulting in a smaller aggregated effect ($5.943 \times 10^{-8} - 2.365 \times 10^{-11}$). On the one hand, estimated coefficients for trading volumes and open interests have opposite signs, while on the other hand, whether the marginal effect of volume on price volatility is enlarged or mitigated depends on whether open interest is reduced or increased. Trades closing, decreasing, or liquidating positions actually reduce open interest, enlarging the effect of trading volume on price volatility[15]. Price would move with larger distance, as less liquidity reacts to absorb a trade. This is reflected by that seven out of eight coefficients for liquidated volume in Binance and Bybit are significant and positive, with expected liquidated volume on short positions for Bybit as the exception. Thus, ceteris paribus, an unexpected rise in liquidation reduces market depth, via lowering open interest and liquidity. Considering the abnormality in the dynamics of liquidation

[15]Trades opening positions or rising positions increases open interests.

data for Binance, the study replicates the regressions in Eq. (5.5) and Eq. (5.6) for two periods dichotomized by 1 May 2021, the date around which liquidations on Binance suddenly dropped and became consistently low. The estimating results and analysis for the two periods separately are included in Section 5.3.2.1. Traders' behavior reflected in the two periods is almost the same with that reflected in Table. 5.3.

TABLE 5.3: Regression Results on Eq. (5.5) and Eq. (5.6)

Variables	**Perpetual Contracts on Bitcoin**				
	GMX	***GNS***	***Perpetual Protocol V2***	***Binance***	***Bybit***
Panel a: Regression Results on Eq. (5.5):					
Intercept	1.438e-12 (16.82)***	0.017 (8.82)***	0.009 (3.48)***	0.011 (6.27)***	2.145 (0.15)
Lagged volatility	0.256 (8.10)***	0.371 (10.57)***	0.252 (8.19)***	0.200 (10.16)***	0.210 (17.19)***
Trading Activity:					
Expected trading volume	1.186e-10 (6.30)***	1.222e-11 (0.19)	2.59e-09 (8.76)***	3.06e-08 (12.87)***	6.041e-08 (8.91)***
Unexpected trading volume	1.29e-10 (9.83)***	4.53e-10 (6.65)***	3.62e-09 (14.42)***	5.943e-08 (24.07)***	1.409e-07 (15.62)***
Expected OI on short	-4.765e-10 (-7.36)***	-2.059e-10 (-1.99)**	-1.678e-09 (-4.40)***	-1.11e-12 (-2.24)***	-8.55e-12 (-8.69)***
Unexpected OI on short	-2.808e-10 (-3.27)***	-4.654e-10 (-3.08)***	1.125e-08 (4.53)***	-2.365e-11 (-8.93)***	-3.138e-11 (-4.65)***
Expected OI on long	-1.88e-10 (-5.99)***	2.98e-11 (0.44)	3.569e-09 (3.98)***	-	-
Unexpected OI on long	-1.75e-10 (-2.16)**	-4.261e-11 (-0.29)	1.481e-09 (0.161)	-	-
Liquidation:					
Expected liquidated volume on short positions	2.449e-09 (1.09)	-1.483e-09 (-1.26)	-5.983e-07 (-2.09)**	2.864e-10 (5.46)***	-2.832e-10 (-2.32)**
Unexpected liquidated volume on short positions	2.007e-09 (1.61)	3.386e-10 (0.835)	-3.032e-08 (-1.61)	1.655e-10 (6.95)***	5.098e-10 (7.22)***
Expected liquidated volume on long positions	1.82e-07 (17.71)***	7.295e-09 (3.26)***	5.008e-07 (4.16)***	8.534e-11 (3.00)***	1.672e-09 (11.96)**
Unexpected liquidated volume on long positions	2.593e-09 (5.08)***	1.448e-09 (1.46)	1.482e-07 (5.39)***	7.143e-11 (6.82)***	1.278e-09 (16.62)***
Adjusted R^2	0.375	0.310	0.507	0.647	0.649
AIC	-4381	-3670	-4067	-6580	-6664

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Table 5.3 (continued)

Variables	***GMX***	***GNS***	***Perpetual Protocol V2***	***Binance***	***Bybit***
No. of obs.	747	628	668	1147	1147
Panel b: Regression Results on Eq. (5.6):					
Intercept	0.021 (18.02)***	0.017 (9.88)***	0.001 (0.51)	-0.003 (-1.46)	0.015 (10.00)***
Lagged volatility	0.260 (8.40)***	0.382 (10.69)***	0.256 (8.18)***	0.224 (11.12)***	0.189 (8.95)***
Trading Activity:					
Trading volume	1.368e-10 (10.58)***	3.007e-10 (4.72)***	3.335e-09 (15.79)***	3.66e-08 (13.28)***	1.096e-07 (9.17)***
OI on short	-4.31e-10 (-8.66)***	-2.802e-10 (-3.33)***	-1.098e-09 (-2.89)***	2e-12 (2.38)**	-7.609e-12 (-5.60)***
OI on long	-1.966e-10 (-6.22)***	6.244e-11 (1.10)	3.74e-09 (3.95)***	-	-
$\mathcal{SI}$ and $\mathcal{LIQ}$:					
$\mathcal{SI}$	-2.597e-05 (-0.63)	-0.001 (-1.79)*	3.000e-04 (3.19)***	0.020 (4.07)***	0.004 (0.40)
$\mathcal{LIQ}_{\text{short}}$	0.004 (1.48)	-0.001 (-0.816)	-0.065 (-2.29)**	0.184 (7.30)***	0.169 (7.58)***
$\mathcal{LIQ}_{\text{long}}$	0.015 (5.78)***	0.017 (2.75)***	0.019 (1.19)	0.156 (11.73)***	0.34 (0.40)
Adjusted R^2	0.380	0.282	0.466	0.600	0.600
AIC	-4389	-3649	-4018	-6435	-6511
No. of obs.	747	628	668	1147	1147

Notes: Panel a of this table reports the regression results of Eq. (5.5) while Panel b reports the regression results of Eq. (5.6). For perpetual futures on both DEXs and CEXs, contract size is undefined and traders trade perpetual futures with arbitrary units of Bitcoins, so trading volumes and open interests are measured in USD. Since for DEXs each future contract is matched with a buyer and a seller, resulting in the same dollar value of open interests for long and short, the study regresses price volatility only on open interest on short. This is only for notation while does not mean CEXs are only with short positions, because the dollar value of open interest on short is always equals to that on long. In each cell, the t-statistics are in the parentheses. $*$, $**$, and $***$ denote significance at 0.1, 0.05, and 0.01 level, respectively.

5.3.2.1 The ADF test and regression results for Binance

The ADF test and regression results of Eq. (5.5) and Eq. (5.6) for Binance using data separately before (Period(1)) and after (Period(2)) 1 May 2021 are reported in Table. 5.4. Same with the case in Table. 5.3, coefficients for both expected and unexpected portion of the trading volume are estimated to be significantly positive, and those for open interest are estimated to be negative, substantiating my notion in Section 5.3 that the increase in open interest mitigates the effects of shocks on price volatility.

Table 5.4: ADF Test and Regression Results with Truncated Data for Binance

Regression Results Eq. (5.5) and Eq. (5.6)			**ADF Test**		
Variables	**Period(1)**	**Period(2)**	**Variables**	**Period(1)**	**Period(2)**
Panel a: Regression Results on Eq. (5.5):			**Panel b: Results of ADF test**		
Intercept	0.011 (3.23)***	0.010 (3.90)***	Trading Volume	-2.775*	-3.172**
Lagged volatility	0.145 (4.58)***	0.041 (2.07)**	OI	-1.051	-3.810***
Trading Activity:			Liquidation on Short	-1.430	-4.583***
Expected trading volume	5.57e-08 (5.10)***	1.84e-08 (8.52)***	Liquidation on Long	-4.977***	-4.939***
Unexpected trading volume	7.208e-08 (8.42)***	3.958e-08 (14.24)***	$\mathcal{SI}$	-2.258	-3.853***
Expected OI	-1.623e-11 (-6.47)***	-1.66e-12 (-2.27)**	$\mathcal{LIQ}_{\text{short}}$	-1.822	-8.152***
Unexpected OI	-5.132e-12 (-0.55)	-1.338e-11 (-5.09)***	$\mathcal{LIQ}_{\text{long}}$	-5.951***	-7.284***
Liquidation:				-	-
Expected liquidated volume on short	3.859e-10 (5.57)***	8.418e-10 (3.41)***		-	-
Unexpected liquidated volume on short	1.083e-10 (4.52)***	1.367e-09 (8.59)***		-	-
Expected liquidated volume on long	1.694e-10 (4.9)***	1.882e-09 (8.59)***		-	-
Unexpected liquidated volume on long	9.729e-11 (8.46)***	9.686e-10 (9.16)***		-	-
Adjusted R^2	0.82	0.76		-	-

(continued on next page)

Table 5.4 (continued)

Regression Results on Eq. (5.5) and Eq. (5.6)			**ADF Test**		
Variables	**Period(1)**	**Period(2)**	**Variables**	**Period(1)**	**Period(2)**
AIC	-1688	-5408		-	-
No. of obs.	269	878		-	-
Panel c: Regression Results on Eq. (5.6):					
Intercept	0.007 (2.30)**	-0.004 (-1.47)		-	-
Lagged volatility	0.176 (5.62)***	0.026 (1.34)		-	-
Trading Activity:					
Trading volume	5.329e-08 (4.27)***	2.725e-08 (5.89)***		-	-
OI	-2.124e-13 (-0.10)	3.563e-12 (3.61)***		-	-
$\mathcal{SI}$ and $\mathcal{LIQ}$:					
$\mathcal{SI}$	-0.009 (-1.37)	0.007 (0.59)		-	-
$\mathcal{LIQ}_{\text{short}}$	0.158 (6.03)***	2.188 (11.03)***		-	-
$\mathcal{LIQ}_{\text{long}}$	0.156 (12.09)***	2.374 (8.15)***		-	-
Adjusted R^2	0.81	0.76		-	-
AIC	-1675	-3649		-	-
No. of obs.	269	878	No. of obs.	269	878

This table reports the estimation results of Eq. (5.5) (Panel a) and Eq. (5.6) (Panel c), as well as the ADF test (Panel b), for Binance in two periods separately. Period (1) presents the time from 5 August 2020 to 30 Apirl 2021, and Period (2) stands for the time from 1 May 2021 to 26 September 2023. ADF test statistics are for the hypothesis that a series contains a unit root. In each cell of Panel a and Panel c, the t-statistics are in the parentheses. $*$, $**$, and $***$ denote significance at 0.1, 0.05, and 0.01 level, respectively.

5.3.3 Empirical results and analysis for Perpetual Protocol V2 (with VAMM Model).

In CEXs, traders are matched by the market maker and provide liquidity. Different from the case of CEXs, traders in DEXs are matched with liquidity pools, in which liquidity providers act passively as the counterparty. Traders' open interest thus does not necessarily influence the market depth in the same way as in CEXs and the theory of market depth by [3] for traditional futures market is inapplicable in this context. For Perpetual Protocol V2, which adopts VAMM as the pricing mechanism, liquidity providers deposit stable coins in the vault based on which the clearing house mints virtual tokens and places those virtual tokens into the Uniswap v3 AMM[16]. For illustration, assume the price of the Bitcoin perpetual is determined by the exchange function defined in Section 2.1.8:

$$Q_{vUSDC} \times Q_{vBTC} = k \tag{5.10}$$

where Q_{vUSDC} and Q_{vBTC} denote the quantities of virtual USDC (vUSDC) and virtual Bitcoin (vBTC) in the liquidity pool, and k reflects the depth of liquidity, which is determined by liquidity providers. With constant k, the price of virtual Bitcoin is determined by the ratio of Q_{vUSDC} and Q_{vBTC}:

$$P_{vBTC} = \frac{Q_{vUSDC}}{Q_{vBTC}} = k \times Q_{vBTC}^{-2}. \tag{5.11}$$

The absolute value of the first derivative of P_{vBTC} with respect to Q_{vBTC} is monotonously decreasing, which can be derived as:

$$\left|\frac{\partial P_{vBTC}}{\partial Q_{vBTC}}\right| = \left|-2 \times k \times Q_{vBTC}^{-3}\right| = 2 \times k \times Q_{vBTC}^{-3}, \tag{5.12}$$

indicating the decreasing rate of change in pricing as vBTC goes abundant in the liquidity pool. The more vBTC there are in the liquidity pool, the lower volatile its price is. When a trader opens a long position, the clearing house swaps vUSDC for vBTC from the liquidity pool, adding vUSDC to and withdrawing vBTC from the pool. Q_{vBTC} decreases while P_{vBTC} becomes more volatile.

[16]Details of how VAMM works in Perpetual Protocol V2 can be found in https://support.perp.com/hc/en-us/articles/9594157347481-How-It-Works.

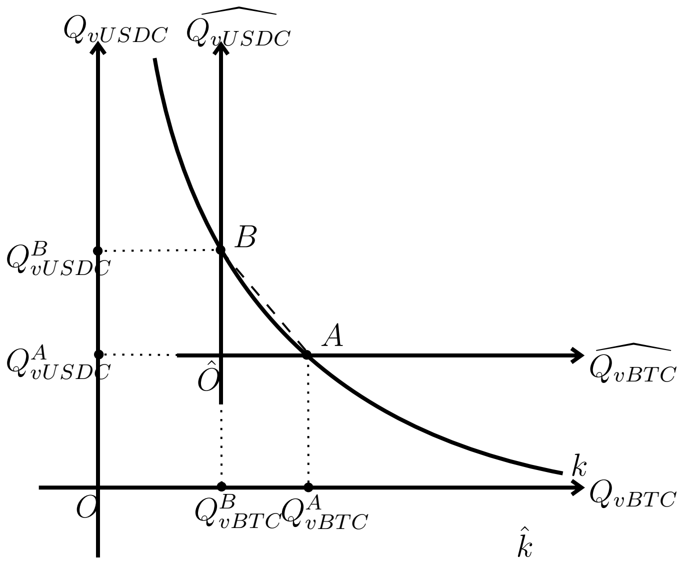

FIGURE 5.6: A Uniswap v3 pool with a single liquidity provider.

Besides, Uniswap v3 AMM implements concentrated liquidity to enhance capital efficiency, where liquidity providers specify a price range, $[\underline{P}, \bar{P}]$, within which to add liquidity[17]. If there is only a single liquidity provider specifying the price interval $\left[P^A_{vBTC}, P^B_{vBTC}\right]$ to add liquidity, where $P^A_{vBTC} = \frac{Q^A_{vUSDC}}{Q^A_{vBTC}}$ and $P^B_{vBTC} = \frac{Q^B_{vUSDC}}{Q^B_{vBTC}}$, this concentrated liquidity can be characterized by drawing a new set of axes, i.e., $\widehat{Q_{vBTC}}$ and $\widehat{Q_{vUSDC}}$ with the origin $\hat{O}$ as shown in Fig. 5.6, to track the real reserve offered in range AB. While the exchange function is defined in the $Q_{vBTC} - Q_{vUSDC}$ space (*virtual* reserve termed by UniSwap v3), the actual reserve specified in the price range is called *real*. Any point (Q_{vBTC}, Q_{vUSDC}) in the *virtual* space can be transformed to a point $(\widehat{Q_{vBTC}}, \widehat{Q_{vUSDC}}) = (Q_{vBTC} - Q^B_{vBTC}, Q_{vUSDC} - Q^A_{vUSDC})$ in the *real* space. The liquidity provider actually defines the coordinate of the *real* origin $\hat{O}$, which is a function of the interval $\left[P^A_{vBTC}, P^B_{vBTC}\right]$.

In practice, liquidity offered by multiple liquidity providers cumulates around the current price level, as illustrated in Fig. 5.7. Trades at the tails of the distribution lead to larger price move, i.e., thus larger price volatility, due to lower liquidity than at the center. Therefore, while the design of concentrated liquidity determines market depth locally, the exchange function Eq. (5.10) forms price globally. In the long-run, (Q_{vBTC}, Q_{vUSDC}) moves along the exchange function and the change in slope determines the price volatility. In the short-run, the liquidity distribution centered at the current average price determines price volatility.

[17] For details of geometric explanation on concentrated liquidity, readers can refer to [54].

FIGURE 5.7: Example of Liquidity Distribution on Uniswap v3 AMM. This figure shows the liquidity distribution for the pool of the pair WBTC/USDC on Uniswap V3. This snapshot is made on 7 Nov 2023. Source: https://dune.com/queries/65034/129883.

The implication of Uniswap v3 AMM on pricing volatility is consistent with the empirical findings. In Table. 5.3, the coefficient for expected open interest on short is estimated to be significantly negative (-1.678×10^{-9}) while that on long is estimated to be significantly positive (3.569×10^{-9}), indicating a negative association between expected open interest on short and price volatility while a positive association for long. Since the expected portion of open interest reflects traders' long-run behavior, e.g., hedgers, in cope with the trend, the change could be mainly be described by Eq. (5.10). When the expected open interest on short rises, the clearing house retrieve vBTC from traders' account and credit to the balance of the liquidity pool. The increased vBTC balance in the liquidity pool helps decrease the rate of pricing change and thus reducing volatility according to Eq. (5.12). Besides, when expected open interest on long increases, the clearing house withdraw vBTC from the pool and credit to traders', decreasing vBTC balance in the liquidity pool and thus increasing price volatility.

While the expected portion of open interest captures how market status moves along the exchange function specified by Eq. (5.10), the unexpected portion reflects traders' unanticipated behavior, e.g., speculation, on the basis of liquidity distribution. In the short-run, liquidity providers are lagged to adjust their bound of price within which to add liquidity, i.e., $[\underline{P}, \bar{P}]$, especially when facing unanticipated change. Therefore, open interest on both long and short positions would drive price to the tails of the liquidity distribution, enlarging pricing volatility due to lower liquidity. In Table. 5.3, the estimated coefficients for the association between price volatility and unexpected open interest are all positive, i.e., 1.125×10^{-8} for short and 1.481×10^{-9} for long, substantiating the prediction based on the Uniswap v3 AMM pricing mechanism.

In the context of Perpetual Protocol V2, liquidity providers have the capability to contribute liquidity utilizing leverage, thereby incurring a risk of passive liquidation when counterparties are liquidated. Transactions that liquidate liquidity providers' positions during a price increase are categorized as *liquidation on short*, whereas those during a price decline are classified as *liquidation on long*. The liquidation of liquidity providers' positions results in a reduction of market depth, which is hypothesized to have a direct correlation with increased price volatility and the frequency of liquidations among liquidity providers.

Regarding the expected liquidation volume of traders' positions, its impact on price volatility is anticipated to be inversely proportional to the effect of increasing expected open interest. Specifically, an expected increase in liquidation on short positions, which reduces open interest in these positions, is posited to have a positive correlation with price volatility, and the converse holds true for long positions. In the case of the unexpected component of liquidation, its influence on price volatility aligns with that of unexpected open interest, with all unforeseen trading activities driving price movements towards the extremities of the liquidity distribution, thereby exacerbating price volatility.

Overall, an increase in unexpected liquidation in both long and short positions is expected to elevate price volatility. This is empirically corroborated in Table. 5.3, where the estimated coefficient for unexpected liquidated volume on long positions is significantly positive (5.008×10^{-7}). Conversely, the aggregated effect of an increase in expected liquidation on short positions should theoretically be positive. However, this is contradicted by the negative sign of the estimated coefficient for expected liquidated volume on short positions (-5.983×10^{-7}). A plausible explanation for this anomaly is that a price rise, typically accompanying an increase in short position liquidations, may attract additional liquidity providers. This influx of liquidity providers potentially mitigates price volatility, with their dampening effect on volatility surpassing the amplifying impact of liquidations. Granger Causality Test is conducted to examine the relationship between the return on Bitcoin and the net change in liquidity in the vBTC-vUSDC pool on Perpetual Protocol V2, which you can find in Section 5.3.3.1. It is shown that return on Bitcoin Granger-cause the net change in liquidity in the vBTC-vUSDC pool, while the reversed relationship does not hold.

The asymmetrical effect of open interest on long and short positions is also predicted in the theoretical work by [55], which suggests that consuming liquidity involves a larger price impact than adding it, resulting in the larger marginal cost of a ETH buy order than the marginal benefit of a ETH sell order. The model proposed in [55] implies an ambiguous reaction of AMM liquidity to asset volatility, driven by the migration of both traders and liquidity providers between CEXs and

Table 5.5: Granger Causality Test of Return on Bitcoin and the Net Change in Liquidity in the vBTC-vUSDC Pool on Perpetual Protocol V2

H_0	**Max-lag**	**F-statistics**	**p-value** ($Prob > F$)
Return on BTC does not Granger-cause net change in liquidity pool	15	1.624	0.079
Net change in liquidity pool does not Granger-cause Return on BTC	15	1.164	0.311

Notes. This table reports the results of Granger Causality Test in dectacting the relationship between return on Bitcoin and the net change in the liquidity contained in vBTC-vUSDC pool on Perpetual Protocol V2.

DEXs. In the test, since liquidation explicitly includes behavior of both traders and liquidity providers, the ambiguity mentioned in [55] may help explain the inconsistency between my predicted effect of expected liquidation on short positions and the estimated coefficient.

5.3.3.1 Granger Causality Test

As conjectured in the analysis on liquidation in Perpetual Protocol V2, there is a hypothesis that price rise in Bitcoin attract liquidity providers in offering liquidity. To detect empirical evidence to my conjecture, the Granger Causality Test is conducted to see the relationship between the return on Bitcoin and the net change in liquidity in the vBTC-vUSDC pool on Perpetual Protocol V2, where the net change is calculated by subtracting the daily added liquidity by the daily withdrawn liquidity from the pool (measured in Bitcoin). Return on Bitcoin is calculated in daily frequency with the log-form return as follows: $R_t = \log\left(\underline{P_t}\right) - \log\left(\overline{P_t}\right)$, where $\underline{P_t}$ and $\overline{P_t}$ denote the close and open price of Bitcoin on day t. The study retrieves data from 15 May 2023 to 15 Oct 2023 on Etherscan (https://optimistic.etherscan.io/). The testing results are reported in Table. 5.5. There exists Granger-causality from the return on Bitcoin to the net change in vBTC-vUSDC liquidity pool, indicated by the statistically significant F-statistic with p-value of 0.079. However, the causality in reversed direction (net change in vBTC-vUSDC liquidity pool Granger-cause return on Bitcoin) is not evidenced, with p-value of 0.311, supporting my hypothesis that more liquidity is injected when Bitcoin price jump. The large lag, i.e., 15 days in this case, may suggests that traders need time to adjust positions in the liquidity pool in reaction to the rise in Bitcoin price. The empirical evidence here shows a rough picture of how traders change their deposit in the liquidity pool while future studies are needed with more factors controlled.

5.3.4 Empirical results and analysis for GMX and GNS (with Oracle Pricing Model).

In the realm of centralized exchanges (CEXs) and Perpetual Protocol V2, traders' behaviors and informational inputs actively shape market prices. Conversely, in decentralized exchanges (DEXs) such as GMX and GNS, traders accept prices as a given, lacking the capacity to exert direct influence on price movements. The pricing mechanism in these DEXs is governed by a Price Oracle, as elaborated in Section 2.1.6, which assimilates prices from various exchanges, thereby rendering transactions on GMX and GNS incapable of impacting the price directly[18]. As a result, trading activities on these platforms, encompassing trading volume and open interest, merely reflect traders' interpretations and reactions to the information encapsulated within the Price Oracle's determined prices.

Drawing upon Shalen's dispersion of beliefs model (1993) [46], which posits a market dichotomy between asymmetrically informed traders, market participants can be categorized into informed and uninformed traders[19]. Uninformed traders, lacking access to private information, often engage in irrational trading based on market noise and tend to overreact to information. They strive, albeit unsuccessfully, to discern private information and market trends from current price fluctuations, leading to heightened position-taking during periods of increased price volatility. In contrast, informed traders, operating on the basis of their private information, exhibit relatively consistent beliefs over time and typically engage in trading within a constrained price range, resulting in a negative correlation between their positions and price volatility [44].

[18] The code for GMX's price feeding smart contract is publicly accessible at: https://github.com/gmx-io/gmx-contracts/blob/master/contracts/oracle/FastPriceFeed.sol.

[19] Private information refers to the advantageous knowledge held predominantly by major market players such as fund companies and institutions, who have superior information gathering capabilities and insights into customer positions, distinguishing them from smaller retail investors.

In Panel a of Table. 5.3, the estimated coefficients that measure the relationship between open interest and price volatility are predominantly negative, except the case of long open interests in GNS. This indicates a more pronounced influence of informed traders' behavior, leading to the negative signs in these estimations. The impact of uninformed traders on open interest is effectively counterbalanced by the actions of informed traders. Notably, traders' behaviors exhibit asymmetry between buyers and sellers, as evidenced by less negative (in the case of GMX) or even insignificant (for GNS) coefficients for long positions. This asymmetry could be attributed to uninformed traders' tendency to overreact more to positive news than negative, leading to an increased propensity for long position accumulation[20].

The asymmetry in long and short positions is further evidenced by variations in liquidated volume in relation to price volatility. As indicated in Table. 5.3, for GMX and GNS, the coefficients linking liquidated volume on long positions are significantly positive, whereas those for short positions are not statistically significant. Additionally, Panel b of Table. 5.3 reveals that long positions are more likely to liquidation than short positions, as denoted by the significantly positive coefficients for $\mathcal{LIQ}_{\text{long}}$ compared to the insignificant coefficients for $\mathcal{LIQ}_{\text{short}}$. This suggests that liquidation on long positions escalates both in frequency and magnitude when price volatility intensifies, corroborating the notion of traders' asymmetric overreaction to good news. Traders tend to overreact by not only increasing long positions but also by employing higher leverage for long positions compared to short, as evidenced in Table. 5.2, resulting in a higher rate of liquidation for long positions in both volume and probability.

Aligned with Shalen's model, it is anticipated that uninformed traders are more likely to increase leverage during periods of heightened price volatility to maximize capital efficiency, thereby enlarging their positions at a lower cost. In contrast, informed traders are less inclined to risk capital under volatile conditions, leading to a negative correlation between leverage and price volatility. Table. 5.6 delineates the estimated results for Eq.(5.7) and Eq.(5.8). All eight coefficients relating price volatility and average leverage are estimated to be negative (as shown in the two columns under *Regression on Eq.*(5.7)), indicating a more pronounced change in leverage as influenced by informed traders compared to uninformed traders. This inference is further substantiated by the estimation results for Eq.(5.8), which

[20] Existing literature on traditional spot and future markets provides evidence of traders' asymmetric reactions to positive and negative news [44, 56].

demonstrate that trading volumes with lower leverages (less than 50×) increase, while those with higher leverages (more than 50×) remain statistically unchanged in response to rising price volatility.

In summation, the analysis reveals that informed traders exhibit a higher level of activity compared to their uninformed counterparts on GMX and GNS, a conclusion substantiated by empirical data pertaining to the dynamics of open interests and leverages. Additionally, the observed asymmetry in open interests and liquidations between long and short positions suggests a tendency among traders to disproportionately overreact to good news. However, it is imperative to acknowledge a critical distinction for analytical purposes: unlike GMX and GNS, centralized exchanges (CEXs) possess a price discovery function, leading to a reciprocal influence between traders' behavior and market prices. Under Efficient-Market Hypothesis [57], the price aggregate and reflect all the current private information and information contained in the past pricing history. Consequently, it is methodologically unsound to interpret changes in trading activities, e.g., volume, open interest, liquidation, and leverage, solely as reactions to price fluctuations. This perspective challenges the conclusions drawn by [32], who posited that changes in liquidation are merely passive responses to price movements, thereby overlooking the role of liquidation as a contributory factor in price formation within BitMEX, a CEX. This oversight underscores the necessity for a nuanced understanding of the interplay between trader behavior and price dynamics, particularly in the context of CEXs where the price discovery process is inherently more complex.

Table 5.6: Regression results on Eq. (5.7) and Eq. (5.8)

	Perpetual Contracts on Bitcoin			
	Regression on Eq. (5.7)		**Regression on Eq. (5.8)**	
Variables	***GMX***	***GNS***	***GMX***	***GNS***
Intercept	2.287e-12 (9.47)***	0.028 (3.84)***	1.609e-12 (15.55)***	9.729e-12 (3.89)***
Lagged volatility	0.229 (7.26)***	0.369 (10.66)***	0.200 (6.37)***	0.374 (10.05)***
Trading Activity:				
Expected trading volume	1.051e-10 (5.60)***	5.201e-11 (0.83)	-	-
Unexpected trading volume	1.359e-10 (10.41)***	4.593e-10 (6.86)***	-	-

(continued on next page)

Table 5.6 (continued)

Variables	Regression on Eq. (5.7)		Regression on Eq. (5.8)	
	GMX	***GNS***	***GMX***	***GNS***
Expected OI on short	-4.405e-10 (-6.52)***	-1.626e-10 (-1.58)	-5.415e-10 (-7.32)***	-1.893e-10 (-1.67)*
Unexpected OI on short	-2.485e-10 (-2.89)***	-4.423e-10 (-2.98)***	-2.767e-10 (-3.01)***	-4.355e-10 (-2.71)***
Expected OI on long	-1.373e-10 (-4.11)***	3.964e-11 (0.58)	-2.318e-10 (-4.76)***	2.426e-11 (0.33)
Unexpected OI on long	-1.091e-10 (-1.36)	-5.505e-11 (-0.38)	-2.97e-10 (-3.61)***	4.033e-11 (0.26)
Liquidation:				
Expected liquidated volume on short positions	2.538e-09 (1.15)	-1.467e-09 (-1.27)	4.888e-10 (0.21)	5.541e-10 (0.40)
Unexpected liquidated volume on short positions	1.891e-09 (1.55)	3.177e-10 (0.80)	2.289e-09 (1.86)*	1.925e-10 (0.42)
Expected liquidated volume on long positions	2.77e-07 (9.14)***	7.573e-09 (3.45)***	1.965e-07 (14.98)***	5.472e-09 (2.27)**
Unexpected liquidated volume on long positions	2.539e-09 (5.06)***	1.384e-09 (1.42)	2.455e-09 (4.78)***	3.984e-09 (3.70)***
Leverage (average level):				
Expected average leverage on short positions	-0.0004 (-2.21)**	-0.0001 (-1.40)	-	-
Unexpected average leverage on short positions	-0.0002 (-3.00)***	-0.0002 (-4.37)***	-	-
Expected average leverage on long positions	-0.0004 (-2.15)**	-1.193e-05 (-0.36)	-	-
Unexpected average leverage on long positions	-0.0003 (-3.65)***	-7.237e-05 (-1.93)**	-	-
Leverage (in categories):				
Expected: less than 1×	-	-	-2.112e-08 (-1.21)	-
Unexpected: less than 1×	-	-	1.688e-08 (3.46)***	-
Expected: 1× to 5×	-	-	1.829e-10 (1.08)	1.684e-08 (0.23)
Unexpected: 1× to 5×	-	-	9.772e-10 (5.51)***	-1.289e-08 (-0.54)
Expected: 5× to 10×	-	-	1.847e-09 (3.44)***	-2.534e-08 (-0.55)
Unexpected: 5× to 10×	-	-	1.012e-09 (5.27)***	1.736e-08 (1.08)

(continued on next page)

Table 5.6 (continued)

Variables	Regression on Eq. (5.7)		Regression on Eq. (5.8)	
	GMX	***GNS***	***GMX***	***GNS***
Expected: 10× to 15×	-	-	-6.697e-10 (-1.50)	5.39e-08 (0.96)
Unexpected: 10× to 15×	-	-	8.724e-11 (0.63)	6.408e-09 (0.44)
Expected: 15× to 20×	-	-	1.998e-09 (3.75)***	9.314e-08 (1.84)*
Unexpected: 15× to 20×	-	-	2.023e-10 (1.28)	5.102e-09 (0.33)
Expected: 20× to 25×	-	-	-1.06e-10 (-0.12)	2.698e-07 (3.89)***
Unexpected: 20× to 25×	-	-	2.66e-10 (2.15)**	6.261e-09 (0.92)
Expected: 25× to 30×	-	-	-9.034e-11 (-0.76)	-4.597e-08 (-1.31)
Unexpected: 25× to 30×	-	-	9.099e-11 (1.70)**	-7.329e-09 (-0.91)
Expected: 30× to 35×	-	-	5.761e-10 (1.91)*	8.934e-08 (1.34)
Unexpected: 30× to 35×	-	-	-3.618e-12 (-0.02)	-3.778e-09 (-0.26)
Expected: 35× to 40×	-	-	2.882e-11 (0.03)	2.465e-07 (3.10)***
Unexpected: 35× to 40×	-	-	2.266e-10 (0.93)	-1.913e-09 (-0.32)
Expected: 40× to 45×	-	-	1.289e-09 (0.51)	-2.922e-10 (-0.01)
Unexpected: 40× to 45×	-	-	3.24e-10 (1.12)	-2.72e-09 (-0.61)
Expected: 45× to 50×	-	-	2.626e-11 (0.15)	1.235e-08 (0.74)
Unexpected: 45× to 50×	-	-	1.692e-10 (1.73)*	9.194e-10 (0.30)
Expected: more than 50×	-	-	-1.529e-10 (-0.29)	-1.466e-09 (-0.13)
Unexpected: more than 50×	-	-	-3.74e-11 (-0.20)	-1.21e-08 (-0.96)
Adjusted R^2	0.398	0.339	0.427	0.260
AIC	-4405	-3693	-4424	-3608
No. of obs.	747	628	747	628

(continued on next page)

Table 5.6 (continued)

	Regression on Eq. (5.7)		**Regression on Eq. (5.8)**	
Variables	***GMX***	***GNS***	***GMX***	***GNS***

Notes. This table reports regression results on Eq. (5.7) and Eq. (5.8). For the regression with Eq. (5.8), *Leverage (in categories)* means trading volumes in leverage within different ranges, which are grouped into categories. For GNS, my dataset does not include any transaction with leverage less than 1×, so the study drops the variables of trading volumes with the leverage less than 1×. In each cell, the t-statistics are in the parentheses. ∗, ∗∗, and ∗ ∗ ∗ denote significance at 0.1, 0.05, and 0.01 level, respectively.

5.4 Conclusion of Traders' Behavior of Perpetual Future Contracts

In conclusion, this study presents an in-depth Systematic Survey of Knowledge (SoK) that effectively contrasts the operational dynamics of Centralized Exchanges (CEXs) and Decentralized Exchanges (DEXs) in the realm of perpetual futures trading. It significantly enriches the academic discourse by meticulously delineating the design elements, order matching mechanisms, price discovery processes, and custody of funds in both CEXs and DEXs, thereby offering a robust foundation for future research in this field. With the models in the framework, any exchange could be classified into one of these predined models and each model corresponds to a sort of distinctive features. The study underscores the necessity of developing new theoretical models, moving beyond conventional frameworks like Kyle's model [3], to aptly comprehend the intricacies of DEX models. Through an empirical analysis of transaction data from August 2020 to September 2023, it reveals a positive correlation between price volatility and trading volumes in exchanges of CEX Model, in line with traditional futures markets. However, it also uncovers distinct variations in DEXs, particularly under the VAMM Pricing Model, where open interest impacts long and short positions differently. The behavior of traders in GMX and GNS, who operate under Oracle Pricing and act as price takers, is found to be consistent with Shalen's dispersion of beliefs model [46]. Together with Table. 4.1, Table. 5.7 summarizes traders' distinctive behavior

Table 5.7: Summary of Empirical Results

Exchange Model	Price Discovering	Price Volatility & Trading Volume	Price Volatility & Open Interest	Symmetry; Explanation	Exchange Analyzed
LOB Models (i.e., CEX Model Hybrid Model)	Yes	Positively correlated	Negatively correlated	Symmetrical; Kyle's model [3]	Binance; Bybit
VAMM Model	Yes	Positively correlated	Negatively correlated for short positions & positively correlated for long positions (in the long-run); positive (in the short-run)	Asymmetrical; Uniswap v3 AMM	Perpetual Prorocol V2
Oracle Pricing Model	No	Positively correlated	Negatively correlated	Asymmetrical; Shalen's dispersion of beliefs model [46]	GMX; GNS

Notes. This table summarizes my empirical results regarding traders' behavior in exchanges of different exchange models. Since both Hybrid Model CEX Model adopt limit-order book to match orders, traders' behavior in exchanges of these two models should be the same. In this table, the study only cares about the symmetry of effects between buyers and sellers.

derived by different design of the models. Furthermore, the study highlights the propensity of uninformed traders to disproportionately react to positive news than negative news, thereby deepening My understanding of trader behavior in DEXs and offering valuable insights for the development of future works modeling the interaction between exchanges of Oracle Pricing Model and the CEXs from which the oracle collects prices. The empirical analysis treats investors in exchanges of Oracle Pricing Model as isolated and independent from other exchanges so as to use Shalen's dispersion of beliefs model to explain their behavior from the perspective of pure price takers. However, if there emerge future models incorporating investors' choice among different exchanges and private information endowed, these new models may provide more solid explanation to my empirical findings while features of the Oracle Pricing Model can be better documented.

Although including three DEXs in the empirical analysis, my study has the potential limitation that these three exchanges are not representative enough as the industry evolves, making it inappropriate to generalize the findings to other new DEXs. Furthermore, given the rapid evolution and innovation in DEX design, new methods of constructing exchanges may emerge, potentially rendering my classification of exchange models incomplete.

5.5 Key Findings

This included an empirical analysis of traders' behavior in exchanges of all the four types of models. Empirical analysis shows that the relationship between market volatility and trader activity varies significantly based on the exchange's mechanical design.

In Decentralized Exchanges (DEXs) utilizing the Virtual Automated Market Making (VAMM) model, open interest on long and short positions affects price volatility in opposite directions, a result of VAMM's unique price formation mechanism. This asymmetrical impact of open interest on long versus short positions aligns with theoretical predictions by Aoyagi (2021) [55], which suggest that consuming liquidity imposes a greater price impact than adding liquidity. In ETH-USDT pair trading pool, this leads to the marginal cost of a buy order for ETH being higher than the marginal benefit of a sell order for ETH.

In the DEXs with Oracle Pricing Model, I observed a distinct asymmetry in trader behavior between buyers and sellers. Such asymmetry might stem from uninformed traders reacting more strongly to positive news than to negative, leading to a tendency to accumulate long positions. It is found to be consistent with Shalen's dispersion of beliefs model [46].

This study analyzed the potential risks and advantages of using perpetual future contracts within the DeFi space while provides mathematical basis and empirical insights based on which future theoretical works can be done.

Chapter 6

Future Work

In a nutshell, this thesis demonstrates initial efforts in revealing the network value and user behaviors within the blockchain network. Future work should be conducted to fully understand how the trust and user behaviors are established towards the blockchain and why people within the blockchain can trust each other. To further improve my data analysis accuracy, our future work will try to group together all addresses belong to the same user. The participants in the blockchain transactions are addresses. However a person or an entity might own multiple addresses. One bot can generate numerous addresses for different types of transactions on blockchain. In the future, more analysis can be done to investigate the difference between the address behaviour and user behaviour, and the difference between experiments when switching blockchain graph nodes from addresses to users.

Unlike centralized services like Apple, Google, and Meta, users rely on more than one service providers (DApps) to finish a task. This is the basic principle of Web3. This thesis analyzed the users and one particular DApp. The interactions between DApps form another graph where DApp smart contract addresses are nodes, and interaction between these addresses are edges. Many interesting research and graph analysis could be constructed on this new graph could be done to understand how trust is built for these DApps over time.

In terms of future work for DeFi applications, firstly, the observed asymmetry in trading behaviors between buyers and sellers within the Oracle Price Model DEX warrants a deeper exploration into the psychological underpinnings of this phenomenon. Future research could delve into whether uninformed traders react disproportionately to positive news compared to negative news, and examine the extent to which cognitive biases or prevailing social norms may influence such behaviors. This line of inquiry could provide valuable insights into the psychological mechanisms at play in decentralized exchange environments.

Secondly, the role of liquidity providers, a novel concept in the decentralized finance (DeFi) ecosystem, presents a rich area for academic investigation. While this paper primarily analyzes the behaviors of traders in Perpetual Future Contracts, a comparative study focusing on their counterparts, the liquidity providers, could yield significant findings. Future research should consider the impact of variables such as interest rates and the availability of alternative DeFi products on the behaviors of liquidity providers, particularly in the context of Perpetual Future Contracts. Understanding how these factors interact to influence liquidity provider behaviors could offer a more comprehensive view of market dynamics in DeFi.

Lastly, the potential of blockchain-based financial instruments to enhance transparency and accountability in micro financial markets is an important avenue for future research. The decentralized and transparent nature of blockchain technology suggests that these instruments could be instrumental in promoting accountability and transparency in micro financial markets, potentially encouraging more ethical investment practices. Future studies should explore the capacity of blockchain-based instruments to achieve these outcomes, examining the factors that may affect their effectiveness in fostering responsible financial practices.

List of Author's Awards, Patents, and Publications[1]

Journal Articles

- **Erdong Chen**, Mengzhong Ma, and Zixin Nie, Perpetual Future Contracts in Centralized and Decentralized Exchanges: Mechanism and Traders' Behavior, Volume 34, article number 35, 19 June 2024, *Electronic Markets 2024**.

Conference Proceedings

- **Erdong Chen**, Mengzhong Ma, and Zixin Nie, Exploring the Impact: How Decentralized Exchange Designs Shape Traders' Behavior on Perpetual Future Contracts, Zurich, Switzerland, *ChainScience 2024*, April 5-6, 2024*.

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