Investigating pair trading opportunities as a form of Maximal Extractable Value on the Ethereum Network

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Abstract

The purpose of this study is to examine whether pair trading opportunities can be used as a Maximal Extractable Value extraction method on Ethereum Network. Maximal Extractable Value refers to a maximum value block producers can extract from an Ethereum block by reordering, inserting, or censoring transactions. Pair trading is an investment strategy which involves identifying two closely related assets and taking simultaneous long and short positions in them. This strategy aims to generate returns by exploiting price disparities between the two assets, regardless of the broader market's direction.

I study decentralized exchange transactions between September 2022 and September 2023 and find trading pairs that pair trading logic can be applied to as a profitable maximal extractable value extraction method over a long period, but individual opportunities tend to make a loss. I also find the strategy to remain profitable during different periods of increased market distress.

The majority of the opportunities are relatively time sensitive with the median entry window for positions lasting for slightly over 10 minutes, and the median position must be held being 16 minutes before the position reverts or diverges.

I do not find unambiguous evidence of pair trading opportunities' characteristics changing under increased market distress. Similarly, I do not find evidence of competition among MEV searchers having increasing or decreasing trend during the observation period.

1 Introduction

1.1 Background and motivation

The decentralized nature of blockchain technology has revolutionized the way financial transactions can be conducted, offering unprecedented opportunities for participants to engage in secure, transparent, and efficient transactions without the need for intermediaries. However, this newfound decentralization has also given rise to a unique set of challenges, one of which is the concept of Maximal Extractable Value (MEV). (Daian et al. 2019)

First gaining wider attention in the Ethereum research community following Daian et al. (2019), MEV refers to a maximum value block producers can extract from an Ethereum block by reordering, inserting, or censoring transactions. Chiplunkar and Neuder (2023) found taking part in MEV extraction to increase profits of block proposers by 55% in April 2023 compared to selecting transactions a block includes solely based on their transaction fees. Well-known MEV strategies include, for example, profiting off liquidating undercollateralized loans and taking advantage of arbitrage opportunities in decentralized exchanges.

First pioneered by quantitative traders in the 1980s, pair trading is an investment strategy that has gained traction in financial markets. It involves identifying two closely related assets, referred to as a trading pair, and taking simultaneous long and short positions in them. The essence of pair trading lies in profiting from the relative price movements between the two assets rather than relying on the overall market direction. This strategy capitalizes on the concept of mean reversion, which suggests that assets with historical price correlations tend to revert to their average price relationship over time. As a result, pair trading aims to generate returns by exploiting price disparities between the two assets, regardless of the broader market's direction. (Jacobs and Weber 2015)

To my knowledge, this study is the first attempt to study statistical arbitrage-based MEV opportunities on top of any blockchain, excluding CeFi-DeFi arbitrage research. This study focuses on studying pair trading-based statistical arbitrage MEV opportunities as pair trading models are unambiguous compared to more sophisticated statistical arbitrage strategies.

The purpose of this study is to perform an analysis of price discrepancies between a pair of assets on decentralized exchanges on top of Ethereum and whether sophisticated MEV searchers can take advantage of such discrepancies. The study aims to identify and quantify the pair trading-based MEV opportunities, analyze how long such price discrepancy can be taken advantage of, how long a position in a price discrepancy must be held, and whether characteristics of pair trading-based MEV opportunities change under increased market distress. The study is limited to analyzing whether pair trading is a viable MEV extraction strategy and does not focus on optimizing different parameters associated with such extraction strategies.

1.2 Research questions and hypotheses

This paper studies whether searchers, discussed in more detail in subsection 2.2.3, can extract MEV on top of Ethereum using pair trading-based extraction logic.

Hypothesis 1: I hypothesize that there exist price discrepancies on top of Ethereum that are not big enough to be a form of atomic arbitrage-based MEV but that are economically significant enough to be a form of pair trading-based MEV. This study aims to identify and quantify how much of such pair trading-based MEV has been available on top of Ethereum since the Paris network upgrade also known as the merge (Edgington 2023).

Hypothesis 2: I hypothesize that during times of increased market distress characteristics of pair trading opportunities' change. If this hypothesis is true, this could be observed as a change in the period reverting pair trading opportunities are present or as a change in the period reverting pair trading opportunities take to revert during increased market distress.

Hypothesis 3: I hypothesize that competition among MEV searchers has increased since the Paris network upgrade. If this hypothesis is true, this could be observed as a negative correlation between block number and the return of opportunities, as a decrease in the period of reverting pair trading opportunities takes to revert, and as a decrease in the period of reverting pair trading opportunities is present.

1.3 Limitations

To my knowledge currently, there is no public data set quantifying statistical arbitrage-based MEV opportunities. The lack of such data limits my ability to draw extensive conclusions about statistical arbitrage-based MEV. Pair trading is only a single statistical arbitrage technique, and one should be careful when generalizing based on such results.

I analyze whether MEV searchers have changed their behavior related to pair trading based on variables related to pair trading. Such analysis is narrow and could be improved, for example, by considering how the available extractable value from pair trading-based MEV opportunities has changed relative to the extracted amount of atomic arbitrage MEV or more sophisticated statistical arbitrage-based extraction models that, to my knowledge, do not have public data available. Such analysis is also unable to capture the actual magnitude of behavior change as it only focuses on a subset of techniques indicating the behavior change.

1.4 Structure of the study

The rest of the study is organized as follows. Chapter 2 discusses the theoretical background and previous literature on pair trading and MEV on Ethereum. Chapter 3 describes the data and methodology including the data sources, identifying and quantifying pair trading opportunities caused by price discrepancies, analyzing time sensitivity and period of pair trading positions, correlation of different variables, and changes of characteristics of pair trading opportunities under different market regimes. Chapter 4 presents the results and analysis. Chapter 5 summarizes the results and discusses the findings. Finally, Chapter 6 concludes the study.

2 Literature review

This chapter provides an overview of the most relevant literature on pair trading and MEV on Ethereum as well as discusses relevant concepts of Ethereum. The first section of this chapter focuses on pair trading in financial markets defining what pair trading is, how pair trading pairs are selected, what challenges and factors affect pair trading, and the empirical results of previous pair trading literature. The second section of this chapter focuses on how transactions and blocks are produced in Ethereum, what are smart contracts and decentralized finance, what is the block production supply chain in the presence of MEV, and what are most common MEV strategies.

2.1 Pair trading in financial markets

Pair trading is a trading strategy used by sophisticated investors that involves identifying two highly correlated assets and taking simultaneous long and short positions in them. The goal of the strategy is to profit from relative price movements between the two assets by exploiting short-term relative mispricing between the assets. The strategy relies on the assumption that the two assets with high historical cointegration tend to revert to their average price relationship over time. As a result, pair trading aims to generate returns by exploiting price discrepancies between two assets, regardless of the broader market directions. (Jacobs and Weber 2015)

Pair traders' strategies can differ from others by having different time frames and parameters in their strategy. For example, one trader might analyze price divergences in a data set consisting of hourly asset prices over the past month, while another analyses daily price data over the past three years. Similarly, one trader might consider prices to have diverged when the z-score of price divergence is four standard distributions from the equilibrium state, while another might count two standard distributions as divergence.

2.1.1 Pair selection in pair trading

Pair trading strategies assume that two assets are cointegrated. This means individual prices may not be stationary, but the spread between them is and it follows a mean-reverting process discussed below. Essentially the prices of two assets move together over time, with deviations from this relationship being only temporary.

There are various approaches to identifying whether two assets are cointegrated. Jacobs and Weber (2015) and Riedinger (2017) identify which assets are the most cointegrated by calculating the sum of squared differences between normalized returns of the two assets over a period and considering the pairs with the lowest sum of squared differences to be good candidates for pair trading. Do and Faff (2010) introduce additional constraints in pair selection by first grouping stocks based on their industry and only considering stock pairs where both stocks are from the same industry. After grouping stocks based on their industries Do and Faff (2010) define the most cointegrated assets based on the sum of squared differences similar to Jacobs and Weber (2015) and Riedinger (2017).

Caldeira and Moura (2013), Clegg (2014), Engle and Granger (1987), and Suzuki (2018) analyze whether trading pairs are cointegrated by assessing the stationarity price spreads using different tests of cointegration such as the Engle-Granger approach and the augmented Dickey-Fuller test. If a trading pair has an order of integration of 1 based on these tests it means the spread is stationary. Like Do and Faff (2010), Suzuki (2018) uses additional constraints in pair selection by first grouping stocks based on their industries and only considering stock pairs from the same industry.

The mean reversion hypothesis is a financial theory suggesting that prices of assets tend to revert to their historical mean over time. Pair trading expands this to the relationship between the prices of two cointegrated assets reverting to their long-term mean over time. Various studies and models are analyzing the mean reversion of two cointegrated assets. Cartea and Jaimungal (2015), Clegg (2014), Elliott et al. (2005), and Suzuki (2018) model the spread between two assets using an Ornstein-Uhlenbeck process, a mean-reverting Gaussian Markov chain:

$$dX_t = \theta(\mu - X_t)dt + \sigma dW_t, \tag{1}$$

where X_t is the spread at time t, θ is the rate of mean reversion, μ is the long-time mean or mean level to which the process reverts, σ is the volatility of the process, and dW_t is a Wiener process. This model assumes future observations of mean-reverting prices can be forecasted using historical prices and, thus, the parameters θ, μ, and σ are estimated from historical data of the price relationship.

Caldeira and Moura's (2013) and Do and Faff's (2010) approaches consider the mean reversion of two cointegrated assets from another point of view. They analyze different parameters used for defining trading rules such as how far from the long-time mean should the z-score be before opening a trade, how long should the positions be kept open, and how quickly mean reversion usually occurs.

2.1.2 Challenges and factors affecting pair trading

The primary assumption underlying pair trading is that the prices of trading pairs will converge in the future, just as they have historically converged. However, Do and Faff (2010) find that profits of pair trading have been on a decreasing trend in their observation period between the 1960s and 2000s as the divergence rates have increased, implying that trading pairs do not converge as expected leading to worse performance of the strategy. Clegg (2014) and Suzuki (2018) suggest that pair traders should adapt their strategies based on shifts in the market regime that can cause changes in the relationship between assets in a trading pair. However, Suzuki (2018) finds this to be a challenging task to execute.

Riedinger (2017) studies how the different legs of pair trading's pairs contribute to the returns of pair trade under different market regimes and finds that under low volatility regimes, the prices tend to converge close to the average of two relative prices while under high volatility regimes, the prices tend to converge to below average of two relative prices. This is an example of how changes in market regimes affect the fundamental functionality of strategies. Gatev et al. (2006) found similar results with prices converging below the average of two relative prices, however, they did not perform subgroup analysis on different volatility regimes. The studies do not discuss how pair traders should adapt their strategies because of changes in expected converge prices.

Suzuki (2018) finds their pair trading position optimization strategy to only work when transaction costs are excluded. However, if transaction costs are considered the strategy no longer works. Similarly, Caldeira and Moura (2013), Cartea and Jaimungal (2015), Clegg (2014), Do and Faff (2010), Gatev et al. (2006), and Riedinger (2017) find that transaction costs impact the profitability of pair trading strategy, yet the impact of the costs is not statistically significant.

Clegg (2014), Do and Faff (2010), and Jacobs and Weber (2015) find that a pair trading strategy is more profitable in assets with lower liquidity. However, they also note that liquidity constraints can make it more challenging to take advantage of a pair trading opportunity. Liquidity refers to the trade-off between how quickly an asset can be sold and at which price it can be sold with high liquidity meaning a smaller trade-off between the two. These findings mean that even if, in theory, there would be a pair trading opportunity present in the market, one might not be able to take advantage of such opportunity. Riedinger (2017) finds similar results suggesting that profits of pair trading strategies are partially explained by liquidity premium.

Riedinger (2017) points out that holding a pair trading position until prices converge might be challenging if the prices diverge. A pair trader might face margin calls, requiring them to deposit additional capital if the prices diverge too much. Furthermore, Riedinger (2017) suggests that the probability of a lender recalling the shorted stock in the trading pair is higher under a market regime with declining prices. Do and Faff (2010) find similar results suggesting quantitative traders suffered significant losses during the financial crisis of 2007-2009 caused by falling prices triggering marking calls. These studies suggest that taking advantage of pair trading opportunities might be challenging due to constraints related to borrowing.

Do and Faff (2010) analyze the impact of earnings events, such as earnings announcements and analyst forecasts, on the performance of pair trading positions. They found that when the pair trading position was initiated by a divergence in prices caused by earning events the performance of such a position was worse than the position not initiated by an earnings event.

2.1.3 Empirical results of pair trading in different markets

Jacobs and Weber (2015) studied daily United States stock data between 1960 and 2008. Authors analyze strategy where the pair trading strategy enters position when the pair's prices' spread exceeds two historical standard deviations and exits position when prices converge or one month has passed, finding pairs converge 36% of the time. Authors find this strategy to be highly profitable with standard finance risk factors, such as Fama and French (1993) factors, not being able to explain the excess returns generated by the strategy.
Furthermore, the study analyses data from different countries globally and finds that as the market volatility increases so do the returns of pair trading, emerging markets tend to have higher pair trading returns, and pair trading profitability is positively related to the degree of individualism.

Do and Faff (2010) study daily United States stock data between 1962 and 2009. The study analyses a pair trading strategy that enters a position when prices diverge above historical two standard deviations, and exits positions when prices converge, or six months pass since position entry. Authors find that the profitability of pair trading has declined over the data set with Jacob and Weber's (2015) observations supporting these findings. The authors claim this to be due to an increase in divergence rates, implying that trading pairs do not converge as expected leading to worse performance of the strategy. The authors also find that about 10% of pair trading positions are initiated by divergence in prices caused by earnings events and that such positions have on average worse performance than positions not initiated by such events. Authors suggest that the profitability of pair trading is due to irrational traders causing prices to diverge from their efficient market price.

Gatev et al. (2006) studied daily data of the United States stocks between 1963 and 2002. Authors analyze a pair trading strategy that enters positions when the pair's prices deviate by two historical standard deviations and exits positions when prices converge or six months pass from opening the position. Like Jacobs and Weber (2015), authors find this strategy to be highly profitable with standard finance risk factors, such as Fama and French (1993) factors, not being able to explain the excess returns generated by the strategy. These results are found to be robust, even when considering transaction and short-selling costs. Authors also find that the profitability of pair trading has declined over the data set like Do and Faff (2010).

Caldeira and Moura (2013) analyzed daily data of the 50 biggest Brazilian stocks between 2005 and 2012. They study a pair trading strategy that enters a position when price divergence exceeds historical two standard deviations and exits a position when prices converge to between historical 0.5 and 0.75 standard deviations, 50 days pass since opening the position or further price divergence causes 7% of losses. Authors find that out of 1 225 studies pairs on average 90 pairs are cointegrated. Furthermore, the authors find that risk-adjusted returns generated by pair trading these pairs outperform Brazil's general index and that returns of pair trading are not correlated with the general index.

Riedinger (2017) studied daily United States stock data between 1990 and 2014. The study analyses a strategy that enters a pair trading position if the pair's prices diverge above historical two standard deviations, and exit position when prices converge, diverge above four standard deviations, or six months pass since position entry. The study finds that volatility is positive, and correlation is negatively correlated with pair trading returns and trading frequency.

Cartea and Jaimungal (2015) analyzed minute-level data for Amazon, Facebook, and Google stocks during one day in 2014. Based on the data authors calibrate a pair trading strategy that enters positions when there are price deviations from the mean-reverting level on minute level.

Authors run 10 000 simulations to analyze the performance of the pair trading strategy and find that the performance of the strategy is driven by short-term price discrepancies.

2.2 Ethereum and Maximal Extractable Value

Ethereum is a decentralized blockchain platform that enables the creation and execution of smart contracts. MEV refers to the maximum value block producers can extract from a block by reordering, inserting, or censoring transactions.

This section first gives a high-level overview of Ethereum, its block production after the Paris network upgrade, and smart contracts and their financial applications, then discusses MEV and the current block production supply chain, and finally, presents different commonly discussed strategies for extracting MEV.

2.2.1 Ethereum, transactions, and block production in Ethereum

This subsection gives a brief overview of Ethereum and the workflow of a transaction excluding the MEV supply chain.

Ethereum is a decentralized blockchain platform that enables the creation and execution of smart contracts. Ethereum operates without a central authority, relying on a distributed network of computers that validates transactions and maintains the network. (e.g., Antonopoulos and Wood 2018 p. 1-12; Edgington 2023)

To maintain the network, computers validate the transactions following a consensus mechanism. Since the Paris network upgrade on September 15, 2022, Ethereum has followed a Proof-of-Stake-based consensus mechanism. Under this consensus mechanism, one validator is randomly selected to propose a new block every 12 seconds. The validator gets rewarded for proposing a block in their time slot in the form of transaction fees associated with the transactions included in the block, and for making votes on the state of the Ethereum network when other validators propose blocks. To participate as a validator, a user must deposit 32 Ethereum, currently worth about $60 000, and run pieces of software that agree on the state of the Ethereum network with other validators. The deposit of 32 Ethereum acts as collateral that can be used to punish a validator if they act maliciously. (e.g. Edgington 2023, “Proof-of-stake (PoS),” 2023)

Blocks are bundles of transactions that must be below a predetermined amount of computational effort that is required to execute operations related to the transactions in the block. These blocks are linked together by each block having a certain cryptographical output from the previous block used as input of a new block which prevents tampering of previous blocks' contents. (e.g., Antonopoulos and Wood 2018 p. 1-12; Edgington 2023)

To get a transaction included in a block a user creates a transaction, defines how much transaction fees they are willing to pay, and submits the transaction to a node. A node verifies the validity of the transaction, adds it to its mempool - a local list of pending transactions - and broadcasts it to other nodes that also add it to their mempools. Certain advanced users might choose to submit their transactions to specialized nodes that do not broadcast their transactions publicly, to prevent other users from gaining information about the transaction or to make the transaction only executed if certain condition is met. This is discussed in more detail in the subsection 2.2.3. (Heimbach & Wattenhofer 2022; Mead 2023; Weintraub et al. 2022)
When a validator is selected to propose a block, they will choose which transactions to include in a block based on their knowledge of pending transactions in a way that maximizes their benefit. Alternatively, validators can choose to outsource building the block to a dedicated builder who is willing to pay them a fee for including transactions they have selected in a block. The workflow of a transaction from creation to being included in a block, excluding the MEV supply chain described in the next subsection, is visualized in Figure 1. (Heimbach & Wattenhofer 2022; Mead 2023; Weintraub et al. 2022)

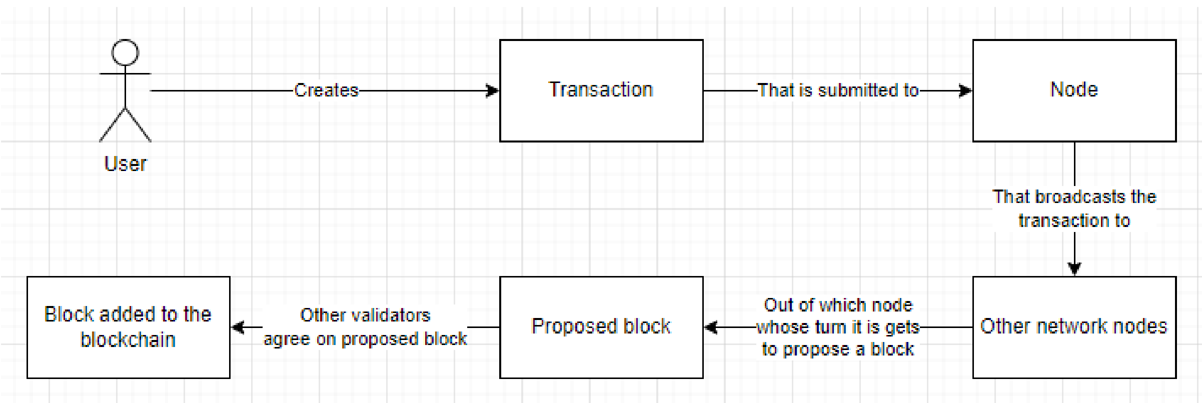

Figure 1: The workflow of transactions excluding MEV supply chain

2.2.2 Smart contracts and Decentralized Finance

This subsection gives a brief overview of smart contracts and decentralized exchanges.

Smart contracts are self-executing contracts running on top of a blockchain. The terms of these contracts are written into code and the decentralized blockchain network enforces that interactions with these contracts are executed as described in the terms. Such contracts allow for the creation of different applications on top of blockchain that do not require middlemen, such as lawyers, as users can directly interact with the contracts. This opens a world of possibilities for decentralized, trustless, and cost-effective applications, revolutionizing the way agreements can be conducted and enforced. (Carter and Jeng 2021)

A subgroup of applications utilizing smart contracts for financial applications is called Decentralized Finance. Popular Decentralized Finance applications include decentralized exchanges, lending protocols, derivatives protocols, and stablecoins (Harvey 2021, p. 13). In this study, I analyze whether price discrepancies arising from activity on decentralized exchanges can be taken advantage of.

Decentralized exchange is a type of cryptocurrency exchange that is on top of blockchain. Such applications allow peer-to-peer trading of cryptocurrencies with terms of the trade execution written into the code of smart contracts. Decentralized exchanges analyzed in this study use automated market maker models to facilitate trades. In such models' certain users provide liquidity to a trading pair and the exchange rate users can swap cryptocurrencies is determined using a mathematical algorithm based on the liquidity provided to the trading pair. The determination of exchange rates in automated market maker models is discussed in more detail in section 3.1. (Harvey 2021, p. 49-54)

2.2.3 Maximal Extractable Value and block production supply chain of Ethereum

Maximal Extractable Value (MEV) refers to the maximum value a block producer can extract from producing a block by reordering, inserting, or censoring transactions. Chiplunkar and Neuder (2023) found taking part in MEV extraction increased the profits of validators proposing the block by 55% in April 2023 compared to selecting transactions a block includes solely based on their transaction fees. Well-known MEV strategies include, for example, profiting off liquidating undercollateralized loans and taking advantage of arbitrage opportunities in decentralized exchanges. Different MEV strategies are discussed in more detail in the next subsection.

As there are significant economies of scale in searching for sophisticated MEV opportunities (e.g., Flashbots 2022, Stokes 2022) the validators typically outsource part of or their whole block to a block builder. In exchange, the block builder gives the validator a part of the revenue generated by the block builder by capturing MEV opportunities.

Currently, 93% of block production is outsourced to block builders using MEV-boost middleware according to Wahrstätter (2022). Under MEV-boost the block production supply chain consists of four key participants that are searchers, builders, relays, and validators (Mead 2023). The block production supply chain under MEV-boost is visualized in Figure 2.

Searchers continuously monitor public mempool, blockchain, and other information sources to find profitable MEV opportunities based on sophisticated models. When a searcher finds a profitable MEV opportunity they make a bundle out of the transactions that are part of the opportunity they would like to execute within the next block. The searcher then delivers the bundle to a block builder. The searcher pays the builder if their bundle is included within the next block. The relationship between the searcher and builder is trust-based as the builder is capable of stealing the searcher's bundle for their economic benefit. (Mead 2023)

Builders use sophisticated models to maximize the combination of profits generated from MEV opportunities and transaction fees by selecting transactions in a block based on both the bundles searchers have delivered them and transactions in their mempool. After a builder has built a block, they forward it to one or more relays. Similar to searchers and builders, the relationship between builders and relays is trust-based as relays can see the contents of the proposed block. (Mead 2023)

Relays act as an escrow between builders and validators, they have relationships with whose turn it is to propose a block. Relays share how much the block with the highest payout to the validator, out of the blocks they received from different builders, is willing to pay the validator to be selected as the next block. MEV-boost acts as a relay aggregator forwarding the highest offers by different relays to the validator. If the validator wants to accept an offer made by the block builder through the relay, they sign the block to be included in the blockchain. (Mead 2023)

Alternatively, the proposer might choose to build their block based on their local mempool. This can be, for example, due to a lack of MEV opportunities or because the validator chooses not to take part in MEV, for example, due to ethical reasons. Such blocks counted for the 7% not produced using MEV-boost. (Mead 2023)

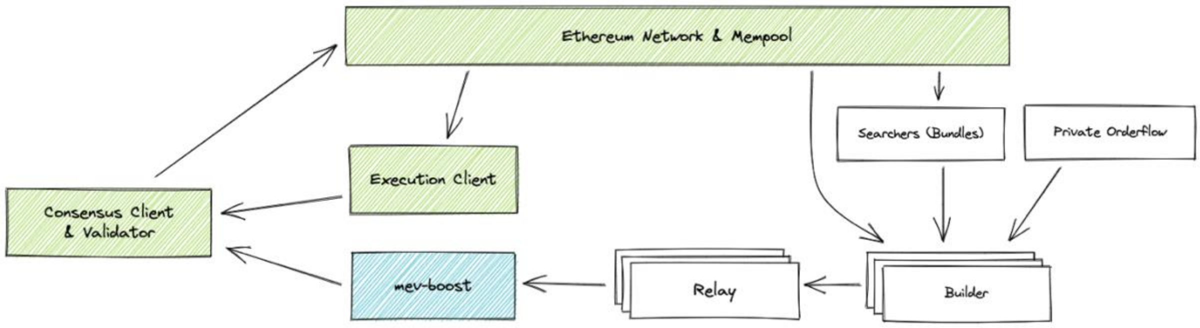

Figure 2: The block production supply chain (Flashbots 2022a)

Examples of ethical reasons a validator might choose not to take part in MEV include the centralization of Ethereum, questions regarding the fairness of MEV, and higher transaction fees and exclusion of transactions due to MEV. One of the main concerns related to MEV is the extraction of MEV would lead to Ethereum becoming more centralized, which is against the core values of the network. Gupta et al. (2023) found empirical evidence of MEV causing centralization of Ethereum and the topic has been widely discussed among MEV participants (e.g., Flashbots 2022b, Stokes 2022).

Another major concern of MEV is whether the system and different value extraction methods can be considered fair. For example, certain frontrunning MEV strategies discussed in the next subsection are considered unfair by some stakeholders as the strategies can extract value directly from a user that would have been allocated to a user if MEV searchers did not exist. (Poux et al. 2022)

Additionally, MEV transactions are included in the same block space all other transactions try to fit into. Thus, including MEV transactions in blocks causes there to be less space available for other transactions resulting in lower throughput for other transactions. This leads to higher average transaction fees associated with transactions and longer average processing times. (Kulkarni et al. 2023; Poux et al. 2022; Qin et al. 2021)

2.2.4 Maximal Extractable Value strategies

Frontrunning refers to a group of strategies where the MEV searcher inserts transactions before victims’ transactions in a block. The simplest form of frontrunning is copying data from the victim’s transaction causing the profits of the transaction to be paid to MEV searcher instead. These strategies include, for example, taking advantage of atomic arbitrage opportunities and liquidations. (Mead 2023; Poux et al. 2022; Weintraub et al 2022)

Atomic arbitrage opportunities arise when prices of assets diverge between different decentralized exchange pairs to a magnitude that the arbitrageur can get risk-free profit from price divergence after trading fees. This can be, for example, due to decentralized exchange pairs of assets A and B having different exchange rates in two exchanges leading to a situation where the arbitrageur can buy asset A in one exchange for a lower price and sell asset A in another exchange for higher price resulting in a risk-free profit after transaction fees.

Similarly, there might be an atomic arbitrage opportunity if there is a discrepancy in prices of over two assets. For example, if there are three assets A, B, and C, with exchange pairs between all possible pairs, in situations where the arbitrageur can get more C for the amount of A after transaction fees by first exchanging A to B and then B to C, the arbitrageur can make risk-free profit by first exchanging A to B, B to C, and then C to A. (Mead 2023; Poux et al. 2022; Weintraub et al 2022)

Liquidation refers to an event where a user has deposited assets as collateral for a loan from lending protocol and their loan amount exceeds the borrowing power of their collateral as a result of price fluctuation in markets. These loans are typically overcollateralized meaning that even if the borrowing power of the collateral is exceeded the collateral is still worth more than the value of the outstanding loan. In liquidation, the MEV searcher offers to pay off the user’s loan that exceeds the borrowing power of its collateral and is rewarded for this action by receiving a liquidation fee paid from the user’s collateral. (Mead 2023; Poux et al. 2022; Weintraub et al. 2022)

Backrunning refers to a group of strategies where an MEV searcher inserts transactions right after a target transaction to capture an MEV opportunity. These strategies include, for example, taking advantage of atomic arbitrage opportunities and taking advantage of mispriced non-fungible token (NFT) sales. (Mead 2023; Weintraub et al. 2022)

Similar to atomic arbitrage opportunities described under frontrunning, in backrunning atomic arbitrage opportunities are caused by including a transaction that causes a price discrepancy in the block and then taking advantage of the discrepancy immediately after. (Poux et al. 2022; Weintraub et al. 2022)

Mispriced NFT sales refer to an event where an NFT is listed for sale below a buying offer it has or a buying offer is made that is higher than the listing price of the NFT. In this case, MEV searchers can take advantage of such mispricing by buying the NFT and immediately selling it to the buying offer.

A sandwich attack refers to a strategy where an MEV searcher makes a transaction right before and right after the victim's transaction. In this strategy MEV searcher takes advantage of swap transactions with high slippage tolerance by buying assets in frontrunning transactions to increase its price resulting in the victim buying the asset at a worse price. The victim's transaction causes the price to increase further resulting in the MEV searcher's backrunning transaction being able to sell assets bought in frontrunning transaction at a profit. (Mead 2023; Poux et al. 2022; Weintraub et al. 2022)

3 Data and methodology

This chapter provides an overview of used data and methodologies. The first section discusses the data sources. The following four sections discuss methodologies used for identifying and quantifying pair trading opportunities caused by price discrepancies, analyzing time sensitivity and the period of pair trading positions, correlation of different variables, and analysis of changes to the characteristics under different market regimes.

3.1 Data sources and data preprocessing

3.1.1 Data sources

I focus on data after the Paris network upgrade also known as the merge (Edgington 2023). The Paris network upgrade significantly modified the block production and MEV supply chain on Ethereum so I will only focus on these blocks. Block number 15 537 394, which was produced on September 15, 2022, is the first block in the data set, and block number 18 083 778, which was produced on September 7, 2023, is the last in the data set.

I collect historical data using Alchemy’s Ethereum RPC endpoint (Alchemy 2022). I start by collecting information on each block during the observation period to get information on which transactions each block consists of. With this information, I can determine whether any of the transactions interact with a smart contract associated with decentralized exchange trading pairs. If a transaction interacts with such a smart contract, I request information about the transaction and the event logs of the transaction.

I limit the scope of my analysis to consist of trading pairs that utilize the constant product market making model used by Uniswap v2 (Adams 2018) and its forks, the concentrated liquidity market making model used by Uniswap v3 (Adams et al. 2021) and weighted and composable stable market making models used by Balancer v2 (Balancer n.d.; Martinelli & Mushegian 2019). The number of different data points are listed in Table 1.

Table 1
Number of different data points

This table reports the number of different data points. Panel A reports different data points of Uniswap v3 trading pairs. Panel B reports different data points of Uniswap v2 and Uniswap v2 fork trading pairs. Panel C reports different data points of composable stable Balancer v2 trading pairs. Panel D reports different data points of weighted Balancer v2 trading pairs.

Panel A. Uniswap v3			
Swaps	Pairs	Mint	Burn
17492812	16180	868045	961244
Panel B. Uniswap v2 and forks			
Syncs	Pairs		
53853034	260254		
Panel C. Balancer stable			
Swaps	Pairs	Poolbalancechanged	
170579	91	16083	
Panel C. Balancer weigh			
Swaps	Pairs	Poolbalancechanged	
381907	24	30666	

3.1.2 Data preprocessing

For trading pairs utilizing a constant product market making model, I collect data from logs of sync and pair creation events. A sync event is emitted after each interaction with the trading pair, giving information on the liquidity of cryptocurrencies in the trading pair. From the sync event, I collect data on the liquidities of the cryptocurrencies in the trading pair and the smart contract address of the trading pair. The exchange rate of trading pairs utilizing constant product market makers can be derived from liquidities following Adams (2020). To do so I first define the relationship of liquidity of different cryptocurrencies in a trading pair as:

$$L_a * L_b = k_{ab}, \tag{2}$$

where L_a and L_b are liquidities of cryptocurrencies in trading pair $S_{(a,b)}$ and k_{ab} is the product of these liquidities that stays constant when trades are performed between cryptocurrencies a and b, excluding the increase in liquidities caused by reaped trading fees $f_{(a,b)}$ as described below.

In a constant product market maker model, the exchange rates can be derived from the liquidity as follows:

$$S_{(a,b)} = \frac{L_a}{L_b}.$$

Considering a swap event where a trade is made, the new liquidities and constant product are:

$$(L_a + \Delta_a) * (L_b - \Delta_b) = k_{ab} * (1 + f_{(a,b)}),$$

where Δ_a and Δ_b are changes in liquidities resulting from the event and $f_{(a,b)}$ is the increase in the constant product resulting from reaped trading fees.

A pair creation event is emitted when a new trading pair is initiated. By observing logs of these events, I collect smart contract addresses for cryptocurrencies in the trading pair. Smart contract addresses for cryptocurrencies in the trading pair can be used to identify which cryptocurrencies each trading pair consists of. The smart contract address of the trading pair can be used to make the connection between liquidities data in trading pairs caused by sync events and other information about the trading pairs defined in the pair creation event. Besides this information, I also collect the block number, timestamp, and log index of these events. If there are multiple events in a block the log index tells the order of the events. This information can be used in the analysis of price discrepancies inside a block.

For trading pairs utilizing the concentrated liquidity market making model, I collect data from logs of swap, mint, burn, and poolcreated events. A swap event is emitted every time there is a trade made in a trading pair. Swap events can be used to determine the exchange rate of a trading pair after every transaction. From swap events, I collect data about the tick used in the event, the amount swapped, and the smart contract address of the trading pair. A mint event is emitted when new liquidity is provided to a trading pair. The mint event states how much liquidity is provided to a trading pair and in which price range it is provided. A burn event is emitted when a liquidity provider removes their liquidity from a trading pair. The event states how much liquidity is removed and from which price range. From these events, I collect data about how much liquidity is provided at each time and each price level to trading pairs and the smart contract address of the trading pair.

The exchange rate of concentrated liquidity market making pairs can be derived from the tick following Adams et al. (2021) using the formula:

$$p(i) = 1.0001^i,$$

where p is the price of a cryptocurrency in terms of the other cryptocurrency in the trading pair and i is the tick.

Information on the exchange rate and the price ranges different liquidity providers provide liquidity at can be used to determine how much liquidity is available at each price point. Liquidity of individual liquidity-providing positions follows Equation (2) inside the price range and the liquidity available at each tick for a liquidity-providing position can be derived from this information. The total liquidity available at each tick can be calculated by summing together these individual positions.

Poolcreated event is similar to pair creation event of constant product market maker trading pairs. By observing logs of this event, I collect smart contract addresses for cryptocurrencies in the trading pair, smart contract addresses of the trading pair, and trading fees associated with the trading pair. Besides this information, I also collect the block number, timestamp, and log index of these events.

For trading pairs utilizing weighted and composable stable market making models, I collect data from logs of the swap and poolbalancechanged events. Besides these events, I also collect fees and weights of cryptocurrencies associated with weighted trading pairs, and fees and amplification parameters associated with composable stable trading pairs. A swap event is emitted every time there is a trade made in a trading pair. Swap events can be used to determine the exchange rate of a trading pair after every transaction. From swap events, I collect data about how much cryptocurrencies have been exchanged from one to another, which cryptocurrencies have been exchanged, and the trading pair the exchange has happened in. The poolbalancechanged event is emitted every time the liquidity provider adds or removes liquidity from the trading pair. From poolbalancechanged events, I collect data about how much the liquidities of the cryptocurrencies have changed because of the events and which trading pair the liquidity change has happened in. Based on these events the liquidities of trading pairs can be calculated after every interaction with a trading pair. Based on the liquidities the exchange rate for a trading pair utilizing a weighted market making model can be calculated as follows (Martinelli and Mushegian 2019) with the formula:

$$S_{(a,b)} = \frac{\frac{L_a}{W_a}}{\frac{L_b}{W_b}},$$

where W_a and W_b are weights of cryptocurrencies determined when creating the trading pair. The process of determining the exchange rate for a trading pair utilizing a composable stable market making model is iterative and described in detail in Balancer documentation Balancer (n.d.).

Besides the transaction data, I acquired a list of different stablecoins tracking US dollars and assets tracking the price of Bitcoin and Ethereum from Etherscan. This information can be used in defining which trading pairs consist of two stablecoins, two assets tracking the price of Bitcoin, or two assets tracking the price of Ethereum, and thus are expected to consistently trade near parity.

3.2 Pair trading opportunities identification and quantification

I start the analysis of pair trading opportunities by filtering the data set to only consist of trading pairs that have at least 1 000 transactions. This way I filter out trading pairs that are not actively traded from the data set.

Pair trading strategies rely on the assumption that the price relationship between two assets is stationary and follows a mean-reverting process. Thus, I identify potential pair trading opportunities by defining which decentralized exchange trading pairs are stationary using the Augmented Dickey-Fuller test (Dickey & Fuller 1979).

After identifying all decentralized exchange trading pairs that are stationary, I analyze which trading pairs are mean-reverting by analyzing whether they follow the Ornstein-Uhlenbeck process (Uhlenbeck & Ornstein 1930) described in Equation (1). If θ, describing the rate of mean reversion, is statistically different from zero this means the trading pair is mean-reverting.

After identifying all decentralized exchange trading pairs that are both stationary and mean-reverting I define pair trading opportunity as a state that fulfils the following criteria:

$$S_{(a,b)} > \mu_{(a,b)} - 2\sigma_{(a,b)} \vee S_{(a,b)} < \mu_{(a,b)} + 2\sigma_{(a,b)}, \tag{3}$$

$$S_{(a,b)} * \left(1 - f_{(a,b)}\right)^2 > \mu_{(a,b)} \vee S_{(a,b)} < \mu_{(a,b)} * \left(1 - f_{(a,b)}\right)^2, \tag{4}$$

and

$$S_{(a,b)} < \mu_{(a,b)} - 4\sigma_{(a,b)} \vee S_{(a,b)} > \mu_{(a,b)} + 4\sigma_{(a,b)}, \tag{5}$$

where $S_{(a,b)}$ is the exchange rate of cryptocurrency a in terms of cryptocurrency b, $f_{(a,b)}$ is fees associated in exchanging cryptocurrency a to cryptocurrency b, $\mu_{(a,b)}$ is the long-run mean exchange rate of cryptocurrency a in terms of cryptocurrency b, and $\sigma_{(a,b)}$ is the volatility of the exchange rate of cryptocurrency a in terms of cryptocurrency b.

$f_{(a,b)}$ includes both the trading pair's fee and gas fee associated with interacting with a trading pair. The gas fee is a fee paid for the computational effort required to include a transaction in the Ethereum blockchain (Frankenfield 2022). I estimate the gas fee associated with interacting with a trading pair by multiplying the amount of gas two transactions in a trading pair consume with the price of Ethereum in Uniswap v3's USDC Ethereum liquidity pool with a 0.05% transaction fee at each block. Based on Etherscan's Gas Tracker I use 305 618 as the gas amount for two transactions in Uniswap v2 pairs, 369 046 as the gas amount for Uniswap v3 pairs, and 393 250 as the gas amount for Balancer pairs.

If Equation (3) is false, the price discrepancy of a trading pair is too close to the long-run mean to be considered a pair trading opportunity following the definition of literature discussed in subsection 2.1.

If Equation (4) is false, the price discrepancy of a trading pair is too small to cover trading fees and, thus, cannot be taken advantage of. There might be a situation where Equation (3) is true, and Equation (4) is false. In such a situation there would be a pair trading opportunity if the trading fees were lower.

If Equation (5) is false, the price discrepancy of a trading pair is so far away from the long run mean that the price of a trading pair has diverged following the definition of literature discussed in subsection 2.1. and, thus, the searcher should not take part in a pair trading position.

If all Equations (3), (4), and (5) are true, there is a price discrepancy present in a trading pair that is significant enough that it can be considered a pair trading opportunity, and the price discrepancy is higher than trading fees associated with taking advantage of the opportunity. A rational searcher will take advantage of such an opportunity if the searcher expects price discrepancy to revert and expects risk-adjusted returns of such an opportunity to be high enough. Such an opportunity can be present for long periods without rational searchers taking advantage of them for various reasons. For example, the left side of Equation (4) is only slightly above the right side of the inequality meaning the potential for monetary gain is small if the price reverts in the future, resulting in the risk relative to potential returns of such opportunity being high. Alternatively, a searcher might be willing to take advantage of such an opportunity but lacks the funds in the correct cryptocurrencies to benefit from the opportunity, or taking advantage of such an opportunity would decrease or increase searcher's inventory in certain cryptocurrency to a level that increases searcher's overall risk too high considering all MEV extraction methods the searcher uses.

After identifying all opportunities fulfilling Equations (3), (4), and (5) I filter out opportunities that revert to the long-run mean or diverge within the same block the opportunity emerges. Such opportunities do not require holding a position as the position is both opened and closed within the same block and thus, is a form of atomic arbitrage instead of statistical arbitrage.

Assuming price discrepancy is expected to revert from the state described in Equations (3) and (4) to a state where the price is the long run mean the expected return zero-investment position can be calculated as:

$$\frac{\left|S_{(a,b)} - \mu_{(a,b)}\right| * (1 - f_{(a,b)})^2}{S_{(a,b)}}.$$

The expected return of pair trading opportunity in terms of dollars can be calculated from this as:

$$\Delta_a * \frac{\left|S^*{}_{(a,b)} - \mu_{(a,b)}\right| * (1 - f_{(a,b)})^2}{S_{(a,b)}},$$

where Δ_a is the change of liquidity in terms of dollars the searcher entering the pair trading opportunity can cause before Equations (3) and (4) no longer hold and $S^*{}_{(a,b)}$ is the average exchange rate paid for the position.

Similarly, if the price diverges to a point described in Equation (5) instead of reverting to the long run mean the loss from taking part in a pair trading opportunity can be calculated as:

$$-\frac{\left|S'{}_{(a,b)} - S_{(a,b)}\right| * (1 + f_{(a,b)})^2}{S_{(a,b)}},$$

and the loss in terms of dollars can be calculated as:

$$-\Delta_a * \frac{\left|S'_{(a,b)} - S^*_{(a,b)}\right| * (1 + f_{(a,b)})^2}{S_{(a,b)}},$$

where $S'_{(a,b)}$ is the new exchange rate of the trading pair after the price has diverged.

To analyze whether the return and risk of executing different pair trading opportunities vary depending on the underlying characteristics of different trading pairs, I study different subgroups of trading pairs. I split the trading pairs into the following subgroups: constant product market making pairs, concentrated liquidity market making pairs with different trading fees, weighted or stable market making pairs, and pairs where both underlying assets are expected to consistently swap at near parity.

3.3 Time sensitivity and the period of pair trading positions

After identifying the pair trading opportunities, I analyze how long these opportunities are present and how long it takes for the discrepancies to revert to the long-run mean or diverge.

I determine the period an opportunity is present as the time the Equations (3), (4), and (5) hold. If the inequalities do not hold a searcher following the pair trading logic should not enter a pair trading position. By analyzing how long the opportunities are present the time sensitivity of taking advantage of opportunities can be analyzed. If the opportunity is present for tens of blocks or more before diminishing this indicates that such opportunity is not as time sensitive as the MEV strategies described in subsection 2.2.4.

I determine the period price discrepancy takes to revert to the long-run mean or diverge by calculating how long it takes between the price first fulfilling Equations (3), (4), and (5) and prices reaching the long-run mean or diverging. By analyzing how long the price discrepancy takes to revert to the long-run mean or diverge, the period a searcher must hold a pair trading position can be determined. This information is interesting as some searchers might choose to only engage in pair trading opportunities if the price discrepancies are expected to return to long-run mean in a certain period as there is an opportunity cost associated with allocating capital to different positions.

3.4 Correlation of variables

I analyze whether different variables are correlated using pairwise Pearson correlation between pairs of different variables. The variables I analyze include the block number of an opportunity, the period a position must be held until the pair trading position either reverts or diverges, the return of the pair trading position, how long the pair trading opportunity can be taken a position in after first emerging, and the fee associated with the pair trading opportunity.

3.5 Changes under different market regimes

I analyze whether different market regimes cause changes in variables considered in subsections 3.2 and 3.3 by considering three subsets of data. I compare these subsets to the rest of the data set before and after the period subset consists of. The purpose of this analysis is to find whether there are statistically significant changes in some of the characteristics of pair trading opportunities under different market regimes.

The first subset is from block 15 880 000 produced on November 2, 2022, to block 15 970 000 produced on November 14, 2022. On November 11, 2022, cryptocurrency exchange FTX filed for bankruptcy. This event was preceded by various events causing distress in the cryptocurrency market.

The second subset is from block 16 790 000 produced on March 9, 2023, to block 16 850 000 produced on March 17, 2023. On March 10, 2023, Silicon Valley Bank collapsed. This caused distress in the cryptocurrency market after the issuer of USDC stablecoin confirmed that 8% of its reserves used for maintaining stablecoin’s parity with the US dollar were stuck at the bank (Huang et al. 2023).

The third subset is from block 17 800 000 produced on July 29, 2023, to block 17 860 000 produced on August 7, 2023. On August 6, 2023, multiple Curve Finance decentralized exchange pools were exploited (Pereira 2023).

4 Results and analysis

This chapter presents the results of different analyses. The first section discusses the results of the identification and quantification of pair trading-based MEV opportunities. The second section discusses the results of time sensitivity and the period of pair trading positions. The third section discusses the results of the correlation of variables. The last section discusses the results of whether and how the characteristics discussed in the first two sections change under different market regimes.

4.1 Identification and quantification of pair trading-based MEV opportunities

This section presents the results of the identification and quantification of pair trading-based MEV opportunities. The results of the identification process are discussed first after which the results of quantifying the results in terms of percentages and dollars are discussed.

After identifying all trading pairs that have at least 1 000 transactions, are stationary and mean-reverting, and have at least one pair trading opportunity I compute the returns of zero-investment pair trading positions in terms of percentages. The results of this analysis are presented in Table 2 and visualized in Figures 3 and B1. The trading pairs with the most trading pairs opportunities are presented in Appendix A.

Column 1 of Table 2 shows different subgroups of analyzed data. The data has been split into Balancer, Uniswap v2 and forks, and Uniswap v3 subgroups based on the market making model the pairs utilize. Data of Uniswap v3 pairs has also been split into two subgroups based on the fees associated with the Uniswap v3 pairs. Lastly, pairs whose underlying cryptocurrencies should trade near parity are shown as their subgroup. Panel A of Table 2 shows returns of all pair trading opportunities while Panel B only shows returns of pair trading opportunities that reverted and Panel C shows returns of pair trading opportunities that diverged.

Column 2 shows the mean of returns for zero-investment positions in terms of percentages. Panel A of column A shows that based on a one-sample t-test (Student 1908) the mean is positively different from zero at 1% significance for the whole data set and Uniswap v2 subgroup, positively different from zero at 5% significance for Balancer subgroup, and negatively different from zero at 1% significance for other subgroups.

Columns 3 through 6 show the standard deviation, minimum, median, and maximum of the returns. In Panel A the mean of returns is higher than the median for all subgroups, excluding Parity, indicating that the returns are positively skewed in the subgroups. Panel A of column 5 shows that based on the Wilcoxon Signed-Ranked Test (Wilcoxon 1945) the median of the data set is statistically significantly different from zero at the 1% level for all subgroups. Finally, Columns 7 and 8 show the number of pair trading opportunities each subgroup has and the number of pairs the subgroup consists of.
Considering whether the pair trading opportunities tend to revert or diverge 3237 out of the 6731 opportunities reverted to their long run mean being 48% of all opportunities. This varied between 36% and 100% between different subgroups.

After analyzing the returns of different zero-investment positions in terms of percentages I repeated the analysis for optimally sized pair trading positions in terms of dollars. The analysis takes into consideration liquidity available for different trading pairs at different price points in trading pairs to calculate the average entry price for each position. The results of this analysis are presented in Table 3 and visualized in Figures 4 and B2.
Similar to percentwise analysis, column 5 shows the median of returns in terms of dollars, and whether the median is statistically significantly different from zero based on the Wilcoxon Signed-Ranked Test. Medians of the whole data set, Uniswap v2, Balancer, and Parity subgroups differ from zero at a statistical significance of 1%. However, the sample size of the Balancer subgroup is small. Like the percentwise analysis in Panel A, the mean of returns is higher than the median for all subgroups, excluding the Balancer subgroup, indicating that the returns are positively skewed in the subgroups. Uniswap v3, Uniswap v3 pairs with 0.3% fee and Uniswap v3 pairs with 1% fee subgroups have positive mean, while in percentwise analysis the mean of these subgroups was negative.

Table 2

Zero-investment pair trading positions' returns in terms of percentages

This table reports results on the analysis of the identification and quantification of pair trading-based MEV opportunities. Panel A reports the summary statistics of returns of identified opportunities in different subgroups. Panel B reports summary statistics of returns of opportunities that reverted to their long-run mean. Panel C reports summary statistics of returns of opportunities that diverged. ***, **, and * denote statistical significance of one-sample t-test and Wilcoxon Signed-Rank Test at the 1%, 5%, and 10% levels.

Panel A. Return of zero-investment pair trading positions

Subgroup	Mean	St. Dev.	Min	Median	Max	N opportunities	N pairs
Whole dataset	3.0%***	42.8%	-100%	-1.8%***	179.9%	6731	580
Balancer	28.0%**	40.1%	5.8%	6.8%***	101.5%	8	2
Uniswap v2 and forks	3.3%***	43.3%	-100%	-1.9%***	179.9%	6495	564
Uniswap v3 all	-6.1%***	24.0%	-100%	-1.5%***	94.2%	228	14
Uniswap v3 0.3%	-4.5%***	15.9%	-76.0%	-1.2%***	29.3%	112	6
Uniswap v3 1%	-7.7%***	29.8%	-100%	-3.0%***	94.2%	116	8
Parity	76.1%***	9.8%	26.0%	75.8%***	99.0%	97	1

Panel B. Return of zero-investment pair trading positions that reverted to long run mean

Subgroup	Mean	St. Dev.	Min	Median	Max	N datapoints	N pairs
Whole dataset	36.2%	31.3%	0.1%	26.8%	179.9%	3237	505
Balancer	28.0%	40.1%	5.8%	6.8%	101.5%	8	2
Uniswap v2 and forks	34.7%	27.1%	0.2%	26.9%	132.2%	3146	491
Uniswap v3 all	12.1%	16.6%	0.1%	8.0%	94.2%	83	12
Uniswap v3 0.3%	7.5%	7.8%	0.1%	6.5%	29.3%	41	6
Uniswap v3 1%	16.7%	21.2%	0.2%	9.9%	94.2%	42	6
Parity	76.1%	9.8%	26.0%	75.8%	99.0%	97	1

Panel C. Return of zero-investment pair trading positions that diverged

Subgroup	Mean	St. Dev.	Min	Median	Max	N opportunities	N pairs
Whole dataset	-27.8%	25.6%	-100%	-21.2%	0%	3494	489
Balancer	-	-	-	-	-	-	-
Uniswap v2 and forks	-28.3%	25.7%	-100%	-21.5%	0%	3349	477
Uniswap v3 all	-16.6%	21.2%	-100%	-8.1%	0%	145	12
Uniswap v3 0.3%	-11.4%	15.4%	-76.0%	-4.5%	0%	71	5
Uniswap v3 1%	-21.5%	24.7%	-100%	-11.3%	-0.2%	74	7
Parity	-	-	-	-	-	-	-

Table 3

Pair trading opportunities' returns in terms of dollars

This table reports results on analysis of identification and quantification of pair trading based MEV opportunities in terms of dollars. Panel A reports the summary statistics of returns of identified opportunities in different subgroups. Panel B reports summary statistics of returns of opportunities that reverted to their long run mean. Panel C reports summary statistics of returns of opportunities that diverged. ***, **, and * denote statistical significance of Wilcoxon Signed-Rank Test at the 1%, 5%, and 10% levels.

Panel A. Return of pair trading opportunities							
Subgroup	Mean	St. Dev.	Min	Median	Max	N opportunities	N pairs
Whole dataset	326	2437	-518	-2***	51238	6731	580
Balancer	33713	21221	76	42605***	51238	8	2
Uniswap v2 and forks	288	2052	-518	-2***	50827	6495	564
Uniswap v3 all	241	1553	-463	-5	15425	228	14
Uniswap v3 0.3%	13	74	-60	-5	540	112	6
Uniswap v3 1%	462	2158	-463	-5	15425	116	8
Parity	4911	7444	3	1820***	36616	97	1
Panel B. Return of pair trading opportunities that reverted to long run mean							
Subgroup volatility	Mean	St. Dev.	Min	Median	Max	N datapoints	N pairs
Whole dataset	748	3463	0	77	51238	3237	505
Balancer	33713	21221	76	42605	51238	8	2
Uniswap v2 and forks	1193	6722	0	84	121222	3146	491
Uniswap v3 all	713	2513	0	33	15425	83	12
Uniswap v3 0.3%	58	109	0	15	540	41	6
Uniswap v3 1%	1352	3431	1	79	15425	42	6
Parity	4911	7444	3	1820	36616	97	1
Panel C. Return of pair trading opportunities that diverged							
Subgroup	Mean	St. Dev.	Min	Median	Max	N opportunities	N pairs
Whole dataset	-65	83	-518	-35	0	3494	489
Balancer	-	-	-	-	-	-	-
Uniswap v2 and forks	-67	82	-518	-37	0	3349	477
Uniswap v3 all	-29	70	-463	-9	0	145	12
Uniswap v3 0.3%	-13	11	-60	-10	0	71	5
Uniswap v3 1%	-44	95	-463	-9	0	74	7
Parity	-	-	-	-	-	-	-

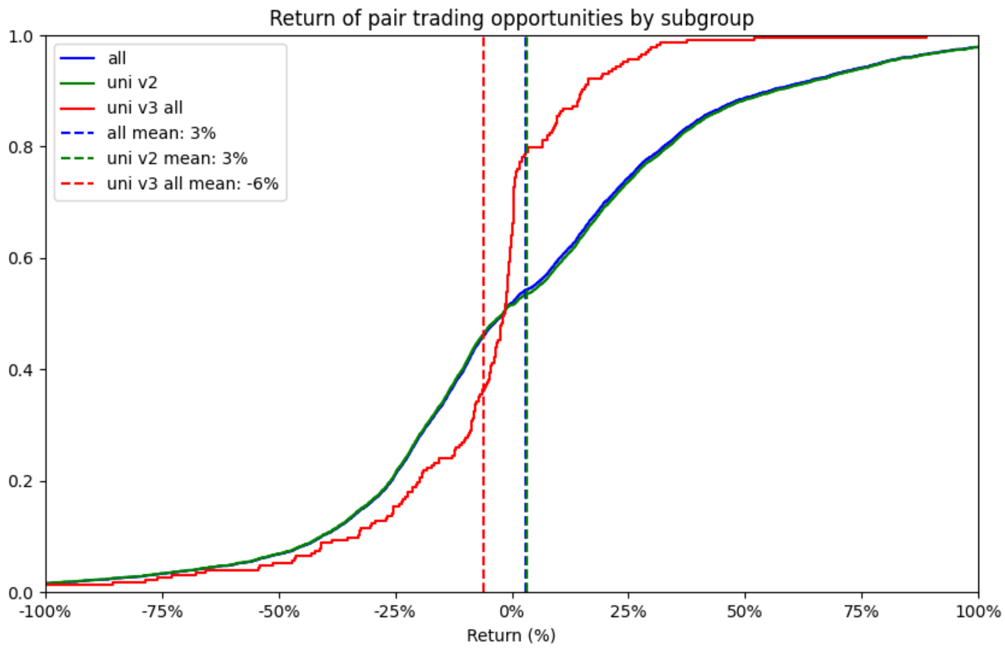

Figure 3: Return of pair trading opportunities in terms of percentages

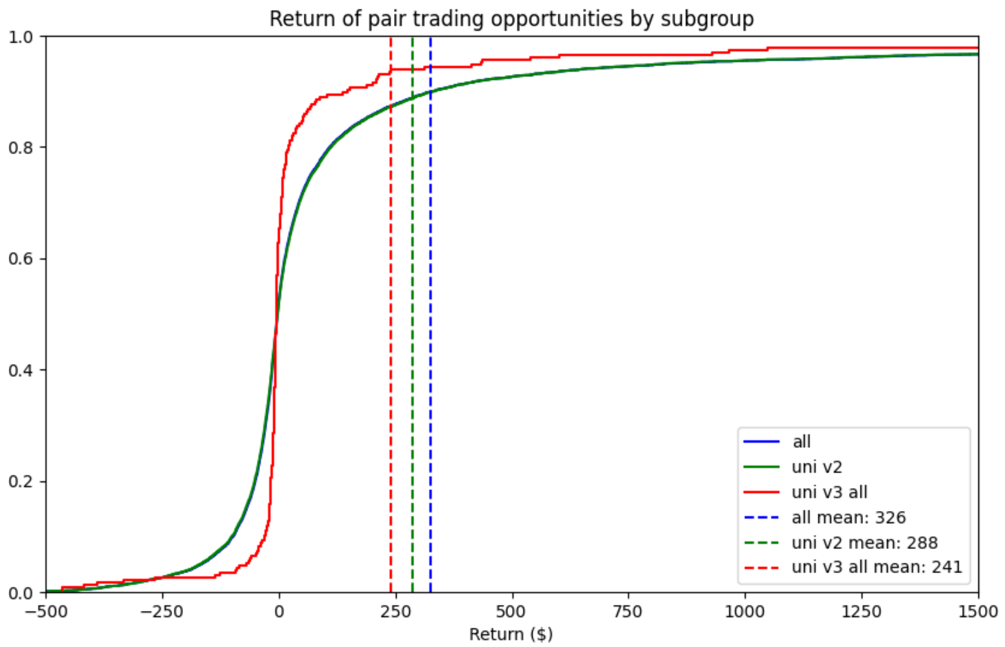

Figure 4: Return of pair trading opportunities in terms of dollars

4.2 Time sensitivity and holding period of pair trading positions

This section first presents the results of the analysis of the time sensitivity of entering a pair trading position immediately after a trading pair reaches a state described in Equations (3), (4), and (5). After that the section presents the results of the analysis of how long a pair trading position has to be held after first entering the state described in Equations (3), (4), and (5) until the position either reverts to the long-run mean or diverges.

The time sensitivity of entering pair trading positions is described in Table 4 and visualized in Figures 5, 6, 7, B3, B4, and B5. The table follows a similar structure as Tables 2 and 3.

For all pair trading opportunities, the minimum entry window for position is 0 blocks meaning some opportunities must be taken position in during a specific block. Panel B and Panel C show that this is the case for both reverting and diverging positions, excluding a few diverging subgroups that have low sample sizes.

The median window for entering a pair of trading positions is 53 blocks corresponding to 10 and a half minutes given the average block time of 12 seconds. This is below the mean window of 1963 blocks corresponding to 6 and a half hours. This is also the case when analyzing the opportunities that reverted and the opportunities that diverged as both are positively skewed in all subgroups.

After analyzing the time sensitivity of entering pair trading positions I analyze how long a position must be held until it reverts to the long-run mean or diverges. These results are described in Table 5 and visualized in Figures 8, 9, 10, B6, B7, and B8.

The minimum time a pair trading position must be held is 1 block. I have excluded positions that revert or diverge in 0 blocks as such positions present atomic arbitrage opportunities the searchers should take advantage of.

The median time a pair trading position must be held before it reverts is 190 blocks corresponding to 38 minutes and the mean is 4131 blocks corresponding to 14 hours. This is also the case when analyzing the opportunities that reverted and the opportunities that diverged as both are positively skewed in all subgroups.

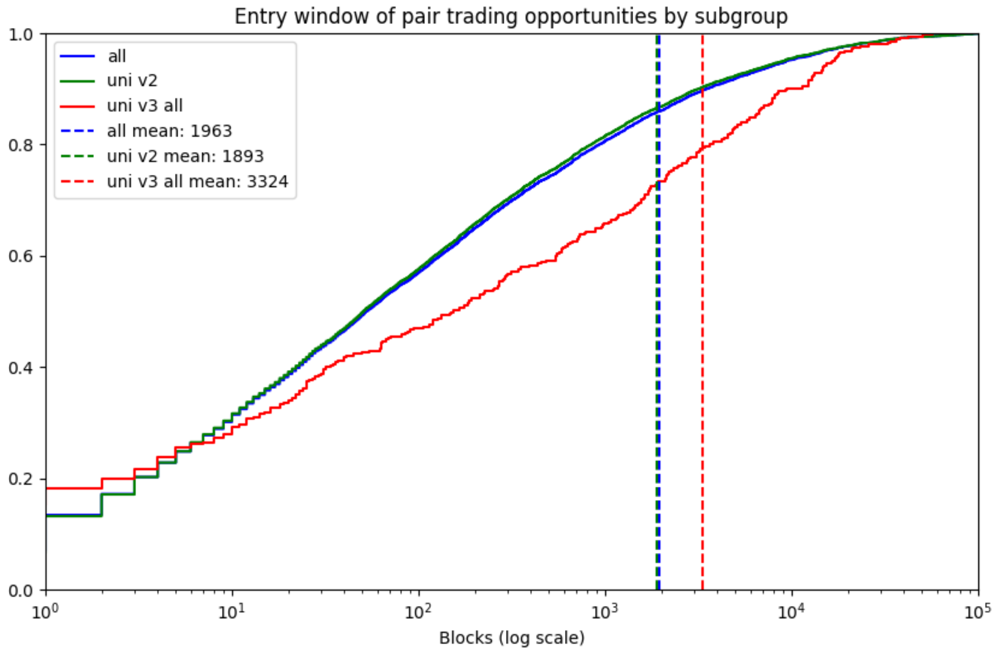

Figure 5: Entry window of pair trading opportunities

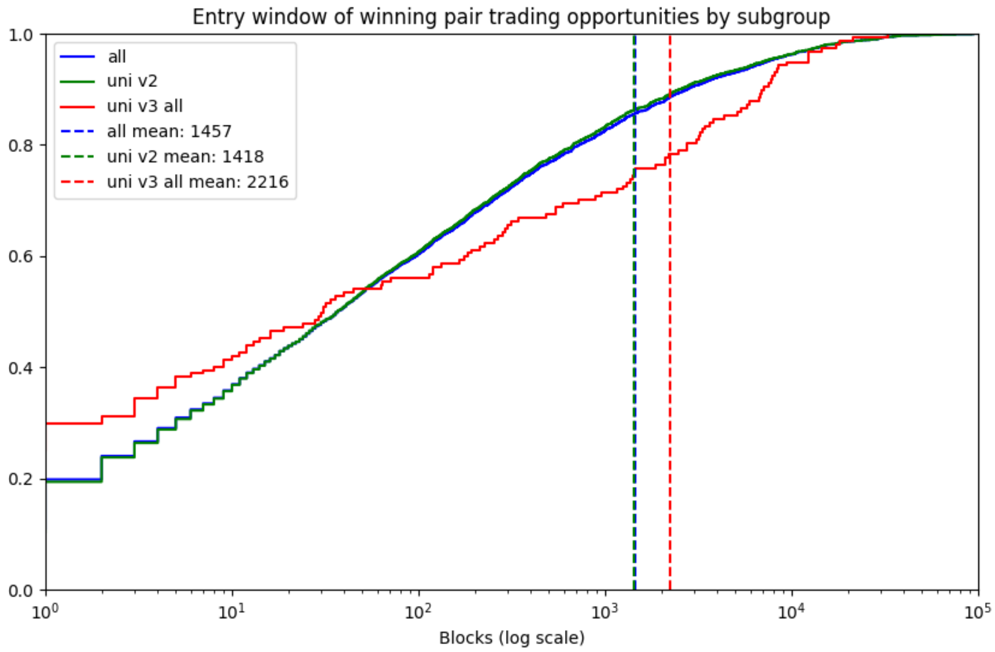

Figure 6: Entry window of winning pair trading opportunities

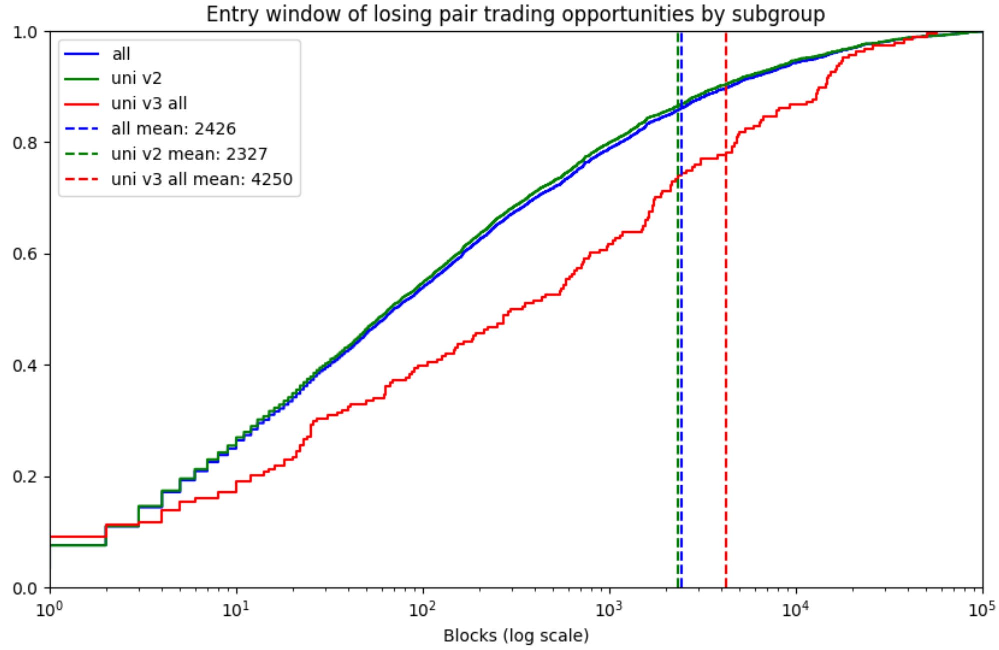

Figure 7: Entry window of losing pair trading opportunities

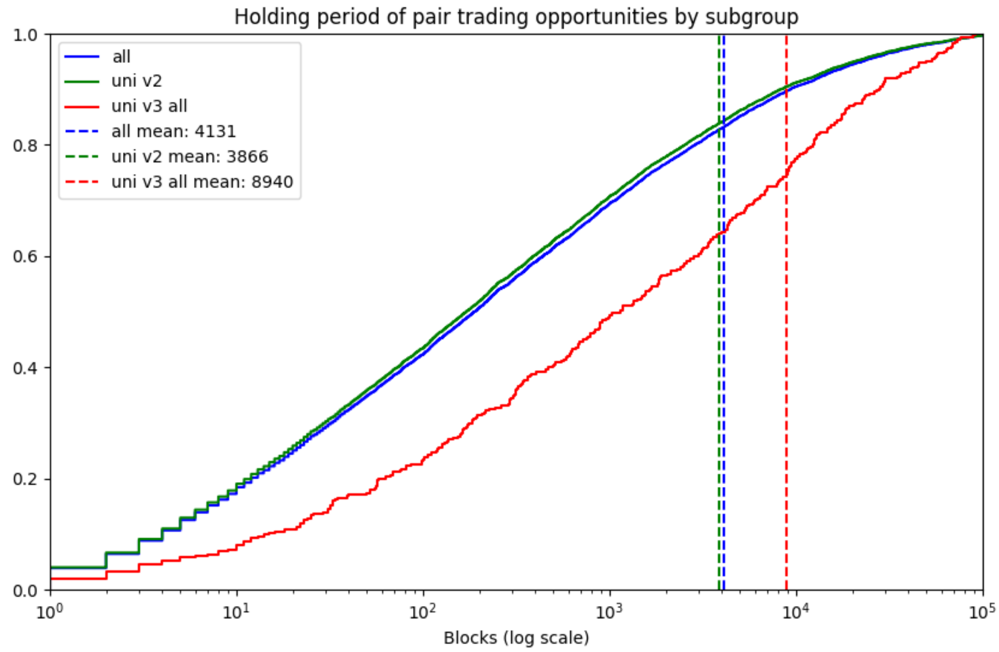

Figure 8: Holding period of pair trading positions

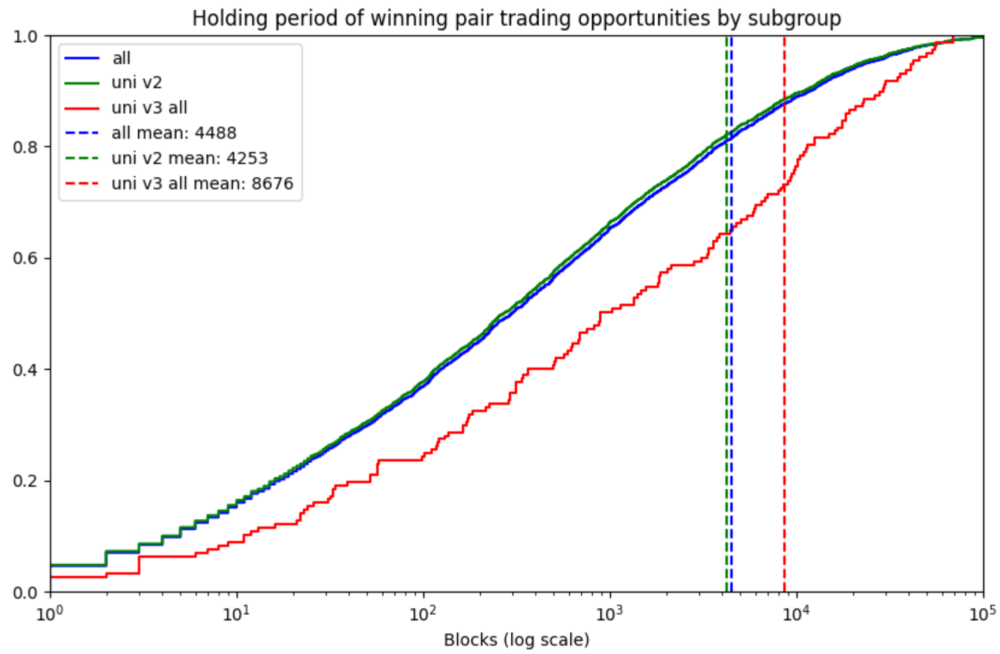

Figure 9: Holding period of winning pair trading positions

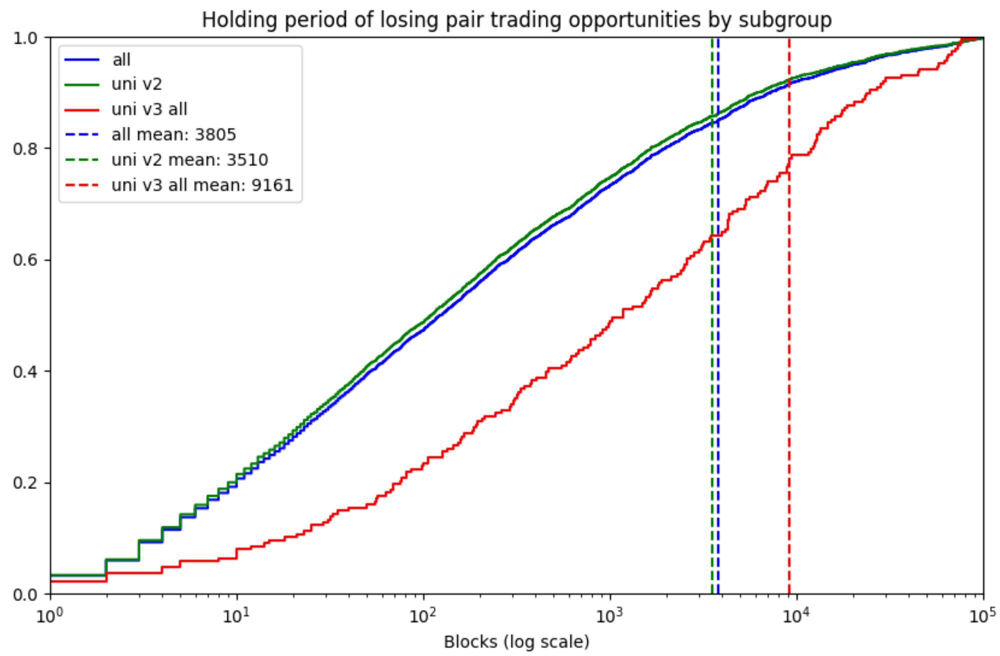

Figure 10: Holding period of losing pair trading positions

Table 4

Time sensitivity of entering pair trading positions

This table reports results on analysis of time sensitivity of pair trading based MEV opportunities in blocks. Panel A reports the summary statistics of entry window of pair trading opportunities in different subgroups. Panel B reports summary statistics of entry window of opportunities that reverted to their long run mean. Panel C reports summary statistics of entry window of opportunities that diverged.

Panel A. Entry window of pair trading opportunities in blocks							
Subgroup	Mean	St. Dev.	Min	Median	Max	N opportunities	N pairs
Whole dataset	1963	7850	0	53	123511	6800	596
Balancer	1344	1742	1	379	5606	25	5
Uniswap v2 and forks	1893	7840	0	51	123511	6430	567
Uniswap v3 all	3324	8185	0	165	72590	345	24
Uniswap v3 0.3%	4041	10282	0	88	72590	144	12
Uniswap v3 1%	2811	6245	0	184	42040	201	12
Parity	254	858	0	45	8076	122	3
Panel B. Entry window of pair trading opportunities that reverted to long run mean in blocks							
Subgroup	Mean	St. Dev.	Min	Median	Max	N opportunities	N pairs
Whole dataset	1457	5859	0	37	105267	3246	508
Balancer	1343	1749	1	616	5606	15	4
Uniswap v2 and forks	1418	5898	0	37	105267	3074	483
Uniswap v3 all	2216	5273	0	31	36510	157	21
Uniswap v3 0.3%	1824	5061	0	11	32900	58	11
Uniswap v3 1%	2445	5406	0	63	36510	99	10
Parity	195	794	0	39	8076	112	3
Panel C. Entry window of pair trading opportunities that diverged in blocks							
Subgroup	Mean	St. Dev.	Min	Median	Max	N opportunities	N pairs
Whole dataset	2426	9280	0	70	123511	3554	504
Balancer	1346	1825	33	225	5041	10	2
Uniswap v2 and forks	2327	9248	0	66	123511	3356	484
Uniswap v3 all	4250	9907	0	349	72590	188	18
Uniswap v3 0.3%	5535	12453	0	564	72590	86	8
Uniswap v3 1%	3167	6973	0	280	42040	102	10
Parity	922	1262	18	527	3830	10	2

Table 5
Time pair trading positions take to revert or diverge

This table reports results on analysis of time it takes pair trading based MEV opportunities to revert or diverge in blocks. Panel A reports the summary statistics of time pair trading opportunities in different subgroups. Panel B reports summary statistics of time of opportunities that reverted to their long run mean. Panel C reports summary statistics of time of opportunities that diverged.

Panel A. The period pair trading position had to be active until price reverted or diverged in blocks

Subgroup	Mean	St. Dev.	Min	Median	Max	N opportunities	N pairs
Whole dataset	4131	12756	1	190	127686	6800	596
Balancer	5989	10520	4	2935	41004	25	5
Uniswap v2 and forks	3866	12422	1	171	127686	6430	567
Uniswap v3 all	8940	17314	1	1174	101564	345	24
Uniswap v3 0.3%	12804	22237	1	2434	101564	144	12
Uniswap v3 1%	6171	11984	1	750	65374	201	12
Parity	2213	7519	3	237	74841	122	3

Panel B. The period pair trading position had to be active until price reverted in blocks

Subgroup	Mean	St. Dev.	Min	Median	Max	N datapoints	N pairs
Whole dataset	4488	12622	1	300	124915	3246	508
Balancer	8705	12857	4	4973	41004	15	4
Uniswap v2 and forks	4253	12405	1	271	124915	3074	483
Uniswap v3 all	8676	15729	1	1026	89141	157	21
Uniswap v3 0.3%	12903	20636	1	3450	89141	58	11
Uniswap v3 1%	6199	11374	1	631	55587	99	10
Parity	2232	7815	3	231	74841	112	3

Panel C. The period pair trading position had to be active until price diverged in blocks

Subgroup	Mean	St. Dev.	Min	Median	Max	N opportunities	N pairs
Whole dataset	3805	12870	1	126	127686	3554	504
Balancer	1915	2693	33	292	7644	10	2
Uniswap v2 and forks	3510	12428	1	111	127686	3356	484
Uniswap v3 all	9161	18574	1	1186	101564	188	18
Uniswap v3 0.3%	12738	23374	1	2010	101564	86	8
Uniswap v3 1%	6144	12605	1	872	65374	102	10
Parity	1996	2617	18	1167	7801	10	2

4.3 Correlation of variables

This section presents the results of the correlation analysis of the variables. The results of the analysis are presented in Table 6.

Variables' correlation coefficients vary between -0.09 and 0.09 for all variables, excluding the holding period and entry window which have a 0.78 correlation coefficient for all pair trading opportunities, 0.68 correlation coefficient for reverting trading opportunities, and 0.87 correlation coefficient for diverging trading opportunities.

The strong correlation between holding periods and entry windows can be partly explained by the definition of holding periods and entry windows. The holding period is defined in this study as the period it takes the price to either revert or diverge after first reaching the state described in Equations (3), (4), and (5). On the other hand, the entry window is defined as the period the price is in the state described in Equations (3), (4), and (5) after first reaching the state, before reverting or diverging. If Equations (3) and (4) hold from the moment the position is entered until the position is exited the opportunity will have identical values for the holding period and entry window.

Block number does not have a strong correlation with any of the variables. This suggests that there is no clear trend of different variables developing over the observation period. Similarly, there is no strong correlation between fees and other variables suggesting fees associated with trading pairs do not have a strong impact on other variables. Finally, the return of the opportunities does not have a strong correlation with other variables suggesting that opportunities with longer holding periods and entry windows should not be expected to have different returns than opportunities with short holding periods and entry windows.

Table 6
Correlation matrix

This table reports results of correlation analysis of different pair trading opportunities related variables. Panel A reports correlation of the variables in all pair trading opportunities. Panel B reports correlation of the variables in pair trading opportunities that reverted. Panel C reports correlation of the variables in pair trading opportunities that diverged.

Panel A. Correlation of variables					
	Block number	Holding period	Return	Entry window	Fee
Block number	1.00				
Holding period	-0.04	1.00			
Return	-0.02	0.03	1.00		
Entry window	-0.01	0.78	-0.07	1.00	
Fee	0.00	0.00	0.00	0.00	1.00
Panel B. Correlation of variables in reverting trading opportunities					
	Block number	Holding period	Return	Entry window	Fee
Block number	1.00				
Holding period	-0.06	1.00			
Return	-0.03	0.09	1.00		
Entry window	-0.04	0.68	0.04	1.00	
Fee	0.00	0.01	-0.04	0.00	1.00
Panel C. Correlation of variables in diverging trading opportunities					
	Block number	Holding period	Return	Entry window	Fee
Block number	1.00				
Holding period	-0.02	1.00			
Return	0.02	-0.08	1.00		
Entry window	0.00	0.87	-0.09	1.00	
Fee	0.00	-0.01	0.04	-0.01	1.00

4.4 Changes under different market regimes

This section presents the results of analyses of whether and how the characteristics discussed in the first two sections change under different market regimes. First, I present the results of analyses of whether the characteristics are different between blocks 15 880 000 and 15 970 000, during which time there was increased market distress due to FTX collapsing, compared to the rest of the data set. Second, I present the results of analyses of whether the characteristics are different between blocks 16 790 000 and 16 850 000, during which time there was increased market distress due to the bankruptcy of Silicon Valley Bank, compared to the rest of the data set. Last, I present the results of analyses of whether the characteristics are different between blocks 17 800 000 and 17 860 000, during which time there was increased market distress due to multiple Curve finance pools being exploited, compared to the rest of the data set.

4.4.1 FTX

This subsection presents the results of analyses of whether different characteristics differ between blocks 15 880 000 and 15 970 000, a period when FTX collapsing caused increased market distress. First, I present the results of the analysis of whether the return of pair trading opportunities differs during this period. Next, I present the results of the analysis of whether the time sensitivity of pair trading positions differs during this period. Last, I present the results of the analysis of whether time pair trading positions must be held differ during this period.

The results of the analysis of whether returns of pair trading opportunities differ during the collapse of FTX are described in Table 7 and visualized in Figure 11. The median returns of pair trading opportunities do not statistically differ in the FTX sample compared to the rest of the returns in the data set based on a Mann-Whitney U test (Mann & Whitney 1947) for any of the subgroups, excluding the Uniswap v3 subgroup. Of the 147 opportunities during the sample period 82 opportunities reverted, which is statistically higher at 10% significance compared to the reversion rate of 48% in the rest of the data set based on the Chi-squared test (Pearson 1900).

The results of the analysis of whether the time sensitivity of pair trading positions differs during the collapse of FTX are described in Table 8 and visualized in Figures 12 and B9. The median of entry windows does not statistically differ from the rest of the data set based on the Mann-Whitney U test.

The results of the analysis of whether the period the pair trading positions must be held differ during FTX collapsing are described in Table 9 and visualized in Figures 13 and B10. The median of the period is statistically higher at 5% compared to the rest of the data set based on a Mann-Whitney U test.

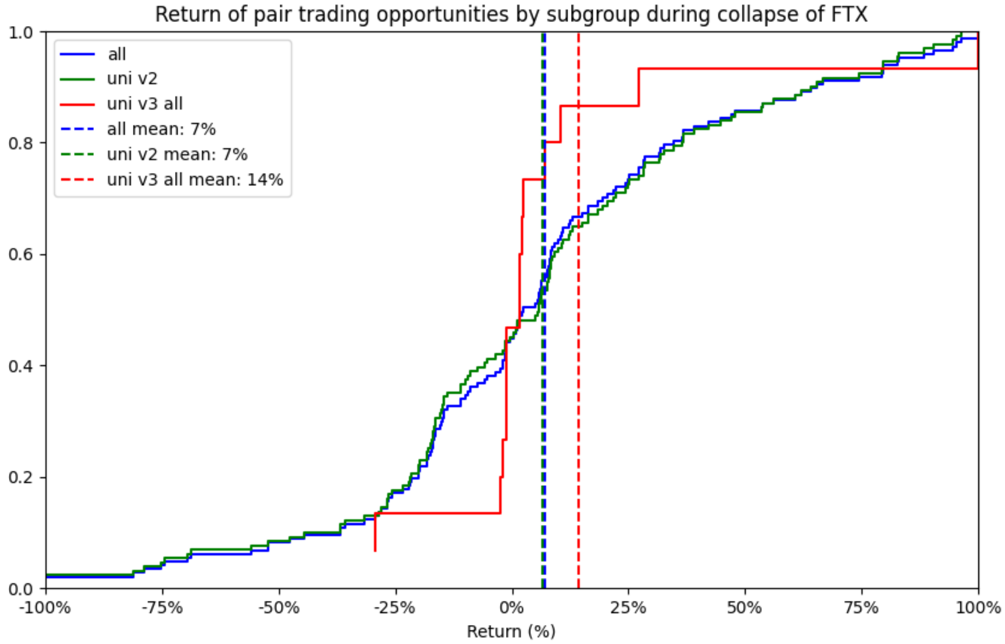

Figure 11: Return of pair trading opportunities in terms of percentages during the collapse of FTX

Table 7

Zero-investment pair trading positions' returns in terms of percentages during market distress caused by FTX

This table reports results on analysis of identification and quantification of pair trading based MEV opportunities between blocks 15 880 000 and 15 970 000. During this time there was increased market distress due to FTX collapsing. Panel A reports the summary statistics of returns of identified opportunities in different subgroups. Panel B reports summary statistics of returns of opportunities that reverted to their long run mean. Panel C reports summary statistics of returns of opportunities that diverged. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels for results of Mann-Whitney U test comparing medians of subset and the rest of the data set.

Panel A. Return of pair trading opportunities

Subgroup	Mean	St. Dev.	Min	Median	p(Median)	Max	N opportunities	N pairs
Whole dataset	7.0%	41.3%	-100%	5.1%	(0.13)	101%	147	53
Balancer	-52.2%	-	-	-	-	-	1	1
Uniswap v2 and forks	6.6%	41.7%	-100%	5.9%	(0.20)	101%	131	46
Uniswap v3 all	14.4%	36.5%	-29.2%	1.8%*	(0.06)	100%	15	6
Uniswap v3 0.3%	29.3%	51.2%	-29.2%	10.5%	(0.18)	100%	7	4
Uniswap v3 1%	1.4%	2.9%	-1.9%	1.7%	(0.25)	7.2%	8	2
Parity	1.2%	-	-	-	-	-	1	1

Panel B. Return of pair trading opportunities that reverted to long run mean

Subgroup	Mean	St. Dev.	Min	Median	p(Median)	Max	N opportunities	N pairs
Whole dataset	33.8%	30.7%	0.3%	24.6%	(0.40)	101%	82	44
Balancer	-	-	-	-	-	-	-	-
Uniswap v2 and forks	34.4%	29.4%	0.3%	25.3%	(0.46)	101%	73	40
Uniswap v3 all	28.1%	41.6%	1.7%	7.2%	(0.11)	100%	9	4
Uniswap v3 0.3%	59.4%	47.4%	10.5%	63.6%**	(0.04)	100%	4	2
Uniswap v3 1%	3.0%	2.3%	1.7%	2.1%	(0.96)	7.2%	5	2
Parity	1.2%	-	-	-	-	-	1	1

Panel C. Return of pair trading opportunities that diverged

Subgroup	Mean	St. Dev.	Min	Median	p(Median)	Max	N opportunities	N pairs
Whole dataset	-26.7%	25.0%	-100%	-18.2%	(0.63)	-0.4%	65	28
Balancer	-52.2%	-	-	-	-	-	1	1
Uniswap v2 and forks	-28.4%	25.1%	-100%	-19.0%**	(0.96)	-0.4%	58	23
Uniswap v3 all	-6.2%	11.3%	-29.2%	-1.6%*	(0.27)	-1.1%	6	4
Uniswap v3 0.3%	-10.9%	15.8%	-29.2%	-2.4%**	(0.90)	-1.1%	3	3
Uniswap v3 1%	-1.4%	-0.4%	-1.9%	-1.3%***	(0.11)	-1.1%	3	1
Parity	-	-	-	-	-	-	-	-

Table 8

Time sensitivity of entering pair trading positions during market distress caused by FTX

This table reports results on analysis of time sensitivity of pair trading based MEV opportunities between blocks 15 880 000 and 15 970 000. During this time there was increased market distress due to FTX collapsing. Panel A reports the summary statistics of entry window of pair trading opportunities in different subgroups. Panel B reports summary statistics of entry window of opportunities that reverted to their long run mean. Panel C reports summary statistics of entry window of opportunities that diverged. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels for results of Mann-Whitney U test comparing medians of subset and the rest of the data set.

Panel A. Entry window of pair trading opportunities in blocks

Subgroup	Mean	St. Dev.	Min	Median	p(Median)	Max	N opportunities	N pairs
Whole dataset	2137	9950	0	69	(0.77)	105267	145	65
Balancer	305	-	-	-	-	-	1	1
Uniswap v2 and forks	2204	10476	0	60	(0.93)	105267	129	44
Uniswap v3 all	1681	3785	0	312	(0.78)	14979	15	6
Uniswap v3 0.3%	2882	5451	0	547	(0.78)	14979	7	4
Uniswap v3 1%	631	690	0	262	(0.88)	1632	8	2
Parity	1	-	-	-	-	-	1	1

Panel B. Entry window of pair trading opportunities that reverted to long run mean in blocks

Subgroup	Mean	St. Dev.	Min	Median	p(Median)	Max	N opportunities	N pairs
Whole dataset	2133	11896	0	28	(0.92)	105267	80	43
Balancer	-	-	-	-	-	-	-	-
Uniswap v2 and forks	2329	12619	0	24	(0.91)	105267	71	38
Uniswap v3 all	587	1052	0	165	(0.90)	3114	9	4
Uniswap v3 0.3%	1140	1482	0	723	(0.81)	3114	4	2
Uniswap v3 1%	144	129	0	165	(0.88)	312	5	2
Parity	1	-	-	-	-	-	1	1

Panel C. Entry window of pair trading opportunities that diverged in blocks

Subgroup	Mean	St. Dev.	Min	Median	p(Median)	Max	N opportunities	N pairs
Whole dataset	2143	6931	0	114	(0.34)	46837	65	52
Balancer	305	-	-	-	-	-	1	1
Uniswap v2 and forks	2053	7130	0	88	(0.74)	46837	58	23
Uniswap v3 all	3323	5740	90	1346	(0.30)	14979	6	4
Uniswap v3 0.3%	5205	8467	90	547	(0.55)	14979	3	3
Uniswap v3 1%	1441	238	1174	1518	(0.26)	1632	3	1
Parity	-	-	-	-	-	-	-	-

Table 9

Time pair trading positions take to revert or diverge during market distress caused by FTX

This table reports results on analysis of time it takes pair trading based MEV opportunities to revert or diverge between blocks 15 880 000 and 15 970 000. During this time there was increased market distress due to FTX collapsing. Panel A reports the summary statistics of returns of identified opportunities in different subgroups. Panel B reports summary statistics of returns of opportunities that reverted to their long run mean. Panel C reports summary statistics of returns of opportunities that diverged. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels for results of Mann-Whitney U test comparing medians of subset and the rest of the data set.

Panel A. The period pair trading position had to be active until price reverted or diverged in blocks

Subgroup	Mean	St. Dev.	Min	Median	p(Median)	Max	N opportunities	N pairs
Whole dataset	5427	14210	1	396**	(0.04)	107520	145	65
Balancer	421	-	-	-	-	-	1	1
Uniswap v2 and forks	5081	14155	1	295	(0.18)	107520	129	44
Uniswap v3 all	8738	15183	31	1654	(0.33)	45423	15	6
Uniswap v3 0.3%	15969	20294	245	6474	(0.26)	45423	7	4
Uniswap v3 1%	2412	3163	31	902	(0.86)	7979	8	2
Parity	11334	-	-	-	-	-	1	1

Panel B. The period pair trading position had to be active until price reverted in blocks

Subgroup	Mean	St. Dev.	Min	Median	p(Median)	Max	N opportunities	N pairs
Whole dataset	6050	15139	1	711*	(0.09)	107520	80	43
Balancer	-	-	-	-	-	-	-	-
Uniswap v2 and forks	5764	15312	1	704	(0.22)	107520	71	38
Uniswap v3 all	8304	14329	31	5063	(0.50)	45423	9	4
Uniswap v3 0.3%	16298	19460	5063	7352	(0.26)	45423	4	2
Uniswap v3 1%	1909	3402	31	591	(0.86)	7979	5	2
Parity	11334	-	-	-	-	-	1	1

Panel C. The period pair trading position had to be active until price diverged in blocks

Subgroup	Mean	St. Dev.	Min	Median	p(Median)	Max	N opportunities	N pairs
Whole dataset	4661	13052	1	171	(0.34)	73967	65	52
Balancer	421	-	-	-	-	-	1	1
Uniswap v2 and forks	4245	12677	1	108	(0.65)	73967	58	23
Uniswap v3 all	9390	17779	245	1414	(0.50)	45348	6	4
Uniswap v3 0.3%	15530	25826	245	997	(0.79)	45348	3	3
Uniswap v3 1%	3250	3190	1174	1654	(0.45)	6923	3	1
Parity	-	-	-	-	-	-	-	-

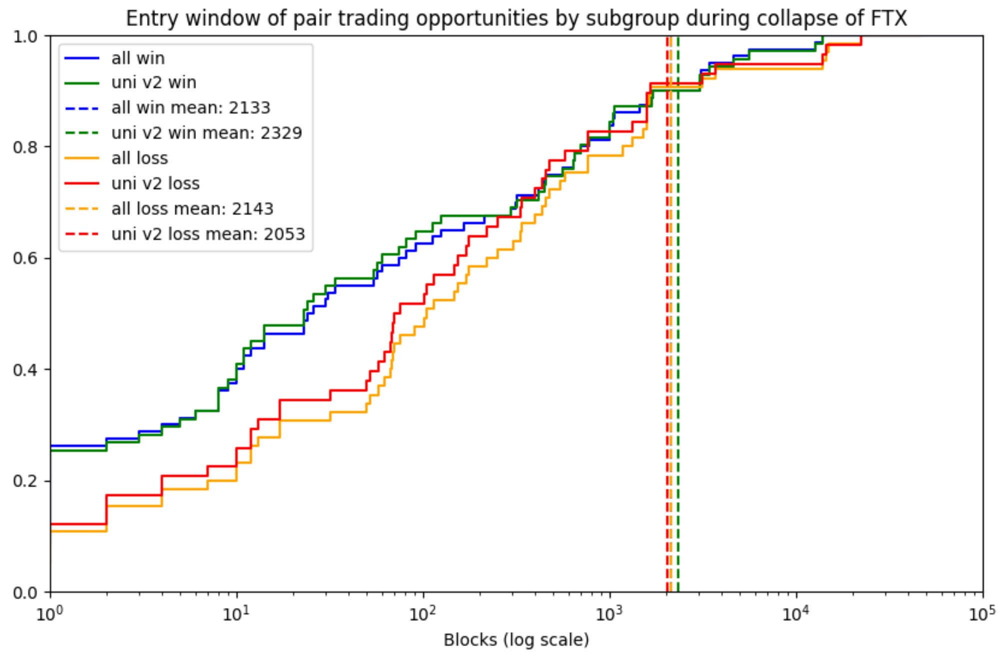

Figure 12: Entry window of pair trading opportunities during the collapse of FTX

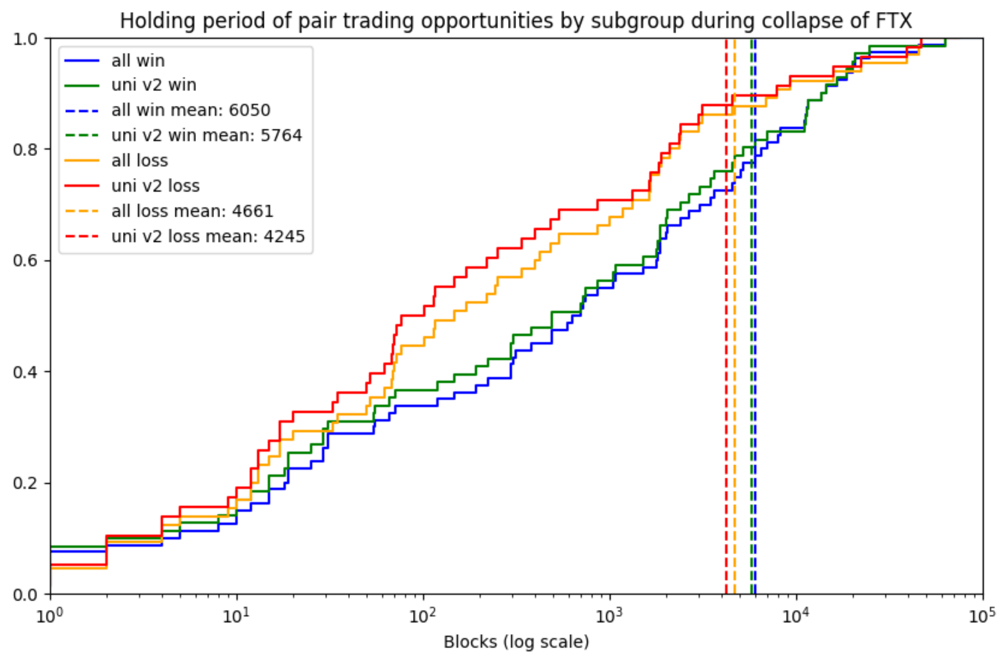

Figure 13: Holding period of pair trading positions during the collapse of FTX

4.4.2 Silicon Valley Bank

This subsection presents the results of analyses of whether different characteristics differ between blocks 16 790 000 and 16 850 000, a period when the bankruptcy of Silicon Valley

Bank caused increased market distress. First, I present the results of the analysis of whether the return of pair trading opportunities differs during this period. Next, I present the results of the analysis of whether the time sensitivity of pair trading positions differs during this period. Last, I present the results of the analysis of whether time pair trading positions must be held differ during this period.

The results of the analysis of whether returns of pair trading opportunities differ during the bankruptcy of Silicon Valley Bank are described in Table 10 and visualized in Figure 14. The median returns of pair trading opportunities are statistically lower compared to the rest of the returns in the data set at 5% significance based on a Mann-Whitney U test. Considering whether the pair trading opportunities tend to revert or diverge 58 out of the 143 opportunities reverted to their long run mean being 41% of all opportunities. This is statistically lower at 10% significance compared to the reversion rate of 48% in the rest of the data set based on a Chi-squared test.

The results of the analysis of whether the time sensitivity of pair trading positions differs during the bankruptcy of Silicon Valley Bank are described in Table 11 and visualized in Figures 15 and B11. The median of entry windows is statistically longer than the rest of the data set based on a Mann-Whitney U test for the whole sample in the Silicon Valley Bank sample at 5% statistical significance. This is mainly due to a longer entry window for diverging positions which is longer compared to the rest of the data set at 5% significance.

The results of the analysis of whether the period the pair trading positions must be held differ during the bankruptcy of Silicon Valley Bank are described in Table 12 and visualized in Figures 16 and B12. The median of the period is statistically longer for the whole sample than the rest of the data set based on a Mann-Whitney U test at 5% significance.

Table 10

Zero-investment pair trading positions' returns in terms of percentages during market distress caused by SVB

This table reports results on analysis of identification and quantification of pair trading based MEV opportunities between blocks 16 790 000 and 16 850 000. During this time there was increased market distress due to bankruptcy of Silicon Valley Bank. Panel A reports the summary statistics of returns of identified opportunities in different subgroups. Panel B reports summary statistics of returns of opportunities that reverted to their long run mean. Panel C reports summary statistics of returns of opportunities that diverged. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels for results of Mann-Whitney U test comparing medians of subset and the rest of the data set.

Panel A. Return of pair trading opportunities

Subgroup	Mean	St. Dev.	Min	Median	p(Median)	Max	N opportunities	N pairs
Whole dataset	-4.0%	38.9%	-100%	-7.4%**	(0.03)	116%	143	44
Balancer	102%	-	-	-	-	-	1	1
Uniswap v2 and forks	-5.5%	39.2%	-100%	-9.4%**	(0.01)	116%	131	39
Uniswap v3 all	4.4%	17.7%	-20.3%	9.1%	(0.24)	31.9%	11	4
Uniswap v3 0.3%	-3.7%	18.0%	-20.3%	-4.5%	(0.97)	14.4%	4	1
Uniswap v3 1%	9.1%	17.0%	-16.7%	14.1%	(0.14)	31.9%	7	3
Parity	-16.1%	32.9%	-65.4%	-0.1%**	(0.02)	1.2%	4	2

Panel B. Return of pair trading opportunities that reverted to long run mean

Subgroup	Mean	St. Dev.	Min	Median	p(Median)	Max	N opportunities	N pairs
Whole dataset	32.6%	27.7%	0.6%	25.4%	(0.71)	116%	58	31
Balancer	102%	-	-	-	-	-	1	1
Uniswap v2 and forks	32.9%	27.3%	0.6%	27.4%	(0.59)	116%	51	27
Uniswap v3 all	18.1%	8.2%	9.1%	15.0%**	(0.01)	31.9%	6	3
Uniswap v3 0.3%	11.7%	3.8%	9.1%	11.7%	(0.51)	14.4%	2	1
Uniswap v3 1%	21.2%	8.2%	14.1%	19.5%**	(0.01)	31.9%	4	2
Parity	0.9%	0.4%	0.6%	0.9%	(0.76)	1.2%	2	1

Panel C. Return of pair trading opportunities that diverged

Subgroup	Mean	St. Dev.	Min	Median	p(Median)	Max	N opportunities	N pairs
Whole dataset	-28.9%	22.2%	-100%	-24.6%	(0.16)	-0.8%	85	38
Balancer	-	-	-	-	-	-	-	-
Uniswap v2 and forks	-30.0%	24.4%	-100%	-25.7%	(0.13)	-0.8%	80	34
Uniswap v3 all	-12.0%	8.9%	-20.3%	-16.7%	(0.68)	-1.2%	5	4
Uniswap v3 0.3%	-19.2%	1.5%	-20.3%	-19.2%	(0.19)	-18.2%	2	1
Uniswap v3 1%	-7.2%	8.4%	-16.7%	-3.5%	(0.56)	-1.2%	3	3
Parity	-33.1%	45.6%	-65.4%	-33.1%	(0.12)	-0.8%	2	2

Table 11

Time sensitivity of entering pair trading positions during market distress caused by SVB

This table reports results on the analysis of the time sensitivity of pair trading-based MEV opportunities between blocks 16 790 000 and 16 850 000. During this time there was increased market distress due to the bankruptcy of Silicon Valley Bank. Panel A reports the summary statistics of the entry window of pair trading opportunities in different subgroups. Panel B reports summary statistics of the entry window of opportunities that reverted to their long-run mean. Panel C reports summary statistics of entry window of opportunities that diverged. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels for results of Mann-Whitney U test comparing medians of subset and the rest of the data set.

Panel A. Entry window of pair trading opportunities in blocks

Subgroup	Mean	St. Dev.	Min	Median	p(Median)	Max	N opportunities	N pairs
Whole dataset	1487	5214	0	154**	(0.01)	37719	142	65
Balancer	616	-	-	-	-	-	1	1
Uniswap v2 and forks	1464	5390	0	138**	(0.03)	37719	130	38
Uniswap v3 all	1834	2882	0	593	(0.50)	9365	11	4
Uniswap v3 0.3%	106	140	0	64	(0.21)	296	4	1
Uniswap v3 1%	2821	3273	482	1415**	(0.05)	9365	7	3
Parity	53	67	0	36**	(0.02)	141	4	2

Panel B. Entry window of pair trading opportunities that reverted to long run mean in blocks

Subgroup	Mean	St. Dev.	Min	Median	p(Median)	Max	N opportunities	N pairs
Whole dataset	694	1729	0	132	(0.27)	9365	58	43
Balancer	616	-	-	-	-	-	1	1
Uniswap v2 and forks	544	1361	0	107	(0.38)	7859	51	27
Uniswap v3 all	1976	3657	0	538	(0.71)	9365	6	3
Uniswap v3 0.3%	0	0	0	0*	(0.10)	0	2	1
Uniswap v3 1%	2964	4288	482	1004	(0.10)	9365	4	2
Parity	1	1	0	1	(0.33)	2	2	1

Panel C. Entry window of pair trading opportunities that diverged in blocks

Subgroup	Mean	St. Dev.	Min	Median	p(Median)	Max	N opportunities	N pairs
Whole dataset	2034	6587	0	164**	(0.04)	37719	84	52
Balancer	-	-	-	-	-	-	-	-
Uniswap v2 and forks	2058	6779	0	154*	(0.06)	37719	79	33
Uniswap v3 all	1663	1997	127	627	(0.46)	4835	5	4
Uniswap v3 0.3%	212	120	127	212	(0.86)	296	2	1
Uniswap v3 1%	2631	2111	627	2432	(0.18)	4835	3	3
Parity	105	51	69	105*	(0.06)	141	2	2

Table 12
Time pair trading positions take to revert or diverge during market distress caused by SVB

This table reports results on analysis of time it takes pair trading based MEV opportunities to revert or diverge between blocks 16 790 000 and 16 850 000. During this time there was increased market distress due to bankruptcy of Silicon Valley Bank. Panel A reports the summary statistics of returns of identified opportunities in different subgroups. Panel B reports summary statistics of returns of opportunities that reverted to their long run mean. Panel C reports summary statistics of returns of opportunities that diverged. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels for results of Mann-Whitney U test comparing medians of subset and the rest of the data set.

Panel A. The period pair trading position had to be active until price reverted or diverged in blocks								
Subgroup	Mean	St. Dev.	Min	Median	p(Median)	Max	N opportunities	N pairs
Whole dataset	3116	7491	3	292***	(0.01)	46022	142	65
Balancer	2935	-	-	-	-	-	1	1
Uniswap v2 and forks	2619	7101	3	264**	(0.02)	46022	130	38
Uniswap v3 all	9011	9959	32	5821	(0.22)	29156	11	4
Uniswap v3 0.3%	1857	3412	32	212	(0.23)	6973	4	1
Uniswap v3 1%	13099	10289	1143	12001***	(0.01)	29156	7	3
Parity	3367	6414	74	204**	(0.02)	12987	4	2
Panel B. The period pair trading position had to be active until price reverted in blocks								
Subgroup	Mean	St. Dev.	Min	Median	p(Median)	Max	N opportunities	N pairs
Whole dataset	3429	7830	3	415*	(0.07)	46022	58	43
Balancer	2935	-	-	-	-	-	1	1
Uniswap v2 and forks	2669	6952	3	316	(0.20)	46022	51	27
Uniswap v3 all	9966	11098	32	6397	(0.29)	29156	6	3
Uniswap v3 0.3%	3502	4908	32	3502	(0.50)	6973	2	1
Uniswap v3 1%	2964	4288	482	1004*	(0.06)	9365	4	2
Parity	6530	9131	74	6530	(0.17)	12987	2	1
Panel C. The period pair trading position had to be active until price diverged in blocks								
Subgroup	Mean	St. Dev.	Min	Median	p(Median)	Max	N opportunities	N pairs
Whole dataset	2900	7431	3	248**	(0.02)	40519	84	52
Balancer	-	-	-	-	-	-	-	-
Uniswap v2 and forks	2586	7240	3	227**	(0.02)	40519	79	33
Uniswap v3 all	7866	9538	127	4310	(0.53)	22595	5	4
Uniswap v3 0.3%	212	120	127	212	(0.36)	296	2	1
Uniswap v3 1%	12969	9181	4310	12001*	(0.06)	22595	3	3
Parity	204	12	195	204**	(0.03)	212	2	2

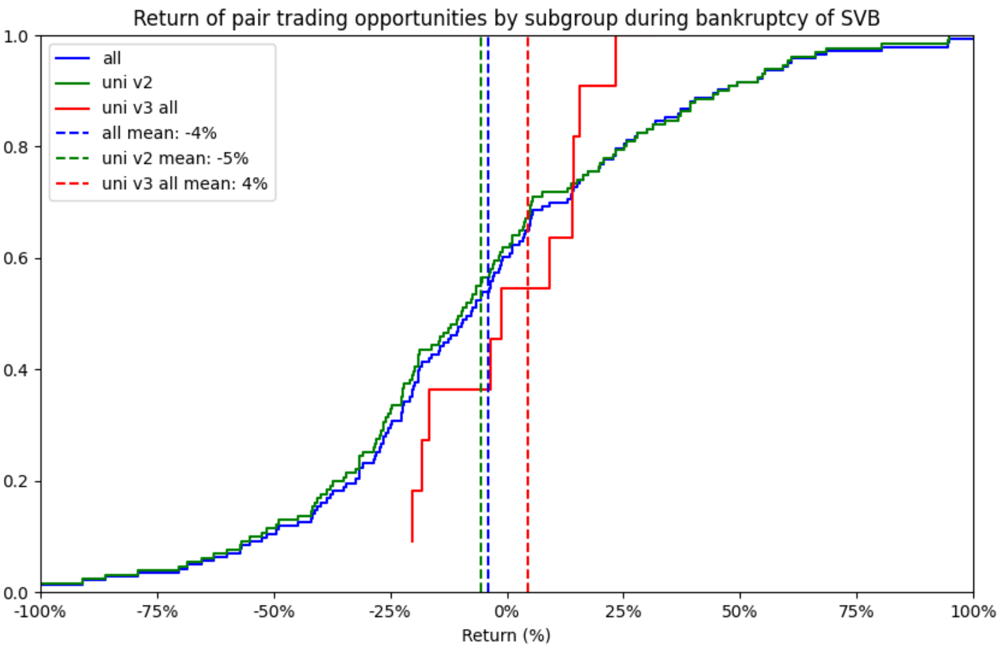

Figure 14: Return of pair trading opportunities in terms of percentages during the bankruptcy of SVB

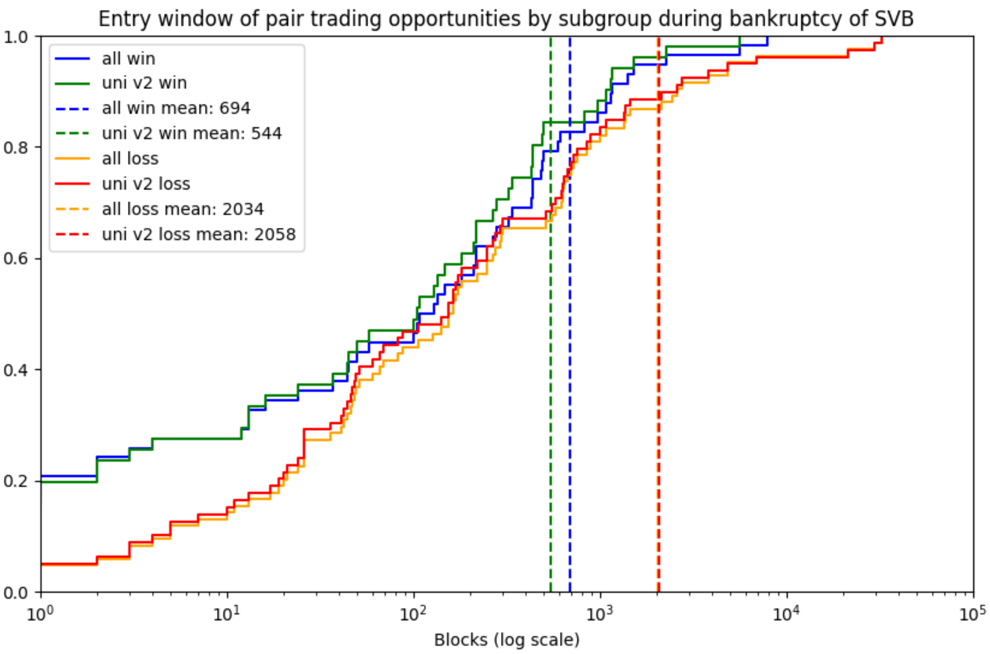

Figure 15: Entry window of pair trading opportunities during the bankruptcy of SVB

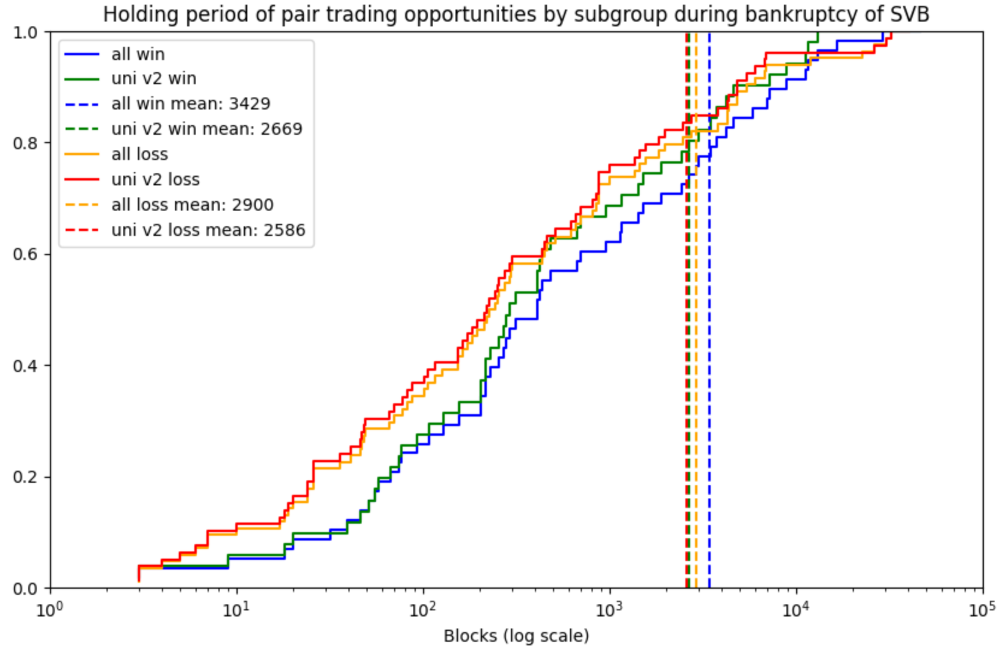

Figure 16: Holding period of pair trading positions during the bankruptcy of SVB

4.4.3 Curve

This subsection presents the results of analyses of whether different characteristics differ between blocks 17 800 000 and 17 860 000, a period when multiple Curve finance pools being exploited caused increased market distress. First, I present the results of the analysis of whether the return of pair trading opportunities differs during this period. Next, I present the results of the analysis of whether the time sensitivity of pair trading positions differs during this period. Last, I present the results of the analysis of whether time pair trading positions must be held differ during this period.

The results of the analysis of whether returns of pair trading opportunities differ shortly after the exploitation of Curve finance are described in Table 13 and visualized in Figure 17. The median returns of pair trading opportunities do not statistically differ from the rest of the data based on a Mann-Whitney U test.

Considering whether the pair trading opportunities tend to revert or diverge 142 out of the 286 opportunities reverted to their long run mean being 50% of all opportunities. This is not statistically different compared to the reversion rate of 48% in the rest of the data set based on a Chi-squared test.

The results of the analysis of whether the time sensitivity of pair trading positions differs shortly after the exploitation of Curve finance are described in Table 14 and visualized in Figures 18 and B13. The median of entry windows is statistically shorter from the rest of the data set for a whole sample at 10% significance and for the Uniswap v2 subgroup at 5% based on a Mann-Whitney U test.

The results of the analysis of whether the period the pair trading positions must be held shortly after exploitation of Curve finance are described in Table 15 and visualized in Figures 19 and B14. The median of the period is statistically shorter for both all and reverting positions of the whole sample compared to the rest of the data set based on a Mann-Whitney U test at 10% significance.

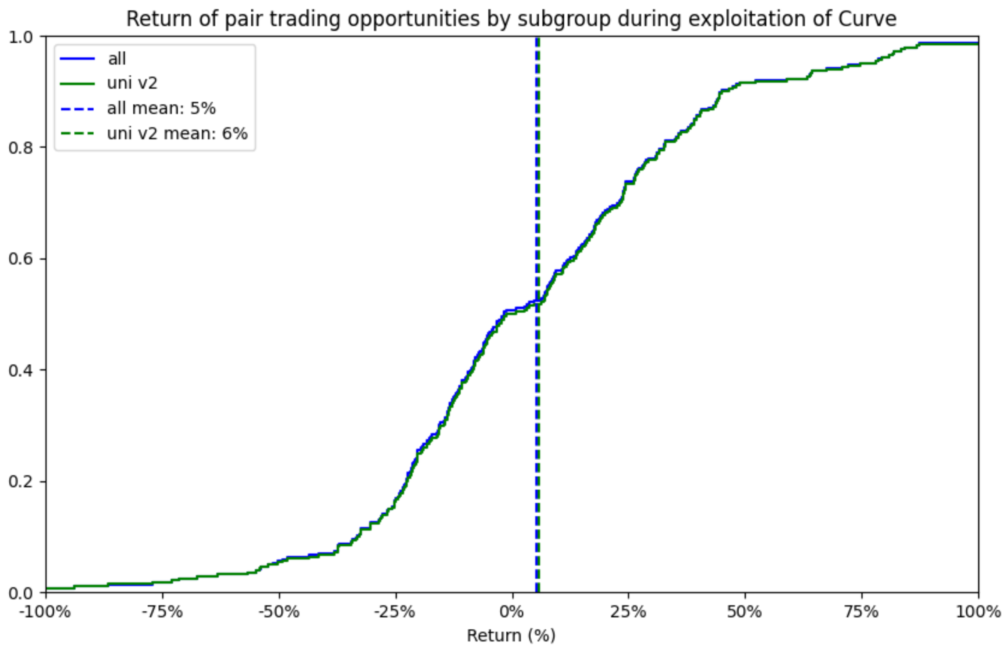

Figure 17: Return of pair trading opportunities in terms of percentages during exploitation of Curve Finance

Table 13
Zero-investment pair trading positions' returns in terms of percentages during market distress caused by Curve

This table reports results on analysis of identification and quantification of pair trading based MEV opportunities between blocks 17 800 000 and 17 860 000. During this time there was increased market distress due to multiple Curve finance pools being exploited. Panel A reports the summary statistics of returns of identified opportunities in different subgroups. Panel B reports summary statistics of returns of opportunities that reverted to their long run mean. Panel C reports summary statistics of returns of opportunities that diverged. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels for results of Mann-Whitney U test comparing medians of subset and the rest of the data set.

Panel A. Return of pair trading opportunities

Subgroup	Mean	St. Dev.	Min	Median	p(Median)	Max	N opportunities	N pairs
Whole dataset	5.4%	36.9%	-100%	-1.4%	(0.18)	130%	286	67
Balancer	-	-	-	-	-	-	-	-
Uniswap v2 and forks	5.9%	36.9%	-100%	1.8%	(0.13)	130%	282	65
Uniswap v3 all	-26.5%	18.0%	-51.2%	-23.2%**	(0.01)	-8.3%	4	2
Uniswap v3 0.3%	-	-	-	-	-	-	-	-
Uniswap v3 1%	-26.5%	18.0%	-51.2%	-23.2%**	(0.01)	-8.3%	4	2
Parity	78.6%	-	-	-	-	-	1	1

Panel B. Return of pair trading opportunities that reverted to long run mean

Subgroup	Mean	St. Dev.	Min	Median	p(Median)	Max	N opportunities	N pairs
Whole dataset	34.4%	26.5%	0.9%	26.8%	(0.39)	130%	142	44
Balancer	-	-	-	-	-	-	-	-
Uniswap v2 and forks	34.4%	26.5%	0.9%	26.8%	(0.88)	130%	142	44
Uniswap v3 all	-	-	-	-	-	-	-	-
Uniswap v3 0.3%	-	-	-	-	-	-	-	-
Uniswap v3 1%	-	-	-	-	-	-	-	-
Parity	78.6%	-	-	-	-	-	1	1

Panel C. Return of pair trading opportunities that diverged terms

Subgroup	Mean	St. Dev.	Min	Median	p(Median)	Max	N opportunities	N pairs
Whole dataset	-23.2%	19.0%	-100%	-19.8%	(0.14)	-1.2%	144	53
Balancer	-	-	-	-	-	-	-	-
Uniswap v2 and forks	-23.1%	19.1%	-100%	-19.3%**	(0.04)	-1.2%	140	51
Uniswap v3 all	-26.5%	18.0%	-51.2%	-23.2%*	(0.09)	-8.3%	4	2
Uniswap v3 0.3%	-	-	-	-	-	-	-	-
Uniswap v3 1%	-26.5%	18.0%	-51.2%	-23.2%**	(0.03)	-8.3%	4	2
Parity	-	-	-	-	-	-	-	-

Table 14
Time sensitivity of entering pair trading positions during market distress caused by Curve

This table reports results on the analysis of time sensitivity of pair trading-based MEV opportunities between blocks 17 800 000 and 17 860 000. During this time there was increased market distress due to multiple Curve finance pools being exploited. Panel A reports the summary statistics of the entry window of pair trading opportunities in different subgroups. Panel B reports summary statistics of the entry window of opportunities that reverted to their long-run mean. Panel C reports summary statistics of entry window of opportunities that diverged. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels for results of Mann-Whitney U test comparing medians of subset and the rest of the data set.

Panel A. Entry window of pair trading opportunities in blocks								
Subgroup	Mean	St. Dev.	Min	Median	p(Median)	Max	N opportunities	N pairs
Whole dataset	2188	8518	0	35*	(0.06)	78565	284	65
Balancer	-	-	-	-	-	-	-	-
Uniswap v2 and forks	2111	8460	0	32**	(0.05)	78565	280	63
Uniswap v3 all	7582	12201	612	1928*	(0.07)	25858	4	2
Uniswap v3 0.3%	-	-	-	-	-	-	-	-
Uniswap v3 1%	7582	12201	612	1928	(0.10)	25858	4	2
Parity	0	-	-	-	-	-	1	1
Panel B. Entry window of pair trading opportunities that reverted to long run mean in blocks								
Subgroup	Mean	St. Dev.	Min	Median	p(Median)	Max	N opportunities	N pairs
Whole dataset	1089	4114	0	22	(0.14)	38189	141	43
Balancer	-	-	-	-	-	-	-	-
Uniswap v2 and forks	1089	4114	0	22	(0.14)	38189	141	43
Uniswap v3 all	-	-	-	-	-	-	-	-
Uniswap v3 0.3%	-	-	-	-	-	-	-	-
Uniswap v3 1%	-	-	-	-	-	-	-	-
Parity	0	-	-	-	-	-	1	1
Panel C. Entry window of pair trading opportunities that diverged in blocks								
Subgroup	Mean	St. Dev.	Min	Median	p(Median)	Max	N opportunities	N pairs
Whole dataset	3272	11204	0	50	(0.32)	78565	143	52
Balancer	-	-	-	-	-	-	-	-
Uniswap v2 and forks	3148	11198	0	48	(0.23)	78565	139	50
Uniswap v3 all	7582	12201	612	1928	(0.12)	25858	4	2
Uniswap v3 0.3%	-	-	-	-	-	-	-	-
Uniswap v3 1%	7582	12201	612	1928	(0.19)	25858	4	2
Parity	-	-	-	-	-	-	-	-

Table 15
Time pair trading positions take to revert or diverge during market distress caused by Curve

This table reports results on analysis of time it takes pair trading based MEV opportunities to revert or diverge between blocks 17 800 000 and 17 860 000. During this time there was increased market distress due to multiple Curve finance pools being exploited. A reports the summary statistics of returns of identified opportunities in different subgroups. Panel B reports summary statistics of returns of opportunities that reverted to their long run mean. Panel C reports summary statistics of returns of opportunities that diverged. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels for results of Mann-Whitney U test comparing medians of subset and the rest of the data set.

Panel A. The period pair trading position had to be active until price reverted or diverged in blocks

Subgroup	Mean	St. Dev.	Min	Median	p(Median)	Max	N opportunities	N pairs
Whole dataset	3658	10484	1	145*	(0.09)	81009	284	65
Balancer	-	-	-	-	-	-	-	-
Uniswap v2 and forks	3580	10438	1	134	(0.14)	81009	280	63
Uniswap v3 all	9124	13983	663	2904	(0.36)	30026	4	2
Uniswap v3 0.3%	-	-	-	-	-	-	-	-
Uniswap v3 1%	9124	13983	663	2904	(0.64)	30026	4	2
Parity	1174	-	-	-	-	-	1	1

Panel B. The period pair trading position had to be active until price reverted in blocks

Subgroup	Mean	St. Dev.	Min	Median	p(Median)	Max	N opportunities	N pairs
Whole dataset	3018	8064	1	213*	(0.08)	50793	141	43
Balancer	-	-	-	-	-	-	-	-
Uniswap v2 and forks	3018	8064	1	213	(0.15)	50793	141	43
Uniswap v3 all	-	-	-	-	-	-	-	-
Uniswap v3 0.3%	-	-	-	-	-	-	-	-
Uniswap v3 1%	-	-	-	-	-	-	-	-
Parity	1174	-	-	-	-	-	1	1

Panel C. The period pair trading position had to be active until price diverged in blocks

Subgroup	Mean	St. Dev.	Min	Median	p(Median)	Max	N opportunities	N pairs
Whole dataset	4289	12415	1	101	(0.37)	81009	142	55
Balancer	-	-	-	-	-	-	-	-
Uniswap v2 and forks	4150	12396	1	89	(0.37)	81009	139	50
Uniswap v3 all	9124	13983	663	2904	(0.35)	30026	4	2
Uniswap v3 0.3%	-	-	-	-	-	-	-	-
Uniswap v3 1%	9124	13983	663	2904	(0.52)	30026	4	2
Parity	-	-	-	-	-	-	-	-

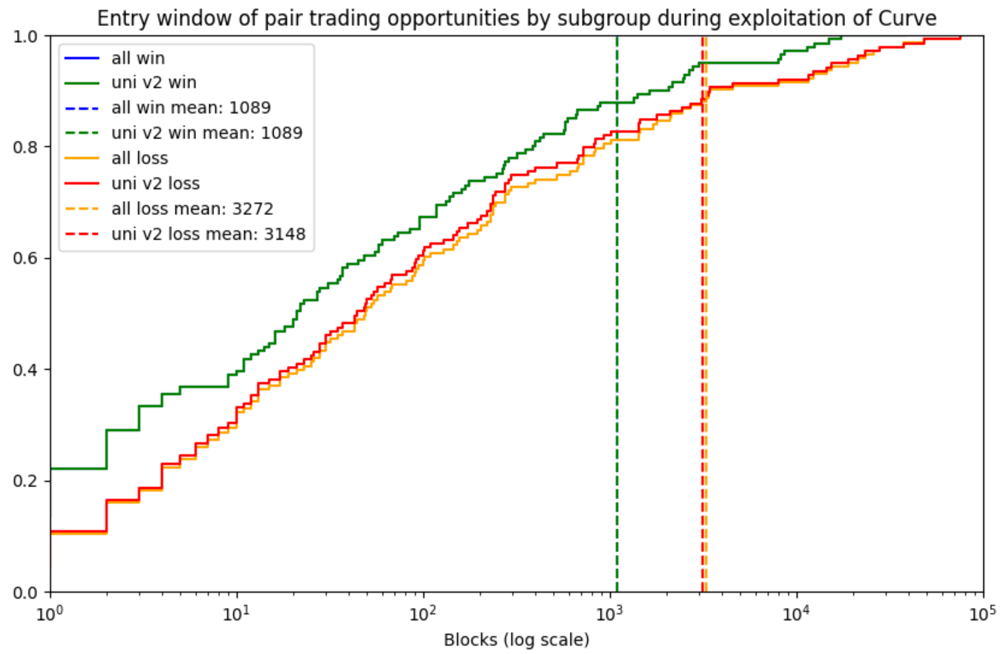

Figure 18: Entry window of pair trading opportunities during exploitation of Curve Finance

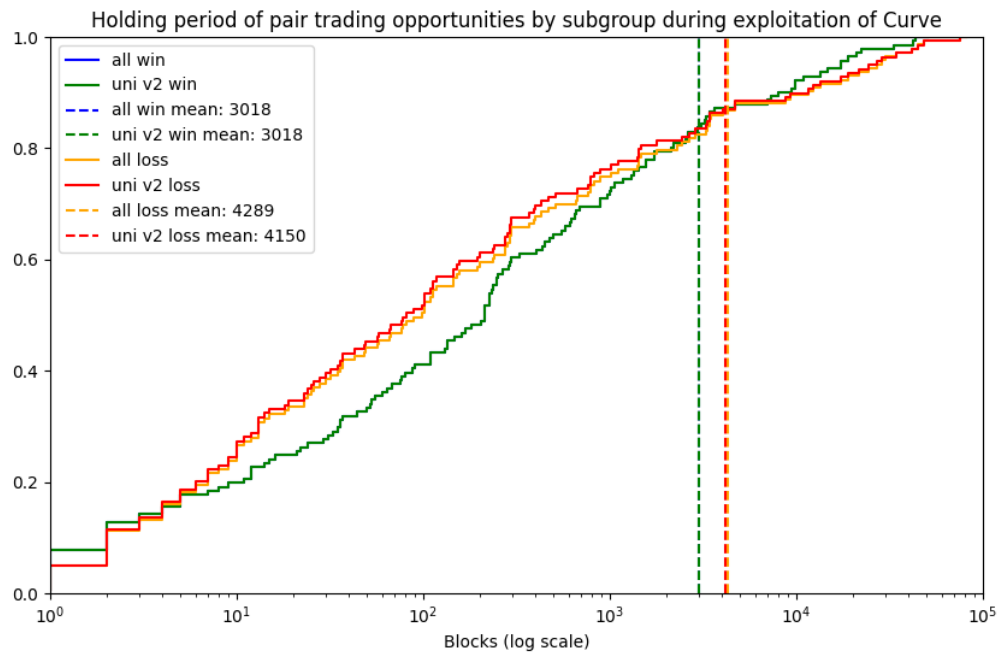

Figure 19: Holding period of pair trading positions during exploitation of Curve Finance

5 Discussion and findings

This chapter discusses the findings of the study. The first section summarizes the results of the research. The second section discusses the implications of the study. The third section suggests directions for future research.

5.1 Summary of results

The pair trading strategy has statistically negative median returns in terms of percentages for all subgroups at 1% significance, except for Balancer and Parity subgroups that are statistically positive at 1% significance. The means are positively different from zero at 1% significance for the whole data set and Uniswap v2 subgroup, positively different from zero at 5% significance for Balancer subgroup, and negatively different from zero at 1% significance for other subgroups.

In terms of dollars pair trading strategy has statistically negative median returns for the whole data set and Uniswap v2 subgroup at 1% significance and statistically positive median returns for Balancer and Parity subgroups at 1% significance. The means of the whole data set and all subgroups are positive. Uniswap v3 subgroups have positive returns in terms of dollars while the returns are negative in terms of percentages. This implies there is a variance in the size of pair trading opportunities and searchers should optimize the sizing of their positions to profit from the opportunities.

A lot of the pair trading opportunities are time sensitive with the shortest ones having an entry window of 0 blocks and half of the opportunities having an entry window of 53 blocks or below corresponding to roughly 11 minutes. The mean and median entry windows of opportunities reverting are shorter than those of diverging opportunities.

The minimum time a pair trading position must be held is 1 block. The median before position reverts is 190 blocks corresponding to 38 minutes. The mean is 4341 blocks corresponding to 14 hours. The mean and median time a diverging position must be held is shorter than that of a reverting position.

During the collapse of FTX, the median return of different subgroups does not statistically differ from the rest of the data, excluding Uniswap v3. During the sample period 48% of the 147 pair trading opportunities reverted, which is statistically higher at 10% significance than that of the rest of the data set. The entry window of pair trading opportunities did not differ from the rest of the data set during the collapse of FTX and the holding period was longer at 5% significance.

During the bankruptcy of Silicon Valley Bank, the median return of the whole data set was lower at 5% significance. 48% of the 143 opportunities reverted, which is statistically lower at 10% significance than that of the rest of the data set. The entry window and holding period pair trading positions are statistically longer in the Silicon Valley Bank sample compared to the rest of the data set.

Shortly after the exploitation of multiple Curve finance pools the median returns of pair trading opportunities do not statistically differ from the rest of the data set and the percentage of opportunities reverting in this sample is not statistically different from that of the rest of the data set. The entry window and holding period pair trading positions are statistically shorter in the sample compared to the rest of the data set.

5.2 Implications of the study

The findings of this research suggest that MEV searchers can use a pair trading strategy as a profitable MEV extraction strategy over a longer period as the mean of returns is positive. However, a negative median of opportunities suggests that individual opportunities tend to make a loss. Furthermore, the Uniswap v3 subgroup having a negative mean return in terms of percentages and positive in terms of dollars suggests sizing of positions plays a crucial part in searchers profiting from pair trading opportunities. Further research should be conducted to analyze what drives the returns of this strategy and whether losing opportunities could be filtered out.

The majority of the opportunities are relatively time sensitive with the median entry window for positions lasting for slightly above 10 minutes the median entry window for reverting positions lasting for 7 minutes and 14 minutes for diverging positions. Further research should be conducted to analyze if there are differing underlying characteristics that can explain why certain opportunities are more time sensitive than others and whether there is an efficient way to filter out diverging positions.

The majority of opportunities take 38 minutes to either revert or diverge with reverting positions taking the median of 60 minutes to revert and diverging positions taking the median of 25 minutes to diverge. Further research should be conducted to analyze if there are differing underlying characteristics that can explain why certain opportunities take longer to revert or diverge than others and whether there is an efficient way to filter out diverging positions.

The median return of pair trading opportunities decreased in two of the three samples with increased market distress. The holding period was longer in two of the three samples and shorter in one sample. The entry window was longer in one sample, was shorter in one sample, and did not change in one sample. A decrease in median returns combined with an increase in the holding period could suggest taking part in a pair trading strategy is less appealing during periods of increased market distress. However, the results are not unambiguous as in one sample the median returns did not change, and the holding period was shortened. Further research should be conducted on the underlying characteristics causing the returns to change in different market regimes. Future research could also analyze the risk and return profile of other statistical arbitrage opportunities compared to pair trading.

Besides unambiguous evidence of pair trading opportunities' characteristics changing under increased market distress, there is no evidence of competition among MEV searchers changing, when it comes to pair trading, during the observation period. There is no correlation between block number and return, entry window length, or holding period of position of the data set suggesting that there is no trend in these variables during the observation period. This suggests that the hypothesis of competition among MEV searchers increasing over the observation period cannot be supported by these pieces of information. This might be caused by pair trading opportunities having unappealing risk-adjusted returns.

6 Conclusion

6.1 Summary of the study

The purpose of this study is to perform an analysis of price discrepancies between a pair of assets on decentralized exchanges on top of Ethereum and whether sophisticated MEV searchers can take advantage of such discrepancies. The study aims to identify and quantify the pair trading-based MEV opportunities, analyze how long such price discrepancy can be taken advantage of, how long the holding period an average position in a price discrepancy has, and whether characteristics of pair trading-based MEV opportunities change under increased market distress.

I analyze a data set consisting of Uniswap v3, Uniswap v2, Uniswap v2 fork, and Balancer trading pairs between block number 15 537 394, which was produced on September 15, 2022, is the first block in the data set, and block number 18 083 778, which was produced on September 7, 2023. I filtered this data to only consist of actively traded trading pairs by removing trading pairs that had less than 1 000 transactions during the observation period. After filtering the data, I identify trading pairs whose price relationship is stationary and mean reverting by performing the augmented Dickey-Fuller test and Ornstein-Uhlenbeck process test to determine which trading pairs are suitable for pair trading.

I identify pair trading opportunities from the suitable trading pairs by considering trading fees and following previous pair trading literature defining price discrepancy that is between 2 and 4 standard deviations from the long-run mean to be a pair trading opportunity. After identifying pair trading opportunities, I determine whether the opportunity reverted to its long-run mean and was profitable, or whether the opportunity diverged to 4 standard deviations from the long-run mean and made a loss. I quantify the profitability of the pair trading strategy based on winning and losing pair trading opportunities.

Besides profitability, I consider how time sensitive entering pair trading opportunities after they are first present is and how long pair trading opportunities take to either revert or diverge. I also consider whether the different variables are correlated and whether the profitability, time sensitivity, or holding period changes during periods of increased market distress.

I find that pair trading logic can be applied as a profitable MEV extraction method over a long period, but individual opportunities tend to make a loss.

I find 600 pairs to be suitable for pair trading potentially. These pairs had over 6700 pair trading opportunities over the observation period of slightly under a year. Of these opportunities, 48% reverted to their long-run mean, while the other 52% diverged.
Reverting pair trading opportunities tend to have a shorter mean and median for a window of entry to take position in compared to pair trading opportunities that diverged. Similarly, diverging pair trading opportunities have shorter mean and median time the position takes to diverge compared to how long reverting opportunities take to revert.

I do not find unambiguous evidence to support a claim of pair trading opportunities' characteristics changing under increased market distress. Similarly, I also do not find competition among MEV searchers for pair trading opportunities having an increasing or decreasing trend during the observation period based on the correlation of time and different characteristics related to pair trading. This might indicate that MEV searchers find pair trading opportunities unappealing in terms of risk-adjusted returns compared to other MEV extraction strategies, but further research should be conducted on the topic.

6.2 Future research directions

While this study has provided valuable insights into the potential of pair trading as a means of capturing MEV on Ethereum, there are several intriguing avenues for further exploration and research. The following are potential future research directions that can deepen understanding of sophisticated MEV extraction methods and their impact on the blockchain industry.

I have analyzed pair trading opportunities based on MEV on top of Ethereum. The research could be replicated on top of other blockchains. This would give a better understanding of MEV under different blockchain microstructures and could potentially help in designing better blockchains in the future.

I have only focused on pair trading opportunities. Future research could study other statistical arbitrage strategies such as CeFi-DeFi arbitrage as a form of MEV. This would help to give a clearer picture of more sophisticated MEV extraction methods and the behavior of MEV searchers over time and under different market regimes. Future research could also analyze risk and return profiles between pair trading opportunities and other MEV extraction strategies. Other MEV extraction strategies might be a lot more appealing to the MEV searchers.

I perform an analysis of price discrepancies and reversion. Future research could build upon this to optimize different parameters to reduce the number and percentage of diverging pair trading positions. Future research could also expand on other relevant questions that have been omitted in this study such as inventory and risk management strategies the searchers taking part in pair trading and other forms of statistical arbitrage-based MEV should use. Future research could also analyze optimal exit points for pair trading positions to define what amount of reversion is optimal for take profit and what kind of stop loss the searchers should use.

The underlying characteristics causing the profitability of the pair trading strategy could be researched further to gain a better understanding of why the pair trading strategy is profitable and why certain price discrepancies last longer than others. Future research could, for example, consider whether the profitability of the pair trading strategy is caused by positions that carry high risk.

Future research could combine analysis of pair trading with analysis of atomic arbitrage opportunities MEV searchers take advantage of and trading activity. Combining these analyses could help in understanding whether MEV searchers change their behavior under increased market distress.

Acknowledgements

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Appendices

Appendix A

Table A1

Most active pair trading pairs

This table lists 25 trading pairs with the most pair trading opportunities.

	Trading pair	Cryptocurrency 1	Cryptocurrency 2	Pair trading opportunities
1	0x6AdA49AECCF6E556Bb7a35ef0119Cc8ca795294A	WETH	WOO	136
2	0xA7a8eDfda2B8bF1e5084E2765811Effee21Ef918	WETH	WXRP	115
3	0x60F6E2200bFEf8b4d120028Faff4D9A4486526f4	WETH	IONX	114
4	0xe219a14e355c1Cb3f43594655A63488DA154E8Eb	USDC	USDT	104
5	0x92CC4300B9FD36242900BcA782b2E9E000BD5099	WETH	ROUTE	103
6	0x1144Bb78DB2dD3D24cA786Ab6AeEBd78B4009a63	WETH	SAFEMOON2	87
7	0x854373387E41371Ac6E307A1F29603c6Fa10D872	WETH	FEG	85
8	0x16f60256a518e5D1dD9cF2Cefc3d4A601c399574	WETH	ZZ	82
9	0xd583D0824Ed78767E0E35B9bF7a636c81C665Aa8	WETH	LYXe	71
10	0x80D972d2a62Ba71814F4e08Bd27F95E5D81d02a9	WETH	STOS	67
11	0xd99563940F296eb2384989F8e7314d7dBdc48535	WETH	BIC	62
12	0x1b8d13207f4b0A47B5086329dc789D712277c9A1	WETH	AI	61
13	0x67aed537eEBA768a07567cBa400489DDd4715Fa5	WETH	SHUGGI	61
14	0x9E1AD82b1d505f8f8Ea10C9F2DA10E94A280Ff79	WETH	BIRD	55
15	0xA1d7b2d891e3A1f9ef4bBC5be20630C2FEB1c470	WETH	SNX	55
16	0x7FdEB46b3a0916630f36E886D675602b1007Fcbb	WETH	VOW	54
17	0xcB36FCC6fdd19d447c84C9122811CbD0cF7fe497	WETH	BFC	52
18	0xf169CeA51EB51774cF107c88309717ddA20be167	WETH	CREAM	52
19	0x990cAa3a8647aF90C308E2d304b6E3ce6728CB46	WETH	SYPHEX	51
20	0xB961e90b10608cFf90A76557a2E02e007Fe2b062	WETH	MIC	49
21	0xe1477227428d56B8d800446396e7306E1449b280	WETH	OMH	48
22	0x8F1aa1648725d136B74048557ed54cf7A5940bDb	WETH	SG	48
23	0x23FD68bdD8A654e56a19eC9eDD73a9900c9d0e7B	WETH	PawZ	45
24	0xd09b631393BA61DA3537451814eBD477D2047183	WETH	SPINU	44
25	0x28B498e35AcE6a51192c88F4362bD4acC3f98165	WETH	TRUMP	42

Appendix B

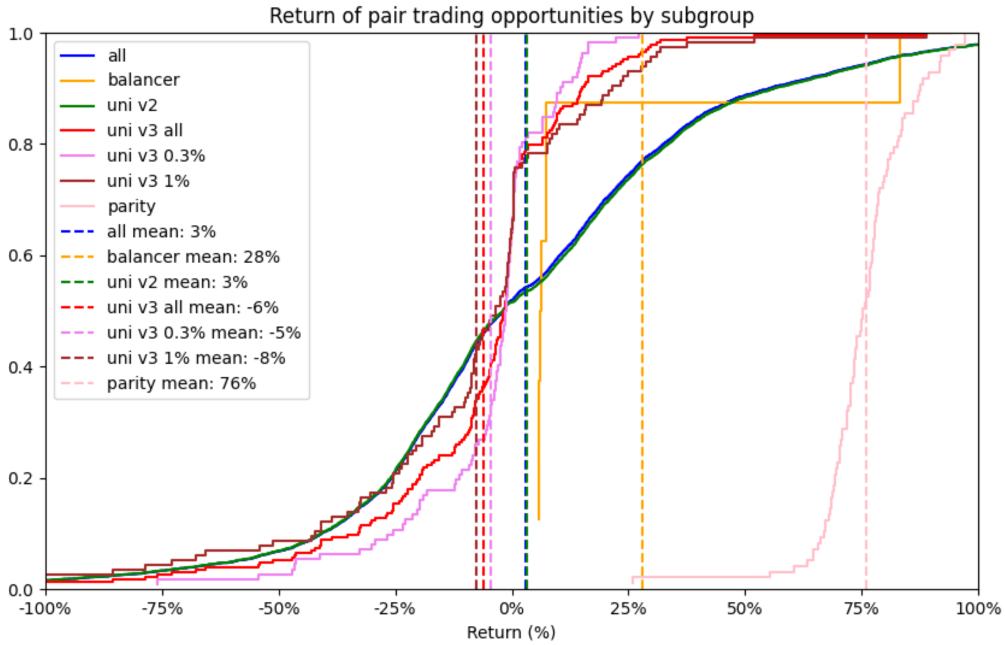

Figure B1: Return of pair trading opportunities in terms of percentages

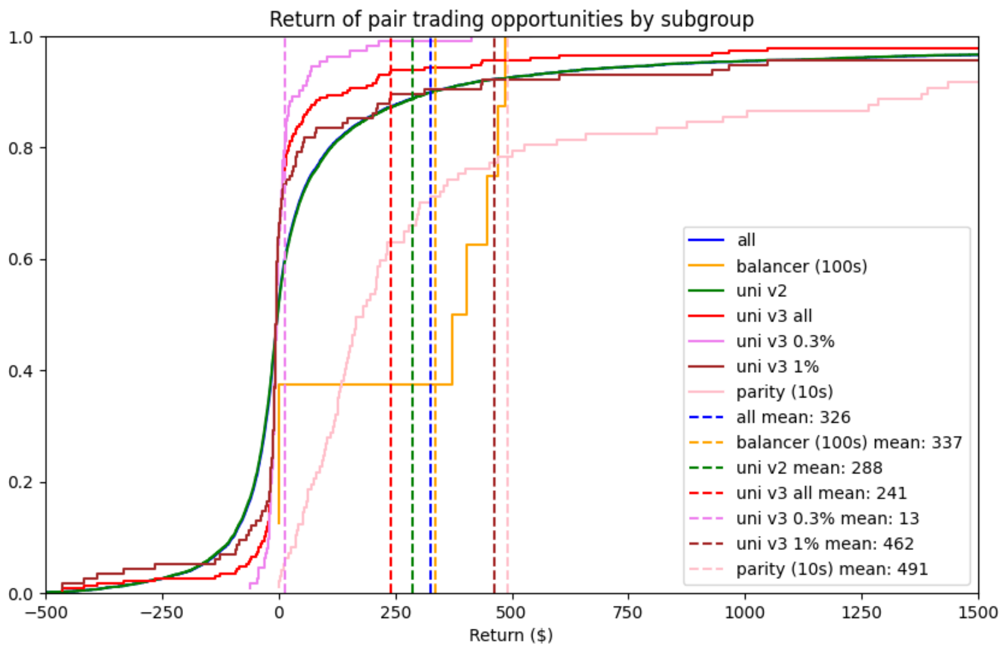

Figure B2: Return of pair trading opportunities in terms of dollars

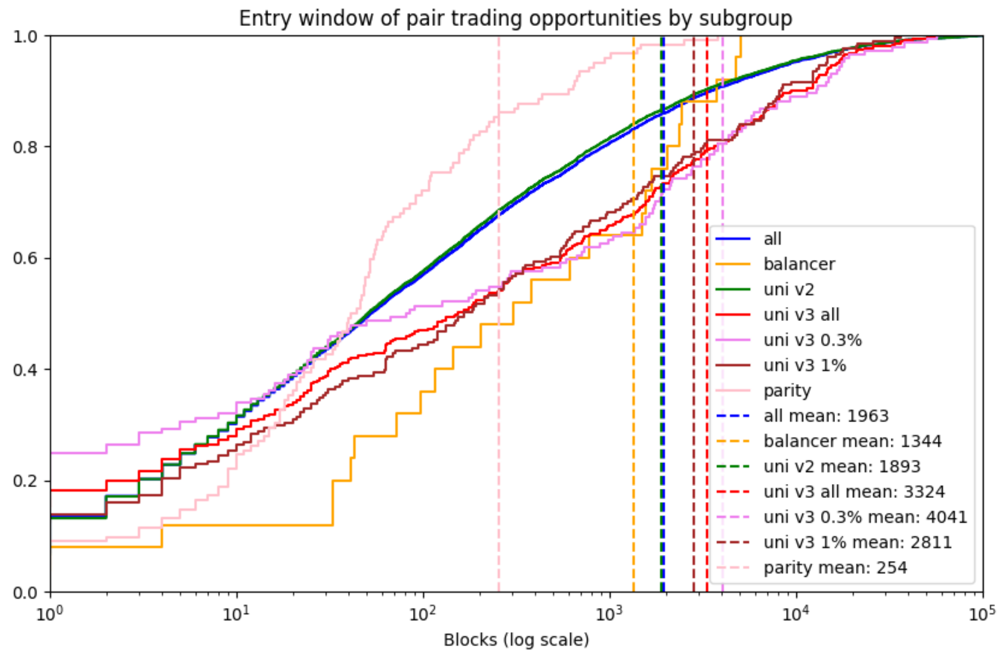

Figure B3: Entry window of pair trading opportunities

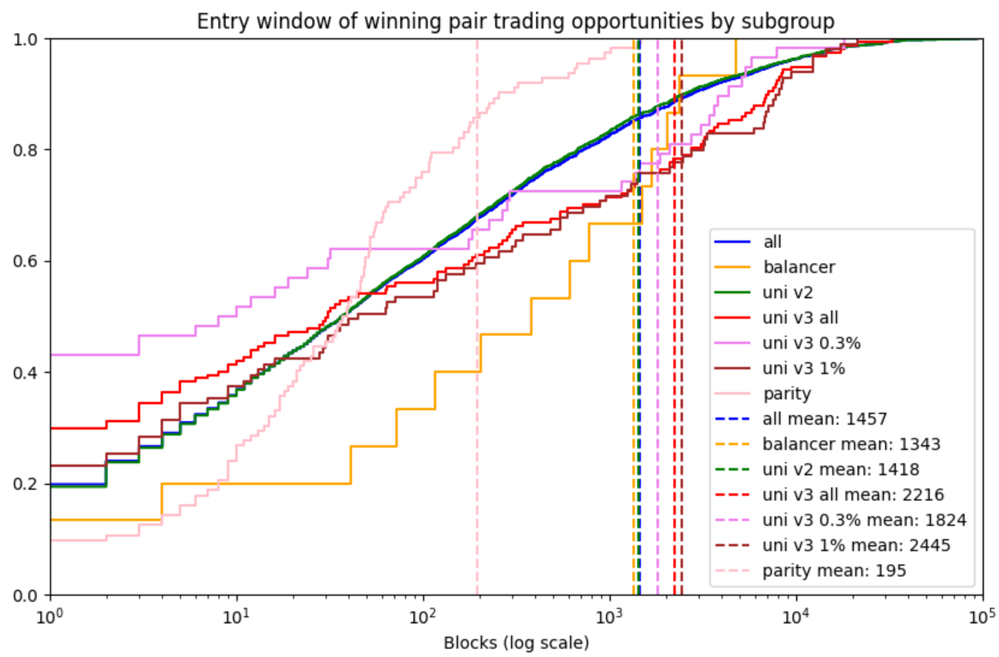

Figure B4: Entry window of winning pair trading opportunities

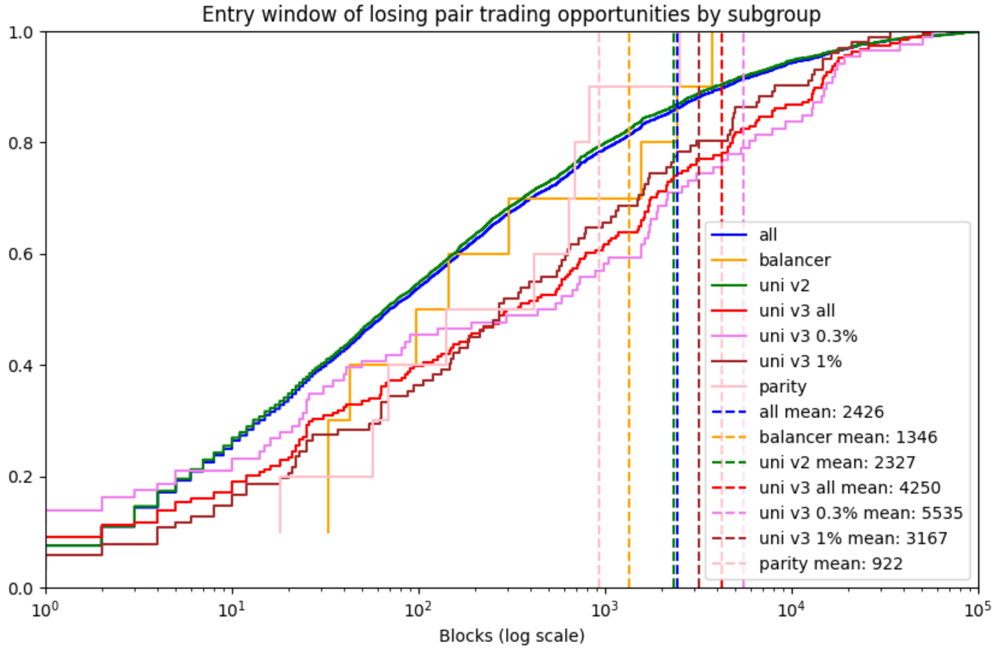

Figure B5: Entry window of losing pair trading opportunities

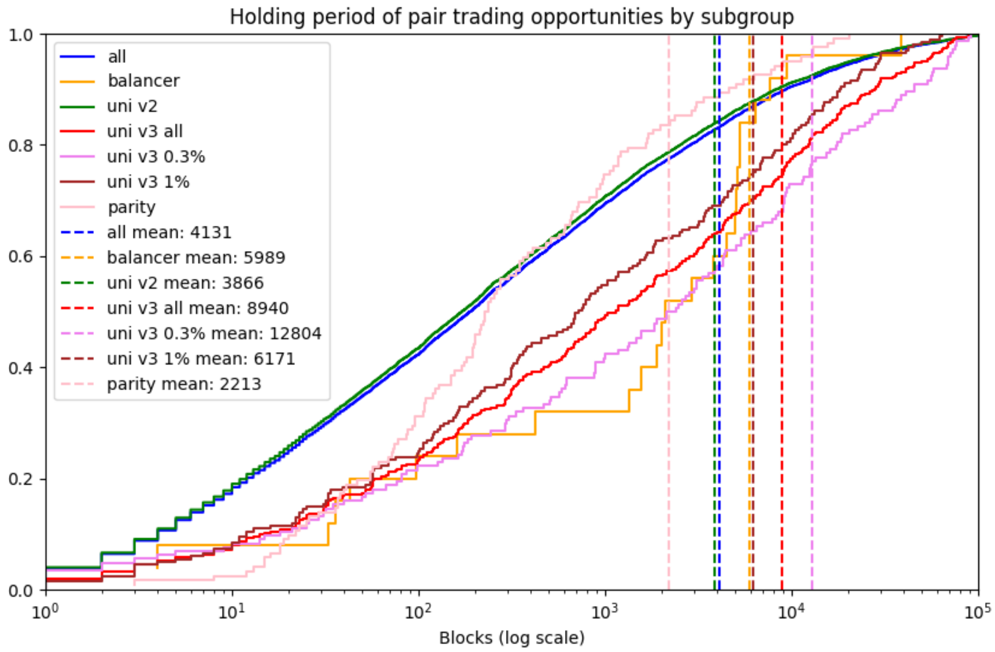

Figure B6: Holding period of pair trading positions

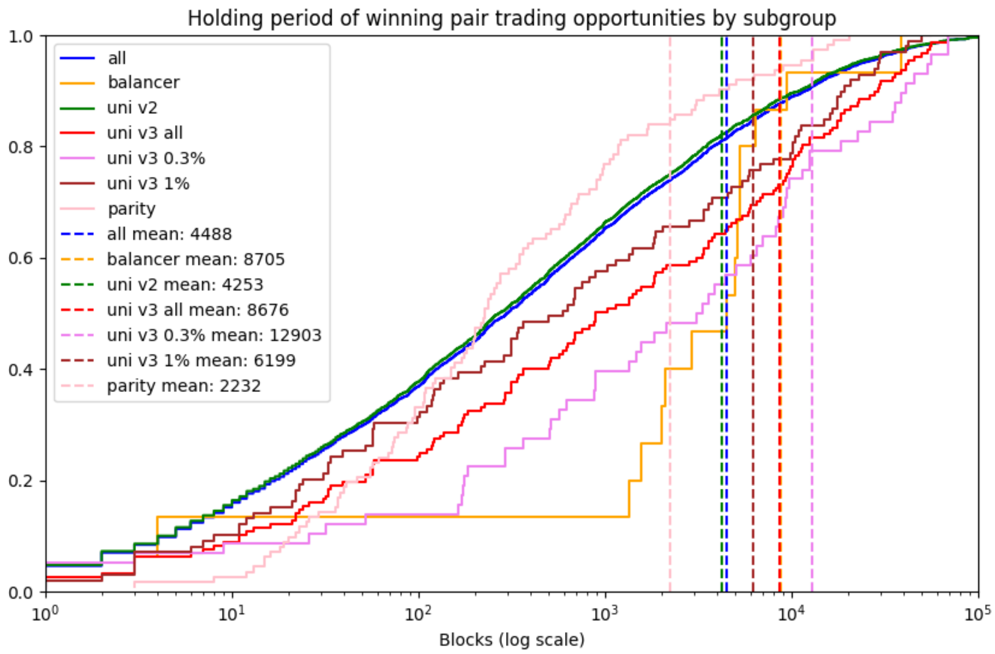

Figure B7: Holding period of winning pair trading positions

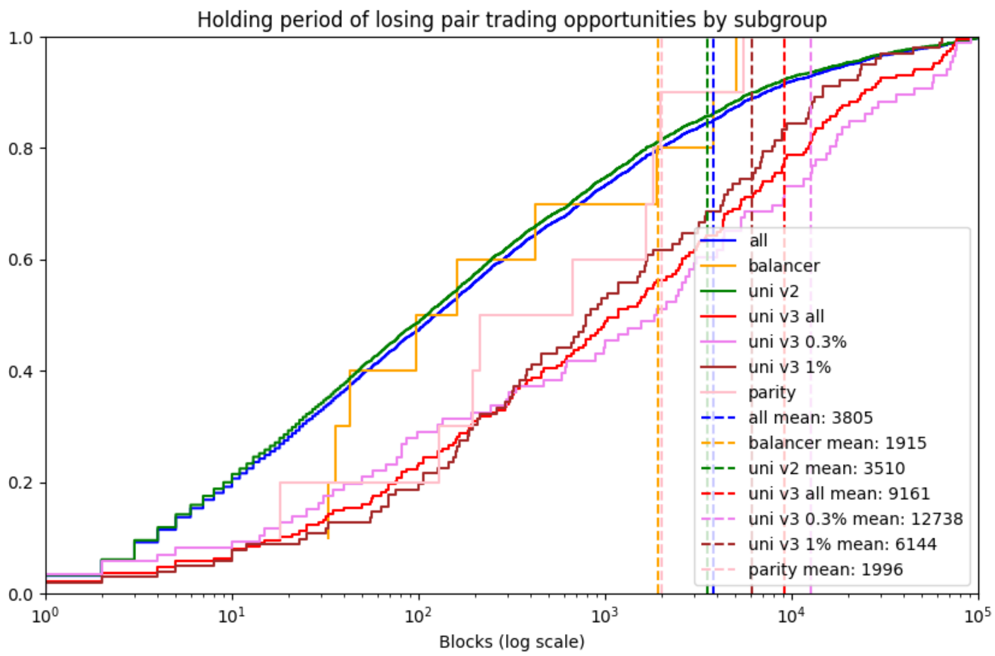

Figure B8: Holding period of losing pair trading positions

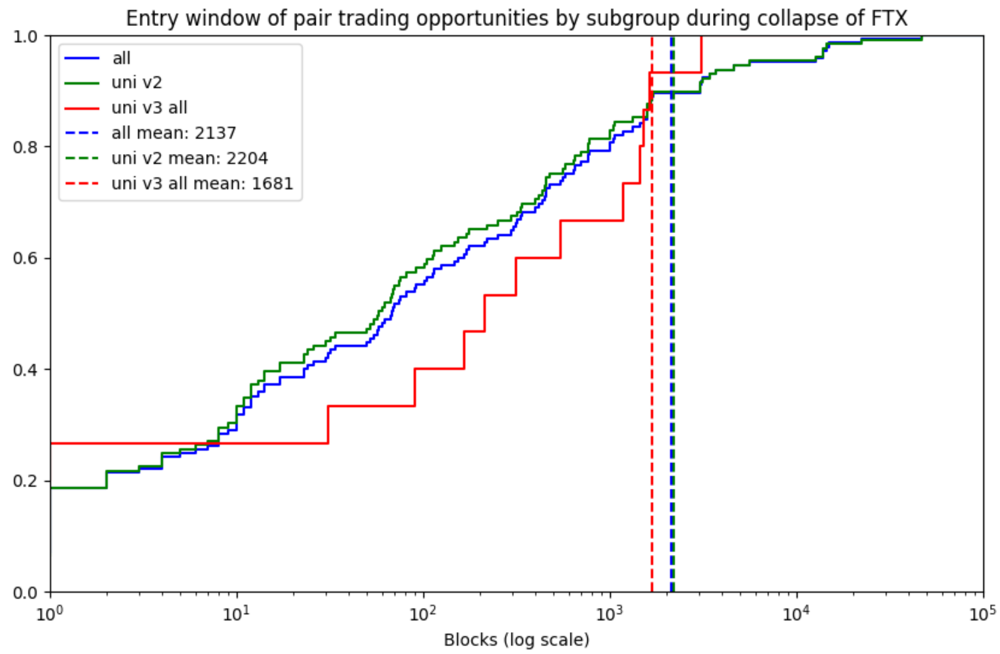

Figure B9: Entry window of pair trading opportunities during the collapse of FTX

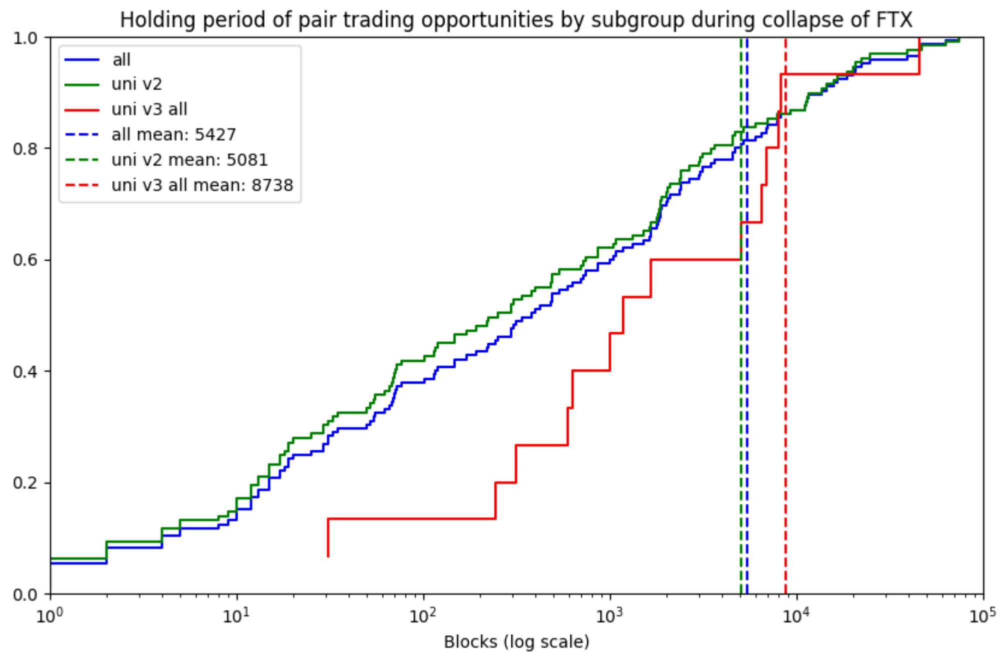

Figure B10: Holding period of pair trading positions during the collapse of FTX

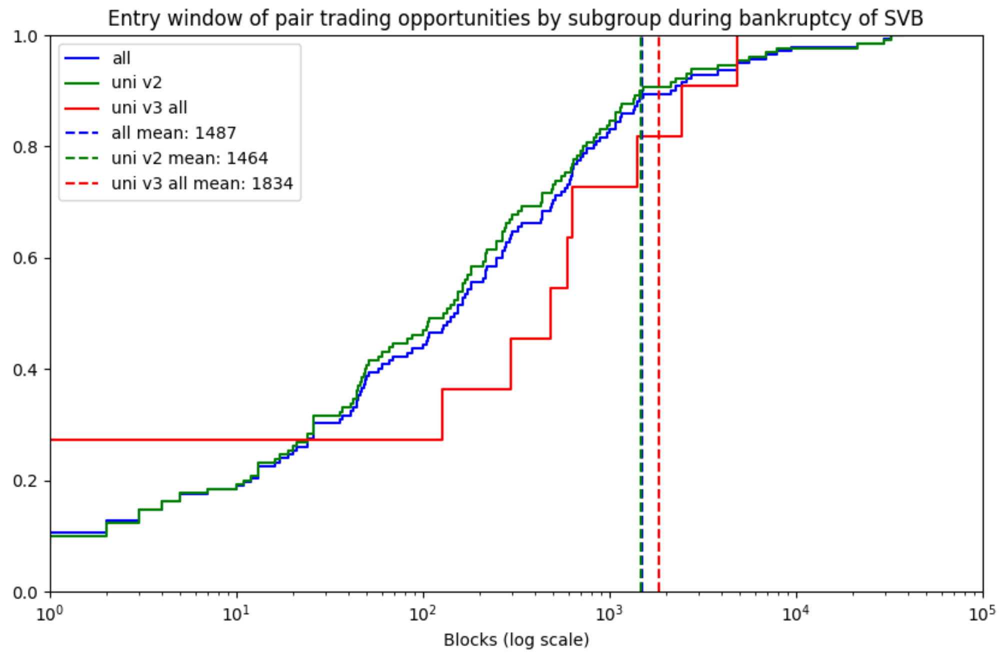

Figure B11: Entry window of pair trading opportunities during the bankruptcy of SVB

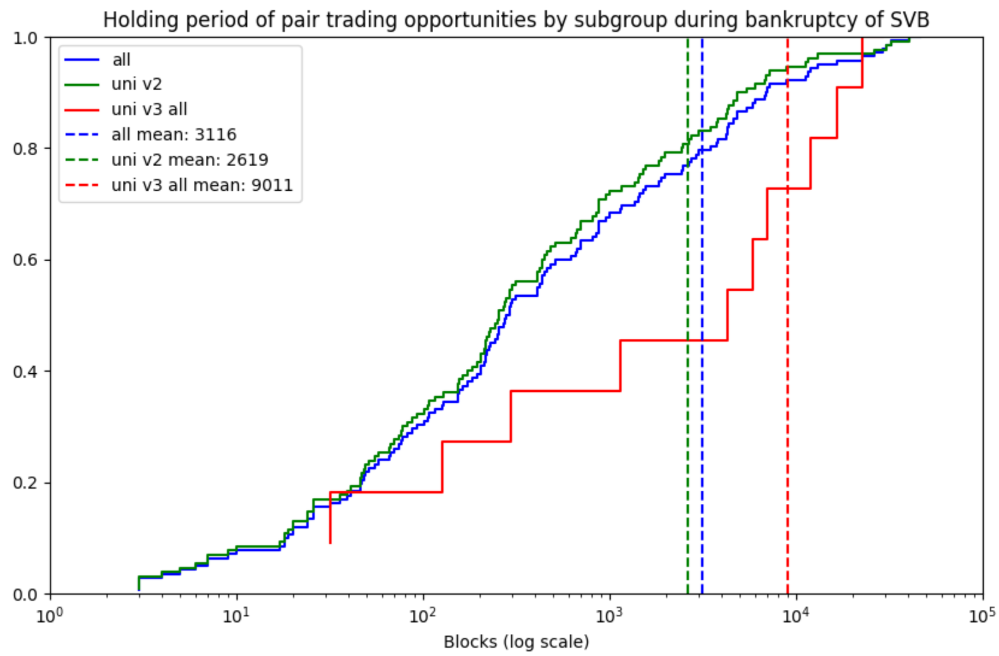

Figure B12: Holding period of pair trading positions during the bankruptcy of SVB

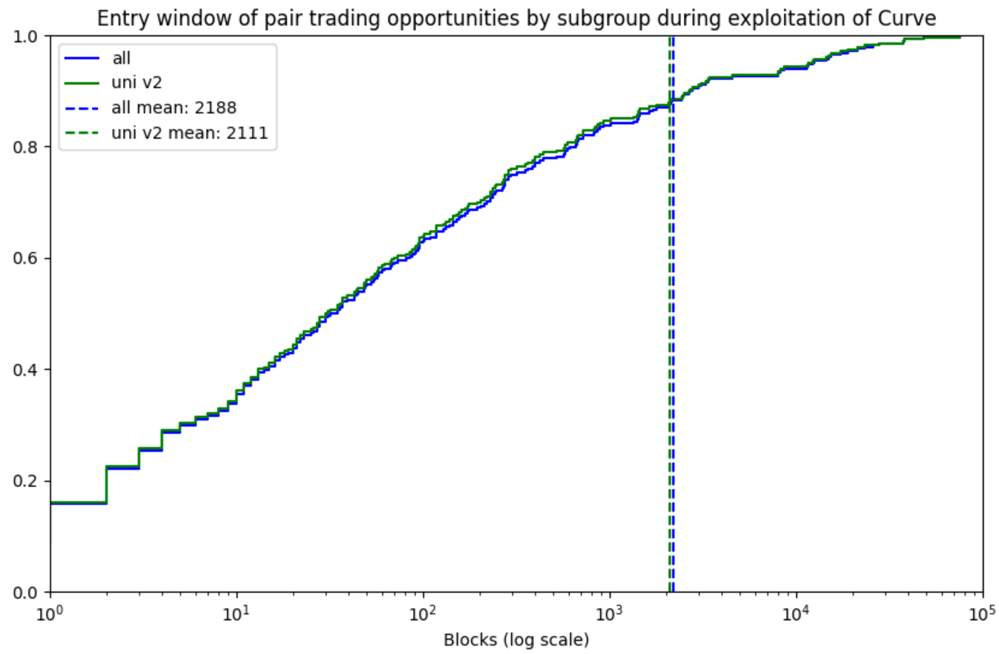

Figure B13: Entry window of pair trading opportunities during exploitation of Curve Finance

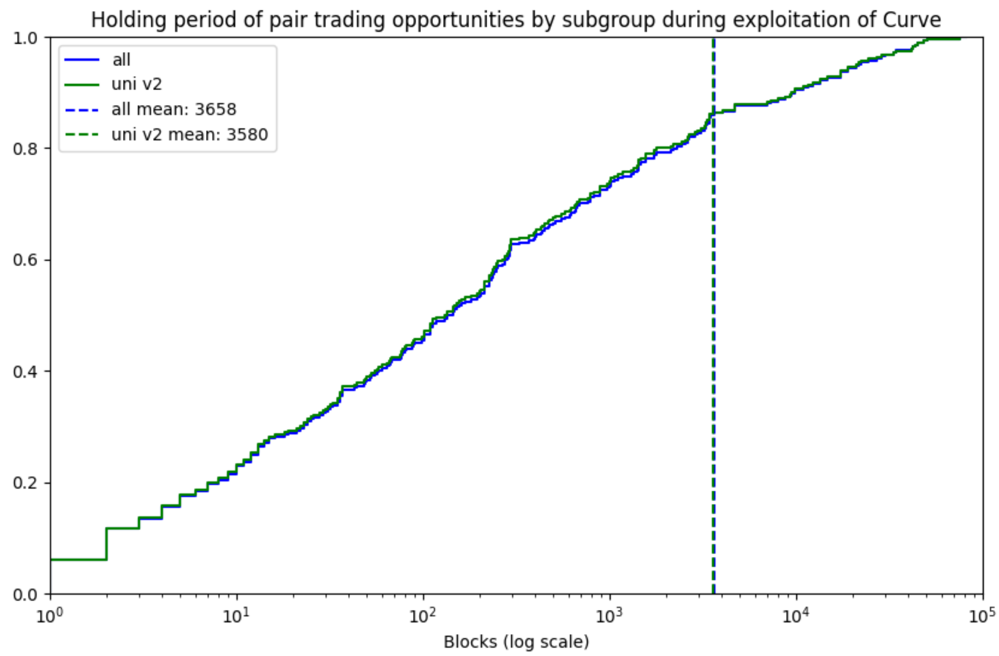

Figure B14: Holding period of pair trading positions during exploitation of Curve Finance