Transaction Cost Analysis in High-Frequency Trading: Active vs Passive Investment Strategies

GitHub

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1 Introduction

In recent years, the landscape of financial trading has been increasingly shaped by advances in algorithmic strategies and the availability of high-frequency data. Among these strategies, high-frequency trading (HFT) has emerged as a dominant force, leveraging rapid market movements and order flow dynamics to generate profits in short time frames. In contrast, passive trading strategies adopt a more deliberate approach, focusing on longer holding periods and minimizing transaction activity. This study aims to compare the effectiveness of these two distinct strategies using a dataset of 1-second trading data for Bitcoin (BTC), Ethereum (ETH) and Cardano (ADA) over 2 weeks.

A key aspect of this analysis is the investigation of how trading fees impact profitability under each strategy. While HFT strategies thrive on frequent, small-margin trades, the associated costs, such as transaction fees and slippage, can significantly impact their returns. On the other hand, passive strategies may achieve higher net returns despite capitalizing on fewer short-term opportunities. By examining the role of fees and the profitability of each approach, this study provides valuable insights into the trade-offs between active and passive trading in high-frequency environments.

2 Datasets

The dataset used in this study consists of three files containing 1-second interval trading data for Bitcoin (BTC), Ethereum (ETH), and Cardano (ADA) from 2021/04/07 until 2021/04/19. Each file includes key market features such as mid price, bid-ask spreads, notional order flow volumes, and distances from the mid point for bids and asks. The dataset is sourced from a publicly available repository on Kaggle[1].

Regarding fees, another dataset has been created containing fees data from 2021/04/07 until 2021/04/19 for BTC, ETH, and ADA. The data sources for each cryptocurrency are as follows:

- **BTC (Bitcoin):** The average ratio of satoshi/byte for a particular day is present in the memory pool. This data can be found at: https://mempool.space/graphs/mempool4y.
- **ETH (Ethereum):** The average Wei fee (1 Wei = 10^{-18} ETH) for a particular day is available at: https://etherscan.io/chart/gasprice.
- **ADA (Cardano):** The average daily fee in ADA can be accessed at: https://cexplorer.io/.

3 Market Microstructure Analysis

The market microstructure analysis1 reveals distinct patterns across the three studied cryptocurrencies. Bitcoin demonstrates the most stable spread characteristics, with consistently tight spreads averaging 0.01% of the midpoint price, indicating superior market liquidity. Ethereum exhibits moderate spread volatility with an average of 0.15%, while Cardano shows the widest and most volatile spreads (averaging 0.20%), reflecting its relatively lower market depth. The correlation heatmaps reveal strong relationships between bid-ask spreads and market depth metrics, particularly for BTC and ETH, suggesting that liquidity dynamics are closely interconnected.

Order flow analysis shows asymmetric patterns between bid and ask sides, with notable spikes in market notional values corresponding to periods of increased volatility.

Temporal analysis of these metrics indicates distinct intraday patterns, with spreads typically

[1] https://www.kaggle.com/datasets/martinsn/high-frequency-crypto-limit-order-book-data

widening during periods of lower liquidity and contracting during peak trading hours. This microstructure analysis suggests that transaction costs vary significantly across these cryptocurrencies, with Bitcoin offering the most favorable execution conditions for high-frequency trading strategies, while Cardano requires more careful execution timing and size consideration to minimize market impact.

4 Decentralized Exchanges (DEX)

For this study, we will focus on decentralized trades. We decided not to analyze centralized exchanges where users deposit cryptocurrency on platforms like Coinbase or Binance, which act as intermediaries for buyers and sellers. For instance, if you wish to trade Ethereum for Bitcoin, the centralized exchange supplies the liquidity necessary to make the trade possible. In return, users pay fees directly to the exchange, which can vary based on multiple factors, including the trading volume and the user's membership tier.

Instead, we chose to work with decentralized exchanges (DEXs), which operate without intermediaries. DEXs allow users to retain control of their funds throughout the trading process. Trades are executed directly between users. This eliminates the need for centralized entities, offering greater transparency and decentralization. However, DEXs introduce unique challenges, such as higher transaction fees during network congestion and the reliance on liquidity pools, which may affect trade execution efficiency.

5 Fees analysis

In this study, we accounted for three types of fees that impact trading strategies:

- **Trading Fees:** A fixed fee of 0.3% of the trade value, charged by the DEX for executing trades.
- **Slippage:** A fixed fee of 0.01% for passive trading and 0.02% for HFT, representing the difference between the expected and actual execution price due to market liquidity.
- **Network Fees:** These are blockchain-specific fees required to process and validate transactions on the network. The calculation of these fees varies depending on the cryptocurrency.

Network fees are small payments made by users to incentivize miners (for BTC) or validators (for

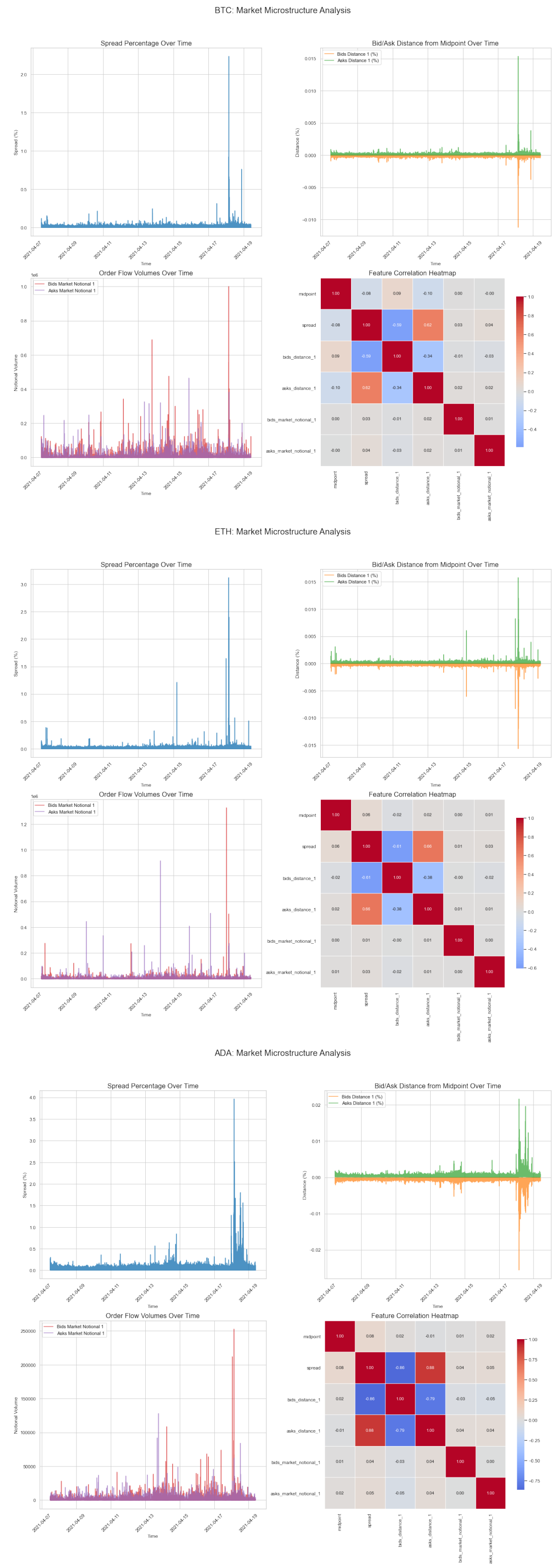

Figure 1: Market microstructure analysis for BTC, ETH and ADA

ETH) to include their transactions in the next block. These fees are fundamental for maintaining the blockchain ecosystems, ensuring transactions are prioritized and validated efficiently. A transaction fee represents the cost of sending funds and it depends on the network demand at that moment (network congestion) and the size of the transaction.

When a user initiates a transaction, they generate a digital message that includes the transfer details, such as the amount being sent, the sender's wallet address, and the recipient's wallet address. This transaction is broadcast to the network and awaits inclusion in a block. Since block space is finite, use can pay more fees to incentivize miners to prioritize their transactions.

5.1 Bitcoin (BTC) Network Fees

Bitcoin fees are determined by two main factors: the size of the transaction in bytes and the level of network congestion. Each block has a fixed size limit of 1 MB, which restricts the number of transactions that can be included. To incentivize miners, users attach fees to their transactions, measured in satoshis per byte (*sat/B*). Transactions with higher fees are given priority during times of congestion, as miners aim to maximize their earnings.

The size of a transaction depends on its complexity. For example, transactions involving multiple inputs or outputs are larger in size and incur higher fees. For our analysis, we will consider a basic transaction with one input and one output. The size of this type of transaction is 258 bytes. The final fee for BTC is calculated using the formula:

$$\text{Fee} = 258 \times (\text{satoshi/byte}) \times 10^{-8}$$

Where:

- **258**: The size of the basic transaction in bytes.
- **satoshi/byte**: The fee rate in satoshis per byte.
- 10^{-8}: The conversion factor from satoshis to Bitcoin (1 BTC = 10^8 satoshis).

5.2 Ethereum (ETH) Network Fees

Ethereum transaction fees are calculated using a mechanism based on *gas*, which measures the computational resources required to process a transaction. For simple fund transfers, the gas usage is at 21,000 units of gas.

Wei is the smallest unit of ETH and corresponds to 10^{-18} ETH. The cost of a transaction depends on the amount of gas used and the prevailing gas price, which fluctuates based on network demand. The formula for calculating the transaction fees is:

$$\text{Fee} = 21,000 \times (\text{Wei price at the moment}) \times 10^{-18}$$

Where:

- **21,000**: The gas required for a simple fund transfer.
- **Wei price at the moment**: The prevailing gas price in Wei.
- 10^{-18}: The conversion factor from Wei to ETH (1 ETH = 10^{18} Wei).

5.3 Cardano (ADA) Network Fees

Cardano's fee structure is deterministic and does not depend on network congestion. The cost of a transaction is calculated using a simple formula:

$$\text{Fee} = a + b \times \text{Transaction Size},$$

where a is a fixed base fee (A=0.155381 ADA), and b is a per-byte cost factor (B=0.000044 ADA/byte). a and b are constants that do not change significantly over time. These parameters are protocol-specific and can vary slightly depending on updates. The transaction size refers to the amount of data contained in the transaction, for our analysis we will use 200 bytes for each transaction. This deterministic approach makes fees stable and predictable, regardless of network demand.

Below is a graphical representation of the network fees trend for BTC, ETH, and ADA over the period from 2021/04/07 to 2021/04/19. The graph has been scaled such that y=0 is the average fee of the analyzed period.

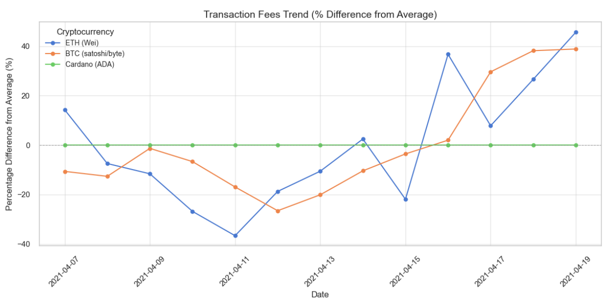

Figure 2: Network Fees Trend for BTC, ETH, and ADA (2021/04/07 - 2021/04/19)

Below is the trend of midprice for BTC, ETH, and ADA over the same period.

We can notice some spikes in the fees graph at the end of our analyzed period for BTC and ETH,

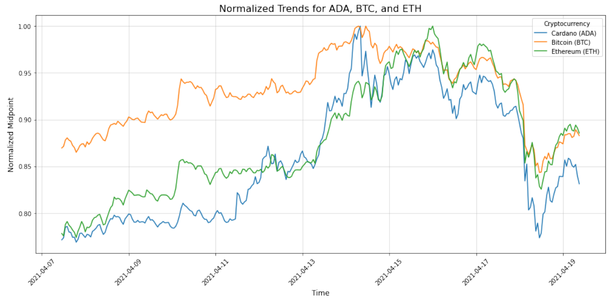

Figure 3: Normalized Midprice Trend for BTC, ETH, and ADA (2021/04/07 - 2021/04/19)

probably caused by a highly congested network, which is probably caused by the high number of transactions since the BTC price has been increasing before.

6 Approach

6.1 Comparing Active and Passive Trading Strategies

We analyzed the performance and characteristics of High-Frequency Trading (HFT) and passive trading. The primary distinction between HFT and passive trading lies in their sensitivity to market signals and trading frequency. HFT operates on shorter time horizons with more frequent trades, leveraging minor price fluctuations. In contrast, passive trading prioritizes fewer, well-informed trades based on broader market trends, reducing transaction costs and slippage.

By simulating both strategies with precised parameters, we analyze their respective performance under identical market conditions, resulting in varying outcomes in terms of profitability, risk, and transaction costs.

6.1.1 Active Trading (High-Frequency Trading)

Active trading, particularly HFT, involves the use of algorithmic strategies to capitalize on small price inefficiencies in the market within extremely short time frames. This strategy seeks to capture larger and more significant price movements rather than react to short-lived fluctuations. The HFT strategy is implemented by combining three key signals:

- **Order Book Imbalance:** Calculated as the relative difference between bid and ask market notional values. If the imbalance exceeds a positive threshold, a buy signal is generated; if it falls below a negative threshold, a sell signal is issued.

- **Momentum:** Measured as the percentage change in the midpoint price over a defined period. A positive momentum exceeding the threshold triggers a buy signal, while a negative momentum triggers a sell signal.

- **Mean Reversion:** Based on the deviation between short-term and long-term moving averages. If the deviation is positive beyond a threshold, a sell signal is issued, indicating potential overpricing; if negative, a buy signal is issued, indicating underpricing.

6.1.2 Passive Trading

Passive trading is a long-term strategy that involves lower trading frequency, aiming to minimize transaction costs and slippage. It relies on broader market trends and longer holding periods.

The passive trading strategy utilizes the same three signals (imbalance, momentum, and mean reversion) but modifies their parameters to capture broader trends:

- **Order Book Imbalance:** Threshold set lower than HFT to filter out smaller price imbalances, reflecting a conservative approach.

- **Momentum:** Calculated over a longer period than HFT, so that positions are hold for longer duration, allowing the strategy to ride out short-term noise and capitalize on broader market trends.

- **Mean Reversion:** The short and long moving averages are set differently to HFT to detect overpricing or underpricing over extended durations.

6.2 Theoretical Models

6.2.1 Epps effect

The analysis of the Epps effect in cryptocurrency markets reveals significant temporal dependencies in cross-asset correlations. Our results demonstrate that BTC-ETH pairs exhibit the strongest average correlation (0.862 ± 0.059), followed by ETH-ADA (0.820 ± 0.089) and BTC-ADA (0.816 ± 0.067).

The correlation strength increases systematically with the sampling interval, confirming the presence of the Epps effect in cryptocurrency markets. This effect is particularly pronounced at shorter time scales (< 5 minutes), where correlations are notably weaker, suggesting that market microstructure effects and asynchronous trading significantly

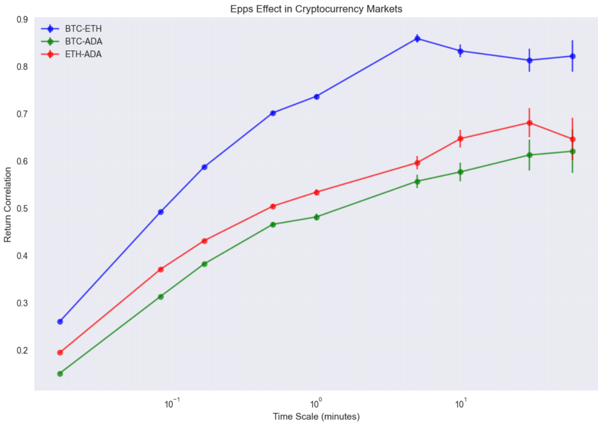

Figure 4: Epps effect analysis for BTC, ETH and ADA

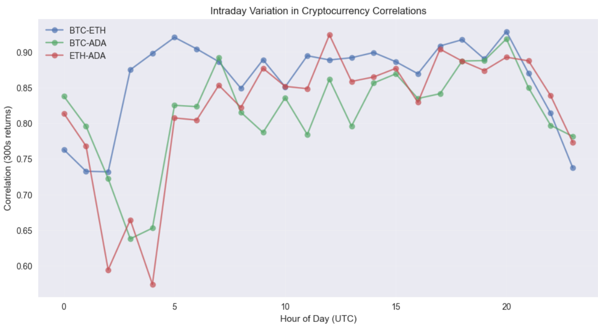

Figure 5: Intraday correlations variations

impact short-term price dynamics. The power law fits to the correlation decay indicate that BTC-ETH pairs show the most stable relationship across time scales, with the smallest standard deviation in intraday correlations. Interestingly, all pairs display higher correlations during periods of high market activity (as evidenced by the intraday patterns), with peak correlations occurring during overlapping high-volume trading hours. This temporal variation in cross-asset dependencies has important implications for high-frequency trading strategies, particularly in risk management and portfolio optimization. The stronger Epps effect at shorter time scales suggests that HFT strategies need to account for these varying correlations when executing rapid trades, as the assumed relationships between assets may break down at very high frequencies.

6.2.2 Discussion on Scalability

The scalability of trading strategies is a critical consideration, particularly when increasing trade sizes. Larger trade sizes can amplify profitability due to higher absolute returns; however, they also introduce challenges related to market impact and transaction costs. For example, executing large trades may cause high slippage costs, where the execution price deviates from the expected price due to insufficient market depth or liquidity. This slippage can significantly erode profits, particularly in less liquid cryptocurrency pairs like ADA.

Additionally, increasing trade sizes can lead to higher trade fees by the exchange. While some exchanges offer volume-based fee discounts, market taker fees often increase with trade size, particularly in low-liquidity conditions where a single large trade may consume multiple levels of the order book.

For passive trading strategies, the scalability challenges are somewhat mitigated as trades are less frequent, and market impact may be reduced. However, increasing trade sizes still requires careful consideration of liquidity conditions, as attempting to liquidate large positions quickly could lead to significant adverse price movements.

Overall, the observed patterns in cross-asset correlations and temporal variations indicate that scalability must be evaluated in conjunction with market microstructure and trading environment dynamics. Larger trade sizes may be feasible during periods of high market activity, where liquidity is higher, and correlations are stronger, reducing the risk of adverse price movements and enabling more efficient execution.

7 Results

The results of our backtesting reveal the trade-offs inherent in these strategies. The HFT strategy demonstrated a capacity to generate consistent, albeit small, profits across many trades, effectively exploiting short-term market inefficiencies. However, the strategy's profitability was highly sensitive to transaction fees and slippage, which could erode returns in lower-liquidity environments.

In contrast, the passive strategy achieved fewer trades but captured larger profit margins per trade. This approach was less affected by transaction costs and slippage but required the presence of strong, sustained market trends to generate significant returns. Passive trading may be better suited for periods of directional price movement, while HFT thrives in environments with high liquidity and frequent short-term price fluctuations.

Table 1: Performance Comparison With Fees (HFT vs Passive)

Strategy / Fees	BTC	ETH	ADA
HFT (With Fees)	$-64.70%	$-78.50%	$-98.57%
Passive (With Fees)	$-4.48%	$-16.69%	$-40.25%

Table 2: Performance Comparison Without Fees (HFT vs Passive)

Strategy / Fees	BTC	ETH	ADA
HFT (No Fees)	$0.86%	$3.46%	$11.47%
Passive (No Fees)	$5.62%	$-0.43%	$-0.09%

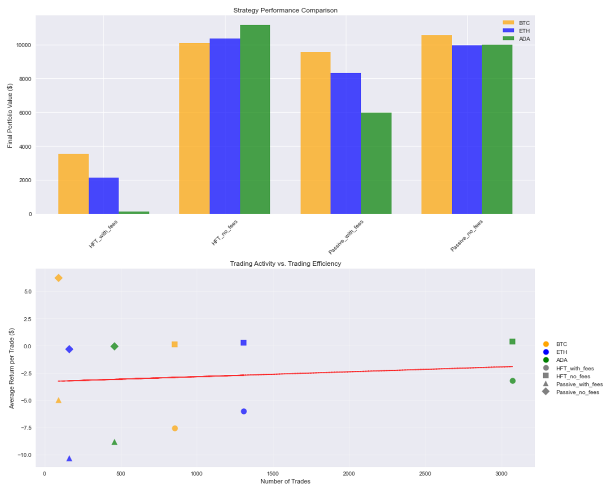

Figure 6: Performance analysis between HFT and Passive strategy

8 Challenges and Future Work

8.1 Challenges

The study faced several challenges that highlight the complexities of analyzing high-frequency trading strategies in decentralized environments:

- **Data Availability:** Obtaining consistent and reliable data from decentralized exchanges proved to be a significant challenge, especially for fees calculation and HFT data with 1-second interval.

- **Computational Limitations for Large-Scale Simulations:** Simulating thousands of investors and their trading strategies, particularly in high-frequency scenarios, demanded significant computational resources. Despite optimization efforts, resource constraints limited the ability to explore more complex trading techniques and longer timeframes.

8.2 Future Work

This research provides a foundation for further exploration, and several directions for future work can be identified to improve and extend the current analysis:

- **Integration of the Work with Centralized Exchanges:** Extending the analysis to incorporate data from centralized exchanges will provide a comprehensive comparison between centralized and decentralized trading environments.

- **Integration with real HFT companies:** Engaging with real HFT companies or incorporating insights from their publicly available strategies could add valuable industry context. This could help refine the assumptions and parameters used in the analysis, ensuring they reflect practical trading scenarios and constraints. Also fees would be different and could lead to different outcomes.

- **Incorporation of Machine Learning Models for Predictive Analytics:** Incorporating machine learning models into the analysis could improve the predictive accuracy of trading strategies. These models could be used to forecast price movements, liquidity conditions, and network congestion, enabling more informed decision-making.

9 Conclusion

The choice between active and passive trading strategies ultimately depends on market conditions, available resources, and risk tolerance. High-frequency trading requires advanced infrastructure, low-latency execution, and a favorable cost structure to be profitable. Passive trading, while less resource-intensive, demands patience and an ability to identify and exploit longer-term market trends. Understanding the strengths and limitations of each approach is essential for designing strategies that align with specific market environments and trading objectives.

10 Appendix

References

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