DETERMINING THE ROLE OF VOLUME IN BUILDING TRADING STRATEGIES IN THE CRYPTOCURRENCY MARKET

by

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ARB – Arbitrum

VWMA – volume weighted moving average

SEC – Securities and Exchange Commission

TVL – total value locked

DEX – decentralized exchange

CHAPTER 1. INTRODUCTION

Research Question

"Can volume analysis effectively be used to trade a specific cryptocurrency?"

Motivation

For the last 10 years the word "cryptocurrency" has been spreading widely across the world because of its peculiarities – key points are in its speed and cost. Overall, it is much faster and cheaper than the traditional money. Since the popularity of crypto is increasing not just from year to year, but day to day, it is 100% understandable that its market attracts attention because of the high volatility and potential benefits.

Nevertheless, this market is relatively new and, therefore, it lacks the long-term historical data that can be found in the traditional markets, because of the main technology that lies underneath the concept of cryptocurrency, it is possible to access the much more "fast" data that can be extracted any time and, therefore, be used to find out some insights about this or that coin.

Frankly speaking, on-chain data (consisting of the information recorded via blockchain) is a very "generous" source of information. Thanks to blockchain technology, we can receive information every second regarding the volume of purchases of a particular asset, the number of active addresses, the accumulation of funds in these wallets, and much more and, what is understandable, by analyzing all this information received, we have a unique opportunity to decide on the possibility of investing in a particular asset.

Although the traditional methods used in financial markets for centuries do not work 100% the same here, the general rules are the same - stockholders are called **"wallets"**, the largest holders are **"whales"**, the purchases or sales of the latter, which in this area are called **"transactions"**, are usually monitored with the same care, because they can signal what will happen to a particular asset in the future. That is why the purpose of this study is to understand how exactly on-chain data can be used to predict future price behavior.

Objectives

1) Analyze volume – we need to investigate volume and determine whether it is possible to use it to indicate the health and potential of a cryptocurrency;

2) Predictive analysis – the usage of statistical methods and machine learning models to predict the potential future performance of a cryptocurrency based on its on-chain data can help;

3) Feasibility assessment – with the help of evaluating the effectiveness and reliability of on-chain data (volume), we can form the tool for making investment decisions;

4) Case studies and practical examples – by providing real-world, practical examples of how volume has been used to make successful (or unsuccessful) investment decisions, we can achieve the goal;

Expected Contributions

a) I want to look deeper into how volume can be used to understand and predict cryptocurrency performance according to 2 different aproaches – theoretical (different regressions, etc) and practical (with the help of volume-based trading strategy);

b) This understanding will offer practical investment strategies that leverage volume data to maximize returns;

C) With the present case studies that highlight both the opportunities and risks of relying on on-chain data for investments;

CHAPTER 2. INDUSTRY OVERVIEW AND RELATED STUDIES

2.1. Cryptocurrency world in the past few years

It should be noted, that the foundation of the cryptocurrency network lies on the blockchain technology that after it's appearance changes lot's of industries because of different principles that are used in the process. The key is the 100% unchangeable method of transaction records that are decentralized and transparent. For the last few years, thousands of cryptocurrencies have appeared and it is really difficult to navigate between them since both institutional and retail investors have shown interest in investing in these fields there is a need to develop a mechanism to simplify the process.

The main problem is that cryptocurrencies can fluctuate significantly even during the day according to various factors that should be taken into consideration while making the decision to invest the funds – we should understand the "underlying" potential that will help not to "full' yourself during the storm. Since the cryptocurrency market is still in its early stages, it lacks standardized analytical tools, in contrast to traditional financial markets, which have a wealth of historical data and established parameters for analysis.

According to the Bloomberg, in this year the combined value of the cryptocurrency market has jumped to around $2 trillion for the first time on almost two years on the back of the ETF-fueled rally in Bitcoin and this brought us to the question of the volume that plays a crucial role in cryptocurrency trading, acting as a signal of market activity and liquidity – high volume often correlates with major price movements, both upward and downward and it is quite undrstandable that since traders, investors, or market makers monitor volume, it becomes a key indicator for understanding market sentiment and future price changes. According to recent data from CoinGecko and CoinMarketCap, the daily trading volume of Bitcoin alone often exceeds $30 billion, with Ethereum and other assets contributing similar figures.

In other words, we can make the prediction that volume often reflects market sentiment and can act as a leading indicator of price changes and, as we will demostrate further in the "related studies" part, Balcilar et al. (2017), for instance, demonstrated that Bitcoin's trading volume can predict price volatility, particularly during periods of high market activity and, similarly, a report from Kaiko in early 2023 found that spikes in volume tend to coincide with price reversals, highlighting the importance of understanding volume dynamics when making trading decisions.

Trying to prevent some misunderstandg, it should be noted that while it is possible to say that we are now witnessing the creation of the totally new finacial market, it also very impacted by the government's action because they are trying to regulate it and this leads to increasing scrutiny from governments and regulators worldwide – in the USA, for example, the Securities and Exchange Commission (SEC) has taken a more proactive stance, cracking down on projects that it deems to be unregistered securities or the introduction or, according to the Forbes, the Biden administration's Executive Order on Ensuring Responsible Development of Digital Assets in March 2022 also signaled the government's interest in creating a clearer regulatory framework for digital assets.

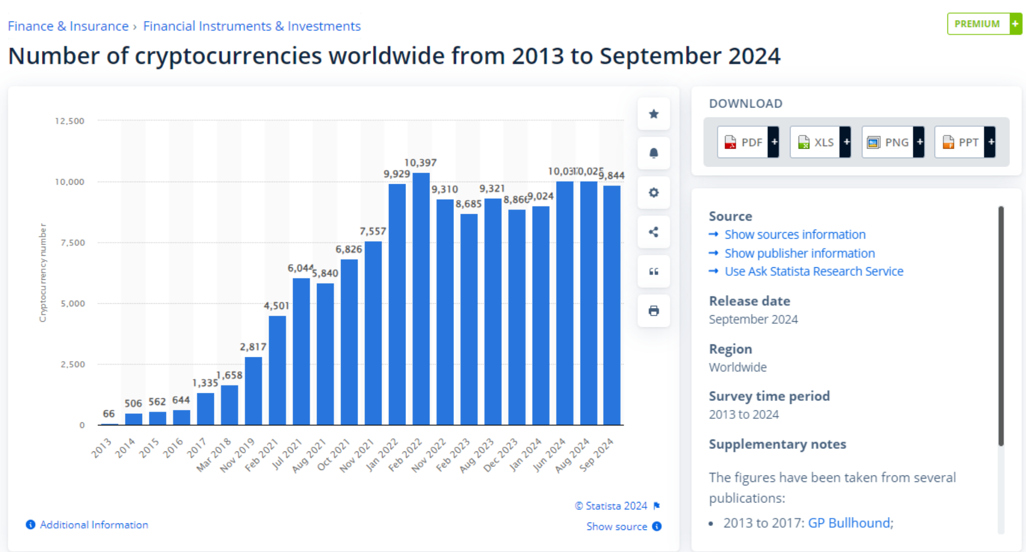
But from our point of view, this is not the future, this is the reality and all of us should try to understand it deeper – it is obvious that the market needs more regulation and in this case we are 100% agree with the note from Coinbase CEO Brian Armstrong that said that clear regulation is necessary for the crypto market to grow sustainably and attract more institutional capital.

On-Chain Data

While we are speaking about the "on-chain data", we are talking about some kind of information that was immediately recorded in the "net" after some kind of transaction has occurred. There are dozens of info that can be noted as transaction volume, addresses that "participate" in it, and some other details that are not the full list that, in total, can help to understand what exactly is happening with this or that coin over time and, therefore, by examining these factors we can build a framework that will simplify the process of understanding.

According to [Statista](), as of September 2024, there are aproximately 10k different cryptocurrency projects and there is a clearly tendency to grow (if we will observe not only the past few years, but all the time of existing of Bitcoin, for example).

Figure 1. Number of cryptocurrencies worldwide from 2013 to 2024.



Source: Statista

One of the most significant trends in recent years has been the increasing institutional adoption of cryptocurrencies and decentralized finance – the growth of some DeFi protocols, such as Aave, Compound, and Uniswap, has introduced a new paradigm of finance, where users can lend, borrow, and trade assets without intermediaries. If we want to go into numbers, according to a [2023 report by DappRadar](), the total value locked (TVL) in DeFi protocols reached over $200 billion at its peak, demonstrating the rapid growth of this sector and the other trend, is the rise of decentralized exchanges (DEXs) and it has also reshaped the crypto trading landscape, with platforms like Uniswap and SushiSwap facilitating billions of dollars in daily volume – in fact, Coinbase's 2023 report highlighted that institutional trading volume on its platform exceeded $1.5 trillion, further underscoring the growing institutional interest in the space.

Such the impact of institutional adoption is, from our point of view, is particularly important for smaller and newer projects, such as **Arbitrum** that will be our "lab rat" for the thesis, which benefit from increased liquidity and trading volume as more institutional capital flows into the ecosystem because as a layer-2 scaling solution for Ethereum, Arbitrum has gained attention for its ability to reduce transaction costs and improve scalability for decentralized applications (dApps) and it's rapid growth is a testament to the growing demand for efficient and scalable blockchain solutions.

According to Bloomberg, while volume serves as a useful indicator of market activity, it can also be a tool for market manipulation – certain actors in the cryptocurrency market engage in wash trading and pump-and-dump schemes to artificially inflate trading volume and manipulate prices and these practices pose significant risks for traders and investors, particularly in less regulated exchanges and, therefore, market manipulation presents a challenge for traders using volume-based strategies, as false volume spikes can lead to misleading signals. This is particularly relevant for smaller assets, like Arbitrum, where speculative trading and liquidity constraints might exacerbate such issues – we will show that our analysis accounts for this risk by incorporating machine learning techniques to filter out noise and better interpret genuine volume signals.

2.2. Volume-related studies in finance

The relationship between trading volume and price movements has long been a topic of interest in financial market research – while in traditional markets, studies have established volume as an important signal for price dynamics and market volatility, as the cryptocurrency market matured, researchers began applying similar frameworks to explore whether these patterns hold in digital assets, where speculation and market inefficiencies are more pronounced.

It should be noted that different research on the role of volume in traditional financial markets has significantly shaped our understanding of market behavior because by focusing, for example, on equities, bonds, and commodities, foundational studies established that volume often acts as a leading indicator of price volatility and, in certain cases, may even predict future price movements.

Volume as a predictor of future prices

Getting back to history, one of the earliest explorations of the price-volume relationship was made by (Osborne 1959), who posited that stock prices follow a random-walk process and that trading volume could provide information about future price movements. On one hand, while his work suggested a connection between volume and price, it did not go into the specifics of how this relationship operates, leaving room for future research to explore the mechanisms behind this connection and, what is quite logical, to be honest, Osborne's early work provided a stepping stone for more quantitative analysis, but it lacked empirical rigor in terms of specifying the nature of the volume-price dynamics.

Using Osborne's ideas, (Clark 1973) introduced the mixture of distributions hypothesis (MDH), which suggested that price and volume are jointly influenced by the arrival of new information. His model was more sophisticated than Osborne's as it recognized that volume spikes often coincide with periods of high information flow, leading to greater volatility. From my point of view, this theory is crucial for understanding cryptocurrency markets, where the arrival of new information, particularly about technological updates or regulatory decisions, can trigger large swings in both volume and price. It should be noted, however, that Clark's hypothesis assumes that information arrives in a homogeneous manner, which may not hold true in modern high-frequency markets, where speculative and algorithmic trading plays a larger role.

Later on, in a more empirical vein, (Karpoff 1987) reviewed numerous studies that established trading volume as a predictor of price volatility and concluded that periods of increased trading volume are generally followed by heightened price volatility, indicating that volume can indeed be used as a leading indicator. Actually, his conclusions provide strong empirical support for the idea that volume spikes, especially those driven by information shocks, lead to more significant price movements but understanding that he focused on equity markets, which are generally more liquid and less volatile than cryptocurrencies (simply because the last did not exist at that time), means his findings may not be fully applicable to the markets under this study, because speculations often drive price movements.

But the main idea that high trading volume predicts future price volatility in equity markets was developed further and (Campbell JY 1993) added another dimension to the literature by offering a strong empirical basis for the idea that volume could be used as a predictive tool for price changes. But while their findings focus primarily on volatility rather than directional price changes, which is a crucial difference, in our analysis of cryptocurrency markets, we are more concerned with whether the volume can predict price direction rather than just price variability. This subtle difference is critical because, in a market as volatile as cryptocurrency, predicting volatility without direction might not provide actionable trading strategies.

At this point, the work of (Bollerslev 1999) also should be mentioned because they expanded on the predictive role of volume in stock markets by showing that volume can predict both volatility and price direction in certain conditions. Speaking shortly, their findings are more aligned with our research on cryptocurrency markets, as they suggest that volume spikes can signal both price direction and intensity. However, their study, like many in traditional markets, assumes a level of market efficiency that cryptocurrencies often lack due to their speculative nature.

Market microstructure and volume

In the realm of market microstructure, (Hasbrouck 1991) explored the information content of trades and demonstrated that larger trades (often associated with higher volume) carry more information, thereby impacting prices more significantly – his study implies that volume is not a uniform indicator but rather one that varies based on trade size and market conditions and this nuanced understanding of volume's impact on price is directly applicable to cryptocurrency markets, where large trades (often referred to as *"whale trades"*) can disproportionately influence prices due to the lack of liquidity and high volatility. However, Hasbrouck's framework does not account for the speculative nature of cryptocurrencies (once again. Because it was just impossible to study it then), where price movements may not always be driven by rational information processing, but rather by hype or fear in the market.

In this case, from our point of view, more related can be (Kyle 1985) that introduced a seminal model on informed trading, suggesting that informed traders increase their trading volume in response to private information, which causes prices to move before the public becomes aware of the information. In other words, his model is particularly relevant to our study because it highlights the role of asymmetric information in markets and in cryptocurrency markets, where information asymmetry is rampant (due to technical complexity, lack of regulation, and insider knowledge), Kyle's model suggests that volume spikes might precede price movements, especially in smaller and less liquid markets like Arbitrum (which we will concentrate in the future). But there is one "small" moment, that we should consider – Kyle's model assumes that informed traders act rationally based on information, whereas, in the cryptocurrency space, speculation and market manipulation often distort this rational behavior.

Volume and price in cryptocurrency markets

In contrast to the relatively mature body of work on volume and price in traditional financial markets, the literature on cryptocurrencies is still developing and, what is even more important, cryptocurrencies present unique challenges, such as 24/7 trading, high retail participation, and susceptibility to market manipulation, which complicate the application of traditional financial theories.

Information asymmetry and market efficiency in cryptocurrencies

Speaking about research on crypto markets, it is not possible not to mention (Urquhart 2016) who conducted one of the first empirical investigations into the efficiency of cryptocurrency markets, particularly Bitcoin. His findings suggested that Bitcoin did not follow a random walk, implying inefficiencies in the market and it is quite understandable that his study is significant because it challenges the notion that cryptocurrency markets are efficient, a key assumption in many traditional financial models. In other words, this inefficiency is relevant for our research on Arbitrum, as it suggests that volume spikes—often triggered by speculative or insider-driven trades—may provide predictive power in ways that would not be possible in more efficient markets. While, Urquhart's focus on Bitcoin, a highly liquid asset compared to Arbitrum, may limit the generalizability of his findings, Arbitrum, on the other hand, being a smaller and less liquid cryptocurrency, might exhibit even more pronounced inefficiencies, making volume a stronger predictor of price movements.

Wanting to study this relationship deeper**,** (Baur 2018) go further and explore the intraday price-volume relationship in Bitcoin, finding a positive correlation between volume and price changes, which is consistent with studies in traditional markets that we mentioned before but they also observed significant volatility clustering in Bitcoin, which is more intense than what is typically seen in equity markets, and found out that volume spikes may not only signal price movements but also *indicate future periods of high volatility*. From our point of view, this insight is critical for our study of Arbitrum, where speculative trading and low liquidity often lead to sharp price swings – in other words, the authors' findings support our hypothesis that volume spikes in Arbitrum could be used as a predictor for future price movements, but the extreme volatility in the market may also mean that this relationship is less stable and more prone to reversals.

Volume – predictor of cryptocurrency prices

Speaking closer to the topic and analyzing how volume can be used to predict future prices, (Balcilar 2017) tested the idea that was mentioned above as well and found out that volume was a significant predictor in certain market conditions, particularly during periods of high volatility and, therefore, we decided to use this in our research on Arbitrum, where we hypothesize that volume spikes may signal future price movements, especially in times of heightened market activity. These recearcers highlighted the serious problem of this method because cautioned that the predictive power of volume diminishes during calm market periods, which presents a limitation for using volume as a sole predictive tool and, speaking frankly, this criticism is relevant for our study, as it suggests that volume should be used in conjunction with other indicators to improve its predictive accuracy, especially in periods of low volatility.

From our point of view, (Lahmiri 2019) did a great job extending the analysis to smaller cryptocurrencies and found that volume plays a more significant role in less liquid cryptocurrencies, such as those with smaller market caps – their findings reinforce our decision to focus on Arbitrum, a relatively new and smaller cryptocurrency, where volume spikes might contain more information than in larger, more liquid markets like Bitcoin but while their study primarily focused on deep learning models and did not address the role of market manipulation or speculative trading, both of which are prevalent in smaller cryptocurrency markets, we suppose that this is a limitation that we address in our study by acknowledging the potential for wash trading and manipulation in the interpretation of volume data.

Volume and market manipulation in cryptocurrencies

The question of the price manipulations in cryptocurrency markets, particularly wash trading and pump-and-dump schemes is rather a popular theme for the discussions in the last years and the most "academic" work in this field can be considered that was done by

(Gandal 2018) because their research highlights the challenge of interpreting volume spikes in cryptocurrencies, where artificially inflated volumes may not reflect genuine market interest but rather manipulative behavior. From our point of view this is a critical consideration for our study of Arbitrum, as distinguishing between genuine and manipulative volume spikes is essential for developing robust predictive models – but, unfortunately, while our strategy attempts to filter out some of this noise using machine learning techniques, it should be noted that the potential for manipulation remains a limitation of any volume-based predictive model in cryptocurrency markets.

A little bit later (Griffin 2020) went further and explored the role of stablecoins, particularly Tether (USDT), in Bitcoin's price manipulation, finding that large volumes of Tether entering the market often led to Bitcoin price spikes – considering how this can be used in our recearch, we should mention that while Arbitrum operates in a different ecosystem, their findings highlight the broader issue of how external factors—such as large stablecoin flows—can distort the volume-price relationship in cryptocurrency markets and this reinforces the need to interpret volume data cautiously, as large volume spikes *might not always reflect genuine market interest* but could be driven by market manipulation or external capital flows.

So, as we demostrated previously, the body of research from both traditional and cryptocurrency markets suggests that volume is a critical factor in price discovery and volatility, especially in smaller and less liquid markets. As we saw, studies from traditional markets, provide strong empirical support for the idea that volume spikes can precede significant price movements, a finding that holds relevance in our exploration of Arbitrum but, at the same time, as demonstrated by more recent studies in the cryptocurrency market, volume's predictive power may vary depending on the liquidity and volatility of the asset and some external factors.

It will be demonstrated further but our empirical analysis of Arbitrum shows that Granger causality tests and correlation analyses suggest that volume can indeed be a leading indicator of price movements, consistent with findings in both traditional and cryptocurrency markets and, what is more important, the high volatility clustering observed in Arbitrum **aligns** with the findings of (Baur 2018), who demonstrated that cryptocurrencies exhibit more intense volatility patterns than traditional assets but, on the other hand, however, our analysis also highlights the limitations of using volume **alone**, as the high *Max Drawdown* in our backtested strategy echoes the concerns raised by (Gandal 2018) and (Griffin 2020) about the potential for market manipulation and speculative trading to distort volume data in cryptocurrency markets.

In order to proceed to the next part of the work, we should say some sort of conclusion, and we want to note that while the related studies from both traditional and cryptocurrency markets provide a robust theoretical and empirical foundation for our analysis of Arbitrum's volume-price dynamics, by drawing on established theories adapting them to the unique characteristics of the cryptocurrency market, we want offer new insights into the predictive power of volume in emerging digital assets.

2.3. Literature gaps

While existing studies have laid a strong foundation for understanding the role of volume in investment decisions, there are still several areas that require further exploration:

- Need to understand how volume data can be integrated with traditional financial metrics to provide a more holistic analysis;
- Wish to validate the predictive power of volume;
- Want to investigate how volume can be correlated to provide broader market insights;
- Wish to construct real-time analytical tools for immediate investment decisions;

By addressing these gaps, future research can significantly enhance the reliability and practical applicability of on-chain data analysis for cryptocurrency investment.

CHAPTER 3. DATA, METHODOLOGY AND RESULTS

As we demonstrated previously in the "related studies" part, the relationship between trading volume and price movements has been a crucial point of financial research for decades because of offering insights into market behavior and helping to refine trading strategies: in traditional financial markets, trading volume has long been considered a critical variable, often correlating with price volatility and providing clues about future price changes. It is quite logical that as the cryptocurrency market continues to evolve, there is a growing interest in determining whether the same principles apply to digital assets and given the unique characteristics of cryptocurrencies, such as high volatility, speculative trading, and market inefficiencies, this research seeks to explore whether changes in trading volume can be used to make informed investment decisions – this analysis focuses on Arbitrum, a layer-2 scaling solution for Ethereum, using a one-year dataset of daily trading data from CoinGecko.

Why we used CoinGecko?

As were mentioned previously, for the purposes of this analysis, we decided to use CoinGecko as the primary data source because being one of the most popular and comprehensive cryptocurrency data aggregators, providing real-time and historical data on a wide range of digital assets. Since it first launh in 2014, CoinGecko offers a wide array of data points, including price, volume, market capitalization, and social metrics for thousands of cryptocurrencies and, unlike other platforms that offer limited information, CoinGecko prides itself on providing transparent, open-source data that is not just price-centric but includes other metrics, such as developer and community activity, which are increasingly important in understanding the health of a cryptocurrency ecosystem.

It should be noted that the free version of CoinGecko API provides access to historical data on a daily candle basis, which makes it suitable for broad analysis over medium-term periods like one year and, unfortunately, the free version does have limitations in terms of the depth and granularity of the data – users can access daily candle data for up to a year, while more granular data (e.g., hourly candles or more extended historical data) is only available through a paid subscription which *costs a lot*. There are several similar agregators as well but it should be noted that all of their APIs are not cheap and the CoinGecko's one is the best (offers more data in other words) and allowed us to explore key dynamics in the Arbitrum market over the past year.

<u>Data scope and limitations</u>

So, just to "draw the line" – the dataset that we are using in this analysis consists of daily price and volume data for Arbitrum over a one-year period on a Daily TF which includes the following key metrics:

Price (USD) – the closing price of Arbitrum in USD;

Volume 24h (USD) – the total value of Arbitrum traded in USD over the 24-hour period;

We are sure that the Daily TF provides an overview of longer-term trends and patterns but limits the ability to detect *intraday* price movements or rapidly changing market conditions and while this is sufficient for exploring the relationship between volume and price in a broad sense, finer details that might emerge from minute-by-minute or hourly data remain unexplored due to the constraints of the free service so as the plan to the future we can consider extending the analysis to more granular data that could provide deeper insights but comes at a significant cost as well, as CoinGecko's premium service offers access to such data at a much higher price point.

** we want to note that it is possible to use all the algorithms for any TF (if you have the API with the needed access) without changing it and this is very suitable for an analysis of any coin because it cannot be used not only for Arbitrum but any other as well;*

So, firstly we extracted the data and organized it into the following data frame:

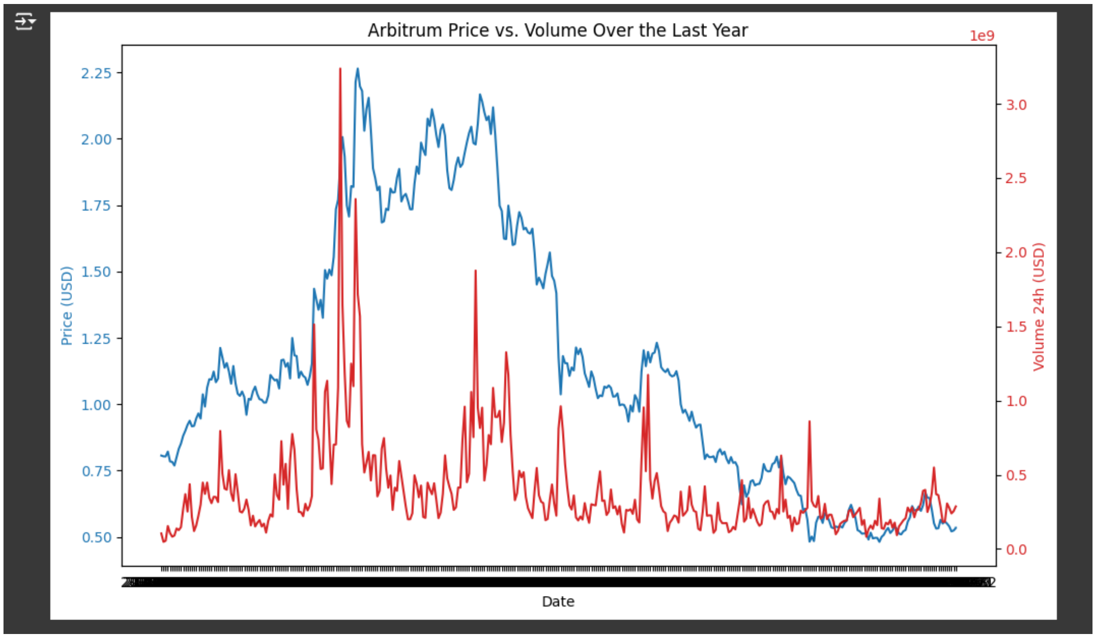
Table 1. Daily dataset for the past year with Price (USD) and Volume 24h (USD) (updated 31.10.2024)

	Date	**Price (USD)**	**Volume 24h (USD)**
1	2023-11-02	1.037258	447,301,883.72
2	2023-11-03	0.991087	370,776,576.23
3	2023-11-04	1.062315	447,347,852.87
4	20213-11-05	1.094236	344,775,143.71
…	…	…	…
362	2024-10-28	0.519418	184,268,666.42
363	20214-10-29	0.522348	317,630,549.80
364	2024-10-30	0.546941	303,496,441.93
365	2024-10-31	0.556826	415,841,224.43

This is the simple representation of the data that we have at the beginning – 365 last days, the price for each day, and the volume for each day as well.

In order to visualize how the volume and Arbitrum's price are correlated between each other – we've built the chart that represents this:

Figure 2. Correlation between Arbitrum's price and volume



While we can clearly see that the price of the token has been declining for the last several months (after the significant upside move, of course, but still), the volume, for the first view, does not change significantly – the only visual difference that can be spotted is while the price of the token was in its bullish scenario → the volume rose accordingly. The interesting moment in this case is that while being at ATH (ATH – all-time high) during some period, the volume declined significantly and this, according to (Griffin 2020) might be the signal that the whole move was manipulative (because there were no interest in buying the token at the mentioned prices).

This drives us to the understanding that we need to look deeper into this correlation and, first of all, we decided to introduce the new variable – logarithmic return with the following formula:

$$\text{Log Return} = \log\left(\frac{\textit{Price at time } t}{\textit{Price at time } t-1}\right)$$

Table 2. Descriptive statistics of Price (USD), Volume 24h (USD) and Log_Returns

	Price (USD)	Volume 24h (USD)	Log_Returns
count	365	365	365
mean	1.139525	404,782,806.65	-0.001217
std	0.505214	329,816,728.87	0.046043
min	0.481722	82,088,538.22	-0.0187042
25%	0.694389	221,120,509.09	-0.027381
50%	1.061609	304,025,103.64	-0.003223
75%	1.571398	457,261,476.25	0.022903
max	2.263961	3,236,014,261.02	0.218638

As we can see from the presented data, coin's price during the 365 days exhibited moderate variability – for example, the average price was recorded at **$1.14**, however, we should note that the price fluctuated significantly, with a standard deviation of **$0.51**, indicating that daily prices deviated from the mean by approximately 51 cents on average → we should understand that such volatility is normal for cryptocurrencies, which tend to experience larger price swings than traditional financial assets. The price ranged from a minimum of **$0.48** to a maximum of **$2.26**, the 25th percentile of $0.69 suggests that prices were below this level for a quarter of the time, while the 75th percentile of $1.57 indicates that three-quarters of the daily prices were below this figure and while the median price was $1.06, which is quite close to the mean, we can say that the price distribution is relatively balanced without significant skewness.

The 24-hour trading volume for Arbitrum over the same period showed substantial variability, reflecting shifts in market activity – the average daily volume was $404.78 million USD, with a standard deviation of $329.81 million USD. Such a high standard deviation indicates that daily trading volumes varied considerably, with some days experiencing much higher trading activity than others: the trading volume ranged from a low of $82.08 million USD to a high of $3.24 billion USD → such a quite large range highlights that, on some days, Arbitrum experienced extreme market activity, due to major news events and periods of market excitement. At the 25th percentile, the daily volume was $221.12 million USD, indicating that 25% of the time, trading volumes were relatively subdued and the 75th percentile volume was $457.26 million USD, meaning that 75% of the time, volumes did not exceed this level.

Speaking about the mean of daily logarithmic return, it was -0.12%, indicating a slight downward trend over the observation period, however, the magnitude of this average is relatively small, and it does not imply a substantial decline – while the standard deviation of the daily returns was 4.6%, highlighting significant day-to-day price fluctuations, we should understand that, once again, such volatility is common in the cryptocurrency market. This is reflected even in the results of the minimum daily return during this period which was 18.7%, representing a significant price drop on the worst-performing day and, conversely, the maximum daily return of 21.86%, indicating a substantial price increase on the best-performing day.

So, before proceeding to the regressions, we decided to run two small tests to test 2 things accordingly – the correlation between the mentioned variables and their stationarity. So, to do the first test, we used the Pearson correlation coefficient and received the following results:

Table 3. Pearson correlation coefficients for Price (USD), Volume 24h (USD) and Log_Returns

	Price (USD)	Volume 24h (USD)	Log_Returns
Price (USD)	1	0.53923	0.07506
Volume 24h (USD)	0.53923	1	0.178032

Log_Returns	0.07506	0.178032	1

As we can see, the correlation between price and volume is **0.54**, indicating a moderate positive correlation → when the price increases, there is often a corresponding increase in trading volume, and vice versa, However, the correlation is not extremely high (e.g., closer to 1), meaning that while price and volume often move in the same direction, this relationship is not perfectly consistent. As for the correlation between price and logarithmic returns, we can observe that it is relatively weak, with a value of 0.075 and this indicates that there is almost no linear relationship between the current price level of the coin and its daily returns – in other words we can say that a low correlation such as this suggests that price changes (returns) are not strongly dependent on the absolute price of the asset (which is quite expected). This result, from our point of view, is in line with the idea of (Gandal 2018) that many cryptocurrencies experience highly volatile and unpredictable price movements that are driven more by market dynamics, external news, and investor sentiment rather than being tied to the actual price level of the token → therefore, the day-to-day price fluctuations do not exhibit a consistent pattern with the asset's price at any given time.

Therefore, the point that the correlation between volume and logarithmic returns, on the contrary, is 0.178, is quite understandable because indicating a weak positive correlation suggests that there is only a slight tendency for higher trading volumes to be associated with larger returns (either positive or negative) and, therefore, in this case, we should understand that this data implies that while there **may be** some relationship between trading volume and price changes, volume alone is not a strong predictor of returns.

Before the regressions, we needed to test the data via the Augmented Dickey-Fuller (ADF) test in order to check whether it is stationary or not. The results are the following:

Table 4. ADF tests for Price (USD), Volume 24h (USD) and Log_Returns

ADF Test for Price (USD)	
ADF Statistic	-0.8553950602886791
p-value	0.8023065159562444
Critical value 1%	-3.4484434475193777
Critical value 5%	-2.869513170510808
Critical value 10%	-2.571017574266393
ADF Test for Volume 24h (USD)	
ADF Statistic	-3.1043892348822646
p-value	0.0262300660516589
Critical value 1%	-3.44880082033912
Critical value 5%	-2.869670179576637
Critical value 10%	-2.5711012838861036
ADF Test for Logarithmic Returns	
ADF Statistic	-19.073828044805616
p-value	0.0
Critical value 1%	-3.4484434475193777

Critical value 5%	-2.869513170510808
Critical value 10%	-2.571017574266393

So, while the p-value for the price is 0.80, which is greater than 0.05, we understand that we cannot reject the null hypothesis → the price series is **non-stationary** but, since, usually, in finance, there are no regressions on the price but, on the contrary, there are regressions on the return, and, as we can see, the p-value for the return is near zero → this means that the return series is **stationary**.

After this we can finally proceed to the regressions and, for the beginning, we decided to review the approach that is taken in the literature and found out that the most "popular" way is to refer to the idea of the lagged volume. According to (Patrick Eugster 2022)**,** we decided to test 3 different regression models as follows:

$$r_t = k + \alpha_1 TA_{t-1} + \varepsilon_t$$

$$r_t = k + \alpha_2 r_{t-1} + \varepsilon_t$$

$$r_t = k + \alpha_1 TA_{t-1} + \alpha_2 r_{t-1} + \varepsilon_t$$

where r_t refers to the arbitrum return in day t calculated using daily closing prices, k is a constant, $T\ A_{t-1}$ is the corresponding volume in day t-1, and ε is the error term. As we mentioned previously, the series is stationary as per the augmented Dickey-Fuller (ADF) test. The results are the following:

Table 5. OLS regression results

	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Combined model**

Intercept	0.0016	0.0020	0.0018	-0.0014	0.0095	0.0189
Lagged volume 1	-0.0028	0.0364	0.0375	N/A	N/A	0.0726
Lagged volume 2	N/A	-0.0395	-0.0550	N/A	N/A	-0.0942
Lagged volume 3	N/A	N/A	0.0145	N/A	N/A	0.0168
Lagged return	N/A	N/A	N/A	0.0327	N/A	-0.0524
Bitcoin price	N/A	N/A	N/A	N/A	-0.00001	-0.00001
R- squared	0.001	0.0034	0.0037	0.0011	0.0020	0.0075
P-value (F- statistic)	0.5483	0.5422	0.7197	0.975	0.3981	0.7419

So, as we can see from the presented table in the first model, we examine the effect of a 1-day lagged volume on Arbitrum's returns, and the coefficient for it is negative and very small (-0.0028) and this suggests an almost negligible impact of volume on returns. This is further confirmed by a high p-value of 0.548, indicating that this relationship is statistically insignificant, and the R-squared value which is 0.001 and shows that the model explains only 0.1% of the variance in returns, suggesting that lagged volume alone does not significantly explain the studied question.

We decided not to stop on the 1 lag and decided to add a second and the third lag of volume in the model as well, so we observed that the coefficients for Lagged volume_1 and Lagged volume_2 are of similar magnitudes but opposite signs and Lagged volume_3 has small, positive coefficient but, as can be seen, none of the coefficients, however, show statistical significance. These results imply that adding a second and third lag of volume does not meaningfully enhance the model's ability to predict returns, pointing to weak overall predictive power from lagged volume and the R-squared, which is unchanged as well at 0.003, reinforcing that even with three lags of volume, the model provides minimal explanatory power for returns

In regression 4, we decided to test whether a 1-day lagged return can help explain current returns, which might indicate trends such as momentum or mean-reversion and since the coefficient for Lagged_Returns is very small and negative (0.0327), with an extremely high p-value of 0.975, it tells us that there is no statistical significance. The R-squared remains close to zero as well, further indicating that lagged returns do not meaningfully predict subsequent returns. These results imply a lack of autocorrelation in Arbitrum's returns, which was discussed by (Gandal 2018) and as they stated – consistent with the efficient market hypothesis, where past returns provide little to no information about future returns.

In regression 5 we wanted to examine the impact of Bitcoin's price on Arbitrum's daily returns and find out that since the coefficient for Bitcoin_Price is also negative but small (-0.00001), with a p-value of 0.398 it can be considered as indicating that Bitcoin's price has minimal explanatory power for Arbitrum's returns and, therefore, the insignificance of Bitcoin's price suggests that despite general market correlations observed in cryptocurrency markets by (Baur 2018), bitcoin's price alone does not strongly influence the daily returns of Arbitrum and this could imply that it's price movements are driven more by other factors than broader market trends (but we will not try to find them in this work since this is far away our topic, actually).

So, in the final model, we combined all variables to assess their collective impact on Arbitrum's returns and, nevertheless, the R-squared increases to **0.0075**, indicating a slight improvement in explanatory power, but it remains very low, suggesting the model still explains less than 1% of the variability in returns and, what is even more important, none of the variables are statistically significant at the 5% level. These results further reinforce that neither lagged volume, lagged returns, nor Bitcoin's price provides meaningful predictive power for Arbitrum's daily returns.

CHAPTER 4. TESTING OF THE VOLUME-BASED STRATEGY

So, as the conclusion to the previous part, we can clearly see that the volume, from the first point of view, can not be used to predict the returns of the cryptocurrencies but, according to (Baur 2018) it can be used as the crucial part of the strategy. Nevertheless, they were talking about Bitcoin, so we decided to test this on the Arbitrim and chose the volume-weighted moving average (VWMA in the future) to test this. In short, it takes both price and volume into account, giving more weight to days with higher trading volume, and can generate both buy or sell signals when the asset's price crosses above or below the VWMA accordingly. The formula for it is the following:

$$VWMA = \frac{\sum(Price * Volume)}{\sum Volume} \ (for\ a\ given\ windoww\ size)$$

Firstly, the idea of the strategy was the following – we decided to test a 20-day window and this means that when the price crosses above the 20-day VWMA, this indicates that the price is gaining momentum with support from trading volume, suggesting a bullish condition → long position is entered (full size), when the price crosses below the VWMA, it suggests a loss of momentum, triggering a sell signal to exit the long position.

In order to evaluate the strategy we decided to chose the traditional metrics such as:

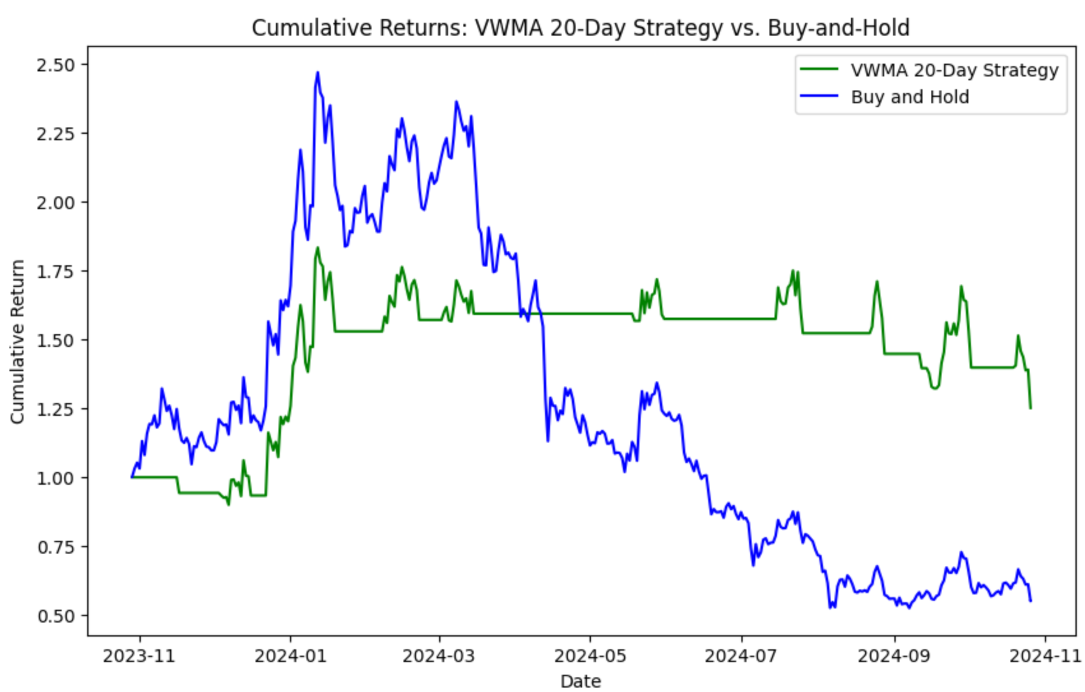
- Final Balance – we decided to imagine that at the start we have 1mln USDT;
- Sharpe Ratio
- Max Drawdown (it is crucial because we use all the capital);
- Number of Trades
- Winning Ratio

So, testing the indicated strategy for the period of last year, we received the following results:

Table 6. 20-Day VWMA strategy results

Final balance	1 251 727.28 USDT
Sharpe ratio	0.55
Max Drawdown	58.19%
Number of trades	13
Winning ratio	38.46%

Figure 3. 20-Day VWMA strategy results VS
Buy and Hold results



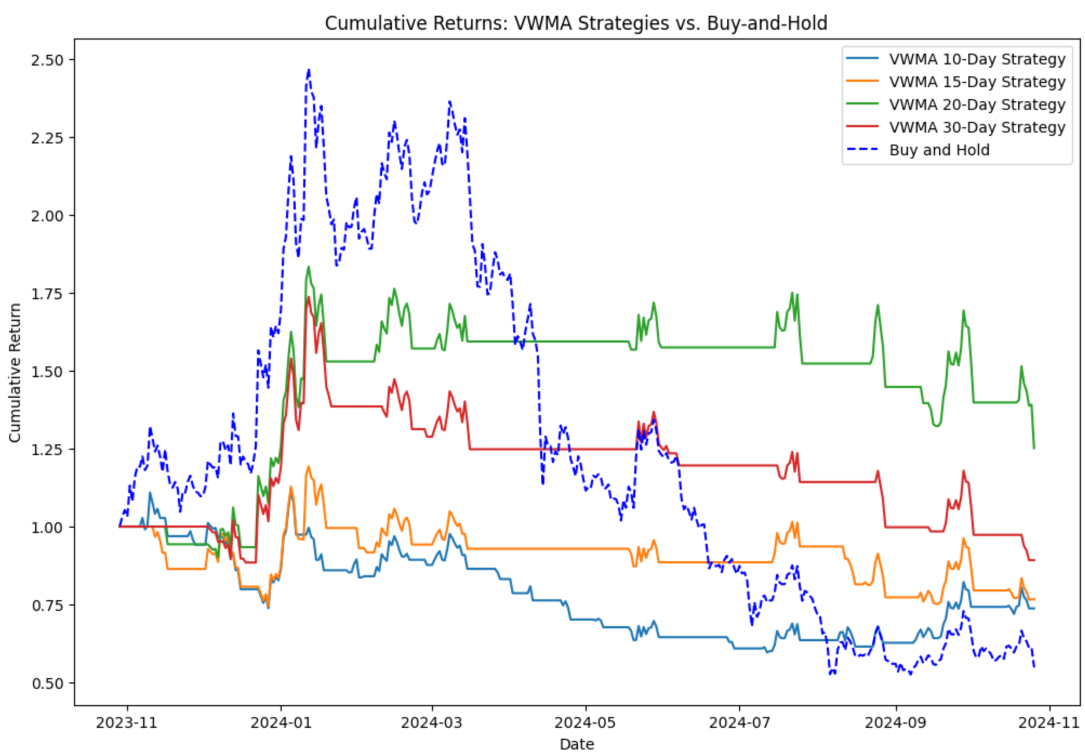
It can be clearly seen that, overall, the strategy outperforms the "investment" strategy where you just buy the asset at the beginning of the tested period and sell it at the end but the results are not as good as we expected and, therefore, we decided to add 10, 15 and 30 days window as well to see the results.

Table 7. 10/15/30-Days VWMA strategy results

10-Day window	
Final balance	737 499.42 USDT
Sharpe ratio	-0.30
Max Drawdown	52.13%
Number of trades	31
Winning ratio	35.48%
15-Day window	
Final balance	766 740.54 USDT
Sharpe ratio	-0.18
Max Drawdown	44.11%
Number of trades	22
Winning ratio	36.36%

30-Day window	
Final balance	892 230.06 USDT
Sharpe ratio	0.06
Max Drawdown	84.48%
Number of trades	15
Winning ratio	6.67%

Figure 4. All VWMA strategies VS Buy and Hold results

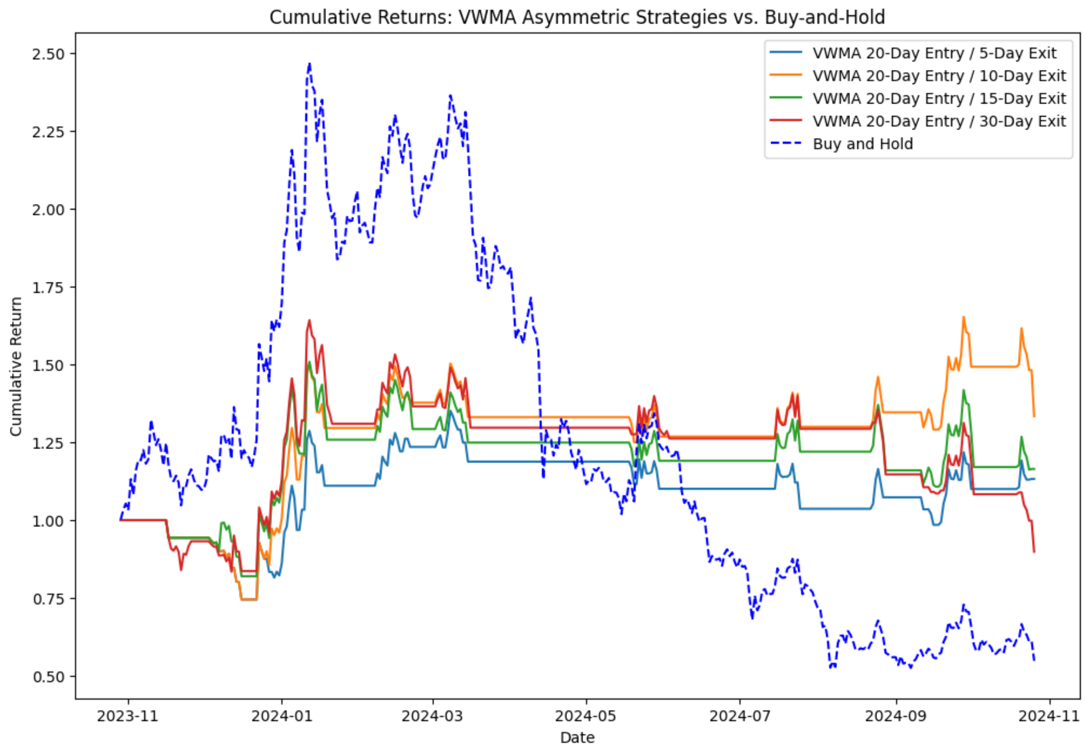


As we can see, overall, we found out that the best strategy among all of the tested is the started one (20-day window) because it demonstrated the best performance across all of them and, therefore, we decided to use it as the main one. Further, we thought that, maybe, it would be useful to apply the asymmetric strategy (where the difference between the opening and closing of the positions). According to (Bollerslev 1999), it is necessary to find the best window for open the trade and then try to estimate the exact same windows to the closing option. So, we did this and received the following results:

Table 8. 5/10/15/30-Day Exits results

	5-Day Exit	**10-Day Exit**	**15-Day Exit**	**30-Day Exit**
Final balance	1 132 213.63 USDT	1 333 425.31 USDT	1 164 257.40 USDT	898 476.30 USDT
Sharpe ratio	0.40	0.65	0.45	0.09
Max Drawdown	36.63%	31.92%	40.13%	74.36%
Number of trades	30	20	15	21
Winning ratio	43.33%	45.00%	46.67%	33.33%

Figure 5. All assymetric exits VS Buy and Hold strategy results



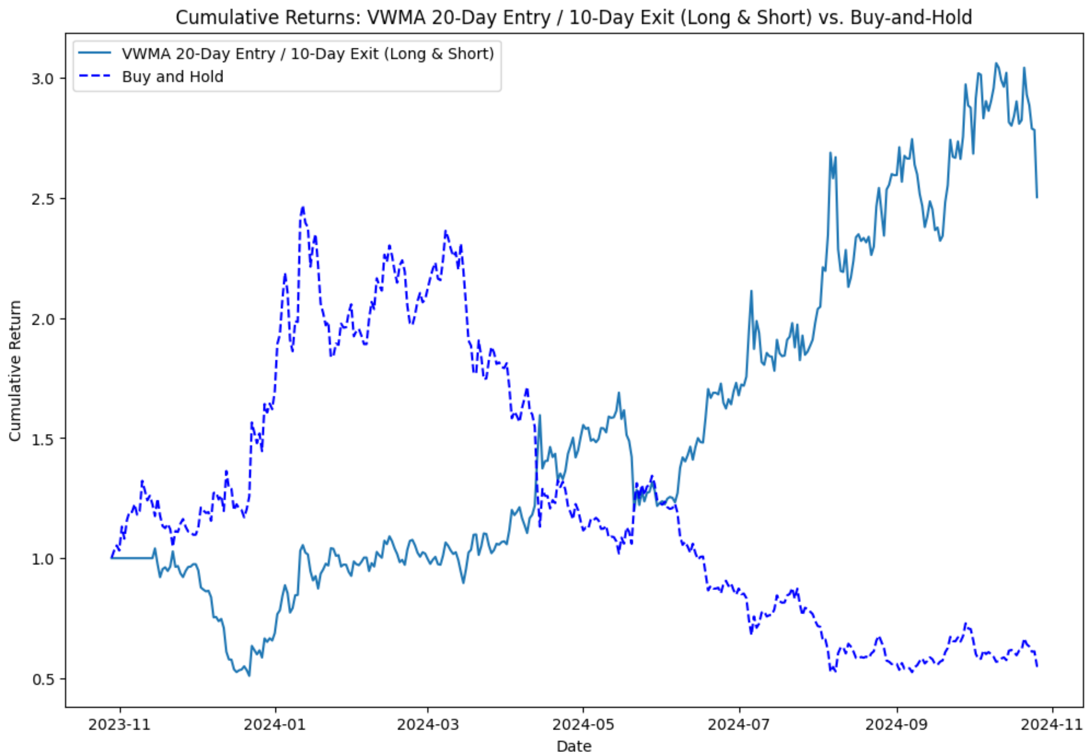
As we can see, the strategy with the "10-days" exit demonstrates the best results and it is quite logical because in the cryptocurrency markets, we need to react almost immediately to the changes in the situation but when we use "5-days' it clearly ruin our results because of the false signals. So, we decided to concentrate on the strategy "20 days to enter / 10 days to close" and develop it further because we see 2 points that can be improved.

Firstly, as seen in the presented graph above, there are periods when the strategy literally does nothing because the required parameters do not exist and this can be explained by the current situation with the cryptocurrency market for the last year – it dropped significantly and since our strategy only "buy" the asset it was hard to implement it in the bear market. From our point of view, this is the problem of adaptation and we can try to solve it by adding the reverse signals as well. In other words, if earlier we used the following parameters: "*…when the price crosses above the 20-day VWMA, this indicates that the price is gaining momentum with support from trading volume, suggesting a bullish condition → long position is entered (full size), when the price crosses below the VWMA, it suggests a loss of momentum, triggering a sell signal to* *exit the long position…"*, therefore now we will not just close the trade when the price crosses below the VWMA but also open the short position as well and vice versa. Let's see the results:

Table 9. 20-Day Entry / 10-Day Exit (Long and Short) results

20-Day Entry / 10-Day Exit (Long and Short)	
Final balance	2 502 892.21 USDT
Sharpe ratio	1.23
Max Drawdown	55.89%
Number of trades	41
Winning ratio	45.00%
Average RR	2.39

Figure 6. 20-Day Entry / 10-Day Exit (Long and Short) VS Buy and Hold results



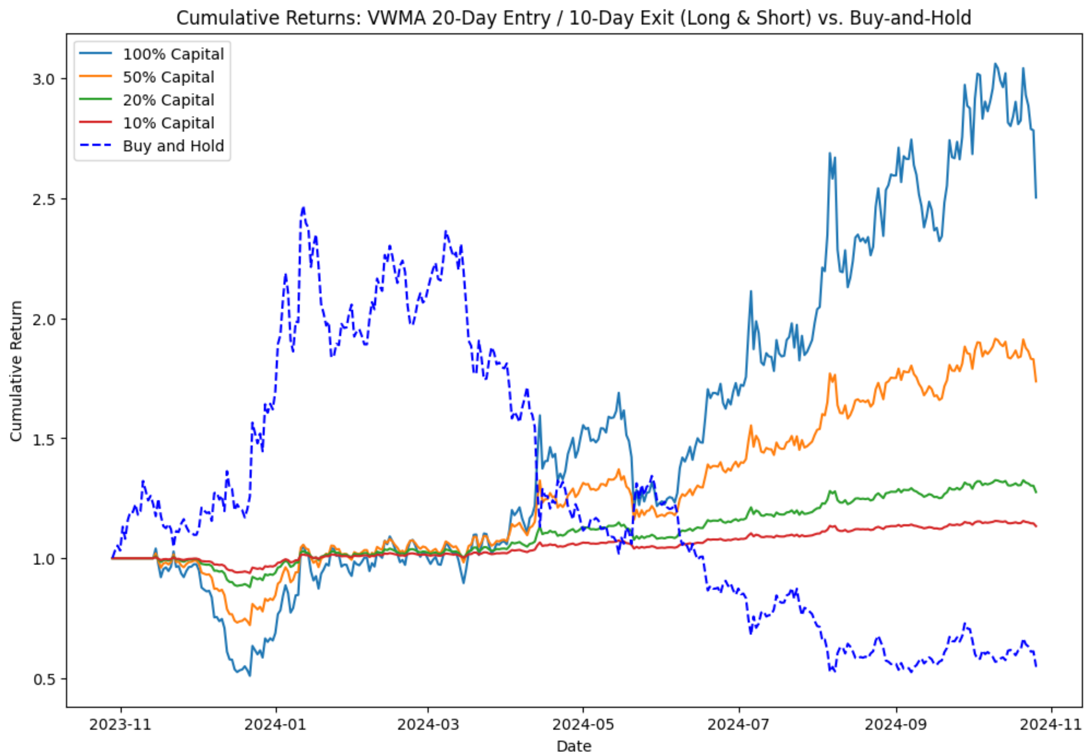
As we can see, the results are quite good and even the Sharpe ratio is above 1, which usually indicates good investment decisions – the idea of adding short signals proved itself because from now on the strategy can be used in any market conditions. The main concern there remains in Max drawdown size because loosing more than 50% of the capital is not good and, therefore, we decided to test different approaches (100%, 50% 25%, and 10% of the capital used in the deal) to demonstrate how the strategy can be adjusted to the risk-averseness. Here are the results:

Table 10. Different shares of the capital used
(without fees) results

	10	25	50	100

Final balance	1 133 838.43 USDT	1 275 823.29 USDT	1 737 138.02 USDT	2 502 892.21 USDT
Sharpe ratio	1.23	1.23	1.23	1.23
Max Drawdown	0.065908	0.128644	0.299041	0.558915
Number of trades	41	41	41	41
Winning ratio	45.00%	45.00%	45.00%	45.00%
Average RR	2.39	2.39	2.39	2.39

Figure 7. Different share of the capital used
(without fees) VS Buy and Hold results



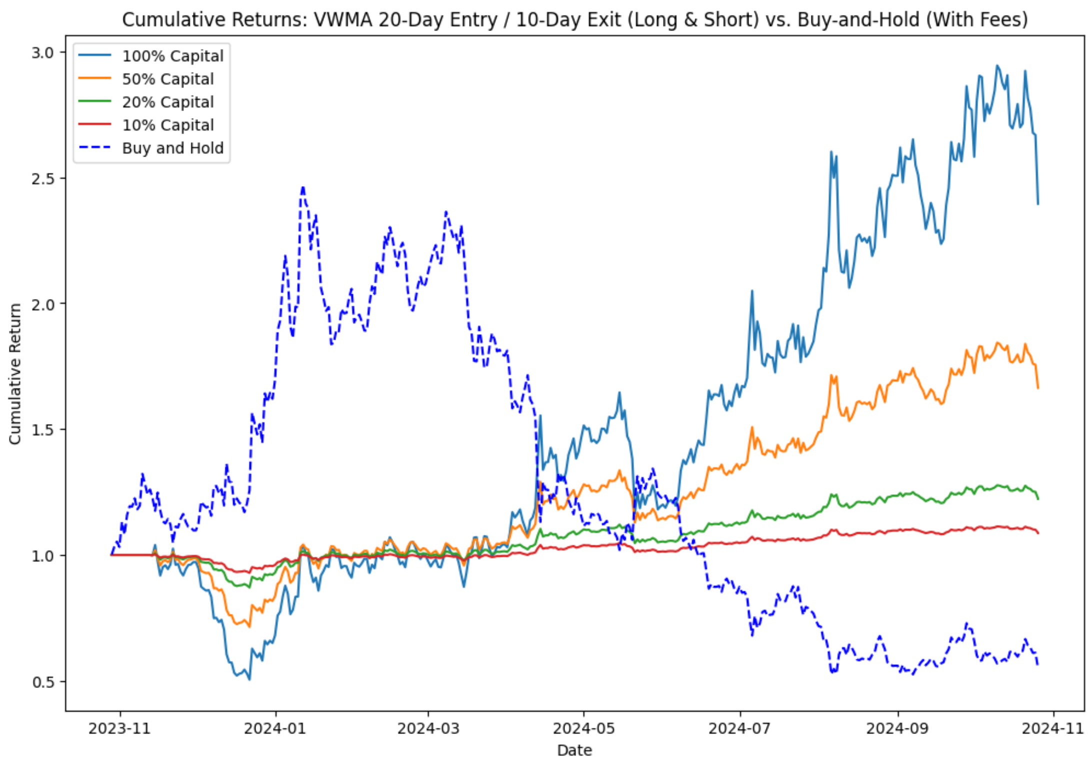
Since we have 41 trades, we decided that it would be right to include fees as well – in order to calculate this, we decided to use the presented fees of the largest cryptocurrency exchange right now (Binance) and, according to their rules, fee is 0.1% per trade and after applied this to the strategy, we received the following results:

Table 5. Different shares of the capital (with fees) used results

	10	25	50	100
Final balance	1 133 838.43 USDT	1 275 823.29 USDT	1 737 138.02 USDT	2 502 892.21 USDT
Final balance (with fees)	1 086 973.63 USDT	1 222 853.31 USDT	1 664 017.32 USDT	2 394 977.71 USDT

Sharpe ratio	1.23	1.23	1.23	1.23
Sharpe ratio (with fees)	0.8	1.01	1.14	1.18
Max Drawdown	0.065908	0.128644	0.299041	0.558915
Number of trades	41	41	41	41
Winning ratio	45.00%	45.00%	45.00%	45.00%
Average RR	2.39	2.39	2.39	2.39

Figure 8. Different share of the capital (with fees) used VS Buy and Hold results



So, to draw the line of all the work, it needs to be said that while, from the first view (that represents, let's say, theoretical findings) can not be used alone to trade a specific crypto asset because did not provide any useful insides but, from the other point of view (that represents the practical findings), it is possible to build the strategy that will be used only volume to trade and it can be quite successful.

CHAPTER 5. CONCLUSIONS AND RECOMMENDATIONS

We believe that this stude provides comprehensive analysis of the determing role of volume in the cryptocurrency market by the example of studying Arbitrum. Looking through the literature, we understood that in the traditional markets, volume has long been studied for its role in reflecting information asymmetry, liquidity, and trader sentiment and with the help of (Osborne 1959) and (Karpoff 1987) we built the theoretical part of our framework in this field. Furthermore, we decided to look deeper into the similar topic in the field of studying creptocurrency markets, finding that while it is hard to use volume alone to predict the price, it is still possible to use volume-based strategies to make some investment decisions (Balcilar 2017).

Therefore, in our empirical analysis, we tested several hypotheses to assess the effectiveness of volume in predicting Arbitrum's daily price movements – our first one proposed that volume could serve as a standalone indicator for future price changes but the results indicated that while there were correlations between volume and price trends, they were relatively weak, suggesting that volume alone may lack sufficient predictive power in isolation. This led us to test a second hypothesis that combined lagged volume with price return data to enhance prediction accuracy but even in the combined model we observed marginally higher explanatory power, and, therefore, we can say that the results remained modest, indicating that volume, while relevant, may not be a fully reliable indicator on its own in the cryptocurrency market context (which correlates with the analyzed studies as well).

Finally, we developed and tested a trading strategy that used a volume-weighted moving average model to generate buy and sell signals and found out that it can be succesfully used to make the investment desions because it demostrated positive returns which are much higher than simple "holding" strategy.

It should be noted, that we conducted our recearch only with one coin and the first further improvement that can be done is to add more “labrats” to receive wider spectre of the results and, what is also important, givind the technical peculiarities, we tested only 1-year period and, form our point of view, it can be extended to analyze more data as well.

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