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Sectoral Dynamics and Investment Strategies by Factors in the Cryptocurrency Market*

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Abstract

This study demonstrates that it is possible to achieve sustained excess returns in the cryptocurrency market by constructing portfolios of cryptocurrencies. To this end, 126 cryptocurrencies were divided into the blockchain and DeFi sectors, and long-only or long/short portfolios were constructed based on strategies such as price momentum, price-to-sales ratio, and revenue growth, with market capitalization or fixed weightings applied in each sector. The risk-adjusted relative returns of each portfolio were derived against the S&P 500. The results showed that the blockchain sector exhibited significant excess returns against the S&P 500 and risk-free rates across all factors in long-only portfolios, while in the DeFi sector, portfolios performance is not robust as in the blockchain sector. The findings of this study suggest the necessity of setting investment strategies that take into account the unique characteristics of each cryptocurrency sector.

KRF Classification : B030603, B050704
Keywords : Cryptocurrency, Factor Investment Strategy, Blockchain, DeFi

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Ⅰ. Introduction

In prior studies, researchers have identified various anomalies in the cryptocurrency market revealing the potential for excess returns. For instance, Shen, Urquhart, and Wang (2020) and Jia, Goodell, and Shen (2022) found that factors such as market capitalization, trading volume, and momentum or reversal strategies can lead to excess returns. Similarly, Chang, Nie, Chang, Cheng, and Yen (2023) demonstrated that cryptocurrency investments could achieve excess returns by leveraging historical price data, particularly price momentum, combined with indicators like the VIX and Economic Policy Uncertainty (EPU) index.

Building on these insights, our study takes a novel approach by investigating how the factors[1)] that drive excess returns can be employed as investment strategies across distinct sectors within the cryptocurrency market. We specifically divide the market into two major sectors: blockchain and Decentralized Finance (DeFi). By constructing sector-specific portfolios based on primary indicators following factors identified in previous studies—such as price momentum, price-to-sales ratio, and revenue growth—we aim to explore how they influence returns in each sector. Our findings reveal that the drivers of excess returns are not uniform across the cryptocurrency market but instead vary significantly between the blockchain and DeFi sectors. Furthermore, we employ different portfolio construction strategies within each sector, including long-only and long/short (zero-investment) approaches, to demonstrate

1) In general, a factor is a zero-investment portfolio based on the specific characteristics that can explain the co-movement of entire asset returns, such as SMB, HML, and UMD. In this study, we employ the factors as useful indicators for constructing strategies, however, they should not be confused with the factors in previous studies of market anomalies (Jia et al., 2022; Asness et al., 2013).

how certain factors can lead to heterogeneous excess returns depending on the portfolio structure. This sector-specific analysis underscores the importance of tailoring investment strategies to the unique characteristics of each segment within the cryptocurrency market.

Recent research has explored various anomalies in cryptocurrency markets, such as the day-of-the-week effect (Tosunoğlu, Abacı, Ateş, and Akkaya, 2023) and the Ramadan effect (Martin, 2022), as well as the relationships between cryptocurrencies and other financial assets (Corbet, Meegan, Larkin, Lucey, and Yarovaya, 2018). Additionally, studies on market reactions to significant events, such as the COVID-19 pandemic (Naeem, Bouri, Peng, Hussain Shahzad, and Vo, 2021), and the role of investor sentiment in price formation (Akyildirim, Aysan, Cepni, and Darendeli, 2021; Li, Urquhart, Wang, and Zhang, 2021; Chang et al., 2023) highlight the dynamic and evolving nature of digital currency markets. Our study contributes to this body of research by focusing on the unique sector-specific dynamics within the cryptocurrency market, particularly within the blockchain and DeFi sectors. We demonstrate that investment by sectors exhibit distinct outcome, which investors must consider when developing their investment strategies.

The structure of the paper is as follows: Section II reviews relevant literature on cryptocurrency market anomalies. Section III outlines the data, methodology, and portfolio construction strategies used in our sector-specific analysis of the blockchain and DeFi markets. Section IV presents the empirical findings, including the performance of various portfolios. Finally, Section V concludes the paper by summarizing key insights, acknowledging limitations, and proposing directions for future research.

Ⅱ. Literature Review

Excess return of portfolio investment and market efficiency has been a subject of prolonged discussion. In general, anomalies in traditional markets and the influence of behavioral factors have raised questions about market efficiency (Li, 2023; Corbet, Lucey, Urquhart, and Yarovaya, 2019). Asness, Moskowitz, and Pedersen (2013) provide insights into market anomalies like value and momentum across different asset classes, suggesting that a sector-based approach to cryptocurrency investment could uncover similar anomalies and opportunities for excess returns. Recent research has explored anomalies in the cryptocurrency market, such as the day of the week effect, the Ramadan effect, and the relationships between cryptocurrencies and other financial assets (Ozili, 2022; Kumar, 2022). Studies have also investigated market reactions to events like the COVID-19 pandemic and the role of investor sentiment in price formation, contributing to the ongoing debate on cryptocurrency market efficiency (Khuntia and Pattanayak, 2021). By examining these anomalies across diverse markets, investors can identify sectors within the cryptocurrency market that offer potential for outperformance through strategic portfolio allocation.

Developing effective cryptocurrency investment strategies requires an understanding of key indicators or factors that influence market behavior, such as price momentum, which play significant roles in shaping investment decisions. Price momentum is a critical factor in cryptocurrency trading, as it reflects the tendency of assets to continue moving in the same direction for some time. Tzouvanas et al. (2020) demonstrated that momentum trading strategies yield positive returns in the short term indicating that the cryptocurrency market exhibits inefficiencies that can be exploited. This finding aligns with Liu et al. (2022), who noted that momentum factors are essential in capturing the cross-section of cryptocurrency returns. The key takeaway is that investors can benefit from identifying cryptocurrencies that are experiencing upward price trends. The P/S ratio, while more commonly used in traditional equity markets, can also be adapted for cryptocurrencies. Chi et al. (2023) highlighted that conventional asset-pricing methodologies, including the P/S ratio, could be effectively applied to cryptocurrency futures. This suggests that investors might consider similar metrics when evaluating cryptocurrencies, particularly those with established revenue streams or utility within their ecosystems. By comparing the P/S ratios of various cryptocurrencies, investors can identify undervalued assets that may have significant upside potential. Revenue growth is another vital indicator, particularly for cryptocurrencies that serve specific functions or have business models tied to revenue generation. Liu and Tsyvinski (2020) emphasized that cryptocurrency returns are influenced by network factors, which can include user adoption and revenue growth metrics. As cryptocurrencies evolve, those with strong revenue growth prospects may attract more investor interest leading to price appreciation. Therefore, monitoring revenue growth can provide insights into the long-term viability and investment potential of specific cryptocurrencies. Volatility is a defining characteristic of the cryptocurrency market, and understanding its implications is crucial for risk management. Novalita et al. (2022) investigated the effects of volatility on cryptocurrency returns, finding that high volatility can lead to significant price swings, which may present both risks and opportunities for investors. Strategies that incorporate volatility analysis, such as using options or derivatives to hedge against potential downturns, can be beneficial. Furthermore, understanding the relationship between volatility and market sentiment can help investors make more informed decisions during periods of market turbulence. Incorporating machine learning and advanced predictive analytics can enhance investment strategies based on these indicators. Kim et al. (2022) proposed a deep learning-based model that utilizes on-chain data to predict cryptocurrency prices, demonstrating the potential for sophisticated algorithms to identify trends and patterns that traditional methods may overlook. By integrating such technologies, investors can refine their strategies, making them more responsive to market changes.

Factors such as market size also plays a significant role in determining the anticipated returns on cryptocurrencies. Moreover, studies have identified calendar anomalies in the cryptocurrency market, such as the turn-of-the-month effect and adaptive calendar effects (Maiti, Vukovic, Krakovich, and Pandey, 2019; Ji, Bouri, Lau, and Roubaud, 2019). These anomalies present opportunities for investors to earn excess profits by strategically timing their positions in different cryptocurrencies based on observed patterns. Research on the integration of cryptocurrencies with classical markets and the spillover effects of volatility can provide valuable insights for investors seeking to optimize their portfolios by including blockchain-based assets (Amirzadeh, Nazari, and Thiruvady, 2022). Furthermore, the emergence of non-fungible tokens (NFTs) and their correlation with decentralized finance (DeFi) assets and cryptocurrencies presents new opportunities for portfolio diversification (Alawadhi and Alshamali, 2022). NFTs and DeFi assets exhibit low correlation with traditional cryptocurrencies, making them attractive options for investors seeking to reduce risk and enhance the resilience of their portfolios. Considering the trend of studies, we are motivated to categorize the cryptocurrency market into two sectors of blockchain-based and DeFi-based asset and inspect investment strategies. Understanding the unique characteristics of each sector and their interactions with factors in traditional financial markets can contribute to the strand of literature.

Ⅲ. Data and Methodology

We analyze daily closing prices of 126 cryptocurrencies[2)] from January 2021 to December 2023. The analysis includes 3-month Treasury Bills as the risk-free asset and the S&P500 index to compare the returns of alternative investment.

1. Cryptocurrency Market Sectors

The segmentation can offer deeper insights into how different factors impact portfolio outcomes in each sector, potentially leading to excess returns for portfolio investments. By dividing the cryptocurrency market into sectors of blockchain and DeFi, researchers can analyze the unique characteristics and behaviors of each sector to identify opportunities for portfolio optimization (Bae and Kim, 2022). However, we need to clarify the criteria of market segmentation, which has not been fully discussed in previous studies. One critical consideration when dividing the cryptocurrency market into sectors is the investment value of cryptocurrencies and blockchain technology.

In distinguishing between DeFi and blockchain within the cryptocurrency market, the key difference lies in their functional objectives and applications. DeFi refers to a set of financial services that operate on a decentralized network, utilizing smart contract to facilitate activities such as lending, borrowing, and asset exchange without the need for intermediaries. These services are typically built on blockchain platforms like Ethereum, which provide the infrastructure for executing and verifying transactions autonomously. DeFi's primary focus is on alternative financial services by offering decentralized

2) The prices are downloadable API services such as CoinGecko. Cryptocurencies are selected based on the ranking of average market share. In order to minimize survivorship bias in the sample we limit the number of cryptocurrencies upto 126.

vehicles that emphasizes transparency, accessibility, and user control. In contrast, blockchain serves as the underlying technology that supports not only DeFi but also a wide range of other applications across industries. Blockchain is a distributed ledger technology that ensures secure, transparent, and immutable records of transactions, which can be applied beyond finance to sectors such as supply chain management, healthcare, and governance. While DeFi operates within the blockchain ecosystem, its scope is narrower, concentrating on financial applications, whereas blockchain, as a foundational technology, facilitates various forms of digital interactions and data storage. We segregate DeFi from blockchain when a cryptocurrency usage is focused on the narrower financial vehicle.

For the classification of sectors, we relied on data provided by our data vendor, Token Terminal Inc., to assign cryptocurrencies to either the blockchain or DeFi sectors. Notably, in our dataset, no cryptocurrency was simultaneously classified as both a native blockchain token and a DeFi token. However, if such a case were to arise, we would prioritize classifying the cryptocurrency under the blockchain sector. This decision is based on the understanding that DeFi services are inherently built upon blockchain infrastructure, making the blockchain functionality more fundamental. In instances where a token serves as both a native blockchain token and supports a DeFi service, it would still be classified as a blockchain asset, given that third-party DeFi services can be developed on top of blockchain networks. This approach ensures consistency in our classification and reflects the foundational role of blockchain technology in supporting broader decentralized applications.

2. Indicators based on Factors

In our investigation, we explore the impact of four key factors—

revenue growth, price momentum, price-to-sales ratio, and low volatility—on excess cryptocurrency returns, each offering a unique lens through which to understand market behaviors.

Revenue growth is an indicator of a cryptocurrency's underlying economic expansion and potential for future profitability. It reflects the increase in income generated by blockchain projects or DeFi platforms over a period. Consistent revenue growth suggests a healthy, expanding ecosystem, which typically drives investor confidence and can lead to sustained price increases over the medium to long term. This relationship between revenue growth and asset pricing is well-documented in traditional finance and has been supported in cryptocurrency markets by studies such as Jegadeesh and Livnat (2006), which demonstrate that companies or assets with strong revenue growth often see their value appreciated as they attract more investment.

Price momentum is another influential factor, capturing the tendency for assets that have performed well in the past to continue performing well in the near future. This concept challenges the Efficient Market Hypothesis (EMH), which posits that past price movements should have no bearing on future returns. However, extensive research (e.g., Jegadeesh and Titman, 2001; Daniel, Hirshleifer, and Subrahmanyam, 1998; Hong and Stein, 1999) has shown that momentum strategies—buying assets that have increased in price and selling those that have decreased—can indeed yield significant returns. In the context of cryptocurrencies, this phenomenon may be driven by factors such as investor sentiment, technological advancements, and network effects that reinforce existing trends.

The price-to-sales ratio (P/S ratio) is particularly relevant for evaluating cryptocurrencies that function as payment systems or securitized assets. The P/S ratio measures the market value of a cryptocurrency relative to its revenue offering insights into how much investors are willing to pay per unit of sales. A low P/S ratio might indicate that an asset is undervalued relative to its sales, potentially signaling a buying opportunity, while a high P/S ratio could suggest overvaluation. This metric helps explain market anomalies where the pricing of assets deviates from fundamental valuations, as highlighted by Nathan, Sivakumar, and Vijayakumar (2001). In the volatile cryptocurrency markets, the P/S ratio can serve as a critical tool for identifying mispriced assets.

Finally, low volatility is a factor that further complicates traditional asset pricing theories. The expectation in conventional finance is that higher risk (or volatility) should be compensated with higher returns. However, studies such as Ang, Hodrick, Xing, and Zhang (2006, 2009) and Baker, Bradley, and Wurgler (2011) have demonstrated the existence of a low-volatility factor, where less volatile assets tend to outperform their more volatile counterparts. In the cryptocurrency market, where volatility is typically high, assets with lower volatility that still manage to deliver substantial returns challenge traditional models and offer attractive risk-adjusted returns. This factor guides our analysis of standard deviations in cryptocurrency returns providing a basis for constructing portfolios that balance risk and reward effectively. The low volatility factor portfolio was constructed by buying (long) the top 20% of tokens with the highest "low volatility" scores. In literature concerning stock market behavior, it is well known that stocks with lower volatility (low-beta or low-volatility) tend to exhibit higher risk-adjusted returns (Baker et al., 2011; Chong & Phillips, 2012; Walkshausl, 2013). The low volatility factor in this study is based on these previous findings. Additionally, volatility was measured using the standard deviation of daily returns and the inverse of volatility was used for the low volatility factor.

By focusing on these four factors—revenue growth, price momentum, price-to-sales ratio, and low volatility—we aim to uncover the underlying drivers of excess returns in the cryptocurrency market. Each factor contributes a different perspective on how cryptocurrencies are valued and how they perform allowing for a more efficient and strategic approach to investment.

3. Portfolio Composition

Our study delves into the construction of cryptocurrency portfolios using a variety of strategies designed to leverage the key factors discussed earlier—revenue growth, price momentum, price-to-sales ratio, and low volatility—while also aiming to reduce specific investment risks as proposed by Markowitz (1952). The portfolio composition process begins with the selection of cryptocurrencies based on these factors employing different strategies to capture potential excess returns.

In constructing the portfolios, we implemented a monthly rebalancing approach to capture the dynamic nature of cryptocurrency markets. At the start of each month, cryptocurrencies were ranked according to the selected factor from the previous period, such as price momentum. For the long strategies, the top 20% of cryptocurrencies for each factor were allocated to the portfolios. For the long-short strategies, the top 20% of cryptocurrencies for each factor were allocated to the long position, while the bottom 20% were allocated to the short position, either with equal weighting or market capitalization weighting applied within each group. This strategy mirrors traditional factor-based investment methodologies commonly used in stock markets allowing for a systematic evaluation of both high- and low-performing assets. By rebalancing monthly, we can account for shifts in factor rankings and ensure that the portfolios remain responsive to changing market conditions and investment environment.

(1) Long 20% Selective Strategy

In this strategy, we select the top 20% of cryptocurrencies ranked by each factor (e.g., the top 20% by revenue growth, price momentum, etc.). These selected cryptocurrencies are then equally weighted within the portfolio. This approach allows us to focus on assets that are most likely to perform well according to each specific factor, ensuring a diversified exposure within the top-performing segment of the market.

(2) Long/Short 20% Selective Strategy

This strategy takes a more dynamic approach by not only buying the top 20% of cryptocurrencies based on each factor but also short-selling the bottom 20%. The assets in both the long and short positions are equally weighted. This strategy is designed to capitalize on the expected outperformance of the top cryptocurrencies while profiting from the underperformance of those ranked lowest. It is particularly useful for exploiting excess returns and maximizing outcomes in both rising and falling market conditions.

(3) Market Capitalization Weighted Strategy

For this strategy, we apply the same long 20% and long/short 20% selective strategies, but the cryptocurrencies within the portfolio are weighted according to their market capitalization rather than equally weighted. This approach ensures that larger, more established cryptocurrencies exert a greater influence on the portfolio's performance. This method also helps in aligning the portfolio more closely with market dynamics reducing the impact of smaller, more volatile cryptocurrencies.

(4) Portfolio Updates and Market Cap Threshold

Portfolios are updated on a monthly basis to reflect the latest data and maintain alignment with the chosen strategies. To avoid the ′small stock effect′—where small-cap cryptocurrencies can disproportionately impact portfolio performance due to their higher volatility and lower liquidity—we include only those cryptocurrencies with a market capitalization exceeding $100 million, as suggested by Shen et al. (2020). This threshold helps in ensuring that the portfolios remain focused on more liquid and stable assets, thereby reducing the risk of extreme volatility.

(5) Sector-Wise Analysis and Portfolio Categorization

In addition to these strategies, our study includes a sector-wise analysis where we categorize the 126 cryptocurrencies into three distinct groups: Blockchain, DeFi, and a combined group that includes cryptocurrencies from both sectors. This classification results in 96 unique portfolios. Each one is tailored to explore the effects of the chosen factors within specific sectors. This sectoral breakdown allows us to conduct a more detailed examination of how different factors impact returns in various segments of the cryptocurrency market, providing insights into sector-specific biases and dynamics.

Through these meticulously designed portfolio strategies, our study seeks to provide a comprehensive understanding of how different factors influence cryptocurrency returns enabling investors to tailor their strategies to capture potential excess returns while managing risk effectively.

4. Performance Metrics

To comprehensively assess portfolio performance, we employ a range of risk-adjusted metrics including the Compound Annual Growth Rate (CAGR), Sharpe ratio, Sortino ratio, and Calmar ratio. Each of these metrics is calculated with adjustments for risk using the 3-month Treasury Bill rate as the risk-free benchmark or the opportunity cost of investment.[3)]

Compound Annual Growth Rate (CAGR): CAGR is a critical measure used to calculate the annualized rate of return of an investment over a specified period. It represents the smoothed annual growth rate, which assumes that the investment grows at a steady rate over the period, even if the actual returns fluctuate year by year. The formula for CAGR is:

$$\mathrm{CAGR} = \left[\left(\frac{EV}{SV}\right)^{1/n} - 1\right] \times 100 \tag{1}$$

Where SV is the starting value of the portfolio, EV is the ending value of the portfolio, n is the number of years. CAGR is particularly useful in comparing the performance of different investments, as it provides a clear picture of how an investment has grown over time, independent of the volatility of periodic returns.

Sharpe Ratio: The Sharpe ratio (Sharpe, 1966) is a widely used metric for evaluating the risk-adjusted return of a portfolio. It measures the

3) Transaction cost such as fees is not considered. Excess returns might be compromised when we include trading cost as discussed by Caporale and Zakirova (2017) and Hudson & Urquhart (2019). However, we disregard trading costs as in most of the literature in cryptocurrency market anomalies and factor analysis.

excess return (the return above the risk-free rate) per unit of volatility or total risk, helping to determine whether a portfolio's returns are due to smart investment decisions or a result of taking on excessive risk. The formula for the Sharpe ratio is:

$$\text{Sharpe Ration} = \frac{P_p - R_f}{\sigma_p} \tag{2}$$

Where R_p is the average portfolio returns, R_f is the risk-free rate (3-month Treasury Bill rate), and σ_p is the standard deviation of the portfolio returns.

Sortino Ratio: The Sortino ratio is similar to the Sharpe ratio but focuses specifically on downside risk, which is more relevant for investors who are primarily concerned with negative returns. Instead of using the standard deviation of the portfolio's returns, the Sortino ratio uses the downside deviation, which only considers the volatility of negative returns. The formula is:

$$\text{Sortion Ration} = \frac{P_p - R_f}{\sigma_d} \tag{3}$$

where R_p is the average portfolio return, R_f is the risk-free rate, and σ_d is the downside deviation. This ratio provides a more accurate assessment of risk-adjusted returns for portfolios that have asymmetrical return distributions or are skewed towards the downside.

Maximum Drawdown: Maximum Drawdown (MDD) is a metric used to quantify the largest decline in the value of an investment portfolio from its peak value ($Peak\ Value$) to the lowest point ($Trough\ Value$)

before a new peak is reached.

$$\text{Mdd} = \frac{Peak\ Value - Trough\ Value}{Peak\ Value} \tag{4}$$

Calmar Ratio: The Calmar ratio is another risk-adjusted metric, which compares the Compound Annual Growth Rate (CAGR) of the portfolio to its Maximum Drawdown (MDD). The formula for the Calmar ratio is:

$$\text{Calmar Ratio} = \frac{CAGR}{MDD} \tag{5}$$

We offer insights by employing these metrics, providing a thorough evaluation of portfolio performance which is balanced with appropriate risk.

Ⅳ. Empirical Analysis

To start with, we assess the performance of our portfolios by comparing their book values against the S&P 500 index, considering various factors, investment strategies, and sector-specific dynamics. Figures 1, 2, and 3 present the normalized book values of these portfolios, which is taken away with the normalized index of the S&P 500. The normalization process starts on January 1, 2021, and extends through December 31, 2023, standardizing both the portfolios and the S&P 500 index to a base value of 100. Therefore, the value becomes zero when the normalized book values of cryptocurrency portfolios equal to that of S&P500 in Figures 1, 2, and 3. This approach provides insights of portfolio performance against a widely recognized market benchmark S&P 500 allowing us to evaluate the relative effectiveness of different investment strategies and sectoral influences over the given time period. Portfolios are constructed based on both monthly (M) and quarterly (Q) factor values to account for any underlying seasonality that may be present. In Figures 1, 2, and 3, left columns are for monthly-based portfolios while right columns are for quarterly-based ones.

As highlighted earlier, we calculated returns of portfolios based on book values against S&P 500, which is considered as the market portfolio in this study. This approach also indicates that the potential excess returns are in vein with CAPM albeit not directly comparable. The key takeaway is cryptocurrency portfolios manifest unique excess returns over the sample periods against the market portfolio and that excess returns also available compared with risk-free rates. These risk-adjusted returns are measured using three key risk-adjusted metrics: the Sharpe ratio, Sortino ratio, and Calmar ratio.

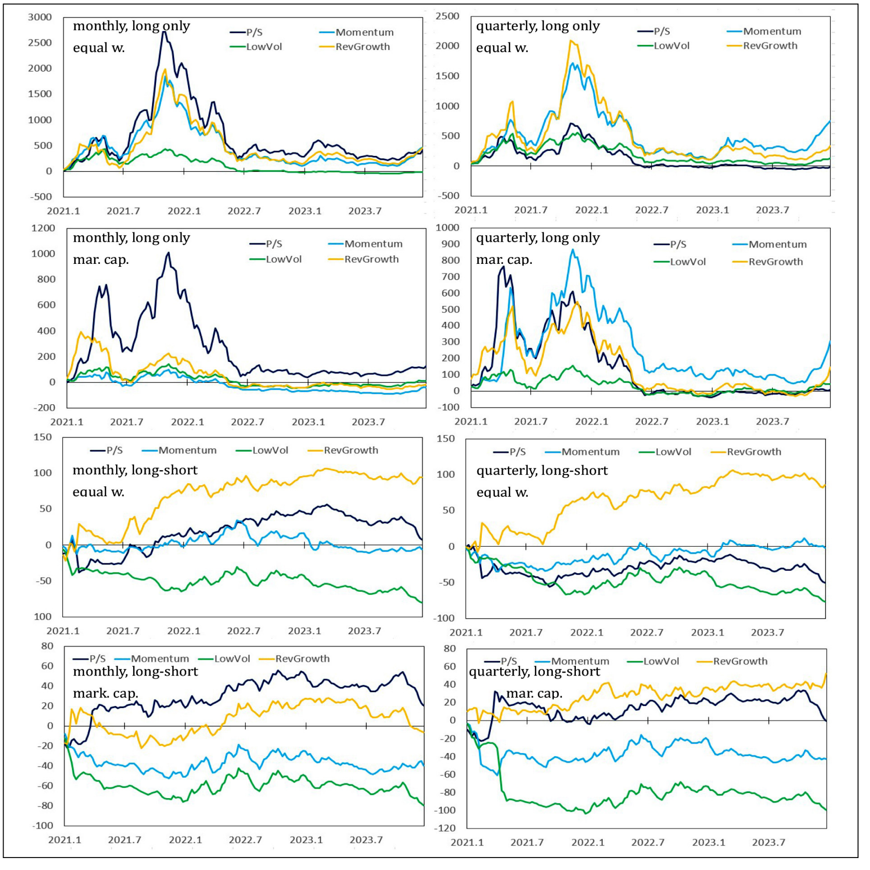
As shown in Table 1, our results indicate that some portfolios defined by specific factors and strategies have significantly outperformed over the three years of sample period. This consistent outperformance underscores the importance of sectoral distinction and tailored investment strategies based on the sectors and factors. Within the blockchain sector, the manifestation of excess returns is particularly pronounced in the long-only portfolios transcending the influence of specific factors and weightings. Concerning the equally weighted portfolios, the Sharpe ratios, a risk-adjusted excess return over risk-free rate, range from 0.39 to 1.19% annually, Sortino ratios range from 0.65 to 1.89% annually, and the Calmar ratio range from -0.01 to 1.58. Based on the Sharpe and Sortino ratios, we can find the portfolios outperforms risk-free rates. Only monthly rebalanced portfolio based on low-volatility factor underperforms in terms of Calmar ratio. With regard to market capital weighted portfolios, the Sharpe, the Sortino, and the Calmar ratios range from 0.10 to 0.96, 0.19

to 1.80, and -0.32to 1.42, respectively. Similarly, for the equal-weighted portfolios, P/S ratio and low-volatility factor portfolios exhibit underperform. Otherwise, the market capital weighted portfolios positively outperform. On the other hand, the excess returns are notably factor-dependent in the blockchain sector when analyzing portfolios that employ long-short strategies. Specifically, portfolios constructed using long-short strategies and based on the P/S ratios, low-volatility tend to underperform within the blockchain sector exhibiting negative risk-adjusted returns to risk-free assets.

In contrast, portfolios within the DeFi sector manifest a different pattern. Both long-only and long-short (zero-investment) portfolios display mixed performance. The difference between long-only and long-short portfolios is revenue growth factor which exhibit negative risk-adjusted returns in term of all three ratios: the Sharp, the Sortino, and the Calmar rations are -0.05, -0.02, and -0.28 respectively for quarterly rebalanced equally weighted long-only portfolios, whereas all positive ratios in long-short portfolios both for equally and market capital weighted. Otherwise, the ratios display underperformance of portfolios based on P/S ratio and low-volatility factors in DeFi sector.

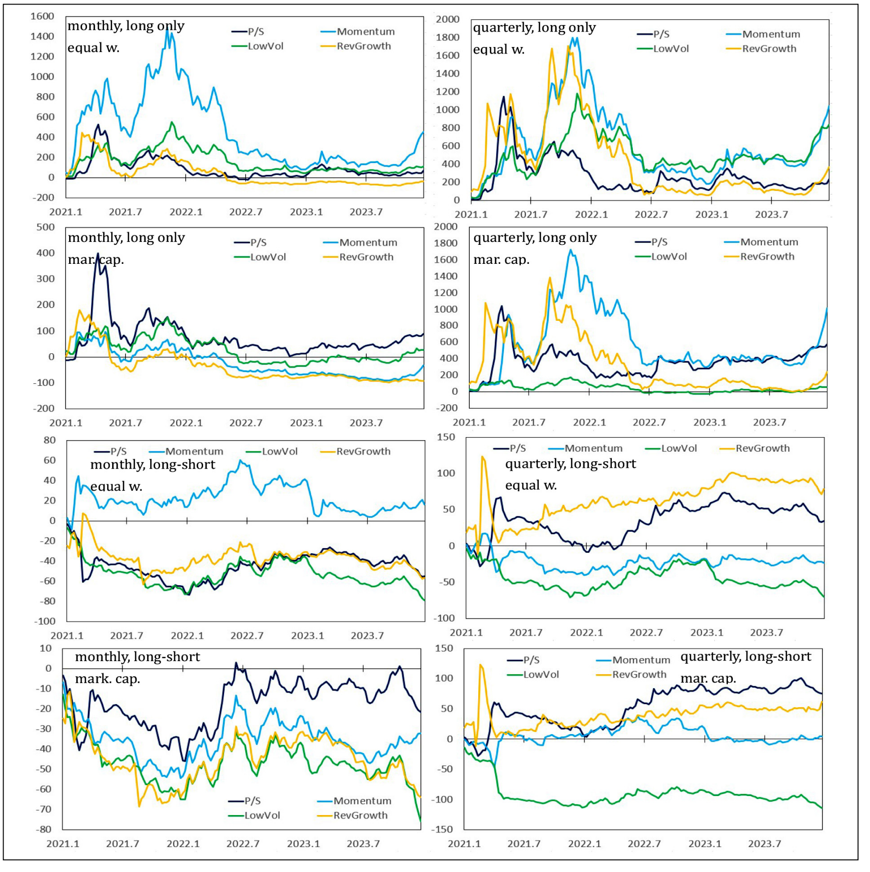
In the combined sector, where all 126 cryptocurrencies are in the basket without considering sectors, the performance metric still shows robust performance but not as much as blockchain sector. This divergence underscores the importance of setting up investment strategies focusing on blockchain sector as well as highlights which strategies based on specific factors are most effective in each sector. The results suggest that price momentum is all time best factors which in quite in line with the strand of literature of price-momentum effects in cryptocurrency market (Asness, Moskowitz, and Pedersen, 2013; Tzouvanas et al., 2020; Shen, Urquhart, and Wang, 2020; Jia, Goodell, and Shen, 2022; Liu, Tyvinsky and Wu, 2022). In contrast, P/S ratio and low volatility do not show robust outcome even within

〈Figure 1〉 Portfolio Book Values juxtaposed against S&P500 Index (Combined Sectors)



Note: These figures delineate the normalized book values of diverse cryptocurrency portfolio investments, juxtaposed against the benchmark S&P 500 index by subtracting S&P 500 index from each portfolio book values. All the book values and the index are normalized to a base value of 100 as of January 1, 2021. Portfolios are categorized by varying composition strategies, grounded in an array of key investment factors: Price to Sales ratio (P/S), Momentum, Low Volatility (LowVol), and Revenue Growth (RevGrowth). The left column is for the portfolios composed based on one-month factor values, whereas the right column is for those based on one-quarter factor values. This dual-column arrangement facilitates a comparison across temporal dimensions. Vertically, the portfolios are segregated by distinct investment strategies. The first row is dedicated to long-only portfolios, adopting a selective diversification approach with a 20% equal weight distribution. Subsequently, the second row presents a parallel analysis of long-only portfolios, albeit with a 20% market capitalization weight distribution. The third and fourth rows diversify the analysis by introducing long/short portfolio strategies. These are again segmented into equal weight and market cap weight distributions, both adhering to the selective 20% threshold. This structured presentation enables a comprehensive examination of the impact of varied factor values and weight distributions on portfolio performance, particularly within the volatile domain of cryptocurrency investments.

〈Figure 2〉 Portfolio Book Values juxtaposed against S&P500 Index (Blockchain Sector)



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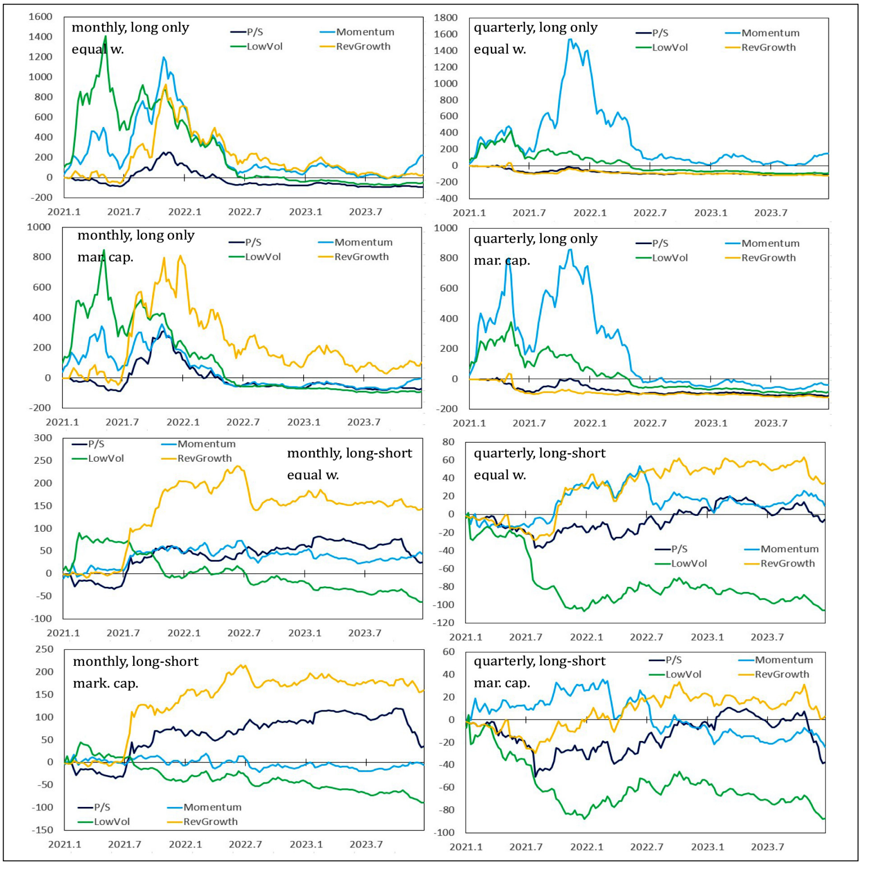
〈Figure 3〉 Portfolio Book Values juxtaposed against S&P500 Index (De-Fi Sector)



Note: These figures delineate the normalized book values of diverse cryptocurrency portfolio investments, juxtaposed against the benchmark S&P 500 index by subtracting S&P 500 index from each portfolio book values. All the book values and the index are normalized to a base value of 100 as of January 1, 2021. Portfolios are categorized by varying composition strategies, grounded in an array of key investment factors: Price to Sales ratio (P/S), Momentum, Low Volatility (LowVol), and Revenue Growth (RevGrowth). The left column is for the portfolios composed based on one-month factor values, whereas the right column is for those based on one-quarter factor values. This dual-column arrangement facilitates a comparison across temporal dimensions. Vertically, the portfolios are segregated by distinct investment strategies. The first row is dedicated to long-only portfolios, adopting a selective diversification approach with a 20% equal weight distribution. Subsequently, the second row presents a parallel analysis of long-only portfolios, albeit with a 20% market capitalization weight distribution. The third and fourth rows diversify the analysis by introducing long/short portfolio strategies. These are again segmented into equal weight and market cap weight distributions, both adhering to the selective 20% threshold. This structured presentation enables a comprehensive examination of the impact of varied factor values and weight distributions on portfolio performance, particularly within the volatile domain of cryptocurrency investments.

〈Table 1〉 Performance Metrics for All Portfolios

Factor	CAGR (%)	MDD (%)	Sharpe	Sortino	Calmar
Combined Sectors					
portfolio: Long (20% selective)					
revenue growth (M)	75.9	-89.0	0.84	1.34	0.85
revenue growth (Q)	61.1	-91.5	0.77	1.23	0.67
price momentum (M)	81.1	-89.8	0.88	1.50	0.90
price momentum (Q)	98.6	-89.5	1.02	1.58	1.10
price/sales (M)	76.5	-89.1	0.84	1.36	0.86
price/sales (Q)	9.1	-92.8	0.41	0.65	0.10
low volatility (M)	8.0	-87.4	0.30	1.21	0.46
low volatility (Q)	35.2	-80.9	0.61	0.94	0.44
portfolio: Long (20% selective, market capital weighted)					
revenue growth (M)	21.3	-74.1	0.46	0.72	0.29
revenue growth (Q)	14.9	-93.3	0.45	0.75	0.16
price momentum (M)	38.7	-88.5	0.62	1.03	0.44
price momentum (Q)	54.9	-84.2	0.72	1.22	0.65
price/sales (M)	33.6	-88.3	0.60	1.00	0.38
price/sales (Q)	0.6	-90.0	0.36	0.56	0.01
low volatility (M)	-6.8	-87.8	0.19	0.34	-0.08
low volatility (Q)	12.7	-77.6	0.35	0.56	0.16
portfolio: Long/Short (20% selective)					
revenue growth (M)	8.3	-32.3	0.24	0.59	0.26
revenue growth (Q)	7.1	-25.9	0.21	0.52	0.27
price momentum (M)	28.9	-24.8	0.75	1.45	1.17
price momentum (Q)	29.7	-29.8	0.77	1.37	0.99
price/sales (M)	12.0	-52.5	0.33	0.57	0.23
price/sales (Q)	-18.5	-50.7	-0.78	-0.84	-0.37
low volatility (M)	-20.0	-51.4	-0.88	-0.94	-0.39
low volatility (Q)	-5.9	-54.0	-0.07	0.02	-0.11
portfolio: Long/Short (20% selective, market capital weighted)					
revenue growth (M)	5.4	-33.0	0.18	0.37	0.16
revenue growth (Q)	-4.2	-30.5	-0.21	-0.10	-0.14
price momentum (M)	15.2	-29.3	0.41	0.75	0.52
price momentum (Q)	20.8	-25.4	0.55	1.08	0.82
price/sales (M)	9.5	-23.8	0.27	0.56	0.40
price/sales (Q)	-19.8	-53.8	-0.74	-0.77	-0.37
low volatility (M)	-32.1	-84.1	-0.06	-0.03	-0.38
low volatility (Q)	-6.4	-66.7	0.03	0.13	-0.10

〈Table 1〉 Performance Metrics for All Portfolios (cont')

Factor	CAGR (%)	MDD (%)	Sharpe	Sortino	Calmar
Blockchain Sector					
portfolio: Long (20% selective)					
revenue growth (M)	72.3	-87.3	0.80	1.43	0.83
revenue growth (Q)	70.7	-93.3	0.79	1.47	0.76
price momentum (M)	112.8	-71.6	1.19	1.89	1.58
price momentum (Q)	121.8	-86.3	1.08	1.78	1.41
price/sales (M)	75.7	-88.8	0.79	1.52	0.85
price/sales (Q)	38.7	-79.9	0.63	1.00	0.48
low volatility (M)	-1.0	-94.3	0.39	0.65	-0.01
low volatility (Q)	41.1	-88.6	0.64	1.07	0.46
portfolio: Long (20% selective, market capital weighted)					
revenue growth (M)	29.5	-80.2	0.56	0.90	0.37
revenue growth (Q)	23.33	-75.0	0.49	0.76	0.31
price momentum (M)	98.6	-79.3	0.93	1.64	1.24
price momentum (Q)	113.1	-79.5	0.96	1.80	1.42
price/sales (M)	48.5	-93.8	0.70	1.28	0.52
price/sales (Q)	-6.2	-87.0	0.20	0.34	-0.07
low volatility (M)	-30.2	-93.0	0.10	0.19	-0.32
low volatility (Q)	16.6	-76.8	0.40	0.65	0.22
portfolio: Long/Short (20% selective)					
revenue growth (M)	0.6	-41.9	0.03	0.20	0.01
revenue growth (Q)	-5.4	-72.9	0.07	0.18	-0.07
price momentum (M)	23.0	-35.6	0.54	1.02	0.65
price momentum (Q)	29.0	-58.4	0.54	1.05	0.50
price/sales (M)	13.0	-32.5	0.34	0.75	0.40
price/sales (Q)	-15.9	-51.2	-0.39	-0.39	-0.31
low volatility (M)	-19.7	-52.1	-0.73	-0.77	-0.38
low volatility (Q)	-9.3	-58.2	-0.04	0.03	-0.16
portfolio: Long/Short (20% selective, market capital weighted)					
revenue growth (M)	3.1	-44.8	0.11	0.29	0.07
revenue growth (Q)	-2.9	-32.3	-0.13	-0.01	-0.09
price momentum (M)	22.7	-58.9	0.46	0.90	0.38
price momentum (Q)	28.9	-35.6	0.66	1.21	0.81
price/sales (M)	7.9	-40.0	0.23	0.53	0.20
price/sales (Q)	-17.8	-51.5	-0.55	-0.58	-0.35
low volatility (M)	-45.7	-94.6	0.21	0.59	-0.48
low volatility (Q)	-14.4	-52.0	-0.20	-0.17	-0.28

〈Table 1〉 Performance Metrics for All Portfolios (cont')

Factor	CAGR (%)	MDD (%)	Sharpe	Sortino	Calmar
De-Fi Sector					
portfolio: Long (20% selective)					
revenue growth (M)	-5.2	-97.2	0.23	0.44	-0.05
revenue growth (Q)	-26.8	-96.6	-0.05	-0.02	-0.28
price momentum (M)	33.5	-93.7	0.60	0.95	0.36
price momentum (Q)	45.9	-92.3	0.68	1.13	0.50
price/sales (M)	13.5	-90.3	0.54	0.93	0.15
price/sales (Q)	-46.3	-94.7	-0.17	-0.20	-0.49
low volatility (M)	-51.9	-95.7	-0.12	-0.13	-0.54
low volatility (Q)	-26.9	-94.5	0.19	0.34	-0.28
portfolio: Long (20% selective, market capital weighted)					
revenue growth (M)	-12.5	-93.2	0.35	0.61	-0.13
revenue growth (Q)	-23.4	-96.2	0.05	0.12	-0.24
price momentum (M)	2.9	-92.7	0.38	0.63	0.03
price momentum (Q)	29.0	-86.5	0.64	1.10	0.34
price/sales (M)	-7.9	-95.6	0.29	0.48	-0.08
price/sales (Q)	-42.4	-95.0	-0.07	-0.06	-0.45
low volatility (M)	-60.1	-98.0	-0.23	-0.29	-0.61
low volatility (Q)	-25.5	-97.9	-0.01	0.04	-0.26
portfolio: Long/Short (20% selective)					
revenue growth (M)	15.8	-27.1	0.40	0.83	0.58
revenue growth (Q)	10.4	-34.1	0.30	0.58	0.31
price momentum (M)	20.8	-27.9	0.55	1.08	0.75
price momentum (Q)	38.3	-29.0	0.85	1.79	1.32
price/sales (M)	18.0	-24.2	0.51	0.95	0.74
price/sales (Q)	-11.7	-71.4	-0.28	-0.28	-0.16
low volatility (M)	-38.3	-80.1	-0.96	-1.11	-0.48
low volatility (Q)	6.9	-24.3	0.20	0.48	0.28
portfolio: Long/Short (20% selective, market capital weighted)					
revenue growth (M)	7.4	-31.7	0.22	0.49	0.23
revenue growth (Q)	0.0	-47.7	0.01	0.16	0.00
price momentum (M)	20.4	-33.5	0.46	0.90	0.61
price momentum (Q)	41.8	-19.0	0.86	1.75	2.19
price/sales (M)	9.7	-25.6	0.28	0.57	0.38
price/sales (Q)	-25.2	-65.5	-0.62	-0.73	-0.39
low volatility (M)	-26.1	-76.6	-0.69	-0.83	-0.34
low volatility (Q)	-1.2	-37.7	0.00	0.14	-0.03

blockchain sector. The implications of these findings are profound, emphasizing the need for investors to adopt a strategic approach tailored to the unique characteristics of each sector within the cryptocurrency market. Our study thus contributes valuable insights into the dynamics of digital assets, illustrating the potential for certain factors to consistently generate excess returns and underscoring the need for continued research into the evolving landscape of cryptocurrency markets.

Ⅴ. Conclusion

Our study investigates the potential for sustained excess returns in the cryptocurrency market by constructing sector-specific portfolios based on key factors such as revenue growth, price momentum, price-to-sales ratio, and low volatility. The analysis has revealed distinct behaviors and opportunities for excess returns within blockchain sector of the cryptocurrency market. Particularly, portfolios focused on price-to-sales ratios and momentum have demonstrated superior performance.

However, our study is not without limitations. The dataset is constrained to a relatively short time frame (2021-2023), which may not fully capture the long-term trends and evolving behaviors in the cryptocurrency market. Additionally, our focus on a specific set of factors may overlook other relevant variables, such as macroeconomic conditions, regulatory changes, or technological advancements, that could also impact portfolio performance. Furthermore, the broad categorization of the cryptocurrency market into blockchain and DeFi sectors may oversimplify the complex and delicate differences within these sectors, potentially limiting the depth of our analysis. Finally, as in the stand of literature, we have not considered trading fee.

Future research could address these limitations by extending the analysis over a longer period to capture more comprehensive market cycles and trends. Incorporating a broader range of factors, including macroeconomic indicators and regulatory developments, would provide deeper insights into the drivers of excess returns in the cryptocurrency market. Additionally, further segmentation within the blockchain and DeFi sectors, perhaps by application type or protocol, could yield more insights into sector-specific dynamics. Exploring the relationship between cryptocurrencies and traditional financial assets within a more integrated framework could also enhance understanding of how cryptocurrencies fit into broader investment strategies.

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암호화폐 섹터별 가격결정 요인과 투자전략*

김 수 현**

논문초록

본 연구에서는 암호화폐의 섹터별로 특정 요인별 포트폴리오를 구성할 경우 지속적인 초과수익이 가능함을 보였다. 이를 위해 시가총액순으로 선정한 126개의 암호화폐를 블록체인과 DeFi 섹터로 구분하여, 각 섹터별로 가격모멘텀, 가격매출비율, 매출성장율, 변동성에 따라 시가총액 또는 고정가중치를 적용한 long-only 또는 long/short 포트폴리오를 구성하였다. 각 포트폴리오의 위험을 고려한 S&P 500 지수 대비 상대수익률 도출한 결과, 블록체인 섹터는 순매수(long-only) 포트폴리오에서 모든 요인에 대해 유의한 초과수익을 보였다. 본 연구의 결과는 가상화폐 섹터 별 특성을 고려하여 투자 전략을 설정할 필요가 있음을 보여준다.

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