Sector Structure in Digital Asset Returns*

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Abstract

This paper provides a comprehensive analysis of the sector structure within the digital asset market. We identify a sector structure within the digital asset market, where different types of digital assets (the "digital asset sectors") exhibit different risk and return characteristics. We examine the observed sectoral variation through two channels: the systematic risk channel and the idiosyncratic risk channel. We find that although overall sectoral differences exist, they are not driven by variations in systematic beta exposures. Instead, sector-specific information emerges through the idiosyncratic risk channel. The sector risk factors, which capture this sector-specific information, exhibit significant variability. Further analysis reveals that such sectoral differences are driven by sector-specific events, sector momentum, and inter-sector spillovers.

Keywords: Digital Asset, Asset Pricing, Sector Structure, Factor Model, IPCA

JEL Codes: G11, G12, C23

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Abstract

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1 Introduction

In the literature, the term "cryptocurrency" often serves as a broad label that covers a variety of digital assets, including decentralized finance (DeFi) applications, non-fungible tokens (NFTs), and smart contract platforms. This broad categorization treats different asset types equally, despite that these assets are based on varying technologies and serve different purposes. For example, while Bitcoin primarily serves for transaction purposes, NFTs gain value through cultural and social utilities. Consequently, different categories of digital assets should, in theory, exhibit distinct risk and return profiles. In this paper, we refer to these different categories of digital assets as "digital asset sectors".

If digital assets sectors explain the cross section of digital asset returns, investors may leverage this understanding to enhance their investment strategies. For example, they might employ sector momentum strategies, buying into high-performing sectors and, where permitted, short-selling those that underperform. In addition, if the sector-level correlations are negative, investors can achieve diversification by reallocating portfolios within the digital asset market, rather than turning to traditional asset classes such as stocks or bonds. In addition, understanding the driving forces behind sector variations can further reveal part of the pricing mechanism for digital assets, an issue that remains underexplored in current literature. To address these gaps, this study examines the sectoral structure of the digital asset market, investigating whether and why different digital sectors have varying risk and return characteristics.

There is not yet a consensus on how to classify digital assets, and such classification inherently involves determining the fundamental drivers of the value of digital assets.[1] Previous theoretical discussions suggest that digital assets primarily derive their value from their functions (See, for example, theoretical discussions in Biais et al., 2023, Schilling and Uhlig, 2019 and Sockin and Xiong, 2023). Therefore, in this paper, we classify digital assets into seven sectors based on their functions and economic sectors. Specifically, we adopt the CoinDesk classification framework, which includes the following categories: Computing, Culture & Entertainment, Currency, DeFi, Digitization, Smart Contract Platform, and Stablecoin. Our sample consists of digital assets with established classifications. In total, we have an unbalanced panel of 425 assets and 1,371 daily observations from March 1, 2020, to December 31, 2023, after the data cleansing.

[1] Various frameworks have been provided by both industries and academics. Table A.1 provides some of the classifications proposed in recent years.

We begin by assessing the overall sector variation by examining the performance of sector portfolios. We find that variations in returns and volatility persist in all sectors. For example, while the DeFi sector portfolio has a daily mean return of 0.05%, the Culture sector portfolio shows a negative daily mean return of -0.013%. Similarly, the Currency sector exhibits the lowest daily standard deviation at 3.79%, whereas the Computing sector reaches the highest at 4.45%. Moreover, certain sectors experience unique shocks that do not affect others.

In general, the observed sector variation can be realized through two channels: the systematic risk channel and the idiosyncratic risk channel. In the systematic risk channel, different sectors can have heterogeneous exposures to systematic risk factors, possibly due to heterogeneity in asset characteristics (such as liquidity or size). In the idiosyncratic risk channel, there might be sector-specific shocks that affect assets within that sector. Those shocks might come from sector-specific events or sector-wide investment sentiments. To separate the systematic and idiosyncratic channels, we adopt a two-step procedure following the top-down strategy described by Beck et al. (2016). First, we construct a set of systematic factors from the asset returns. We examine whether the sector variation is reflected in the exposure to the systematic risk. Second, we remove the systematic component from the asset returns and construct sector-specific factors from the remaining idiosyncratic information.

We first analyze whether the sector variation is realized through the systematic risk exposure (the systematic risk channel). We construct systematic risk factors using Instrumented Principal Components Analysis (IPCA) developed in Kelly et al. (2019) and Kelly et al. (2020). The IPCA enables us to examine how effectively a set of asset-specific characteristics explains exposures to systematic risks. For the choice of characteristics, we start with 15 characteristics that can be classified into four categories: size, risk, liquidity, and momentum. We then select one characteristic from each category and form the subset of characteristics with the highest explanatory power on average returns.

In implementing the IPCA, we decompose the asset-level characteristics into two orthogonal parts following Langlois (2023): the sector component and sector-adjusted component. The sector component represents the portion of characteristics shared by assets within the same sector, whereas the sector-adjusted component represents the portion of those characteristics after removing the sector component. Under the IPCA framework, this decomposition implies that beta exposures are explained by two types of variations: first, sector-level variations in characteristics (represented by the sector component) and second, sector-unrelated variations in characteristics (represented by the sector-adjusted component). If sector-level differences through the systematic risk channel exist, then the sector component should explain at least part of these beta exposures.

We find that although there exist the sector-level variations in characteristics, such variations do not lead to variations in beta exposures. In contrast, the sector-adjusted component dominates the explanatory power on the beta exposure. Therefore, the sector variation through the systematic risk channel (beta exposure) is limited. This finding aligns with some evidence from traditional stock markets, where research suggests that stock industries are less likely to serve as the primary drivers of international market comovement (e.g., Bekaert et al., 2009; Langlois, 2023).

If the systematic beta exposure does not vary across sectors, then the observed sector variation is mainly through the idiosyncratic risk channel. To investigate the issue, we remove systematic components from digital asset returns, and use the residuals to construct the **Sector Risk Factor** by averaging residuals among assets in the same sector. While systematic risk factors include shocks that are common to all assets in the market, sector risk factors contain information specific to assets within the corresponding sector. Unlike sector portfolios, sector risk factors display distinct patterns and exhibit low inter-sector correlations (mostly below 0.1). This finding suggests that a portion of sector-level variation in digital asset returns is realized through the idiosyncratic channel.

We further investigate several potential drivers of sector risk factors to gain insight into the observed sector variations. Since sector risk factors contain information specific to assets, our first conjecture centers on the role of sector-specific events. Such events originate within individual sectors and can have market-wide and sector-wide impacts. Those with market-level impacts are transmitted through systematic risk channels and thus do not appear in the sector risk factors. These market-wide events contribute to sector variations by having varying impacts among different sectors. For example, during the $600 million hack of the Ronin Network—one of the largest hacks in the DeFi sector at the time—the Culture sector remained relatively unaffected, while the DeFi sector experienced a much larger impact.

Events with only sector-wide impacts are transmitted through the idiosyncratic risk channel. To illustrate this, we examine the sector factors surrounding two specific events: the surpassing of the one billion milestone by MakerDAO, the oldest DeFi protocol, and the debut of the Bored Ape Yacht Club (BAYC), one of the most renowned NFT collections. When these events took place, we observed unique significant shocks in the corresponding sector factors. Thus, the presence of sector-specific events contributes to sector-level variation.

The second possible driver for the sector factor is sector-specific time-series momentum and reversal. The "sector-specific" here means momentum/reversal shared by all assets within a specific sector. For example, in 2021, the DeFi sector experienced a sharp increase in the inflow of funding, with the total value locked rising from \$19 billion to \$250 billion; there was a craze for NFT investment (the Culture sector) in 2021. The literature has documented some evidence of momentum effects in the digital asset market (e.g.Fieberg et al., 2023, Liu and Tsyvinski, 2021 and Grobys and Sapkota, 2019). We find that since 2020, both momentum and reversal effects have been present in sector factors, although the reversal effect is more pronounced. These patterns differ across sectors, with the Currency sector exhibiting the strongest momentum and reversal. When we perform sub-sample analyses, the momentum and reversal effects remain statistically significant, but do not persist across the entire sample period, indicating that the observed effects are short-lived.

What drives the observed time-series sector momentum and reversal? We examined two potential driving factors: asset visibility and sector-specific sentiment persistence. We find that short-term momentum (within 60 days) predominantly arises from low-visibility assets, whereas longer-term momentum (beyond 120 days) is more pronounced among high-visibility assets. In terms of sentiment, we find meaningful connections between the persistence of sector sentiment and sector-level momentum and reversal. Higher levels of persistence can both increase and decrease the likelihood of reversal. In contrast, we observe a positive relationship between sentiment persistence and sector momentum.

Finally, another potential driver for the sector variation is the spillover relationships among sector risk factors, because different pairs of sectors may exhibit varying levels and directions of spillovers. We find that the spillover occurs only in some sector pairs (mostly from the Culture sector to other sectors), and most pairs do not exhibit a significant spillover relationship. It takes up to 8 days for the spillover to occur and, for some pairs, it happens within a single day. In addition, the overall spillover level is low: the total connectedness index is around 3.3%, indicating that, on average, only 3.3% of total shocks in one sector originate from other sectors. In comparison, using sector portfolios in the network (which include both systematic and idiosyncratic information), the connectedness index exceeds 70%, implying that most spillovers in the digital market are driven by the systematic factor structure. The spillover levels vary among sector pairs and change over time – for some sectors, the role shifted from net risk receiver to net giver over time. Therefore, although the spillover relationship between sector factors is weak, it does contribute to the sector variation.

Taken together, our results suggest a sector structure in the cross-section of digital asset returns, in addition to the common risk factor structure discussed in the literature. The sector portfolios are largely influenced by systematic factors and exhibit high correlations, suggesting that simply diversifying across digital sectors may not provide sufficient risk mitigation. However, idiosyncratic variations stemming from sector-specific information do exist, and leveraging these insights can yield potential advantages.

Recent studies find that the cross-section industry momentum in the stock market is, in fact, driven by varied systematic factor exposures (Arnott et al., 2023). Our results show that the digital asset market differs from traditional markets. Although assets across digital sectors exhibit different "fundamentals" (size, liquidity, etc.), these differences do not account for sector variations. Instead, the channels we have examined—sector-specific events, sentiments, and spillovers—all point to behavioral factors, which confirm previous empirical findings (e.g., Anastasiou et al., 2021 and Kraaijeveld and Smedt, 2020) that the digital asset market is sentiment-driven.

We evaluated the robustness of our results in different settings. First, we apply a different sector classification scheme, as in the market there is no consensus on how to classify digital assets. We apply the classification scheme from 21Shares & Gecko, which differs significantly from that of CoinDesk. While CoinDesk classifies digital assets into seven sectors, 21Shares & Gecko categorize them into ten sectors, with some of CoinDesk's sectors further decomposed and reorganized. Under the alternative sector classification scheme, the sector-common component is still insignificant in terms of explaining the exposure to systematic risks. In contrast, the sector risk factors under the new classification scheme become different – this is sensible in that we have regrouped assets. However, the sector structure still exists as we observe heterogeneous patterns in sector risk factors.

Second, we repeat the analysis with a weekly frequency dataset that is often seen in the literature. The vast majority of information is omitted under a weekly frequency. We find that the sector-common components of characteristics still poorly explain the beta exposure. As expected, sector risk factors at a weekly frequency experience fewer shocks than those at a daily frequency. However, we still observe varied patterns between weekly sector risk factors, which means that the sector structure still exists (though weaker) under a lower data frequency.

Third, we also consider using the observed factors as systematic risk factors. We construct the observed risk factor following Liu et al. (2022), where three common risk factors are found for the digital asset market: liquidity, momentum, and market. We find that the observed factors carry a similar set of information to the IPCA latent factors. We perform the IPCA analysis by replacing three latent factors with the observed factors constructed. The results are comparable to those with all latent factors. Therefore, our results are robust to the observed factors established in the literature. Finally, our conclusion is less likely to be affected by survivorship bias, as we have sufficient cross-sectional data from early years, and shocks in dying digital assets do not constitute sector-wide information.

Related Literature. Our study contributes to the growing literature on empirical asset pricing of digital assets. Studies in the equity market emphasize the importance of industry components in the context of asset pricing (see Heston and Rouwenhorst, 1994; Griffin and Karolyi, 1998; Moskowitz and Grinblatt, 1999; Cohen et al., 2003; Bekaert et al., 2009; Langlois, 2023). To the best of our knowledge, this study represents the first comprehensive exploration of the sector structure within the digital asset market. Recent studies attempt to identify common risk factor structures in the digital asset market. Liu et al. (2022) discovered market, size, and momentum factors. Liu and Tsyvinski (2021) finds that investors' attention and momentum predict returns in the digital asset market. Dobrynskaya (2024) studies the downside risk premium in the cryptocurrency market. Bianchi and Babiak (2021), using IPCA models similar to ours, studies the risk factor in the digital asset market. They find that liquidity, size, reversal, market, and downside risks drive expected returns. Bhambhwani et al. (2023) associate the cross-section of cryptocurrency prices and returns with blockchain characteristics such as network size and computing power affects.

In this literature, the paper closest to ours is Cong, Karolyi, Tang and Zhao (2022), who are the first to notice the risk-return difference brought by digital asset categories.[2] They perform factor models (CAPM, 3-factor and 5-factor) within each category and find that factor models have varying explanation power in different categories, which implies potential market segmentation in the digital asset market. Differently, we focus on a more refined classification that combines both function and technology. Instead of applying factor models within each

[2] They classified digital assets into general payment, platform token, product token and security token based on functions, as proposed in the book chapter of Cong and Xiao, 2021. In their sample, the majority of the token belongs to the platform token.

sector as in Cong, Karolyi, Tang and Zhao (2022), we use a top-down approach that separates the sector variation into systematic and idiosyncratic channels, and find that sector variation through the systematic channel is not significant. We also investigate the potential economic drivers in the idiosyncratic channel (sector events, momentum/reversal and sector spillover), which brings new insights on how information has been incorporated into the digital asset market.

We also relate our work to recent theoretical studies on the valuation of digital assets. Different types of digital assets might have different pricing mechanisms. Biais et al. (2023) model that the Bitcoin value is the present value of future transaction benefits. Danos et al. (2023) show that tokens are valuable due to their accessibility. Schilling and Uhlig (2019) show that the value of cryptocurrency comes from its utility as a medium of exchange and a store of value. Sockin and Xiong (2023) show that the value of a utility token is associated with the network effect and user sentiment. Differently, Cong, Li and Wang (2022) and Cong et al. (2020) take the view of the interaction between token supply and demand in a platform. Our results provide empirical evidence to those studies; we show digital asset fundamentals are less likely driving force that differentiate. Instead, behavioral factors such as investor's expectations drives short-term pricing movement of digital assets.

The remainder of the paper is organized as follows. In Section 2, we discuss how to classify digital assets, as well as a conceptual framework of sector variation in digital asset returns. Then, we describe the data and setting in Section 3. Next, we discuss how we decompose the sector variation and propose a multilevel factor model for asset returns in Section 4. We study the potential mechanism behind the sector variation 5. Section 6 provides robustness results in different settings. We conclude the paper in Section 7.

2 Digital Asset Sectors and Returns

2.1 Digital Asset Sectors

The terms "cryptocurrency" and "digital assets" are often used interchangeably in the literature. In this paper, we distinguish the two concepts following the US Internal Revenue Service.[3] Specifically, cryptocurrency refers to a type of digital currency that uses cryptography and blockchain for security, which allows it to operate in a decentralized manner without the need

[3] https://www.irs.gov/businesses/small-businesses-self-employed/digital-assets

for a central authority (e.g., Bitcoin, Ethereum, Ripple, and Litecoin).[4] In comparison, digital assets incorporate a broader category that includes any type of digital creation. This category extends beyond cryptocurrencies to non-fungible tokens (NFTs), digital files (like music, videos, and digital art), and even virtual items used in video games.

There is not yet a consensus on how to classify digital assets. Various taxonomies are provided by the literature and industry. Table A.1 provides some of the classifications proposed in recent years. As can be seen, these classifications vary in terms of standards, ranging from functions (e.g., medium of exchange, security tokens) to technology (blockchain types) to economic sectors (e.g., entertainment, financial, computing, etc.). Within each classification, multiple standards are also used to provide a precise description of a digital asset.

Choosing the classification standard to study the risk-return profile involves answering the following question: What determines the fundamental value of a digital asset? If the value of digital tokens comes from their technological structures, then we might classify them based on the underlying technology. If the value of digital assets comes from how they are used, then classification by functions is more appropriate. The theoretical literature on digital asset pricing supports the latter hypothesis. Biais et al. (2023) models that the value of Bitcoin comes from the future transaction benefits. Schilling and Uhlig (2019) shows that the value of cryptocurrency comes from its utility as a medium of exchange and a store of value. Transaction benefits can vary significantly depending on the specific use case and utility of each token. Sockin and Xiong (2023) shows that the value of a utility token, a type of token that is based on decentralized digital platforms, is associated with the network effect and user sentiment. Corbet et al. (2023) finds that the DeFi market can be regarded as a separate asset class, due to the different return behaviors from conventional cryptocurrencies.

For this reason, we employ the classification based on the Digital Asset Classification Standard (DACS) created by CoinDesk, a news media specialized in digital assets. Compared to other classification schemes, the DACS has a more comprehensive classification that considers both the economic sector and the function of digital assets. Specifically, digital assets are classified into seven sectors based on their functions and economic sectors: Computing, Culture & Entertainment, Currency, DeFi, Digitization, Smart Contract Platform, Stablecoin. Each sector can be further classified into different industry groups and then industries. Following

[4] Earlier official reports like International Monetary Fund (2019), however, use cryptocurrency to describe Bitcoin-like crypto assets (BLCAs) and digital tokens.

this taxonomy, we use "digital asset sectors" to refer to different classifications of digital assets. Detailed definitions and examples of sectors are listed in Table A.2. We also provide a robustness check using different classification standards in Section 6.

2.2 Sector Variations in Risks and Returns

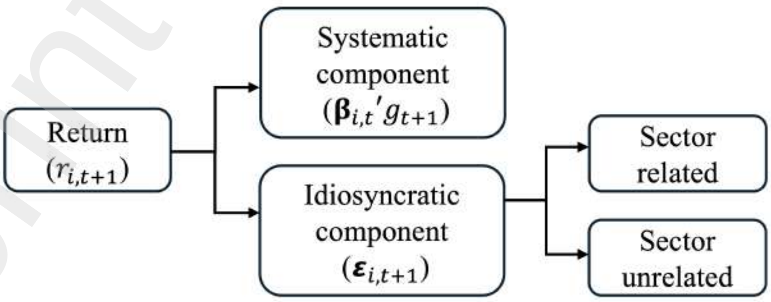
In analyzing the stock market, classifying stocks into different sectors appears to be a logical choice, because each sector has distinct business models and characteristics, which result in varied risk-return profiles. This might also be the case for the cryptocurrency market. Several mechanisms might drive variations in risks and returns in different sectors of digital assets. In general, these can be categorized into two channels: the systematic risk channel and the idiosyncratic risk channel.

Specifically, we consider the following decomposition of digital asset returns[5],

$$r_{i,t+1} = \alpha_{i,t} + \beta'_{i,t} g_{t+1} + \varepsilon_{i,t+1}, \tag{2.1}$$

where $i = 1, \ldots, N$ and $t = 1, \ldots, T_i$. $r_{i,t+1}$ is the logarithmic return of a digital asset i at time $t+1$, g_{t+1} is an $r_g \times 1$ vector of systematic factors, and T_i is the total number of time periods for the asset i. That is, the digital asset return $(r_{i,t+1})$ is decomposed into a systematic risk component $(\beta'_{i,t} g_{t+1})$ and an idiosyncratic risk component $(\varepsilon_{i,t+1})$. Sector variations can thus be reflected in both components. Figure 1 illustrates a conceptual framework for this decomposition.

Figure 1: A Conceptual Framework for Sector Variation



Note: For the systematic component, the beta exposure may exhibit sectoral variation such that $\bar{\beta}_{j,t} \neq \bar{\beta}_{k,t}$ for sector $j \neq k$ where $\bar{\beta}_{j,t} = \frac{1}{N_{j,t}} \sum_{i \in j}^{N_{j,t}} \beta_{i,t}$ and $N_{j,t}$ is the number of assets in sector j. For the idiosyncratic component, the sector related part may contain sector-specific shocks.

[5] Lettau and Pelger (2020*b*) show that a constant loading model is not appropriate to model individual stock returns over longer time horizons.

In terms of the systematic risk channel, the sectoral variation in returns may arise from differences in systematic factor exposures across sectors. For example, digital assets in the DeFi sector may exhibit different systematic risk exposures compared to those in the Currency sector. Sectoral variations in systematic risk exposure may arise from differences in asset characteristics across sectors. This is closely related to earlier research such as Moskowitz and Grinblatt (1999), Cohen et al. (2003) and Hou and Robinson (2006), which show that sector components in firm characteristics are associated with the cross-section of stock returns. Langlois (2023) decomposes stock-specific characteristics into sector, country, and idiosyncratic components, and finds that the country component dominantly explains expected returns and co-movements. In the case of digital assets, different sectors might have different levels of liquidity or trading volume, leading to varied exposure to systematic risk factors.

Another possible factor contributing to the varied systematic risk exposure is the differing pricing mechanisms for different tokens. The determinants of a token's value can vary; for instance, utility tokens may derive their value from the services they provide within a specific platform, while security tokens might be tied to the underlying assets they represent.

The idiosyncratic component may also provide information about the sector variation in asset returns. To understand this, consider that the specification in (2.1) indicates that only systematic risk influences asset prices, since asset-level idiosyncratic risks can be diversified away. However, this assumption might not be met in the real situation because a subset of the assets (e.g., assets within a certain sector) can be exposed to a "weak factor". It is called a weak factor because it affects only a small subset of assets compared to the total number of assets, and therefore cannot be identified as a systematic factor.[6] Recent studies have extensively investigated the weak factor structure in the context of a linear asset pricing model (see, for example, Lettau and Pelger, 2020*a*; Giglio et al., 2021; Anatolyev and Mikusheva, 2022; Dello Preite et al., 2024). In particular, Dello Preite et al. (2024) emphasizes the importance of unsystematic risk in asset pricing models.

In this paper, we focus on a specific form of weak factors: those that affect only particular sectors. These weak factors are considered part of the idiosyncratic risk and are referred to as "sector-specific factors". The sector-specific factor structure may contain valuable information about the risks and returns within that sector, since it is treated as a common factor structure

[6] Note that the weak factor can be regarded as a common factor if we limit our asset universe to a specific asset group, as it impacts all assets in that group. In other words, the strength of a factor (i.e., weak or common) is not an inherent property of the factor: it is a property of the cross section used in the analysis.

for that sector. We employ a top-down strategy to construct sector-specific factors. Specifically, these factors are constructed from the residuals that remain after the systematic component has been removed from the asset returns. Economically speaking, sector-specific factors can be related to events that impact only digital assets within a sector. For example, DeFi (Decentralized Finance) protocols can be highly sensitive to regulatory changes, security breaches, or technological advances specific to the DeFi sector. The value creation process mentioned above might also be relevant: Sector-specific events can directly impact the perceived utility and future transaction benefits of tokens within that sector. In addition, there can be spillovers among sector-specific factors. For example, a significant innovation or regulatory change in the DeFi sector could have ripple effects on other sectors like centralized finance (CeFi) or utility tokens, as market participants adjust their expectations and reallocate across sectors.

All of the aforementioned factors might contribute to the varied risk and returns in digital asset returns across different sectors. However, there are few studies in the literature that address this issue in studying digital asset pricing, probably because there is not yet an official classification of digital assets (due to a lack of regulation) and investors have not yet realized the crucial differences in the digital asset characteristics.

Our research design aims to answer two questions not addressed in the literature: 1) Are there variations among digital asset sector returns? and 2) If so, what are the potential drivers behind these variations?

3 Data

3.1 Digital Assets Transaction Data

We download closing prices, trading volume and market capitalization from Coinmarketcap.com, where daily prices and volume are aggregated across more than 80 different centralized exchanges. The data are sampled daily from January 1st, 2020 to December 31st, 2023, with a day defined at a start time of 00:00:00 UTC.[7] All digital assets in the sample use USD as the quote currency; that is, USD represents the "domestic" currency in the sample. We use the constituents of the DACS 500 index, where we have the digital sector information, as our cross-section of digital asset.[8]

[7]We set the starting date of the sample as 1 January, 2020 to ensure that sufficient cryptocurrencies are available in each sector at all time periods.

[8]The classification data can be found in https://www.coindesk.com/indices. Data downloaded as of April 10th, 2024. In May 2024, CoinDesk has readjusted the size of their index to 250 and thus the number of classification

Following the literature (Bianchi and Babiak, 2021 and Liu et al., 2022), we conduct several data cleansing measures. First, we exclude observations with zero trading volume or a zero price or a zero market cap for any day t. Second, we exclude digital assets with an average market value less than 1 million USD during our sample period. Third, we winsorize (trim) the return at each day t at the 1% and 99% level to take out extreme values. In addition, since stablecoins are pegged to the fiat currency, we exclude them from the analysis. Finally, we exclude the Digitization sector because it is just the virtual form of a real-world contract, with only a few digital assets being classified in this sector. Table 1 presents the distribution of digital assets in different sectors.

Table 1: Number of Assets in Digital Assets Sectors

Year	Total Number of Digital Assets	Computing	Culture & Entertain-ment	Currency	Decentralized Finance (DeFi)	Smart Contract Platform
2020	217	42	26	55	32	61
2021	305	49	46	63	67	79
2022	346	52	62	68	73	90
2023	426	63	87	82	89	104
Average	323.5	51.5	55.25	67	65.25	84.5

Note: This table presents the total number of digital assets each year and in each sector.

3.2 Asset Characteristics

We follow Freyberger et al. (2020), Liu et al. (2022) and Bianchi and Babiak (2021) to consider 15 asset-level characteristics. Detailed definitions are listed in the Appendix A.3. In general, the characteristics can be divided into four categories: size, risk, liquidity, and momentum. Table A.3 provides statistics and correlation between the characteristics of digital assets. Within expectations, characteristics within the same category have a relatively high correlation and a low correlation between categories.

Table 2 provides the summary statistics of the characteristics for each sector. Panel A shows the return distribution characteristics of each sector. The return distribution varies among sectors. For example, the DeFi sector has positive skewness (fat tail), while the Smart Contract sector has negative skewness. All sectors have a negative mean return. Panel B shows the average characteristic of each sector. The Currency sector has the largest size, followed by

data that are publicly available are around 250. We still use the 500 coins to ensure we have enough number of coins in the cross-section. Interested readers may contact CoinDesk for more information.

the Smart Contract sector. The Culture sector is the smallest among all sectors. Liquidity varies greatly between sectors. The Computing and Culture sector is the least liquid. In comparison, the risk level is quite similar between sectors.

Table 2: Summary Statistics of Sector Characteristics

Panel A: Return characteristics

Sector	Asset-day Obs.	Mean	SD	Skewness	Kurtosis
Computing	65750	-0.0512	6.6075	-0.1712	11.4883
Culture & Entertainment	65948	-0.1222	6.2452	-0.0839	13.3793
Currency	87613	-0.0149	5.9175	-0.0951	13.8723
Decentralized Finance (DeFi)	77184	-0.1032	6.3615	0.1842	12.8122
Smart Contract Platform	106635	-0.0377	6.0877	-0.3710	13.0098

Panel B: Other characteristics

Characteristics/Sectors		Computing	Culture & Entertainment	Currency	Decentralized Finance (DeFi)	Smart Contract Platform
Size	market_cap (million $)	410.0000	311.0000	10600.0000	415.0000	4820.0000
	volume (million $)	56.9000	55.6000	742.0000	44.9000	416.0000
Risk	realized_vol (%)	6.2232	5.7798	5.6005	5.8881	5.5296
	capm beta	1.0830	1.0535	0.9690	1.0692	1.0562
	Ido vol. (%)	4.4119	4.0914	3.7297	4.1290	3.8107
	VaR5 (%)	-9.5423	-8.9333	-8.3627	-9.0364	-8.8417
Liquidity	spread (%)	0.0236	0.0212	0.0211	0.0230	0.0206
	illiquidity	0.0000	0.0000	0.0002	0.0064	0.0001
	turnover	0.7708	0.7360	33.3396	102.7896	3.1204
Momentum	max7 (%)	8.4087	7.7122	7.3461	7.9149	7.5891
	max21 (%)	12.2829	11.4483	10.8403	11.5510	11.0044
	mom3	-0.0004	-0.0026	-0.0001	-0.0030	-0.0002
	mom7	0.0017	-0.0023	0.0017	-0.0049	0.0010
	mom14	0.0066	-0.0009	0.0059	-0.0078	0.0033
	mom21	0.0111	0.0006	0.0101	-0.0104	0.0050

Note: This table presents statistics of digital asset characteristics. Panel A shows the return characteristics for each sector (pooled average across time and assets). Panel B shows the average value of the 15 characteristics for each sector.

4 Decomposing Digital Asset Returns

4.1 Econometric Framework

4.1.1 The model

Denote $x_{i,t}$ the $K \times 1$ vector of observed asset-specific characteristics at time t for asset i. Following Langlois (2023), we decompose $x_{i,t}$ into two orthogonal parts: $x_{j,t}^{sec}$ and $x_{i,t}^{adj}$, where $x_{j,t}^{sec}$ is the $K \times 1$ sector-level characteristics, which is common to all firms i in sector j (i.e., $x_{j,t}^{sec} = x_{i,t}^{sec}$ for all $i \in j$), and $x_{i,t}^{adj}$ is the $K \times 1$ sector-adjusted characteristic component, representing the portion of the characteristic that remains after removing the sector-level effect ($x_{j,t}^{sec}$).[9]

Then we model the alpha, $\alpha_{i,t}$, and the systematic factor betas, $\beta_{i,t}$ in (2.1) as follows

$$\alpha_{i,t} = A_0 + A_1' x_{j,t}^{sec} + A_2' x_{i,t}^{adj} + u_{i,t}, \text{ and } \beta_{i,t} = B_0 + B_1' x_{j,t}^{sec} + B_2' x_{i,t}^{adj} + v_{i,t}, \tag{4.1}$$

where A_0, A_1, and A_2 are 1×1, $K \times 1$, and $K \times 1$ vectors of parameters, respectively. B_0, B_1, and B_2 are $r_g \times 1$, $r_g \times K$, and $r_g \times K$ matrices of parameters, respectively. That is, we decompose the alpha and beta exposures to a sector-related part and a sector-unrelated part. This decomposition allows us to examine the importance of the sector structure in explaining the exposure to systematic factors. In this sense, sector variations in beta exposure arise from differences in the asset characteristics across various sectors. Then, we have the following factor model for $r_{i,t+1}$,

$$r_{i,t+1} = A_0 + A_1' x_{j,t}^{sec} + A_2' x_{i,t}^{adj} + (B_0 + B_1' x_{j,t}^{sec} + B_2' x_{i,t}^{adj})' g_{t+1} + e_{i,t+1}, \tag{4.2}$$

where $e_{i,t+1} = u_{i,t} + v_{i,t}' g_{t+1} + \varepsilon_{i,t+1}$ is the composite error.

To recover the sector structure in the idiosyncratic channel, we decompose the error term in (2.1) as follows

$$\varepsilon_{i,t} = \sum_{j=1}^{S} f_{j,t} \mathbb{I}_{i \in j} + \nu_{i,t}, \quad i = 1, \ldots, N_t, \tag{4.3}$$

where $\mathbb{I}_{i \in j}$ is the sector dummy variable for sector j, $f_{j,t}$ is the sector-specific risk factor for

[9]The detailed method of decomposing characteristics and specific form of $x_{j,t}^{sec}$ and $x_{i,t}^{adj}$ are provided in Section A.4.2.

sector j, S is the total number of sectors, and $\nu_{i,t}$ is the asset-specific idiosyncratic shock.

4.1.2 Estimation Method

To separate the systematic and idiosyncratic channels, we adopt a two-step procedure, following the top-down strategy described in Beck et al. (2016). In the first step, we construct a set of systematic factors from the asset returns. In the second step, we remove the systematic component from the asset returns and construct sector-specific factors from the remaining idiosyncratic information.

Specifically, the first step is conducted using the Instrumented Principal Components Analysis (IPCA) method developed by Kelly et al. (2019) and Kelly et al. (2020). Given the estimated model (4.2), we obtain the residuals

$$\hat{e}_{i,t+1} = r_{i,t+1} - \hat{A}_0 - \hat{A}_1' x_{j,t}^{sec} - \hat{A}_2' x_{i,t}^{adj} - (\hat{B}_0 + \hat{B}_1' x_{j,t}^{sec} + \hat{B}_2' x_{i,t}^{adj})' \hat{g}_{t+1}. \tag{4.4}$$

Then in the second step, the sector-specific factors are constructed as equal-weighted sector portfolios for each sector: $\hat{f}_{j,t} = \frac{1}{N_{t,j}} \sum_{i=1}^{N_t} \hat{e}_{i,t} \mathbb{I}_{i \in j}$, for $j = 1, \dots, S$ and $t = 1, \dots, T$, where $N_{t,j}$ is the number of assets in sector j at time t[10].

4.2 Overall Sector Variation

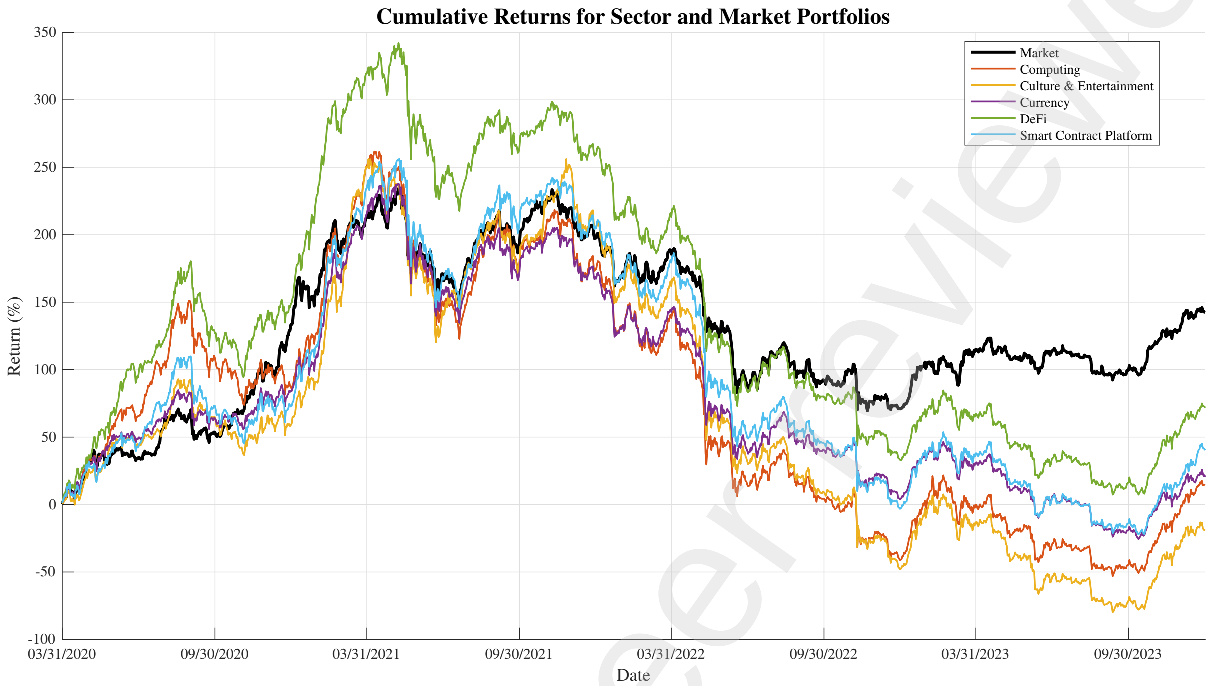
We first give an overview of the sector variation through the performance of sector portfolios, which contain both systematic and sector-level information. Figure 2 provides the cumulative value of equal-weighted sector portfolio returns as well as the market portfolio return. The cumulative returns for the sector portfolios generally co-move with those of the market portfolio, indicating that sector returns are largely dominated by market forces.

Table 3 presents the sector portfolio statistics and their correlation matrix. In line with the results in the graph, the average return and volatility vary among sector portfolios. For example, the Currency sector portfolio has a daily mean return of 0.015%, while the Culture sector portfolio has a daily mean return of -0.013%. The Currency sector also has the lowest daily standard deviation at 3.79%, in contrast to the Computing sector's 4.45%, the highest among all sectors. Furthermore, specific shocks are observed in certain sectors but not in others (e.g., by the end of 2021, the Culture sector). The DeFi sector has the highest mean return.

[10]Since $u_{i,t}$ and $v_{i,t}$ contain no sector-specific information, sector-specific risks in these two residual components are expected to be diversified away once sector averages are taken.

All sector portfolio pairs have a relatively high correlation (more than 0.9), partly due to the fact that most of the performance is driven by systematic risk factors.

Figure 2: Sector and Market Portfolios



Note: This figure shows the cumulative equal-weighted return for sector portfolios and the market portfolio.

Table 3: Summary Statistics of Sector Portfolios

Panel A: Portfolio return characteristics

Sector	Mean	SD	Beta
Computing	0.0106	4.4531	0.6970
Culture	-0.0139	4.3547	0.6994
Currency	0.0150	3.7928	0.8723
DeFi	0.0523	4.3605	0.7144
Smart Contract	0.0295	4.3120	0.7350

Panel B: Correlation Matrix

Sector	Correlation				
Computing	1				
Culture	0.939	1			
Currency	0.957	0.939	1		
DeFi	0.941	0.904	0.933	1	
Smart Contract	0.971	0.948	0.972	0.947	1

Note: This table presents statistics of equal-weighted portfolio. Panel A shows the return characteristics for each sector portfolio. Panel B shows the correlation matrix among sector portfolio returns.

For comparison purposes, we also provide in Figure A.2 and Table A.5 the performance of value-weighted portfolios, where the weight is adjusted using the market value of each day. While the return characteristics and correlation are slightly different from those of equal-weighted portfolios, we still find sector variations in risks and returns.

4.3 Systematic and Idiosyncratic Sector Variations

4.3.1 Characteristics Selection

In this section, we determine the set of characteristics that will be used in the IPCA estimation. We consider the set of 15 asset-specific characteristics outlined in Section 3.2 as potential candidate characteristics. As shown in Table A.3, the correlation between characteristics in the same category is likely to be high. For example, the overall correlation between market_cap and volume over all assets and time periods is 0.735 and the correlation between mom14 and mom21 is 0.818. The correlation can be even higher if we consider the cross-section in a single time period. The high correlation between instruments included in the model indicates redundant information and may also pose serious problems in the inference.

To avoid high correlations between instruments and to also make the best use of the information in the characteristics, we select one characteristic from each of the four categories to form a subset of characteristics with the highest explanatory power. Specifically, we select the set of combination with the highest Total R^2 in (A.5) from all possible combinations of characteristics. In fact, Kelly et al. (2019) shows that a parsimonious subset of 10 significant characteristics yields a factor model with comparable explanatory power to that derived from the full 36-characteristic dataset. We find that the set of characteristics with the highest Total R^2 is {volume, CAPM beta, spread, mom3}, with which we implement the IPCA estimation.

4.3.2 Exposure to Systematic Risk Factors

Denote $A = (A_0, A_1', A_2')'$ and $B = (B_0', B_1', B_2')'$. Table 4 reports the IPCA performance[11] (Total R^2s and Predictive R^2s) of the model with different numbers of latent factors (ranging from $r_g = 1$ to $r_g = 6$) for the restricted model ($A = 0$) and the unrestricted model ($A \neq 0$). The results in Panel A show that the Total R^2 generally increases with the number of latent factors and the Predictive R^2 is close to zero for all different numbers of latent factors.

Panel B shows the results of the asset pricing test $H_0 : A = 0$. For $r_g = 1, 2, 3, 4$, the bootstrap results of the asset pricing test indicate a strong rejection of the null $H_0 : A = 0$.

[11] As we do not have prior knowledge of the true number of systematic risk factors forming the common risk factor structure, we examine the IPCA model performance up to six factors.

However, we fail to reject the asset pricing test for alpha after the fifth latent factor is included in the model, which means that there is not enough evidence to conclude that there are alphas determined by our choice of instruments with five latent factors included in the model. Since the model with five latent factors is the most parsimonious model without mispricing, for the following analysis, we take the number of latent factors $r_g = 5$.

The rth column of the B_1 and B_2 matrices describes how each characteristic maps into an asset's beta on the rth factor. Inspection of this mapping offers information on the nature of estimated IPCA risk factors. Figure 3 shows the estimated parameters $\hat{B}_1$ and $\hat{B}_2$ from the IPCA estimation with the decomposed characteristics.[12] The plots in the first column of Figure 3 report the estimated parameters $\hat{B}_1$ in (4.1) associated with the sector component of characteristics and the plots in the second column of Figure 3 report the estimated parameters $\hat{B}_2$ in (4.1) associated with the adjusted component of characteristics. The plots show that the magnitudes of the estimated parameters are larger for the adjusted component than for the sector component of characteristics.

We examine the role of the sector component in explaining exposure to systematic factors by testing the joint significance of the sector component and the adjusted component among the five factors. Table 5 reports the test results. The results show that the sector component is insignificant at the 5% level and the adjusted component is significant at the 5% level, indicating that the sector component of the chosen characteristics may not be material in explaining the exposure to the systematic factors. In other words, sector variations through the systematic risk channel are limited.

Cong, Karolyi, Tang and Zhao (2022) perform crypto factor models (CAPM, three-factor, and five-factor) within each category and find that these models' explanatory power varies across cryptocurrency categories. They further conclude that such variation implies potential market segmentation in the digital asset market. Our results partly confirm their findings but provide further explanation. The source of market segmentation does not stem from the systematic component but rather from the idiosyncratic component. Different types of digital assets may share similar exposures to systematic risk factors.

Since the adjusted component of characteristics provides statistically significant and stronger results, we focus on the adjusted component when interpreting the IPCA risk factors. The

[12] Since the alpha is statistically insignificant in the model with five latent factors, we do not report the estimation results for $\hat{A}_1$ and $\hat{A}_2$.

exposure to the first systematic factor is primarily determined by the adjusted components of two characteristics, CAPM beta and spread. These two characteristics enter into the exposure to the first systematic factor with similar magnitude. Further, the exposure to the second systematic factor is mainly determined by the adjusted component of spread. The exposure to the third systematic factor is predominantly explained by 3-day momentum. The exposure to the fourth systematic factor is mainly determined by CAPM beta. Lastly, for the exposure to the fifth systematic factor, volume explains most of the variation. In this regard, based on our classification of characteristics, we may interpret the first systematic factor as risk and liquidity factor[13], the second factor as liquidity factor, the third factor as momentum factor, the fourth factor as risk factor, and the fifth factor as size factor.

Table 4: IPCA performance: Systematic factor structure

		Number of systematic factors					
		$r_g = 1$	$r_g = 2$	$r_g = 3$	$r_g = 4$	$r_g = 5$	$r_g = 6$
Panel A: IPCA performance for individual assets (r_t)							
Total R^2	$A = 0$	0.4789	0.5316	0.5420	0.5491	0.5537	0.5575
	$A \neq 0$	0.4796	0.5320	0.5423	0.5494	0.5539	0.5576
Pred. R^2	$A = 0$	0.0000	0.0000	-0.0001	-0.0001	0.0000	0.0002
	$A \neq 0$	0.0009	0.0004	0.0003	0.0003	0.0003	0.0003
Panel B: Asset pricing test							
W_α p-value		0.0000	0.0000	0.0000	0.0100	0.8000	0.9000

Note: The Z-score of the sector-common component of characteristics ($x^{sec}_{j,t}$) and sector-adjusted component of characteristics ($x^{adj}_{i,t}$) are used in the IPCA estimation. The decomposed characteristics include (volume, capm_beta, spread, mom3).

Table 5: Joint Significance of Characteristic Components When $r_g = 5$

	Characteristic components	
Parameters	Sector components (B_1)	Adjusted components (B_2)
B	0.9500	0.0500

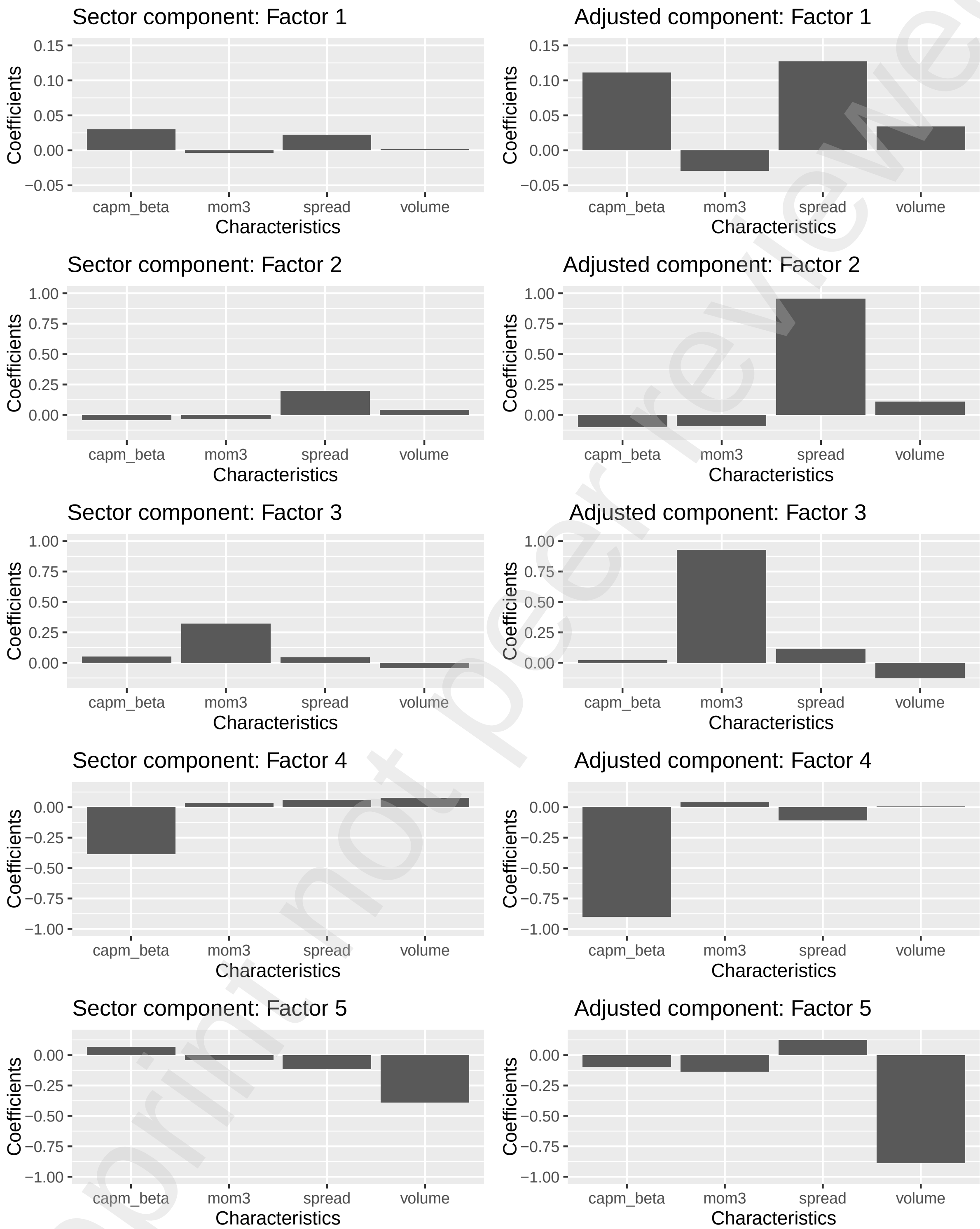
Note: p-values for the joint tests are reported in the table. Five latent factors are included in the model. The results are obtained from 100 bootstrap iterations.

4.3.3 Sector Factors: Stylized Facts

We first present in Table 6 the summary statistics of sector factors. The mean is close to zero for all sector factors, with the Culture sector factor having the highest mean return (different from the observation in the sector portfolios). The volatility is the highest for the Culture sector

[13]We find that the first factor has a high correlation of more than 0.7 with the market factor.

Figure 3: Exposure to Systematic Risk Factors across Sector and Adjusted components of Characteristics



Note: The graphs display the estimated loading parameters corresponding to the first to the fifth systematic factors in the model 4.2. The decomposed characteristics include (volume, capm_beta, spread, mom3).

and the lowest for the Smart Contract sector. The correlation is not significant for most pairs, partly because the common information from the systematic component has been filtered out.[14]

Table 6: Summary Statistics of Sector Factors

Panel A: Factor return characteristics

	Computing	Culture & Entertain-ment	Currency	Decentralized Finance (DeFi)	Smart Contract Platform
Mean	-0.0019	0.0075	-0.0053	0.0070	-0.0026
Std.	0.6038	0.7259	0.5255	0.6958	0.4866
Max.	2.7814	2.7919	3.1099	3.6330	1.7298
Min.	-2.5510	-2.4885	-1.5562	-3.0818	-1.9761
t-Stat.	-0.1189	0.3801	-0.3767	0.3722	-0.1983

Panel B: Correlation among sector factors

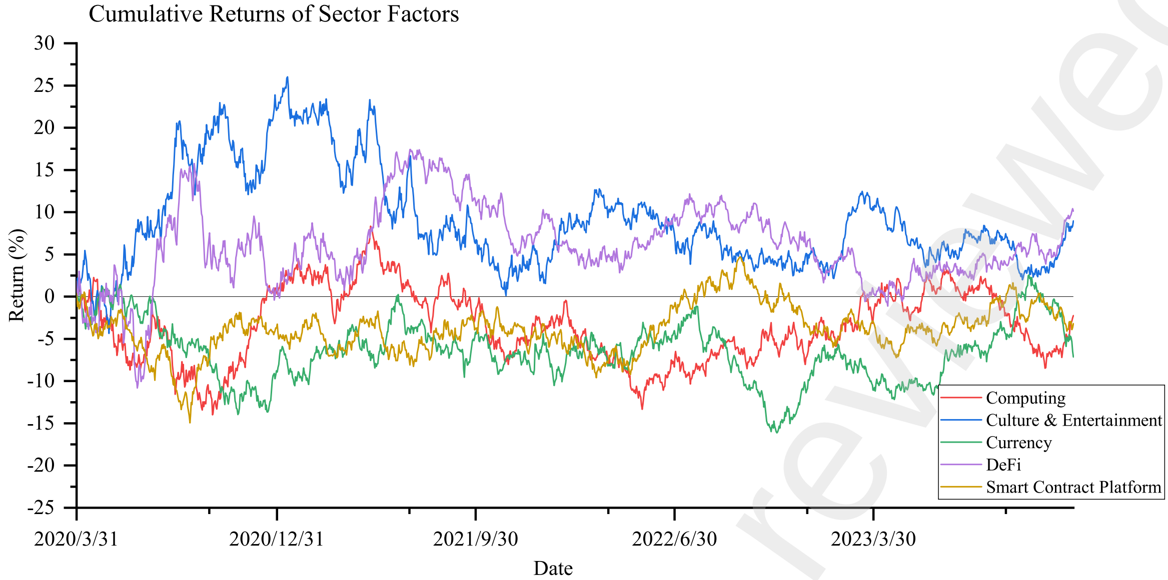
Variables	(1)	(2)	(3)	(4)	(5)
(1) Computing	1				
(2) Culture & Entertainment	-0.009	1			
(3) Currency	-0.028	-0.081*	1		
(4) Decentralized Finance (DeFi)	0.019	-0.049	-0.022	1	
(5) Smart Contract Platform	0.011	0.000	-0.005	-0.002	1

Note: This table presents statistics of sector factors. Panel A shows the return characteristics for each sector factor. Panel B shows the correlation among sector factors. The t-Stat. is estimated as $\frac{\text{Mean}}{\text{Std}}\sqrt{T}$. "*" means significance at 5% level. Returns are expressed in percentage.

Figure 4 shows the cumulative value of sector-specific risk factors. The sector risk factors are different from the sector portfolios shown in Figure 2: The patterns among different sector factors vary. The observed variation might come from several sources. First, there are shocks unique to each sector. Then, there might exist time-series momentum. For example, in the Culture sector, there was strong momentum during 2020 and for the Currency sector, there was momentum during early 2023. Finally, there might be a spillover relationship among some pairs – that is, shocks in some sectors lead to shocks in other sectors. For example, at the beginning of 2021, there might exist a spillover between the Culture and the Currency sectors. This will lead to sector variation as the level and direction of spillover differ among sectors. We will further explore these forces in the next section.

[14]Note that, even if the systematic component has been removed, sector risk factors might also have sizable correlation among some pairs if there are common information shared between the pairs.

Figure 4: Cumulative Returns for Sector Factors



Note: This figure shows the cumulative return for sector factors.

5 Chasing Sector Factors

The previous analysis indicates that sector variation is primarily driven by the idiosyncratic channel. In this section, we delve deeper into digital asset sector variations by examining the factors that influence sector-specific risk. Specifically, we focus on three potential drivers: sector-specific events, sector momentum, and inter-sector lead-lag effects.

5.1 Sector Events

Sector-specific events could serve as a potential source of common shocks affecting all assets within a particular sector. For instance, a technological breakthrough might impact all digital assets in the sector. Similarly, the launch of a new marketplace for a specific asset type, such as NFTs, could trigger reactions within certain sectors.

We define events that have a contemporaneous or lagged impact on a specific sector as sector events. In general, sector events can be classified into four types according to their impacts:

- Type 1: Events affect only one sector on the first day, with possible spillover to other sectors in the following days.
- Type 2: Events affect some (not all) sectors on the first day, with possible spillover to other sectors in the following days.

- Type 3: Events affect all sectors on the first day, with possible spillover to other sectors in the following days.

Type 1–2 events can be captured by sector factors and type 3 events are included in systematic factors (the market factor). In practice, it is hard to distinguish each type of events unless explicitly modeled within the framework.

We provide two examples of events that might be captured by sector factors (types 1–2): the historical milestone of MakerDAO surpassing USD one billion and the sale of the Bored Ape Yacht Club (BAYC) NFTs.[15] MakerDAO is the oldest and largest DeFi protocol. Its reaching the one billion milestone could have strengthened market confidence and driven further investments into the DeFi sector. Similarly, the BAYC, one of the most well-known NFT collections, gained rapid fame after its launch, selling $7.3 million worth of NFTs within a week. Both events are expected to impact only the digital assets within their respective sectors. If this is the case, we should observe shocks around the event dates for these two sectors.

Figure 5 shows the cumulative value of sector factors (Panel A) and the box plot of all asset residuals ($\hat{e}_{i,t}$) around the event day (Panel B). As for the event in the DeFi sector (left graph of each panel), there is a large positive shock in the sector factor three days after, with an up movement in the residual distribution (indicating that the large positive shock in the sector factor is not due to some extreme changes in a single asset but sector-wide movements). Regarding the event in the Culture sector (right graph of each panel), there are large positive shocks right after the launching date (May 1st), with more assets having positive residuals on May 3rd and more assets with extreme positive shocks.

We also consider another two events that might be associated with the systematic risk factor (type 3): the crash of the Luna cryptocurrency (a type of stablecoin) in May 2022 and the $600 million hack of the Ronin Network (one of the largest hacks in the DeFi sector at that time) in March 2022.[16] They contribute to sector variations as different sectors may react differently to the same event.

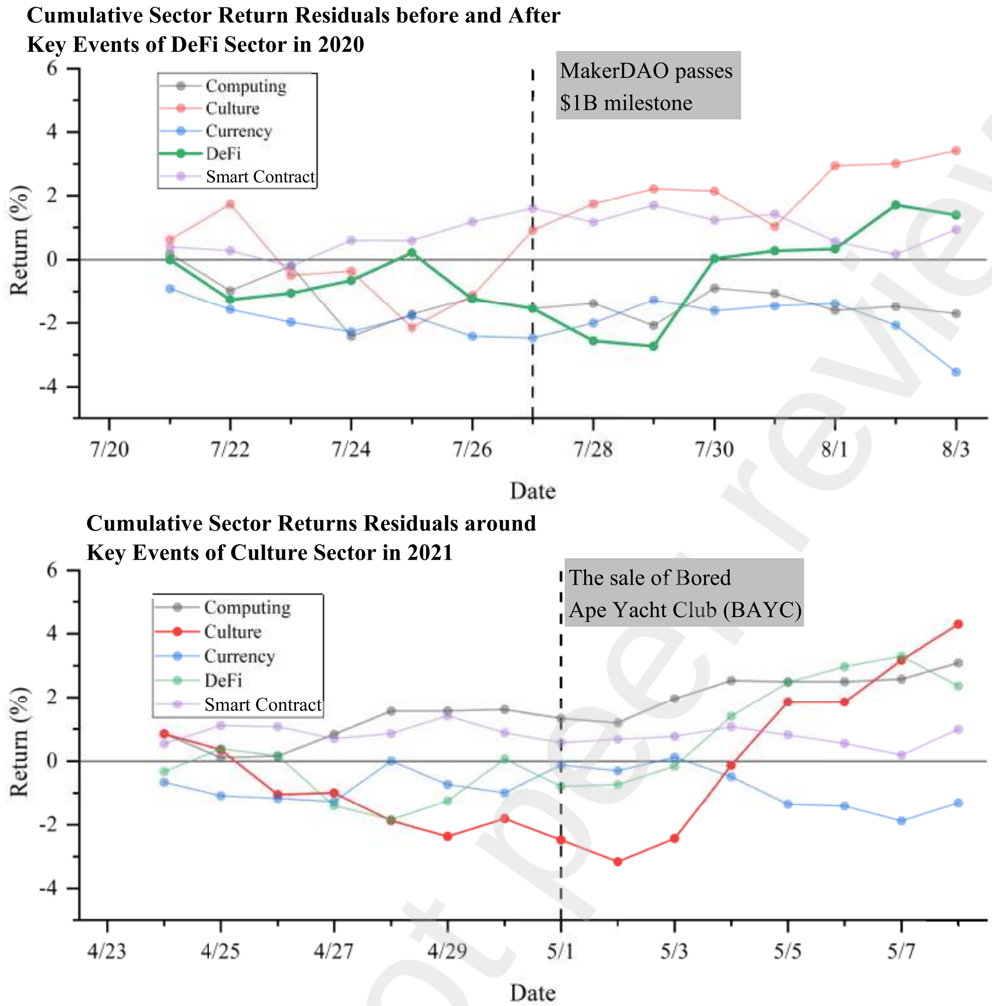
Figure 6 shows the cumulative sector portfolio returns (Panel A) and asset returns (Panel B) around two key events mentioned above. As can be seen, although the event is sector-specific, it triggers market-wide reactions, probably because there were market-wide sentiment shocks.

[15] https://www.nasdaq.com/articles/makerdao-passes-$1b-milestone-in-defi-first-2020-07-27; https://nftplazas.com/bored-ape-yacht-club-nft/.

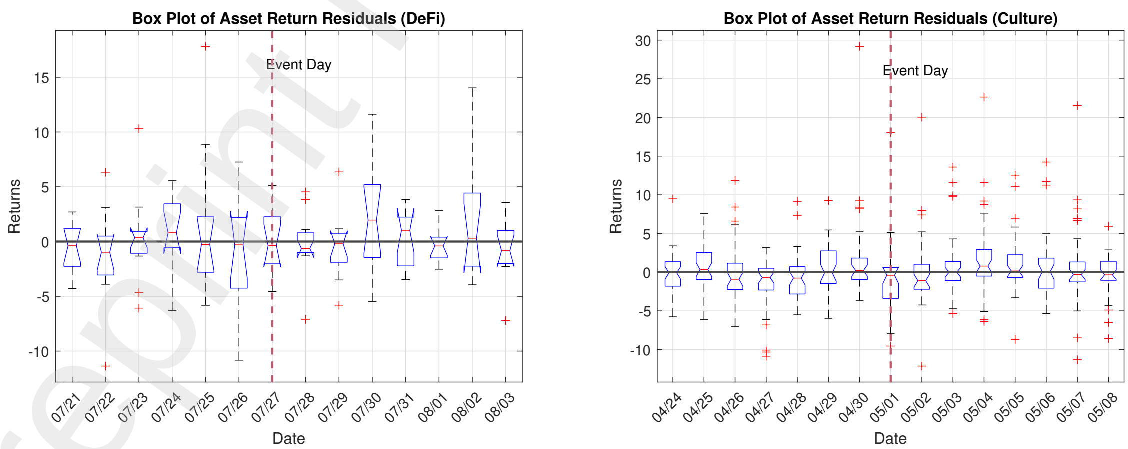
[16] https://www.coindesk.com/learn/the-fall-of-terra-a-timeline-of-the-meteoric-rise-and-crash-of-ust-and-luna/; https://www.securityweek.com/hackers-steal-over-600m-major-crypto-heist/

Figure 5: Sector Factor Returns around Key Events

Panel A: Sector factor returns around key events



Panel B: Box plots of all asset return residuals in the cross-section around key events



Note: This figure shows the performance of sector factors around the given event. Panel A shows the cumulative value of sector factors. Panel B shows the box plot of all asset residuals ($\hat{e}_{i,t}$) around the two events. In each panel, the left graph shows the event with MarkerDao and the right graph shows the event of the sale of BAYC.

However, the level of shocks is different for different sectors. For example, the Currency and Smart Contract sectors experienced less drop than other sectors during the Luna crypto crash; the Culture sector was less affected by the Ronin Network hack.

In sum, sector-specific events play a role in determining the sector structure in digital asset returns. On the one hand, variations in the sector-specific factors are partly driven by local events that have local impacts. On the other hand, local events that have a global impact also provide varied systematic risk contributions across sectors.

5.2 Time-Series Sector Momentum/Reversal

Literature on stock market finds the existence of sector momentum (e.g., Moskowitz and Grinblatt, 1999 and Hoberg and Phillips, 2018). Further, such sector momentum can be explained by momentum from the factor structure (Arnott et al., 2023). Empirical studies have also documented momentum effects in the digital asset market (e.g.,Fieberg et al., 2023 and Grobys and Sapkota, 2019). Therefore, one possible source of the observed sector variation might be the sector-specific momentum.

While we have considered market-wide momentum in the systematic risk channel (different sectors have different exposures to system-wide momentum factors), sector momentum here refers to momentum effects shared by all assets within a specific sector. In this section, we first study whether there exists sector momentum/reversal. Then, we examine two possible drivers behind the observed momentum/reversal effects: the asset visibility and sentiment persistence.

5.2.1 Does Sector Momentum/Reversal Exist?

We follow Ehsani and Linnainmaa (2022) and Moskowitz et al. (2012) to conduct the following time series regression for sector j and lag length L:

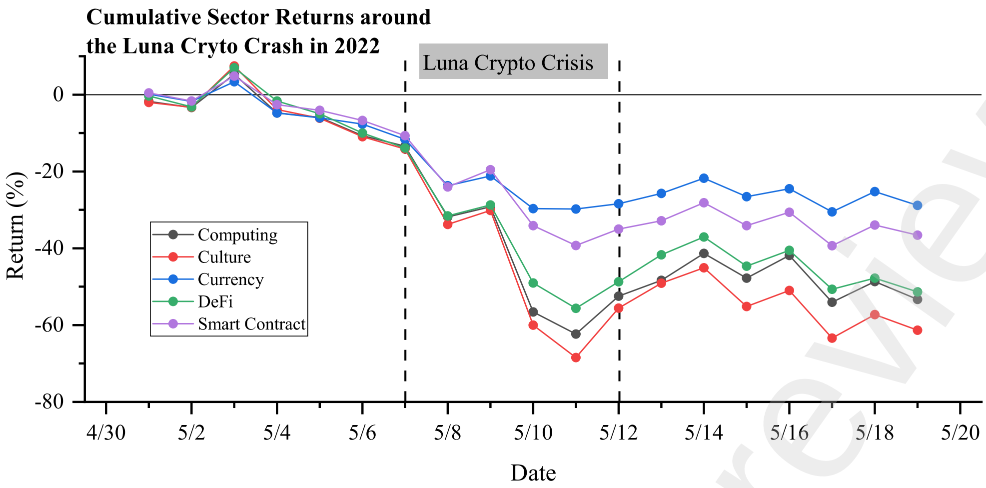
$$f_t^j = \theta_{0,j} + \theta_j \text{sign}(\overline{f}_{t-L,t-1}^j) + u_{j,t}. \tag{5.1}$$

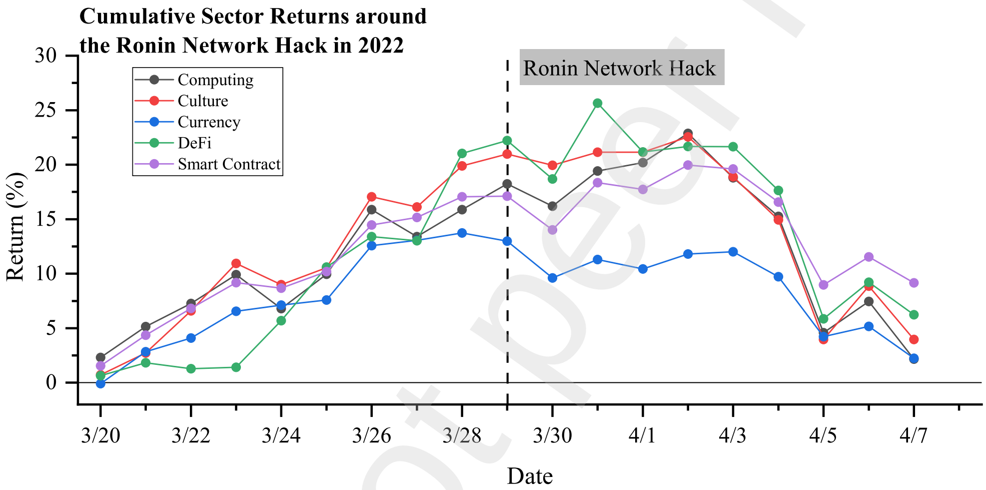
where $\overline{f}_{t-L,t-1}^j := \frac{1}{L}\sum_{l=1}^{L} f_{t-l}^j$ and f_t^j are the factor returns for sector j at time t. The momentum signal, $\text{sign}(\overline{f}_{t-L,t-1}^j)$ takes the value 1 if $\overline{f}_{t-L,t-1}^j > 0$ and -1 if $\overline{f}_{t-L,t-1}^j < 0$. f_t^j is standardized to have unit variance so that the estimated $\hat{\theta}_j$ values are comparable across sectors.[17] We differentiate between momentum ($\theta_j > 0$) and reversal ($\theta_j < 0$) in our analysis.

[17]We use GARCH(1,1) model to estimate the dynamic volatility σ_t^j for the sample period, and standardize the sector factor as $f_t^{*j} = \frac{f_t^j}{\sigma_t^j}$.

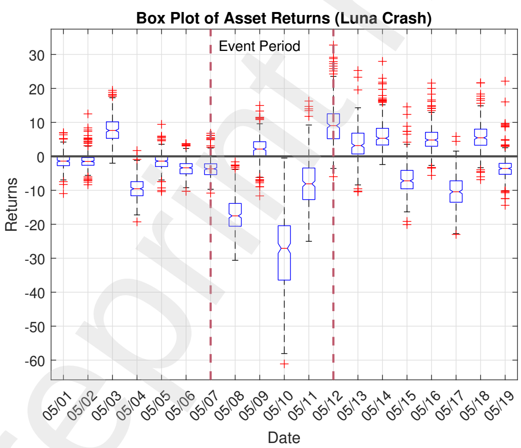
Figure 6: Sector Portfolios Returns around Key Events

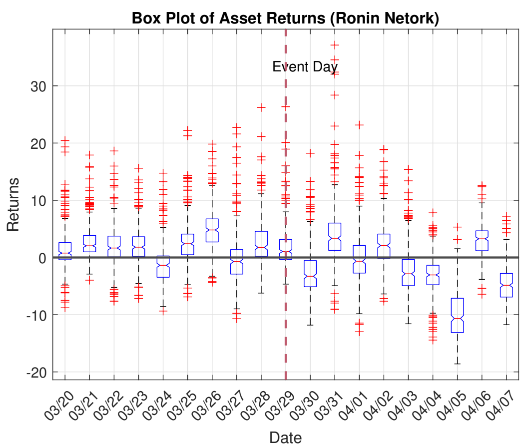
Panel A: Sector portfolio returns around key events





Panel B: Box plots of all assets in the cross-section around key events





Note: This figure shows the performance of sector portfolios around the given event. Panel A shows the cumulative value of portfolio returns. Panel B shows the box plot of all asset returns ($r_{i,t}$) around the two events. In each panel, the left graph shows the event with Luna crypto and the right graph shows the event of Ronin Network.

If momentum (reversal) effects are present in the sector factors, the factors' past return signals should significantly positively (negatively) predict their future returns. We consider L from one day to 180 days.

The results are presented in Figure A.3. We find limited evidence of the presence of momentum/reversal in the long term. The momentum at all lags for all sectors is insignificant, which implies that either there is no sector-specific momentum or the momentum is a short-lived phenomenon.

To further investigate the issue, we repeat the above analysis under a rolling window setting, with a window size of 365 days and step size of one day. The first period starts from March 31, 2020. In total, we have 1007 windows. Still, we consider the lag length L from one day to 180 days. Table 7 presents the percentage of windows with significant momentum/reversal. A higher percentage means that there are more sub-periods with momentum/reversal effects and thus the level is higher. When we consider a shorter period than the full-sample periods (in our case, one year), we start observing momentum and reversal effects. The level of reversal is much higher than that of the momentum, with a higher percentage of significant windows.

Finally, to demonstrate at which time the momentum/reversal is present, Figure 7 presents the heat map for different sectors. Similar to the observation in Table 7, the reversal force dominates the momentum force, which is presented in most of the windows and lags. In addition, most of the time, the momentum comes with reversal, which means that the digital asset market is dominated by speculative forces. Some momentum effects can be identified. For example, during late 2020 and 2021, there was a craze for NFT investments (momentum observed in 2021 for the Culture sector). Similarly, in 2021, there was substantial investment sentiment in the DeFi sector, with the total value locked increasing from \$19 billion to \$250 billion.[18]

In addition, the momentum/reversal pattern varies across sectors in terms of time, strength, and lags, which contributes to sector variations. For example, in the Currency sector, we observe short-term (within 30 days of lags) momentum during mid-2023, while in the Culture sector there is strong long-term momentum (more than 150 days of lags) at mid-2021. The above observation confirms that the observed sector momentum in the digital asset market is a short-lived phenomenon.

[18] https://www.kucoin.com/fr/blog/2021-year-in-review-a-progressive-year-for-defi

Table 7: Percentage of Windows with Momentum/Reversal

Panel A: Percentage of windows with momentum (%)

Lag	Computing	Culture & Entertain-ment	Currency	Decentralized Finance (DeFi)	Smart Contract Platform
1-30	1.82	0.79	2.47	0.66	0.62
30-60	0.29	0.00	3.11	0.04	0.00
60-90	0.49	0.00	0.07	0.00	0.01
90-120	0.00	0.00	0.00	0.00	0.15
120-150	0.47	4.75	0.00	0.00	0.00
150-180	0.03	1.60	0.00	0.00	0.00

Panel B: Percentage of windows with reversal (%)

Lag	Computing	Culture & Entertain-ment	Currency	Decentralized Finance (DeFi)	Smart Contract Platform
1-30	8.13	9.23	7.52	2.10	12.35
30-60	12.82	9.91	13.97	3.98	8.03
60-90	13.45	1.06	16.09	7.57	17.05
90-120	11.04	4.29	5.70	0.00	6.66
120-150	2.74	3.40	18.64	1.06	8.41
150-180	3.02	0.17	29.04	7.65	22.25

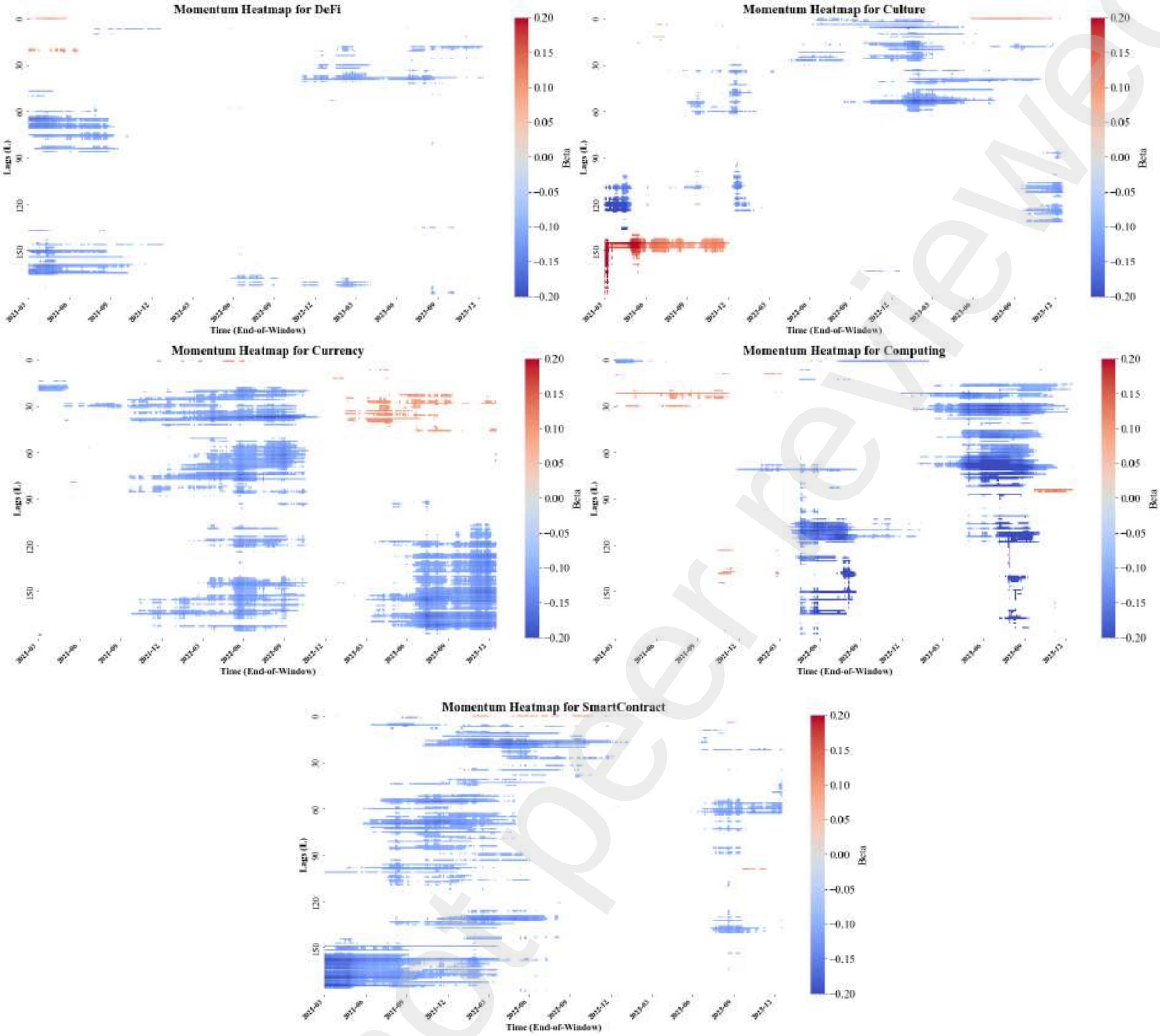
Note: This table presents the percentage of windows with significant beta coefficient from equation (5.1). In the regression, the dependent variable is the daily sector factor return and the independent is the sign (signal) of the average factor return over the past L days. We consider L ranging from one day to 180 days. The regression is performed under a rolling window setting, with a window size of 365 days and a step size of one day. We then calculate the percentage of windows with a coefficient at 10% significance level. A higher percentage means that there are more sub-periods with momentum/reversal effects and thus the level is higher. Panel A shows the results with momentum (positive coefficient) and Panel B shows the results with reversal (negative coefficient).

5.2.2 Sector Momentum/Reversal and Asset Visibility to Investors

Several studies on the stock market relate industry momentum to the lead-lag effects within the industry (e.g., Hou, 2007 and Hoberg and Phillips, 2018). Similarly, the sector-wide momentum in the digital asset market may be explained by two factors. First, investors chase focal assets in the sector because they place more trust in highly visible digital assets than in relatively unknown ones. Second, assets that are less visible to the investment community within the sector tend to react more slowly to sector-wide shocks, causing a delayed realization of information and resulting in momentum effects.

We define asset visibility as the extent to which a particular asset attracts trading activity beyond what would be expected given overall market conditions. Empirically, we measure asset visibility using the abnormal turnover ratio, which is obtained as the residual ($\widehat{TR}_{i,t}^{abn}$) from the following time-series regression of an asset's turnover ratio on the market's turnover ratio

Figure 7: Sector Momentum/Reversal across Time



Note: This figure shows the heat map of sector momentum (marked in red) and reversal (blue) across time. We plot the beta coefficient from the regression (5.1). The left y-axis shows the lags (L) and the right y-axis shows the beta coefficient. A deeper color means a stronger momentum/reversal effect. We only plot the coefficient with a significance level at 10%.

(following Pan et al., 2016):

$$TR_{i,t} = \omega_{0,i} + \omega_i TR_{i,t}^{mkt} + TR_{i,t}^{abn}, \tag{5.2}$$

where $TR_{i,t}$ is the turnover ratio (trading volume to market value) for asset i in day t. $TR_{i,t}^{mkt}$ is the turnover ratio for the entire market, and $TR_{i,t}^{abn}$ is the error term. The regression is estimated using observations from the past 60 days.

In other words, if an asset's turnover ratio is substantially higher than what the market-wide turnover ratio would predict, it is considered highly visible. This higher-than-expected trading activity reflects greater investor attention and trust in that asset, and it also indicates that transaction activities tend to cluster around it more intensively than for less visible assets.

To examine the role of asset visibility in driving the sector momentum, we rank assets by their visibility in the cross-section into three groups (within each sector). Assets ranked below the 30% percentile are labeled as low-visibility and high-visibility when above 70%. Then, we construct sector factors within each group. In other words, for each sector, we have three types of factors based on their visibility.

Using the three types of factors, we repeat the regression (5.1) under the same rolling-window setting, with a window size of 365 days and a lag length from one day to 180 days. If the sector momentum/reversal is driven by the asset visibility, we should observe momentum/reversal levels, represented by the percentage of significant windows, to be higher in either low or high asset groups (or both). Figure 8 presents the stacked bar plot for different visibility groups at different lags.

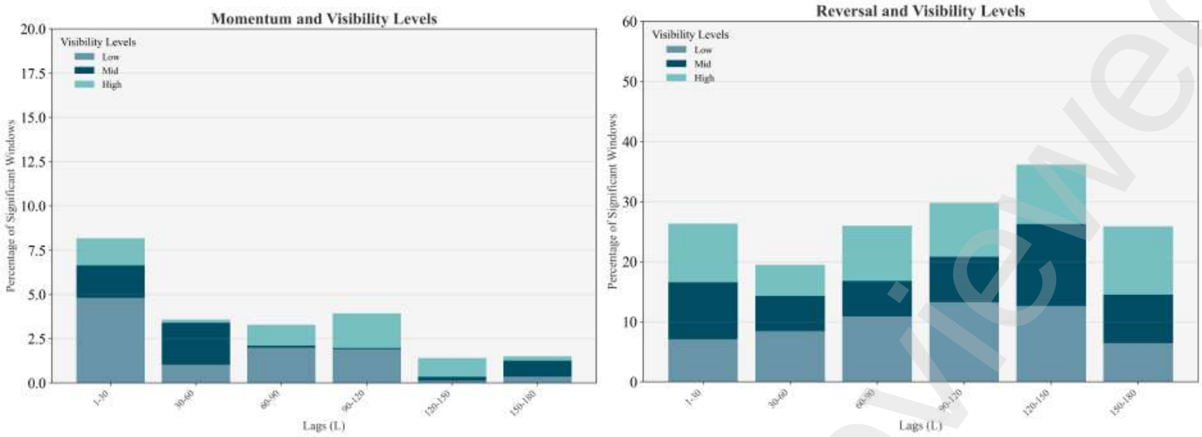
The visibility is unlikely to play a dominating role in deciding the sector reversal, because the level of reversal is similar across different visibility groups. However, for the momentum effect, we observe some evidence of effects from asset visibility. For example, for the low visibility group, we only observe momentum (left graph) at a shorter lag length (1-30 days). In addition, the overall momentum level represented by the low-visibility group is much higher than that of the high- and mid-visibility groups.

5.2.3 Sector Momentum/Reversal and Sentiment Persistence

Another potential explanation for the sector momentum is the influence of sector-specific sentiments. This is closely aligned with previous literature identifying sentiment as a key driver of the digital asset market. (e.g., Aysan et al., 2024, Anastasiou et al., 2021 and Kraaijeveld and Smedt, 2020). Kozak et al. (2018) also shows that persistence in the investor sentiment explains the factor momentum. In this subsection, we investigate whether the observed momentum/reversal is associated with persistence in sector sentiment.

We measure the sector-specific sentiment based on the abnormal turnover ratio discussed in the last section. Specifically, we define the sentiment for sector j as $ST_{j,t} = \frac{1}{N_{t,j}} \sum_{i=1}^{N_{t,j}} \widehat{TR}_{i,t}^{abn} \mathbb{I}_{i \in j}$. We then construct the measure of sector-specific sentiment persistence based on the following

Figure 8: Momentum/Reversal Levels and Asset Visibility



Note: This figure shows the stack bar plot for the momentum/reversal. The results are obtained using the following procedure: first, within each sector, we divide assets based on their visibility into three groups: low, mid and high, from which we estimate the sector factor with different visibility levels; next, we repeat the regression (5.1) under the rolling-window setting, with a window size of 365 days and a lag length from one day to 180 days; finally, we calculate the percentage of window with significant (10%) coefficient and use it to represent the momentum/reversal level. A higher percentage means stronger momentum/reversal effects.

regression for each sector j:

$$ST_{j,t} = \phi_{0,j} + \phi_j ST_{j,t-1} + u_{j,t}, \tag{5.3}$$

where $ST_{j,t}$ is the sentiment of sector j at time t. We conduct the above regression for the past L days, which corresponds to the momentum lag. The resulting estimates, $\hat{\phi}_{j,L,t}$, $t = L, \dots, T$, are the measure of sentiment persistence for sector j at time t, which captures the degree of sentiment persistence over the preceding L days.

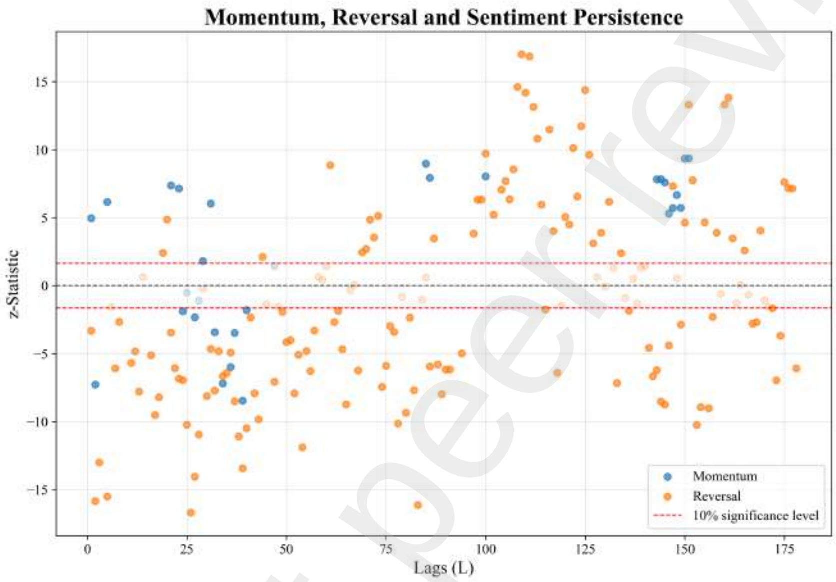
Define $y^{mom}_{j,L,m} = 1$ if, within window m with window size 365 days and step size one day, $m = 1, \dots, M$, the estimated coefficient of $\text{sign}(\overline{f}^{j}_{t-L,t-1})$ in (5.1) is significant at the 10% level and 0 otherwise. To examine the relationship between sentiment persistence and sector momentum, we conduct the following regression for sector j and lag length L:

$$\Pr(y^{mom}_{j,L,m} = 1 | \Delta\bar{\hat{\phi}}_{j,L,m}) = \Phi(\psi_{0,j,L} + \psi_{j,L}\Delta\bar{\hat{\phi}}_{j,L,m}), \tag{5.4}$$

where $\Phi(z)$ is the standard normal CDF. $\Delta\bar{\hat{\phi}}_{j,L,m}$ is the change of $\bar{\hat{\phi}}_{j,L,m}$ from window $m-1$ to window m and $\bar{\hat{\phi}}_{j,L,m}$ is the average L-period persistence level within window m. In our case, $M = 1006$ and the lag length L range from 1 day to 180 days.

Figure 9 shows the regression results for different lags. We find mixed evidence. First, the sentiment persistence is playing a role in determining the momentum and reversal effects, as $\hat{\psi}_{j,L}$ is significant in some lags. However, the relationship between the persistence level and reversal is not constant and changes with the lag. Second, for the momentum (blue plots), most of the time there are positive relationships. As a robustness check, we use the Google Trends index as the sentiment measure and repeat the above analysis in Figure A.4. We still find a significant relationship, and the results are similar.

Figure 9: Momentum, Reversal and Sentiment Persistence



Note: This figure shows the z-Statistics of the marginal effect of $\Delta\bar{\hat{\phi}}_{j,K,m}$ in regression (5.4). We conduct the regression analysis across lag lengths ranging from one day to 180 days, examining momentum and reversal effects separately.

5.3 Inter-Sector Spillover Effects

In Figure 4, there is evidence of spillover relationships between series of sector factors. For example, during mid-2020, the Culture and DeFi sectors exhibit similar patterns. If spillover relationships are present, they could contribute to sector variations, as they may occur only in specific sectors, with their magnitude and direction potentially differing from one sector to another. In general, the lead-lag relationship might come from the following two situations:

- Situation 1: There are events that affect all sectors but with different lag lengths. The global events can either have simultaneous shocks (captured by the systematic risk factor) or have only lagged effects.

- Situation 2: There are sector-specific events that spillover to other sectors.

It is hard to distinguish the above two situations unless we can identify all shocks observed in the sector factor. In this section, we first examine whether there exists a spillover relationship among digital asset sectors. Then, we estimate the level of spillover for the full sample and over time.

Since we have no prior knowledge about the existence of a spillover relationship, we first examine the spillover based on the VAR system. Specifically, we consider a S variable VAR(p) model for the sector-specific factor time series in the form:

$$\hat{F}_t = c + \sum_{l=1}^{p} \Theta_l \hat{F}_{t-l} + \epsilon_t, \quad t = 1, \ldots, T, \tag{5.5}$$

where $\hat{F}_t = (\hat{f}_{1,t}, \ldots, \hat{f}_{S,t})'$ is the $S \times 1$ vector of sector factors at time t, c is the $S \times 1$ vector of intercepts, Θ_l for $l = 1, ..., p$ are the $S \times S$ matrices of coefficients, ϵ_t is the error term. Each equation in the VAR system is estimated separately by OLS. In our case, $S = 5$ and $p = 14$.

We test the existence of spillover by performing the pairwise Granger causality test (Granger, 1969) under different lag lengths. To mitigate the effects of sector sizes, we also standardize the sector factor to have a variance of one as before (i.e., we focus on the shocks in the lead-lag relationship).

Table 8 shows the pairwise Granger causality test for different lag lengths. We set the maximum lag to 14 days. In line with the observation in Figure 4, there are spillovers between the currencies and the cultures sectors (with a one-day delay). The connection is the strongest in the Currency and DeFi sectors, where there are more significant relationships than in other sectors. At around 8 days, we observe all available spillovers, though for some pairs, it only takes one day for the spillover to happen. For most pairs, there are no spillover relationships, which implies that the spillover is not present most of the time.

We then measure the level of inter-sector spillover by constructing the connectedness network discussed in Diebold and Yılmaz (2014), under both static (full-sample) and dynamic (rolling window) settings. Table 9 presents the spillover index for the whole sample period. The spillover index is estimated using a maximum lag length of 8 days. The "From" column measures the percentage of local shocks arising from past shocks in other sectors. The bottom-right element is the total spillover index, estimated as the average of the elements in the "From" column. Elements in the "Net" are calculated as "To" minus "From" and are interpreted as the "netted" risk spillover level after considering the amount of shocks received and given by one sector.

Table 8: Granger Causality Test

Sectors	Lags (days)	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Computing	Culture-Computing	0.32	0.63	0.67	0.66	0.55	0.59	0.61	0.02	0.02	0.02	0.01	0.01	0.02	0.03
	Currency-Computing	0.99	0.49	0.70	0.55	0.72	0.79	0.38	0.49	0.59	0.61	0.67	0.72	0.75	0.64
	DeFi-Computing	0.99	0.91	0.37	0.55	0.60	0.62	0.66	0.47	0.52	0.57	0.60	0.64	0.57	0.59
	SmartContract-Computing	0.14	0.34	0.45	0.56	0.70	0.61	0.67	0.68	0.75	0.81	0.86	0.87	0.90	0.46
Culture	Computing-Culture	0.53	0.70	0.88	0.83	0.77	0.81	0.84	0.67	0.67	0.71	0.39	0.46	0.56	0.66
	Currency-Culture	0.39	0.54	0.68	0.36	0.20	0.26	0.31	0.45	0.50	0.49	0.53	0.47	0.58	0.66
	DeFi-Culture	0.14	0.31	0.53	0.69	0.76	0.82	0.58	0.61	0.75	0.76	0.86	0.73	0.76	0.71
	SmartContract-Culture	0.57	0.85	0.95	0.91	0.90	0.54	0.60	0.18	0.27	0.37	0.43	0.43	0.49	0.46
Currency	Computing-Currency	0.84	0.38	0.25	0.25	0.31	0.40	0.48	0.05	0.05	0.08	0.10	0.11	0.14	0.17
	Culture-Currency	0.03	0.08	0.16	0.23	0.23	0.12	0.17	0.19	0.22	0.17	0.10	0.15	0.11	0.15
	DeFi-Currency	0.10	0.15	0.03	0.06	0.12	0.20	0.19	0.20	0.25	0.32	0.39	0.40	0.44	0.18
	SmartContract-Currency	0.15	0.11	0.18	0.33	0.44	0.55	0.65	0.78	0.66	0.54	0.45	0.58	0.46	0.37
DeFi	Computing-DeFi	0.24	0.09	0.09	0.11	0.06	0.00	0.01	0.01	0.02	0.01	0.01	0.02	0.02	0.03
	Culture-DeFi	0.03	0.12	0.19	0.30	0.40	0.32	0.19	0.21	0.28	0.34	0.30	0.33	0.48	0.44
	Currency-DeFi	0.50	0.17	0.44	0.52	0.10	0.12	0.12	0.14	0.11	0.16	0.13	0.11	0.16	0.29
	SmartContract-DeFi	0.44	0.77	0.55	0.61	0.78	0.91	0.82	0.88	0.91	0.80	0.76	0.75	0.75	0.80
SmartContract	Computing-SmartContract	0.54	0.01	0.02	0.02	0.04	0.08	0.05	0.04	0.06	0.08	0.11	0.13	0.16	0.24
	Culture-SmartContract	0.31	0.54	0.35	0.48	0.50	0.45	0.61	0.62	0.67	0.66	0.71	0.78	0.79	0.85
	Currency-SmartContract	0.71	0.72	0.87	0.90	0.82	0.88	0.88	0.94	0.93	0.91	0.93	0.95	0.79	0.85
	DeFi-SmartContract	0.39	0.30	0.23	0.15	0.14	0.21	0.24	0.08	0.08	0.10	0.15	0.07	0.10	0.14

Note: The table shows the number of pairs with significant Granger test results at different lag lengths. "Culture–Computing" means we test if there are spillovers from the culture sector to the computing sector. Each cell shows the p-value of test results. Cells are colored when $p < 0.1$).

Table 9: Spillover Indices (%) among Sectors

	Computing	Culture	Currency	DeFi	SmartContract	From
Computing	96.846	1.424	0.646	0.668	0.416	3.154
Culture	0.451	96.945	1.069	0.724	0.811	3.055
Currency	1.235	1.174	96.465	0.747	0.379	3.535
DeFi	1.298	0.918	0.886	96.599	0.299	3.401
SmartContract	1.195	0.591	0.201	1.234	96.778	3.222
To	4.179	4.107	2.802	3.373	1.905	**3.273**
Net	1.025	1.052	-0.733	-0.028	-1.316	

Note: The table shows the sector spillover network. The "From" column shows total directional spillover from all other sectors to sector j, whereas the "To" row shows total directional spillover to all other sectors from sector j. The row "Net" is the total net pairwise directional spillover (calculated as "To" minus "From"). The bottom-right element (bold one) is the total spillover, which measures the total level of spillover of the network. The spillover index is estimated using a maximum lag length of 8 days.

The overall spillover level is low; on average, only 3% of the shocks in one sector originate from other sectors, consistent with the findings of the previous Granger causality test. One possible explanation is the rapid flow of information in the digital asset market, causing impacts to spill over to other sectors almost instantaneously—often within the same day—making them undetectable using daily data.

For comparison purposes, we also provide in Table A.6 the spillover index using sector portfolio returns. In this case, we find a much stronger spillover level: on average, more than 70% of the shocks are transmitted across sectors. Therefore, while spillovers are detected among sector factors, most spillovers in the digital asset market are due to the systematic risk factor structure.

In summary, sector spillovers contribute to the observed sector variations. First, spillovers occur only between specific pairs of sectors, and the time required for these spillovers to materialize varies. Second, while the overall level of spillover is low, the magnitude and direction of spillovers differ across sector pairs. Finally, the inter-sector spillover effects evolve over time.

6 Robustness and Further Results

In this section, we explore several alternative settings in addition to the main results. Additional empirical results are provided in the Appendix A.5.

6.1 Alternative Classification Schemes

As discussed in Section 2, various classification schemes exist, each based on different criteria. As a result, the same digital asset may be assigned to different groups. For instance, while Ethereum is classified as part of the Smart Contract Platform sector by DACS due to its smart contract functionality, it could also be grouped with Bitcoin, as both are used as payment methods. The challenge lies in the lack of consensus among investors regarding the classification of digital assets. Consequently, altering the classification scheme could lead to insignificant sectoral variations and a different sector structure.

To examine to which extent our results are affected by the choice of classification scheme, we consider another classification scheme provided by 21Shares and CoinGecko (hereafter, 21Shares), who classify digital assets into 10 sectors: Application Development, Centralized Finance (CeFi), Decentralized Finance (DeFi), Entertainment/Leisure, Identity, Infrastructure, Interactive Media, Internet of Things (IoT), Metaverse, Storage. Table A.7 reports the mapping between the classification of DACS and 21Shares. In general, there are re-groupings in terms of industry group in the DACS. For example, while Transparent DeFi Currency is considered as DeFi in 21Shares (due to its technology traits) but Currency in DACS (due to its functionality). Table A.8 shows the distribution of 21Shares sectors over time. The distribution of sectors is totally different from that of DACS. Sectors like entertainment did not have assets during the early years while the DeFi and infrastructure sectors hold most of the assets. To make sure each sector has observations in the cross-section, our sample ranges from January 2022 to December 2023.

We repeat the processes of IPCA estimation and decomposition of characteristics. The set of characteristics selected with the highest Total R^2 for the alternative classification scheme is {volume, CAPM beta, spread, mom21}. Figure A.5 shows the estimated loading matrix of sector-common and sector-adjusted components. Coefficients of the sector component are smaller than the sector-adjusted component. The coefficients associated with the sector component are also jointly insignificant. Therefore, the sector variation through the systematic risk channel is also limited under the alternative classification scheme.

Figure A.8 shows the sector-specific factors for each sector under the alternative classification scheme. Different sectors still exhibit different patterns, and the sector's factors are different from those of DACS. However, we observe similar patterns between some sector pairs (e.g., the CeFi and DeFi sectors). Therefore, while a different classification scheme might yield a different sector structure, the sector variation still exists.

6.2 Weekly Data

We also investigate whether sectoral variation diminishes when using weekly data, as adopted by some studies in the literature (e.g., Liu et al., 2022 and Baybutt, 2024). Theoretically, sectoral variation in the idiosyncratic channel should be reduced with weekly data because short-term, sector-specific shocks are excluded. Furthermore, since weekly data contains less information compared to daily data, the sector factor structure may also become weaker.

We estimate the model using IPCA with average values of each characteristic in each week. The set of characteristics selected with the highest Total R^2 is {size, CAPM beta, spread, mom14}. Figure A.6 shows the estimated loading matrix of sector and sector-adjusted components. This time the sector component plays a larger role than the daily situation – with comparable coefficients to that of the sector-adjusted component. However, for the first factor and the fifth, the coefficient of the sector component is still very small. Our joint test also shows a smaller p-value for the sector component coefficients (though still insignificant). Therefore, when using a lower data frequency, the sector variation observed through the systematic channel becomes more pronounced.

Figure A.9 presents the cumulative value of weekly sector risk factors. The pattern is quite similar to that of the daily sector factor series in Figure 4. However, we observe fewer shocks and thus weaker variations compared to the daily situation, which implies that the sector variation in the digital asset market may come from the daily information.

6.3 Observed Systematic Factors

We construct the observed risk factors following Liu et al. (2022), where three common risk factors are found for the digital asset market: market, size, and momentum. In this section, we conduct the analysis by replacing three of the latent factors with three observed factors and compare the results with the previous findings.

Figure A.10 shows the cumulative return of both the global factors under IPCA estimation and the observed factors. Similar patterns are observed between the two sets of factors. For example, the market factor corresponds to the first latent factor; the size factor looks quite similar to the second latent factor; common shocks are observed between the third latent factor and the momentum factor.[19] This evidence indicates that the two groups of factors might carry a similar set of information.

Figure A.7 shows the estimated loading matrix of sector and sector-adjusted components when the latent factors are replaced by the observed factors. The results show that the adjusted component of characteristics still delivers stronger results than the sector component in explaining the systematic factors. Specifically, in terms of the adjusted component, the first latent factor together with the market factor and the size factor are largely explained by capm_beta and volume. The second latent factor is mainly explained by the bid-ask spread. Finally, the momentum factor is largely explained by mom3 as expected.

Finally, Figure A.11 shows the cumulative returns of sector risk factors obtained based on the observed systematic factors. Compared to Figure 4, the patterns in the factor returns are almost the same. In fact, the correlation is more than 0.95 between sector risk factors obtained based on latent and observed systematic factors. Therefore, our conclusion remains the same using the observed factors.

6.4 Survivorship Bias

Our sample construction may be subject to survivorship bias. We collected the data in April 2024, and digital assets that ceased to exist before this date are unavailable on both CoinDesk and CoinMarketCap.com. This is evident from Table 1, which shows an increasing number of coins in the cross-section over the years. Two potential issues could introduce bias into our results. First, the incomplete cross-sectional data in the early years might lead to biased estimation of global factors. Second, the exclusion of digital assets with significant negative shocks (i.e., dead coins that experienced large price drawdowns prior to their demise) could bias the estimation of sector factors within the idiosyncratic channel.

Our conclusion should remain unchanged regarding the two issues mentioned above. First, Liu et al. (2022) incorporate dead coins as a robustness check to assess whether the results are affected. They find that the estimated observed factor remains largely unchanged when dead digital assets are included. In addition, during the early years, the cross-section still contains a sufficient number of assets (over 100 digital assets), collectively accounting for more than 80% of the total market capitalization. Therefore, the estimation of systematic risk factors under

[19] Note that the observed factor can also be the linear combination of latent factors – an one-on-one relationship might not be the case.

the IPCA framework is unlikely to be affected by the inclusion of dead digital assets. Second, the sector risk factor captures sector-wide shocks, which represent information distinct from the extreme idiosyncratic shocks associated with dying assets. In other words, sector-wide shocks persist regardless of the presence of dying digital assets.

7 Conclusion

This paper uncovers a sector-based structure in digital asset returns, demonstrating that risk and return differ across various digital asset sectors. These sectors refer to distinct categories of digital assets, each defined by its unique functions and underlying technologies. The observed sector variation might not be realized through the systematic risk channel – different sectors have similar exposures to systematic risk factors.

The sector variation can also be attributed to the idiosyncratic risk channel. We construct sector risk factors by removing the systematic components, ensuring that these factors capture information unique to each corresponding sector. Unlike the sector portfolio, these sector risk factors exhibit different patterns and have low correlations. We find several possible drivers for the sector risk factors. First, there are sector-specific events – events that are originated from one sector and will only affect assets in that sector. Second, there is sector momentum. Finally, there are inter-sector spillovers. Although the overall spillover level is low, spillover among sectors still differs in terms of direction and strength, and varies over time, which further contributes to the sector variation.

The key conclusion is that there exists a sector structure in the digital asset market similar to that of the traditional stock market. However, it is overly simplistic to assume that the sectors in both markets are identical. In the traditional market, sectors arise because companies differ in their business operations. Conversely, in the digital asset market, the existence of sectors may stem from their usage and pricing, as there are no actual corporate operations behind them. Nonetheless, our findings provide empirical evidence for further analysis of the pricing mechanisms of digital assets.

References

21Shares and CoinGecko (2023), The Global Crypto Classification Standard, Technical report, 21Shares AG and Gecko Labs Pte. Ltd.

Abdi, F. and Ranaldo, A. (2017), 'A Simple Estimation of Bid-Ask Spreads from Daily Close, High, and Low Prices', *The Review of Financial Studies* **30**(12), 4437–4480.

Amihud, Y. (2002), 'Illiquidity and stock returns: cross-section and time-series effects', *Journal of Financial Markets* **5**(1), 31–56.

Anastasiou, D., Ballis, A. and Drakos, K. (2021), 'Cryptocurrencies' Price Crash Risk and Crisis Sentiment', *Finance Research Letters* **42**, 101928.

Anatolyev, S. and Mikusheva, A. (2022), 'Factor models with many assets: strong factors, weak factors, and the two-pass procedure', *Journal of Econometrics* **229**(1), 103–126.

Arnott, R. D., Kalesnik, V. and Linnainmaa, J. T. (2023), 'Factor Momentum', *The Review of Financial Studies* **36**(8), 3034–3070.

Aysan, A. F., Caporin, M. and Cepni, O. (2024), 'Not all words are equal: Sentiment and jumps in the cryptocurrency market', *Journal of International Financial Markets, Institutions and Money* **91**, 101920.

Bali, T. G., Cakici, N. and Whitelaw, R. F. (2011), 'Maxing out: Stocks as lotteries and the cross-section of expected returns', *Journal of Financial Economics* **99**(2), 427–446.

Baybutt, A. (2024), 'Empirical Crypto Asset Pricing'.

Beck, G. W., Hubrich, K. and Marcellino, M. (2016), 'On the importance of sectoral and regional shocks for price-setting', *Journal of Applied Econometrics* **31**(7), 1234–1253.

Bekaert, G., Hodrick, R. J. and Zhang, X. (2009), 'International stock return comovements', *The Journal of Finance* **64**(6), 2591–2626.

Bhambhwani, S. M., Delikouras, S. and Korniotis, G. M. (2023), 'Blockchain characteristics and cryptocurrency returns', *Journal of International Financial Markets, Institutions and Money* **86**, 101788.

Biais, B., Bisiere, C., Bouvard, M., Casamatta, C. and Menkveld, A. J. (2023), 'Equilibrium bitcoin pricing', *The Journal of Finance* **78**(2), 967–1014.

Bianchi, D. and Babiak, M. (2021), 'A risk-based explanation of cryptocurrency returns', *Available at SSRN 3935934* .

Büchner, M. and Kelly, B. (2022), 'A factor model for option returns', *Journal of Financial Economics* **143**(3), 1140–1161.

Chamberlain, G. and Rothschild, M. (1982), 'Arbitrage, factor structure, and mean-variance analysis on large asset markets'.

Cohen, R. B., Polk, C. and Vuolteenaho, T. (2003), 'The Value Spread', *The Journal of Finance* **58**(2), 609–641.

CoinDesk (2021), Digital Asset Classification Standard Methodology, Technical report, CoinDesk.

Cong, L. W., Karolyi, G. A., Tang, K. and Zhao, W. (2022), 'Value Premium, Network Adoption, and Factor Pricing of Crypto Assets'.

Cong, L. W., Li, Y. and Wang, N. (2020), 'Tokenomics: Dynamic Adoption and Valuation', *The Review of Financial Studies* **34**(3), 1105–1155.

Cong, L. W., Li, Y. and Wang, N. (2022), 'Token-based platform finance', *Journal of Financial Economics* **144**(3), 972–991.

Cong, L. W. and Xiao, Y. (2021), Categories and Functions of Crypto-Tokens, *in* M. Pompella and R. Matousek, eds, 'The Palgrave Handbook of FinTech and Blockchain', Springer International Publishing, Cham, pp. 267–284.

Connor, G. and Korajczyk, R. A. (1988), 'Risk and return in an equilibrium APT: Application of a new test methodology', *Journal of financial economics* **21**(2), 255–289.

Corbet, S., Goodell, J. W., Gunay, S. and Kaskaloglu, K. (2023), 'Are DeFi tokens a separate asset class from conventional cryptocurrencies?', *Annals of Operations Research* **322**(2), 609–630.

CryptoCompare (2018), Cryptoasset Taxonomy Report 2018, Technical report, CryptoCompare.

Danos, V., Marcassa, S., Oliva, M. and Prat, J. (2023), 'Fundamental Pricing of Utility Tokens'.

Dello Preite, M., Uppal, R., Zaffaroni, P. and Zviadadze, I. (2024), 'Cross-Sectional Asset Pricing with Unsystematic Risk'.

Diebold, F. X. and Yılmaz, K. (2014), 'On the network topology of variance decompositions: Measuring the connectedness of financial firms', *Journal of Econometrics* **182**(1), 119–134.

Dobrynskaya, V. (2024), 'Is downside risk priced in cryptocurrency market?', *International Review of Financial Analysis* **91**, 102947.

Ehsani, S. and Linnainmaa, J. T. (2022), 'Factor Momentum and the Momentum Factor', *The Journal of Finance* **77**(3), 1877–1919.

Fama, E. F. and French, K. R. (2015), 'A five-factor asset pricing model', *Journal of Financial Economics* **116**(1), 1–22.

Fieberg, C., Liedtke, G., Metko, D. and Zaremba, A. (2023), 'Cryptocurrency factor momentum', *Quantitative Finance* **23**(12), 1853–1869.

Freyberger, J., Neuhierl, A. and Weber, M. (2020), 'Dissecting characteristics nonparametrically', *The Review of Financial Studies* **33**(5), 2326–2377.

Giglio, S., Xiu, D. and Zhang, D. (2021), Test assets and weak factors, Technical report, National Bureau of Economic Research.

Granger, C. W. J. (1969), 'Investigating Causal Relations by Econometric Models and Cross-spectral Methods', *Econometrica* **37**(3), 424–438.

Griffin, J. M. and Karolyi, G. A. (1998), 'Another look at the role of the industrial structure of markets for international diversification strategies', *Journal of Financial Economics* **50**(3), 351–373.

Grobys, K. and Sapkota, N. (2019), 'Cryptocurrencies and momentum', *Economics Letters* **180**, 6–10.

Heston, S. L. and Rouwenhorst, K. G. (1994), 'Does industrial structure explain the benefits of international diversification?', *Journal of Financial Economics* **36**(1), 3–27.

Hoberg, G. and Phillips, G. M. (2018), 'Text-Based Industry Momentum', *Journal of Financial and Quantitative Analysis* **53**(6), 2355–2388.

Hou, K. (2007), 'Industry Information Diffusion and the Lead-lag Effect in Stock Returns', *The Review of Financial Studies* **20**(4), 1113–1138.

Hou, K. and Robinson, D. T. (2006), 'Industry Concentration and Average Stock Returns', *The Journal of Finance* **61**(4), 1927–1956.

International Monetary Fund (2019), Balance of Payments and International Investment Position Manual (Sixth Edition): Clarifications and Interpretations, Technical report, International Monetary Fund.

International Monetary Fund (2022), Recording Crypto Assets in Macroeconomic Statistics, Technical report, International Monetary Fund.

Kelly, B., Palhares, D. and Pruitt, S. (2023), 'Modeling corporate bond returns', *The Journal of Finance* **78**(4), 1967–2008.

Kelly, B. T., Moskowitz, T. J. and Pruitt, S. (2021), 'Understanding momentum and reversal', *Journal of Financial Economics* **140**(3), 726–743.

Kelly, B. T., Pruitt, S. and Su, Y. (2019), 'Characteristics are covariances: A unified model of risk and return', *Journal of Financial Economics* **134**(3), 501–524.

Kelly, B. T., Pruitt, S. and Su, Y. (2020), 'Instrumented principal component analysis', *Available at SSRN 2983919* .

Kozak, S., Nagel, S. and Santosh, S. (2018), 'Interpreting Factor Models', *The Journal of Finance* **73**(3), 1183–1223.

Kraaijeveld, O. and Smedt, J. D. (2020), 'The predictive power of public Twitter sentiment for forecasting cryptocurrency prices', *Journal of International Financial Markets, Institutions and Money* **65**, 101188.

Langlois, H. (2023), 'What matters in a characteristic?', *Journal of Financial Economics* **149**(1), 52–72.

Lettau, M. and Pelger, M. (2020*a*), 'Estimating latent asset-pricing factors', *Journal of Econometrics* **218**(1), 1–31.

Lettau, M. and Pelger, M. (2020*b*), 'Factors that fit the time series and cross-section of stock returns', *The Review of Financial Studies* **33**(5), 2274–2325.

Liu, Y. and Tsyvinski, A. (2021), 'Risks and returns of cryptocurrency', *The Review of Financial Studies* **34**(6), 2689–2727.

Liu, Y., Tsyvinski, A. and Wu, X. (2022), 'Common risk factors in cryptocurrency', *The Journal of Finance* **77**(2), 1133–1177.

Milken Institute (2021), A Taxonomy of Digital Assets, Technical report, Milken Institute.

Moskowitz, T. J. and Grinblatt, M. (1999), 'Do Industries Explain Momentum?', *The Journal of Finance* **54**(4), 1249–1290.

Moskowitz, T. J., Ooi, Y. H. and Pedersen, L. H. (2012), 'Time series momentum', *Journal of Financial Economics* **104**(2), 228–250.

Pan, L., Tang, Y. and Xu, J. (2016), 'Speculative Trading and Stock Returns*', *Review of Finance* **20**(5), 1835–1865.

Schilling, L. and Uhlig, H. (2019), 'Some simple bitcoin economics', *Journal of Monetary Economics* **106**, 16–26.

Sockin, M. and Xiong, W. (2023), 'A Model of Cryptocurrencies', *Management Science* **69**(11), 6684–6707.

Tapscott, D. (2020), Token Taxonomy: The Need for Open-Source Standards Around Digital Assets, Technical report, Blockchain Research Institute.

Yang, D. and Zhang, Q. (2000), 'Drift-Independent Volatility Estimation Based on High, Low, Open, and Close Prices', *The Journal of Business* **73**(3), 477–492.

Online Supplementary Appendix to "Sector Structure in Digital Asset Returns"

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In this supplementary file, Appendix A.1 presents the classifications of digital assets in recent years. A.2 presents the definitions of digital asset sectors used in the main paper. A.3 presents the definitions of digital asset characteristics. A.4 presents the IPCA framework used in the main paper. A.5 presents additional results.

Appendix A

A.1 Classifications of Digital Assets

Table A.1 shows the classifications of digital assets proposed in recent years.

Table A.1: Classifications of Digital Assets

Entities	Standards	References
Milken Institute	Legal status; Technological structures; Fungibility; Convertibility	Milken Institute (2021)
CoinDesk	Functions; Technological structures	CoinDesk (2021)
Block Chain Research	Functions; Fungibility	Tapscott (2020)
21Shares & CoinGecko	Technological structures; Functions; Economic sectors	21Shares and CoinGecko (2023)
CryptoCompare.com	Legal status; Technological structures; Functions; Economic sectors	CryptoCompare (2018)
IMF	Legal status; Functions	International Monetary Fund (2022)

Note: the table shows the summary of classification standards used by different entities. While Different classifications vary in terms of jargon, we summarize the standards they used into the following categories:

- Legal status: whether the token is issued by the government.
- Technological structures: blockchain, non-blockchain, other distributed ledger technology (DLT).
- Economic sectors: the business sector related to the token, for example entertainment or financial.
- Convertibility: whether the token can be converted into fiat money.
- Fungibility: whether the token is interchangeable with other tokens or not.
- Functions: how the token is used (e.g., general medium of exchange, payment tokens, security tokens and protocol tokens).

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A.2 Definitions of Digital Asset Sectors

Table A.2 shows the definition of digital asset sectors.

Table A.2: Digital Asset Sector Definition and Examples

Sectors	Definition	Examples
Computing	The Computing sector consists of projects that aim to decentralize the sharing, storing, and transmission of data by removing intermediaries and ensuring privacy for all users. This includes on-chain and off-chain data transmission, social data platforms, peer-to-peer secure data transactions, open networks, free market private computation, and decentralized file storage and file sharing.	Filecoin, Akash Network, IoTeX
Currency	Currency sector refers to any non-pegged digital asset acting exclusively as a medium of exchange and unit of account, running on a blockchain network with the ability to complete cross-border transactions without restriction.	Bitcoin, Dogecoin, Litecoin
Decentralized Finance (DeFi)	Defi refers to digital assets that support financial products and services that are not facilitated or controlled by any central entity. All DeFi tokens must be created on smart contract platforms and offer open-sourced liquidity with the ability for token holders to reserve governance rights.	Uniswap, Ribbon Finance, Creditcoin
Culture & Entertainment	Culture & Entertainment includes all projects that aim to decentralize social media platforms, create decentralized gaming worlds, and increase direct peer-to-peer interaction between content creators and their audience, while at the same time maintain user privacy, security, and ownership of data and digital assets	Rollbit Coin, GameFi, PlayDapp
Smart Contract Platform	Smart contracts are computerized blockchain protocols that execute terms of a contract. Smart Contracts represent computer code that ensures when the terms of the contract are met by both parties. Smart contract platforms are designed for the building of decentralized applications, layer 2 scaling solutions, DAO's, and custom protocols. Each platform has a unique open-source user and miner incentive structure and utilizes BFT consensus mechanism. Each platform utilizes a native token for the payment towards building on the platform.	Ethereum, Celestia, Starknet
Digitization	Digitization refers to the process by which real world documents, contracts, public names, etc. are uploaded to a blockchain for the purpose of transparency, publicly verifiable ownership, and immutability. Proof of ownership, identity, and authenticity are both valuable traits that are made possible by blockchain technology.	FirmaChain, Hippocrat, Metadium
Stablecoin	Stablecoins are a set of protocols whose native token is pegged to a fiat currency, most commonly the US dollar. Stablecoin issuers may use one of several methods to maintain their peg such as 1:1 dollar-backed reserves, multi-asset treasuries, collateralized lending, or mint-and-burn mechanisms, etc.	Tether, USDC, EURC

Note: This table presents the definition of digital asset sectors provided by CoinDesk. More details can be found at: www.coindesk.com/indices/crypto-index-research

A.3 Definitions of Digital Asset Characteristics

We provide a detailed definition of the characteristics used in our analysis. The list of characteristics follows closely to those Bianchi and Babiak (2021), Freyberger et al. (2020) and Liu et al. (2022). We categorize the characteristics into roughly four categories:

Size:

- Volume (USD): The total spot trading volume reported by all exchanges over the last 24 hours for the cryptoasset, calibrated by Coinmarketcap.
- Size (USD): the existing reference price of the cryptoasset by the current circulating supply.

Risk:

- Daily realized volatility (%): We follow Yang and Zhang (2000) to calculate the daily realized volatility calculated based on daily OHLC prices, using the data for the past 2 days.
- CAPM beta: We estimate the market beta using the past 30-day data on a rolling window basis. We use value-weighted average of the asset returns available on each day t for the market return.
- Idiosyncratic risk: The standard deviation of the residuals from the CAPM regression.
- VaR (5%): The value-at-risk at 5% quantile for the past 90 days.

Liquidity:

- Bid-ask spread : The bid-ask spread is the average of two alternative synthetic approximations based on OHLC prices by Abdi and Ranaldo (2017).
- Illiquidity: We follow Amihud (2002) to construct the illiquidity measure for company in day t.
- Turnover ratio: the trading volume in day $t-1$ over the current coin supply (estimated as the total market cap divided by the closing price).

Momentum:

- Maximum return (7, 21): We follow Bali et al. (2011) to use maximum daily return in the previous 7 or 21 days.
- Momentum ($r_{3,0}$ to $r_{21,0}$): Following Liu et al. (2022), we construct the past 3-day , 7-day, 14-day and 21-day returns, estimated as $ln(p_t/p_{t-k})$, where p_t is the closing price for day t and $k = 3, 7, 14, 21$.

A.4 Instrumented Principal Components Analysis

A.4.1 The IPCA Method

In (2.1), the nature of factors g_{t+1} is left unspecified by the asset pricing theory. One approach is to proxy g_{t+1} using a zero-cost long-short portfolios built upon some observable stock features or characteristics, such as market capitalization, book-to-market, etc. This approach is elaborated in Fama and French (2015). A second approach is to treat g_{t+1} as latent and use factor analytic techniques, such as principal components analysis (PCA) to estimate the factors and loadings. This line of research follows the setting of approximate factor model outlined in Chamberlain and Rothschild (1982) and Connor and Korajczyk (1988). However, as summarised in Bianchi and Babiak (2021), there are shortcomings in both approaches when applied to digital asset markets. For example, constructing g_{t+1} as a characteristic-based portfolios requires a perfect understanding of the driving forces behind digital asset markets. However, in reality, our understanding of cross sectional variation in digital asset returns is limited. For the latent factor approach, the factors and loadings are estimated solely based on asset returns and usually lack interpretability.

To mitigate the above issues, Bianchi and Babiak (2021) propose to model the factor structure in digital asset market based on the instrumented principal components analysis (IPCA) method developed by Kelly et al. (2019) and Kelly et al. (2020). This method has been widely used in the finance literature for various purposes (e.g. Kelly et al., 2021; Büchner and Kelly, 2022; Kelly et al., 2023; Langlois, 2023; Bianchi and Babiak, 2021).

Following the IPCA framework, the alpha, $\alpha_{i,t}$, and the systematic factor betas, $\beta_{i,t}$ in (2.1) are specified as linear functions of a $K \times 1$ vector of asset-specific instruments $z_{i,t}$ as

$$\alpha_{i,t} = A' z_{i,t} + u_{i,t}, \text{ and } \beta_{i,t} = B' z_{i,t} + v_{i,t}, \tag{A.1}$$

where A and B are a $K \times 1$ vector and a $K \times r_g$ matrix of parameters, respectively. Then we have the following factor model for $r_{i,t+1}$,

$$r_{i,t+1} = z'_{i,t} A + z'_{i,t} B g_{t+1} + e_{i,t+1}, \tag{A.2}$$

where $e_{i,t+1} = u_{i,t} + v_{i,t} g_{t+1} + \varepsilon_{i,t+1}$ is the composite error. The setting and assumptions of the model are analogous to the IPCA model in Kelly et al. (2019) and Kelly et al. (2020).

To identify the loading matrices and factors from rotational indeterminacy, we impose the following normalisation restrictions: $B'B = I_{r_g}$ and the unconditional second moment matrix of g_t is diagonal with descending diagonal entries. We also impose the restriction that the mean of g_t is non-negative.

In addition, to resolve an identifiability issue in the factor structure in (A.2), we assume, without loss of generality, that

$$A'B = 0_{1\times r_g}. \tag{A.3}$$

The identifying assumption in (A.3) also has an economic content. That is, by imposing the restrictions, we allow risk loadings to explain as much of assets' mean returns as possible. Of the total return predictability possessed by the instruments, only the orthogonal residual left unexplained by systematic factor loadings is assigned to the intercept.

A.4.2 Decomposition of Characteristics

To investigate the role of the sector component of asset characteristics in risk factor exposure, following Langlois (2023), we decompose each of the K characteristics into the sector component and the sector-adjusted component. Specifically, each time period and for each characteristic, we run a cross-sectional regression of characteristic k for asset i at time t, $x_{i,t}^{(k)}$, using all available assets.

$$x_{i,t}^{(k)} = \sum_{j=1}^{S} \phi_{j,t}^{(k)} \mathbb{I}_{i\in j} + \varepsilon_{i,t}^{(k)}, \quad i = 1, \ldots, N_t. \tag{A.4}$$

In this equation, $\phi_{j,t}^{(k)}$ is the coefficient for sector j's effect for characteristic k at time t, $\mathbb{I}_{i\in j}$ is an indicator variable equal to one if asset i is in sector j, $\varepsilon_{i,t}^{(k)}$ is the regression error that captures the adjusted component for characteristic k of asset i, N_t is the number of stocks at time t, and S is the number of sectors. In a second step, we standardize the estimated sector effects $\phi_{j,t}^{(k)}$ and the adjusted effect, $\varepsilon_{i,t}^{(k)}$, by computing the Z-score period by period. We refer to these normalized coefficients as $\tilde{\phi}_{j,t}^{(k)}$ and $\tilde{\varepsilon}_{i,t}^{(k)}$, respectively.

To evaluate the sector effects, we estimate the factor model in (A.2) using different sets of instruments $z_{i,t}$,

1. $z_{i,t} = (1, \tilde{x}'_{i,t})'$ where $\tilde{x}_{i,t} = (\tilde{x}_{i,t}^{(1)}, \ldots, \tilde{x}_{i,t}^{(K)})'$ is the vector of the Z-score of all the unadjusted characteristics;

2. $z_{i,t} = (1, \tilde{\phi}'_{j_i,t}, \tilde{\varepsilon}'_{i,t})'$ where $\tilde{\phi}_{j_i,t} = (\tilde{\phi}^{(1)}_{j_i,t}, \ldots, \tilde{\phi}^{(K)}_{j_i,t})'$, and $\tilde{\phi}^{(k)}_{j_i,t} = \sum_{j=1}^{S-1} \tilde{\phi}^{(k)}_{j,t} \mathbb{I}_{i \in j}$ is the Z-score of asset i's sector coefficient. [1]

Comparing (1) and (2) allows us to determine the benefit of adjusting for sector effects in characteristics. In particular, case (2) allows us to assess the importance of the sector component in asset characteristics for explaining expected returns. We can then evaluate whether sector information influences the exposure to systematic risk in (2.1).

A.4.3 Evaluation of Results

A.4.3.1 Asset pricing tests

In this section we present two hypothesis tests. Both are conducted by bootstrap procedures.

- Testing $H_0 : A = 0_{K\times 1}$ against $H_1 : A \neq 0_{K\times 1}$, where K is the number of instruments.

  Test statistic: $W_\alpha = \hat{A}'\hat{A}$.

- Testing instrument significance. That is, we specifically investigate whether a given instrument (or a set of instruments) significantly contributes to $\beta_{i,t}$.

  Test statistic: $W_\beta = \sum_{r=1}^{r_g} \hat{B}'_{sr}\hat{B}_{sr}$, where $\hat{B}_s$ is the sub-vector of coefficients in $\hat{B}$ that correspond to sector components.

The p-value of the tests is obtained through a bootstrap procedure as specified in Kelly et al. (2019) and Langlois (2023).

A.4.3.2 The asset pricing performance

We use the following R^2 measures to evaluate the performance of the asset pricing models.

$$\text{Total } R^2 = 1 - \frac{\sum_{i,t}\left(r_{i,t+1} - z'_{i,t}\hat{A} - z'_{i,t}\hat{B}\hat{g}_{t+1}\right)^2}{\sum_{i,t} r^2_{i,t+1}}, \tag{A.5}$$

$$\text{Predictive } R^2 = 1 - \frac{\sum_{i,t}\left(r_{i,t+1} - z'_{i,t}\hat{A} - z'_{i,t}\hat{B}\hat{g}^*\right)^2}{\sum_{i,t} r^2_{i,t+1}}. \tag{A.6}$$

[1] $x^{sec}_{j,t}$ and $x^{adj}_{i,t}$ in (4.1) correspond to $\tilde{\phi}_{j_i,t}$ and $\tilde{\varepsilon}_{i,t}$, respectively.

where $\hat{g}^* = \frac{1}{T}\sum_{t=1}^{T}\hat{g}_t$ is the unconditional systematic risk price estimate. In the predictive R^2, the estimated risk prices are held constant and predictive information enters return forecasts only through the instrumented loadings and anomaly intercepts.

A.5 Additional Results

A.5.1 Section 1

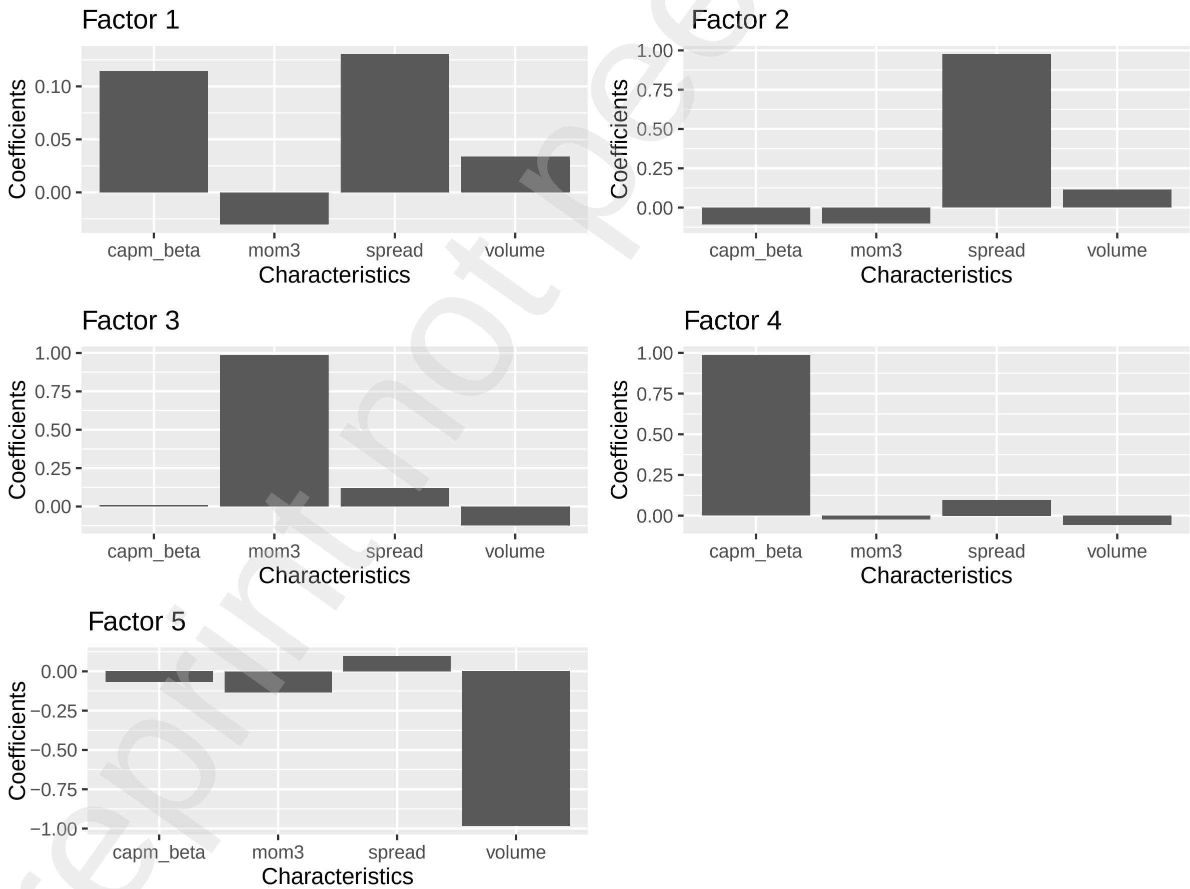
Table A.3 present the pair-wise correlation between different asset characteristics.

A.5.2 Section 2

Table A.4 shows the IPCA performance without decomposing the characteristics.

Figure A.1 shows the estimated IPCA parameters without decomposing the characteristics.

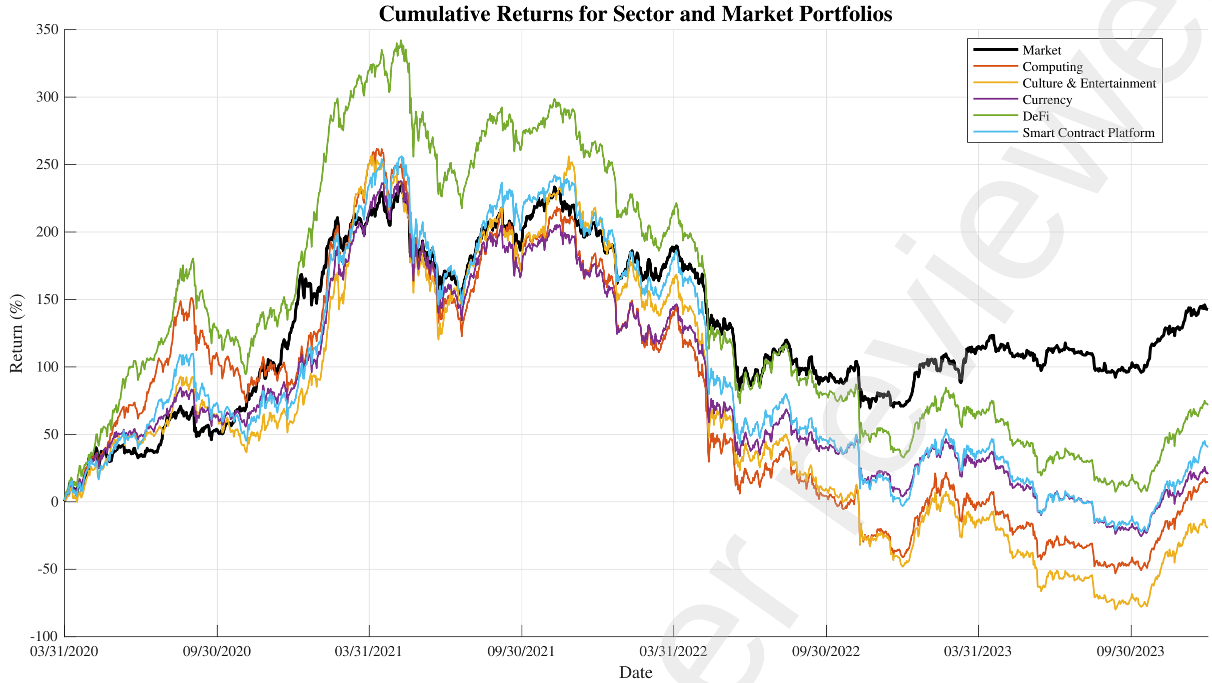
Figure A.1: Exposure to systematic risk factors across characteristics.



Note: The graphs display the estimated loading parameters corresponding to the first to the fifth systematic factors in the model. The model is estimated with five latent systematic factors. The unadjusted characteristics are used as instruments, i.e. $z_{i,t} = (1, \tilde{x}'_{i,t})'$, where the unadjusted characteristics include (trading volume, CAPM beta, bid-ask spread and 3-day momentum return).

Figure A.2 shows the cumulative return for value-weighted sector portfolio.

Figure A.2: Sector and Market Portfolios



Note: This figure shows the cumulative value-weighted return for sector portfolios and the market portfolio.

Table A.5 shows the summary statistics of value-weighted portfolios.

A.5.3 Section 3

Figure A.3 shows the sector momentum and reversal for different sectors and lag length (L).

Figure A.6 shows the regression (5.4) using the Google Trends index as sector sentiment measure.

Table A.6 shows the spillover index estimated using all sector portfolio returns.

A.5.4 Section 4

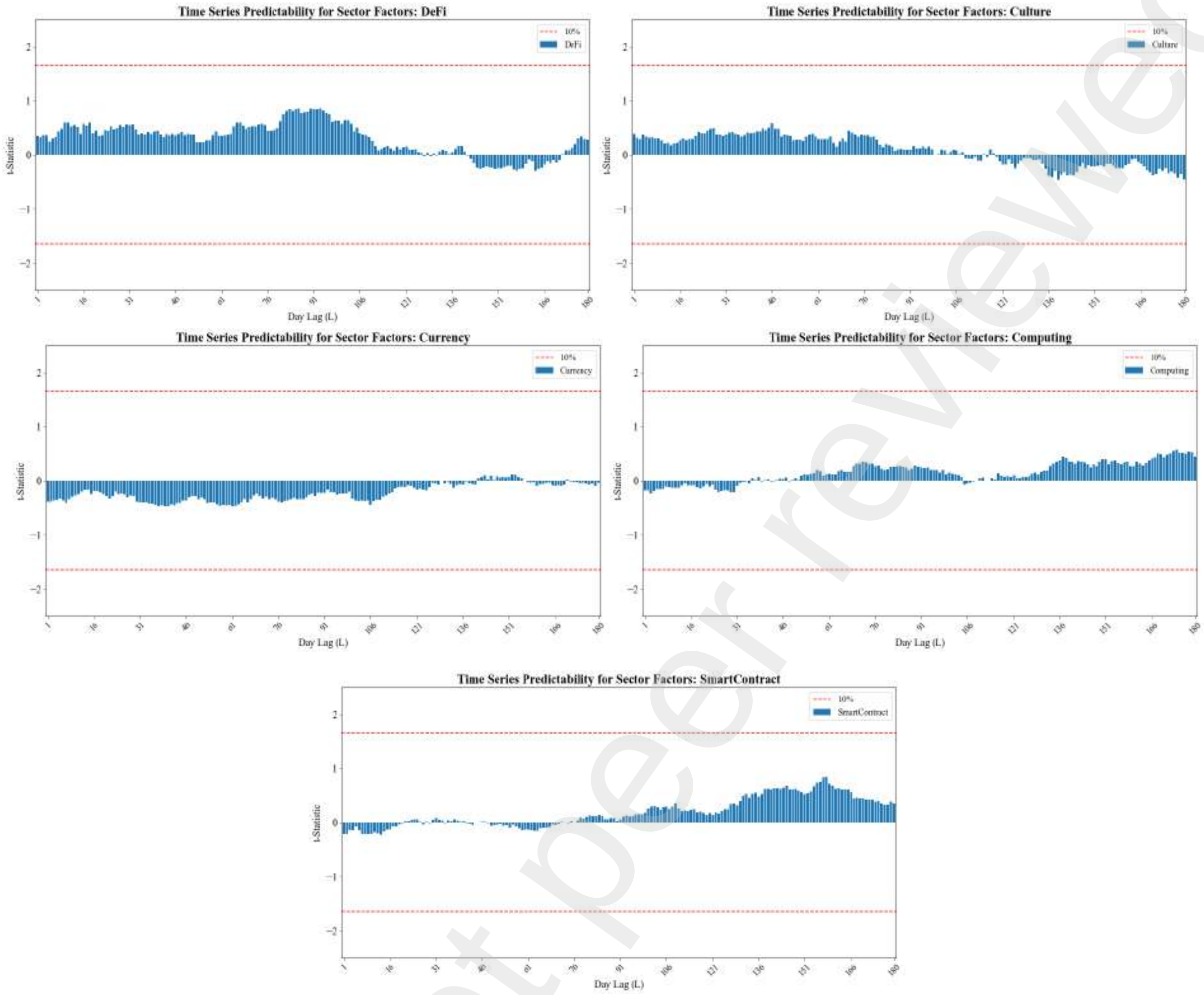
Table A.7 reports the mapping between the classification of DACS and 21Shares.

Table A.8 shows the distribution of sectors based on the classification of 21Shares.

Figure A.5 shows the estimated loading matrix of sector-common and sector-adjusted components, under the classification scheme of 21Shares.

Figure A.6 shows the estimated loading matrix of sector-common and sector-adjusted components, using a weekly data frequency.

Figure A.3: Sector Momentum and Reversal for Different Lag Length (L)



Note: This figure shows the t-Statistic of θ_j in regression (5.1). We perform the regression for L ranging from one day to 180 days for each sector factor.

Figure A.7 shows the estimated loading matrix of sector-common and sector-adjusted components, with three of the latent factors replaced by the observed factors.

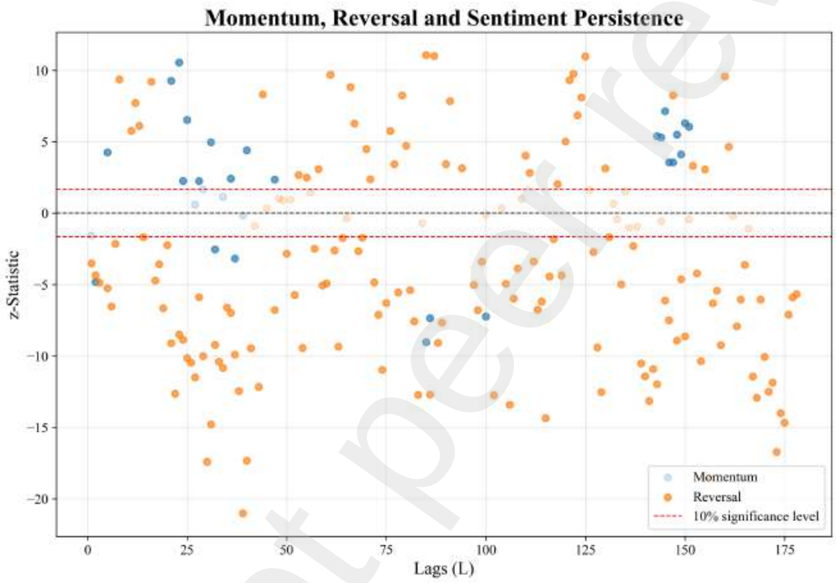
Figure A.8 shows the sector risk factors for 21Shares' sectors.

Figure A.9 shows the sector risk factors with weekly frequency.

Figure A.10 shows the systematic risk factors estimated using the observed factor approach and the IPCA method.

Figure A.11 shows the cumulative value of sector risk factors estimate using observed factors.

Figure A.4: Momentum, Reversal and Sentiment Persistence



Note: This figure shows the z-Statistics of the marginal effect of $\Delta\bar{\bar{\phi}}_{j,K,M}$ in regression (5.4). We conduct the regression analysis across lags ranging from one day to 180 days, examining momentum and reversal effects separately. We build the sentiment index for each sector based on the sets of keywords related to the sector listed below:

- Computing: IoT/Oracle/Computing/Storage/Network + Crypto/Coin/Token/Blockchain
- Culture: Topics for NFT and Metaverse
- Currency: Topics for Bitcoin, Litecoin and Dogecoin
- DeFi: Topics for Decentralized Finance
- Smart Contract: Smart Contract Crypto/Coin/Token/ Blockchain

Table A.3: Correlation Matrix

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
(1) market value	1														
(2) volume	0.735*	1													
(3) realized vol.	-0.034*	-0.005*	1												
(4) CAPM beta	-0.008*	0.003*	0.076*	1											
(5) Idovol	-0.096*	-0.069*	0.473*	0.109*	1										
(6) VaR5	0.072*	0.047*	-0.341*	-0.314*	-0.539*	1									
(7) spread	-0.018*	-0.004*	0.376*	0.052*	0.250*	-0.179*	1								
(8) illiquidity	0.00	0.00	0.024*	0.00	0.004*	0.00	0.040*	1							
(9) turnover	0.142*	0.149*	0.013*	0.017*	0.010*	-0.007*	0.006*	0.00	1						
(10) max7	-0.027*	0.005*	0.428*	0.142*	0.615*	-0.352*	0.231*	0.003*	0.020*	1					
(11) max21	-0.036*	-0.004*	0.402*	0.197*	0.800*	-0.444*	0.215*	0.00	0.021*	0.708*	1				
(12) mom3	0.005*	0.015*	0.054*	-0.067*	0.063*	0.047*	0.007*	-0.011*	0.005*	0.263*	0.122*	1			
(13) mom7	0.006*	0.019*	0.081*	-0.096*	0.117*	0.064*	0.019*	0.00	0.007*	0.383*	0.180*	0.631*	1		
(14) mom14	0.008*	0.023*	0.112*	-0.126*	0.199*	0.076*	0.041*	0.005*	0.008*	0.348*	0.261*	0.441*	0.698*	1	
(15) mom21	0.009*	0.027*	0.126*	-0.133*	0.269*	0.082*	0.052*	0.004*	0.009*	0.328*	0.331*	0.364*	0.574*	0.818*	1

Note: This table presents the correlation of characteristics. "market value" is the market capitalization of each asset. "volume" is the daily trading volume. "realized vol. " is the realized volatility. "capm beta" is the beta from CAPM model. "idovol" is the idosyncratic volatility. "VaR5" is the 5% value at risk. "spread" is the bid-ask spread. "illiquidity" is the daily illiquidity measure. "Turnover" is the daily turnover ratio. "max7" and "max21" are the maximum return over the past 7 and 21 days. mom7 to mom21 are 7-day to 21-day momentum return. Detailed definitions of each variable are provided in the Appendix A.3. * means significant at 5% level.

Table A.4: IPCA performance: Systematic factor structure

		Number of systematic factors					
		$r_g = 1$	$r_g = 2$	$r_g = 3$	$r_g = 4$	$r_g = 5$	$r_g = 6$
Panel A: IPCA performance for individual assets (r_t)							
Total R^2	$A = 0$	0.4789	0.5317	0.5421	0.5492	0.5538	0.5538
	$A \neq 0$	0.4794	0.5319	0.5424	0.5494	0.5538	0.5538
Pred. R^2	$A = 0$	0.0000	0.0000	0.0000	0.0000	0.0001	0.0001
	$A \neq 0$	0.0079	0.0002	0.0002	0.0000	0.0001	0.0001
Panel B: Asset pricing test							
W_α p-value		0.0000	0.0000	0.0000	0.0000	0.9700	1.0000

Note: The Z-score of the unadjusted characteristics are used as instruments, i.e. $z_{i,t} = (1, \tilde{x}'_{i,t})'$, where the unadjusted characteristics include (volume, capm_beta, spread, mom3).

Table A.5: Summary Statistics of Sector Portfolios

Panel A: Portfolio return characteristics

Sector	Mean	SD	CAPM Beta
Computing	0.0427	5.0884	0.5851
Culture	0.0148	4.9867	0.5829
Currency	0.1128	3.3245	1.0418
DeFi	0.0119	4.7974	0.6205
Smart Contract	0.1660	4.1559	0.7999

Panel B: Correlation Matrix

Sector	Correlation				
Computing	1				
Culture	0.820	1			
Currency	0.770	0.764	1		
DeFi	0.834	0.783	0.761	1	
Smart Contract	0.858	0.794	0.860	0.877	1

Note: This table presents statistics of value-weighted digital sector portfolios. Panel A shows return characters. Panel B shows the correlation matrix among sector portfolio returns.

Table A.6: Spillover Indices among Sector Portfolios

	Computing	Culture	Currency	DeFi	SmartContract	From
Computing	26.080	17.858	16.170	19.537	20.355	73.920
Culture	19.370	28.258	16.256	17.862	18.254	71.742
Currency	17.538	16.219	27.994	16.937	21.312	72.006
DeFi	19.728	16.767	15.759	26.600	21.146	73.400
SmartContract	19.528	16.204	18.849	20.043	25.376	74.624
To	76.163	67.047	67.033	74.379	81.068	**73.138**
Net	2.243	-4.695	-4.973	0.980	6.445	

Note: The table shows the sector spillover network. The “From” column shows total directional spillover from all other sectors to sector j, whereas the “To” row shows total directional spillover to all other sectors from sector j. The row “Net” is the total net pairwise directional spillover (calculated as ”To” minus ”From”). The bottom-right element (bold one) is the total spillover, which measures the total level of spillover of the network.

Table A.7: Mapping between Different Classification Schemes

21Shares&CoinGecko Sector Classification	Industry Group in DACS	Sector Group in DACS
Application Development	Oracle, Private Computing, Shared Network	Computing
Centralized Finance (CeFi)	Stablecoin (all), Baas, Transparent CeFi Currency	Currency, Stablecoin
Decentralized Finance (DeFi)	Asset Management, Atomic Swaps, Credit Platform, DAO, Derivatives, Exchanges, Insurance, Yield, Transparent DeFi Currency (ext. Bitcoin), Private	DeFi, Currency
Entertainment / Leisure	Art	Culture & Entertainment
Identity	Digitization	Digitization
Infrastructure	Layer 0/1/2, Bitcoin, Transparent (Other)	Smart Contract Platform, Currency
Interactive Media	Media	Culture & Entertainment
Internet of Things(IoT)	IoT	Computing
Metaverse	Metaverse	Culture & Entertainment
Storage	Shared Storage	Computing

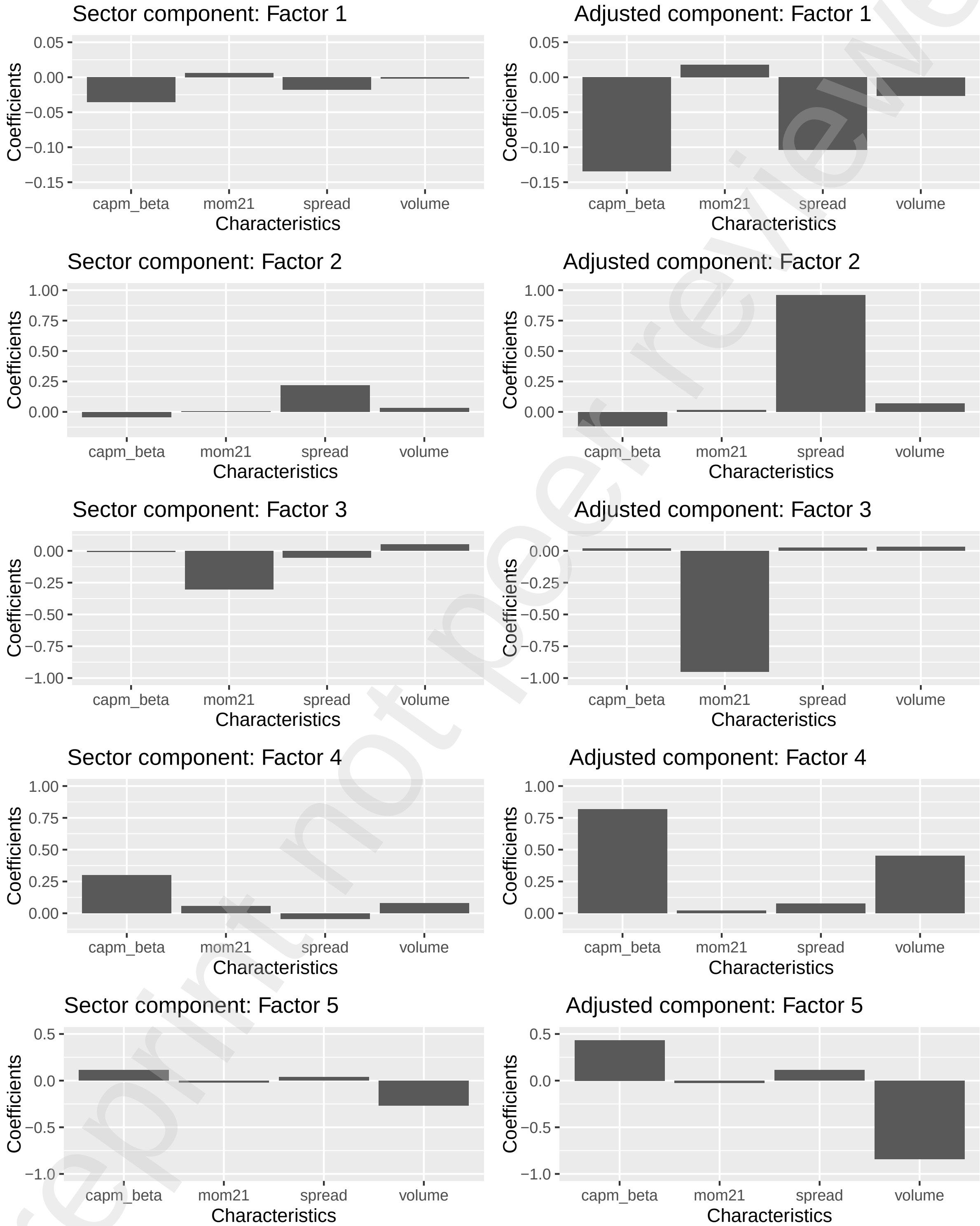
Note: This table presents the mapping of sectors by 21Shares&CoinGecko and DACS. More details can be found at: https://connect.21shares.com/global-crypto-classification-standard.

Table A.8: Distributions of Digital Sectors (21Shares&CoinGecko)

Year	2020	2021	2022	2023
Application Development	30	35	37	45
CeFi	33	37	41	44
DeFi	53	91	98	125
Entertainment/Leisure	0	3	4	10
Infrastructure	62	81	92	106
Interactive Media	13	15	20	29
IoT	4	5	6	9
Metaverse	13	28	38	48
Storage	8	9	9	9
Number of Digital Assets	216	304	345	425

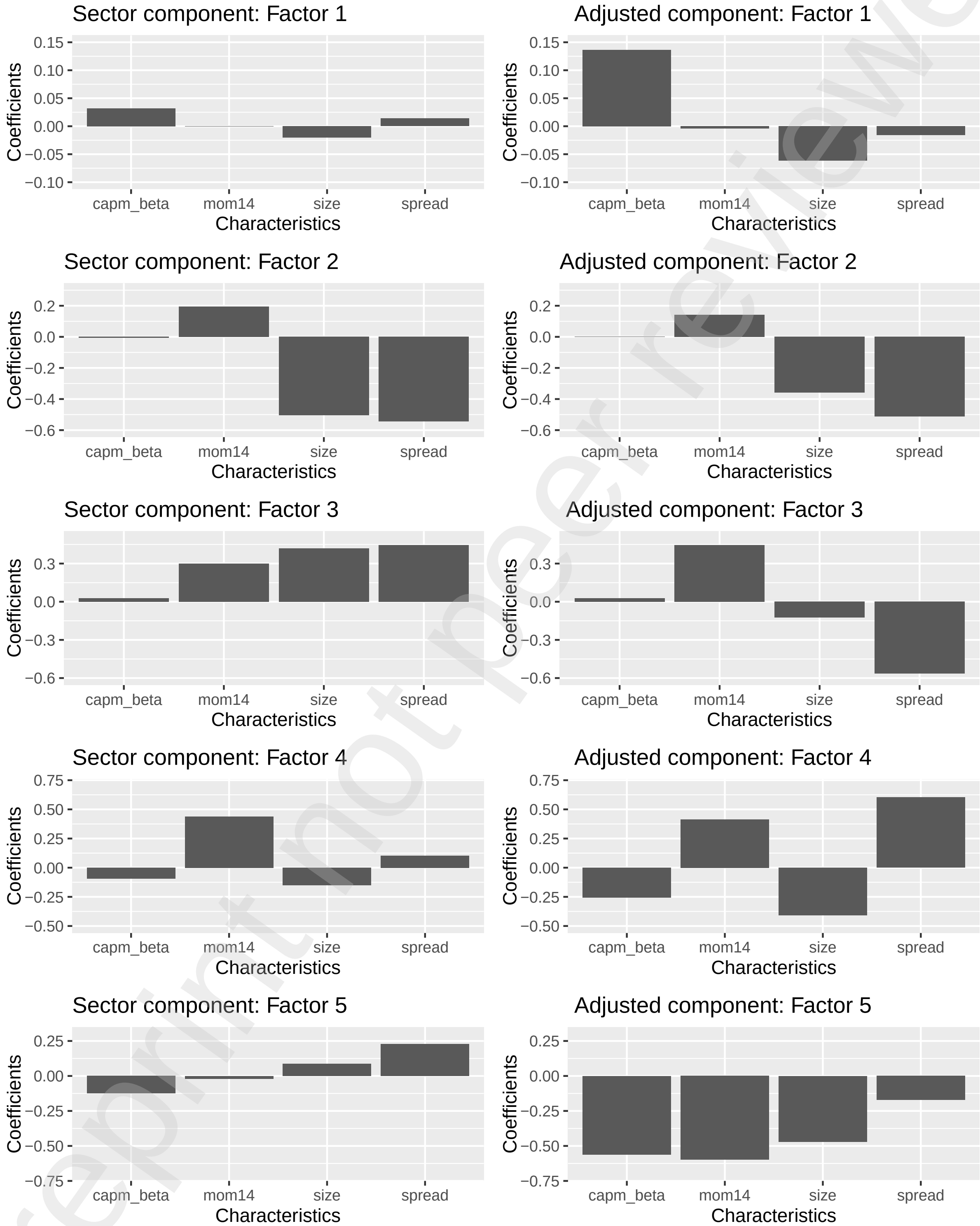
Note: This table presents the total number of digital assets each year and in each sector. The classification comes from 21Shares&CoinGecko.

Figure A.5: Robustness: Exposure to Systematic Risk Factors across Sector and Adjusted Components of Characteristics (21Shares)



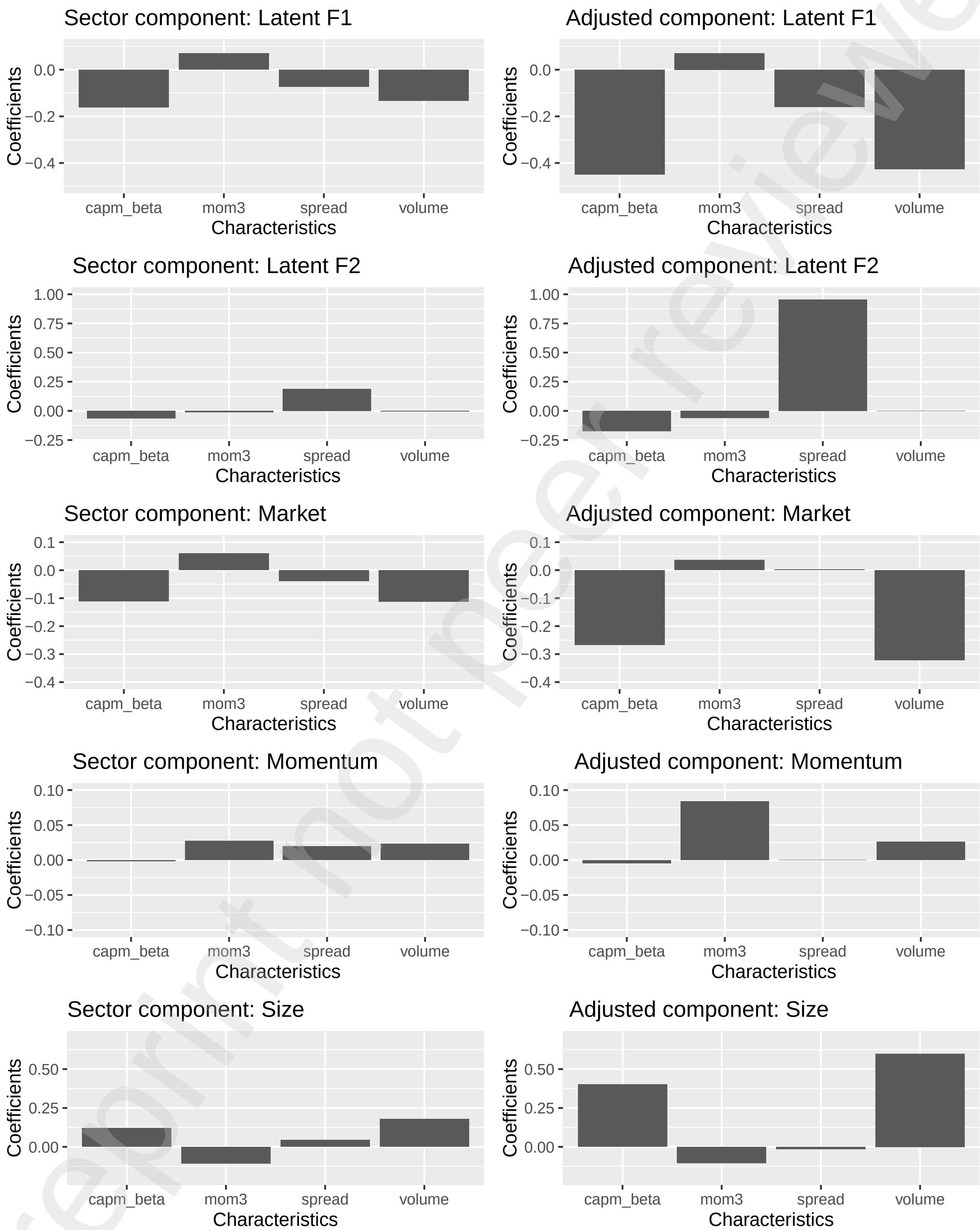
Note: The graphs display the estimated loading parameters corresponding to the first to the fifth systematic factors in the model. The model is estimated with five systematic factors and with instruments $z_{i,t} = (1, x_{j,t}^{sec\prime}, x_{j,t}^{adj\prime})'$, where the decomposed characteristics include (volume, capm_beta, spread, mom21).

Figure A.6: Robustness: Exposure to Systematic Risk Factors across Sector and Adjusted components of Characteristics (Weekly)



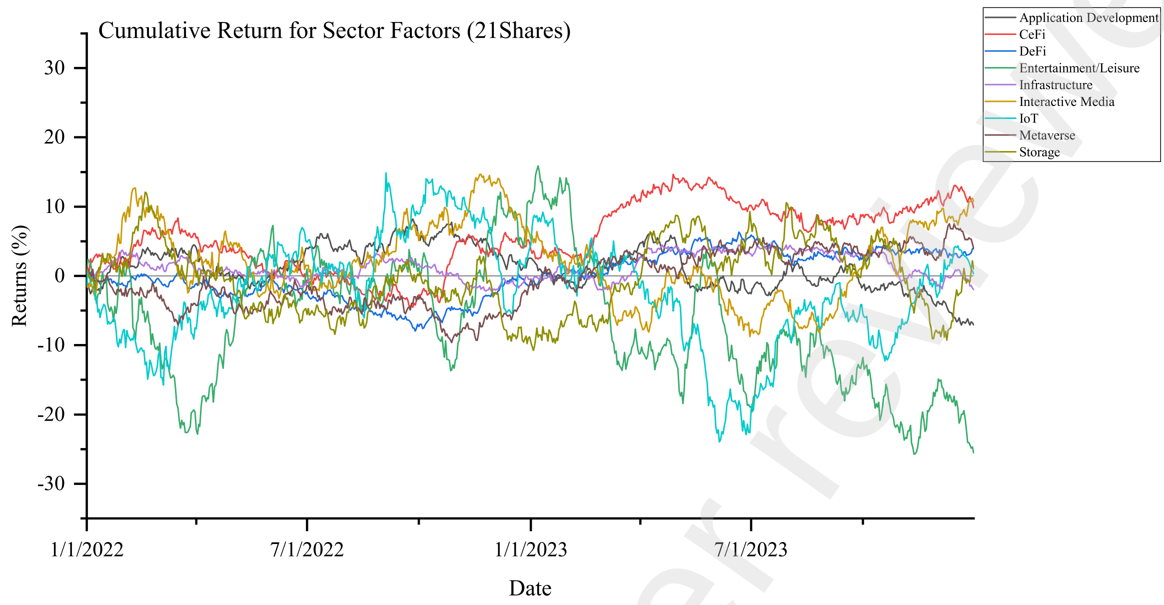
Note: The graphs display the estimated loading parameters corresponding to the first to the fifth systematic factors in the model. The model is estimated with five systematic factors and with instruments $z_{i,t} = (1, x_{j,t}^{sec\prime}, x_{j,t}^{adj\prime})'$, where the decomposed characteristics include (size, capm_beta, spread, mom14).

Figure A.7: Robustness: Exposure to Systematic Risk Factors across Sector and Adjusted Components of Characteristics (With observed factors)



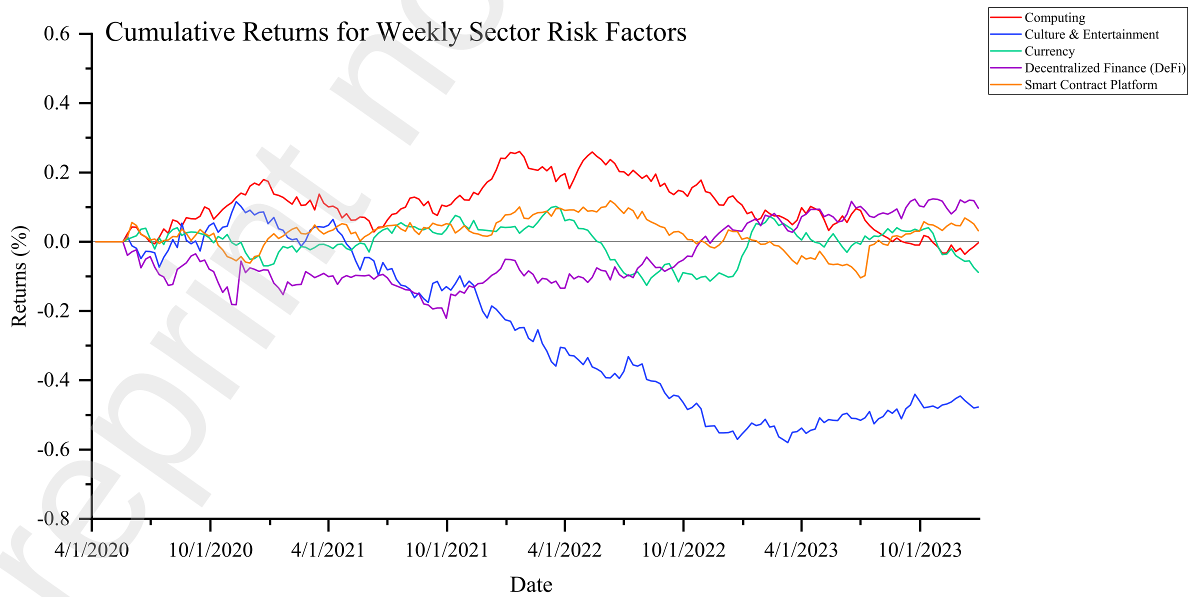
Note: The graphs display the estimated loading parameters corresponding to the first to the fifth systematic factors in the model. The model is estimated with five systematic factors and with instruments $z_{i,t} = (1, x_{j,t}^{sec\prime}, x_{j,t}^{adj\prime})'$, where the decomposed characteristics include (volume, capm_beta, spread, mom3).

Figure A.8: Robustness: Sector Factor Returns (21Shares)



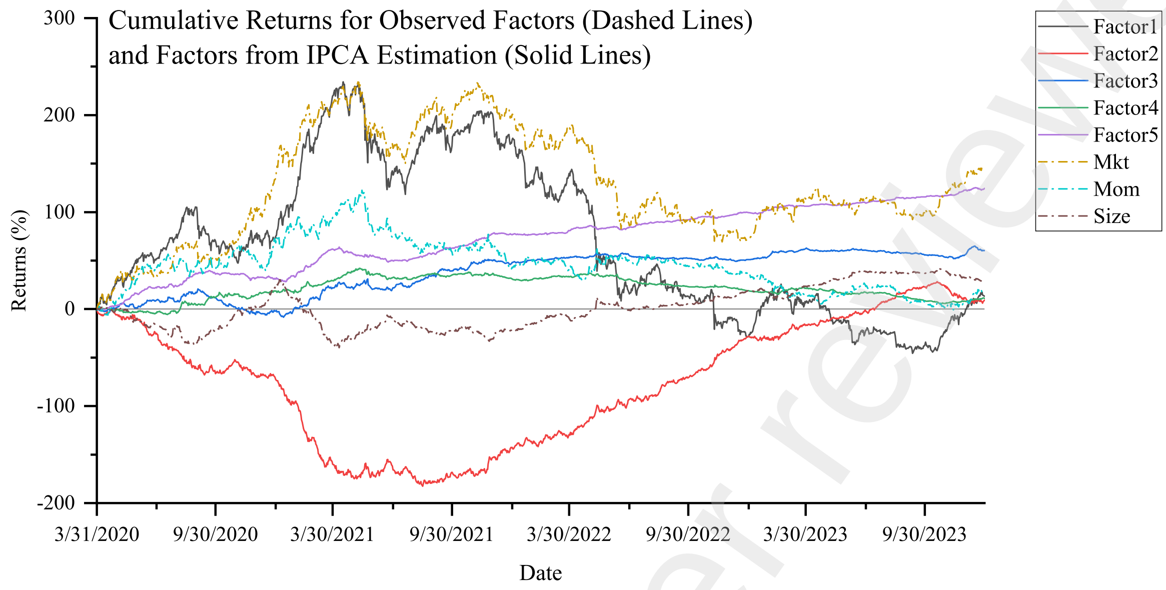
Note: This figure shows the cumulative return for sector factors. The sector classification comes from 21Shares. In total, we have 9 sectors.

Figure A.9: Robustness: Weekly Sector Factor Returns



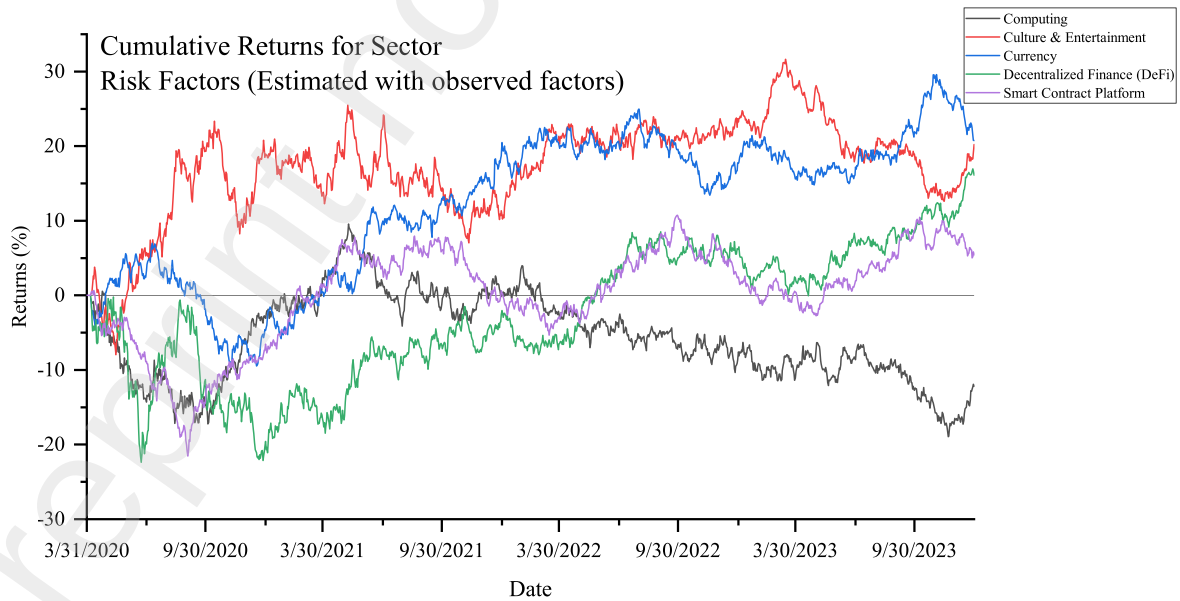
Note: This figure shows the cumulative return for weekly sector factors.

Figure A.10: Robustness: Observed Factors and IPCA Latent Factors



Note: This figure shows the cumulative return for the observed factors (dashed lines) estimated following Liu et al. (2022) as well as the systematic risk factors (solid lines) estimated through IPCA.

Figure A.11: Robustness: Sector Risk Factors Estimated based on Observed Factors



Note: This figure shows the cumulative value of sector risk factors estimate using observed factors.