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Steffen Günther, Tobias Glas, Thorsten Poddig

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Editor:

Prof. Dr. Lars Hornuf

Phone: +49(0)421 218 66820

E-mail: [hornuf@uni-bremen.de](mailto:hornuf@uni-bremen.de)

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# Asset Pricing in Digital Assets

**Steffen Günther, Tobias Glas and Thorsten Poddig**

## **Abstract**

Digital assets are continually evolving into a “mainstream” asset class. Institutional interest is growing every day, with the market capitalization of digital assets rising in value and importance not only for retail investors, but also for global banks, hedge funds and regulators. This chapter provides an overview for interested readers of how digital assets compare to traditional asset classes, how a blockchain works, and an assessment of whether academic research has uncovered first trading strategies and other relevant findings in this emergent asset class of virtual tokens.

## 7.1 Digital Assets On the Rise

With the rise of “meme” stocks in Q1 of 2021, the power of large internet communities became apparent once again. Retail investors frequently meet to discuss investment strategies on social media platforms like Reddit. In the latest and most prominent examples of GameStop or AMC Entertainment, this has led to rectified actions even against large institutional investors. Thus, private investors again proved to have a significant impact on the market when synchronizing their behavior, which can result in subsequent returns of several hundred percent. Such sharp rises in the value of these stocks are not connected to the fundamentals of the firm, but only driven by the online community itself.

While a similar phenomenon could be observed for digital assets in their infancy, large virtual coins depend less and less on internet communities today. Small digital assets nevertheless remain dependent on retail investor sentiment, which leads to large swings in their prices. Large digital assets are more mature than small ones, which results in a very heterogeneous digital asset universe. Bitcoin, for instance, which was created in 2009, was one of the first digital assets as we know them today. However, the idea of a means of anonymous and digital payments dates back to Chaum (1983), who also founded the company DigiCash, which used private and public keys to make payments untraceable. His idea turned out to be too revolutionary for its time, leading to a default of his company (see Pitta, 1999). After that venture, other web-based forms of payments emerged, including such companies as PayPal, WebMoney and e-gold (see Griffith, 2014). It took some years before the idea of bitcoin was formulated.

Bitcoin is also currently the largest cryptocurrency<sup>1</sup> by market capitalization, trading at prices above US\$40,000 per coin as of September 2021. The tradable universe of digital assets grew from only a handful in 2009 to almost 10,000 in 2021.<sup>2</sup> Hedge funds, banks, treasury departments of big firms and institutional investors began adopting digital assets in 2020 and 2021, leading to investments in bitcoin of US\$1.5 billion by Tesla and over US\$1 billion by MicroStrategy, with many others following that trend. Hence, the importance and value of bitcoin and other digital assets are no

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<sup>1</sup> The terms “digital asset” and “cryptocurrency” are used interchangeably in this chapter.

<sup>2</sup> See <https://coingecko.com/>, last visited September 30, 2021.

longer determined by small internet communities, but by many private and professional investors around the world.

This chapter focuses on digital assets as a new asset class from a financial perspective and investigates whether traditional financial theory is applicable to them. This chapter is divided into two major parts. Section 7.2 provides a general introduction to digital assets from a technical and institutional perspective. The aim is to provide a basic understanding of the cryptocurrency universe for every reader, not necessarily those in the finance community. It is also demonstrated how the cryptocurrency universe relates to other asset classes such as the stock market, pointing to similarities and differences from an economic perspective.

Section 7.3 focuses on asset pricing, which was traditionally developed with respect to stocks, but is now also applicable to different types of assets such as bonds, currencies and even commodities. We revisit important topics in asset pricing theories, and examine whether these findings may be applicable to digital assets, providing results from the academic literature and the authors' own research. The power of an internet community, for example, could be used to determine the "fair" value of virtual coins. The internet community could be seen as the network of a specific digital asset. According to Metcalfe's law, the value of a network is proportional to the square of the number of users, which can be easily determined for bitcoin and other digital assets. This could be a first step in arriving at a fair value for assets that only exist in virtual form. Other questions related to asset pricing are: Is there a common source of variation in digital assets (e.g., risk factors) that explains the cross-section of cryptocurrency returns? If so, can the returns be predicted? Are the risk factors priced significantly? Is there a market beta, as proclaimed by the capital asset pricing model? These are only some of the questions the academic community faced decades ago with respect to stocks and are highly relevant today, especially with respect to digital assets.

Section 7.3 takes a more practical orientation by concretely addressing how well-known investment strategies in stocks may or may not apply to digital assets. Perhaps the most prominent and most intuitive example is momentum. Momentum strategies in stocks rely on the empirically observed phenomenon that winners (stocks showing a high price increase) tend to outperform losers in the future, and vice-versa. This allows for simple and successful investment strategies in stocks. Does this also apply to the digital asset universe? No! This section draws from past and present research

to demonstrate a very strong reversal effect in digital assets – simply speaking, the extreme opposite of momentum. This shows that we cannot simply transfer knowledge from stocks to this young asset class; digital assets are thus emerging as a compelling subject for asset pricing studies of their own.

## 7.2 Digital Assets and Their Role in the Global Financial System

### 7.2.1 How Does a Blockchain Work?

While the term “cryptocurrency” is very common nowadays, it does not apply to every digital asset. The term rather describes digital assets with their own blockchain, such as bitcoin, litecoin and forks thereof. A fork in this context is a cryptocurrency based on the same underlying code but with slight adjustments. An example would be bitcoin cash, which is a fork of bitcoin. A cryptocurrency is thus a sort of virtual coin that is connected to its own blockchain and which can be mined (i.e., created) and sent to other users connected to the same blockchain. It can also be used as a general means of payment.

A blockchain is the basis of every cryptocurrency and is also known as the “digital ledger.” The digital ledger stores information in the form of “blocks” and adds one block to another with each transaction that occurs. This concatenation is the “chain” of blocks storing transaction information until a predefined block size is reached. The process of adding blocks to the blockchain is essentially as follows:

1. Users of the blockchain send virtual coins to each other
2. These transactions are stored in the “mempool”
3. Miners draw transactions from the mempool and store them in a block until the maximum block size is reached
4. In order to add the block to the blockchain, miners complete a mathematical calculation using trial-and-error
5. The miner who first finds the solution to the problem – i.e., the “nonce” (number used once) – adds the block to the blockchain

6. Other miners in the network acknowledge the newly mined block by confirming the transactions inside the block

After the newly mined block has been confirmed by other miners, the transactions actually take place. That process can range from a few seconds to several minutes and depends on various factors such as network hash rate or difficulty. This whole process serves two main purposes: first, it makes the transactions made by users actually happen; second, it ensures that the whole system works properly, that there are no transactions processed twice and that there is a record of all the processed transactions.

## 7.2.2 Digital Asset Classification

Although cryptocurrencies were the first digital assets and dominated the digital asset universe in the first years starting in 2009,<sup>3</sup> other digital assets evolved, especially starting around 2016. Cryptocurrencies, despite what the name might suggest differently, are overwhelmingly not currencies in the sense of being a common basis for storing value and exchanging goods and services. In fact, a distinction in digital assets is made between “cryptocurrencies” and “tokens,” with the main difference being that the former have their own blockchains while the latter are built upon existing blockchains. Digital assets include any form of virtual asset, such as ERC-20 tokens, stablecoins, and NFTs. The ethereum blockchain, for example, allows its users to create various virtual coins (i.e., ERC-20 tokens) that do not have their own blockchain, but instead use the ethereum blockchain for transactions and other tasks. Digital assets are also distinguished in a financial context, namely as currencies, utility tokens and security tokens.<sup>4</sup> Stablecoins, in contrast, are said to be backed by some other asset, such as the US dollar or gold. A relatively new phenomenon is NFTs (non-fungible tokens), which essentially track the ownership of digital files like artworks, videos and images. They can be compared to traditional (fungible) artworks or prints, with the sole difference being their virtual character.

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<sup>3</sup> See <https://www.blockchain.com/btc/block/0>, last visited May 24, 2021.

<sup>4</sup> A digital (crypto-) currency serves the purpose of transferring value from one user to another. Utility tokens can be used to access different services or information on a web platform connected to that specific utility token. Security tokens, on the other hand, are able to track or mimic the price behavior of any other asset, such as the S&P 500 stock index or even the temperatures in northern California.

The term digital asset thus carries a variety of technological and financial connotations that coalesced rather quickly from 2009 to 2021 – a very short time when compared to other asset classes. Perhaps the oldest form of asset class as we know it today are bonds or, in broader terms, debt. People in ancient times were accustomed to borrowing and lending money and repaying their debts. That debt market evolved into a highly regulated tradeable market with different kinds of debt which can still be traded today, both on exchanges and over-the-counter. Another very common asset class is equities or stocks. A stock is a part of the equity of a firm or company. Hence, stockholders are also the owners of a specific company, unlike bond holders. Other asset classes like FX (foreign exchange) or commodities are not necessarily tied to a specific firm and might be comparable to digital assets. With an overall market capitalization of US\$1.56 trillion,<sup>5</sup> digital assets are rather small compared to the market capitalization of global equity markets, which amounts to approximately US\$44 trillion.<sup>6</sup>

Digital assets thus differ clearly from other traditional asset classes. Investors own a claim against the assets of a specific company through stocks and debt, and FX is a claim against a currency-issuing central bank; however, digital assets, in terms of “economic” value, are more comparable to commodities such as oil, gold or silver. Gold, for example, has no “intrinsic” value and its industrial use cases are limited. Gold (and thus ostensibly bitcoin) is often seen as a store of value or even a safe haven asset, which performs well if financial markets crash. This proposition is rejected by Smales (2019), who finds that bitcoin cannot be seen as a (safe) haven asset even during normal market states due to its high volatility and other factors. Klein and colleagues (2018) even argue that the opposite behavior is true of bitcoin when compared to gold. Haven properties are also rejected by Wang and colleagues (2019) when comparing to international financial indices, although they do find some hedging effectiveness<sup>7</sup> for larger and more liquid virtual coins. Such a hedging ability is also documented by Fang and colleagues (2019), depending on global economic uncertainty and the asset class under consideration. Baur and Hoang (2021) propose

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<sup>5</sup> See <https://coinmarketcap.com/>, last visited May 24, 2021.

<sup>6</sup> See <https://www.nasdaq.com/articles/us-stock-market-biggest-most-expensive-world-us-economy-not-most-productive-2018-04-02>, last visited June 6, 2021.

<sup>7</sup> In this context, the term “hedge” can be interpreted as a protection against a loss in market value.



that stablecoins such as tether (which is said to be backed by one US dollar per unit)<sup>8</sup> however do exhibit haven properties.

Since digital assets do not inherently have such properties, finance research has debated whether this new financial product comprises its own asset class. Following the original definition by Sharpe (1992), desirable attributes of asset classes are to be “mutually exclusive,” “exhaustive” and to “have returns that ‘differ’” (Sharpe 1992, p. 8). This means that digital assets would need to be distinct from other asset classes (in the sense of purpose or regulatory categorization), that they should include a variety of different “coins,” and that their return/risk behavior needs to differentiate itself from other asset classes. To investigate these propositions, researchers often measure the dependence between asset classes. The most common and “easiest” statistical tool to do so is correlation analysis. If there are no clear links (i.e., significant correlations) to other asset classes, a certain group of digital assets can be termed an “independent” asset class. Sifat (2021) finds that the cryptocurrency market is not connected to global investor sentiment and therefore supports the idea of virtual assets being an independent class. Charfeddine and colleagues (2020) also find only weak and changing correlations of crypto assets to traditional assets, which are sensitive to external events. However, they also find no hedging abilities. Such a relationship is documented by Khelifa and colleagues (2021), who find interactions between digital assets and some hedge fund strategies, especially hedge funds investing in virtual assets. Glas (2019), on the other hand, finds virtually no connection to more established asset classes like equities, commodities or FX.

### 7.2.3 The Global Digital Asset Market

The digital asset market has developed rapidly since its inception. While there were only about a dozen digital assets at the early stages (see Glas & Poddig, 2018), the digital asset market now consists of 9,456 actively tradable virtual coins<sup>9</sup> and 1,673 “dead” (i.e., inactive) coins.<sup>10</sup> Dead coins can constitute failed projects, scam coins, and those with low or even no trading volume or an inactive developer community.

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<sup>8</sup> See <https://tether.to/faqs/>, last visited June 6, 2021.

<sup>9</sup> See <https://www.coingecko.com/>, last visited September 30, 2021.

<sup>10</sup> See <https://99bitcoins.com/deadcoins/>, last visited September 30, 2021.

That also means that about one-fifth of the whole digital asset universe is made up of dead coins, with probably more to follow.

Another interesting point about the digital asset market is its concentration. Just a few digital assets account for most of the US\$1.92 trillion total market capitalization of all coins.<sup>11</sup> The top three coins (as of September 30th, 2021) are valued at a combined US\$1.242 trillion (bitcoin accounts for approximately \$819 billion, ethereum accounts for \$355 billion and tether is valued at about \$68 billion).<sup>12</sup>



**Fig. 7.1** Relative market share of selected digital assets over time. Data is retrieved from [www.coinpaprika.com](http://www.coinpaprika.com)

Hence, only three coins account for about two-thirds of the total market value of digital assets (approximately 42% market share for bitcoin, 19% for ethereum, and 4% for tether). Within this group of three, bitcoin's clear dominance in terms of market value points to its importance for the whole digital asset space, as illustrated in Figure 1, which plots the relative market share of bitcoin, ethereum, litecoin and ripple over time. Table 1 provides context for understanding the return behavior of large digital assets.

<sup>11</sup> See <https://coinmarketcap.com/charts/>, "Total Cryptocurrency Market Cap," last visited September 30, 2021.

<sup>12</sup> See <https://coinmarketcap.com/charts/>, last visited September 30, 2021.

<b>Asset</b>	<b>Mean (%)</b>	<b>Median (%)</b>	<b>Std (%)</b>	<b>Start</b>	<b>Max Drawdown (%)</b>
<b>BTC</b>	1.496	1.224	77.0	2014-01	-79.17
<b>ETH</b>	4.237	1.531	142.77	2015-08	-93.72
<b>LTC</b>	1.650	0.539	121.44	2014-01	-84.84
<b>XRP</b>	3.726	-0.617	253.99	2014-01	-94.91
<b>Index</b>	2.425	1.661	83.73	2014-01	-83.83
<b>S&amp;P500</b>	0.245	0.377	16.40	2014-01	-33.93

**Table 7.1** Descriptive summary statistics of four of the leading cryptocurrencies and a value-weighted market index. “BTC” is bitcoin, “ETH” is ethereum, “LTC” is litecoin and “XRP” is the currency used on RippleNet. “S&P500” denotes the Standard & Poor’s stock market index of the largest US companies. Mean (%) and Median (%) are from weekly discrete returns. Std (%) denotes the annualized standard deviation of weekly returns. Start indicates the year and month of the first observation in the data sample, with observation ranges ending at June 2021. Data is retrieved from [www.coinpaprika.com](http://www.coinpaprika.com)

The most obvious key figure turns out to be the risk, with annualized volatilities up to 254%. The maximum drawdown (i.e., the percentage of invested capital an investor would have lost if investing at the peak and selling at the lowest price), shows high possible losses. Digital assets are thus highly risky assets for which a near total loss is highly plausible.

Another interesting effect can be observed in the trade volume on digital asset exchanges. The daily total spot crypto trading volume amounts to around US\$95 billion USD on September 30th, 2021.<sup>13</sup> The highest trading volume is handled by the exchange Binance, which accounts for approximately US\$18 billion (19% market share). The second most volume is traded on the Mandala exchange (US\$15 billion), followed by BKEX (US\$9 billion) and OKEx (US\$5 billion). The remaining volume is traded on more than 300 other crypto exchanges, which means trading is also dominated by few exchanges, but to a lesser extent than the largest three crypto assets dominating all other digital assets.<sup>14</sup>

All these numbers refer to spot trading, which is buying or selling the digital asset under consideration “physically.” It is also possible to trade derivatives<sup>15</sup> on digital

<sup>13</sup> See <https://coinmarketcap.com/>, “24h Vol,” last visited September 30, 2021.

<sup>14</sup> See <https://coinmarketcap.com/rankings/exchanges/>, last visited September 30, 2021.

<sup>15</sup> Derivatives are products referenced to an underlying, such as a stock. As such the value of a derivative product is *derived* from its underlying. Futures, forwards, options or swaps are all examples

coins on those exchanges. The total derivative trading volume on the same day is even higher (US\$151 billion) than the spot trading volume and is dominated by the exchange Binance. On September 30, 2021, derivative trades on Binance amounted to US\$58 billion, followed by Huobi Global with US\$19 billion, OKEx with almost US\$14 billion, FTX with US\$10 billion, Bybit with US\$9 billion and CoinTiger with US\$8 billion.<sup>16</sup>

Only 37 of the 312 crypto exchanges offer derivative trading, but the trade volume in derivatives clearly exceeds the spot trading volume, making the whole crypto space vulnerable to large derivative bets, which might need to be liquidated at large adverse price moves. In traditional asset classes, the derivative trading volume exceeds spot trading volume as well.<sup>17</sup> However, with clear regulations in place, the effect of derivative trading on spot market volatility is heavily debated in the academic literature. There are no clear indications for stabilizing or even destabilizing effects, which means derivative trading does not necessarily have an impact on spot market trading. The striking difference between derivatives in traditional asset classes and crypto derivatives is regulation and organization. Equity futures, for example, are based on a sound regulatory framework and open positions on one exchange can be closed on another exchange. The same does not apply to digital assets. There remains no clear regulatory framework and positions cannot be transferred, which makes the trader dependent on the crypto derivative's exchange of choice.

Spot trading volume, on the other hand, is not dominated by bitcoin, but by the stablecoin tether. Tether is said to be backed by US\$1 per unit and therefore provides an easy way to convert crypto holdings into fiat money and vice-versa. It is also heavily relied on by crypto exchanges, which explains its high trade volume of US\$67 billion. Tether is followed by bitcoin and ethereum, with US\$31 billion and US\$18 billion trade volume, respectively.<sup>18</sup>

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for derivatives which can have stocks, bonds, exchanges rates or even houses as an underlying. Derivatives tend to be more liquid than the underlying.

<sup>16</sup> See <https://coinmarketcap.com/rankings/exchanges/derivatives/>, last visited September 30, 2021.

<sup>17</sup> The daily derivatives trading volume for DAX index futures on July 19, 2021 amounted to 49,992,040,175 EUR on the EUREX exchange (see [https://www.eurex.com/resource/blob/2721176/029c20796dfde46909b3de42ef061610/data/dailystat\\_20210719.xls](https://www.eurex.com/resource/blob/2721176/029c20796dfde46909b3de42ef061610/data/dailystat_20210719.xls), last visited July 20, 2021), whereas the spot trading volume was only 4,398,312,516 EUR at Börse Frankfurt at the same day (see <https://www.boerse-frankfurt.de/indices/dax/price-history/historical-prices-and-volumes>, last visited July 20, 2021).

<sup>18</sup> See <https://coinmarketcap.com/>, "Volume (24h)," last visited September 30, 2021.

There is thus significant concentration in many parts of the digital asset market, which can have a large impact on any scientific study focusing on this young and emerging asset class. For example, when using market- or volume-weighted market indices, the results are driven by bitcoin or tether, respectively. Therefore, researchers need to account for these market structural implications in their studies. Asset pricing studies are especially prone to such dominance, since asset pricing often uses portfolio (sorts) and indices to arrive at conclusions. The next section thus discusses asset pricing methods and how to cope with skewed or missing data, and details the results of some published studies and their implications for crypto investment strategies. Section 7.3 also focuses on investments into digital assets and various investment strategies that can be used to harvest the high return potential of this emerging asset class.

First, we look at digital assets in combination with other asset classes. Especially for retail or institutional investors, the question arises of whether digital assets increase diversification when added to a portfolio of traditional asset classes. This is important for justifying investments into digital assets from a multi-asset perspective, and digs deeper into the question of whether digital assets constitute a unique asset class with relevance for private and institutional investors.

## 7.3 Investments into Digital Assets

### 7.3.1 Can Digital Assets be a Good Diversifier?

With the increasing importance of hedge funds in the 1990s and early 2000s, researchers confronted the question of whether hedge funds can add value to a portfolio consisting of traditional assets.<sup>19</sup> The same question applies to digital assets today. To conduct such an analysis, different methods can be used. One is the application of spanning tests, which investigate whether the addition of digital assets to a portfolio of reference (traditional) assets shifts the return/risk relationship significantly to the upside. Markowitz (1952, 1959) introduced efficient portfolios with optimal trade-off between risk and return. Efficiency in this context refers to a portfolio with minimal risk for a given level of desired return. For digital assets with low or almost

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<sup>19</sup> See for example Edwards and Liew (1999), Schneeweis and Martin (2001), and Karavas and Georgiev (2000).

no correlation to traditional asset classes, the addition of these assets to a portfolio of traditional assets might reduce standard deviations while simultaneously keeping the same return potential.

Chuen and colleagues (2018) find favourable results for the inclusion of the CRIX index,<sup>20</sup> while Glas and Poddig (2018) do not arrive at a significant upward shift of the efficient frontier (i.e., return/risk profile) when adding an index of digital assets. Schmitz and Hoffmann (2020) also find that digital assets do not shift the efficient frontier upwards in general, but only in some specific periods of time. Similar results are reported by Kajtazi and Moro (2019), who attribute their findings to the positive performance of bitcoin, especially in 2013. Symitsi and Chalvatzis (2019) also arrive at only limited benefits when adding bitcoin to various types of portfolios. They additionally find that commodities are a better way to increase diversification than by adding bitcoin.

There is thus no clear evidence of a positive contribution of digital assets to portfolios made up of traditional assets or asset classes. This comes as no surprise, due to the high volatility of digital assets. Most of the traditional portfolio construction approaches aim to reduce risk, which results in only a minimal inclusion of digital assets in such a portfolio. As such, the impact of digital assets is limited and most of the studies above find no clear benefits for an addition of digital assets to a portfolio of reference assets. Right now, it does not seem to be reasonable for multi-asset investors to add digital assets to their portfolios. Nevertheless, even with these disappointing results, digital assets still provide interesting investment opportunities. It is only necessary to shift from an external view on digital assets to an internal perspective. That is, questions remain on how to structure a portfolio consisting of digital assets exclusively and which digital assets to invest in at which point in time. Some digital assets offer a low correlation to traditional assets such as stocks, bonds or commodities by having a large return potential and high standard deviations (i.e., “risk”) at the same time. Therefore, it is even more important to search for drivers of digital asset returns and ways to structure a portfolio containing virtual coins only. In terms of traditional finance, digital asset management needs to follow a strict risk-management approach to cope with the high risk and volatility of digital assets. Consequently, to be able to harvest

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<sup>20</sup> The CRIX index is an index that includes the largest digital assets by market capitalization and thus tracks the broader market movements. It can be retrieved here: <https://thecrix.de/>, last visited July 21, 2021.

the high-risk premiums in digital assets, digital asset investors need to be aware of the possible risks and get a sense of how to manage their portfolios without losing all of their invested capital (drawdowns of 90%, for example, are not uncommon for digital assets; see Table 1).

### 7.3.2 Asset Pricing and Investments

Switching to an “internal” perspective to investigate how digital assets can be priced efficiently, it is advisable to construct investment strategies based on asset characteristics. A characteristic in this context is a variable that describes the price action in the asset class under consideration. Examples of such characteristics are the momentum of all single digital assets, fundamental variables like network hash rate or number of transactions of a blockchain, or simply the nominal price of an asset. Such a characteristic might or might not predict future returns of (digital) assets. For instance, in the stock market, momentum predicts future stock returns — stocks with high momentum are likely to show high returns in the near future. Do we find this in digital assets, too?

To answer such questions, one must grasp the fundamentals of today’s empirical asset pricing, which dates back over 300 years to the times when European explorers started exchanging goods with East India and Asia. The financial requirements for such journeys were huge, and while providing lucrative possible returns, the risk of not succeeding was tremendous. To fund such activity, companies began to publicly offer stocks to investors. Remarkably, little was understood about risk and return until the early 1950s with the emergence of modern portfolio theory (see Markowitz 1952, 1959).<sup>21</sup> Tobin’s separation theorem (1958), which adds a risk-free investment to the Markowitz model in order to show the independence of investors’ risk preference to a portfolio’s risk composition itself, is the underlying concept of the well-known capital asset pricing model (CAPM). Sharpe (1964), Lintner (1965) and Mossin (1966) introduce this model proposing a linear relationship between risk and return, specifically between the expected return of an asset and its covariance with the market (portfolio). Thus, referring back to Tobin’s separation theorem, it is not the composition

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<sup>21</sup> See Perold (2004).

of risky assets in the market portfolio that is of interest, but the sensitivity of an asset's return to the return of the market portfolio (the return of the market portfolio is also called market factor). Although this concept was revolutionary and worthy of the 1990 Nobel Memorial Prize in Economics, the single-factor model lacks empirical evidence. After decades of further research and dozens of new proposed risk factors, Fama and French (1993) augmented the CAPM, by adding a value and size factor, to form the Fama–French three-factor model. While the former novelty relies on accounting measurements and covers the effect of higher (lower) returns of firms with higher (lower) book-to-market ratios, size – originally introduced by Banz (1981) – refers to the observation of smaller firms (on average) outperforming larger capitalized companies over long horizons. However, the augmented model is insufficient to cover the full variation in the cross-section of stock returns, leaving possibilities for further research. Most prominently, Carhart (1997) added momentum, a factor originally introduced by Jegadeesh and Titman (1993), and even Fama and French proposed two more risk-factors (profitability and investment), to the Fama–French five-factor model (2015). Today, a proverbial “factor zoo” exists (Cochrane, 2011), counting several hundreds of factors being described in the empirical asset pricing literature (see Harvey et al., 2015). These factors shape the return behavior of various asset classes, but research on digital asset factors is still in its early stages. Therefore, all these prior studies in other asset classes serve as the methodological framework for studies looking at digital assets specifically.

The diversity of factors found in the empirical asset pricing literature raises questions about market efficiency. Are these factors an expression of the pricing mechanism of efficient markets or do they contradict the assumption of efficient markets? Without going into detail exceeding the scope of this chapter, it should be stated that there exist two strands of literature. First is the covariance story based on the efficient market hypothesis of Fama (1970), whose rationale is that factors represent systematic risk, which is priced by the markets. A certain factor model (e.g., the three-factor model) leaving significant intercepts (i.e., alphas) in the regression of returns on these risk factors is due to misspecification and simply calls for more complex models. However, another strand of literature (e.g., Daniel & Titman, 1997) rejects this assumption, arguing that the excess return results from the factor itself (often called a characteristic in this context), rather than the additional risk. The implications for investors



nevertheless are tremendous. If the covariance story is true, investors can do no better than holding a combination of risk factors. Deviations from this efficient portfolio would only increase its variance but not expected returns (Daniel & Titman, 1997). However, if differences in stock returns occur due to mispricing, investors should build hedge portfolios on characteristics by going long (buying) on firms with a high characteristic (e.g., high momentum) value and short-selling firms with low characteristic (e.g. momentum) values (or vice-versa, depending on the characteristic) (Fieberg et al., 2016). These so-called portfolio sorts are common practice in empirical asset pricing (for factor/characteristic exploration) and the investment literature (called investment styles). Applying the same methodology of risk factors and investment styles to digital assets is described in more detail below.

### 7.3.3 Investment Strategies across Asset Classes

The heterogeneity of digital assets as discussed above might raise questions about the comparability of different virtual assets in asset pricing and investment studies. Intuitively, does it make sense to mix assets representing a currency, utility, or traditional security together? One would not mix stocks, bonds, currencies or commodities and treat them equally in traditional market studies. This topic may be addressed in two ways. First, from the authors' own (unreported) results, and in line with the findings of Nakavachara and colleagues (2019), we can not find statistical differences in returns between different groups of digital assets; however, this issue is still relatively unexplored and in need of further research. Additionally, the previous sub-section mainly focuses on the stock market for asset pricing studies. However, a large strand of literature has transferred portfolio sorts to other asset classes, such as currencies, bonds and commodities. Asness and colleagues (2013; 2015) show that several characteristics (i.e., investment styles) are indeed present in and create significant spreads in returns across different asset classes, including stocks. In particular, the authors show that value, momentum and defensive are robust across asset classes and the time periods under investigation and fulfil liquidity concerns. That being said, even if different digital assets are distinguishable with longer time-series availability, one can expect several characteristics to be asset-class-independent.

The rationale for using certain characteristics as investment styles is straightforward. For a large cross-section of (digital) assets and a predefined reallocation period (normally weeks, for stocks months), assets are sorted into portfolios depending on their characteristic (e.g., in ascending order into quantile or decile portfolios) in period  $t = 0$ , and the portfolio returns are then value-weighted or equally weighted asset returns in  $t = 1$ . The process is repeated for the entire sample period. As an example, and for the sake of simplicity, imagine the whole sample of cryptocurrencies contains ten different assets and only two portfolios (high and low). The high portfolio buys all its assets (i.e., going long), whereas the low portfolio short sells all its assets (i.e., going short). To form the momentum characteristic, which simply states that past winners will continue to outperform past losers, the five assets with returns above the 50th percentile (median) in  $t = 0$  are sorted into the high portfolio, whereas the five assets below the median are sorted into the low portfolio. The portfolio returns of the next period  $t = 1$  are then calculated before moving one period further in the dataset and repeating the same procedure again. Given that the theoretical background of a characteristic holds, the portfolio returns should differ significantly between the lowest and the highest portfolio – that is, past winners do continue to outperform past losers. This is commonly tested by subtracting the returns of the lowest (short) from the returns of the highest (long) portfolio (i.e., net-zero-investment-strategy or hedge-portfolio, as one would sell the short portfolio in order to finance the long position) and running a simple t-test on the average return of the hedge-portfolio against the null hypothesis of a zero-mean return. Of course, this approach can be applied to any other characteristic under consideration (e.g., nominal price, market capitalization, hash rate).

Characteristics used in recent studies, including our own, are so far only derived from price, turnover and market capitalization data. The horizon under investigation does not normally start before the beginning of 2014, due to the lack of time-series data as well as cross-sectional availability of cryptocurrencies. Broadly speaking, characteristics in cryptocurrency research can be grouped into (1) momentum/reversal based, (2) size based, (3) volume based, and (4) volatility-based characteristics (e.g., Liu et al., forthcoming; Günther et al., 2020; Han et al., 2021). Fundamental characteristics such as hash rate are also applicable in principle, but have rarely been used.

### 7.3.4 Investment Characteristics in Digital Assets

Here, we present results from several peer-reviewed studies, including the authors' own, performing portfolio sorts on well-known and established characteristics, especially but not exclusively from the equity market. The reader may stumble over the high returns. After all, 3% weekly returns results in an astonishing 365% annualized.<sup>22</sup> For comparison, the mean annual return of the S&P 500 for the past 30 years lies around 10%. However, focusing on returns alone conceals that the digital asset market itself is extremely volatile. Risk-adjusted performance measures (e.g., the ratio of return to risk, also called the Sharpe ratio) produce far less impressive results. Furthermore, the reader may be confused at negative returns. This results from the direction of sorting. It is therefore noteworthy that only the absolute value of the returns really matters, whereas the sign just indicates the direction of effect. For example, as shown below, sorting digital assets in ascending order by the turnover volume in the week of the portfolio formation leads to negative hedge-portfolio returns (resulting from a long position in the high portfolio and a short position in the low portfolio). This means that digital assets with low previous turnover volume create higher returns in the future than assets with high previous turnover volume. Knowing the direction of effects, investors would sell the "high" portfolio and buy the "low" portfolio in real-world practice to make profit. However, in academic studies it is common to sort in ascending order by the value of the characteristic (i.e., high characteristic value in the high portfolio and vice-versa). Thus, we follow this academic practice and leave the sign in order to report the direction in which the characteristic affects returns.

Among the first to investigate common risk characteristics in cryptocurrencies are Liu and colleagues (forthcoming), with data ranging from January 2014 to December 2018. They find several momentum characteristics in particular that create significant hedge-portfolio returns (one-week, two-week, three-week and four-week momentum strategies with 2.5%, 3.3%, 4.1% and 2.5% average weekly returns, respectively), as well as the last week's (US) dollar quoted turnover volume (-3.2%) and the respective standard deviation of last week's dollar volume (-3.0%). Interestingly, last day's

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<sup>22</sup> Imagine you invest US\$1,000 today and earn 3% each week. Then your invested funds rise to US\$4,650 after 52 weeks. The formula for calculation is  $4,650 = 1000 * (1 + 3\%)^{52}$ . Your return after one year is therefore:  $365\% = (4,650 - 1,000) / 1,000$ .

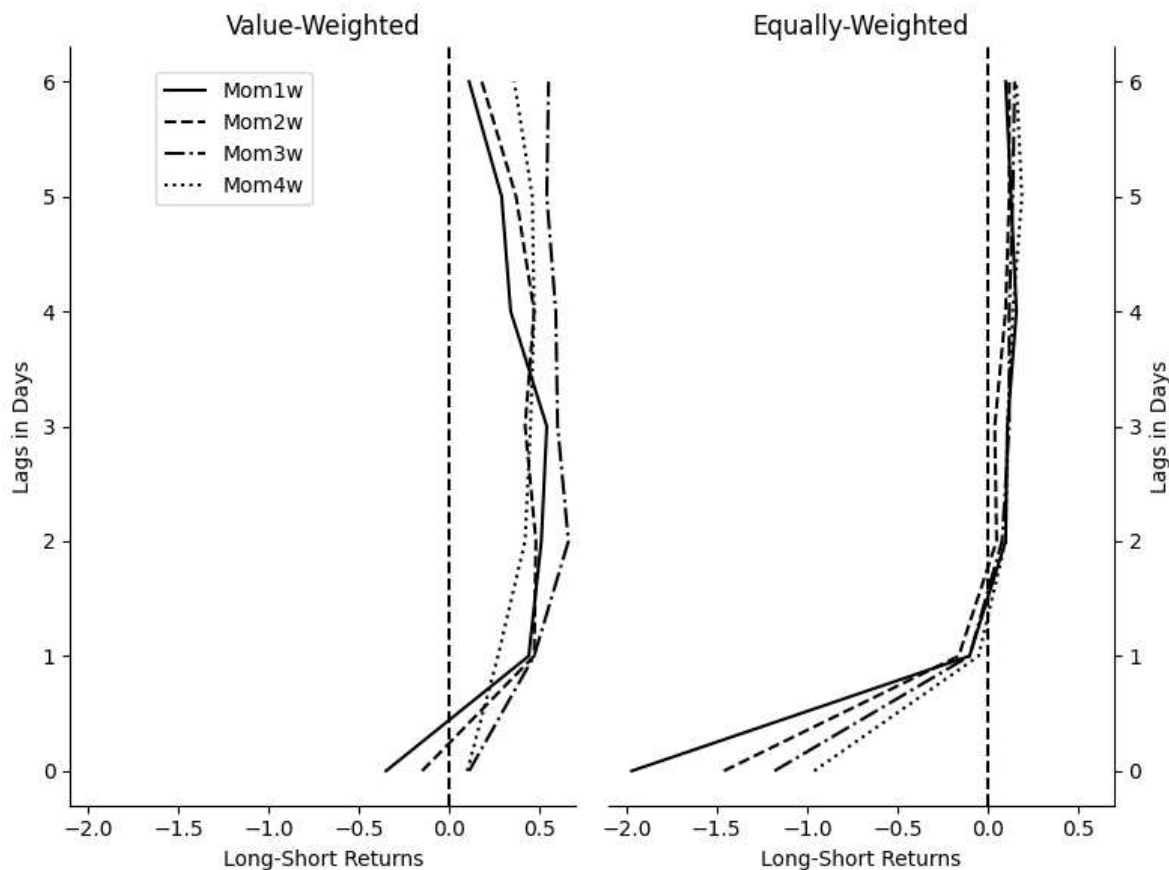
nominal price (-3.9%), last week's maximum dollar price (-4.1%) and last day's market capitalization (-3.4%) are highly significant, suggesting a size effect in cryptocurrency. This effect is in line with the usual stock market literature finding that small-cap stocks on average outperform large-cap ones. Therefore, the authors augment the cryptocurrency CAPM with momentum and size to form a three-factor cryptocurrency risk model, similar to the Fama–French three-factor model described above. Building upon these results and with data reaching until January 2020, Han and colleagues (2021) revisit most of these characteristics and find similar results. The momentum portfolios, ranging from one to four weeks, exhibit weekly (mean) excess hedge-portfolio returns of 3.4%, 3.7%, 3.3% and 0.96%, respectively. Last day's dollar price (-3.3%), last week's maximum dollar price (-2.5%) and last day's market capitalization (-4.6%) share the same sign, although they differ slightly in magnitude. The turnover volume in notional value creates a spread of -7.4%, and sorting for the standard deviation of trading volume creates a spread of -7.1% for weekly excess returns.

Shen and colleagues (2020) also introduce a three-factor model; however, instead of a momentum factor, the authors find the exact opposite, a reversal. This is in line with Glas (2019) and Günther and colleagues (2020), who find a strong reversal effect in a large cross-section of cryptocurrencies, although in daily instead of weekly data. With some caution, one could interpret several signs of short-term reversal price movements in the characteristics results of the studies reported above. For example, last day's dollar price, or market capitalization, in the portfolio formation week leads to high negative spreads in expected returns the following period. This is in fact a reverse reaction to a former price appreciation. Next, we examine the reversal effect in cryptocurrency in greater detail.

An outstanding difference in the mentioned publications is the characteristic construction. While the stock market momentum is normally calculated as the past year's cumulative monthly returns, excluding the most recent month (Jegadeesh & Titman, 1993), researchers in cryptocurrency have tended to increase the data frequency to weekly observation, simply due to limited historical data feeds. Excluding Glas and Poddig (2018), who are among the first to investigate characteristics in cryptocurrencies and use the classical momentum portfolios of Jegadeesh and Titman (1993), most researchers nowadays focus on the past week's (or weeks') performance of a digital asset, without excluding the most recent period. However, as already mentioned earlier, characteristics representing very short-term changes in price or

market capitalization (i.e., previous day) predominantly create large negative hedge-portfolio returns. Liu and colleagues (forthcoming) report -4.6% average weekly returns from last day's market capitalization, similar to Günther and colleagues (2020) (-2.79% daily) and Han and colleagues (2021) (-4.8%). The divergent results in magnitude, but not sign, may be explained by technical differences. Often value-weighted returns are calculated; however, as seen in Figure 2, bitcoin has always had an overwhelming market share and subverts most influences of the large cross-section of digital assets. Figure 2 displays this effect. The interconnection of momentum and reversal is therefore examined in more detail. Specifically, Günther and colleagues (2020) investigate this phenomenon by calculating both equally- and value-weighted portfolios of several momentum/reversal strategies. The y-axis displays the periods excluded before portfolio formation.

Consider the different (equally weighted) returns between lag zero and lag one on the y-axis. For all momentum strategies (one-week to four-week), the returns of the strategy are highly negative when taking all data into consideration (lag zero). However, if the last observation before forming the portfolios is omitted, the returns for all strategies are close to zero and even positive when omitting the last two observations. This shows that the last observation before forming the portfolios has a high negative impact and does not support the idea of momentum strategies (i.e., that past winners continue to outperform). In contrast, in the very short term this dependency reverts, and hence is called the reversal effect.



**Fig. 7.2** Two weighting methods for momentum portfolios. The y-axis denotes the excluded periods prior to portfolio formation. The x-axis denotes the mean daily returns of the hedge-portfolio. Data is retrieved from [www.coingecko.com](http://www.coingecko.com)

The two plots differ significantly, indicating large reversal movements in smaller cryptocurrencies and no momentum effect. Value-weighted portfolios however do have both a smaller reversal of around -0.5% daily returns in the very short term (equal to -3.5% weekly returns) and over 0.5% daily returns (3.5% weekly) if lags are included. The most powerful (momentum) predictor of future returns is the three-weeks' cumulative returns with exclusion of the last two days. These results show the differences occurring due to portfolio construction but coincide with the findings of the literature introduced earlier. Furthermore, the importance of details in implementing the investment strategy are highlighted, as the impact on returns are drastic and can even shift from a reversal to a momentum.

## 7.4 Conclusion

This chapter introduces the new and emerging asset class of cryptocurrencies. After presenting several technical details on blockchains and their functionality, the differences between cryptocurrencies are laid out. The chapter continues with descriptive statistics regarding market growth, performance and risk. After introducing classical financial asset pricing theory, we show that empirical evidence from other asset classes such as stocks cannot simply be transferred. Specifically, we show that the well-known momentum effect, known and observed across several asset classes, is dominated by a very short-term reversal effect. Furthermore, we show that the construction of the characteristic, especially heavy exposure to cryptocurrencies with large market share such as bitcoin, drastically changes the results compared to the equally weighted counterpart. Although investment strategies in digital assets can generate very high returns, it is co-moving with high risk exposures.

Digital assets therefore offer high uncorrelated returns; however, they are connected to large price swings and the risk of a total loss of the initial investment. Investments into this asset class should thus rely on strict risk management principles and must be monitored carefully. The risk of hacks, fraud or a changing regulatory framework still exist, and need to be taken into account when investing into this asset class.

Research on this young asset class is still in its early stages. Since traditional finance theories cannot easily be transferred, there are many other (mostly) uncovered or emergent topics. One topic, the search for risk factors, needs to be taken on the same methodological basis as equities and other asset classes. The question nevertheless remains whether “fundamental” characteristics of digital assets (e.g., hash algorithms or data from the blockchain itself) shape return behavior. Other topics, including clusters in digital assets, have not yet been researched as intensively. Much work thus remains to be done to fully understand the behavior of digital assets and their impact on more traditional asset classes.

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