Unraveling Cryptocurrency Returns: Insights from Methodological Replication and Cross-Sectional Analysis

Part I: Explaining the Cross-Section of Cryptocurrency Returns – under the supervision of Professor Massimo Guidolin (Bocconi University)

Part II: Replicating the Methodology of "Common Risk Factors in Cryptocurrency": A Python Approach – under the supervision of Professor Adrien d'Avernas (Stockholm School of Economics)

Part I: Explaining the Cross-Section of Cryptocurrency Returns

Table of contents

1. Introduction

Ever since Ross (1976) developed the arbitrage pricing theory, plenty of empirical evidence on the existence of factor structures in the returns of a number of financial asset classes, including equities (Fama and French (1992a)), corporate bonds (Fama and French (1992b)), and currencies (Lustig, Roussanov, and Verdelhan (2011)), has been brought forward. Many major players in the asset management industry have been capitalizing on these findings. For instance, Ang, Goetzmann, and Schaefer (2009) have provided convincing evidence that the active investments of the Government Pension Fund of Norway exploit precise factor loadings.

Simultaneously, spurred by the explosive growth of peer-to-peer exchanges and blockchain technology in recent years, cryptocurrencies have gained momentum in the worldwide financial markets.[1] At the time of this writing, there are about 10,397 actively quoted cryptocurrencies, a steep increase from just 66 in 2013.[2,3] By August 31, 2022, the cumulative market capitalization of all crypto assets has reached approximately $945 billion.[4] The best-known cryptocurrency is Bitcoin, which has recently been classed as a commodity in the U.S., and therefore is now covered by the Commodity Exchange Act, along with gold and oil (see Yang, 2022).[5] Because they are a relatively young asset class, cryptocurrencies are traded on exchanges that offer the functionality of traditional exchanges, but also fail to provide institutional investors with the protection they can expect when trading more established asset classes. Nevertheless, this has not stopped institutional investors, especially hedge funds and other smaller institutions, from investing in digital assets (see Karniol-Tambour, Tan, Tsarapkina, Sondheimer, and

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[1] A blockchain is an open and distributed ledger that records all transactions occurring, called blocks. The blocks are sequentially linked and protected in a permanent and verifiable manner using cryptography. In addition, each block contains the transactional details and a timestamp to trace the timing of the transaction (see Yang, 2018).
[2] The information is retrieved from the plot found at https://www.statista.com/statistics/863917/number-crypto-coins-tokens/ that depicts the number of cryptocurrencies worldwide as of August 31, 2022.
[3] Note, however, that these cryptocurrencies differ widely in significance and popularity. In fact, barriers to entry are relatively low due to how easy it is to create a new cryptocurrency. Thus, the success of a cryptocurrency project and the consequent adoption of the asset highly depend on intangible factors, such as the quality of the team behind the cryptocurrency.
[4] This information is retrieved from the collection of charts found at https://coinmarketcap.com/charts/ as of August 31, 2022.
[5] In 2008, the anonymous entity "Satoshi Nakamoto" introduced Bitcoin as a purely peer-to-peer version of electronic cash that allowed online payments to be transmitted directly from one party to another without going through a financial intermediary (see Satoshi Nakamoto, 2008).

Barnes, 2022).[6] These new developments are expected to give comfort to fund managers and attract more institutional capital to crypto assets in the near future.

Given the evidence of ubiquitous factor structures among mainstream asset classes, a natural question arises about whether similar factor structures would also emerge among crypto assets. Thus, this thesis aims to provide a summary of the findings of the literature on the risk factors in the returns of cryptocurrencies. To this end, this dissertation provides an extensive comparative analysis of the current and arguably quite young academic research concerning the cross-section of cryptocurrency returns, accompanied by an introduction to cryptocurrency features as well as to mainstream asset-pricing models as applied to digital assets. Specifically, this dissertation seeks to understand what risk factors can best explain the variability in cryptocurrency returns, how these relate to their characteristics, how different cryptocurrencies differ in that regard, and what drives their uniqueness within the spectrum of financial assets. To the best of my knowledge, over the past decade, no other paper has comprehensively discussed the empirical evidence on a factor structure in cryptocurrency returns. Because the current literature suggests a multitude of findings, diverging opinions, and alternating approaches to asset pricing, investigating this issue from different angles and revealing any emerging consensus as well as disagreement, may contribute to a better understanding of this important matter.

In fact, given the emergent status of cryptocurrency markets, understanding the investment properties of cryptocurrencies and their relationships to other global asset classes could prove highly relevant to a broad audience. Academics, for one, can see this thesis as a summary of this branch of the literature to date. Moreover, this dissertation may offer a starting point for further research into the economic aspects of cryptocurrencies or even for proposing new design perspectives on cryptocurrencies. Despite the prevailing controversy surrounding digital assets, the literature on cryptocurrencies is still remarkably underdeveloped compared to that concerning traditional asset classes and thus constitutes a potentially fruitful research area. Institutional investors, on the other hand, can be counted among the parties potentially profiting the most from this research in practical terms. Most investors are still in the very

[6] In this thesis, the terms "digital assets" and "crypto assets" are taken to be synonyms for "cryptocurrencies".

early stages of developing exposures to crypto assets, but their adoption in standard portfolio management set-ups looks likely to pick up in the coming years. Quite recently, for example, the Swiss bank UBS has announced that they are exploring ways to offer digital currency investments to wealthy customers and BlackRock CEO Larry Fink has stated that the company is studying cryptocurrencies (see Koltrowitz, 2021, and Vigna, 2022). Karniol-Tambour et al. (2022) mention three main motives that explain why institutions are beginning to access crypto markets: 1) outright exposure to cryptocurrencies, 2) exposure to arbitrage and money-making opportunities, and 3) exposure to technological growth via venture capital or equities. The information contained in this thesis may therefore prove useful to institutional investors for achieving these objectives. Furthermore, Neureuther (2021) of Fidelity Digital Assets mentions that the main reasons for the slow institutional pick-up of digital assets are the lack of fundamentals and valuation methodologies (beyond volatility, market manipulation, regulatory classification, and security of asset custody). This dissertation may therefore help diminish these obstacles by summarizing the views of the leading academics on the fundamental value of cryptocurrencies, as well as the methods they favor in determining the value of these assets.

Of course, my survey efforts could also help the same investors get a clearer idea of how crypto assets would come to play a role in portfolio diversification. Particularly active portfolio managers, such as hedge funds, can use the key findings reported here to design investment strategies that neutralize specific risks or exploit mispricing in a particular factor to yield sizable, abnormal returns. There are even crypto-specific hedge funds starting to emerge, which specialize in strategies primarily intended to access crypto markets directly, and, in some cases, bridge inefficiencies between crypto-linked assets in traditional financial markets and their corresponding on-chain products. Karniol-Tambour, Tan, Tsarapkina, Sondheimer, and Barnes (2022) explain that these hedge funds come in two primary flavors: those that perform highly risky directional strategies and those that set up market-neutral strategies. Both try to take advantage of arising alpha opportunities. Furthermore, investment-savvy retail investors could also benefit from my reviewing work for the sake of educating themselves on how to establish portfolio exposures to certain risk factors through cryptocurrencies and, perhaps more importantly, to learn about any cryptocurrencies' hedging benefits, in general. In the face of rising uncertainties the in global political and economic systems – consider, for example, the Russian invasion of Ukraine and the ensuing sanctions on Russian banks and flows of Ukrainian refugees, as well as the increasingly evident threat of inflation in combination with the currently prevailing low-interest-rate environment – prudent private investors would be well-advised to at least consider cryptocurrencies for personal wealth management purposes. Finally, financial regulators, such as the most significant worldwide central banks, should seek to comprehend the trading motives and the market structure supporting digital assets to make better predictions in terms of how crypto holdings can affect the asset-side of banks and other institutions under their supervision. Lastly, the findings in this thesis may guide regulators in revealing potential determinants of the whole banking sector's stability, should cryptocurrencies take up a significant share of bank balance sheets in the future.

The remainder of this dissertation is organized as follows: Chapter 2 summarizes essential background knowledge about cryptocurrencies. Chapter 3 presents the most widely applied asset pricing models in the literature. Chapter 4 reviews the main empirical results of cross-sectional studies, whereas chapter 5 lists areas for further research. Finally, chapter 6 concludes.

2. Background on cryptocurrencies and blockchains

This section aims to educate a Reader on the individual and common features of crypto assets, as well as their diverse value propositions. This knowledge is essential for understanding the risk factors that affect cryptocurrency returns. To achieve this, this chapter presents the universe of cryptocurrencies, including their defining technical and economic characteristics, and discusses whether cryptocurrencies can be seen as a medium of exchange and/or a store of value.

2.1 The universe of cryptocurrencies and their institutional adoption

Bitcoin is just one currency in a broader universe of alternative, yet mostly relatively similar, cryptocurrencies called altcoins. Over the course of the past decade, numerous altcoins have sprung up, promising value in widely different ways. Figure 1 tracks their ever-increasing total market capitalization. Some altcoins have effectively gone extinct, while new ones emerge in the market. Their steady growth is partially driven by the circumstance that developing and issuing a new cryptocurrency in a so-called initial coin offering (ICO) is relatively easy (see Narayanan, Bonneau, Felten, Miller, and Goldfeder, 2016). Templates for new cryptocurrencies are easily accessible, especially for existing blockchains, such as the Ethereum blockchain. Ethereum is also known for its smart contract capabilities.[7] Further well-known altcoins include Litecoin, Dash, and Zcash (see Yang, 2018). Figure 2 shows the distribution over time of the ten largest cryptocurrencies in terms of market capitalization. One can see that until 2017 the market used to be heavily concentrated on the original cryptocurrency Bitcoin. Recently, however, altcoins have gained on Bitcoin. New cryptocurrencies like Cardano, Avalanche, Ripple, and Polkadot are on the rise, standing out against Bitcoin by offering more functionalities. Likos (2022) believes that the main reasons for this development also include that cryptocurrencies' uses are expanding on the whole, that altcoins constantly innovate, and that institutional investments in altcoins are growing.

Indeed, over the past decade, institutional interest in altcoins and Bitcoin has consistently increased. While banks initially faced cryptocurrencies with skepticism – at the 2014 World Economic Forum in Davos, Jamie Dimon, the chief executive of JPMorgan Chase, put Bitcoin into question as a store of value and stressed that it was being used for unlawful purposes – they now seek portfolio exposure (see Flitter, 2021). Figure 3 shows the steep hike in the adoption of digital assets by institutional investors from 2019 to 2021 throughout the world. There are multiple ways for institutions to access the crypto asset market, including primary market participation in ICOs, secondary market trading of cryptocurrencies, crypto derivatives trading, venture capital investments into related start-ups, or secondary market equity investments in public firms. Both IBM and Microsoft, for instance, have made significant investments in blockchain technology and related businesses (see Enterprise Ethereum Alliance, 2017). Institutional investors still face some obstacles in accessing cryptocurrencies, however. Holding cryptocurrencies outright requires the development of new operational capabilities and approval processes. Nevertheless, direct allocation by institutions is likely to rise going forward (see Karniol-Tambour et al., 2022).

[7] A smart contract is a computer program that executes automatically when the predefined terms of an agreement are met. The main objectives of smart contracts are disintermediation, the reduction of arbitration and enforcement costs, and the prevention of fraud losses (see Narayanan et al., 2016).

2.2 Technical and economic characteristics of cryptocurrencies

A branch of economics, monetary economics, is concerned with different competing theories of money. A growing number of researchers in this field are analyzing the technical and economic aspects of cryptocurrencies and blockchain technologies, such as the benefits and shortcomings of consensus mechanisms, the consumer welfare induced by using cryptocurrencies, and the incentives provided by different fee structures. This section intends to present some of the findings and perspectives offered by this line of research since the fundamental value and the risk factors of cryptocurrencies are presumably related to these economic particularities. The likely most relevant question in cryptocurrency economics today pertains to their monetary nature. Chapter 2.4 delves into this ongoing debate.

Catalini and Gans (2019) offer an explanation for how blockchain technology helps reduce two key costs in the economy – the cost of verification and the cost of networking. According to them, digital cryptocurrency exchanges allow participants to make joint investments in digital public utilities and shared infrastructure without transferring market power to a central operator. Such exchanges then feature a lower privacy risk, lower barriers to entry, and increased competition. Abadi (2022) argues that while on the positive side blockchain technologies offer the decentralization of record-keeping, proof of work (PoW) constitutes a wasteful expenditure of computational resources.[8] According to him, an optimal consensus mechanism would be resilient against errors, avert wasting computational resources, and be capable of executing all individually rational transfers of value among parties. He proceeds to substantiate the blockchain trilemma in economic terminology:[9] any method of consensus, be it centralized or decentralized, must forfeit 1) full transferability, 2) resource efficiency, or 3) fault tolerance. Kroll, Davey, and Felten (2013) show that there is a Nash equilibrium in which all players behave consistently with Bitcoin's reference implementation, but with infinitely many equilibria in which they

[8] PoW is a cryptographic consensus mechanism in which one party proves to others that a certain amount of computational work has been expended. The counterparty can subsequently verify this expenditure with no effort on its part. On the other hand, proof of stake (PoS) is a kind of proof that works by selecting validators in proportion to their quantity of holdings in the respective cryptocurrency, thereby avoiding the computational cost of PoW. The debate about the relative merits of PoW versus PoS is still active (see Narayanan et al., 2016).

[9] The idea of the blockchain trilemma has gone mainstream in the blockchain literature and is mentioned in almost every discussion on the topic. The concept was coined by Ethereum founder Vitalik Buterin (see CoinMarketCap, 2022).

behave otherwise.[10] They also show how an adversary might be able to disrupt the Bitcoin system and drive the price to zero. Huberman, Leshno, and Moallemi (2021) find that the decentralized design of some blockchain protocols prevents monopoly pricing. Free entry and the competition among service providers within the system imply no entity can profitably affect the level of transaction fees users pay. Instead, the fees are determined in a market for transaction processing, thereby avoiding processing delays. Chiu and Koeppl (2018) study the ideal design of cryptocurrencies and evaluate quantitatively how well such currencies can promote bilateral trade. They claim that the important issue of double-spending might be solved by depending on competition to update the blockchain and by delaying settlement, though this causes a consumption welfare loss. Similarly, Dwyer (2014) stresses that any currency must deter users from spending their balances more than once. He further explains how the use cases of digital assets and their limited supply can create an equilibrium in which cryptocurrencies have positive value. Evans (2014) characterizes blockchains as incentive systems that evoke efforts from a distributed global workforce to verify and record transactions on the public ledger. He asserts that the economic efficiency and viability of a public ledger platform ultimately depend on the design of its incentive systems. The author concludes that public ledger platforms are potentially more efficient than alternative platforms for undertaking financial transactions. Fernández-Villaverde (2018) draws a comparison between traditional fiat currencies and cryptocurrencies. He argues that, as pure fiduciary private money, cryptocurrencies are a bubble without fundamental value. Nevertheless, he continues, cryptocurrencies can play a role in improving the current instruments of payments and in reprimanding central banks into providing better government-run monies. Further papers in this field discuss, for example, the economics of transaction fees – compare, for instance, Houy (2014). Questions that are yet to be addressed by this branch of economic research include whether there is a critical mass in the number of users for such platforms to improve efficiency.

In summary, economists have found that blockchain technology can both promote and impede economic efficiency (for example, in conducting financial transactions). The

[10] A Nash equilibrium is the state where the optimal outcome of a strategic interaction is one where no player has an incentive to deviate from their chosen strategy after considering all opponents' choices and vice versa (see Nash, 1951).

former is one of the justifications for a fundamental value in cryptocurrencies.[11] There is no definite agreement regarding an optimal consensus mechanism and important trade-offs among the desired features for a cryptocurrency need to always be considered.

2.3 The differences of cryptocurrencies vs. traditional currencies and among themselves

Cryptocurrencies are hailed by many as the next step in the evolution of money – but what makes them different from their traditional counterparts? In an attempt to answer this question, Fernández-Villaverde (2018) draws a comparison between traditional fiat currencies and cryptocurrencies, stressing the advantages of the latter over the former. First, the application of a network of computers for the issuance and control of the cryptocurrency alleviates the deficits of traditional currencies related to the fast clearing and settlement of payments. Second, cryptocurrencies solve most of the problems regarding forgery and fraud and offer a higher degree of anonymity, owning to modern cryptographic techniques. Third, cryptocurrencies enforce a form of self-commitment. Specifically, cryptocurrency protocols can contain rules whereby the issuance of new money is automatized at a predetermined speed and with a preset limit, instead of having to depend on a central bank determining how many banknotes to print. Fourth, the software ecosystem built around cryptocurrencies offers many relatively easy ways to generalize smart contracts.

Cryptocurrencies differ not only from fiat currencies but also among themselves. Broadly speaking, cryptocurrencies can be divided into two categories: coins and tokens. Coins exhibit similarities with traditional currencies, and hence generally aim to compete with them. Typically, they have their own blockchain and offer unique benefits in terms of efficiency, security, and transaction privacy. Tokens are often created on top of other blockchains and are tied to a platform that offers a specific product or service. Furthermore, cryptocurrencies have different consensus mechanisms. Most prominently, the PoW mechanism used in Bitcoin requires significant computing power and thus electricity, whereas the PoS algorithm requires fewer resources (see Saleh, 2020).

[11] The debate on whether cryptocurrencies have fundamental value is a noteworthy discussion in itself. One convincing perspective is proposed by Biais, Bisière, Bouvard, Casamatta, and Menkveld (2022) who argue that the *core* fundamental value of a cryptocurrency is its stream of net transactional benefits which depend on its future prices. Garcia, Tessone, Mavrodiev, and Perony (2014) assert that the cost of production via mining could matter in coming up with a fundamental value for cryptocurrencies, insofar as it represents a lower bound.

Accordingly, coins with similar consensus mechanisms may comove due to exposure to similar news about technical advances in computing performance or related factors, such as electricity prices. Moreover, some cryptocurrencies are "hard forks" of other cryptocurrencies.[12] For instance, Bitcoin Cash and Bitcoin Gold are two of Bitcoin's forks. According to Shams (2020), to the extent that the value of cryptocurrencies depends on their underlying technology, forks on the same blockchain might show a higher correlation. The author also relates the non-technical features of cryptocurrencies to the correlations among them. He finds that cryptocurrencies with similar market capitalization, trade volume, and age covary significantly more. Lastly, he finds that exposure to similar investor bases in terms of trading location explains by far the most covariation in cryptocurrencies. The author analyzed 486 cryptocurrencies over a period from 2017 until 2020. Taking a different approach, Shams (2019) defines a connectivity measure as the degree of intersection in the set of exchanges two cryptocurrencies trade on to demonstrate that connected currencies have a considerable correlation. The author looked at the returns of 554 cryptocurrencies from 2017 to 2018. Mayer (2018) finds mostly statistically significant positive covariation coefficients among the cryptocurrencies he analyzed, but not between cryptocurrencies and established asset classes in a sample of five cryptocurrencies spanning the period of 2015 to 2017. On the contrary, Elender, Trimborn, Ong, and Lee (2016) document that cryptocurrency returns are slightly correlated both in their cross-section as well as with other financial assets. Their sample comprises the returns of ten major cryptocurrencies from the period 2014 until 2016.

Taken together, most papers find that cryptocurrencies exhibit statistically significant positive correlations among themselves. These parallel price movements are mainly driven by their technical and non-technical features. Similar cryptocurrencies tend to covary due to exposure to the same risk factors. The evidence on the correlation with other asset classes, however, is less clear. The few papers addressed here represent merely a small fraction of the research done on this topic, though.[13] The main analysis in chapter 4 is partially in reference to the findings presented here.

[12] A hard fork of a cryptocurrency is a modification to its original protocol, resulting in a new cryptocurrency. One type of change is introducing new features (see Narayanan et al., 2016).

[13] To my knowledge, there are regrettably no comprehensive literature reviews on the topic of cryptocurrency correlations.

2.4 Are cryptocurrencies a medium of exchange or a store of value?

Monetary economists have proposed three key functions of money. They are distinguished as a medium of exchange, a unit of account, and a store of value (see Mankiw, 2016). While this identification provides a clear definition of what money does, the question of what makes something money is rarely addressed satisfactorily. By the same token, cryptocurrencies have been discussed for their use as a medium of exchange and a store of value. The purpose of this section is to capture the state of debate on this question.

In an early assessment study, Yermack (2013) argues that Bitcoin largely fails to satisfy the standard criteria of money. According to him, Bitcoin has achieved only scant consumer transaction volume and it is common knowledge that its volatility is greatly higher than that of traditional fiduciary currencies, imposing large short-term risk upon users. Moreover, Bitcoin is prone to manipulation, lacks access to deposit insurance, and is not used to denominate loan contracts or consumer credit. He concludes by claiming that Bitcoin appears to behave more like a speculative investment than a true currency. His argumentation is mainly based on practical considerations and fails to address cryptocurrencies' theoretical functions. Of course, much has changed since this paper has been published, but especially concerns about short-term price volatility remain. In another early assessment, Woo, Gordon, and Iaralov (2013) of Bank of America Merrill Lynch voice their belief that Bitcoin may emerge as a serious competitor to traditional money transfer providers, especially in e-commerce, since Bitcoin offers low transaction costs. Concerning Bitcoin's usefulness as a store of value, though, they argue that its role is severely compromised by its elevated price volatility. Again, we still see that today. Glaser, Zimmermann, Haferkorn, Weber, and Siering (2014) look at the question of whether users' interest in digital currencies is chiefly driven by their appeal as a currency or a different kind of asset. They find strong evidence that particularly uninformed users are not seeking an alternative transaction system but are interested in entering an "exotic" investment vehicle. Using a GARCH model, Dyhrberg (2015) shows that Bitcoin has many similarities to both gold and the dollar.[14] He argues that the medium of exchange characteristics are clear, supported by the observation that Bitcoin reacts

[14] A GARCH (generalized autoregressive conditional heteroskedasticity) model is commonly used for analyzing time-series data where the variance error term is believed to be serially autocorrelated.

significantly to the Federal Funds Rate. At the same time, Bitcoin also exhibits features that make it unlike any other currency: it is both decentralized and unregulated to a large extent. Indeed, Bitcoin also shares many aspects with gold, since they covary with similar variables, possess almost identical hedging capabilities, and react in the same way to bad and good news announcements. This suggests that Bitcoin is a hybrid between a currency (medium of exchange) and a commodity (store of value). Taking another view, Baur, Hong, and Lee (2017) describe Bitcoin as a blend of a commodity currency without intrinsic value and a fiat currency. The analysis of Bitcoin transaction data suggests that Bitcoins are mainly used as a speculative investment and not as a medium of exchange. Contrary to Dyhrberg (2015), the findings of Al-Khazali, Elie, and Rouband (2018) support the idea that gold, the traditional store of value, is different from Bitcoin. Specifically, the returns and variance of gold systematically react to macroeconomic news surprises in a way consistent with its traditional role as a safe haven, whereas the prices and variance of Bitcoin do not respond similarly. Finally, Zimmermann (2020) argues that the blockchain composition of a cryptocurrency constrains settlement capacity, limiting the value of cryptocurrencies as a medium of exchange. Higher speculative demand then overburdens the blockchain and lowers the currency's price.

Summing up, while early research has doubted cryptocurrency's capabilities as a store of value – the main reason being its volatility – more recent works have called into question its ability to serve as a medium of exchange. Additional investigations into cryptocurrencies' bid-ask spread, as well as their fee structures, could further emphasize their shortcomings as a medium of exchange. Ever since Bitcoin's inception about a decade ago, volatility has been a constant menace to short-term wealth preservation, but has mostly vanished over longer investment horizons. Accordingly, it would seem that most research on the topic should agree that cryptocurrencies' main strength lies in their capabilities as a store of value, similar to gold. Supporting this idea, as mentioned in chapter 1, cryptocurrencies are already treated like a commodity in the U.S. Regardless, no academic consensus has been reached yet on this point. The prevalent view still is that Bitcoin is mainly held for speculative purposes. Likewise, according to Fidelity Digital Assets' 2021 survey of 1,100 professionals from a variety of firms, the main reason for investing in digital assets for institutional investors remains a high potential upside (see Neureuther, 2021).

This chapter has provided the necessary background knowledge to understand what fundamental factors could affect cryptocurrency returns. The next chapter addresses two main types of asset pricing models: fundamentals- and sentiment-based asset pricing models.

3. The most common asset pricing models

Over the years, the field of asset pricing has churned out a variety of approaches to determining fair asset prices. The models are usually derived from either general equilibrium asset pricing or rational asset pricing, the latter corresponding to risk-neutral pricing (see Qian, 2019). Multiple factor models – a variant of equilibrium pricing models – are arguably the most widely applied approach. These models extend the well-known (single-factor) capital asset pricing model (CAPM) by additional factors which represent sources of fundamental risk that asset buyers and sellers explicitly or implicitly consider in their transactions.[15] The following sections consider two important groups of risk factors used to construct multi-factor models: fundamentals- and sentiment-based asset pricing models.

3.1 Fundamentals-based asset pricing models

Many academics have attempted to construct factor models with a preferably small number of parameters. These include the Fama-French three-factor model (1992), the Carhart four-factor model (1997), and the Fama-French five-factor model (2015). These models are widely referred to as the fundamentals-based asset pricing models. The Fama-French three-factor model was developed by Eugene Fama and Kenneth French, and published in their seminal 1992 paper. They included the "small minus big" (SMB) and "high minus low" (HML) risk factors to improve upon the explanatory power of the CAPM and better describe the market fluctuations. The inclusion of these two factors is usually justified by their ability to capture additional sources of fundamental risk besides market risk. The SMB factor accounts for small-cap stocks that generate returns higher than predicted by the CAPM, while the HML factor considers the fact that stocks with high book-to-market ratios outperform markets on a regular basis. Whether the

[15] The CAPM was independently introduced by Jack Treynor (1961, 1962), William F. Sharpe (1964), John Lintner (1965a, 1965b), and Jan Mossin (1966), extending Harry Markowitz's earlier work on diversification and modern portfolio theory.

outperformance tendency is due to market efficiency or market inefficiency is a matter of current debate. A high book-to-market ratio is usually taken as an indication that the value of the firm is driven mainly by existing assets, rather than the expectation of high growth in the future. These are called "value" firms. On the other hand, a low book-to-market ratio characterizes firms whose market value derives primarily from multiple growth opportunities. One channel through which a high book-to-market ratio may capture aspects of systematic risk is the effect of large fixed assets. When the economy goes into recession, companies cannot use these assets at full capacity, significantly diminishing their value. Thus, a high book-to-market ratio, which may be due to substantial investments in fixed assets, can entail higher systematic risk than predicted by the CAPM. Firm size may also indicate some aspects of risk. Other things being equal, the equity of major firms may be less risky than that of their smaller counterparts, because more analysts cover it, hence providing more accurate information. It is commonly held that with better-informed investors, prices reflect more reliably the true value and are less prone to systematic as well as firm-specific volatility. With more disposable cash and a greater capacity for debt financing, large firms are also better prepared for economic downturns. On both counts, investors demand higher risk premia on small firm stocks than conceded by the CAPM alone (see Bodie, Kane, and Marcus, 2019). Obviously, there are still other interpretations of how these factors represent fundamental risks. In any case, in the Fama-French three-factor model, the SMB and HML factors are constructed as factor-mimicking portfolios. SMB is defined as the average return on three portfolios consisting of small stocks minus the average return on three portfolios comprised of large ("big") stocks.

$$SMB = \frac{1}{3}(Small\ Low + Small\ Neutral + Small\ High) - \frac{1}{3}(Big\ Low + Big\ Neutral + Big\ High) \tag{1}$$

HML, on the other hand, is defined as the average return on two value portfolios minus the average return on two growth portfolios (see Fama and French, 1992b).

$$HML = \frac{1}{2}(Small\ High + Big\ High) - \frac{1}{2}(Small\ Low + Big\ Low) \tag{2}$$

In 1997, Carhart published a paper in which he extended the three-factor model by a momentum factor. Broadly speaking, momentum investing is a trading strategy in which an investor buys securities that are increasing in price and sells them when he/she expects their prices to fall. The momentum effect is commonly explained by behavioral phenomena, such as overreaction to news and investor sentiment. Carhart's factor for momentum "winners minus losers" (WML) is a factor-mimicking portfolio for one-year return momentum.[16] The WML factor can be built by subtracting the average of the weakest performing firms ("losers") from the average of the best performing firms ("winners"), lagged by one month.

$$MOM = \frac{1}{2}(Small\ Winners + Big\ Winners) - \frac{1}{2}(Small\ Losers + Big\ Losers) \tag{3}$$

In his analysis of mutual fund performance, he found statistically significant coefficients for the WML factor (Carhart, 1997). Most recently, in 2015, Fama and French extended their previous model by adding two factors: profitability and investment. Defined analogously to the HML factor, the profitability factor "robust minus weak" (RMW) is the difference between the returns of firms with high ("robust") and low ("weak") operating profitability.

$$RMW = \frac{1}{2}(Small\ Robust + Big\ Robust) - \frac{1}{2}(Small\ Weak + Big\ Weak) \tag{4}$$

Furthermore, the investment factor "conservative minus aggressive" (CMA) is the difference between the returns of firms that invest conservatively and firms that invest aggressively.

$$CMA = \frac{1}{2}(Small\ Conversative + Big\ Conservative) - \frac{1}{2}(Small\ Aggressive + Big\ Aggressive) \tag{5}$$

The additional explanatory variables have been demonstrated to improve explanatory power in analyses of various asset classes (see Fama and French, 2015). Some papers are now even speaking of the Fama-French six-factor model. They are usually referring to the Fama-French five-factor model plus a WML factor, as proposed by Carhart (see AQR

[16] In the following parts of this thesis, the author may refer to the essential factors "SMB", "HML", and "WML" as "size", "value", and "momentum", respectively. "CAPM" and "market returns" are used synonymously, as well. Still, one has to be careful to distinguish the factors called "SMB" from the ones called "size" in the literature. The former is usually set up as the returns of smaller assets minus the returns of larger assets, while the latter is simply the market capitalization. So, although they measure the same phenomenon, the two factors point in different directions.

Capital Management, LLC, 2014, and Fama and French, 2017).

Academic studies implementing these three models are abundant. A number of seminal papers applying these approaches to various asset classes have been mentioned in chapter 1. Modern asset pricing papers will usually apply at least one of these standard models, but add one or multiple extra variables, which are specific to an asset class, to reveal potential additional risk factors. In fact, Harvey, Liu, and Zhu (2016) catalog 316 anomalies and regard them as potential factors in asset pricing models. Nevertheless, Fama and French (2018) argue that these anomalies may produce similar results to the combinations of the six factors mentioned above. Even so, studies may produce varying results for even the same anomaly due to different data sets and choices of proxies for the factors. Moreover, the six factors take perfect rationality as given, a requirement financial markets rarely fulfill. The six factors mentioned in this section are the most widely adopted ones, although there are still many others being proposed in the hope of contributing to the explanation of average returns variance. Additional factors often include sentiment-based risk factors that are addressed in the following section.

3.2 Sentiment-based asset pricing models

Beyond fundamental risk factors, the asset pricing literature seems to agree that investor sentiment plays a role in determining the returns of an asset. De Long, Shleifer, Summers, and Waldmann (1990) have defined investor sentiment as a belief about future cash flows and risks of securities not supported by the economic fundamentals of the underlying asset. Investor sentiment is a vital feature of the capital market, since it contributes to the prevalence of stock price fluctuations, and thereby creates uncertainty about future returns on investments. Since the fundamental value of cryptocurrencies is hard to comprehend – especially because of their digital nature – some researchers argue that the cryptocurrency market is mainly driven by investor sentiment, leading to high volatility (see Lee, Guo, and Wang, 2018). Hence, capturing investor sentiment could significantly improve existing asset pricing models. The purpose of this section is to address some of the contemporary approaches to analyzing investor sentiment.[17]

The concept of sentiment has been studied by researchers with widely differing

[17] In their recent paper, P H and Rishad (2020) provide an extensive explanation of the role of investor sentiment in financial markets and also include a comprehensive literature review.

approaches. A paper will usually present a proxy of investor sentiment and then regress it on the returns of a certain asset or asset class, controlling for a relatively standardized set of variables, including the fundamental factors introduced in the previous section. There are no definitive or uncontroversial measures, however. An important paper in the field was written by Stambaugh, Yu, and Yuan (2012), who examine the role of sentiment-related overpricing in the eleven most popular asset-pricing anomalies. Strikingly, they considered constraints to short selling as the most important obstacle to eliminating sentiment-driven mispricing. To the extent that such mispricing exists, overpricing should then be more prevalent than underpricing. Also, overpricing should predominate when market-wide sentiment is high. They use the University of Michigan Consumer Sentiment Index as a proxy for sentiment. Another widely accepted behavioral finance paper about investor sentiment was written by Baker and Wurgler (2006), who argue that market-wide sentiment should strongly affect stocks that are hard to arbitrage and difficult to value.[18] They create a composite index based on the common variation in six underlying proxies for sentiment: the dividend premium, the number and average first-day returns on IPOs, the closed-end fund discount, the equity share in new issues, and NYSE share turnover. Lastly, Chiu, Harris, Stoja, and Chin (2016) investigate the relationship between macroeconomic fundamentals, investor sentiment, and financial market volatility. They adopt a two-factor model to decompose volatility into a transitory short-run and a persistent long-run component. In particular, the authors discover that the transitory component is closely linked with changes in investor sentiment. Quite different than the previous paper, they use the U.S. Crash Confidence Index provided by Robert Shiller as a proxy for investor sentiment.

In summary, there are clearly multiple ways to proxy for sentiment, a concept that is ambiguous in nature. If we could manage to capture investor sentiment, it may reveal more information about the risk-return structure of an asset. We are likely to see more research in this field in the future since irrationality is arguably harder to explore than rationality. Sentiment- and fundamentals-based asset pricing models have been applied to all traditional asset classes. Compared with the mature research on stock markets, though, the study of asset pricing for cryptocurrencies is still in its infancy. Let us now

[18] Behavioral finance is a branch of behavioral economics according to which biases and psychological influences affect the behavior of investors and financial practitioners.

turn to the literature that employs these models to examine the cross-section of cryptocurrency returns.

4. Summary of the key empirical results

Now that a Reader has gained a solid understanding of the features of cryptocurrencies and standard asset-pricing models, we turn toward to main part of this dissertation: discussing the empirical results of the contemporary asset pricing literature regarding the cross-section of cryptocurrency returns. The general asset pricing literature has existed for a few decades now and has accumulated a considerable body of research. Empirical research specifically on cryptocurrencies is comparatively young, though. Notably, the pace at which the scientific world produces papers on this topic has consistently accelerated in recent years. Indeed, García-Corral, Cordero-García, de Pablo-Valenciano, and Uribe-Toril (2022) have written a detailed bibliometric study, in which they find that the number of publications has steadily grown in the last three years. This abundance of literature has made filtering out eligible papers a laborious activity. Thus, this thesis applied a stepwise process for selecting the most suitable papers. Relevant literature was searched via academic online databases using different keywords. The papers were then filtered by the period of interest (roughly from 2013 onward), context (cryptocurrency returns), and type of publication (articles and journals). Importantly, the author considered only research on the cross-section of cryptocurrency returns (the average return of one or many cryptocurrencies as the dependent variable) and almost entirely ignored papers that apply time series methods. Even though this stream of research is quite abundant, as well, surveying it would go beyond the scope of this dissertation. Critical sources of studies were found in other literature reviews, as well as in the reference sections of papers. Existing literature reviews were always part of empirical papers and hence were limited in scope and scale. In addition, they tended to lag behind the current state of the literature by about two to three years. This thesis is intended as an improvement upon these literature reviews in both regards. After carefully scanning the assembled host of papers, the author determined his final selection of 26 empirical studies. Table 1 constitutes a list of the cited papers.

The following paragraphs discuss the findings of different authors regarding the cross-section of cryptocurrency returns. Similar to chapter 3, this chapter mainly distinguishes between fundamentals- and sentiment-based asset pricing models, since these constitute the main approaches used in the current literature. Next to explaining the steps in constructing the factors and mentioning the overall findings, this chapter intends to analyze how the cryptocurrencies investigated differ in terms of explanatory factors. Regrettably, though, most papers do not provide a comparative analysis of the different crypto assets they set out to analyze in cross-section. Hence, one can rarely find this type of analysis. Unless specifically mentioned, the respective paper does not provide such analysis. In addition, this section sets as its objective to reveal and compare similarities and differences among the papers as to methodology and results, considering the specific context per paper. Obviously, some of the papers use more than one line of asset pricing model. In such cases, the respective paper is mentioned only in one of the subchapters. Within each subchapter, the papers are addressed in chronological order by publication date. Individual coefficient magnitudes are usually not mentioned for being hardly comparable across papers. Moreover, the papers tend to run the models for several different investment strategies, so reporting all coefficients would exceed the scope of this dissertation. What matters for the interpretation is their sign and that they are statistically significant. Furthermore, although research is plentiful, most published papers exhibit a publication and/or data lag, typically of at least three years, implying that the examined data stream usually ends three years before the publication date – compare Table 1. Therefore, the reviewable data period starts in 2010 and ends in 2021. As a general pattern, early papers investigate exclusively Bitcoin returns, as Bitcoin was the only mainstream crypto asset in the first couple of years of cryptocurrency history.

4.1 Fundamentals-based asset pricing models

As mentioned in chapter 3.1, fundamentals-based asset pricing models are the most commonly applied class of asset pricing models. Importantly, though, this section only focuses on models that follow a similar factor structure as the models by Fama and French and Carhart. In particular, for the WML factor, this thesis states the respective time horizon if mentioned in the paper. In the original 1997 paper, Carhart considered a 1-year momentum effect. To remind a Reader, the size and SMB factors describe a similar, if not the same phenomenon but point in opposite directions. Moreover, in the cryptocurrency literature, several authors – for example, Bhambhwani, Delikouras, and Korniotis (2019) – have proposed different cryptocurrency features as drivers of fundamental value. This definition of fundamental value is not to be confused with the one used in this section but is further addressed in chapter 4.3.

Asset manager Hubrich (2017) claims to provide the first application of the standard asset pricing models to cryptocurrencies. He shows that WML, HML, and an additional factor, carry, are effective at explaining the returns of eleven major cryptocurrencies. The WML factor is cryptocurrency-based and straightforward to construct. The HML factor, however, is traditionally based on the book-to-market ratio of a firm, which cannot be directly observed for cryptocurrencies. Therefore, the author argues that the HML factor is at its core a mean-reverting relationship describing the value of the asset divided by a more exogenous fundamental variable. Accordingly, he suggests that the ratio of the market capitalization of a cryptocurrency and the dollar-transaction volume on its blockchain could proxy for the HML factor. Finally, carry is measured as the inverse of a cryptocurrency's rate of inflation and describes the price of a cryptocurrency if the underlying demand did not change. Thus, high carry in a cryptocurrency is equivalent to having low inflation in the form of new coin issuances. In robustness checks, momentum seems to work most reliably as a predictor. The results indicate that all three factors are statistically significant at a weekly sampling frequency with small, positive values. The alphas are statistically insignificant. In particular, 1-day and 1-week momentum are statistically significant and have a positive sign. 1-month momentum is statistically insignificant, and though 3-month momentum is statistically significant, it has a negative sign, contradicting the author's hypothesis. The positive signs found for 1-day and 1-week momentum and carry make intuitive sense and similar results will be discovered by the following publications, but the positive sign on HML is more striking. It shows that, similar to stocks, cryptocurrencies that are believed to exhibit higher value have also higher returns, on average. Such cryptocurrencies are more attractive to investors just by virtue of being more actively traded. The author then also demonstrates how portfolios that are based on these factors have statistically significant alphas and attractive risk-adjusted, value-adding characteristics when controlling for the overall cryptocurrency market.

The next application of fundamentals-based asset pricing models is provided by Stoffels (2017). The author develops a novel three-factor model using a market factor, a size factor, and a factor related to the transactional volume relative to an asset's market capitalization that is supposedly partially referring to investor sentiment. Referring back, one can see the similarity between the latter factor and Hubrich's (2017) HML factor. As an alternative to this factor, this paper used data from Google Trends to estimate a factor that is intended to measure a similar underlying risk. Chapter 4.2 shows that the sentiment literature likes to incorporate Google Trends data in general. The author finds varying statistical significance for the 15 analyzed cryptocurrencies chosen by their market capitalization. Overall, though, the author's three-factor model outperforms a simple intercept model for every cryptocurrency in terms of explanatory power. Relating to what has been said in chapter 2.3, the author finds that cryptocurrencies that are based on the same codebase – the same underlying technology – tend to correlate in the factors they are significant in. Dogecoin, for example, is based on the Litecoin code. Surprisingly, though, the market beta of Ethereum is not statistically significant. Considering its share of about 20% of the market capitalization of all cryptocurrencies, one would expect otherwise. Strikingly, the size factor is mostly significant for smaller cryptocurrencies. Still, the sign of this factor varies, and the interpretation is left unclear. The sentiment factor is statistically significant in most cases, taking on a positive value in all these cases. Older cryptocurrencies, such as Bitcoin and Litecoin, are less affected by this factor, showing that they are less susceptible to market sentiment. Separately, the author finds momentum premia, which are similar in nature to Carhart's WML factor, at 1-week to 4-week time horizons. The author suggests that they might arise due to information taking longer to disseminate, as the information channels for cryptocurrencies are less efficient than for traditional asset markets. The author stresses, though, that when the results are interpreted, one has to take into consideration that the market conditions were quite favorable in the observed period (600% increase in the main cryptocurrency market performance index). This is an important limitation rarely addressed by other papers.

Taking a different approach, Gilbert and Loi (2018) do not examine Bitcoin within the cryptocurrency universe but compare it to the larger stock market (as in the original application of the three-factor model by Fama and French (1992)). The SMB and HML factors are also stock market-based. In fact, all data except for the Bitcoin returns is taken from Professor French's website. The aim of this study is to analyze Bitcoin's systematic risk. In the simple CAPM, Bitcoin returns exhibit a beta of only 0.44 – barely significant at the 10% significance level. In the Fama-French three-factor model none of the three factors is statistically significant, except for the alpha. The same observations are made when one distinguishes between different regions. Thus, the authors find that despite its high volatility, Bitcoin does not appear to carry significant systematic risk, and is thus a proper candidate for inclusion in investment portfolios. It remains questionable, though, whether the stock market is eligible as the market portfolio for cryptocurrencies, specifically Bitcoin. The same goes for the other factors. In this regard, other papers, for instance, Li and Yi (2019), provide a more plausible analysis. For the same reason, the findings of this paper are also not directly comparable to the previous literature.

In another early empirical assessment of cryptocurrency returns, Li and Yi (2019) investigate potential factor structures in the expected returns of crypto assets. Similar to Fama and French, they set up a model using a market, a size, and an HML factor. While the authors can easily measure the size factor by the cryptocurrency market capitalizations, they need to derive two HML proxies – nodes and transaction volumes – to mimic the value premium which was observed for many other asset classes. This is reminiscent of Stoffels' (2017) and Hubrich's (2017) approaches. In addition to Carhart's classic momentum factor (at different horizons), they also include a volatility factor they call "betting-against-volatility".[19] Overall, this paper delivers mixed evidence for the viability of the fundaments-based asset pricing models in explaining the returns of the 89 analyzed cryptocurrencies, which were selected for each having a market capitalization greater than $1 million. The results indicate that a factor structure in cryptocurrency returns, even if existing, may not perfectly align with that from stock returns. Specifically, regarding the size factor, large-cap assets tend to outperform small ones. This result is not solely driven by large crypto assets, such as Bitcoin. In stock markets, small-cap assets usually outperform large ones. Regrettably, unlike Fama and French for the stock market (compare chapter 3.1), Li and Yi (2019) neglect to provide a theory to explain this pattern. For the HML factor, no clear pattern of excess returns shows up across sorted portfolios. This result could be interpreted as an indication that the used proxies are not suitable for measuring value, or that cryptocurrencies differ from other financial assets that feature a value effect. For this reason, the authors refrain from drawing conclusions on this particular point. Then again, some findings from the stock market do carry over to the cryptocurrency market. In particular, the authors find evidence of a betting-against-volatility factor and strong support for a momentum effect. These effects are found to be

[19] Betting-against-volatility is a proxy for risk according to which crypto assets with high volatility tend to be outperformed by ones with low volatility. A similar investigation has already been performed for stocks by Baker, Bradley, and Wurgler (2010) and Blitz and van Vliet (2007).

especially pronounced in shorter time horizons, reflecting the pace of the cryptocurrency markets. Moreover, they find statistically significant and positive 14-day, 1-month, 2-month, and 4-month momentum effects. Overall, the authors conclude that these findings are suggestive of an emerging factor structure, even though crypto asset returns are still widely dominated by idiosyncratic noise.

In a more recent analysis, Gregoriou (2019) demonstrates that investors obtain abnormal returns by trading cryptocurrencies daily on the London Stock Exchange (LSE) from 2014 to 2017. The author adjusts the returns for Fama and French's three and five factors. Similar to Gilbert and Loi (2018) and Liu and Tsyvinski (2021), he constructs these factors using stock market data, though for the LSE only. Applying the analysis to the ten largest cryptocurrencies separately, the author finds the alphas for all of the fundamentals-based asset pricing models listed in chapter 3.1 to be statistically significant. Abnormal returns persist after accounting for systematic risk, size, value, 2-week momentum, profitability, and investment. Hayes (2016) and Gilbert and Loi (2018) have had similar results for the alphas. Unfortunately, though, this paper does not report the statistical significance of the individual factors.

Similarly, Liu, Liang, and Cui (2020) yet again consider three fundamental risk factors for the cryptocurrency market: the cryptocurrency market return, size, and 1-year momentum. Investigating a sample of 78 cryptocurrencies (including large, medium, and small cryptocurrencies), they show that the three proposed factors have significant coefficients and that the alphas are statistically insignificant, suggesting that they explain average cryptocurrency returns comparatively well. Specifically, the authors conclude that cryptocurrency returns increase with momentum and decrease in size (increase in SMB), though the momentum effect is more significant in small cryptocurrencies. The former result immediately contradicts the finding of Li and Yi (2019) regarding the size factor. While the analyses of Stoffels (2017) and Liu, Tsyvinski, and Wu (2022) regarding this factor remain ambiguous, Li and Yi (2019) find that large-cap assets tend to outperform small ones. As a Reader might recall, a negative sign on the size factor (a positive sign on the SMB factor) is in-line with what has been observed for stock market returns. The result for the momentum factor has already been noted by the previous publications that constructed the fundamentals-based factors specifically for the cryptocurrency market, though they usually found evidence only for shorter time horizons.

Proposing a simple three-factor pricing model consisting of cryptocurrency-based market, size, and 1-week reversal factors (a factor similar to momentum), Shen, Urquhart, and Wang (2020) find that small cryptocurrencies outperform larger ones and that the reversal returns are also higher for the smaller cryptocurrencies than for their larger counterparts. Their three-factor model delivers more convincing results than the cryptocurrency-CAPM and its performance is robust to different factor constructions. They seem to care little about the interpretation of the risk factors they have found. They run the analysis for more than 1,700 cryptocurrencies.

In a contemporaneous paper, Liu and Tsyvinski (2021) provide a more detailed analysis of cryptocurrency returns. In particular, beyond the stock market, they look into the relationship between cryptocurrencies (Bitcoin, Ripple, and Ethereum), traditional currencies, and precious metals. As mentioned in chapter 2.4, cryptocurrencies are seen as both a medium of exchange, similar to other currencies, and a store of value, like gold or other precious metals. This study offers novel evidence for this still ongoing discussion. Similar to Gilbert and Loi (2018), the authors of this paper again use stock market data to construct the three-factor model but add the RMW and CMA factors to test the Fama-French five-factor model. They show that the CAPM betas are again statistically insignificant but the alphas remain large and statistically significant. Similar to the findings of Gilbert and Loi (2018), the exposures to other common risk factors in the stock market are minimal. Compared to Bitcoin, Ripple and Ethereum have higher unconditional alphas, a smaller CAPM beta, and a strong exposure to the HML factor. The authors also explore 155 anomaly factors documented in the finance literature but find no discernible patterns. Next, the authors study the exposure of cryptocurrency returns to major currencies (Australian dollar, Canadian dollar, euro, Singaporean dollar, and UK pound) and find that they are small and not statistically significant, refuting the popular view that cryptocurrency may serve as a medium of exchange. Regarding the exposure to precious metals commodities, the authors find no statistically significant exposures, with the exception of the exposure of Ethereum to gold. This contradicts the idea that cryptocurrencies can act as an alternative store of value. Furthermore, the authors fail to find statistically significant exposures to macroeconomic factors (non-durable consumption growth, durable consumption growth, industrial production growth, and personal income growth). Summarizing this paper thus far, the authors establish that the risk-return tradeoff of cryptocurrencies is distinct from those of stocks, currencies, and precious metals. So, similar to Gilbert and Loi (2018), they put forth the idea that cryptocurrencies are a respectable candidate for portfolio inclusion. But by considering more than one cryptocurrency and comparing them to several other asset classes, they provide a detailed extension to the research of Gilbert and Loi (2018). Going even further, the authors formulate and investigate cryptocurrency-specific factors that mirror those of traditional asset classes. Specifically, they construct cryptocurrency momentum, proxies for average and negative investor attention (a factor similar to sentiment), a proxy for price-to-dividend ratio, realized volatility, and proxies for the supply conditions. First, similar to Hubrich (2017), Stoffels (2017), and Li and Yi (2019), they find some statistically significant momentum effects for the 1-week to 8-week time horizons. Second, the authors show that high investor attention predicts higher future returns for different horizons for the different cryptocurrencies. Like Stoffels (2017) and Polasik, Piotrowska, Wisniewski, Kotkowski, and Lightfoot (2015), they incorporate the number of Google searches for the word "Bitcoin", but also look at Twitter posts containing the same expression. Third, the authors create a proxy for the price-to-dividend ratios for Bitcoin and find that it has no predictive power. Finally, like in the approach of Hayes (2016), they construct proxies for the cost of mining to capture supply factors and find that those have low magnitudes for Bitcoin and Ripple. For Ethereum, there is some evidence that returns are exposed to the stock returns of Advanced Micro Devices, Inc. (also known as AMD), one of the main manufacturers of specialized mining hardware. This finding relates to what has been said in chapter 2.3; Advances in mining hardware allow transaction fees to decrease and adoption to rise. From this second part of the paper, the authors conclude that cryptocurrency indeed represents an asset class that can be assessed using relatively simple risk factors. At the same time, cryptocurrencies comprise an asset class that differs considerably from traditional asset classes.

Wang and Chong (2021) comprehensively investigate market efficiency, as well as factors that affect the excess return of 59 cryptocurrencies. They test the CAPM, fundamentals-based factors (size, HML, and 1-week momentum), volatility factors (jump, volatility, and skewness), liquidity factors (the bid-ask spread, trading volume, and Roll's measure), a sentiment factor (Twitter attention factor), and macroeconomic factors (hash rate, LIBOR rate, and fundamental build-up) using Fama–MacBeth regressions.[20,21] All factors are based on the cryptocurrency market, except for the LIBOR rate. The HML factor is proxied by the returns from tokens divided by the returns from coins (the interpretation of this factor is poorly explained). The fundamental build-up factor describes the number of blockchain projects on GitHub. The authors find mixed evidence for the different portfolios they construct. For the individual cryptocurrencies, only the HML and bid-ask spread factors are statistically significant. The HML factor takes on a positive sign, posing a similarity to Stoffels' (2017) result, though the interpretation remains unclear. What is more, the authors fail to report their results for the sentiment factor, casting doubts on the quality of this publication.

In a short study, Barrera and Minovitsky (2021) of MSCI Research test whether factors that are important in the cross-section of equity returns are also significant for cryptocurrencies. They create a multi-factor model with market, size, 3-month momentum, liquidity, residual volatility, and age (the logarithm of days since a cryptocurrency's inception) factors as independent variables. All factors are based on the cryptocurrency market (Bitcoin, Ethereum, and Dogecoin). Notably, like the previous literature, they conclude that it is difficult to define the HML factor for the cryptocurrency market. The authors find that the basic price- and market-based factors, such as size, volatility, market return, and momentum are crucial for explaining systematic risk for cryptocurrencies. Remarkably, the age factor is the first implementation of the link observed by Shams (2020), mentioned back in chapter 2.3.

Borri and Shakhnov (2022) develop a complex research model with the objective of explaining why Bitcoin prices are different on exchanges located in different countries. Their main analysis is not of cross-sectional nature, but they dedicate a section in the appendices to examining the cross-section of Bitcoin returns nonetheless. The authors pick up the factor structure of Liu et al. (2022) mentioned next and supplement it with liquidity measures (that is, volume and bid-ask spread), as well as a sentiment factor

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[20] According to Roll (1984), the effective bid-ask spread can be derived from the first-order auto-covariance of price changes. The implicit percentage spread is then $s_j = 200\sqrt{-cov_j}$ where s_j is the spread and cov_j is the autocovariance of returns for asset j.

[21] The London Interbank Offered Rate (LIBOR) is a benchmark interest rate calculated from estimates provided by the largest banks in London. It is the primary index for short-term interest rates globally.

based on Google Trends (similar factors are used in the papers discussed in chapter 4.2). The authors find that the coefficient of the cryptocurrency market factor is statistically significant at a magnitude of 0.74. Unlike previous research, however, they note that the size and 1-week momentum factors turn out statistically insignificant. One has to consider, though, that they are using considerably more control variables than earlier papers. On the other hand, the sentiment factor is statistically significant. Despite having a small value of merely 0.06, the sign of the coefficient makes intuitive sense: More searches usually indicate positive sentiment or at least increased attention, which supposedly positively correlates with returns. However, the economic significance of this finding remains questionable. Finally, the liquidity measure is statistically insignificant.

Finally, the paper of Liu et al. (2022) reformulates the classic fundamental factors for cryptocurrencies. This is similar to what Stoffels (2017) and Li and Yi (2019) have previously attempted. In particular, the authors construct a cryptocurrency market factor, an SMB factor, and a momentum factor (at 1-week to 4-week, 2-month, 4-month, 1-year, and 2-year time horizons). Through the papers of Stoffels (2017) and Li and Yi (2019), we have already learned that these factors are straightforward to construct for cryptocurrencies. The main finding of the paper is that compared to the one-factor model (cryptocurrency CAPM), the new three-factor model renders all of the alphas of the nine different proposed cryptocurrency investment strategies statistically insignificant. None of these strategies is exposed to the market factor only. In other words, both the SMB and momentum factors are important in explaining the cross-section of the expected returns of cryptocurrencies. The authors find statistically significant positive momentum effects for the 1-week to 4-week time horizons, but not at longer time spans. In addition, the authors test whether the nine successful long-short strategies can be explained by the stock market risk factors. Similar analyses have been performed by Gilbert and Loi (2018), Liu and Tsyvinski (2021), and Gregoriou (2019) before them. As Asness, Moskowitz, and Pedersen (2013) have found in a prior study that value and momentum strategies comove strongly across different asset classes, the authors of this paper argue that the cryptocurrency strategies may comove with their corresponding counterparts in the equity market, as well. After applying all of the fundamentals-based asset pricing models mentioned in chapter 3.1, they find that the alphas of the nine strategies remain statistically significant and are similar in magnitude to the unadjusted excess returns. This is in line with the previous findings for stock market factors. Unfortunately, the authors do not seem to attach importance to an explicit interpretation of the coefficients, even though their signs differ by strategy. The authors only considered cryptocurrencies that have information on price, volume, and market capitalization and excluded coins with market capitalizations of less than $1 million.

Overall, the literature seems to apply two main approaches: While some authors choose to reformulate the fundamentals-based asset pricing models for the cryptocurrency market, others opt for sticking to stock market-based factors. Almost all of the papers that decided to adjust the original fundamentals-based asset pricing models substituted at least one existing factor for a new one. The market, SMB, and WML factors are straightforward to implement for the cryptocurrency market, but only Hubrich (2017), Stoffels (2017), and Li and Yi (2019) have attempted to proxy for HML, for which it turns out difficult to find an appropriate counterpart in the cryptocurrency market. The authors seem to agree, though, that transactional volume can be used as an indicator of cryptocurrency value. Most, if not all, papers seem to proxy the market return with the Cryptocurrency Index (CRIX). One can also observe general patterns in the findings of these two sub-streams of research. In stock market-based models, only the intercept is statistically significant, while in cryptocurrency market-based models, the factors are statistically significant, but the intercept is not. This goes to show that the stock market-based factors are not capable of explaining the cross-section of cryptocurrency returns and that the cryptocurrency market is largely isolated from the stock market in terms of correlation. Moreover, we learn that cryptocurrencies do indeed exhibit correlations to the cryptocurrency analogs of the classic fundamental factors. Most strikingly, all publications find momentum effects, which tend to be more significant at shorter time horizons.

4.2 Sentiment-based asset pricing models

Sentiment factors constitute the second crucial group of explanatory factors. Some papers – for example, Bhambhwani et al., who assert that momentum effects have been linked to investor psychology – may regard the HML or WML factors as sentiment factors, but these have already been covered within the previous subchapter. As was explained in chapter 3.2, the definition of sentiment is arguably ambiguous. Importantly, though, most contemporary sentiment-based asset pricing models are based on social media and internet trend analyses, as shall be shown in the following paragraphs.

The earliest study here is provided by Polasik et al. (2015). In their comprehensive empirical study, they discover that Bitcoin returns are driven primarily by three factors. The authors consider a multitude of explanatory variables with which they aim to capture both supply and demand drivers. They find that the popularity factor measured by the number of Google searches using the word “Bitcoin” strongly affects returns. This is similar to what Borri and Shakhnov (2022) have found (though at a much later point). Similarly, the number of English-language newspaper articles mentioning the same keyword constituted another significant factor – a new finding in the literature. The tone of those articles was quantified by using automated content analysis. Finally, the number of transactions also exerts a strong influence on returns, supporting the idea that there is a connection between the investment and payment capabilities of Bitcoin. Further, a group of macroeconomic factors, which have been previously shown to affect stock and bond returns, turn out to be statistically insignificant. They include the change in Bitcoin supply, the continuously compounded percentage growth rate in the U.S. dollar broad index, the continuously compounded percentage growth rate in the trade-weighted euro index, productivity growth via the OECD industrial production growth, unemployment via the OECD harmonized unemployment rate, and inflation via OECD inflation in consumer prices.

Halaburda and Gandal (2016) regress the returns of a representative cryptocurrency sample of 13 cryptocurrencies on the number of Google searches for the terms “cryptocurrency” and “virtual currency” to measure the general interest for cryptocurrencies, and an interaction term between the two. While the control “change in Bitcoin volatility” is statistically insignificant, the results show that the number of Google searches in a given week is positively correlated with returns on each individual altcoin. The effect of the interaction term is even stronger for all of the altcoins. Bitcoin returns are more important for altcoins which exhibit more search activity and hence stronger general interest in cryptocurrencies. The importance of Google searches as a sentiment factor has also been noted by Stoffels (2017), Polasik et al. (2015), Liu and Tsyvinski (2021), Borri and Shakhnov (2022), and Pagano and Sedunov (2020). The sample period used in this paper is quite limited, though, since it ranges only from May 2013 to July 2014.

Wang and Vergne (2017) investigate a concept closely related to sentiment, calling it the “buzz” surrounding cryptocurrencies in online media. They find that the buzz is negatively correlated with the returns of five major cryptocurrencies after controlling for a range of factors, including supply growth, liquidity, and a week trend to capture fixed effects (the first two are statistically significant, as well). The buzz is measured by two separate variables: public interest and negative publicity. Negative publicity contains suspicious or fraudulent activities pertaining to the respective cryptocurrency. It turns out that fraudulent activity is not exerting a negative influence on cryptocurrency returns, further qualifying the media's influence on cryptocurrencies. Furthermore, the authors find that innovation potential, as measured by eight indicators of technological development in cryptocurrency projects, is in fact the most vital factor connected to increases in the returns of cryptocurrencies. These results hold after several robustness checks. Taken together, this study highlight that cryptocurrencies do not act like commodities or traditional currencies. Moreover, this paper suggests that the digital assets industry is more developed and less speculative than the preceding research has claimed – compare, for example, Yermack (2013).

Lee et al. (2018), a group of prolific authors in their field, conduct an investigation of the diversification role of cryptocurrencies. They first evaluate the co-movement between traditional asset classes and the CRIX by studying the respective correlation coefficients. Their results show little correlation between the CRIX and traditional assets, suggesting that the cryptocurrency asset class is a good diversifier, and hence a sensible addition to a traditional portfolio. Moreover, the authors claim that the high variance in digital assets is primarily caused by investor sentiment; not by changing fundamentals. They argue that a reasonable explanation using traditional fundamental analysis is yet to be found. Indeed, either the old factor structure is not appropriate for the new and intricate technology of cryptocurrencies, or sentiment proxies for immeasurable fundamentals. The authors then present a sentiment measure based on media news and the past average returns. This measure discloses a significant return reversal effect after one trading day, giving rise to the idea that rational investors exploit sentiment-induced mispricing. They conclude by proposing a sentiment-based investment strategy, which shows a positive average annualized return, even after multiple robustness checks. Overall, their results provide slight evidence of cryptocurrencies being a useful investment class. They analyze the top ten cryptocurrencies based on the frequency with which they are included in the CRIX.

Overall, also taking into account the sentiment results in the two other subchapters, this part of the literature seems to agree that sentiment factors measuring the public attitude toward cryptocurrencies contribute significantly to explaining the cross-section of cryptocurrency returns. As a general pattern, one can see that the sentiment factors are often based on either Google Trends or crypto-specific factors. One relevant finding from chapter 4.1 to be mentioned here again is that older cryptocurrencies are less susceptible to market sentiment. Further research into this phenomenon could deliver useful insights. In general, though, there are only a few and not quite recent papers on sentiment. The next section looks at additional factors that can be used to explain cryptocurrency returns.

4.3 Other models

Besides the standard asset pricing models used most often in the literature, a few publications have examined the explanatory power of alternative factors. The most informative alternative factors include the returns of commodities and traditional currencies since these might also help in answering the question posed in chapter 2.4 of whether Bitcoin can be seen as a medium of exchange and/or a store of value. Moreover, many of the authors of this part of the literature have a unique view on what constitutes the fundamental value of cryptocurrencies, and they create corresponding factors. The following paragraphs present a couple of the remarkable papers.

van Wijk (2013) offers an early assessment of Bitcoin returns using non-standard explanatory variables. Specifically, this paper tries to answer the question of how day-to-day financial data affects the price of Bitcoin. The author regresses the price of Bitcoin on the euro-dollar and yen-dollar exchange rates, the Dow Jones, the FTSE 100, the Nikkei 225, and the Brent, WTI, and CMCI oil prices. After several robustness checks, the author finds that the only statistically significant factor is the level of the Dow Jones index with a positive sign. This speaks against the role of Bitcoin as either a medium of exchange or a store of value. Nevertheless, one has to consider how early this paper was published.

Using cross-sectional empirical data, Hayes (2016) examines 66 of the most widely used cryptocurrencies. His regression model identifies three main determinants of cryptocurrency returns: the rate of unit production, the level of competition in the network of block miners, and the difficulty of the mining algorithm (hash function).[22] The

[22] The hash function is the computational puzzle used for PoW. The function of Bitcoin, for example, is SHA-256. Different cryptocurrencies are using different hash functions, which are mainly distinguished in how easy they are to solve.

various mining algorithms result in relative differences in the marginal production cost since higher computational performance goes hand in hand with increasing electricity consumption. This perspective is reminiscent of the earlier take of Garcia et al. (2014) mentioned above, who assert that the cost of mining constitutes a lower bound of the fundamental value of cryptocurrencies. Noteworthy, two additional factors turn out statistically insignificant in the author's multi-variate regression: a factor that describes the share of coins that have been mined to date compared to the theoretical supply limit and the number of days from a cryptocurrency's inception until September 2014. The author performs his cross-sectional analysis for one day only, September 18, 2014. This is surely an important shortcoming of this paper.

In their paper, Baur et al. (2017) investigate the question of whether Bitcoin can act as a safe haven against financial unrest or a breakdown of the financial system, regardless of the fact that it exhibits higher volatility than gold and other currencies. They regress the return of Bitcoin on FX volatility and the S&P 500 (and quantile dummies for both), as well as crisis event interaction terms. If Bitcoin returns could act as a protection against FX volatility, the S&P 500, and crisis events, then one would sensibly expect the first variable to be positive, the second variable to be negative, and the third to be positive. The estimation results show that Bitcoin is both uncorrelated with FX volatility and the S&P 500. Similarly, the authors show that there is no substantial effect of the crisis events on FX volatility. Moreover, natural disasters appear to exert a statistically significant and positive effect on the S&P 500, whereas terrorism/war has no such effect. The former effect suggests that during such events the S&P 500 and Bitcoin returns become more positively linked. Finally, the fact that the financial crisis interaction terms show no statistical significance contradicts the role of Bitcoin as a hedge against sovereign risk, as maintained by Bitcoin advocates. Overall, there is mixed to weak evidence for the role of Bitcoin as a safe haven asset.

Regressing a portfolio of 117 altcoins on gold prices and the S&P 500 market index, Hu, Parlour, and Rajan (2018) find no statistically significant coefficients. They find a strong correlation with Bitcoin returns, though, suggesting that altcoins trade against Bitcoin as opposed to fiat currencies. Bitcoin returns, similarly, show no link to gold and stock market returns.

As mentioned at the beginning of chapter 4.1, some papers have defined fundamental blockchain characteristics and tested their performance as explanatory factors. Bhambhwani et al. (2019) propose factors describing computing power and network, which are related to blockchain trustworthiness and transaction benefits, that is to say, network effects.[23] They measure network by the number of unique users that conduct transactions on the blockchain. Computing power is measured in terahashes and is proportional to the resources needed to add new blocks to the blockchain.[24] These resources include the sourcing of hardware and software, electricity usage, and the cost of installing so-called mining farms. These ideas are not too different from the factors proposed by Hayes (2016) and certainly reminiscent of the AMD factor employed by Liu and Tsyvinski (2021). The authors document that the returns of 39 cryptocurrencies are exposed to these fundamental risk factors, also after controlling for cryptocurrency 1-week momentum and Bitcoin returns. The alpha is statistically insignificant in this model.

Though the analysis of Bianchi (2020) is based on time series regressions, his results still offer useful information for the cross-section of cryptocurrency returns. After regressing a time series of a value-weighted index of cryptocurrency prices calculated based on the top 300 cryptocurrencies on various traditional asset classes, the results indicate that there is no significant correlation among them for daily returns. At a monthly return level, there is mild evidence that cryptocurrency returns correlate with the returns on commodities and precious metals. This result resembles the findings of Liu and Tsyvinski (2021).

Similar to Baur et al. (2017), Hu et al. (2018), and Liu and Tsyvinski (2021), Pagano and Sedunov (2020) regress the returns of Bitcoin on gold returns. In addition, they use Bitcoin's transaction fees, volatility, and bid-ask spread; Google searched for the words "Payment System", "Store of value" (to test Bitcoin meaningfulness as a medium of exchange or store of value), and "Bitcoin value"; the euro/U.S. dollar exchange rate; the VIX; the TED spread; the St. Louis Fed Financial Stress Index; the U.S. Economic Uncertainty Index; emerging market stress; lagged Bitcoin and market returns to proxy the level of speculation; and momentum effects (1-week, 1-month, 3-month, and 6-month

[23] In economics, a network effect is a phenomenon by which the value a user receives from claiming a good or service increases with the number of users using the same good or service.
[24] One terahashes is a unit equivalent to 1 trillion hashes and indicates the power of a computer or mining machine.

momentum effects) as explanatory variables.[25,26,27,28] Unlike the previous research, they implement independent variables as the elements of first principal components.[29] Though the set of independent variables is more extensive than in most other papers, almost none of these factors exhibits statistical significance, and the alpha is statistically insignificant, as well. Strikingly, the coefficient on the 6-month momentum factor is significantly negative, suggesting a reversal effect. This is contrary to what almost all previous papers have found in terms of momentum, though the papers are hardly directly comparable, especially in view of the sheer number of explanatory variables used in this paper, increasing the risk of biases. Moreover, previous papers have analyzed momentum effects for different time horizons. The authors conclude that their findings provide weak evidence of demand for bitcoin as a speculative asset.

Zhang and Li (2020) investigate how idiosyncratic volatility affects the cross-section of cryptocurrency returns. Using the regression procedure developed by Fama and MacBeth (1973), they show that idiosyncratic volatility is positively associated with the returns of 500 cryptocurrencies that have a trading record of not less than two years. This result holds after controlling for factors that proxy for size, liquidity, 3-month momentum, price, and volume, and withstands several robustness checks. Among the listed controls, only size and price have a significantly negative relation with cryptocurrency returns. The negative size factor points to smaller cryptocurrencies outperforming larger ones. The alpha is statistically significant, as well.

The study of Long, Zaremba, Demir, Szczygielski, and Vasenin (2020) investigates the cross-sectional seasonality effect of Keloharju, Linnainmaa, and Nyberg (2016) in the cryptocurrency market. They find compelling evidence for a considerable seasonality

[25] The VIX (the Chicago Board Options Exchange's Volatility Index) is a popular measure of the stock market's expectation of volatility. Its level is implied by the price of S&P 500 index options.
[26] The TED (an acronym for "T-Bill" and "Eurodollar") spread is the difference between the interest rates on interbank loans and on short-term U.S. government debt. The TED spread is usually taken as an indicator of perceived credit risk.
[27] The St. Louis Fed Financial Stress Index gauges the degree of financial market stress and is constructed from 18 data series, each capturing some aspect of financial stress.
[28] The U.S. Economic Uncertainty Index measured policy-related economic uncertainty and is constructed from three types of underlying components that quantify newspaper coverage, reports by the Congressional Budget Office, and the Federal Reserve Bank of Philadelphia's Survey of Professional Forecasters.
[29] Roughly speaking, the first principal component is derived as a linear combination of the original variables under the condition that it explains the most variance.

pattern. Cryptocurrencies with large past same-weekday returns keep overperforming thereafter. This effect survives multiple robustness checks and alternative factor specifications. The authors argue that since the seasonality pattern could serve as a starting point for a successful cryptocurrency picking method, it could also be used to construct practical investment strategies. In addition, they find a significantly negative association to a 20-week momentum factor and to an idiosyncratic volatility factor. The coefficient on the size factor is statistically significant, but economically insignificant (magnitude of 0.00). The coefficient on the market return, the turnover ratio (the ratio of daily dollar trading volume to capitalization), and an illiquidity ratio turn out statistically insignificant. The factors are based on cryptocurrency market data.

Finally, Zhang, Li, Xiong, and Wang (2021) demonstrate downside risk's role in determining the cross-section of returns in the cryptocurrency market. They document a positive link between cryptocurrency returns and downside risk. This result withstands controlling for a group of cryptocurrency features, employing different downside risk proxies, and applying various screens. In addition to the classic idea of the tradeoff between risk and return, limits to arbitrage could also serve as an explanation for these findings, at least partially. Moreover, contrary to the authors' expectations, they fail to find a significant intertemporal relation between cryptocurrency returns and downside risk. They employ a long list of cryptocurrency-specific control variables, of which only a few, that is, SMB, 3-week momentum, low trading volume, idiosyncratic volatility, and volatility, are statistically significant. Apparently, downside risk constitutes useful information for predicting cryptocurrency returns beyond the information contained in the standard cryptocurrency factors analyzed in chapter 4.1. The alpha is statistically significant, as well.

In summary, other currencies and precious metal prices have been shown to be plausible external explanatory factors, though the evidence is not unambiguous. This tends to support the view that cryptocurrencies can serve both as a store of value similar to gold and as a medium of exchange like traditional currencies. Intrinsic value factors, such as computing power, network size, as well as the state of technological development within a cryptocurrency project also seem to be useful predictors of a cryptocurrency's success on the market. Such factors usually capture the idea of transactional benefits for a growing number of users and trustworthiness. Some other papers propose alternative approaches to determining a cryptocurrency's fundamental value by different technical aspects of a cryptocurrency. The explanatory factors analyzed in this subchapter offer a useful extension to the ones from the fundamentals- and sentiment-based asset pricing models.

Summing up, this section has given an extensive account of the current research applying cross-sectional methods to cryptocurrency returns. All three different streams of approaches to asset pricing have delivered a range of statistically significant explanatory factors. The fundamentals- and sentiment-based models tend to intersect in their use of Google Trends data, which some authors in the fundamentals-based literature seem to regard as a proxy for value. Generally speaking, there seems to be more consensus than disagreement regarding the research findings in the analyzed papers. Obviously, the more recent papers provide more reliable results, as the amount of available data increases over time. But beyond this, one can see that the quality of papers has increased steadily, also considering the number of analyzed cryptocurrencies, the number of factors investigated, the level of detail, etc. While the prevalence of fundamentals-based asset pricing model applications is satisfactory, more research on sentiment and alternative factors could make for an even better understanding of the cross-section of cryptocurrency returns. Some concerns and doubts regarding this field remain, as well as areas where further research could be fruitful. The next section addresses some of them.

5. Limitations and areas for further research

Cryptocurrencies are slowly but surely becoming a mainstream asset class. Though data is widely available, the amount that one can retrieve is simply confined by their young age, making empirical research more challenging than for, say, stocks. This is only one reason why the current research on cryptocurrencies is faced with considerable limitations. This section first lists such limitations pertaining to the previous results and then proposes areas for further research.

First, we notice that each of the listed papers analyzes data from only a limited time period, and cryptocurrency market conditions can vary considerably by period – compare Stoffels (2017). This challenges the generalizability of the findings and highlights the importance of updating past research at an ample pace. However, when one considers the market conditions for each sample period and then aggregates the results, one can gain a comprehensive understanding of the findings. In addition, more recent papers can mitigate this problem, since they tend to include longer time periods and extend their preceding research. Thus, more value should be attached to those papers. Second, related to this, we should repeat that many of the presented papers, especially the ones from early on, only analyze Bitcoin returns. The natural question arising from this is whether these findings can be generalized to all cryptocurrencies. Given the state of the literature, analyzing the factor structure of individual cryptocurrencies is hardly possible. It is rather sensible to speak about trends pertaining to the spectrum of cryptocurrencies as a whole. Third, Stoffels (2017) has remarked on a general selection bias in the literature: Cryptocurrencies that suffered from hacker attacks or had other problems tend to get excluded from the analysis due to the data selection process. The returns of these cryptocurrencies might have contained information useful for improving the factor structure in the proposed models. This problem is familiar from the research on investment fund performance, where it is known as "survivorship bias". Fourth, as stated in the introduction of chapter 4, time-series papers were almost completely ignored in the paper selection procedure. Such papers can also provide important insights into factor structures (e.g. via cointegration relations) and future literature meta-analyses might be well-advised to include them. Fifth, the literature has not resolved the debate about whether the stock market- or cryptocurrency market-based factors are better suited to explain market fluctuations. The current research indicates that there is little correlation between cryptocurrencies and stocks, but as cryptocurrencies mature as an asset class, this might change. Sixth, regarding active asset management, we should mention a problem of practical nature that concerns the entire universe of cryptocurrencies: setting up short positions in cryptocurrencies will be necessary to exploit factor mispricing but doing so is difficult, if not impossible in a cryptocurrency market that is much less mature than the traditional financial markets (see Li and Yi, 2019). This circumstance limits the applicability of the findings of this dissertation. Nevertheless, the existing literature has already managed to propose alpha-yielding investment strategies – for example, Hubrich (2017).

After gaining a good understanding of the current state of the literature, we feel qualified to propose potentially fruitful areas of research. First, there is a growing body of research on cryptocurrency volatility and how it relates to returns. For instance, Qi, Wang, Zhu, and Bai (2020) provide a neat overview of the literature on cryptocurrency price volatility, up until 2019. Studying volatility could be insightful for understanding investor utility more broadly insofar as modern portfolio theory presumes mean-variance optimization; investor utility increases in expected return but decreases in variance, the proxy for risk (see Markowitz, 1952). Second, the question of what cryptocurrency returns are correlated with constitutes a useful preliminary examination for the analysis of explanatory factors. Thus, more research in this area could open new paths for asset pricing models. Third, the papers addressed in this thesis have not considered limits to arbitrage across exchanges. They might explain parts of the observed volatility and an investigation into this phenomenon might improve the current models. Fourth, we have seen how successful different approaches to asset pricing are in chapter 4.1. Still, the fundamentals- and sentiment-based factors, as well as the additional factors mentioned in chapter 4.3 are mostly applied in isolation. More papers using a combination of fundamentals- and sentiment-based models, in addition to some novel factors, could drive up explanatory power even further and deliver a comprehensive description of the cross-section of cryptocurrency returns. Finally, there is a list of factors that future papers could include in their analysis. So-called "pump and dump" schemes are known to play a significant role in the volatility of cryptocurrencies. Measuring the price impact of fraudulent transactions and price manipulation could thus provide new factors. Moreover, various industry professionals have stressed that they look at the founding team plus the community of new cryptocurrency projects first and foremost in preparation for cryptocurrency investments. Hence, further emphasizing the technology and community aspects of cryptocurrencies could constitute factors that are especially in step with actual practice. At the same time, flawed technological conceptualizations could also pose risks to the success of individual cryptocurrencies, though (see Mayer, 2018). One also has to wonder whether event studies could help in detecting additional factors, in particular, ones relating to regulatory or sentiment changes (caused by tweets, for example). Not least, future research can draw inspiration from the background descriptions regarding cryptocurrency characteristics and economics given in chapter 2.

6. Conclusion

To summarize, this dissertation set as its objective to provide an overview of the recent asset pricing literature's findings on the risk factors that characterize cryptocurrencies. To this end, chapter 2 started off by enhancing a Reader's understanding of the current state of institutional adoption, of the technical and economic characteristics of cryptocurrencies, and of the differences and similarities among cryptocurrencies in terms of their features, also compared to traditional currencies. These topics are arguably quite important to comprehend this line of research. To get a grasp of the methodologies used in the asset pricing literature, chapter 3 introduced the most commonly applied asset pricing models, distinguishing between so-called fundamentals- and sentiment-based models. Hence, chapter 4 was divided along the lines of these two approaches. Chapter 4.3 was instead dedicated to surveying the approaches not based on fundamentals or sentiment factors.

Regarding the fundamentals-based approaches, most papers find similar tendencies for the crypto-based factors as were observed for other asset classes, most prominently stocks. In particular, smaller cryptocurrencies outperform larger ones and momentum can be observed at several different horizons, though usually shorter than one year. The stock-based factors are usually statistically insignificant and leave a significant alpha to be explained. The sentiment-based asset pricing models have delivered less unanimous results. While some authors argue that the WML factor would represent market psychology, others have found widely differing ways to measure sentiment. The other factors summarized in chapter 4.3 mainly comprise cryptocurrency-specific factors that are related to actual cryptocurrency fundamentals and not to fundamental risks, as well as currency and commodity returns.

The literature on the sentiment and alternative factors has provided heterogeneous results and papers in these areas, in particular, could expand the understanding of cryptocurrency return dynamics in the future by revealing new risk factors. Easily visible limitations of the results include restricted sample sizes in terms of the variety of cryptocurrencies and the lengths of the sample periods. More recent papers are less prone to these deficits. A less apparent limitation is the survivorship bias in the data caused by the disappearance and emergence of cryptocurrencies. Regarding areas of further research, not only would it make sense to extend the sentiment and alternative factor models, but it could also be fruitful to study the role of volatility, correlations to new variables, the consequences of limits to arbitrage, consolidated factor models, etc.

Cryptocurrencies are a new asset class that is here to stay. Initially receiving attention for being decentralized payment systems, they have recently begun to grow in popularity due to their features as stores of value in times of rising inflation. For similar reasons and the promise of portfolio diversification, even conservative investors show increasing interest in them. On the contrary, the issue of cryptocurrencies' energy consumption is still unsolved, especially in view of rising energy prices. PoS could remedy this, but this more energy-efficient consensus mechanism is yet to be widely implemented. In light of rising environmental awareness, not changing their current ways might cause cryptocurrency developers to miss growth opportunities and eventually lead to stagnating adoption. In spite of this, the sheer resource abundance of financial investors is bound to drive up investments in further research. In this regard, the results of this thesis have already provided the insight that especially fundamentals-based asset pricing models that are derived from cryptocurrency data deliver relatively consistent predictions. Thus, at least partially, a factor structure does indeed emerge. As noted in chapter 1, finding ways to explain the cross-section of cryptocurrency returns is a central interest of numerous parties. Specifically institutional investors, such as banks or insurances, who are just beginning to build exposure, stand to profit from knowing what risk factors affect cryptocurrency returns, since this is also tied to their understanding of how cryptocurrencies can enhance portfolio diversification. In fact, this summary of 26 empirical studies could help them better comprehend the investment characteristics of cryptocurrencies, at least partially alleviating the prevailing limited institutional pick-up. Going forward, they will need to learn to look closely at the intrinsic value factors of cryptocurrencies and relate these to the fundamental risk factors. At the same time, they need to understand what drives a cryptocurrency's uniqueness among other cryptocurrencies and how the asset class of cryptocurrencies is distinct from other asset classes. Ultimately, a better understanding of the factor structure may increase confidence in cryptocurrencies as an asset class and reduce barriers to investing.

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Figure 1

Total Cryptocurrency Market Capitalization

Retrieved on August 31, 2022 from https://coinmarketcap.com/charts/.

Figure 2

Major Crypto Assets by a Percentage of Total Market Capitalization

Retrieved on August 31, 2022 from https://coinmarketcap.com/charts/.

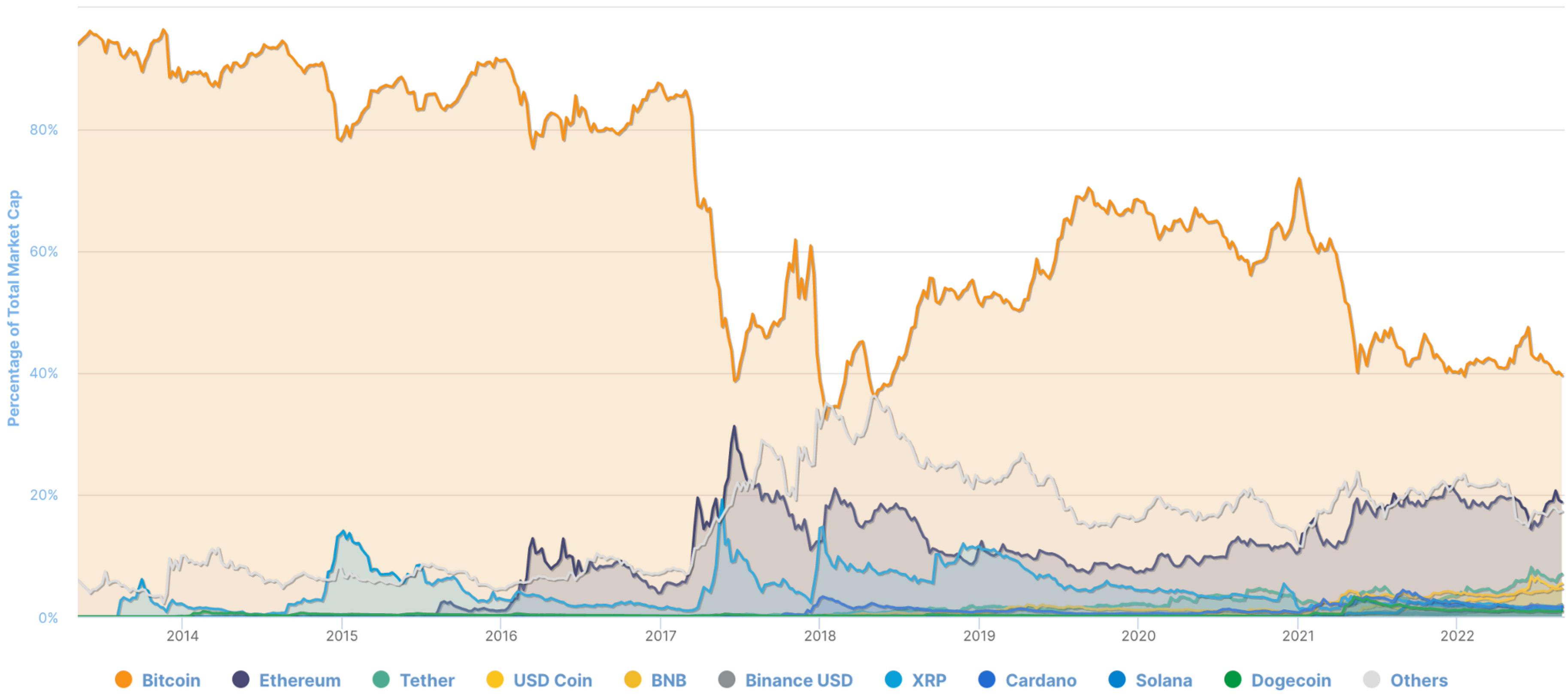


Figure 3

The Adoption of Digital Assets by Region

Adoption is measured by the share of investors surveyed who have an allocation to digital assets. Adapted from Neureuther (2021).

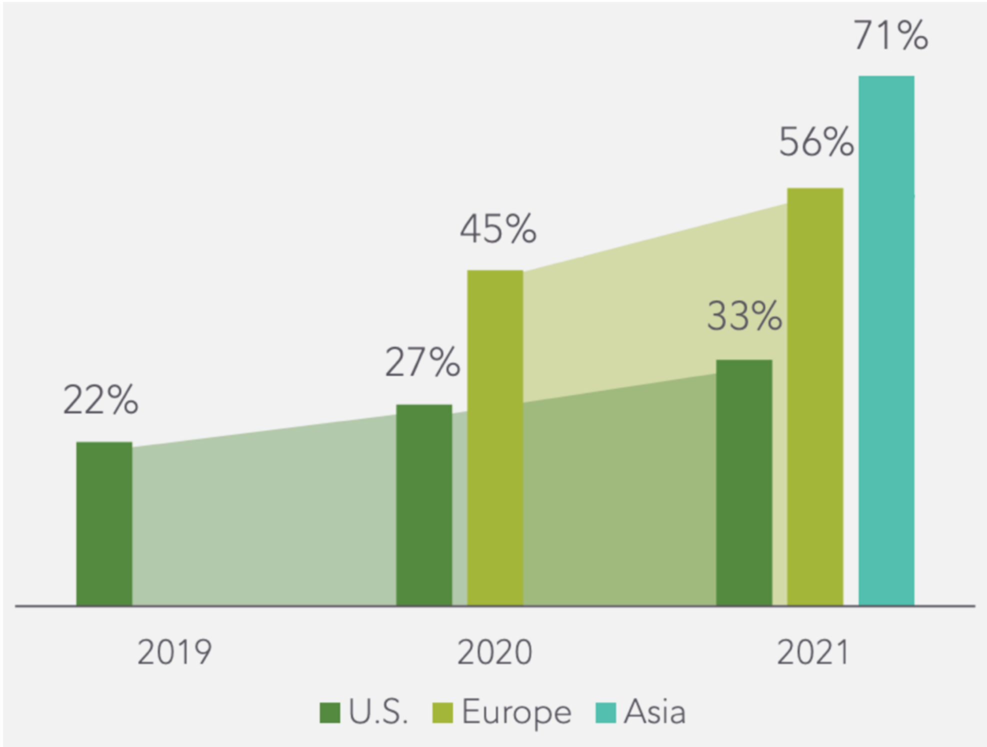


Table 1

A List of the Papers Discussed

The papers are in chronological order and categorized by the kind of asset-pricing model they apply (if multiple factor categories are used, they are listed in order of their importance). The fundamentals-based factors can be constructed using either cryptocurrency or stock market data, as indicated by the source in parentheses. The explanatory factors are not fully specified here for the sake of simplicity.

Author (Year)	Sample Period	Cryptocurrencies	Explanatory Factors	Category (Source)
van Wijk (2013)	07/2010 – 06/2013	Bitcoin	Stock indices, major currencies, commodities	Other
Polasik, Piotrowska, Wisniewski, Kotkowski, and **Lightfoot (2015)**	07/2010 – 03/2014	Bitcoin	Google searches, tone of newspaper mentions, number of blockchain transactions, macroeconomic factors	Sentiment, other
Hayes (2016)	09/2014	66 cryptocurrencies	Level of competition in the network, rate of unit production, difficulty of the algorithm used to mine, percentage of coins mined thus far compared to the total that can ever be found, age	Other
Halaburda **and** Gandal (2016)	05/2013 – 07/2014	13 cryptocurrencies	Bitcoin returns, Google searches, interaction term, volatility	Sentiment, other
Hubrich (2017)	04/2014 – 08/2017	11 cryptocurrencies	CAPM, HML, WML, Carry	Fundamentals (crypto-based), other
Baur, Hong, **and** Lee (2017)	07/2010 – 06/2015	Bitcoin	FX volatility, CAPM	Other, fundamentals (stock-based)
Wang **and** Vergne (2017)	09/2014 – 08/2015	5 cryptocurrencies	"Buzz" in online media, innovation potential, cryptocurrency supply growth, liquidity, week trend	Sentiment, other
Stoffels (2017)	04/2016 – 07/2017	15 cryptocurrencies	CAPM, SMB, HML, WML	Fundamentals (crypto-based)
Hu, Parlour, **and** Rajan (2018)	04/2013 – 11/2017	118 cryptocurrencies	Gold, CAPM, Bitcoin returns	Other, fundamentals (stock-based)
Gilbert **and** Loi (2018)	07/2010 – 06/2014	Bitcoin	CAPM, SMB, HML	Fundamentals (stock-based)
Lee, Guo, **and** Wang (2018)	08/2014 – 03/2017	10 cryptocurrencies	Media news, past average returns	Sentiment
Li **and** Yi (2019)	07/2014 – 06/2018	89 cryptocurrencies	CAPM, SMB, HML, WML, volatility	Fundamentals (crypto-based), other
Gregoriou (2019)	01/2014 – 12/2017	10 cryptocurrencies	CAPM, SMB, HML, WML, RMW, CMA	Fundamentals (stock-based)
Bhambhwani, Delikouras, **and** Korniotis (2019)	07/2015 – 06/2019	39 cryptocurrencies	Computing power, network	Other
Liu, Liang, **and** Cui (2020)	08/2015 – 12/2018	78 cryptocurrencies	CAPM, SMB, WML	Fundamentals (crypto-based)
Bianchi (2020)	12/2013 – 03/2019	300 cryptocurrencies	CAPM, commodities, precious metals, other asset classes	Other, fundamentals (stock-based, crypto-based)
Shen, Urquhart, **and** Wang (2020)	04/2013 – 03/2019	> 1,700 cryptocurrencies	CAPM, SMB, WML	Fundamentals (crypto-based)

Table 1

A List of the Papers Discussed (Continued)

Author (Year)	**Sample Period**	**Cryptocurrencies**	**Explanatory Factors**	**Category (Source)**
Zhang **and** Li (2020)	01/2014 – 09/2019	> 500 cryptocurrencies	Idiosyncratic volatility, SMB, WML, liquidity, volume, price level	Other, fundamentals (crypto-based)
Pagano **and** Sedunov (2020)	01/2013 – 12/2017	Bitcoin	Bitcoin, gold, transaction fees, volatility, bid-ask spread, Google searches, currencies, VIX, TED spread, stress index, economic uncertainty index, lagged returns, WML	Other, fundamentals (crypto-based)
Long, Zaremba, Demir, Szczygielski, and **Vasenin (2020)**	08/2016 – 12/2019	151 cryptocurrencies	Seasonality, WML, idiosyncratic volatility, SMB, CAPM, turnover ratio, illiquidity ratio	Other, fundamentals (crypto-based)
Wang **and** Chong (2021)	12/2013 – 08/2018	59 cryptocurrencies	CAPM, SMB, HML, WML, volatility factors, liquidity factors, sentiment factor, macroeconomic factors	Fundamentals (crypto-based), sentiment, other
Zhang, Xiong, **and** Wang (2021)	01/2016 – 12/2020	Unspecified, but large number of cryptocurrencies	Downside risk, SMB, WML, volume, idiosyncratic volatility, volatility	Other, fundamentals (crypto-based)
Barrera **and** Minovitsky (2021)	07/2017 – 03/2021	Bitcoin, Ethereum, Dogecoin	CAPM, SMB, WML, liquidity, volatility, age	Fundamentals (crypto-based), other
Liu **and** Tsyvinski (2021)	01/2011 – 05/2018	Bitcoin, Ripple, Ethereum	CAPM, SMB, HML, RMW, CMA, 155 anomalies, major currencies, precious metals, macroeconomic factors, cryptocurrency-specific factors, sentiment factor	Fundamentals (stock-based), sentiment, other
Liu, Tsyvinski, **and** Wu (2022)	01/2014 – 12/2018	1,707 cryptocurrencies	CAPM, SMB, WML	Fundamentals (crypto-based)
Borri **and** Shakhnov (2022)	05/2015 – 10/2019	Bitcoin	CAPM, SMB, WML, liquidity, sentiment	Fundamentals (crypto-based), sentiment, other

Part II: Replicating the Methodology of "Common Risk Factors in Cryptocurrency": A Python Approach

1. Introduction

The cryptocurrency market has experienced significant growth in recent years, attracting both academic and practical attention. In response, numerous studies have been conducted to investigate the factors driving the market and associated risks. Among these studies, "Common Risk Factors in Cryptocurrency" by Yukun Liu, Aleh Tsyvinski, and Xi Wu (2022) stands out as a comprehensive and influential work in the field.[1] In their paper, the authors find that three factors – cryptocurrency market, size, and momentum – are the primary drivers of cross-sectional expected cryptocurrency returns. They use an extensive list of price- and market-related return predictors, which have previously led to important results for equities, and find that ten cryptocurrency characteristics can be used to form successful long-short investment strategies. The authors then show that these investment strategies are explained by the cryptocurrency three-factor model.

This thesis aims to closely replicate the methodology used in "Common Risk Factors in Cryptocurrency" by implementing it in python code as a step-by-step guide with the goal of verifying the robustness of the findings and making the methodology more accessible and replicable for future researchers.[2] Throughout the thesis, the original methodology is thoroughly examined and any limitations and areas for improvement are identified.

The following section provides a comprehensive overview of the methodology, detailing the data sources, variables, and statistical methods employed, and compares the findings of the original paper with the new results. Subsequently, the thesis concludes with a discussion of the implications and recommendations for future research.

[1] We henceforth refer to this paper as the "original paper".

[2] We confine our analysis to chapters II and III of the original paper, excluding the principal component analysis.

2. Methodology and comparison

In this section, we outline our efforts to replicate the methodology from the original paper using python. We detail the steps taken to produce each table and figure, then briefly compare our results to those in the original paper, though our primary goal is to replicate the methodology. The accompanying python file can be found at github.com/MarcGehring97/Crypto-Currency-Asset-Pricing.

In this thesis, we utilize a Jupyter notebook as the platform for our main analysis, taking advantage of its user-friendly interface and seamless integration of code, text, and visualizations. The structure of the notebook closely follows the sections of the original paper, starting with chapter *I. Data*. In this section, the researcher can filter coins based on criteria, such as market capitalization, and modify any additional assumptions made. Chapter *II. Cross-Sectional Return Predictors* involves the identification of long-short investment strategies that generate positive, statistically significant returns. Finally, a small number of explanatory factors for these strategies are investigated in chapter *III. Cryptocurrency Factors*. The goal of each section is to match the relevant tables from the original paper. Since direct LaTeX tabular format rendering is not possible in a Jupyter notebook, we created a PDF file to display the tables below each block of code. It is important to note that this file is overwritten each time a new table is rendered and must be copied if the researcher intends to save it.

The study begins by setting the start date to January 1st, 2014, as prior to this time, Bitcoin was the only actively traded cryptocurrency. The end date is set to July 31st, 2020 to make the results comparable with the original paper. The researcher is expected to specify the storage directory for the data. The code checks for the presence of relevant data files and skips the data generation section if these files already exist. The retrieval of the data involves obtaining the main data set, for which the authors of the original paper used CoinMarketCap (coinmarketcap.com). CoinMarketCap might be considered the most popular crypto data platform, but it does not provide access to historical data as part of its free plan. In this study, we propose the utilization of CoinGecko (coingecko.com) as an alternative data source. CoinGecko is the second largest crypto data platform and offers a free API for data gathering. However, it should be noted that the API has limitations, such as only allowing 50 calls per minute. The code for retrieving the data from CoinGecko is available in the *coingecko_data.py* file located in the *data_retrieval* folder. This folder also contains additional files that allow for the retrieval of data from other sources. We have decided to include additional data sources to enable researchers to explore additional explanatory factors. Given the API traffic limitation, it is advisable to download the data sets in smaller chunks to avoid having to restart the entire process in case of interruption. The code provides functionality for this purpose. Following the methodology described in the original paper, we transform the daily frequency of the data set to a weekly frequency by taking the last available data point each week, with a week being defined as starting on Monday and ending on Sunday. To account for potential artificial or erroneous returns, all returns greater than 80% in absolute value were set to missing. This threshold can be considered generous, and other researchers may adjust it to their preference. The data points where the market capitalization was below $1 million were filtered out, in line with the exclusion principle proposed in the original paper. However, all values for Bitcoin, Ripple, and Ethereum are still retained since these cryptocurrencies were considered the most important ones in the early days of public cryptocurrency trading.[3] Next, the risk-free rate is retrieved as the one-month Treasury bill rate from French's website (https://mba.tuck.dartmouth.edu/pages/faculty/ken.french). In the original paper, the authors are using the same rate. The code for this can be found in the *stock_factors_data.py* file located in the *data_retrieval* folder. For missing values that occurred on weekends, we impute the average of the values of Friday and Monday. After preprocessing the data, we compute the weekly value-weighted coin market return series and the coin market excess return series using the risk-free rate. We reindex the dataframes to the full date range after each operation to ensure consistency in the dimensionality of the data. Finally, the summary statistics for the daily and weekly return series are presented in Table I. Comparing this to the matching table in the original paper, we can see that all numbers differ substantially. This divergence can mainly be explained by the different data source, the possibly differing filtering process, and the assumptions made regarding the frequency conversion. In particular, we can see that the number of coins differs from the data in the original paper every year. This could mean that the data set we use contains fewer coins or that we are applying a finer filtering procedure.

[3] Unfortunately, the authors of the original paper do not provide an explanation for how they dealt with missing values. They neither include an explanation in their internet appendix.

Table I
Summary Statistics

Panel A reports the number of coins, the mean and median of market capitalization, and the mean and median of daily trading price volume by year. Panel B reports the characteristics of coin market index returns, Bitcoin returns, Ripple returns, and Ethereum returns. The coin market index returns, Bitcoin returns, and Ripple returns start from the first week of 2014. The Ethereum returns start from the 32^{nd} week of 2015.

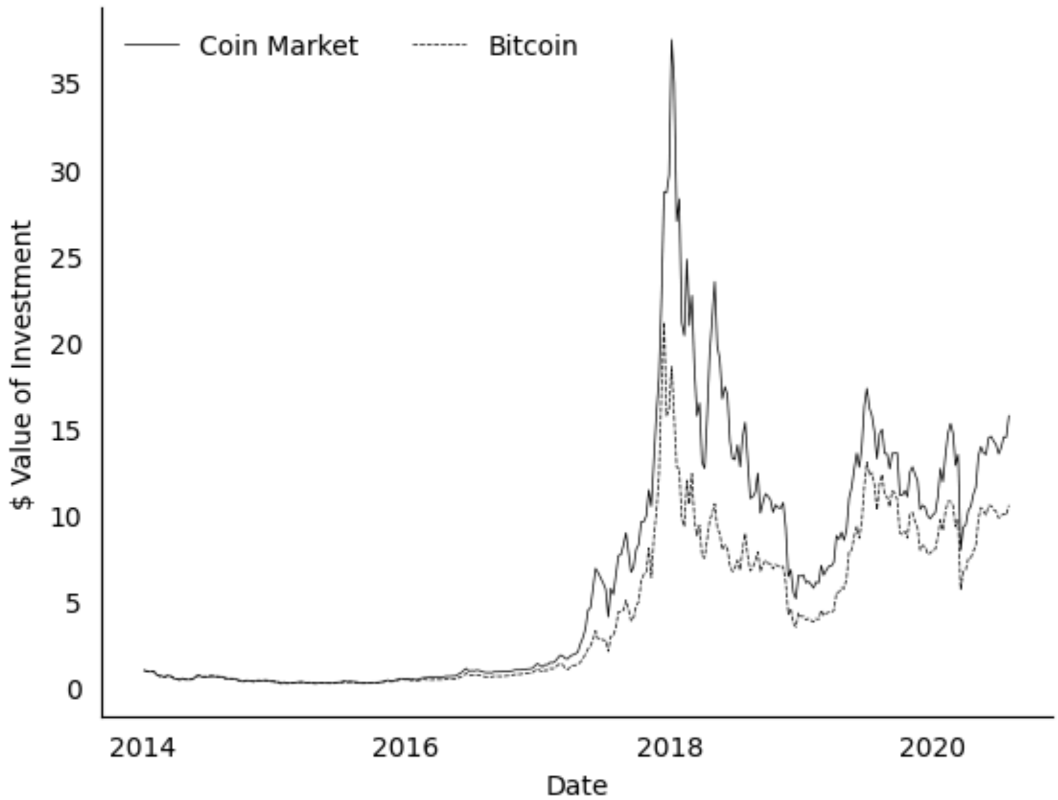
Panel A. Characteristics by Year

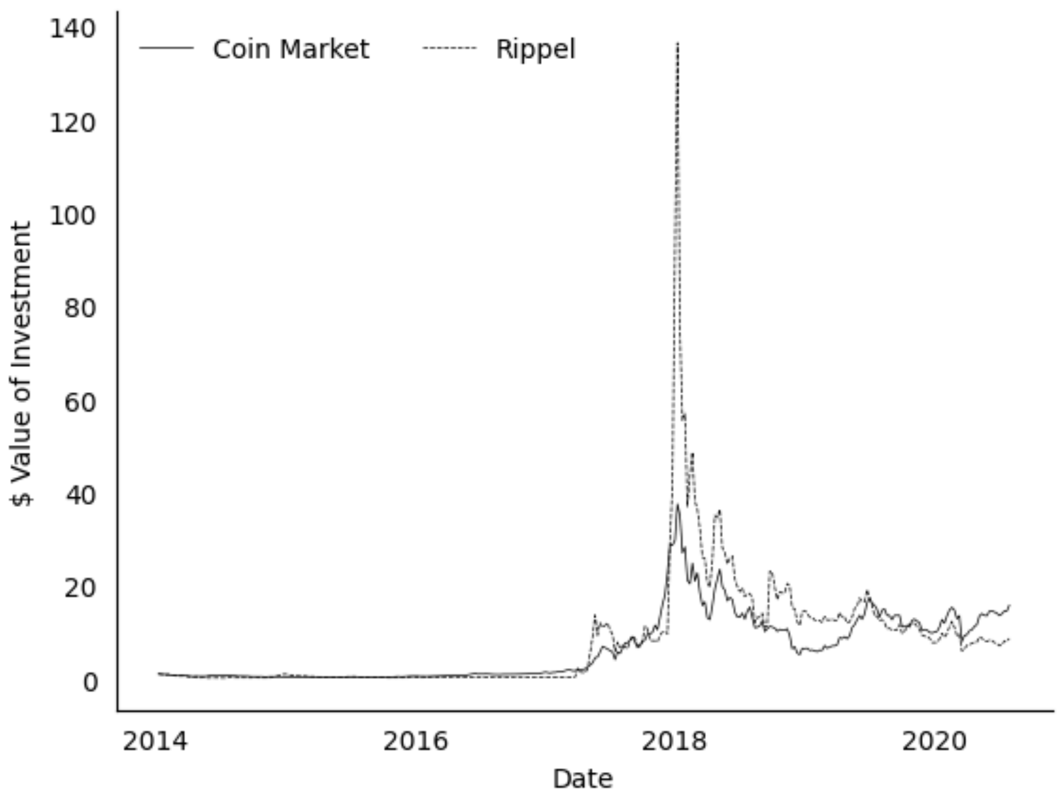
		Market Cap (mil)		Volume (thous)	
Year	Number	Mean	Median	Mean	Median
2014	63	100.21	0.27	2,452.33	42.18
2015	42	36.28	0.12	13,389.12	16.28
2016	91	70.93	0.30	43,115.99	24.43
2017	386	554.03	5.80	25,091.91	243.43
2018	891	414.55	6.75	23,510.86	255.38
2019	888	220.53	2.01	121,192.48	304.53
2020	819	237.15	1.39	204,838.37	434.33
Full	12,468	281.48	2.07	91,964.79	263.86

Panel B. Return Characteristics

	Mean	Median	*SD*	Skewness	Kurtosis
Coin Market Return	0.013	0.012	0.103	0.019	1.554
Bitcoin Return	0.013	0.007	0.107	0.177	1.750
Ripple Return	0.037	0.013	0.188	1.329	3.762
Ethereum Return	0.033	-0.009	0.341	8.922	111.075

We use the next block of code to visualize the return indices of the market return series and the return series of the major cryptocurrencies Bitcoin, Ripple, and Ethereum in Figure I. The indices are normalized to a value of 1 on the 1st of January, 2014. In the event of missing data, the last observed value is employed for imputation purposes. As mentioned earlier, we adjusted the filtering threshold for excessively high and low returns to more closely replicate the coin market return trajectory from the original paper. Interestingly, though, the Ethereum return series exhibits a far larger series maximum at about 1,000 times compared to 500 times in the original data. Still, the overall shape of the graphs looks almost identical. Apparently, the two data sources differ in a few Ethereum data points that make the series jump higher in this case. The Bitcoin and Ripple return series seem to resemble the ones in the original paper in both shape and magnitude.





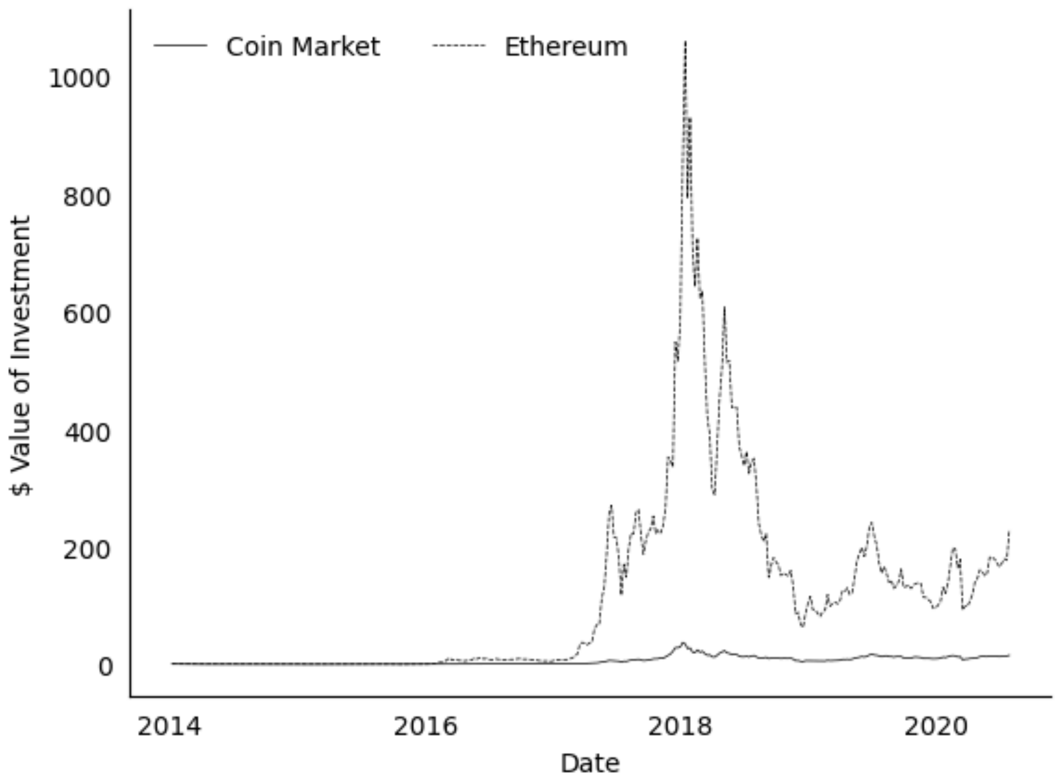


Figure 1. Cryptocurrency market and major coins. This figure plots the aggregate cryptocurrency market against Bitcoin, Ripple, and Ethereum.

In the following section of the notebook, the computation of the five quintile excess return series as well as the long-short investment strategies for different cryptocurrency trading variables is performed. Section A focuses on computing these returns for size characteristics such as *MCAP* (log last-day market capitalization in the portfolio formation week), *PRC* (log last-day price in the portfolio formation week), *MAXDPRC* (the maximum price of the portfolio formation week), and *AGE* (number of days listed since the time period began on January 1st, 2014). The quintile return series are computed by dividing all coins into quintiles based on each of the aforementioned characteristics on a weekly basis and calculating the value-weighted return of each quintile in the following week. Subsequently, the risk-free rate is subtracted from the individual quintile return series for each characteristic. The results of the size strategy returns are presented in Table II. The results agree with the original paper regarding the market capitalization factor but unlike the original paper deliver statistical insignificance for the other three factors.

Table II
Size Strategy Returns

This table reports the mean quintile portfolio returns based on the market capitalization, last-day price, and maximum day price measures. The mean returns are the time-series averages of weekly value-weighted portfolio excess returns. *, **, and *** denote significance at the 10%, 5%, and 1% levels.

	Quintiles					
	1	2	3	4	5	5-1
MCAP	**Low**				**High**	
Mean	0.050***	0.014*	0.014**	0.012*	0.011*	-0.039***
t(Mean)	(7.30)	(1.93)	(2.00)	(1.82)	(1.90)	(-7.45)
PRC	**Low**				**High**	
Mean	0.014*	0.021**	0.001	0.002	0.011*	-0.003
t(Mean)	(1.74)	(2.44)	(0.19)	(0.27)	(1.90)	(-0.50)
MAXDPRC	**Low**				**High**	
Mean	0.015*	0.019**	0.002	0.002	0.011*	-0.004
t(Mean)	(1.82)	(2.25)	(0.25)	(0.34)	(1.90)	(-0.64)
AGE	**Low**				**High**	
Mean	0.005	0.015*	0.016*	0.033***	0.010*	0.005
t(Mean)	(0.59)	(1.71)	(1.79)	(3.19)	(1.75)	(0.78)

Additionally, in section B we also calculate the quintile return series for the momentum characteristics, including *r 1,0* (past one-week return), *r 2,0* (past two-week return), *r 3,0* (past three-week return), *r 4,0* (past four-week return), *r 4,1* (past one-to-four-week return), *r 8,0* (past eight-week return), *r 16,0* (past 16-week return), *r 50,0* (past 50-week return), and *r 100,0* (past 100-week return). The results are shown in Table III. Here, we observe similarities to the original paper in terms of the signs and magnitudes of the quintile returns and the long-short investment strategies. Strikingly, we obtain the tendency that longer-term momentum strategies are less likely to yield statistically significant long-short returns.

Table III
Momentum Strategy Returns

This table reports the mean quintile portfolio returns based on the past one-week, two-week, three- week, four-week, and one-to-four-week return measures. The mean returns are the time-series averages of weekly value-weighted portfolio excess returns. *, **, and *** denote significance at the 10%, 5%, and 1% levels.

	Quintiles					
	1	2	3	4	5	5-1
r 1,0	**Low**				**High**	
Mean	0.001	0.003	0.011	0.009	0.027***	0.026***
t(Mean)	(0.16)	(0.48)	(1.48)	(1.29)	(3.17)	(3.29)
r 2,0	**Low**				**High**	
Mean	0.002	-0.003	0.005	0.017**	0.027***	0.025***
t(Mean)	(0.29)	(-0.39)	(0.73)	(2.28)	(3.30)	(3.27)
r 3,0	**Low**				**High**	
Mean	0.005	-0.004	0.005	0.017**	0.033***	0.028***
t(Mean)	(0.60)	(-0.62)	(0.66)	(2.31)	(3.81)	(3.36)
r 4,0	**Low**				**High**	
Mean	0.012	0.002	0.006	0.010	0.029***	0.017**
t(Mean)	(1.50)	(0.21)	(0.87)	(1.37)	(3.63)	(2.18)
r 4,1	**Low**				**High**	
Mean	0.009	0.001	0.009	0.015**	0.024***	0.015*
t(Mean)	(1.05)	(0.12)	(1.25)	(2.06)	(2.93)	(1.88)
r 8,0	**Low**				**High**	
Mean	0.017**	0.002	0.012	0.009	0.029***	0.012
t(Mean)	(2.17)	(0.33)	(1.64)	(1.27)	(3.61)	(1.49)
r 16,0	**Low**				**High**	
Mean	0.019**	0.014*	0.015**	0.014*	0.027***	0.009
t(Mean)	(2.55)	(1.81)	(2.03)	(1.82)	(3.36)	(1.08)
r 50,0	**Low**				**High**	
Mean	0.011	0.008	0.014*	0.009	0.015**	0.004
t(Mean)	(1.61)	(0.96)	(1.81)	(1.07)	(2.11)	(0.52)
r 100,0	**Low**				**High**	
Mean	0.011	0.006	0.016*	0.005	0.010	-0.001
t(Mean)	(1.36)	(0.72)	(1.72)	(0.42)	(1.20)	(-0.06)

For the volume characteristics in section C, we consider the predictors *VOL* (log average daily volume in the portfolio formation week), *PRCVOL* (log average daily volume times price in the portfolio formation week), and *VOLSCALED* (log average daily volume times price scaled by market capitalization in the portfolio formation week). The results of this analysis are depicted in Table IV. Contrary to the original paper, *PRCVOL* is statistically insignificant, while *VOL* shows convincing evidence of statistical significance.

Table IV
Volume Strategy Returns

This table reports the mean quintile portfolio returns based on the price volume measure. The mean returns are the time-series averages of weekly value-weighted portfolio excess returns. *, **, and *** denote significance at the 10%, 5%, and 1% levels.

	Quintiles					
	1	2	3	4	5	5-1
VOL	**Low**				**High**	
Mean	0.022***	0.016**	0.013*	0.013*	0.011*	-0.012**
t(Mean)	(3.39)	(2.33)	(1.84)	(1.80)	(1.92)	(-2.29)
PRCVOL	**Low**				**High**	
Mean	0.016*	0.021**	0.003	0.002	0.011*	-0.005
t(Mean)	(1.96)	(2.39)	(0.36)	(0.28)	(1.88)	(-0.84)
VOLSCALED	**Low**				**High**	
Mean	0.010	0.006	0.019**	0.013*	0.007	-0.003
t(Mean)	(1.29)	(0.81)	(2.21)	(1.87)	(1.09)	(-0.37)

Finally, we examine the quintile return series for the volatility characteristics in section D. The predictors for this analysis include *BETA* (The regression coefficient ${\beta^i}_{CMKT}$ in$R_i - R_f = \alpha^i + {\beta^i}_{CMKT} CMKT + \epsilon_i$ using daily returns of the previous 365 days before the formation week), *BETA2* (*BETA* squared), *IDIOVOL* (idiosyncratic volatility, measured as the standard deviation of the residual after estimating $R_i - R_f = \alpha^i + {\beta^i}_{CMKT} CMKT + \epsilon_i$ using daily returns of the previous 365 days before the formation week), *RETVOL* (standard deviation of daily returns in the portfolio formation week), *MAXRET* (maximum daily return of the portfolio formation week), *DELAY* (the improvement in R^2 in $R_i - R_f = \alpha^i + {\beta^i}_{CMKT} CMKT + {\beta^i}_{CMKT_{-1}} CMKT_{-1} + {\beta^i}_{CMKT_{-2}} CMKT_{-2} + \epsilon_i$ where $CMKT_{-1}$ and $CMKT_{-2}$ are the lagged one- and two-day coin market index excess returns, compared to using only current coin market excess returns using daily returns of the previous 365 days before the formation week), *STDPRCVOL* (log standard deviation of price volume in the portfolio formation week), and *DAMIHUD* (average absolute daily return divided by price volume in the portfolio formation week). The results of this analysis are presented in Table V. Unlike the authors of the original paper, we do not obtain statistical significance for the *STDPRCVOL* factor but find that the *BETA* factor is statistically significant at the 1% significance level.

Table V
Volatility Strategy Returns

This table reports the mean quintile portfolio returns based on the standard deviation of price volume. The mean returns are the time-series averages of weekly value-weighted portfolio excess returns. *, **, and *** denote significance at the 10%, 5%, and 1% levels.

	Quintiles					
	1	2	3	4	5	5-1
BETA	**Low**				**High**	
Mean	-0.002	0.005	0.017*	0.014*	0.016**	0.019***
t(Mean)	(-0.33)	(0.66)	(1.84)	(1.69)	(2.58)	(2.90)
BETA2	**Low**				**High**	
Mean	0.003	0.003	0.015*	0.017**	0.015**	0.012*
t(Mean)	(0.42)	(0.36)	(1.67)	(2.14)	(2.26)	(1.80)
IDIOVOL	**Low**				**High**	
Mean	0.013*	0.016*	0.017**	0.009	-0.001	-0.013**
t(Mean)	(1.92)	(1.92)	(2.05)	(1.17)	(-0.11)	(-2.07)
RETVOL	**Low**				**High**	
Mean	0.009	0.006	0.012	0.016**	0.015	0.006
t(Mean)	(1.41)	(0.87)	(1.55)	(1.99)	(1.55)	(0.73)
MAXRET	**Low**				**High**	
Mean	0.000	0.013*	0.011	0.018**	0.011	0.011
t(Mean)	(0.03)	(1.84)	(1.48)	(2.24)	(1.23)	(1.39)
DELAY	**Low**				**High**	
Mean	0.014**	0.015*	0.008	0.016**	0.018**	0.004
t(Mean)	(2.01)	(1.81)	(1.21)	(2.26)	(2.19)	(0.67)
STDPRCVOL	**Low**				**High**	
Mean	0.017**	0.016**	0.016**	0.011	0.011*	-0.005
t(Mean)	(2.45)	(2.24)	(2.26)	(1.62)	(1.96)	(-1.02)
DAMIHUD	**Low**				**High**	
Mean	0.011*	0.010	0.013*	0.015**	0.021***	0.010*
t(Mean)	(1.93)	(1.35)	(1.77)	(2.09)	(2.92)	(1.85)

The subsequent chapter of the analysis investigates whether a limited number of factors can explain the long-short investment strategies identified previously. To this end, a one-factor model is run using the cryptocurrency market excess return (*CMKT*), also referred to as the cryptocurrency Capital Asset Pricing Model (CAPM). The dependent variables in this analysis are the various long-short investment strategies minus the risk-free rate. The results of the one-factor model are presented in Table VI. Notably, we receive similar results for the alphas of the momentum strategies in terms of their signs, magnitudes, and levels of significance. Yet, the results for the other factors converge widely from the ones obtained in the original paper.

Table VI
Cryptocurrency One-Factor Model

This table reports results for the cryptocurrency one-factor model adjustment of the 10 successful long-short strategies. The pricing model is

$$R_i - R_f = \alpha^i + \beta^i_{CMKT} CMKT + \epsilon_i,$$

where $CMKT$ is the cryptocurrency excess market return. t-Statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels. m.a.e. and $\overline{R^2}$ are the mean absolute pricing error and the average R^2 of the five portfolios, respectively.

	α	$t(\alpha)$	β_{CMKT}	$t(\beta_{CMKT})$	R^2	m.a.e.	$\overline{R^2}$
MCAP	-0.045***	(-8.66)	0.204***	(4.12)	0.048	0.069	0.625
PRC	-0.007	(-1.09)	0.056	(0.90)	0.002	0.079	0.582
MAXDPRC	-0.008	(-1.19)	0.042	(0.66)	0.001	0.081	0.580
AGE	0.001	(0.08)	0.143**	(2.22)	0.014	0.082	0.566
r 1,0	0.022***	(2.75)	0.085	(1.12)	0.004	0.103	0.520
r 2,0	0.021***	(2.77)	0.035	(0.48)	0.001	0.099	0.536
r 3,0	0.024***	(2.89)	0.048	(0.59)	0.001	0.108	0.538
r 4,0	0.013*	(1.66)	0.072	(0.93)	0.003	0.105	0.537
r 4,1	0.012	(1.47)	-0.002	(-0.03)	0.000	0.104	0.554
r 8,0	0.007	(0.82)	0.195**	(2.45)	0.018	0.107	0.539
r 16,0	0.001	(0.19)	0.287***	(3.82)	0.043	0.101	0.513
r 50,0	-0.004	(-0.53)	0.276***	(3.99)	0.052	0.086	0.470
r 100,0	-0.012	(-1.47)	0.458***	(5.94)	0.128	0.093	0.392
VOL	-0.017***	(-3.47)	0.213***	(4.53)	0.057	0.062	0.621
PRCVOL	-0.009	(-1.41)	0.050	(0.79)	0.002	0.081	0.590
VOLSCALED	-0.007	(-0.92)	0.087	(1.22)	0.004	0.091	0.550
BETA	0.009	(1.44)	0.407***	(7.21)	0.153	0.064	0.562
BETA2	0.003	(0.55)	0.282***	(4.77)	0.073	0.071	0.566
IDIOVOL	-0.008	(-1.45)	-0.635***	(-12.72)	0.360	0.057	0.536
RETVOL	0.002	(0.25)	0.089	(1.07)	0.003	0.110	0.535
MAXRET	0.006	(0.82)	0.124	(1.63)	0.008	0.101	0.556
DELAY	0.001	(0.15)	-0.037	(-0.62)	0.001	0.075	0.564

	α	$t(\alpha)$	β_{CMKT}	$t(\beta_{CMKT})$	R^2	m.a.e.	$\overline{R^2}$
STDPRCVOL	-0.011**	(-2.12)	0.218***	(4.41)	0.054	0.064	0.625
DAMIHUD	0.008	(1.55)	-0.152***	(-2.98)	0.026	0.068	0.606

We finally set up three multi-factor models, adding the size and the momentum factors. The size factor, *CSMB*, is determined by comparing the returns of small and large portfolios. The *CMOM* is established by utilizing three-week momentum and forming portfolios by combining 2 sets of 3 portfolios. Each week, coins are divided into two groups based on their size, then further separated into three portfolios based on their past three-week performance. These portfolios consist of the bottom 30%, middle 40%, and top 30% of coins ranked by their past returns. The momentum factor is then constructed as

$$CMOM = \frac{1}{2}(Small\ High + Big\ High) + \frac{1}{2}(Small\ Low + Big\ Low).$$

Model (1) incorporates the *CMKT* and *CSMB* factor, Model (2) includes the *CMKT* and momentum factor, and Model (3) includes all three factors, i.e. *CMKT*, *CSMB*, and *CMOM*. The results of these models are reported in Table VII, including the model statistics. Comparing these results to the findings of the original paper, we notice again that there appears to be most agreement for the momentum factors. All other factors differ in terms of sign, magnitude, and statistical significance from the original paper.

Table VII
Cryptocurrency Factor Models

This table reports results on the cryptocurrency factor adjustments of the 10 successful long-short strategies. $CMKT$ is the cryptocurrency excess market return, $CSMB$ is the cryptocurrency size factor, and $CMOM$ is the cryptocurrency momentum factor. $t-Statistics$ are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels. m.a.e. and $\overline{R^2}$ are the mean absolute pricing error and the average R^2 of the five portfolios, respectively.

		Cons	t	CMKT	t	CSMB	t	CMOM	t	R^2	m.a.e.	$\overline{R^2}$
MCAP	(1)	-0.048***	(-9.25)	-0.101	(-0.94)	-0.101	(-0.94)			0.075	0.066	0.642
MCAP	(2)	-0.050***	(-9.79)	0.168***	(3.47)			0.168	(3.47)	0.108	0.066	0.645
MCAP	(3)	-0.053***	(-10.26)	-0.098	(-0.93)	-0.098	(-0.93)	0.353	(2.86)	0.129	0.064	0.660
PRC	(1)	-0.013**	(-2.08)	-0.485***	(-3.64)	-0.485***	(-3.64)			0.060	0.077	0.593
PRC	(2)	-0.005	(-0.73)	0.073	(1.16)			0.073	(1.16)	0.011	0.079	0.587
PRC	(3)	-0.011*	(-1.68)	-0.488***	(-3.68)	-0.488***	(-3.68)	0.743***	(4.76)	0.073	0.076	0.600
MAXDPRC	(1)	-0.014**	(-2.13)	-0.484***	(-3.54)	-0.484***	(-3.54)			0.053	0.078	0.591
MAXDPRC	(2)	-0.005	(-0.80)	0.061	(0.94)			0.061	(0.94)	0.011	0.081	0.586
MAXDPRC	(3)	-0.011*	(-1.70)	-0.488***	(-3.59)	-0.488***	(-3.59)	0.727***	(4.54)	0.068	0.078	0.598
AGE	(1)	-0.004	(-0.53)	-0.209	(-1.48)	-0.209	(-1.48)			0.037	0.080	0.574
AGE	(2)	0.002	(0.33)	0.157**	(2.40)			0.157	(2.40)	0.019	0.082	0.571
AGE	(3)	-0.002	(-0.26)	-0.212	(-1.50)	-0.212	(-1.50)	0.488	(2.94)	0.044	0.081	0.580
r 1,0	(1)	0.018**	(2.20)	-0.258	(-1.54)	-0.258	(-1.54)			0.019	0.103	0.527
r 1,0	(2)	0.019**	(2.31)	0.055	(0.72)			0.055	(0.72)	0.019	0.103	0.527
r 1,0	(3)	0.015*	(1.87)	-0.253	(-1.52)	-0.253	(-1.52)	0.408	(2.08)	0.031	0.103	0.535
r 2,0	(1)	0.020**	(2.50)	-0.101	(-0.63)	-0.101	(-0.63)			0.003	0.100	0.542
r 2,0	(2)	0.016**	(2.15)	-0.004	(-0.06)			-0.004	(-0.06)	0.031	0.100	0.547
r 2,0	(3)	0.015**	(1.98)	-0.095	(-0.60)	-0.095	(-0.60)	0.120	(0.64)	0.032	0.100	0.554

		Cons	t	CMKT	t	CSMB	t	CMOM	t	R^2	m.a.e.	$\overline{R^2}$
r 3,0	(1)	0.022**	(2.59)	-0.124	(-0.69)	-0.124	(-0.69)			0.005	0.108	0.543
r 3,0	(2)	0.018**	(2.14)	-0.005	(-0.07)			-0.005	(-0.07)	0.047	0.107	0.549
r 3,0	(3)	0.017*	(1.95)	-0.116	(-0.66)	-0.116	(-0.66)	0.146	(0.71)	0.049	0.107	0.556
r 4,0	(1)	0.009	(1.16)	-0.253	(-1.50)	-0.253	(-1.50)			0.016	0.104	0.544
r 4,0	(2)	0.008	(1.00)	0.028	(0.37)			0.028	(0.37)	0.037	0.104	0.546
r 4,0	(3)	0.005	(0.61)	-0.247	(-1.48)	-0.247	(-1.48)	0.364	(1.86)	0.047	0.104	0.553
r 4,1	(1)	0.011	(1.29)	-0.107	(-0.62)	-0.107	(-0.62)			0.001	0.104	0.558
r 4,1	(2)	0.007	(0.86)	-0.043	(-0.55)			-0.043	(-0.55)	0.029	0.105	0.561
r 4,1	(3)	0.006	(0.77)	-0.100	(-0.59)	-0.100	(-0.59)	0.076	(0.38)	0.029	0.105	0.566
r 8,0	(1)	0.003	(0.33)	-0.124	(-0.71)	-0.124	(-0.71)			0.030	0.107	0.546
r 8,0	(2)	-0.000	(-0.03)	0.132*	(1.68)			0.132	(1.68)	0.077	0.106	0.549
r 8,0	(3)	-0.003	(-0.37)	-0.113	(-0.67)	-0.113	(-0.67)	0.328	(1.64)	0.084	0.106	0.556
r 16,0	(1)	0.002	(0.21)	0.301*	(1.87)	0.301*	(1.87)			0.043	0.101	0.518
r 16,0	(2)	-0.005	(-0.58)	0.235***	(3.17)			0.235	(3.17)	0.094	0.099	0.524
r 16,0	(3)	-0.004	(-0.45)	0.311**	(1.98)	0.311**	(1.98)	-0.103**	(-0.55)	0.095	0.099	0.529
r 50,0	(1)	0.000	(0.00)	0.523***	(3.66)	0.523***	(3.66)			0.065	0.084	0.489
r 50,0	(2)	-0.002	(-0.24)	0.296***	(4.24)			0.296	(4.24)	0.063	0.087	0.473
r 50,0	(3)	0.002	(0.21)	0.518***	(3.64)	0.518***	(3.64)	-0.310***	(-1.79)	0.073	0.085	0.492
r 100,0	(1)	-0.005	(-0.54)	0.837***	(5.60)	0.837***	(5.60)			0.159	0.091	0.398
r 100,0	(2)	-0.012	(-1.40)	0.462***	(5.86)			0.462	(5.86)	0.128	0.093	0.396
r 100,0	(3)	-0.005	(-0.56)	0.838***	(5.60)	0.838***	(5.60)	-0.556***	(-2.94)	0.159	0.091	0.403
VOL	(1)	-0.020***	(-4.12)	-0.081	(-0.79)	-0.081	(-0.79)			0.085	0.061	0.634
VOL	(2)	-0.019***	(-3.90)	0.198***	(4.18)			0.198	(4.18)	0.071	0.061	0.627
VOL	(3)	-0.022***	(-4.48)	-0.080	(-0.78)	-0.080	(-0.78)	0.369	(3.07)	0.096	0.061	0.639
PRCVOL	(1)	-0.016**	(-2.37)	-0.489***	(-3.60)	-0.489***	(-3.60)			0.057	0.079	0.603
PRCVOL	(2)	-0.008	(-1.15)	0.061	(0.96)			0.061	(0.96)	0.005	0.081	0.595
PRCVOL	(3)	-0.014**	(-2.06)	-0.491***	(-3.62)	-0.491***	(-3.62)	0.733***	(4.59)	0.064	0.079	0.610
VOLSCALED	(1)	-0.010	(-1.28)	-0.159	(-1.01)	-0.159	(-1.01)			0.013	0.090	0.555
VOLSCALED	(2)	-0.000	(-0.05)	0.137*	(1.94)			0.137	(1.94)	0.058	0.088	0.564
VOLSCALED	(3)	-0.004	(-0.49)	-0.166	(-1.09)	-0.166	(-1.09)	0.402	(2.23)	0.072	0.088	0.571
BETA	(1)	0.004	(0.67)	0.131	(1.13)	0.131	(1.13)			0.175	0.063	0.572
BETA	(2)	0.010*	(1.70)	0.422***	(7.41)			0.422	(7.41)	0.161	0.064	0.565
BETA	(3)	0.006	(0.92)	0.126	(1.10)	0.126	(1.10)	0.415	(2.96)	0.186	0.063	0.576
BETA2	(1)	-0.002	(-0.25)	-0.029	(-0.24)	-0.029	(-0.24)			0.101	0.069	0.576
BETA2	(2)	0.005	(0.76)	0.295***	(4.92)			0.295	(4.92)	0.079	0.071	0.569
BETA2	(3)	-0.000	(-0.04)	-0.033	(-0.28)	-0.033	(-0.28)	0.459	(3.13)	0.109	0.069	0.580
IDIOVOL	(1)	-0.005	(-0.93)	-0.478***	(-4.65)	-0.478***	(-4.65)			0.366	0.057	0.544
IDIOVOL	(2)	-0.010*	(-1.84)	-0.655***	(-13.06)			-0.655	(-13.06)	0.373	0.057	0.539
IDIOVOL	(3)	-0.007	(-1.27)	-0.472***	(-4.64)	-0.472***	(-4.64)	-0.256***	(-2.06)	0.382	0.056	0.548
RETVOL	(1)	0.003	(0.39)	0.199	(1.08)	0.199	(1.08)			0.005	0.110	0.540
RETVOL	(2)	-0.001	(-0.07)	0.079	(0.94)			0.079	(0.94)	0.007	0.109	0.542
RETVOL	(3)	0.001	(0.07)	0.197	(1.08)	0.197	(1.08)	-0.157	(-0.73)	0.008	0.109	0.547
MAXRET	(1)	0.006	(0.70)	0.054	(0.32)	0.054	(0.32)			0.008	0.101	0.559
MAXRET	(2)	0.003	(0.43)	0.107	(1.38)			0.107	(1.38)	0.015	0.101	0.562
MAXRET	(3)	0.003	(0.35)	0.055	(0.33)	0.055	(0.33)	0.068	(0.34)	0.016	0.101	0.565
DELAY	(1)	0.004	(0.67)	0.173	(1.40)	0.173	(1.40)			0.014	0.074	0.571
DELAY	(2)	-0.001	(-0.19)	-0.058	(-0.95)			-0.058	(-0.95)	0.016	0.075	0.567
DELAY	(3)	0.002	(0.37)	0.179	(1.45)	0.179	(1.45)	-0.331	(-2.21)	0.033	0.074	0.575
STDPRCVOL	(1)	-0.015***	(-2.89)	-0.131	(-1.22)	-0.131	(-1.22)			0.090	0.062	0.639
STDPRCVOL	(2)	-0.013**	(-2.57)	0.200***	(4.00)			0.200	(4.00)	0.070	0.063	0.629
STDPRCVOL	(3)	-0.017***	(-3.25)	-0.129	(-1.21)	-0.129	(-1.21)	0.436	(3.46)	0.102	0.062	0.644
DAMIHUD	(1)	0.011**	(2.02)	0.079	(0.71)	0.079	(0.71)			0.041	0.067	0.618
DAMIHUD	(2)	0.012**	(2.17)	-0.128**	(-2.51)			-0.128	(-2.51)	0.051	0.067	0.612
DAMIHUD	(3)	0.014**	(2.55)	0.077	(0.70)	0.077	(0.70)	-0.272	(-2.09)	0.063	0.066	0.624

3. Conclusion

To summarize, this thesis aimed to provide a tool kit for other academics to replicate the methodology used in the paper by Liu, Tsyvinski, and Wu (2022). While some results obtained in this thesis differ from the original paper's findings, the primary goal was to replicate the methodology. The differences can mainly be explained by the different data sources, the possibly differing filtering process, and the assumptions made regarding the frequency conversion. Nonetheless, the signs and significance levels of the long-short investment strategies tend to agree with the findings of the original paper, underlining the validity of the replication.

The tool kit is valuable for both academia and practitioners in the cryptocurrency industry and provides a strong foundation for future research, making it easier for others to replicate the results. Future research can expand the analysis to include more cryptocurrencies and a longer time frame to gain a more comprehensive understanding of the factors affecting the cryptocurrency market and their impact on expected returns.

Furthermore, examining the interaction between these factors and other market variables, such as regulation and technology advancements, can add depth to our understanding of the cryptocurrency market and inform investment decisions.

References

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