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UNIVERSIDADE Ð COIMBRA

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NATIVE PRICING FACTORS OF THE CRYPTOCURRENCIES ECOSYSTEM

Master's dissertation in Economics, in the specialty of Financial Economics, advised by Professor Doutor Helder Miguel Correia Virtuoso Sebastião, presented to the Faculty of Economics of the University of Coimbra.

February 2021

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Resumo

O mercado das criptomoedas tem aumentado freneticamente em termos do número de criptomoedas, de bolsas online, e da capitalização do mercado. Esta tendência ampliou a necessidade de criação de um modelo de avaliação compreensivo e robusto. Com recurso a uma base de dados composta por todas as criptomoedas elegíveis e listadas no site do CoinMarketCap, estudamos a relação entre os retornos e os vários potenciais factores de avaliação, tal como o tamanho (capitalização de mercado), momentum, liquidez, volatilidade, volume de transacções, e idade. Esta análise foi feita entre 27 de Dezembro de 2013 e 31 de Dezembro de 2020, usando tanto uma frequência diária como uma frequência semanal, para um total de 3667 criptomoedas. Os portefólios de criptomoedas foram construídos utilizando tanto uma ordenação sequencial como intersecções. Confirmamos que portefólios com criptomoedas com menor capitalização de mercado, menor liquidez, maior volatilidade, menor idade, e menor volume de transacções tendem a oferecer retornos maiores. Por sua vez, criptomoedas com maior momentum tendem a ter retornos menores, implicando que a melhor estratégia seja baseada não em momentum mas em reversão. Os resultados tendem a ser mais expressivos para a frequência semanal que para a frequência diária. Para mais, construímos um modelo de cinco factores que supera o CAPM e o modelo de três factores proposto anteriormente na literatura. Os resultados do modelo de cinco factores são robustos a diferentes construções tanto dos portefólios como dos factores.

Palavras-chave: Bitcoin, criptomoedas, avaliação de activos, modelos de factores.

JEL: G12, G14, G15.

Abstract

The cryptocurrencies market has been frenetically increasing in terms of number of cryptocurrencies, online exchanges, and market capitalization. This trend has amplified the need for a comprehensive and robust pricing model. Using a database of all eligible cryptocurrencies listed at the CoinMarketCap website, we study the relationship between returns and several potential pricing factors, such as size (market capitalization), momentum, liquidity, volatility, trading volume, and age. This analysis was conducted from December 27, 2013 to December 31, 2020 using both daily and weekly frequencies, for a total of 3667 cryptocurrencies. The cryptocurrencies' portfolios were constructed using sequential and intersect sorting. We confirm that portfolios of cryptocurrencies with smaller market capitalization, lower liquidity, higher volatility, lower age, and lower trading volume tend to offer larger returns. In turn, cryptocurrencies with higher momentum tend to have lower returns, implying that the best strategy is based not on momentum but on reversal. The results tend to be more expressive for the weekly frequency than for the daily one. Furthermore, we devised a five-factor model that outperforms the CAPM and the three-factor model previously proposed in the literature. The 5-factor model results are robust to different constructions of portfolio and factors.

Keywords: Bitcoin, cryptocurrencies, asset pricing, factors models.

JEL: G12, G14, G15.

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1. Introduction

Since the creation of the first cryptocurrency, Bitcoin, in 2009, the interest on this type of financial asset has increasingly grown, capturing the attention of investors and academics from different fields of knowledge, from Mathematics and Engineering to Economics and Law.

Naturally, the first Economics studies about cryptocurrencies, focused exclusively on the Bitcoin. But, since 2017, due to the increasing popularity, number of cryptocurrencies available and their market capitalization, there has been a mounting interest in approaching other cryptocurrencies besides Bitcoin, and there have been some attempts to study many cryptocurrencies aiming at analyzing the overall cryptocurrency market.

In this line of thought, the main objectives of this research are twofold. First, to produce an embracing analysis of several features that drive the prices of cryptocurrencies. Second, to use this information to construct different portfolios and produce a pricing model using a methodology similar to Fama and French (1993, 2012, 2015). Thus, the principal data and methodological innovations that this study brings to the literature are the following:

- Usage of the most complete dataset of cryptocurrencies of any study published so far, employing all the information in the CoinMarketCap website, from December 27, 2013 to December 31, 2020.
- Consideration of several features of the cryptocurrencies' ecosystem, namely returns, market capitalization, trading volume, liquidity, volatility, age, and momentum.
- Application of four different methodologies to construct the portfolios used as the left-hand side of the pricing regressions, namely, sequential double-sort equally and value-weighted, and intersecting double-sort equally and value-weighted.
- Evaluation of two different market portfolios, a total market index, constituted by the value-weighted returns of all cryptocurrencies, and a Bitcoin index, with the returns of Bitcoin.
- Creation of a 5-factor model that outperforms both the CAPM and the 3-factor model created by Shen et al. (2020), with factors based on a preliminary analysis on the cryptocurrencies' portfolios.
- Assessment of empirical results using two frequencies, daily and weekly.

The remainder of this paper is organized as follows. Section 2 provides a literature review on the efficient market hypothesis and on the pricing models, its applications to the cryptocurrencies market, and some stylized facts of cryptocurrencies, in respect to returns, market capitalization, trading volume, liquidity, volatility, age, and momentum. Section 3 explains the raw dataset and presents a first look at that dataset from April 30, 2013 to December 31, 2020. Section 4 explains the methodology employed to filter the raw data, the formulas used to calculate the financial features of the cryptocurrencies, and the methodology applied to construct the portfolios and the factors used in the regressions' framework. Section 5 shows the results and performs some robustness checks. Section 6 concludes this work project.

2. Literature Review

To understand what a cryptocurrency is, it is important to look at the technology behind it. The blockchain, as the name indicates, adds blocks of information to a ledger,[1] using cryptography. The information contained in each block is a record of tokens' transactions.[2] Due to the encryption of digital entities and to the huge amount of computer power necessary to add a block to the chain (the process usually referred as mining), these blocks cannot be modified after creation, ensuring that the record of tokens' transactions are immutable and secure. Although not mandatory in the blockchain technology, the ledgers of cryptocurrencies are mostly public and decentralized, allowing for pseudo-anonymity and transaction transparency. These tokens are entities of the traded digital asset, the cryptocurrency per se, which is our research object.

To study any financial asset, cryptocurrencies included, it is essential to start by characterizing the most fundamental features, such as market capitalization, trading volume, returns, liquidity, and volatility. As the market matures and the number of effective and potential investors increases, the demand for financial analyses also increases, resulting in an exponential growth in the Empirical Finance literature applied to cryptocurrencies. Until 2017, most of the attention was focused on a few major cryptocurrencies, such as Bitcoin, Ethereum, Litecoin, Tether and Ripple. More recently, more and more papers consider bigger samples, embracing several cryptocurrencies and larger time periods. Those initial

[1] A very illustrative and complete video describing the process of adding blocks to the ledger can be accessed at https://www.youtube.com/watch?v=bBC-nXj3Ng4&ab_channel=3Blue1Brown
[2] On February 4, 2021, the average number of transactions per block of the Bitcoin ledger was 2154. https://tradeblock.com/bitcoin/historical/1d-f-tsize_per_avg-01101-txs_blk_avg-01071

papers argue that Bitcoin is prone to extreme volatility, has fatter positive and negative tails (Bouri et al., 2017), and that Bitcoin and other cryptocurrencies are predisposed to speculative bubbles (Cheah & Fry, 2015, Cheung et al., 2015).

These early studies raised the issue of whether cryptocurrencies were informational efficient or not. Most notably, the focus was on testing the weak form of the efficient market hypothesis (EMH) of Fama (1970), according to which the price system should contain all the relevant information on historical prices and other market-related variables, so that future prices cannot be predicted using past information. Urquhart (2016) is one of the first papers to study the weak efficiency of Bitcoin. The author uses a sample from August 1, 2010 to July 31, 2016 and applies several metrics of linear and non-liner dependence, concluding that the Bitcoin is not weakly efficient although it tends to be more efficient in the second half of the sample. This study was revisited and further developed by several authors, such as Nadarajah and Chu (2017), Bariviera (2017) and Bariviera et al. (2017). Nadarajah and Chu (2017) analyse the same dataset and conclude that, after a power transformation of returns, there was no evidence against the weak efficiency of the Bitcoin market. Bariviera (2017) and Bariviera et al. (2017) use the Hurst exponent to conclude that from 2011 to 2014 the market was inefficient, when there was a regime shifting, and that afterward the market became efficient.

More recently, due to the increasing number of new altcoins[3] with considerable market capitalization, several studies begun testing the EMH on other cryptocurrencies besides Bitcoin. Wei (2018) analyses 456 cryptocurrencies during the year of 2017, when the value of the cryptocurrencies market was skyrocketing. The author uses the Amihud illiquidity ratio (Amihud, 2002) to sort the cryptocurrencies into five groups from most to less liquid, and then applies the tests used in Urquhart (2016). Wei (2018) argues that, as more active and informed traders enter the market, liquidity increases while volatility decreases, creating less arbitrage opportunities, and hence, highly liquid cryptocurrencies tend to be more efficient. In the same line of thought, Brauneis & Mestel (2018), use 73 cryptocurrencies from August 31, 2015 to November 30, 2017, and conclude that as the liquidity of cryptocurrencies increases, they became less predictable and therefore more efficient. Zhang et al. (2020) use the Hurst exponent applied to high frequency data (1h to 12h) from February 25, 2017 to August 17, 2017 on the top 4 cryptocurrencies, and conclude, as it was the case of Bariviera (2017) for daily data, that these cryptocurrencies were efficient

[3] The term altcoins means alternative to Bitcoin, and represents all cryptocurrencies except Bitcoin.

in 2017. Al-Yahyaee et al. (2020), analyse the six cryptocurrencies with the highest market capitalization during the period August 7, 2015 to July 3, 2018, using a methodology like Bariviera (2017) and Zhang et al. (2020). They show that informational efficiency is directly linked to liquidity and that efficiency tends to increase as the market matures. Most of the aforementioned studies arrive to a similar conclusion, namely that although the cryptocurrencies market is weak-form inefficient, it tends to become more efficient as the market matures.

Another strand of the literature tries to understand what factors are priced in the cryptocurrencies market. Our paper directly addresses this issue. In the traditional financial markets, namely in the stock market, several studies have attempted to identify the main pricing factors, being the Capital Asset Pricing Model (CAPM) the most simple and well-known of such models. On this topic, the work of Eugene Fama and Kenneth R. French has been ground-breaking, and the unavoidable reference for many contributions from renowned Economists. For instance, Fama and French (1992) test for other factors than the overall market, namely, earning-price ratio (E/P), market equity (ME), book equity (BE), leverage and book-to-market ratio (BE/ME). The authors conclude that although, when individually tested, all these factors help to explain returns, when used together, the BE/ME seems to englobe the leverage and the E/P impacts. Fama and French (1993) present a 3-factor model, which includes, besides the market portfolio, a small minus big portfolio (SMB) and a high minus low portfolio (HML), which intend to measure the size and BE/ME factors. Carhart (1997) adds a new factor, momentum, drawn from the observation that, on average, high performance stock portfolios tend to continue to outperform low performance portfolios. Also, Fama and French (2015) add two new variables of interest, the operating profitability (OP), and the investment (INV). OP is defined as revenues minus the operating costs divided by book equity, and INV is defined as the change in total assets between the two previous periods. According to the authors, higher OP entails higher returns, and higher expected growth in the book equity originate a lower expected return. Hence the OP factor, robust minus weak (RMW), is constructed by the difference between portfolios of high earnings and low costs stocks, and portfolios of lower earnings or higher costs stocks, whilst the INV factor, conservative minus aggressive (CMA), is built considering the difference between portfolios of lower growth in book equity stocks, and portfolios of higher growth in book equity.

In the cryptocurrencies market, this analysis is only beginning and some of the factors designed for the stock market are not applicable. Shen et al. (2020), construct a 3-factor model for cryptocurrencies, which encompass the market factor, a SMB factor and a down minus up (DMU) factor, representing the momentum reversal. Since BE/ME is not applicable to cryptocurrencies, the size factor is constructed using the size and the momentum reversal. Shahzad et al. (2020) elaborate on this model, adding a contagion factor.

Several studies have tried to identify variables that have a significant relationship with the returns of cryptocurrencies, among these variables stand out liquidity, trading volume, volatility, and age. Kyriazis & Prassa (2019), analyse 846 cryptocurrencies from April 1, 2018 to January 31, 2019, when the market capitalization of cryptocurrencies was decreasing. They argue that during downward market movements, cryptocurrencies with higher market capitalization are also the ones with higher liquidity. The reasoning is that during bearish periods, investors in most markets tend to prefer assets with higher market capitalization and lower volatility. Brauneis et al. (2020) conclude that the cryptocurrencies market' liquidity is mostly independent from other financial markets and depends mainly on the intrinsic volatility and trading volume. Brauneis et al. (2021) explore high and low frequency data for Bitcoin and Ethereum, test different liquidity measures, and conclude that the measures that better describe the liquidity of cryptocurrencies are the Amihud illiquidity ratio (Amihud, 2002) and the Kyle and Obizhaeva estimator (Kyle and Obizhaeva, 2016).

Balcilar et al. (2017) show that trading volume can be used to predict Bitcoin returns but only when the market is performing around the median. When returns are in higher and lower percentiles, this relationship disappears. Liu et al. (2019) create several quintile portfolios using a single sort on an attribute, such as size, trading volume, volatility, and age, to produce a cross-sectional analysis of the cryptocurrencies market.

Burggraf & Rudolf (2020), using a data on 1000 cryptocurrencies from April 28, 2013 to November 1, 2019, show that higher volatility produces higher return, and conclude that the cryptocurrencies market is "more efficient than expected". Anastasiou et al. (2021) consider the top 6 cryptocurrencies in terms of market capitalization and relate them to Google trends. They conclude that, since cryptocurrencies have high volatility and periods of extreme bubbles, their prices are driven by the investors' attention to the probability of a price crash. Yin et al. (2021) approach the relationship between volatility of cryptocurrencies and oil prices, concluding that although oil prices' shocks are related to cryptocurrencies volatility, however volatility changes are mostly caused by other macroeconomic factors. The authors defend that volatility of the cryptocurrencies market is connected to uncertainty in the traditional economic world.

In a nutshell, we may conclude from all these studies, that cryptocurrencies may indeed price other factors besides the overall market, size and momentum. Amongst the candidates are liquidity, volatility, trading volume and age.

3. Data and Preliminary Analysis

Having the goal of studying the overall cryptocurrency market, we decided to use the most complete dataset possible. With this purpose, the raw dataset was retrieved from https://coinmarketcap.com, which is one of the most complete and reliable sources of financial information on cryptocurrencies. Additionally, the legitimacy of this website derives from its use by most of the studies reported in the previous section. This website uses objective criteria according to which cryptocurrencies and online exchanges must comply to be listed.[4] For the cryptocurrencies, the main criteria are: (1) Using blockchain technology as a mean of store of value, (2) having a functional website and a block explorer, and (3) being traded publicly on an exchange already listed on CoinMarketCap. For the exchanges, the criteria are more specific, being the main ones: (1) Having a functional website with information matching its API data,[5] (2) this API must follow certain guidelines, such as, having an endpoint that presents the last price and the daily volume, and (3) being in operation for at least sixty days.

The initial raw dataset, which has daily frequency, was formed by 5763 cryptocurrencies. For each cryptocurrency we retrieved the Open-High-Low-Close (OHLC) prices, the trading volume, and the market capitalization, in USD, from April 30, 2013 to December 31, 2020. Since the cryptocurrencies market trades 24/7, this raw dataset covers a period of 2803 days. Considering all the variables for all cryptocurrencies, these represents a total of 18.237.696 data points. According to CoinMarketCap, the OHLC prices are volume weight index prices and daily volumes results are the sum of the trading volume considering several listed online exchanges.

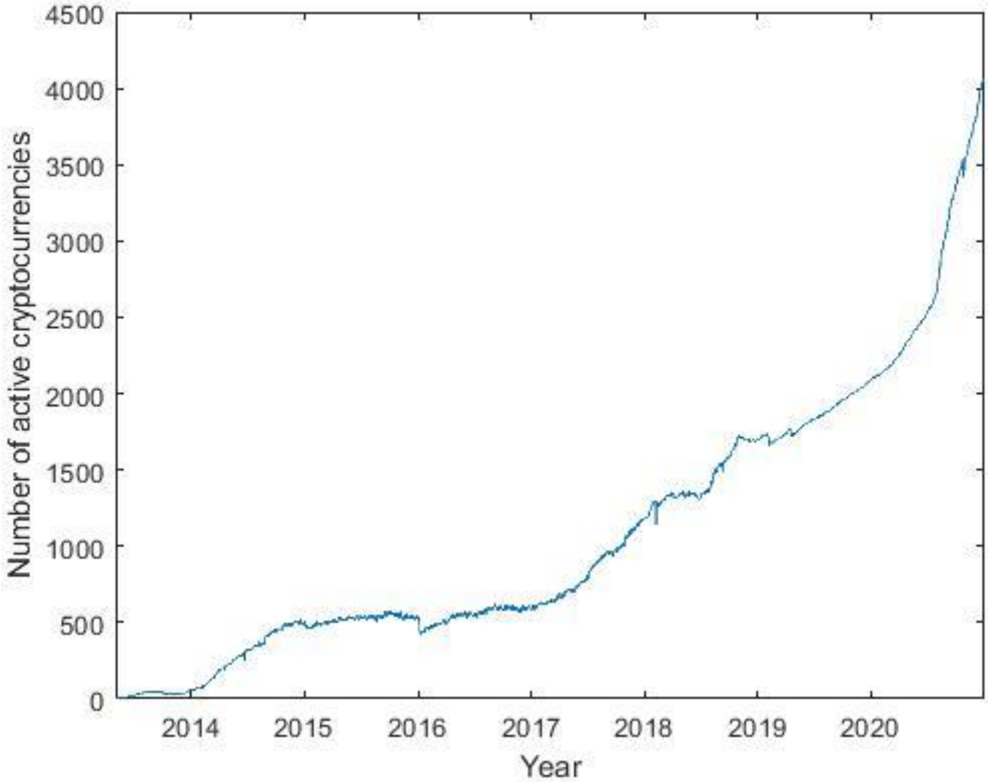
Given that we use the complete set of cryptocurrencies, it is important to mention that the data does not suffer from a survival bias, as some of the cryptocurrencies analysed

[4] The complete listings criteria can be accessed at https://support.coinmarketcap.com/hc/en-us/articles/360043659351-Listings-Criteria .
[5] API stands for Application Programming Interface.

were only present during a certain period of observations but did not reach the last day in the sample.

Figure 1 shows the number of active cryptocurrencies during the period from April 30, 2013 to December 31, 2020. The number of cryptocurrencies increased steadily from 7 in the first day to 4073 in the last day. During the overall period covered, 5763 cryptocurrencies were listed, hence 1690 cryptocurrencies ceased to exist or were removed from the CoinMarketCap listing. This represents around 30% of all cryptocurrencies, meaning that around 70% survived until December 31, 2020.

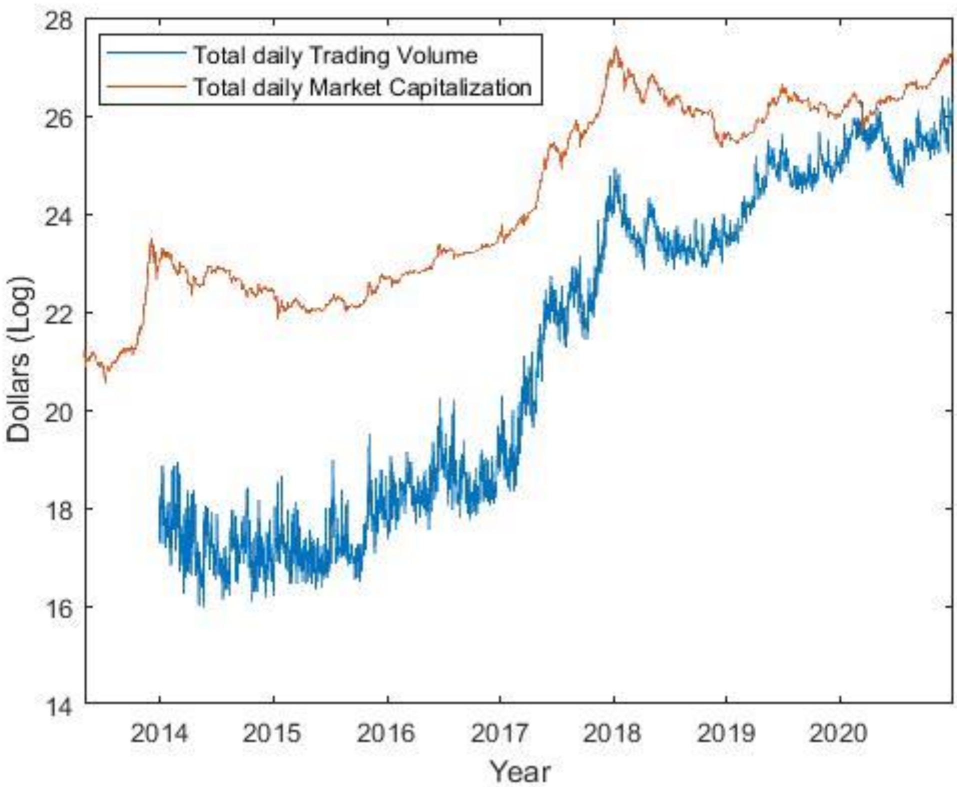
Figure 1 - Number of active cryptocurrencies



Source: Author’s own calculations.

Figure 2 presents the daily evolution of the market capitalization and trading volume of all cryptocurrencies in our database, respectively. On April 30, 2013, the market capitalization was $1.6348 billion, which rose to $15.8080 billion on December 4, 2013. The market capitalization fell during 2014, maintained stable during 2015, rose in 2016, reaching a market capitalization of $17.5580 billion on December 31, 2016. During 2017 raised steeply until it peaked on January 7, 2018 at $818.3830 billion, before falling until December 15 of that year to $101.4991 billion dollars. From there on, the market capitalization has shown a tendency to grow, although with periods of large rises and periods of abrupt falls. As of mid-January 2021, the total market capitalization is already higher than the 2017 maximum. The trading volume share the same dynamics of the market capitalization. The daily trading volume until January 2014 appears to be zero. In fact, after further investigating the raw dataset, we discovered that CoinMarketCap has not recorded any trading volume before December 27, 2013. Hence, from this point on we continue our analysis from this date onwards.[6]

Figure 2 – Total daily market capitalization and total daily trading volume



Source: Author's own calculations.

The second step in preparing the dataset was filtering the raw data. This was conducted using several filter rules:

- Some cryptocurrencies coins had days missing, probably due to communication failures between the exchanges that trades the cryptocurrencies and the CoinMarketCap website. If a particular day was missing, the gap was fulfilled by linear interpolation. We proceed in this way when there were a maximum of three

[6] However, we should notice that for computing the volatility series we use daily prices since November 29, 2013, to have thirty days of previous prices to allocate the first value of volatility series to December 27, 2013. For the age attribute, all the time frame available was used, as to best represent that feature.

days missing in a row. Larger gaps, mainly due to provisionally listing in the CoinMarketCap website, were treated as if the cryptocurrency was inexistent during that period.

- When a cryptocurrency was added to CoinMarketCap, usually the information for the first few days was not complete, having the market capitalization value missing or equal to 0. These days were ignored for these cryptocurrencies until they present information on all variables of interest.[7]

After applying these filters, we end up with 3667 cryptocurrencies, 2562 days, corresponding to 366 weeks. The weakly database was constructed using information Wednesday-to-Wednesday, until December 29, 2020, the last Wednesday of the data.

Besides data on the cryptocurrency market, we also collected data on the risk-free rate. Following the literature, and since cryptocurrencies data are expressed in USD, we collected from https://fred.stlouisfed.org/data the yield-to-maturity of 1-month US Treasury Bills.

4. Methodology

Subsection 4.1 explains the construction of the returns and other features' time series for each cryptocurrency. These other features are size, trading volume, illiquidity, volatility, momentum, and age. Subsection 4.2 explains the construction of portfolios and presents some preliminary results that where then used to construct the pricing factors. Subsection 4.3 presents the procedures used to compute the pricing factors.

4.1 Returns and other features

Since cryptocurrencies are studied in aggregated terms, i.e. using portfolios, we use discrete returns which are aggregable in the asset space. Following the convention, the close-

[7] When a cryptocurrency has clear mistakes in the market capitalization, those days are ignored for that cryptocurrency. This situation only occurred once, with the cryptocurrency Exchange Union, between June 24, 2020 and July 1, 2020, when the market capitalization is 100 times bigger than the combined market capitalization of all the other cryptocurrencies.

to-close prices are used to compute the returns of cryptocurrency i. The daily returns and the weekly returns[8] at day t are obtained respectively by:

$$R_{i,t}^{D} = \frac{P_{i,t} - P_{i,t-1}}{P_{i,t-1}} \tag{1}$$

$$R_{i,t}^{W} = \frac{P_{i,t} - P_{i,t-7}}{P_{i,t-7}} \tag{2}$$

As expected, when calculating the returns, we noticed that they present massive extreme values, with some cryptocurrencies having returns over 1,000,000% for both the daily and the weekly frequency. To winsorize the outliers but still maintaining the main features of the data, namely volatility, we use an interquartile distance to identify outliers. We consider an outlier any observation that is outside the interval of $[p_{25} - k(p_{75} - p_{25}), p_{75} + k(p_{75} - p_{25})\ ]$, where p_{25} and p_{75} are the 25th and 75th percentiles, respectively and k is a multiplier factor. We tested several multipliers $k = 1.5, 3, 4.5, 6$ and $7,$ and decided to use a factor of 6. Using this criterium, from the total of 3667 cryptocurrencies, for the daily returns, 99.75% of cryptocurrencies have less than 10% of outliers, 98.58% have less than 5% of outliers and 85.71% have less than 1% of outliers. For the weekly returns, 100% of the cryptocurrencies have less than 10% outliers, 99.81% have less than 5% of outliers, and 89.96% have less than 1% of outliers.

The size is simply proxied by the market capitalization and trading volume is the value in USD of all trades reported in a given day or week.

Illiquidity is measured by the Amihud illiquidity ratio (Amihud 2012), which assesses the price impact of $1 of trading volume. Theoretically, the ratio ranges from 0 to +∞, with 0 being most liquid, and +∞ most illiquid. For a given cryptocurrency i, the illiquidity was calculated as:

$$Illiquidity_{i,t-1} = \frac{1}{d} \sum_{\tau=t-d}^{t-1} \frac{\left|R_{i,\tau}^{D}\right|}{V_{i,\tau}} \tag{3}$$

where, d represents the number of days with trading volume used to compute the measure for period t, $R_{i,\tau}^{D}$ and $V_{i,\tau}$ are the arithmetic return and the volume traded in USD on day τ, respectively. For the daily analysis, the d used is 1, while for the weekly analysis the d used

[8] There is an exception to the use of seven days to compute the weekly returns, which may happen in the first week of trading of a given cryptocurrency if the first trading day is not a Wednesday. In that week, the return is computed using the data from the first trading day until the next Wednesday. For example, if a cryptocurrency was only listed for the first time on a Thursday, that week's return was calculated as from Thursday close price to Wednesday close price, and hence only considers 5 days.

is 7. During this analysis, we used the method mentioned by Amihud (2012) in which the days with no volume should not be considered.

The volatility is measured using the Parkinson estimator, which only considers the highest and lowest prices per day. Other volatility range estimators, such as the Garman and Klass estimator, also use the daily open and close prices, but since the cryptocurrencies market is open 24/7, these open and close prices are completely artificial. The close price just represents the last price before midnight and the open price, the first price after midnight.

The Parkinson volatility is defined as:

$$\sigma_{i,t-1} = \sqrt{\frac{1}{4\ d\ ln2}\sum_{\tau=t-d}^{t-1}\left(ln\frac{H_{i,\tau}}{L_{i,\tau}}\right)^2} \tag{4}$$

where d represents the number of days used to compute the estimator at day t , $H_{i,\tau}$ and $L_{i,\tau}$ represent the highest and the lowest price of cryptocurrency i at day τ, respectively. For the daily volatility, we used $d = 1$ for weekly volatility we use only $d = 7$, so that in the case of weekly frequency the volatility estimator represents the volatility of the specific week.

For the momentum measure, we followed Shahzad et al. (2020) and Shen et al. (2020), who use data with daily, and weekly frequency respectively, and conclude that, independently of the data frequency, the best strategy, i.e., the one where the returns of the portfolios formed have a higher t-statistic, results from forming buy-sell portfolios based on the previous returns observation for a one-time holding period. This means constructing the portfolios at time $t - d$, based on the returns of the cryptocurrencies from $t - 2d$ to $t - d$, and holding it until t. The d used was 1 and 7, respectively for the daily and weekly frequencies, which translates into the following formulas:

$$Momentum_{i,t}^{D} = R_{i,t-1}^{D} \tag{5}$$

$$Momentum_{i,t}^{W} = R_{i,t-7}^{W} \tag{6}$$

where, $R_{i,t-1}^{D}$ is daily the return of cryptocurrency i in $t - 1$, and $R_{i,t-7}^{W}$ is weekly the return of cryptocurrency i in $t - 7$.

For measuring age of a given cryptocurrency we considered the number of days or number of weeks with valid data since its launching until day t, for the daily and weekly analyses, respectively. To compute this measure, we use all the data available since April 30, 2013. On April 30, 2013 only seven cryptocurrencies were listed, hence for all other cryptocurrencies there is no measurement error.

4.2 Portfolios

Before we proceed with the double-sort portfolios usually used in this type of analysis, we first analysed the returns of each group of quintile value-weighted portfolios sorted according to a unique feature. There are 6 features: size (market capitalization), trading volume, Illiquidity, measured by the Amihud illiquidity ratio, volatility, measured by the Parkinson estimator, momentum, and age. Hence, we have 6 sets of quintile portfolios for which we compute the daily and weekly returns. These portfolios are constructed on $t - d$ and kept until t. The d used is 1 and 7, respectively for the daily and weekly frequencies. This analysis allows us to see if there is any pattern in the returns according to a particular feature, hence, to get a first glance on the importance of the resulting pricing factor and on the way that portfolios should be combined to compute these factors.

The daily and weekly returns of portfolios sorted on size are Table A.1 of the appendix. For both the daily and the weekly returns we notice a pattern, with smaller quintiles portfolios having larger returns. Hence the size factor should be constructed by Small portfolio minus Big portfolio.

The daily and weekly returns of portfolios sorted on trading volume are Table A.2 of the appendix. For the daily returns, portfolios with higher transactions volume have higher returns. On the contrary, for the weekly returns, the pattern is that smaller trading volume have higher returns than the ones with higher trading volume. Considering the daily analysis, the volume factor should be constructed as High volume portfolio minus Low volume portfolio.

The daily and weekly returns of portfolios sorted on the Amihud illiquidity ratio are Table A.3 of the appendix. As expected, considering the results presented in Wei (2018) and Kyriazis & Prassa (2019), the cryptocurrencies with lower liquidity offered the highest returns for the weekly analysis, hence the liquidity factor should be constructed by Illiquid portfolio minus Liquid portfolio.

The daily and weekly returns of portfolios sorted on the Parkinson volatility estimator are Table A.4 of the appendix. For the daily returns, it appears that Stable portfolios offer higher returns that Volatile portfolios. For the weekly analysis, the relationship between returns and volatility appears as Volatile portfolios have higher returns than Stable portfolios, hence the volatility factor is constructed by Volatile portfolio minus Stable portfolio.

The daily and weekly returns of portfolios sorted on momentum are Table A.5 of the appendix. We observe that the portfolios with the higher momentum (Up) were the ones with lower returns, while the portfolios with the lower momentum (Down) were the ones with higher returns. This confirms the results from the literature (see Shahzad et al.,2020, Shen et al., 2020), that, contrary to the stock market where we observe a momentum dynamic, in the cryptocurrencies market we observed a reversal dynamic. Hence the "momentum" factor is constructed by the Down portfolio minus the Up portfolio.

The daily and weekly returns of portfolios sorted on age are Table A.6 of the appendix. Older cryptocurrencies have higher returns than younger cryptocurrencies, hence there is the indication that the age factor should be formed by the Older portfolio minus the Younger portfolio.

In other to form double-sort portfolios of cryptocurrencies we use a sequential procedure. This procedure is the following: (1) At each $t - d$, with $d = 1, 7$, all cryptocurrencies are sorted based on the market capitalization (i.e., size) at $t - d$ and are grouped into quintiles, (2) within each quintile, cryptocurrencies are then sorted by the second feature that we intend to study and once again clustered into quintiles, (3) we then form value-weighted portfolios, using market capitalization as the weighting scheme; and compute their returns from $t - d$ to t, which are then used to compute the excess returns in relation to the risk-free rate (1-month US Treasury-bill). Hence according to each pair size/other feature we obtain 25 value-weighted portfolios. This approach is slightly different from Fama and French (1993, 2012, 2015), that form the 25 value-weighted portfolios by intersecting quintiles from a sort on size (market capitalization), with the quintiles from an independent sort on the second feature. The main difference is that this second approach gives portfolios with a variable number of cryptocurrencies, whilst our procedure produces 25 portfolios with the same number of cryptocurrencies. Other approach, such as the one used by Carhart (1997), is to construct equally weighted portfolios. Later we will conduct several robustness checks to see if our results are robust to the sorting procedure and to the weighting scheme of the portfolios.

For each pair size /other feature we obtained 25 portfolios with the same cardinality (except the last quintile portfolios which include the remaining cryptocurrencies, once the total number is not a multiple of 5). Because we consider initially 5 potential factors (liquidity, volatility, momentum, volume, and age) we end up with 125 portfolios, updated at each time $t-1$. The daily excess returns and weekly excess returns of these portfolios are presented in Table 1 and Table 2, respectively.

For the daily returns, we observed that most of the portfolios have significance at the 1% level. The portfolios with lower momentum, higher trading volume, and higher age have higher excess returns. The relationships in the portfolios sorted by liquidity and volatility are not apparent. For the weekly portfolios, the majority of our 125 portfolios have a significance at the 1% level, and portfolios with cryptocurrencies of small, high illiquidity and high volatility have higher excess returns. For the momentum reversal and the trading volume, we found that portfolios with down momentum, low trading volume offer higher excess returns. For the age, and agreeing with the information on a single sort on age portfolios, this sequential double-sort indicates that portfolios of smaller and older cryptocurrencies have higher returns. From all the different portfolios, we also concluded that portfolios with smaller size offer higher excess returns.

Table 1 – Daily excess returns of sequential double sorted value-weighted portfolios

			Size and volume			
	High - 1	**2**	**3**	**4**	**Low - 5**	**H - L**
Big - 1	0.0019**	0.0009	0.0001	-0.0014	-0.0052**	0.0070***
2	-0.0013	0.0021**	0.0007	0.0013	-0.0037***	0.0024*
3	0.0028**	0.0058***	0.0058***	0.0051***	0.0019	0.0009
4	0.0086***	0.0120***	0.0147***	0.0158***	0.0094***	-0.0007
Small - 5	0.0313***	0.0317***	0.0288***	0.0269***	0.0250***	0.0063***
S - B	0.0294***	0.0308***	0.0287***	0.0282***	0.0302***	
			Size and illiquidity			
	Illiquid - 1	**2**	**3**	**4**	**Liquid - 5**	**I - L**
Big - 1	-0.0084***	0.0005	0.0014	0.0010	0.0019**	-0.0103***
2	-0.0061***	0.0016	0.0011	0.0023**	-0.0007	-0.0055***
3	0.0001	0.0071***	0.0062***	0.0068***	0.0023**	-0.0022
4	0.0131***	0.0137***	0.0139***	0.0132***	0.0065***	0.0067***
Small - 5	0.0359***	0.0340***	0.0346***	0.0298***	0.0193***	0.0166***
S - B	0.0443***	0.0336***	0.0332***	0.0288***	0.0174***	
			Size and volatility			
	Volatile - 1	**2**	**3**	**4**	**Stable - 5**	**V - S**
Big - 1	-0.0067 ***	0.0019	0.0016	0.0012	0.0015 **	-0.0082 ***
2	-0.0092 ***	0.0029 **	0.0030 ***	0.0014	-0.0001	-0.0091 ***
3	0.0025	0.0090 ***	0.0062 ***	0.0043 ***	0.0008	0.0017
4	0.0208 ***	0.0162 ***	0.0114 ***	0.0071 ***	0.0053 ***	0.0155 ***
Small - 5	0.0680 ***	0.0304 ***	0.0181 ***	0.0149 ***	0.0167 ***	0.0512 ***
S - B	0.0746 ***	0.0285 ***	0.0164 ***	0.0137 ***	0.0152 ***	
			Size and momentum			
	Down - 1	**2**	**3**	**4**	**Up - 5**	**D - U**
Big - 1	0.0045***	-0.0005	0.0012	0.0035***	-0.0040***	0.0085***
2	0.0329***	0.0049***	0.0000	-0.0027***	-0.0324***	0.0653***
3	0.0610***	0.0090***	0.0020**	-0.0006	-0.0443***	0.1053***
4	0.0915***	0.0154***	0.0072***	0.0028**	-0.0506***	0.1420***
Small - 5	0.1379***	0.0263***	0.0156***	0.0186***	-0.0376***	0.1754***
S - B	0.1334***	0.0267***	0.0144***	0.0151***	-0.0336***	
			Size and age			
	Old - 1	**2**	**3**	**4**	**Young - 5**	**O – Y**
Big - 1	0.0019**	0.0009	0.0007	0.0003	-0.0033**	0.0052***
2	0.0022**	0.0005	-0.0011	-0.0010	-0.0012	0.0034***
3	0.0090***	0.0080***	0.0030**	0.0014	0.0009	0.0081***
4	0.0144***	0.0156***	0.0111***	0.0082***	0.0104***	0.0040***
Small - 5	0.0307***	0.0286***	0.0297***	0.0243***	0.0308***	-0.0001
S - B	0.0288***	0.0277***	0.0290***	0.0240***	0.0341***	

Notes: In each day $t-1$, all active cryptocurrencies were sorted into quintiles by daily size (market capitalization) and then, within these quintes were sorted, by the second feature. The excess returns of day t were computed using the yield-to-maturity of the 1-month US Treasury Bills. The portfolios are updated in a daily basis. For each of the 25 portfolios there are 2561 daily observations, from December 28, 2013 to December 31, 2020. The last column is obtained by subtracting in each day the portfolios in column 5 from the column 1 (or the reverse). Line S-B is obtained by subtracting in each day the line Big from the line Small. ***, **, * indicates significance at the 1%, 5 % and 10% level, respectively.
Source: Author's own calculation.

Table 2 – Weekly excess returns of sequential double sorted value-weighted portfolios

Size and volume						
	High - 1	**2**	**3**	**4**	**Low - 5**	**H - L**
Big - 1	0.0130**	0.0084	0.0054	0.0075	0.0213	-0.0085
2	0.0065	0.0134*	0.0186**	0.0143*	0.0340***	-0.0276***
3	0.0141	0.0245***	0.0255***	0.0348***	0.0582***	-0.0442***
4	0.0260**	0.0470***	0.0531***	0.0644***	0.0680***	-0.0421***
Small - 5	0.0542***	0.0873***	0.0919***	0.1219***	0.1265***	-0.0725***
S - B	0.0410***	0.0788***	0.0864***	0.1143***	0.1051***	
Size and illiquidity						
	Illiquid - 1	**2**	**3**	**4**	**Liquid - 5**	**I - L**
Big - 1	0.0152	0.0034	0.0136	-0.0019	0.0132**	0.0019
2	0.0303***	0.0172**	0.0155**	0.0121*	0.0108	0.0193**
3	0.0733***	0.0277***	0.0217***	0.0233***	0.0151*	0.0580***
4	0.1007***	0.0573***	0.0401***	0.0464***	0.0210**	0.0795***
Small - 5	0.1529***	0.1149***	0.0888***	0.0877***	0.0476***	0.1051***
S - B	0.1375***	0.1113***	0.0750***	0.0895***	0.0343***	
Size and Volatility						
	Volatile - 1	**2**	**3**	**4**	**Stable - 5**	**V - S**
Big - 1	-0.0057	-0.0001	0.0008	0.0118	0.0137**	-0.0196
2	0.0163*	0.0128	0.0209**	0.0165**	0.0150**	0.0012
3	0.0470***	0.0303***	0.0342***	0.0221***	0.0212***	0.0256***
4	0.0921***	0.0472***	0.0498***	0.0398***	0.0303***	0.0617***
Small - 5	0.1437***	0.1161***	0.0778***	0.0708***	0.0587***	0.0849***
S - B	0.1492***	0.1161***	0.0768***	0.0588***	0.0448***	
Size and momentum						
	Down - 1	**2**	**3**	**4**	**Up - 5**	**D - U**
Big - 1	0.0041	0.0033	0.0111*	0.0176**	0.0151	-0.0111
2	0.0738***	0.0131*	0.0089	0.0077	-0.0180**	0.0916***
3	0.1187***	0.0313***	0.0243***	0.0222***	-0.0354***	0.1540***
4	0.1882***	0.0552***	0.0365***	0.0301***	-0.0466***	0.2346***
Small - 5	0.3120***	0.0926***	0.0590***	0.0540***	-0.0324***	0.3443***
S - B	0.3078***	0.0891***	0.0477***	0.0362***	-0.0476***	
Size and age						
	Old - 1	**2**	**3**	**4**	**Young - 5**	**O – Y**
Big - 1	0.0129**	0.0098	0.0097	0.0125	-0.0022	0.0150*
2	0.0181**	0.0238***	0.0116	0.0158**	0.0145	0.0034
3	0.0277***	0.0418***	0.0330***	0.0274***	0.0224**	0.0051
4	0.0519***	0.0565***	0.0453***	0.0442***	0.0523***	-0.0006
Small - 5	0.0850***	0.0895***	0.0975***	0.0767***	0.1052***	-0.0203
S - B	0.0719***	0.0796***	0.0876***	0.0640***	0.1072***	

Notes: In each week $t - 1$, all active cryptocurrencies were sorted into quintiles by weekly size (market capitalization) and then, within these quintes were sorted, by the second feature. The excess returns of week t were computed using the yield-to-maturity of the 1-month US Treasury Bills. The portfolios are updated in a weekly basis. For each of the 25 portfolios there are 365 weekly observations, from January 1, 2014 to December 29, 2020. The last column is obtained by subtracting in each day the portfolios in column 5 from the column 1 (or the reverse). Line S-B is obtained by subtracting in each day the line Big from the line Small. ***, **, * indicates significance at the 1%, 5 % and 10% level, respectively.
Source: Author's own calculation.

4.3 Pricing Factors

The pricing factors are built on the previous portfolios, conditional on the pair size/other feature. For the market factor, like in CAPM, we consider two candidates: the value-weighted market index using all the cryptocurrencies in our final database and the Bitcoin index using only the returns of Bitcoin, denoted by *BKT*. The total market index (MKT) is defined as:

$$MKT_t = \sum_{i=1}^{N} \frac{MarketCap_{it} \times R_{it}}{\sum_{i=1}^{N} MarketCap_{it}} \tag{7}$$

where R_{it} is the return on the cryptocurrency i on time t, $MarketCap_{it}$ is the market capitalization of cryptocurrency i on time t, and $\sum_{i=1}^{N} MarketCap_{it}$ is the overall market capitalizations in t.

Since cryptocurrencies do not have a book equity, used by Fama and French (2015) to construct the size factor, we follow the approach suggested by Shen et al. (2020), and use the momentum as the second sort. From these two independent sorts, and similar to Fama and French (2015), we divide the size sort by the percentile $[0\%, 10\%]$ (Small) and the percentile $[90\%, 100\%]$ (Big), and the momentum sort by the percentile [0%, 30%] (Low momentum, denoted by Down), the percentile $[30\%, 70\%]$ (Medium momentum) and the percentile $[70\%, 100\%]$ (Higher momentum, denoted by Up). After, we intersect the size momentum partitions, creating six value-weighted portfolios, respectively, SD, SM, SU, BS, BM and BU.

From the evidence presented in Table 1 and Table 2, Small portfolios offer higher returns than Higher portfolios, hence the size factor is defined as Small minus Big (SMB):

$$SMB_t = \frac{SD_t + SM_t + SU_t}{3} - \frac{BD_t + BM_t + BU_t}{3} \tag{8}$$

For the remaining factors, we proceeded in the same way but dropping the medium interval on the second feature. Our factors, were, respectively, Down momentum minus Up momentum (DMU), Illiquid minus Liquid (IML), Volatile minus Stable (VMS) and Low Volume minus High Volume (LMH), and Young minus Old (YMO). That is:

$$LMH_t = \frac{BL_t + SL_t}{2} - \frac{BH_t + SH_t}{2} \tag{9}$$

$$IML_t = \frac{BI_t + SI_t}{2} - \frac{BL_t + SL_t}{2} \tag{10}$$

$$VMS_t = \frac{BV_t + SV_t}{2} - \frac{BS_t + SS_t}{2} \tag{11}$$

$$DMU_t = \frac{BD_t + SD_t}{2} - \frac{BU_t + SU_t}{2} \quad (12)$$

$$YMO_t = \frac{BY_t + SY_t}{2} - \frac{BO_t + SO_t}{2} \quad (13)$$

Tables 3 present the summary statistics and Table 4 presents the correlation matrices for the daily and weekly factors.

Table 3 – Summary statistics for the pricing factors

	MKT	BKT	SMB	LMH	IML	VMS	DMU	YMO
DAILY								
Mean	0.0035	0.0022	0.0416	0.0131	0.0068	0.0147	0.0650	0.0064
Median	0.0394	0.0379	0.0681	0.1330	0.1524	0.0980	0.0868	0.0934
Skewness	0.4103	0.0072	-0.3567	0.6156	-1.5899	1.8784	-0.3456	-0.2378
Kurtosis	13.5719	7.8919	20.8050	27.7280	50.2764	26.5487	17.6942	20.6507
WEEKLY								
	MKT	**BKT**	**SMB**	**LMH**	**IML**	**VMS**	**DMU**	**YMO**
Mean	0.0200	0.0150	0.1072	0.0684	0.0857	0.0066	0.1194	0.0212
Median	0.1096	0.1044	0.1640	0.3263	0.2825	0.3240	0.1836	0.1952
Skewness	0.6813	0.6022	1.0416	-2.3169	1.6513	-6.2643	0.2883	-0.1645
Kurtosis	5.7319	4.9434	6.7478	31.5803	17.2408	99.5570	8.1517	8.0839

Notes: MKT – Market index, BKT – Bitcoin index, SMB – Size factor, LMH –Volume factor, IML – Liquidity factor, VMS – Volatility factor, DMU – Momentum reversal factor, YMO – Age factor. The daily statistics use 2561 days from December 28, 2013 to December 31, 2020. The weekly statistics use 365 weeks, from January 1, 2014 to December 29, 2020.
Source: Author's own calculation.

The most important inference that we can withdraw from these tables is that the factors LMH and VMS are highly correlated both in daily and weekly periodicities with the IML. Also, the factor VMS is highly correlated with the YMO factor. Because most of the literature points out the importance of liquidity, we resolve to estimate the pricing models without LMH and VMS.

Table 4 – Correlation matrices for the pricing factors

				DAILY				
	MKT	**BKT**	**SMB**	**DMU**	**IML**	**VMS**	**LMH**	**YMO**
MKT	1.0000							
BKT	0.9152	1.0000						
SMB	-0.1147	-0.0223	1.0000					
DMU	0.0040	-0.0078	0.1504	1.0000				
IML	0.0503	-0.0205	-0.0051	-0.0050	1.0000			
VMS	0.1443	0.0193	-0.0549	0.0272	0.3719	1.0000		
LMH	0.0525	-0.0292	0.0137	-0.0120	0.4394	0.2066	1.0000	
YMO	0.0406	-0.0400	-0.0494	-0.0395	0.1314	0.2854	0.0680	1.0000
				WEEKLY				
	MKT	**BKT**	**SMB**	**DMU**	**IML**	**VMS**	**LMH**	**YMO**
MKT	1.0000							
BKT	0.8957	1.0000						
SMB	-0.1274	-0.0357	1.0000					
DMU	-0.0187	0.0373	0.2862	1.0000				
IML	0.0758	-0.0562	0.0690	-0.0072	1.0000			
VMS	0.0037	-0.1149	-0.2308	-0.2483	0.2357	1.0000		
LMH	-0.1490	-0.1800	0.1294	-0.0243	0.4542	0.0546	1.0000	
YMO	-0.0129	-0.1799	0.0268	-0.0556	0.2646	0.3222	0.0677	1.0000

Notes: MKT – Market index, BKT – Bitcoin index, SMB – Size factor, DMU – Momentum reversal factor, IML – Liquidity factor, VMS – Volatility factor, LMH –Volume factor, YMO – Age factor. The daily correlations use 2561 days from December 28, 2013 to December 31, 2020. The weekly correlations use 365 weeks, from January 1, 2014 to December 29, 2020.
Source: Author's own calculation.

5. Empirical Results

Section 5.1 presents the 1-factor (CAPM), 3-factor and 5-factor models and summarizes the main results. Section 5.2 presents some robustness checks on the methodology used, namely on the construction of portfolios and pricing factors.

5.1 Factor models

With all the variables defined and all the portfolios and factors constructed, we are in conditions to estimate the factor models. These models are estimated using Ordinary Least Square (OLS) regressions on each of the 125 portfolios. The daily regressions were done for

2561 days, from December 28, 2013 to December 31, 2020, while the weekly regressions were done for 365 weeks, from January 1, 2014, to December 29, 2020.

The first model only considers the market factor, RM, similar to CAPM, which is proxied by the value-weighted market index, MKT, or by the Bitcoin index, BKT.

$$R_{i,t} - Rf_t = \alpha + \beta(RM_t - Rf_t) + e_t \tag{14}$$

where $R_{i,t}$, Rf_t and RM_t are the return of portfolio i in t, the risk-free interest rate, and MKT_t is the market return at time t, respectively.

As in Fama and French (2012), we defined the Sharpe Ratio as:

$$SR(a) = (a'S^{-1}a)^{\frac{1}{2}} \tag{15}$$

where a is the column vector of the intercepts of the 125 regressions and S is the covariance matrix of the errors e_t.

The results in Table A.7 show that the market portfolio MKT is better than the Bitcoin index BKT, once it provides, for daily and weekly regressions, a lower average absolute interception, a lower average standard error and a higher R^2. For this reason, the remaining regressions use MKT as the proxy for the overall market.

For the 3-factor model, we followed Shen et al. (2020) and defined it as:

$$R_t - Rf_t = \alpha + \beta_1(MKT_t - Rf_t) + \beta_2 SMB_t + \beta_3 DMU_t + e_t \tag{16}$$

where SMB and DMU are respectively the size and momentum factors previously defined. The more encompassing model is the 5-factors model, defined as:

$$R_t - Rf_t = \alpha + \beta_1(MKT_t - Rf_t) + \beta_2 SMB_t + \beta_3 IML_t + \beta_4 DMU_t + \beta_5 YMO + e_t \tag{17}$$

where IML and YMO are the illiquidity and age factors, respectively.

Table 5 presents a summary on the average statistics for the daily and weekly regressions on the CAPM, 3-factor, and 5-factor models. This table highlights that we concluded that the 5-factor model improves on the CAPM and on the 3-factor model for both frequencies. The average absolute intercept decreases and the GRS statistic on the null hypothesis that the intercepts are jointly equal to zero (Gibbons et al., 1989), although still significant at the 1% level, decrease substantially. The average standard error of the intercepts decreases and the adjusted R^2 increases. Notice however, that although these additional factors are important in explaining the returns of cryptocurrencies, the market factor is undoubtedly the most important one.

Table 5 – Summary statistics from regressions on CAPM, 3-factor and 5-factor models

	|a|	R^2	s(a)	SR(a)	GRS
DAILY REGRESSIONS					
	|a|	$\boldsymbol{R^2}$	**s(a)**	**SR(a)**	**GRS**
CAPM	0.0120	0.3237	0.0011	1.0326	142.1106 ***
3-factor	0.0084	0.3436	0.0014	0.7695	52.1884 ***
5-factor	0.0083	0.3505	0.0014	0.7610	51.1218 ***
WEEKLY REGRESSIONS					
	|a|	$\boldsymbol{R^2}$	**s(a)**	**SR(a)**	**GRS**
CAPM	0.0319	0.3432	0.0076	1.0521	15.1242***
3-factor	0.0214	0.4074	0.0093	0.9181	7.0763***
5-factor	0.0204	0.4170	0.0094	0.7663	5.0777***

Notes: This table presents the summary statistics from daily and weekly regressions on CAPM, 3-factor and 5-factor models. Each column corresponds to the averaged statistics for the regressions on 125 sequential double-sort value-weighted portfolios. |a| is the average absolute intercept, R^2 is the average adjusted R^2, s(a) is the average standard error of the intercepts. SR(a) is the Sharpe Ratio computed according to Equation (13). GRS are the statistics on the null hypothesis that all the intercepts for a set of regressions are jointly zero (Gibbons et al., 1989). The significance at the 1%, 5% and 10% are denoted by ***, **, *, respectively. The daily regressions were done for 2561 days, from December 28, 2013 to December 31, 2020. The weekly regressions were done 365 weeks, from January 1, 2014 to December 29, 2020.
Source: Author's own calculation

5.2 Robustness

The results presented in the previous subsection may be sensitive to the way that portfolios and factors are constructed, hence here we conduct several robustness checks on the CAPM, 3-factor and 5-factor models. (1) We use the same sequential double-sort methodology but instead of using value-weighted portfolios when grouping the cryptocurrencies, we consider equally-weight portfolios. (2) We create for each pair size / another feature, portfolios resulting not from a sequential double-sort, but using instead the Fama and French (1993, 2012, 2015) procedure, that is, create portfolios by intersecting the independent sort on size with an independent sort on another feature. From these intersections we formed both (2.1) value-weighted and (2.2) equally weighted portfolios. (3) We constructed the factors with the same methodology mentioned previously, but we changed the partition points for size. On the previous factors we used the percentile $[0\%, 10\%]$ as small size cryptocurrencies and the interval $[90\%, 100\%]$ as big size cryptocurrencies. Here we use the percentiles [0%, 50%] and [50%, 100%], that is the median to divide the cryptocurrencies into Small and Big. The breakpoints on the second feature are the same as before using the intervals $[0\%, 30\%]$, $[30\%, 70\%]$ and $[70\%, 100\%]$. Using these factors, we estimate the 3 models for the following portfolios: (3.1) sequential double-sort value-weighted, (3.2) sequential double-sort equally weighted, (3.3) double-sort intersection value-weighted, and (3.4) double-sort intersection equally weighted.

The results of robustness check (1) and (2), in Table A.9, and the results of robustness check (3), in Table A.10, are like the ones of the baseline models, implying that our previous results and inferences are robust to the procedure used to construct the portfolios and pricing factors. These results also reinforce the claim that adding the liquidity and the age as pricing factors improves the 3-factor model from Shen et al. (2020) and, in fact, this is especially true when using the median as the partition point for the size factor.

6. Conclusion

This study explores several pricing factors of the cryptocurrencies market, for the period from December 27, 2013 to December 31, 2020, using both daily and weekly frequencies. The methodology is similar to the one used in the stock market by Fama and French (1993, 2012, 2015), with some nuances on the portfolio and factor constructions. Noticeably, our baseline approach, contrary to Fama and French (2015) and Shen et al. (2020), who produce the value-weighted portfolios by intersecting two independent sorts, is a sequential double-sort procedure that produces portfolios with the same cardinality. However, our main results are not sensitive to the way that portfolios or even pricing factors are constructed.

We were able to identify 7 pricing factors: The market, size, trading volume, illiquidity, volatility, reversal, and age. Clearly the returns of cryptocurrencies are directly related to the evolution of the overall market, the most important pricing factor. However, there is compelling evidence that cryptocurrencies with lower market capitalization (small size), less traded, more illiquid, volatile, with higher momentum reversals present higher returns. Also, there is weak evidence that younger cryptocurrencies present higher returns. This is so in a daily basis, but even more for weekly horizons.

Our 5-factor pricing model enters into account with the market portfolio, size (Small minus Big - SMB), illiquidity (Illiquid minus Liquid - IML), momentum reversal (Down minus Up - DMU), and age (Younger minus Older (YMO). The inclusion of illiquidity and age improves the results in relation to the 3-factor model of Shen et al. (2020).

Although we have excluded from our pricing model the volatility and volume factors, due to multicollinearity concerns, additional analysis is needed, namely by running competing models to see if these factors are more or less important than illiquidity. Also, we should highlight that we are only dealing with native factors of the cryptocurrency market, i.e., factors that use the information intrinsic to this market, other external factors such the investor's attention, proxied for instance, by Google searches may be important as it seems to be the case for Bitcoin (see, for instance, Kristoufek, 2015, Dastgir et al., 2019).

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Appendix

Table A.1 – Returns from portfolios sorted on size (market capitalization)

Daily returns					
Quintiles	**Big – 1**	**2**	**3**	**4**	**Small – 5**
Mean	0,0017	-0,0002	0,0044	0,0120	0,0288
Median	0,0017	0,0009	0,0052	0,0111	0,0248
Minimum	-0,2323	-0,3460	-0,3124	-0,2930	-0,2433
Maximum	0,1988	0,2739	0,2279	0,2576	0,3560
Std deviation	0,0377	0,0436	0,0445	0,0457	0,0514
Skewness	-0,3744	-0,4246	-0,4067	-0,1906	0,3310
Kurtosis	7,9894	8,4611	7,5915	6,1874	5,7416
Weekly returns					
Quintiles	**Big – 1**	**2**	**3**	**4**	**Small – 5**
Mean	0,0130	0,0167	0,0308	0,0506	0,0914
Median	0,0072	0,0181	0,0295	0,0423	0,0842
Minimum	-0,3349	-0,3866	-0,3787	-0,3932	-0,3826
Maximum	0,4323	0,7989	0,7554	0,8814	1,0667
Std deviation	0,1039	0,1333	0,1368	0,1418	0,1496
Skewness	0,2983	0,8883	0,9101	0,8935	0,9557
Kurtosis	4,8661	8,0002	7,5898	7,2992	8,2765

Notes: This table presents the summary statistics for the daily and weekly returns of value-weighted quintiles portfolios. Each day/week, all cryptocurrencies were sorted by market capitalization and partitioned into quintiles. From each quintile we calculated a value-weighted portfolio. For each of the five portfolios obtained daily, we get 2561 entries of data, from December 28, 2013 to December 31, 2020. For each of the five portfolios obtained weekly, we get 365 entries of data, from January 1, 2014 to December 29, 2020.
Source: Author's own calculation.

Table A.2 – Returns from portfolios sorted on trading volume

Daily returns					
Quintiles	**High – 1**	**2**	**3**	**4**	**Low – 5**
Mean	0,0018	-0,0014	-0,0051	-0,0015	-0,0042
Median	0,0018	0,0005	-0,0024	-0,0034	-0,0058
Minimum	-0,2318	-0,3566	-0,9620	-0,8580	-0,8415
Maximum	0,1989	0,4118	0,3491	2,4152	2,4847
Std deviation	0,0376	0,0500	0,0687	0,1135	0,1407
Skewness	-0,3706	-0,3962	-3,0772	6,2326	8,0239
Kurtosis	8,0268	9,6964	38,8682	124,0821	126,2050
Weekly returns					
Quintiles	**High – 1**	**2**	**3**	**4**	**Low – 5**
Mean	0,0127	0,0043	0,0146	0,0618	0,0675
Median	0,0071	0,0094	0,0121	0,0234	0,0223
Minimum	-0,3479	-0,5319	-0,4486	-0,7868	-0,6029
Maximum	0,4327	0,7009	0,8059	3,5575	3,3379
Std deviation	0,1038	0,1372	0,1431	0,3160	0,2937
Skewness	0,2918	0,4934	0,8538	5,3676	4,5441
Kurtosis	4,9398	7,2788	7,7443	51,7437	45,8959

Notes: This table presents the summary statistics for the daily and weekly returns of value-weighted quintiles portfolios. Each day/week, all cryptocurrencies were sorted by trading volume and partitioned into quintiles. From each quintile we calculated a value-weighted portfolio. For each of the five portfolios obtained daily, we got 2561 entries of data, from December 28, 2013 to December 31, 2020. For each of the five portfolios obtained weekly, we got 365 entries of data, from January 1, 2014 to December 29, 2020.
Source: Author's own calculation.

Table A.3 – Returns from portfolios sorted on Amihud Illiquidity ratio

Daily returns					
Quintiles	**Illiquid – 1**	**2**	**3**	**4**	**Liquid – 5**
Mean	-0,0118	-0,0091	-0,0036	-0,0015	0,0018
Median	-0,0155	-0,0066	-0,0021	0,0010	0,0019
Minimum	-0,9968	-0,8957	-0,6556	-0,5577	-0,2309
Maximum	2,5257	1,6790	0,4499	0,4278	0,1988
Std deviation	0,1759	0,1008	0,0673	0,0558	0,0376
Skewness	6,0627	2,2421	-0,5436	-0,9641	-0,3704
Kurtosis	85,5799	53,3369	13,1136	14,7265	8,0230
Weekly returns					
Quintiles	**Illiquid – 1**	**2**	**3**	**4**	**Liquid – 5**
Mean	0,0915	0,0327	0,0066	0,0018	0,0128
Median	0,0339	0,0207	-0,0016	0,0067	0,0071
Minimum	-0,8417	-0,6671	-0,7203	-0,5518	-0,3478
Maximum	3,6363	1,3093	0,8428	0,7181	0,4322
Std deviation	0,3902	0,2161	0,1686	0,1322	0,1039
Skewness	5,3576	1,5431	0,8388	0,2405	0,2961
Kurtosis	44,6280	10,2714	8,2853	7,6092	4,9373

Notes: This table presents the summary statistics for the daily and weekly returns of value-weighted quintiles portfolios. Each day/week, all cryptocurrencies were sorted by the Amihud illiquidity ratio and partitioned into quintiles. From each quintile we calculated a value-weighted portfolio. For each of the five portfolios obtained daily, we got 2561 entries of data, from December 28, 2013 to December 31, 2020. For each of the five portfolios obtained weekly, we got 365 entries of data, from January 1, 2014 to December 29, 2020.
Source: Author’s own calculation.

Table A.4 – Returns from portfolios sorted on Parkinson volatility estimator

Daily returns					
Quintiles	**Volatile – 1**	**2**	**3**	**4**	**Stable – 5**
Mean	-0.0193	0.0011	0.0014	0.0013	0.0015
Median	-0.0191	-0.0004	0.0004	0.0003	0.0015
Minimum	-0.9735	-0.3917	-0.4192	-0.3063	-0.2087
Maximum	2.2160	0.5912	0.2837	0.2756	0.1896
Std deviation	0.1421	0.0700	0.0577	0.0517	0.0365
Skewness	3.9757	0.6737	-0.0614	0.1121	-0.3145
Kurtosis	65.5735	9.8302	8.0140	7.0503	8.1379
Weekly returns					
Quintiles	**Volatile – 1**	**2**	**3**	**4**	**Stable – 5**
Mean	0,0142	-0,0102	0,0083	-0,0001	0,0135
Median	-0,0155	-0,0171	-0,0012	-0,0061	0,0080
Minimum	-0,9095	-0,6538	-0,4725	-0,5089	-0,3411
Maximum	3,4282	0,8468	0,7870	0,6351	0,5354
Std deviation	0,3295	0,1709	0,1595	0,1498	0,1044
Skewness	4,1699	0,5977	0,8860	0,4059	0,5255
Kurtosis	38,9785	6,3477	6,3206	5,4566	5,6689

Notes: This table presents the summary statistics for the daily and weekly returns of value-weighted quintiles portfolios. Each day/week, all cryptocurrencies were sorted by the Parkinson volatility estimator and partitioned into quintiles. From each quintile we calculated a value-weighted portfolio. For each of the five portfolios obtained daily, we got 2561 entries of data, from December 28, 2013 to December 31, 2020. For each of the five portfolios obtained weekly, we got 365 entries of data, from January 1, 2014 to December 29, 2020.
Source: Author’s own calculation.

Table A.5 – Returns from portfolios sorted on momentum

Daily returns					
Quintiles	**Up – 1**	**2**	**3**	**4**	**Down – 5**
Mean	-0.0122	0.0033	0.0015	-0.0006	0.0166
Median	-0.0131	0.0010	0.0014	0.0000	0.0155
Minimum	-0.9172	-0.3078	-0.2415	-0.3673	-0.8250
Maximum	1.4145	0.3214	0.2806	0.2977	1.9459
Std deviation	0.0880	0.0479	0.0403	0.0489	0.0871
Skewness	1.6341	0.4476	-0.1065	-0.1794	3.9065
Kurtosis	42.8943	9.1033	8.8201	9.3535	104.2181
Weekly returns					
Quintiles	**Up – 1**	**2**	**3**	**4**	**Down– 5**
Mean	0.0106	0.0182	0.0055	0.0064	0.0294
Median	-0.0124	0.0091	0.0021	-0.0082	0.0124
Minimum	-0.6335	-0.4046	-0.4560	-0.3994	-0.5618
Maximum	2.4109	0.6891	0.5209	0.7908	1.8507
Std deviation	0.2170	0.1336	0.1168	0.1456	0.1995
Skewness	4.1117	1.1821	0.5858	1.2202	2.1313
Kurtosis	43.6748	7.7770	6.3143	7.7346	21.9495

Notes: This table presents the summary statistics for the daily and weekly returns of value-weighted quintiles portfolios. Each day/week, all cryptocurrencies were sorted by momentum and partitioned into quintiles. From each quintile we calculated a value-weighted portfolio. For each of the five portfolios obtained daily, we got 2561 entries of data, from December 28, 2013 to December 31, 2020. For each of the five portfolios obtained weekly, we got 365 entries of data, from January 1, 2014 to December 29, 2020.
Source: Author's own calculation.

Table A.6 – Returns from portfolios sorted on age

Quintiles	**Old – 1**	**2**	**3**	**4**	**Young – 5**
Mean	0,0019	0,0011	-0,0006	-0,0003	-0,0032
Median	0,0018	0,0011	-0,0007	-0,0008	-0,0028
Minimum	-0,2187	-0,5400	-0,3552	-0,6473	-0,9738
Maximum	0,1884	0,2605	0,3241	0,9316	1,2940
Std deviation	0,0375	0,0532	0,0536	0,0767	0,0812
Skewness	-0,2272	-0,4927	0,2009	1,2747	0,7687
Kurtosis	7,7451	10,8750	9,5717	31,6399	43,5820
Weekly returns					
Quintiles	**Old – 1**	**2**	**3**	**4**	**Young – 5**
Mean	0,0132	0,0150	0,0030	0,0191	-0,0073
Median	0,0061	0,0084	-0,0002	0,0166	-0,0154
Minimum	-0,3435	-0,4349	-0,3967	-0,6459	-0,6201
Maximum	0,4539	0,8470	1,0035	1,9247	0,8144
Std deviation	0,1027	0,1444	0,1496	0,1915	0,1886
Skewness	0,3519	1,0440	1,4672	3,1443	0,7168
Kurtosis	4,8249	7,9677	10,4475	31,5269	6,3959

Notes: This table presents the summary statistics for the daily and weekly returns of value-weighted quintiles portfolios. Each day/week, all cryptocurrencies were sorted by age and partitioned into quintiles. From each quintile we calculated a value-weighted portfolio. For each of the five portfolios obtained daily, we got 2561 entries of data, from December 28, 2013 to December 31, 2020. For each of the five portfolios obtained weekly, we got 365 entries of data, from January 1, 2014 to December 29, 2020.
Source: Author's own calculation.

Table A.7 - Average statistics for the regressions on the CAPM

DAILY					
MKT (market value-weighted portfolio) as the market factor					
Portfolios	**Size / Volume**	**Size / Illiquidity**	**Size / Volatility**	**Size / Momentum**	**Size / Age**
|a|	0.0089	0.0095	0.0092	0.0236	0.0089
p-value < 0.05	22	21	20	21	21
p-value < 0.01	20	20	18	21	21
s(a)	0.0011	0.0011	0.0011	0.0011	0.0011
R^2	0.3177	0.3178	0.3365	0.3217	0.3248
GRS	54.1545***	54.8499***	59.7483***	490.5175***	51.2828***
SR(a)	0.7335	0.7382	0.7704	2.2074	0.7137
BKT (bitcoin index) as the market factor					
Portfolios	**Size / Volume**	**Size / Illiquidity**	**Size / Volatility**	**Size / Momentum**	**Size / Age**
|a|	0.0089	0.0095	0.0092	0.0238	0.0088
p-value < 0.05	18	16	16	21	16
p-value < 0.01	17	16	16	20	16
s(a)	0.0011	0.0012	0.0011	0.0011	0.0011
R^2	0.2944	0.2944	0.3115	0.2928	0.2990
GRS	56.2589***	57.1040***	60.2114***	496.1234***	55.2334***
SR(a)	0.7460	0.7516	0.7717	2.2153	0.7392
WEEKLY					
MKT (market value-weighted portfolio) as the market factor					
Portfolios	**Size / Volume**	**Size / Illiquidity**	**Size / Volatility**	**Size / Momentum**	**Size / Age**
|a|	0.0292	0.0300	0.0286	0.0450	0.0270
p-value < 0.05	14	13	17	16	15
p-value < 0.01	12	12	12	13	11
s(a)	0.0076	0.0077	0.0077	0.0074	0.0075
R^2	0.3408	0.3375	0.3416	0.3492	0.3470
GRS	12.8707***	13.1838***	11.6446***	27.8311***	10.0908***
SR(a)	0.9890	1.0010	0.9407	1.4543	0.8757
BKT (bitcoin index) as the market factor					
Portfolios	**Size / Volume**	**Size / Illiquidity**	**Size / Volatility**	**Size / Momentum**	**Size / Age**
|a|	0.0314	0.0319	0.0305	0.0458	0.0290
p-value < 0.05	13	13	13	15	14
p-value < 0.01	12	10	13	14	12
s(a)	0.0079	0.0081	0.0080	0.0078	0.0078
R^2	0.2648	0.2626	0.2659	0.2646	0.2718
GRS	13.1753***	12.2363***	10.3285***	27.4781***	9.9926***
SR(a)	0.9945	0.9584	0.8805	1.4361	0.8661

Notes: This table presents the results of 1-factor (CAPM) daily and weekly regressions considering two candidates for the market factor: MKT, the market value-weighted portfolio, and BKT, the Bitcoin index. Each column corresponds to the average statistics for the regressions on 25 double-sort value-weighted portfolios. |a| is the average absolute intercept for a set of regressions. p-value < 0.05 and p-value < 0.01 are the number of times the p-value of the set of regression is inferior to 0.05 and 0.01, respectively. s(a) is the average standard error of the intercepts. R^2 is the average adjusted R^2. GRS are the statistics on the null hypothesis that all the intercepts for a set of regressions are jointly zero (Gibbons et al., 1989). The significance at the 1%, 5% and 10% are denoted by ***, **, *, respectively. SR(a) is the Sharpe ratio computed according to Equation (13).
Source: Author's own calculation.

Table A.8 - Average statistics for the regressions on the 3-factor and 5-factor models

DAILY					
3-factor model					
Portfolios	**Size / Volume**	**Size / Illiquidity**	**Size / Volatility**	**Size / Momentum**	**Size / Age**
|a|	0.0051	0.0059	0.0058	0.0202	0.0051
p-value < 0.05	15	18	16	22	14
p-value < 0.01	12	14	15	20	13
s(a)	0.0015	0.0015	0.0014	0.0014	0.0014
R^2	0.3342	0.3345	0.3557	0.3509	0.3428
GRS	11.4269***	12.2394***	13.7700***	211.5718***	11.9340***
SR(a)	0.4549	0.4708	0.4994	1.9575	0.4649
5-factor model					
Portfolios	**Size / Volume**	**Size / Illiquidity**	**Size / Volatility**	**Size / Momentum**	**Size / Age**
|a|	0.0051	0.0057	0.0056	0.0201	0.0050
p-value < 0.05	15	17	16	22	14
p-value < 0.01	12	14	15	20	12
s(a)	0.0014	0.0015	0.0014	0.0014	0.0014
R^2	0.3428	0.3431	0.3628	0.3536	0.3502
GRS	10.9731***	11.1670***	12.7591***	208.5502***	12.1597***
SR(a)	0.4477	0.4516	0.4827	1.9517	0.4713
WEEKLY					
3-factor model					
Portfolios	**Size / Volume**	**Size / Illiquidity**	**Size / Volatility**	**Size / Momentum**	**Size / Age**
|a|	0.0184	0.0214	0.0180	0.0373	0.0117
p-value < 0.05	15	16	14	17	7
p-value < 0.01	9	11	6	15	5
s(a)	0.0093	0.0095	0.0094	0.0090	0.0092
R^2	0.4040	0.3999	0.4069	0.4197	0.4067
GRS	7.0564***	7.3852***	3.9837***	13.9633***	2.9929***
SR(a)	0.9499	0.9718	0.7137	1.3362	0.6186
5-factor model					
Portfolios	**Size / Volume**	**Size / Illiquidity**	**Size / Volatility**	**Size / Momentum**	**Size / Age**
|a|	0.0173	0.0193	0.0173	0.0365	0.0118
p-value < 0.05	15	15	13	16	7
p-value < 0.01	9	10	6	14	5
s(a)	0.0093	0.0095	0.0095	0.0092	0.0093
R^2	0.4153	0.4114	0.4180	0.4240	0.4166
GRS	3.2588***	3.3165***	2.8969***	13.8751***	2.0414***
SR(a)	0.6599	0.6657	0.6222	1.3616	0.5223

Notes: This table presents the results of 3-factor and 5-factor daily and weekly regressions. Each column corresponds to the average statistics for the regressions on 25 double-sort value-weighted portfolios. |a| is the average absolute intercept for a set of regressions. p-value < 0.05 and p-value < 0.01 are the number of times the p-value of the set of regression is inferior to 0.05 and 0.01, respectively. s(a) is the average standard error of the intercepts. R^2 is the average adjusted R^2. GRS are the statistics on the null hypothesis that all the intercepts for a set of regressions are jointly zero (Gibbons et al., 1989). The significance at the 1%, 5% and 10% are denoted by ***, **, *, respectively. SR(a) is the Sharpe ratio computed according to Equation (13).
Source: Author’s own calculation.

Table A.9 – Robustness checks on the portfolio construction

	|a|	R^2	s(a)	SR(a)	GRS
DAILY					
Sequential double-sort equally weighted portfolios					
	|a|	R^2	**s(a)**	**SR(a)**	**GRS**
CAPM	0.0144	0.3381	0.0010	1.2521	190.7170***
3-factor	0.0093	0.3667	0.0013	0.9600	69.4410***
5-factor	0.0093	0.3702	0.0013	0.9525	68.1813***
Double-sort intersection value-weighted portfolios					
	|a|	R^2	**s(a)**	**SR(a)**	**GRS**
CAPM	0.0120	0.2758	0.0014	1.0173	139.7805***
3-factor	0.0084	0.2932	0.0019	0.7647	51.0589***
5-factor	0.0084	0.3013	0.0018	0.7603	50.3239***
Double-sort intersection equally weighted portfolios					
	|a|	R^2	**s(a)**	**SR(a)**	**GRS**
CAPM	0.0131	0.2750	0.0013	1.4272	229.1090***
3-factor	0.0086	0.3014	0.0017	1.4252	121.7437***
5-factor	0.0086	0.3069	0.0017	1.4252	120.6816***
WEEKLY					
Sequential double-sort equally weighted portfolios					
	|a|	R^2	**s(a)**	**SR(a)**	**GRS**
CAPM	0.0371	0.3484	0.0074	1.1521	17.9675***
3-factor	0.0227	0.4268	0.0089	0.7575	5.4514***
5-factor	0.0221	0.4286	0.0091	0.7502	5.2012***
Double-sort intersection value-weighted portfolios					
	|a|	R^2	**s(a)**	**SR(a)**	**GRS**
CAPM	0.0296	0.2912	0.0093	1.0253	14.7009***
3-factor	0.0224	0.3439	0.0116	0.8452	5.9305***
5-factor	0.0208	0.3538	0.0117	0.7336	4.5204***
Double-sort intersection value-weighted portfolios					
	|a|	R^2	**s(a)**	**SR(a)**	**GRS**
CAPM	0.0313	0.2813	0.0085	1.3043	22.7047***
3-factor	0.0207	0.3478	0.0104	1.4616	17.0357***
5-factor	0.0202	0.3517	0.0106	1.5238	17.7640***

Notes: This table presents the summary statistics from daily and weekly regressions on CAPM, 3-factor and 5-factor models considering different ways to construct the portfolios. The alternatives are the sequential double-sort but with equally weighted portfolios, the double-sort intersection value-weighted portfolios of Fama and French (1993, 2012, 2015), and the double-sort intersection but with equally weighted portfolios. Each column corresponds to the average statistics for the regressions on 125 portfolios. |a| is the average absolute intercept for a set of regressions. R^2 is the average adjusted R^2. s(a) is the average standard error of the intercepts. SR(a) is the Sharpe ratio computed according to Equation (13).
Source: Author's own calculation.

Table A.10 – Robustness checks on the portfolio and factor constructions

	|a|	R^2	s(a)	SR(a)	GRS
DAILY					
Sequential double-sort value-weighted portfolios					
	|a|	R^2	**s(a)**	**SR(a)**	**GRS**
CAPM	0.0120	0.3237	0.0011	1.0326	142.1106***
3-factor	0.0101	0.3595	0.0015	0.8610	52.4476***
5-factor	0.0101	0.3746	0.0014	0.8740	54.2792***
Sequential double-sort equally weighted portfolios					
	|a|	R^2	**s(a)**	**SR(a)**	**GRS**
CAPM	0.0144	0.3381	0.0010	1.2521	190.7170***
3-factor	0.0118	0.3700	0.0014	1.0644	73.2652***
5-factor	0.0118	0.3771	0.0014	1.0702	74.2804***
Double-sort intersection value-weighted portfolios					
	|a|	R^2	**s(a)**	**SR(a)**	**GRS**
CAPM	0.0120	0.2758	0.0014	1.0173	139.7805***
3-factor	0.0101	0.3074	0.0019	0.8575	51.3458***
5-factor	0.0102	0.3244	0.0019	0.8777	53.6262***
Double-sort intersection equally weighted portfolios					
	|a|	R^2	**s(a)**	**SR(a)**	**GRS**
CAPM	0.0131	0.2750	0.0013	1.4272	229.1090***
3-factor	0.0107	0.3031	0.0017	1.4769	122.3067***
5-factor	0.0108	0.3131	0.0017	1.4820	123.2213***
WEEKLY					
Sequential double-sort value-weighted portfolios					
	|a|	R^2	**s(a)**	**SR(a)**	**GRS**
CAPM	0.0319	0.3432	0.0076	1.0521	15.1242***
3-factor	0.0271	0.4828	0.0079	1.1510	12.9345***
5-factor	0.0247	0.5093	0.0082	0.9796	8.7113***
Sequential double-sort equally weighted portfolios					
	|a|	R^2	**s(a)**	**SR(a)**	**GRS**
CAPM	0.0371	0.3484	0.0074	1.1521	17.9675***
3-factor	0.0315	0.4921	0.0077	1.0112	10.3778***
5-factor	0.0295	0.5079	0.0080	1.0130	9.4491***
Double-sort intersection value-weighted portfolios					
	|a|	R^2	**s(a)**	**SR(a)**	**GRS**
CAPM	0.0296	0.2912	0.0093	1.0253	14.7009***
3-factor	0.0267	0.4142	0.0101	1.0988	11.8139***
5-factor	0.0242	0.4393	0.0104	0.9343	8.0331***
Double-sort intersection equally weighted portfolios					
	|a|	R^2	**s(a)**	**SR(a)**	**GRS**
CAPM	0.0313	0.2813	0.0085	1.3043	22.7047***
3-factor	0.0276	0.4030	0.0092	1.4199	19.2930***
5-factor	0.0264	0.4198	0.0095	1.4921	19.0313***

Notes: This table presents the summary statistics from daily and weekly regressions on CAPM, 3-factor and 5-factor models considering different ways to construct the portfolios and to construct the pricing factors. Now factors are constructed using the median to divide the cryptocurrencies into Small and Big. The breakpoints on the second attribute are kept as before using the intervals [0%,30%], [30%,70%] and [70%,100%]. The alternatives for the portfolios are the sequential double-sort with equally and value-weighted portfolios, the double-sort intersection with equally and value-weighted portfolios. Each column corresponds to the average statistics for the regressions on 125 portfolios. |a| is the average absolute intercept for a set of regressions. R^2 is the average adjusted R^2. s(a) is the average standard error of the intercepts. SR(a) is the Sharpe ratio computed according to Equation (13).
Source: Author's own calculation.