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Erasmus School of Economics

Bachelor Thesis [Finance programme]

Aggregate Volatility Risk in the Cryptocurrency Market

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Abstract

In this paper, I research the aggregate volatility risk (AVR) factor for the cryptocurrency (CC) market. AVR refers to risk of changing market volatility, which has been researched for the stock market by Ang et al. (2006). In this research, I apply regression analyses and t-tests to data of nine cryptocurrencies, the CRIX (Trimborn & Härdle, 2018) and the VCRIX (Kim et al., 2021) from September 15th 2019 to April 19th 2022. I found that an increase of the VCRIX of 1 is associated with a significantly increase of expected CC returns of between 0.000077 to 0.0002. I constructed a monthly rebalanced Long-short portfolio called the Insensitive-Minus-Sensitive (IMS) portfolio, which selects its contents based on assets' AVR sensitivity in the month prior. However, the group of CCs with lowest sensitivity to aggregate volatility risk did not generate significantly higher returns than the group with the highest sensitivity. Therefore, the IMS had an overall poor performance compared to the market index. Finally, I found the AVR factor to be affected by the 2020/2021 CRIX shock. Both the coefficient and significance of AVR appeared to be stronger post-shock, compared to the pre-shock period.

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I. Introduction

The investing world knows many sorts of investible assets. Besides the usual investment types like stocks, bonds, real estate et cetera, a recently emerging asset is the cryptocurrency (CC). A cryptocurrency is a decentralised digital valuta. Decentralised indicates it does not rely on a central authority, such as a bank. Cryptocurrencies are based upon a blockchain, which contains the history of all CC transactions. Bitcoin emerged in 2009, making it the first ever cryptocurrency. Over the past few years, the cryptocurrency market has been gaining increasingly more attention and interest from the media and investors. Recently, some companies, such as Tesla, even started accepting Bitcoin as a valid payment method. To this day, Bitcoin remains the largest and most dominant cryptocurrency, with an all-time high value of over 60,000$. CCs are not backed up by a firm and do not ever pay dividends, making them different from regular stocks.

As CCs are relatively new, not nearly as much is known of its market the compared to the regular stock market. This combined with the growing interest of investors led many financial researchers to shift their attention to the CC market. Baek & Elbeck (2015) conclude that there is yet to be a conclusive answer to the question whether crypto is a market for speculation or serious investment. According to their study, the answer to this debate lies in the investors' willingness to take risks. To examine the riskiness of Bitcoin (the most prominent CC), they compared the standard deviations of detrended ratios of Bitcoin and the Standard and Poor's 500 index (S&P 500). It was found that Bitcoin is approximately 26 times more volatile than the S&P 500. In addition, Bitcoin returns appeared to be unaffected by any external economic factors. Also, contrary to regular stocks, CCs do not appear to be influenced by non-economic events such as calendar and natural condition-based anomalies (Qadan, 2022). Therefore, CC returns are hard to predict, making them more attractive to speculators, compared to investors[1]. Gregoriou (2019) showed it is even possible to obtain abnormal returns, using pure speculation on cryptocurrencies. A Bitcoin spread strategy, for example, was able to generate 10% in excess of the three-factor model (FF-3) of Fama & French (1993).

Besides research on speculation, multiple studies have recently been dedicated to the application of factor models in CC market. Factor models are a core topic in modern asset pricing. Asset pricing entails exploring certain characteristics (factors) of an asset for explanatory and/or predictive power over its returns and it has been a subject of interest of many economists and researchers for the past decades. This concept changed the investment world for good. Revolutionary models, such as the Capital Asset Pricing Model (CAPM) of Sharpe (1964) and the FF-3 of Fama & French (1993) play vital roles in

[1] Speculator = investor with very high risk appetite looking for leverage or betting on market movement.
Investor = Rational mean-variance investor or long only investor

modern-day finance. Considering the recent surge of interest in the cryptocurrency market, it is not surprising that multiple researchers have tried to create crypto asset pricing models.

In this paper, I research the aggregate volatility risk (AVR) factor for the CC market. AVR refers to risk of changing market volatility, which was researched for the stock market by Ang et al. (2006). They found that the group of assets with lowest sensitivity to aggregate volatility generates higher total returns compared to the group with the highest sensitivity. I attempt to research the importance of AVR for the CC market, using the existing literature and statistical analyses comparable to those used by Ang et al. (2006). *Precisely, I examine how aggregate volatility risk is priced in the cryptocurrency market, and whether there is a difference between pre- and post-shock?* The shock here refers to a supposed CC market shock at the turn of the year 2020/2021. In the following sections I first review the existing literature. Next, I show the data and the methodology used in this research. After this, I present the results of this research accompanied by a discussion of these results. Finally, I provide a conclusion followed by the bibliography and the appendix.

II. Literature Review

In this section, I examine the existing literature on cryptocurrencies. Since the aim of this research is to assess aggregate volatility risk pricing in the cryptocurrency market, I first examine the existing literature on factor models in the CC market. To get a better grasp of the CC environment, I also assess the CRIX, a CC market index and the VCRIX, a CC market volatility index. Finally, I address aggregate volatility risk in the stock market and use the aforementioned literature to construct my hypotheses.

a. Factor Models in the CC Market

Asset pricing models such as the Capital Asset Pricing Model (CAPM) of Sharpe (1964) and the FF-3 of Fama & French (1993) play vital roles in modern day stock market investing. These factor models provide a framework which allows investors to determine a predicted price of an asset based on the characteristics of its underlying firm. Comparing the actual price of an asset to this predicted price can provide information as to whether an asset is currently over- or undervalued, potentially leading to interesting investment opportunities. For this reason, it is not surprising that these stock market models have been researched for the cryptocurrency market as well. Despite the models performing well for the stock market, Coelho (2020) argued that CAPM and FF-3 are not suitable asset pricing models for the CC market. FF-3 was found to produce a low mean R^2 and found the factors to be insignificant in predicting CC returns. It was also concluded that CAPM performs even worse than FF-3 in predicting CC returns. Coelho (2020) did however acknowledge that her analysis was limited by having a small sample size and a short timeframe. Contrary to Coelho's findings, Shen et al. (2020) found evidence for a three factor CC pricing model. The relevant factors include the Market, Size and Reversal factors (of which the first two are also included in FF-3). Liu et al. (2020) similarly identified three risk factors in the CC market, namely the Market, Size and Momentum factors. The market factor refers to market excess return, the Size factor refers to the outperformance of small versus big companies and Momentum trading refers to buying past winner stocks and selling past loser stocks as in Jegadeesh & Titman (1993). In line with Liu et al. (2020), Tsyvinski (2021) also argues that momentum is a relevant factor for CC pricing. The size factor was also researched and considered relevant for the cryptocurrency pricing by Li et al. (2020). In summary, evidence appears to be mixed as to whether asset pricing models can be used for the CC market.

b. CRIX; a Cryptocurrency Market Index

One of the most central factors in all famous asset pricing models is the market factor. This factor played a pivotal role in the first asset pricing model, i.e., the CAPM by Sharpe (1964). The market factor used in asset pricing models is usually equal to the excess return of the market of the CAPM model. To research models using the market factor, one can use market data in the form of an index. For the CC market, indices were only developed recently. This is because before the recent introduction of *altcoins*, one could hardly speak of a crypto 'market' as it merely consisted of Bitcoin. The term altcoin includes all CCs other than Bitcoin, such as Tether and Ethereum. With a wide variety of new and different cryptocurrencies, it became more difficult to follow the developments of the cryptocurrency market. In order to make this easier, Trimborn & Härdle (2018) introduced the CRIX; a daily updated market index for cryptocurrencies. They chose to include merely a handful of CCs in their market index, opposed to including many or even every CC available on the market. The latter would be unattainable and inefficient, as over the past years the amount of CCs has increased rapidly and there are currently over 10.000 different CCs (Appendix, Figure 1). Furthermore, most of these CCs are not nearly as significant as the few big cryptocurrencies, as the top 20 CCs make up close to 90% of the total market (statista.com). For example, Walther et al. (2019) used this index to establish that the Global Real Economic Activity is the main driver of the volatility of the CRIX. Chen et al. (2018) used the CRIX to lay the framework of CC option pricing.

c. VCRIX; a Cryptocurrency Market Volatility Index

Another development in the regular equity markets was the launch of the CBOE's Volatility Index (VIX) by Bob Whaley in January 1993. The VIX, also known as the Fear Index, is an index that depicts expected volatility of Standards and Poor's 500 index options. As this measure is widely used, it makes sense that this index is recreated for the CC market. Kim et al. (2021) founded the VCRIX, which is a cryptocurrency market volatility index. They constructed the VCRIX to capture the investors' expectations of the cryptocurrency ecosystem. As stated before, the VIX is based on the derivatives market, which does not (yet) exist for the majority of the cryptocurrency market. Hence, Kim et al. (2021) reverted to constructing the VCRIX using Heterogeneous Auto-Regressive (HAR) model on the previously created CC market index, the CRIX. The HAR model is a model that estimates volatility using previously realized volatility over different interval sizes. To justify the method used to construct the VCRIX, the authors applied the HAR model to the regular stock market to create a testing volatility index called AVIX. Comparing the AVIX to the VIX showed a 78% correlation, confirming the applicability of their model. The introduction of the VCRIX allowed researchers to monitor the CC market volatility developments and determine the consequences of these developments for individual asset movements.

d. Aggregate Volatility Risk

Market Volatility measures how rapid the market index can shift in a given timeframe. Higher market volatility implies a higher risk of market returns. The level market volatility itself can also shift over time, which introduces an additional form of risk. Precisely, the risk of changing market volatility is referred to as Aggregate Volatility Risk. Ang et al. (2006) argued that, in the regular stock market, Aggregate Volatility Risk is a priced risk factor. This means that an asset's exposure to this risk, is negatively related to its expected returns. They used a data from January 1986 to December 2000. Ang et al. (2006) established that stocks differ in sensitivity to changes in market volatility and found higher returns in the group of assets with the lowest sensitivity to AVR, compared to the group of assets with the highest sensitivity. They concluded that changes in market volatility have a statistically significant price of risk of approximately −1% per annum. AVR is not accounted for in the commonly used asset pricing models such as FF3 and CAPM. Despite this, AVR persisted to be significantly negatively related to expected returns throughout various validation processes. Detzel et al. (2019) were able to successfully replicate the main results of the paper by Ang et al. (2006). Their results confirmed the negative relationship between aggregate volatility risk and expected returns for an extended version of the sample period of Ang et al. (2006), namely from January 1987 to 2016.

In summary, Ang et al. (2006) and Detzel et al. (2019) both find support in favour of the hypothesis that aggregate volatility risk is a priced risk factor in the stock market. Both papers indicate a significant negative relationship between a stocks sensitivity to changes in aggregate volatility and its expected return. How does AVR affect investors' behaviour? Often, long-term, or buy-hold investors do not like to be fully exposed to the risk of changing market volatility, which leads to the investors' desire to hedge against this risk (Campbell, 1993; Campbell, 1996; Chen, 2002). Here, the strategy of hedging entails taking counter positions in stocks or derivatives to neutralize the exposure to changes in market volatility. Hence, hedging investors require stocks that are less sensitive to changes in aggregate volatility.

In summary, literature shows that equity markets and CC markets share characteristics in the forms of market indices, priced risk factors and volatility measures. Due to these commonalities, which depict the rapid development of the CC market into an established equity market, I expect the AVR-factor to be of importance to the CC market, as it is to the stock market. When ranking stocks based on their AVR sensitivity in ascending order, Ang et al. (2006) found that the bottom 20% of assets had an average total (not excess) return of 1.64%. For the top 20% of assets this was an average total (not excess) return of 0.60%, showing a 1.04% difference. Therefore, the core of my AVR expectation translates to the AVR insensitive CCs outperforming the sensitive CCs. This led me to my first hypotheses:

H1a: Aggregate volatility risk has a significant impact on expected returns in the cryptocurrency market

H1b: AVR insensitive CCs generate higher average monthly returns than AVR sensitive CCs

Tzouvanas et al. (2020) showed that, in the CC market, positive returns can be derived from using 1-month momentum strategies in the short run. Gu et al. (2020) found that the 1-month momentum is among the top predictors in the cross-section of equity returns. The results of Tzouvanas et al. (2020) raises the natural question as to whether other risk factor strategies can also be used to generate positive returns. For this reason, my study is also aimed at creating investing strategies in the CC market, besides from investigating the theoretical existence of priced factors in the CC market. This is beyond the research of Ang et al. (2006), as they did not investigate AVR investment strategies. If a negative relationship between a CC's sensitivity to changes in market volatility and its expected return could be determined, it could make CC returns more predictable. Investors could profit from this as it would determine their position in the CC market (long/short)[2]. Assuming AVR is a negatively priced risk factor one might construct the following Insensitive-Minus-Sensitive (IMS) portfolio: a portfolio that takes a long position in cryptocurrencies with lower sensitivity to aggregate volatility risk and takes a short position in cryptocurrencies with higher sensitivity to aggregate volatility risk.

Since, by construction, the IMS portfolios returns rely on exposure to changes in market volatility, an interesting avenue is to study its performance during recent booms and crises. Over the past years, the CC market went through speculative booms and crises (Wątorek et al., 2021) as well as macro-economic crises, such as the Covid-19 pandemic. James (2021) found that the CC characteristics, especially correlation to each other, were sharply affected by the Covid-19 crisis. Furthermore, Mandaci and Cagli (2022) argued that during the Covid-19 pandemic, the amount of herding intensity in the CC market increased, leading to bubbles, crashes, and volatility changes. This is in line with the idea that market stress and herding are positively related (Raimundo Júnior et al., 2022). Besides research on the impact of the Covid-19 crisis on CCs, literature concerning economic crises point out that these crises have great impact on stock market volatility. Schwert (1989) showed that stock market volatility rapidly changes during an economic recession like the great depression. Karunanayake et al. (2010) also found market volatility to be significantly impacted by financial crises. Considering the increased cross-correlations of the equity markets and the CC market during turbulent periods (Kwapień et al., 2021), it is likely that the CC market experienced similar market volatility changes during these crises. In theory, the IMS portfolio should be able to benefit from these volatility changes. In summary, the CC market went through various (speculative) booms and crises, which influenced market volatility, from which the IMS should be able to benefit. Therefore, I expect the IMS portfolio to outperform the market portfolio in the period September 2019-April 2022. This leads to the second hypothesis:

H2: The IMS portfolio outperforms the cryptocurrency market index

Lastly, I investigate the pre- and post-CRIX-shock periods to assess whether the AVR-factor is affected by CC market shocks. Figure 2 shows the CRIX chart from the period 2016 to 2022. One can argue the CRIX experienced two major shocks, after which the index remained on a relatively higher level than prior to the shock. The supposed shock of our interest occurred roughly late 2020/early 2021, marked by a red line in Figure 2. This shock was also deemed a crypto boom by Chowdhury et al. (2022).

[2] A long position entails purchasing an asset now and selling it later. A short position entails "borrowing" an asset, selling it now and repurchasing it later.

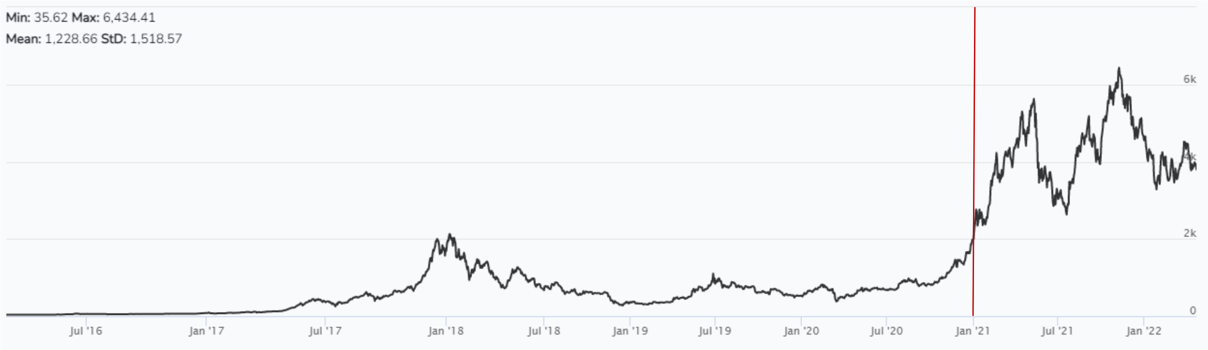

Figure 2, The CRIX: the cryptocurrency market index. *Obtained from https://www.royalton-crix.com/ on 22-04-2022. I modified the graph by inserting the red line, which divides the CRIX into pre- and post-shock periods.*

Baur & Dimpfl (2018) showed that, in the CC market, positive shocks lead to an increase of volatility. They reason the main culprit of this phenomena is the "fear of missing out" of uninformed investors. If the supposed shock qualifies as a significant shock, it would indicate an increase of market volatility around the beginning of 2021. As AVR entails changes in market volatility, I expect supposed shock to have had an impact on the effect of the AVR factor. Determining whether the AVR performs differently pre- and post-shock would be of great importance for the validity of this research. If a shock alters the sign, size or significance of the AVR factor, it might be necessary to reassess the factor in case another shock takes place in the future. Assuming the market index has gone through numerous volatility shocks, I expect inconsistencies in the AVR factor between the pre- and post-shocks market index. Therefore, my third and final hypothesis is:

H3: The aggregate volatility risk factor is affected by CRIX shocks

III. Data

In this section, I review the data used in this research. I use daily data of the CRIX, a market index for cryptocurrencies as constructed by Trimborn and Härdle (2018), and the VCRIX, a volatility index for cryptocurrencies as constructed by Kim et al. (2021) and data from individual CCs from Yahoo Finance (YF). Please note that the VCRIX does not contain data from weekends. Opposed to regular value-weighting, Trimborn and Härdle used liquidity weighting to assign weights to altcoins (see Table I). This decision was based on the idea that a CC which has a high market cap, but is infrequently traded, does not add sufficient information to a market index. As of June 11th 2022, the CRIX consists out of the following nine cryptocurrencies:

Table I: CRIX Components. *Data obtained from https://www.royalton-crix.com/ on 11-06-2022.*

Cryptocurrency	Ticker	Market Cap (BLN $)	Index Weight (%)
Bitcoin	BTC	558.0	57.43
Ethereum	ETH	225.1	27.38
Binance Coin	BNB	45.5	5.25
Ripple	XRP	19.9	2.42
Solana Token	SOL	16.1	2.19
Cardano	ADA	17.8	2.12
Polkadot	DOT	9.7	1.24
Avalanche	AVAX	7.5	1.08
Terra	LUNA1	1.4	0.90

I use the data between September 15th 2019 and April 19th 2022. This period is chosen under the conditions that the data of at least six cryptocurrencies are simultaneously available on Yahoo Finance *and* that the pre- and post-shock periods contain an equal amount of CRIX datapoints. Looking at Figure 2, the market shock of interest occurred roughly at the turn of the year 2020/2021, I divide the time-period into the following windows:

Pre-shock: September 15th, 2019 – December 31st, 2020
[Observations: 3347 YF; 474 CRIX; 338 VCRIX]
Post-shock: January 1st, 2021 – April 19th, 2022
[Observations: 4198 YF; 474 CRIX; 337 VCRIX]

Figure 3, The VCRIX: the cryptocurrency market volatility index. *Obtained from https://www.royalton-crix.com/ on 26-04-2022.*

Figure 3 shows the VCRIX, which is a volatility index for the cryptocurrency market, comparable to the regular stock market's VIX. Kim et al. (2021) used a Heterogeneous Auto-Regressive model, which uses the 30 days mean annualized volatility and realized volatility to forecast future volatility. Testing this method on the regular stock market led to a 78% correlation with the actual VIX. This proved that their model is in fact suitable for predicting future volatility. The VCRIX is an index with a starting value of 1000. The starting value could have been any number, as absolute values of the index itself do not hold much valuable information, it is the relative values (changes) that matter.

Table II, Descriptive Statistics. *Numbers are rounded tot the third decimal. Count means number of observations and Std is standard deviation. 25%, 50% and 75% correspond to the first quartile, median and third quartile, respectively.*

	Count	**Mean**	**Std**	**Min**	**25%**	**50%**	**75%**	**Max**
VCRIX	675	809.180	212.491	355.974	650.337	779.640	947.010	1430.019
CRIX	948	2694.431	1807.004	379.710	754.450	2918.720	4197.420	6434.410
Close	5437	3750.849	11468.734	0.024	0.926	21.970	336.810	67566.828
Return	5428	0.008	0.079	-0.423	-0.030	0.002	0.038	1.016
ΔVCRIX	674	0.029	44.597	-418.016	-9.729	0.000	8.462	503.981
CRIX Return	947	0.004	0.044	-0.239	-0.020	0.004	0.029	0.204

Table II shows the descriptive statistics of the data used in this research. The CRIX and VCRIX are index levels. Close is the daily closing price (last price for which a cryptocurrency got traded during a trading session) in dollars of all individual cryptocurrencies. The large difference between the lowest (Min) and highest (Max) values of Close shows how much CCs can differ from each other. ΔVCRIX is the difference between the VCRIX levels at time t and t-1. Return and CRIX Return are calculated by dividing closing price at time t by the closing price a t-1, after which I subtract 1 (for the individual CCs and the CRIX, respectively). The (CRIX) Return mean of 0.008 (0.004) corresponds to a return of 0.8% (0.4%). This format of the returns is to be preferred to percentages as it allows for direct multiplication.

Finally, In this research, I use the risk free rates from the Kenneth R. French Data Library (https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html). For the period of September 2019 up and including to April 2022, the average monthly r_f is equal to 0.00033871.

IV. Methodology

a. Models

In this section I cover the methods used in this research. To examine the relation between AVR and expected returns in the CC market, I follow a similar approach to that of Ang et al. (2006). Ang et al. (2006) use an OLS-regression that attempts to predict an asset's expected return using risk factors as explanatory variables. The full-sized form of this equation would include a summation of innovations[3] of the entire set of risk factors multiplied by their corresponding betas. However, Ang et al (2006) did not include these as the true set of factors is unknown and the true conditional factor loadings are unobservable. Therefore, they used a simplified multi-factor regression of the following form:

$$(1)\ r_t^i = \beta_0 + \beta_M^i M_t + \beta_{AVR}^i \psi AVR_t + \varepsilon_t^i,$$

where r_t^i is the expected return of asset (cryptocurrency) i, β_M^i is the loading on the excess market return, β_{AVR}^i is the asset's sensitivity to aggregate volatility risk. The symbol ψ stands for innovation. However, Ang et al. (2006) argued that the true values for M_t and ψAVR_t are unobservable. To still observe the effect of AVR, Ang et al. (2006) used the CRSP value-weighted market index as a proxy for the market factor. To proxy for aggregate volatility risk, the authors used changes in the VIX index from the Chicago Board Options Exchange. This led Ang et al. (2006) to use the following modified version of Eq. (1):

$$(2)\ r_t^i = \beta_0 + \beta_{MKT}^i MKT_t + \beta_{\Delta VIX}^i \Delta VIX_t + \varepsilon_t^i$$

Ang et al (2006) aimed to research the effect of AVR on expected returns on regular stocks. However, in this thesis I research this effect for the cryptocurrency market. Therefore, I neither use the CRSP market index, nor the changes of the VIX. Rather, I use the cryptocurrency counterparts of the aforementioned proxies. To proxy for the market factor, I use the CRIX, a market index for cryptocurrencies as constructed in Trimborn and Härdle (2018). To proxy for AVR, I use the changes in VCRIX, a volatility index for cryptocurrencies as constructed in Kim et al. (2021). This leads to a OLS regression of the following form:

$$(3)\ r_t^i = \beta_0 + \beta_{CRIX}^i CRIX_t + \beta_{\Delta VCRIX}^i \Delta VCRIX_t + \varepsilon_t^i,$$

where,

$$(4)\ \Delta VCRIX_t = VCRIX_t - VCRIX_{t-1}$$

However, as shown by the existing literature, the market and AVR factors are not the only relevant factors for explaining CC returns. As previously mentioned, Liu et al. (2019) identified three

[3] An innovation is formally defined as the difference between the best prediction and the actually observed value

common risk factors for cryptocurrency returns. Apart from the market return factor, which has already been accounted for, the authors found that the momentum and size factors are able to explain average CC returns very well. Therefore, the full regression model also needs to account for these factors. However, as the CC market caps proved to be not (fully) obtainable, the full regression model does not account for the size factor. The full-sized OLS regression model has the following form:

$$(5)\ r_t^i = \beta_0 + \beta_{CRIX}^i CRIX_t + \beta_{\Delta VCRIX}^i \Delta VCRIX_t + \beta_{MOM}^i MOM_t + \varepsilon_t^i,$$

where 1-month momentum (Carhart (1997)) is calculated using:

$$(6)\ MOM_t = Closing\ Price_{t-1} / Closing\ Price_{t-30} - 1,$$

where Closing Price refers to the last price for which a cryptocurrency got traded during a trading session. To calculate monthly momentum, I use data from time t-30 to obtain data from a month prior to time t. From Eq. (3) and (5), the main variable of interest is the $\beta_{\Delta VCRIX}^i$, representing the coefficient of the AVR proxy. The other factors are included to validate the coefficient and significance of the AVR factor.

b. AVR Sensitivity

To measure the CCs' AVR sensitivity, I use daily data of the CRIX, VCRIX and individual CCs within each month. Then, for each month, I run the OLS regression from Eq. (3) for each of the cryptocurrencies. I specifically use Eq. (3) instead of Eq. (5) to stay in line with Ang et al. (2006). Each monthly regression of CC 'x' will have as many observations as the amount of datapoints CC x has in that month. For example, in January 2020, Bitcoin had 22 datapoints, therefore the regression of Bitcoin of that month had 22 observations. Using these monthly regressions, I obtain monthly $\beta_{\Delta VCRIX}$ values for each of the CCs, representing their sensitivity to AVR in that particular month. A higher $\beta_{\Delta VCRIX}$ value, represents a higher sensitivity to AVR. At the beginning of every month, the cryptocurrencies will be ranked and sorted based on their $\beta_{\Delta VCRIX}$ value of the month prior. Due to the relatively small amount of between six and nine cryptocurrencies included in the dataset, it is unpractical to sort the assets into five groups as done by Ang et al. (2006). For this reason, I divide the assets into the portfolios Insensitive and Sensitive. Insensitive contains the two cryptocurrencies with the lowest exposure (lowest β) and Sensitive contains the cryptocurrencies with the highest exposure (highest β). Next, I calculate the average monthly returns of group 1 and 3 and compare them using a two-sided independent t-test on equal means with an α=0.05. In doing so I perform the following hypothesis testing:

$$\text{H0: } \bar{\mu}_i = \bar{\mu}_s$$

$$\text{Ha: } \bar{\mu}_i \neq \bar{\mu}_s,$$

where $\bar{\mu}_i$ ($\bar{\mu}_s$) is the average monthly return of the insensitive (sensitive) portfolio.

c. Insensitive-Minus-Sensitive

Next, the Insensitive and Sensitive portfolios are used to construct the Insensitive-Minus-Sensitive portfolio. The portfolio takes long positions in AVR insensitive CCs and short positions in AVR sensitive CCs and is monthly rebalanced. At the turn of each month, the IMS portfolio is adjusted to any changes in components of the groups. IMS monthly return calculation can be expressed using the following algorithm:

Algorithm 1: IMS CC Selection and Returns Pseudo Code

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t = month, where T is the final observation (April 2022).
Create empty vector IMS_port of length T.

While t ≤ T:
1: Compute $\beta_{\Delta VCRIX}$ for all cryptocurrencies (CCs) using Eq. (3).
2: Sort CCs based on their $\beta_{\Delta VCRIX}$ value of the previous month in ascending order.
3: Insensitive = Mean Return of Bottom two CCs in terms of $\beta_{\Delta VCRIX}$
Sensitive = Mean Return of Top two CCs in terms of $\beta_{\Delta VCRIX}$
4: IMS = 1 * Insensitive + -1 * Sensitive
IMS_port[t] = IMS
Return IMS_port

To compare the performance of the IMS portfolio to the CRIX performance, the monthly returns of the CRIX are calculated using the following formula:

$$(7)\ Return_t^{CRIX} = Closing\ Price_t^{CRIX} / Closing\ Price_{t-1}^{CRIX} - 1,$$

where t is in months. This formula allows me to compare the average returns of the two portfolios. Average returns, however, do not show the full picture. It is possible for two portfolios to have equal average monthly returns and, at the same time, have totally different exposures to risk. For this reason, the Sharpe ratio of the IMS portfolio and the CRIX are also compared to each other. Sharpe Ratio is calculated by the following formula:

$$(8)\ Sharpe\ Ratio: \frac{\mu_{R_p} - r_f}{\sigma_P} * \sqrt{12},$$

where μ_{R_p} is the average monthly return of the portfolio, r_f is the monthly risk-free rate and σ_P is the standard deviation of the monthly returns of the portfolio $P \in \{IMS, CRIX\}$. As stated in the Data section, for this research' time-period the average monthly r_f is equal to 0.00033871. To annualize the monthly Sharpe Ratio ($\frac{\mu_{R_p} - r_f}{\sigma_P}$), it is multiplied by $\sqrt{12}$.

d. CRIX Shock

To test whether the AVR factor performs differently pre- and post-CC market shock, I first must define this shock. Upon examination of the CRIX graph (Figure 2), a potential shock, or *breakpoint* in the graph occurs around January 1st 2021. To formally test whether this qualifies as a breakpoint, I perform a Chow break test (Chow, 1960). In case it does qualify as breakpoint, the AVR factor is examined separately pre- and post-shock. This is done using the same examination methods used in hypotheses 1 and 2. The goal of this separate examination is to test whether AVR experiences changes in sign (+ or -), size (value) and/or significance (p-value) in case of a shock. When any major changes occur, it could entail that the AVR factor needs to be re-evaluated in case of a future shock. Therefore, this examination is of great importance to the validity of this paper.

e. OLS assumptions

Finally, I cover the OLS assumptions concerning endogeneity and homoskedasticity. The most important OLS assumption is the assumption of endogeneity. As my full model contains merely three independent variables, it is very possible that my regression suffers from Omitted Variable Bias, implying exogeneity. Considering this, I only speak of correlation rather than causation when interpreting the OLS results. Furthermore, the White's test on heteroskedasticity showed that the data used for the OLS regressions suffer from heteroskedastic variance, which means variance is not constant throughout the time period. For this reason, I use heteroskedasticity-robust standard errors in all my regressions.

V. Results

In this section I present the results of this research. The regressions as specified in Eq. (3) and (5) led to the following results:

Table III, OLS Regression results. *The dependent variable is in these regressions is expected return. To calculate the effect on expected return in percentages, multiply the coefficient by 100%. Numbers are rounded to the sixth decimal. The stars show significance at different critical values: * = p < 0.1, ** = p < 0.05 and *** = p < 0.01*

	Eq. (3)	**Eq. (5)**
ΔVCRIX	0.000100***	0.000200***
CRIX	0.000001**	0.000001
Momentum		0.005600***
Constant	0.003900**	-0.004400**
Observations	5428	5109
Adjusted R^2	0.007	0.012

In Table III, one can see that the addition of the market and momentum factors leads to an increase of the adjusted R^2. Eq. (5) has a higher adjusted R^2 than Eq. (3), which means it is able to explain a larger part of the variance of the expected returns. Also, upon including momentum, the coefficient of the constant goes from 0.003900 to -0.004400. This indicates that momentum explains a part of the variance that previously unexplained and therefore got included in the constant. Considering the inclusion of momentum leads to a significant momentum coefficient and a better adjusted R^2, I conclude that momentum is a valuable addition to the model.

The β-coefficient of ΔVCRIX in Eq. (3) means an increase of 1 in the difference between $VCRIX_t$ and $VCRIX_{t-1}$ is correlated with an increase of 0.01% of expected return. In Eq. (5) this is an increase of 0.02% of expected return. This coefficient remains significant across the equations. To test hypothesis 1a, I use a two-sided t-test with an α=0.05. Considering the p-value of ΔVCRIX is approximately equal to 0.000<0.025, I fail to reject the hypothesis that AVR has a significant impact on expected cryptocurrency returns. (H1a)

The CRIX coefficient indicates that an increase of 1 of the CC market index is correlated with an increase of 0.000001 of expected return. This appears to be a small coefficient. However, the CRIX approximately reaches values of up to 6434. At that time, the CRIX' part of the regression adds up to 6434*0.000001 = 0.006434 (0.6434%) to expected CC return.

The Momentum coefficient means an increase of 1 momentum is correlated with an increase of 0.0056 of expected return. This entails that when the closing price of yesterday has increased by 1 since the month prior, this is correlated with an additional 0.56% of expected CC return. Note that the amount of observations is lower in Eq. (5) than in Eq. (3). This is because, by construction, the calculation of monthly momentum requires data of one month prior to the month you calculate the momentum for. The first month of the timeframe has no data prior to it, hence momentum cannot be calculated for this month. This regression uses the data of the first month only to calculate the momentum in the second month. The data usage of the other months remains unchanged.

Figure 3 shows the great similarities between the monthly returns of the insensitive and sensitive portfolios. Furthermore, Figure 4 shows that towards the end of the timeframe, the Sensitive portfolio had a higher cumulative return than the Insensitive portfolio. These observations raise doubts as to whether the Insensitive portfolio actually generated significantly higher average monthly returns than the Sensitive portfolio. In Table IV one can see that the Insensitive portfolio in fact does have a higher average return than the Sensitive portfolio. However, using a one-sided independent t-test with $\alpha=0.05$, I established that there is no significant positive difference in average monthly returns between the insensitive and sensitive cryptocurrencies. Furthermore, changing the amount of assets contained by each portfolio from 2 to either 1 or 3 did not make a significant difference. Therefore, there is not enough evidence to claim that AVR insensitive CCs produce higher average monthly returns than AVR sensitive CCs. (H1b)

Table IV, Portfolio Results. *Values are calculated by annualizing monthly results and are rounded to the second decimal.*

	Average Return	**Sharpe Ratio**
Market (CRIX)	1.06	1.40
Insensitive	2.98	1.36
Sensitive	2.91	1.75
Insensitive-Minus-Sensitive	0.07	0.04

From Table IV one can conclude that the IMS underperforms compared to the CRIX, both in average return as Sharpe Ratio. On top of this, the IMS' monthly return has a volatility of 0.47, while the CRIX' has a volatility of 0.22. The flatness of the IMS plot in Figure 4 also illustrates its poor performance, generating the worst cumulative return. Considering I established in hypothesis 1b that the Insensitive and Sensitive portfolios performed equally (no significant positive difference), this poor performance is not completely surprising. The average return, cumulative return and Sharpe Ratio of the IMS portfolio are all worse than those of the Market (CRIX). Having a higher risk and lower return, the IMS portfolio underperforms in all measures used compared to the CRIX. Therefore, I can safely reject the hypothesis that IMS outperforms the Market index. (H2)

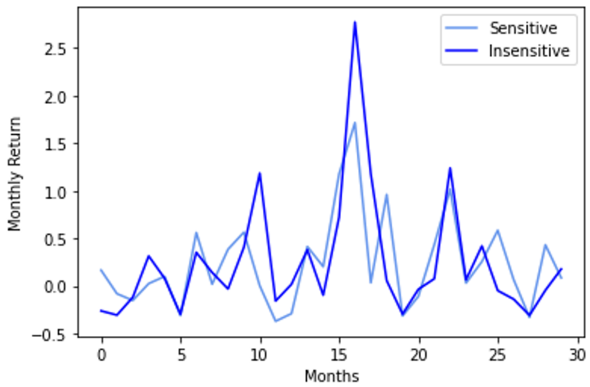

Figure 4, Monthly Return plot. *Month 0 is October 2019; Month 29 is March 2022.*

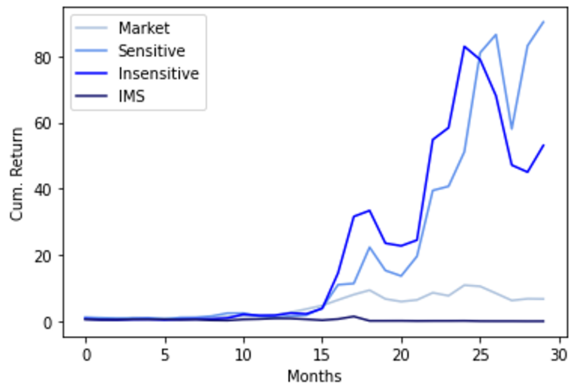

Figure 5, Cumulative Return plot. *Month 0 is October 2019; Month 29 is March 2022*

The cumulative returns of the four portfolios are presented in Figure 4. This figure clearly shows that the Market index performed worse than the individual Insensitive and Sensitive portfolios. The reason behind this lies in the weights of the portfolios (Table I). Even though the CRIX weights change, the most dominant CC has always been Bitcoin. Table V shows that in the chosen timeframe, Bitcoin has had the biggest growth in absolute terms, but the second lowest growth in relative terms. The contents of the Insensitive and Sensitive portfolios, however, were skewed towards the CCs with smaller absolute returns, but higher relative returns, such as LUNA1. Due to its weights, the CRIX experienced lower relative returns compared to the Insensitive and Sensitive portfolios, despite the CRIX containing all Insensitive and Sensitive CCs. Table V also shows how different individual CC returns can be from each other. The difference in absolute growth between Bitcoin (BTC) and Ripple (XRP) is a total of 31225.49$. Meanwhile Solaris (SOL) managed to grow by a factor of more than 100, while Ripple grew by a factor of 3.

Table V, Absolute and Relative CC growth. Numbers (except percentages) are rounded to the second decimal. Close_Start (End) is the Closing Price of the CC at the first (Last) occurrence of the CC in the data frame. Close_Start, Close_End and Absolute Growth are all expressed in dollars.

	Close_Start	**Close_End**	**Absolute Growth**	**Relative Growth**
ADA	0.05	0.95	0.91	1925%
AVAX	4.90	80.29	75.39	1540%
BNB	20.40	422.39	401.99	1971%
BTC	10276.80	41502.80	31226.00	304%
DOT	2.90	20.25	17.35	598%
ETH	197.11	3104.11	2907.00	1475%
LUNA1	1.01	95.62	94.60	9331%
SOL	0.95	108.58	107.63	11317%
XRP	0.26	0.78	0.51	197%

To formally test whether the turn of the year 2020/2021 qualifies as a shock, I used a Chow Break test. This test produced a p-value of approximately $1.11*E^{-16} < \alpha = 0.05$, allowing me to reject the hypothesis that the periods do not have significantly different CRIX level. Therefore, I can speak of a significant CRIX breakpoint/shock.

Applying the research methods used in H1 and H2 individually to the pre- and post-shock sections, did not lead to many significant differences in the results. For both periods, the positive difference in average monthly return between Insensitive and Sensitive remains insignificant. This indicates that the IMS portfolio does not perform well in either period. The regressions from Eq. (3) also does not produce significantly different coefficients or p-values from those presented in Table III. The only major differences arises when re-evaluating Eq. (5). In table VI, one can see that upon splitting the data frame into pre- and post-shock, the CRIX coefficient turns significant, and the Momentum coefficient turns insignificant. It is also important to notice that from going pre- to post-shock, the coefficient of CRIX drops with 72%, but the coefficient of ΔVCRIX more than doubles and becomes more significant. AVR appears to be more important in determining the expected CC return post-shock, compared to pre-shock. Remarkably, the R^2 from the pre-shock period is more than twice as high as the R^2 from the post-shock period. Despite this difference, both periods have a higher R^2 than the full period from Table III. Considering the increase of its coefficient and significance, AVR did indeed change between the periods. Therefore, I fail to reject the hypothesis that the aggregate volatility risk factor is affected by CRIX shocks. (H3)

Table VI, Pre- and post-shock OLS Regression results. *The dependent variable is in these regressions is expected return. To calculate the effect on expected return in percentages, multiply the coefficient by 100%. Numbers are rounded to the sixth decimal. The stars show significance at different critical values: * = p < 0.1, ** = p < 0.05 and *** = p < 0.01.*

	Eq. (5) pre-shock	**Eq. (5) post-shock**
ΔVCRIX	0.000077**	0.000200***
CRIX	0.000025***	0.000007***
Momentum	0.000600	0.002300
Constant	-0.014700***	-0.024800***
Observations	2124	2124
Adjusted R^2	0.045	0.016

VI. Discussion

From the OLS regressions, presented in Table III and V, I obtained significant ΔVCRIX β-coefficients between 0.000077 and 0.0002. The implies a positive relationship between Aggregate volatility Risk and expected CC returns. One possible explanation for this positive relationship could be that higher market volatility attracts more interest from speculators. This is line with the idea that, apart for Bitcoin and Ethereum, the cryptocurrency market is dominated by herding speculators who suffer from fear of missing out (Baek & Elbeck (2015)). This creates a pump and dump market, where either everybody gets in or gets out. A more volatile market allows for more pump and dump action, making it more interesting to speculators.

Even though the ΔVCRIX β-coefficients are significant, I cannot say with certainty that AVR has a significant effect on expected CC returns, due to the limitations of this study. Firstly, the regressions do not account for size and other possibly relevant factors. Secondly, ΔVCRIX is merely a proxy for AVR. Further research would be needed to determine how suitable this proxy is in capturing AVR in the CC market. Lastly, this research is limited by a low number of cryptocurrencies and a relatively short timeframe.

From Table IV and Figure 4 it is apparent that the Insensitive-Minus-Sensitive strategy is not a relevant investment strategy. The problem possibly arises from what appears to be a broader problem with Long-Short strategies in the CC market. In the regular stock market, stocks can simultaneously have both negative and positive correlation with other stocks. This is possible because the stock market has a wide variety of firms, differing in sector, business structure et cetera. This is vastly different for the CC market, as there are no different CC sectors. Upon investigating the poor performance of the IMS, I established that the (CRIX) CCs are all positively correlated with each other (Appendix, Table VII). This positive correlation gives CCs the tendency to experience co-movement with each other, which, generally, makes the CC market go up or down as a whole. Therefore, if the long part of the portfolio contains winner stocks, the short part will also contain winners and vice versa. Any profits in one part of the portfolio will generally be compensated by the other part's losses. This does not imply the portfolio can never create any profits, however, it does imply the portfolio is unlikely to gain profits on both its long and short part.

Aside from having a worse average monthly return, the IMS also has a higher volatility than the CRIX. Long-short portfolios are used as a hedging strategy which historically has had lower volatility than equity markets. However, this lower volatility benefit does not hold for the IMS portfolio. The volatility of the monthly returns of the IMS portfolio is more than twice as high than the volatility of the monthly returns of the CRIX. A possible explanation for this could be that, in this paper, the long and short parts of the portfolio merely include 2 assets each, which is not enough to provide diversification.

Therefore, the portfolio still contains idiosyncratic risk. Changing the amount of assets per part to 3 or 4 does not lead to significantly different results. To fairly research the performance of the IMS, future research should, if available by that time, include a larger number of cryptocurrencies into the portfolio.

When examining the effect of the CRIX shock, the biggest difference between Table V and Table III is the disappearance of significance of the momentum factor and the reappearance of significance of the market factor. This could possibly have happened, because the pre- and post-shock periods are too short for momentum to be of any effect. An alternative explanation could be that splitting the timeframe at the time of the shock led to the loss of important data. The momentum at time t is calculated using data from t-30. This means that for the month of the shock (the first month of the second period), there is no data to calculate momentum. Future research should consider including an extra month prior to the shock.

A possible explanation for the CRIX coefficient becoming significant is that the CRIX factor absorbs variance left unexplained due to the absence or insignificance of the momentum factor. This is in line with the fact that without the inclusion of momentum, the CRIX factor also had a significant coefficient (Eq. (5), Table II).

Finally, I established that the R^2 from the pre-shock period is more than twice as high as the R^2 from the post-shock period. One possible reason for this could be that the post-shock period contains the crypto boom, which might have introduced a lot of unexplained variance.

VII. Conclusion

In the recent years, the cryptocurrency market (CC) has gained increasingly more attention from investors. This led researchers to investigate asset pricing models for the CC market. When examining factor models, Liu et al. (2019) identify three common risk factors for cryptocurrency returns: Market, Size and Momentum. In this thesis, I use OLS regressions and t-tests to research relevance of the Aggregate Volatility Risk (AVR) factor for the CC market. Ang et al. (2006) researched the AVR factor for the regular stock market, where AVR refers to the risk of changing market volatility. I use data from September 15th 2019 to April 19th 2022. The data included two CC market indices: the CRIX, a CC market index constructed by Trimborn and Härdle (2018) and the VCRIX, a volatility index for cryptocurrencies, constructed by Kim et al. (2021). I also use data from individual CCs from Yahoo Finance.

In conclusion, I find AVR to have a significant impact on expected cryptocurrency returns. When proxied by changes in the VCRIX, AVR appears to be positively correlated to expected returns in the cryptocurrency market. Using an OLS model that regresses expected returns on changes in the VCRIX, the CRIX, monthly momentum and a constant, I find that an increase of aggregate volatility of 1 is associated with a 0.02% increase of expected CC returns. Even though the impact of AVR on expected cc returns might seem to be marginal, the effect is significant at a two-sided critical value (α) of 0.05.

Ang et al (2006) found that the AVR insensitive stocks outperform AVR sensitive stocks based on average monthly returns. In this thesis, I research whether this is also true for the cryptocurrencies. I use a monthly OLS regression to calculate the monthly sensitivities to AVR for each individual CC. Each month, the CCs are sorted based on their sensitivity of the month prior, in ascending order. The bottom two CCs are labeled Insensitive and the top two CCs are labeled Sensitive. The contents of these groups are monthly rebalanced. In addition, the average monthly returns of both these groups are calculated and compared to each other. Using a one-sided independent t-test with an α of 0.05, I conclude that there is not enough evidence to claim that the group of AVR insensitive CCs generates significantly higher average monthly returns compared to the group of AVR sensitive CCs.

I also test the performance of the Insensitive-Minus-Sensitive portfolio, which is a Long-short portfolio that selects its contents based on the CCs sensitivity to changes in market volatility. This monthly rebalanced portfolio is constructed by going long in the two least AVR sensitive CCs and going short in the two most AVR sensitive CCs. Despite having a positive return, the Insensitive-Minus-Sensitive portfolio does not appear to be a relevant investment strategy. Mainly because the Insensitive portfolio did not significantly outperform the Sensitive portfolio, the IMS was not able to generate high returns. Apart from this, the monthly IMS returns were more volatile than the monthly CRIX returns.

This led to the IMS having a worse average return, cumulative return and Sharpe Ratio compared to the CRIX.

Finally, using a Chow Break test, I establish that the CRIX surge, at the turn of the year 2020/2021, qualifies as a significant shock/break point. I use this break point to split my timeframe into pre- and post-shock periods and I reuse the methodology of the other hypotheses on the individual periods. The Insensitive CCs did not significantly outperform the Sensitive CCs, neither did the IMS outperform the CRIX in any period. Hence, splitting the time frame did not lead to significant changes. However, the effect of AVR on expected CC returns does appear to be stronger and more significant post-shock, compared to the pre-shock period.

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Appendix

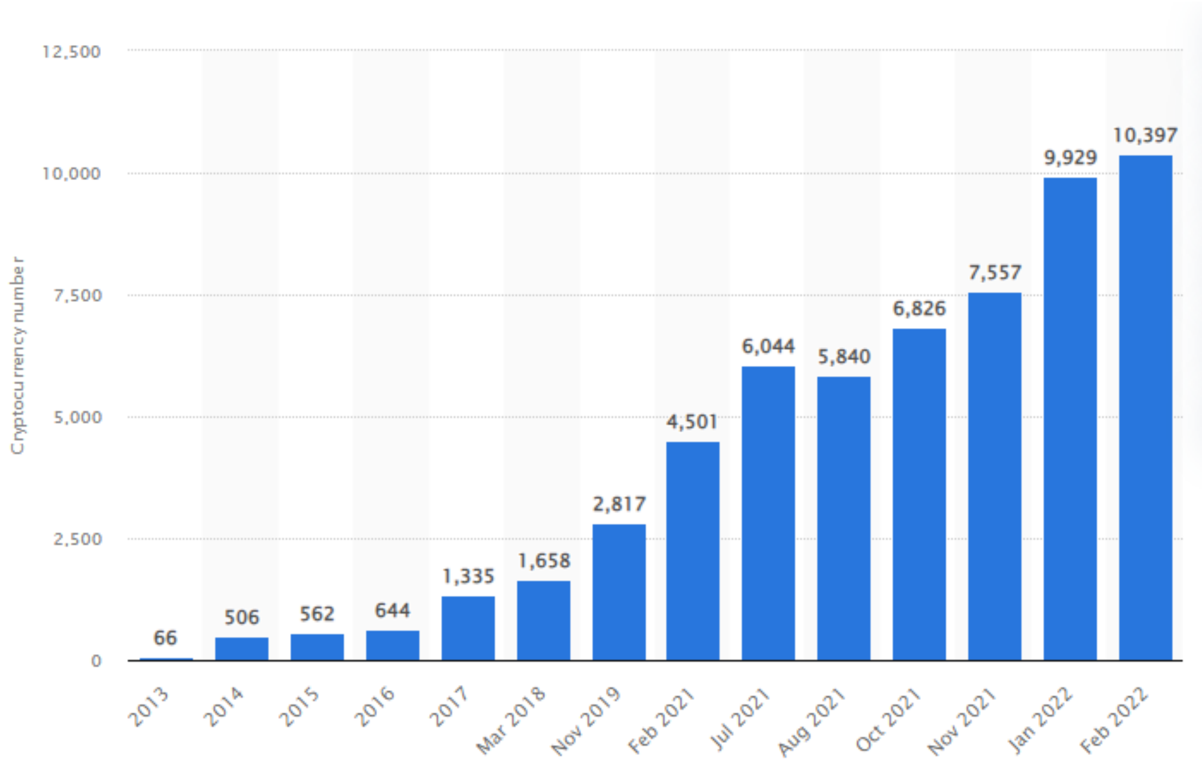

Figure 1: Amount of Cryptocurrencies. *Obtained from https://www.statista.com/statistics/863917/number-crypto-coins-tokens/ on 06-06-2022.*

Table VII, Cryptocurrency correlation matrix. *Numbers are rounded to the second decimal.*

	ADA	**AVAX**	**BNB**	**BTC**	**DOT**	**ETH**	**LUNA1**	**SOL**	**XRP**
ADA	1.00	0.52	0.58	0.65	0.48	0.69	0.42	0.40	0.57
AVAX	0.52	1.00	0.43	0.40	0.41	0.36	0.44	0.35	0.36
BNB	0.58	0.43	1.00	0.63	0.44	0.62	0.34	0.36	0.51
BT	0.65	0.40	0.63	1.00	0.49	0.78	0.46	0.34	0.49
DOT-	0.48	0.41	0.44	0.49	1.00	0.54	0.34	0.37	0.39
ETH	0.69	0.36	0.62	0.78	0.54	1.00	0.40	0.43	0.53
LUNA1	0.42	0.44	0.34	0.46	0.34	0.40	1.00	0.38	0.32
SOL	0.40	0.35	0.36	0.34	0.37	0.43	0.38	1.00	0.35
XRP	0.57	0.36	0.51	0.49	0.39	0.53	0.32	0.35	1.00