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Quality Minus Junk in Cryptocurrencies

The valuation and excess returns of quality in cryptocurrencies

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NON-PLAGIARISM STATEMENT

By submitting this thesis, the author declares to have written this thesis completely by himself/herself, and not to have used sources or resources other than the ones mentioned. All sources used, quotes and citations that were literally taken from publications, or that were in close accordance with the meaning of those publications, are indicated as such.

Abstract

The aim of this paper is to study whether it is possible to analyze quality and its aspects and apply the findings to the management of cryptocurrency portfolios. In this paper, quality scores per cryptocurrency per time period are created, based on variables that have backing in the relevant literature. These quality scores are afterwards used in order to analyze the valuation of quality in cryptocurrencies. The results show that high-quality coins are overall relatively cheaper, but do not earn excess returns over low-quality cryptocurrencies. The second part of this paper focusses on the creation of a Quality Minus Junk factor (QMJ), that goes long in high-quality, and short in low-quality cryptocurrencies, while accounting for market cap size. Results show that portfolios that employ this factor do not earn a significant excess return. Lastly, it is also shown that deploying a portfolio utilizing the Fama French 3-factor and QMJ factor has strong hedging capabilities in severe bear markets.

Keywords:

Cryptocurrency, Quality, Valuation, Portfolio Management, Asset Model

JEL classification: C01, D84, G11, G12

Table of Contents

List of Tables

Robustness Tables

List of Figures

1. Introduction

In the short timespan between the first appearance of Bitcoin just more than a decade ago, to now, cryptocurrencies have become a significant financial asset class used by financial institutions and investors. With Bitcoin having a market capitalization of around 1 trillion dollars (as of May 2021), the cryptocurrency market has shown one of the most rapid rises seen in the financial market world in recent times. This revolution has led to an immense dosage of pros and cons like related research in the literature, innovation, but also multiple scams and fraud.

Due to the sheer amount of information and complexity of information surrounding the different cryptocurrencies and market, it makes it difficult and time consuming to be involved from the investor's perspective. This creates multiple research incentives, one being, what makes for good quality in the industry. Getting a grip and understanding the difference between good quality and bad quality cryptocurrencies, might lead to a better understanding of the underlying value. This in turn has the possibility of constructing an investment strategy that creates a systematic positive excess return. Furthermore, due to the capabilities as stores of value, the need to assess the risk and return of hundreds and thousands of cryptocurrencies rises (Elendner et al., 2016).

The combination of quality assessment with portfolio management analysis leads to an interesting line of research. The well-known paper of Asness et al. (2019), called "Quality Minus Junk", covers this exact framework for firms and stocks. The authors of the paper show that investors are more willing to pay for high-quality stocks. They construct a quality score, based upon several variables that are backed up by related literature. Furthermore, they show that not only do high-quality stocks have higher risk-adjusted returns but, going long in high-quality and short low-quality creates a positive excess return also. The methodology of this paper is using the same main structure as the paper of Asness et al. (2019), applied for the cryptocurrency market.

To begin with, the research question that fuels this study is "Do high-quality cryptocurrencies have a lower speculative value and higher risk-adjusted returns than low-quality cryptocurrencies?". The question is multi-layered, which leads to the creation of three hypotheses, each covering a different specific section.

The research section in this study is divided into multiple parts. The first part of the analysis will be dedicated to the construction of the quality score. Just as in the paper of Asness et al. (2019), the quality score is made out of three subcomponents. These subcomponents are based on the financial and cryptocurrency literature. With this, cryptocurrencies will each have their specific quality score per time period. In the second part of the analysis, these scores will be used to analyze the price of quality first. In other words, do high-quality cryptocurrencies have higher prices than low-quality cryptocurrencies? This question is asked to observe whether quality corresponds with an over- or undervaluation of the coins and tokens. The second and last part of the main analysis is researching the return of quality in cryptocurrencies. Here, the excess returns over T-bills and alphas will be analyzed with respect to different well-known asset models. To conclude, after the main research, multiple robustness checks are being run, including the different constructions of the quality score and for heteroskedasticity.

The results are mixed. High-quality cryptocurrencies do have to lower speculative value than low-quality cryptocurrencies. However, this does not translate into higher risk-adjusted returns for high-quality cryptos. Furthermore, it is observed that constructing a portfolio that goes long in high-quality and short in low-quality cryptocurrencies, does not earn an excess return. Although the results might be perceived as lacking, considering the efficiency in the stock market equivalent and the variation in constructions of the quality score, the pathways for future research in this area are promising.

2. Literature Review

2.1 Introduction

The first cryptocurrency was Bitcoin in 2008, as an attempt to develop a decentralized digital cash system (Coelho, 2020). Although Bitcoin is the most popular cryptocurrency, it has many shortcomings such as slow transaction times and a completely predetermined number of coins in the Bitcoin system. This led to the creation of altcoins (short for alternative coins), which are crypto assets other than Bitcoin (Steinert & Herff, 2018). Several cryptocurrencies, like Litecoin and Peercoin, were developed to fix what their developers considered were deficiencies of Bitcoin (Gondal et al., 2016).

Although the majority of altcoins have been inspired by Bitcoin, many of them are nothing more than a minor change to the source-code of Bitcoin (Krafft et al., 2018). The paper gives Auroracoin as an example, which was a trivial technical modification to Litecoin, but was branded as the official cryptocurrency of Iceland. On the other hand, there are coins associated with real technical innovations, such as Ether. This diverse experimentation with digital cryptocurrencies is possible due to the open source-code publicly available at github.com (Elendner et al., 2016).

Until recently, investors in altcoins had to first purchase Bitcoin using fiat currency and then convert Bitcoin to a specific altcoin (Adedokun, 2019). Exchanges with altcoins operate one order book per currency pair. Only the most popular altcoins are traded with fiat currencies on these exchanges (Elendner et al., 2016). Thus, it may be unclear to determine why the price of Bitcoin kept increasing in a certain period and which is the nature of the price relationship between altcoin and Bitcoin. The paper of Cagli (2019) studied this relationship, and reveals the presence of significant pairwise co-movement relationships between the Bitcoin-altcoin and also altcoin-altcoin.

This relationship in the cryptocurrency market raises the question of, "could there be one or multiple winners"? And further, if that is the case, is there a way to predict it? The paper of Gondal et al. (2016) explains that just like in the (fiat) currency market, two opposing forces are found in the cryptocurrency market. On the one hand, there are positive network effects, where the more popular a currency is, the more useful it is, and the easier it attracts new users. This leads to the most popular currency dominating the whole market. On the other hand, currencies differ in their attributes, and some of those that arrived later to the market may have higher quality. This leads to the possibility of a substitution effect, where better or differentiated cryptocurrencies replace other coins. The Bitcoin dominance on the crypto market compared to the altcoins could be seen as a representation of these two effects. Rysman (2009) does argue though, that when users have different needs, competing networks may coexist despite the presence of network effects. Due to the sheer difference between multiple cryptocurrencies, this might be the effect that takes place in the market.

2.2 Financial capabilities of the cryptocurrency market

The emergence of a new financial asset, leads to a general analysis of financial capabilities of an asset and the reactivity to the variance of other assets as well as the hedging abilities of the asset in question (Dyhrberg, 2016). The most notable aspect of Bitcoin and cryptocurrencies in the literature, has been the hedging capabilities against other financial assets. Dyhrberg (2016) states that Bitcoin is a functional hedge against the Financial Times Stock Exchange Index and the American dollar.

As for the reactivity to the variance, some evidence has been provided. The paper of Bouri et al. (2017) shows that there is a negative relation between the volatility index of the S&P 500 (short: VIX), and the volatility of Bitcoin. As of consequence, they conclude that adding Bitcoin to a US based portfolio leads to an effective risk reduction. Dyhrberg (2016) then uses this conclusion to show the similarities between gold and Bitcoin, and leads to the suggestion that Bitcoin might become the new gold in this aspect.

Concerning the relation to other stock market indices, there has been mixed evidence. The study of Gil-Alana et al. (2020) finds that there is very little evidence of cointegration between the six main cryptocurrencies studied at that time, and the stock market indices. Furthermore, price movements in the traditional asset classes have no direct influence in the price movement of the cryptocurrency market. Caferra et al. (2021) explain this dissonance by stating that public companies are strictly connected with the state of economy, whereas cryptocurrencies prices are primarily related with the behavior of the traders that is separated from any economic fundamental value. The stock price of a public company is based on multiple factors, like financial constraints and management decisions, which have nothing to do with virtual currencies. The authors state that the expression of cryptocurrency prices in fiat currencies is the only real connection between the cryptocurrency market and the real economy.

The reasoning behind this lack of correlation was partly demonstrated, as it was clear from the empirical results that cryptocurrencies and stock markets are only correlated at specific periods, like the crash of March 2020 due to COVID-19. On the other hand, Klein et al. (2018) conclude that Bitcoin has an asymmetric response to market shocks, which demonstrates a link to the stock market (Lopez-Cabarcos et al., 2019). The study also suggests that Bitcoin investors are more technologically oriented. This would indicate that these investors are also more likely to invest in the NASDAQ and other technology focused indices and stocks.

Lastly, the empirical results of the study of Sami et al. (2020) show that there is a significant relationship between the stock performance in the MENA region (Middle East and North Africa) and the cryptocurrency market. More concretely, an increase of 1% in the cryptocurrency market return corresponds with a decrease between 0.13% and 0.15% in the performance of the stock market in MENA countries.

2.3 Downsides of the cryptocurrency market

Just like with other financial markets and instruments, the cryptocurrency market has multiple pitfalls and downsides. In addition, being as new as it is right now, the cryptocurrency market suffers especially. Coelho (2020) states that the crypto market has an incredible volatility, and suffered numerous crashes, like in the beginning of 2018 and 2020. Furthermore, the author mentions that the market has also experienced a series of hacks. The lead example given is the massive attack in 2011 on Mt. Gox, one of the main Bitcoin exchanges at the time. Due to these factors, it is not yet understood what the main drivers of the prices of cryptocurrencies are and their response to different conditions. This raises concerns about the speculative nature of cryptocurrencies and it being one of the main sources of its market volatility (Bekaert et al., 2009).

The combination of large amounts of money invested and traded and the lack of regulation and a plethora of technical complexity, creates rooms for scams in the cryptocurrency market.

The first and most common scam is the pump-and-dump scheme. Kramer (2005) describes it as where bad actors attempt to make a profit by spreading misinformation about a commodity (i.e., a specific cryptocurrency) to artificially raise the price. After that, those actors sell off what they bought at a higher price, called the dumping phase. Pump-and-dumps are easier to create and organize with smaller coins with a lower market capitalization (Kamps & Kleinberg, 2018). Access to information about for example the underlying technology or core team is usually more difficult with small coins.

Besides the pump-and-dump scheme, there is also the Initial Coin Offering (ICO) scam. This is when creators and developers of the specific coin disappear after crowdsourcing Bitcoin, or any cryptocurrency with a high trading volume, from the community (Elendner et al., 2016). To perform an ICO, there is no regulatory oversight on the company or team, which makes the phenomenon more occurring. The only thing needed is the provision of a white paper to back up the project, where there is a high degree of freedom in terms of content (Coelho, 2020).

Based on all these doubts, there is an unquestionable uncertainty hanging around this new financial market and asset. Jahani et al. (2018) asks the question: “Are cryptocurrencies merely a temporary investment hype, or do they offer genuine technological innovation that facilitates transactions in the digital economy and stand the test of time?”. Based on the financial capabilities of the cryptocurrency market in its entirety and specific coins, it is clear that this emerging financial asset is not purely hype based. The question is however, to what extent? While the overall consensus is that cryptocurrencies and the technology behind it have value and is/will become a fundamental part of the economy and the financial world, some have argued that the fundamental value is zero (Cheah & Fry, 2015).

2.4 Quality

The paper of Elendner et al. (2016) argues that these scams and fraudsters do not imply a fundamental weakness of the cryptocurrency market and assets class. This market is still in its early stages and, in addition with the fact that these nuisances happen to other asset classes like stocks and currencies as well. Even so, “evaluating the prospective returns from investing in any of these coins is difficult and time-consuming, and requires expertise in both cryptography and economics.” (Krafft et al., 2018).

In view of such uncertainty, it would be relevant to analyze and research the actual quality of the cryptocurrency. What makes for a good quality or bad cryptocurrency, and is there a way to arbitrage this factor of quality crypto coins?

As mentioned before, the paper by Asness et al. (2019) analyses the performance of the quality of specific firms and constructs a QMJ factor (Quality Minus Junk) which is used to go long-short on high-quality and low-quality. The authors start by defining general quality as a characteristic that investors should be willing to pay a higher price for, everything else equal. The paper then shows that investors pay more for firms with higher quality characteristics, although the explanatory power of quality for prices is limited. Quality does provide a good means of explaining the price-to-book ratio, even when controlling for other factors like firm size or age. Furthermore, high-quality stocks have delivered high risk-adjusted returns while low-quality junk stocks have delivered negative risk-adjusted returns. The three quality measures used in the paper are based on the theoretical model of the authors. The first is profitability, which includes gross profits, margins, earnings, etc. The other two measures are growth and safety. The second part of the paper is the construction of QMJ factor (Quality Minus Junk) that goes long on the top 30% quality stocks (high-quality stocks), and shorts the bottom 30%

stock (junk stocks). It measures the average excess returns and the alphas with respect to the CAPM, three-, and four-factor models and concludes that the overall QMJ factor is in general the strongest of the three. Finally, the authors conclude that quality stocks are underpriced, and junk stocks overpriced.

2.5 Quality measures in cryptocurrencies

2.5.1 Information and volatility

What characteristics create high-quality in a *cryptocurrency*? This question has been asked and studied in the crypto literature, although limited. The paper of Jahani et al. (2018), called "ScamCoins, S*** Posters, and the Search for the Next Bitcoin™: Collective Sensemaking in Cryptocurrency Discussions", analyses the quality factor of cryptocurrencies and tries to distinguish the difference between hype from fundamental value based on the cryptocurrency community discussions and available information. This social attention is being investigated by Jahani et al. (2018) through the quality and quantity of discussion in discussion threads. These measure the amount of information available about each cryptocurrency.

The authors find that coins with lower measures of collective intelligence, have higher market price volatility and less substantial technical innovations associated with them. Furthermore, "more serious" coins are cryptocurrencies where there is more information available or more inherent innovation. Another metric the authors use is volatility. They explain their reasoning by stating that the riskier the security is due to incomplete information about its fundamentals, the higher its volatility becomes. This ties in with the fact that pump-and-dump schemes happen to less popular cryptocurrencies, where there is a higher uncertainty about their true nature, as confirmed by aforementioned literature. Moreover, studies have shown that the crypto market is even more reactive to sentiment, compared to other markets. The study of Baek & Elbeck (2015) states that it does not seem that the cryptocurrency market is influenced by economic factors. Lastly, Glaser et al. (2014) explain this market instability by stating that prices seem to react mostly to market sentiments and psychological factors.

2.5.2 Patenting

Due to the infancy of cryptocurrencies, innovation is one of the main pillars of this financial asset class. The diffusion of new knowledge, innovation and inventions are protected and supported through the use of patents, also known as intellectual property (IP) (Jackson, 2003). The paper of Greasley & Oxley (2007) states that patented inventions are a consequence of innovation, and are vital through innovative revolutions. The role of finance patents is very important, as is demonstrated in the literature. The paper of Lerner et al. (2020) states that finance patents were on average 25% more impactful than the typical award. Furthermore, the finance patents were four-and-a-half times more valuable than non-finance related patents (Kogan et al., 2017). Financial innovation has surged, judging by the increase in financial patenting. The paper mentions that this is driven by information technology and other non-financial firms, instead of banks and financial institutions. Technologies behind financial innovation have been the focus of intensive investments by major financial institutions, large technology companies, and start-ups. In the database as of January 2020 used by the authors, around 20% of all ventures are associated with the term “Blockchain” (Lerner et al., 2020).

2.5.3 Technicality

Next to working with volatility to measure the fundamental value, technicality is equally important according to Jahani et al. (2018). The paper uses a binary variable with analysis of its GitHub repository. For this study however, the technicality of a coin will be measured through its consensus mechanism.

A cryptocurrency maintains a distributed public ledger among the users without any central authority. This ledger, called the Blockchain, contains every transaction that occurs in the network (Hazari et al., 2019). The consensus mechanism plays a key role in the performance of the Blockchain (Cao et al., 2020). The instrument ensures that every single one of the transactions happening on the system is real and that all members concur on the status of the ledger.

The most well-known and implemented consensus algorithms are Proof-of-Work (PoW) and Proof-of-Stake (PoS) (Shanaev et al., 2019). PoW is the first and most classical one, it is based on the idea where miners use their computing power in order to solve certain advanced mathematical problems. The main downside of this approach is sustainability i.e., where the power consumption reaches massive scales due to the computing power.

King and Nadal (2012) proposed a new mechanism, Proof-of-Stake (PoS), which was intended to replace PoW. PoS provides consensus and security that reduces the mining difficulty and power consumption (Vashchuck & Shuwar, 2018). The main problem with PoS however, is that it does not properly protect distributed systems. That is why all cryptocurrencies based on PoS use additional mechanisms to solve security issues (Vashchuck & Shuwar, 2018). In addition, the paper mentions that combining different protocols lead to significantly better results in security, power consumption, etc.

These two solutions (PoW and PoS) have been part of a major discussion in terms of centralization, scalability and sustainability. There is evidence that the consensus mechanism is an essential tool to the performance and technical innovation of a cryptocurrency. The study of Vashchuck & Shuwar (2018) also finds that the coin performance is driven by the fundamental consensus mechanisms. A qualitative comparison between the main consensus mechanisms will be used in a later section in this paper.

2.5.4 Third Party Quality Assessments

The analysis of the quality of fundamentals of different cryptocurrencies and giving it a single score has been done before. The startup “Flipside Crypto” has raised 4.4 million dollars to develop a system to evaluate coins “objectively”. The specific rating is named FCAS, short for Fundamental Crypto Asset Score. In March of 2019, it was added on the “Ratings” tab on coinmarketcap.com for every supported coin. FCAS is a comparative metric used to assess the fundamental health of crypto projects. The score, which is given on a 0–1000-point scale, is derived from the interactivity between primary project lifecycle fundamentals. The rating for a certain project consists of three components: *User Activity*, *Developer Behavior* and *Market Maturity* (https://cryptofinance.ai/docs/fcas-flipside-crypto-asset-score/).

User Activity consists of Project Utilization and Network Activity. Project Utilization is calculated based on the activity of user-operated wallets, whereas Network Activity is based on wallet address classifications, focusing on the actions of wallets operated by agents.

Developer Behavior consists of changes and improvements in its code, and community involvement. The data is obtained by ingesting and evaluating events that occur in public and private developer code repositories like GitHub and Gitlab.

Market Maturity consists of liquidity and market risk. This component represents the likelihood a cryptocurrency will provide consistent returns across various market scenarios by combining multiple assessments of market risk.

Even though this FCAS score will not be part of the main research of this paper, it is still insightful to observe how financial start-ups tackle the creation of a quality score. Part of the objective of this paper will be creating a similar score as to the FCAS, which will be applied to the analysis of valuation and portfolio management.

3. Research Question and Hypotheses

3.1 Research question

Based on the literature study, there is a clear indication that there is the possibility to commence a comprehensive study that analyses the quality of cryptocurrencies based on different characteristics. These characteristics will be further explained and studied in this paper. In addition, it seems that quality in cryptocurrencies is related with overall certainty. Combining these aspects with the fact that the study of Asness et al. (2019) showed that high-quality also brings higher risk-adjusted returns, the following research question for this paper is formulated:

Do high-quality cryptocurrencies have a lower speculative value and higher risk-adjusted returns than low-quality cryptocurrencies?

The research of this study is split into different parts. The first part focuses on understanding what makes for higher quality cryptocurrencies, and if there is a way to quantify this into a quality score. This quality score is aimed to be straightforward in its result, while also consisting out of a range of subcomponents. The second part is to research if higher quality also actually brings better valuation of the cryptocurrency and thus create a predictable pricing outcome. Finally, the last part of this study is to analyze if there is a way to create an investment strategy based on high-quality and low-quality, in order to earn excess returns.

3.2 Hypotheses

In order to answer the research question in a more efficient way, three hypotheses have been formed that handle a different section of the question. The three hypotheses are the following:

$H_{0,1}$. *High-quality cryptocurrencies are relatively cheaper than low-quality cryptocurrencies*.

$H_{1,1}$. *High-quality cryptocurrencies are relatively not cheaper than low-quality cryptocurrencies.*

$H_{0,2}$. *High-quality cryptocurrencies have higher risk-adjusted returns than low-quality cryptocurrencies.*

$H_{1,2}$. *High-quality cryptocurrencies do not have higher risk-adjusted returns than low-quality cryptocurrencies.*

$H_{0,3}$. *Going long in high-quality cryptocurrencies and shorting low-quality cryptocurrencies earn significant risk-adjusted returns.*

$H_{1,3}$. *Going long in high-quality cryptocurrencies and shorting low-quality cryptocurrencies does not earn significant risk-adjusted returns.*

4. Data, quality measure, and preliminary analysis

The aforementioned study by Asness et al. (2019) is meant as a guideline for this paper. Naturally, the composite quality measures will be different for the crypto space since the authors use measures that are not applicable to a cryptocurrency such as; return on equity, cash flow over assets, low bankruptcy risk and so forth. The methodology for the main research however, will be quite similar in this thesis.

4.1 Quality Score and data sources

The quality score will consist of three composite quality measures: *Intellectuality, Significance* and *Safety*. The three composite quality measures will have equal weighing between them, following the same methodology as Asness et al. (2019). Every three months, the variables of each quality measure will be standardized to obtain a z-score. The standardization of the variables happens through converting them into z-scores by subtracting the cross-sectional mean, and dividing it by the standard deviation.

Out of the top 1000 cryptocurrencies, ranked on market capitalization size, there is historical data available on 175 coins. In addition, 8 of those cryptocurrencies have been taken out due to a shorter trading range of 50 days, which leaves a total of 167 cryptocurrencies. Finally, the pricing data ranges from 06/05/2016 to 06/05/2021.

4.1.1 Subcomponents

Intellectuality and Significance: As mentioned before in the literature review, financial patents are an indication for innovation and magnitude of emerging instruments. For this study, the subcomponents *Intellectuality* and *Significance* are represented by the quantity of patents and articles surrounding a cryptocurrency. The data for both the number of articles and patents is retrieved from Google Scholar and Google Patents respectively. Multiple papers in the crypto space literature have used Google as their data source. Yelowitz et al. (2015) analyze the characteristics of Bitcoin with the use of Google search data. In addition, Stephens-Davidowitz (2014) argues that Google data are unlikely to suffer from major social censoring and Kristoufek (2013) demonstrates a strong positive correlation between Bitcoin searches and exchange prices. Finally, the study of Sovbetov (2018) perceives a rise in prices due to increase in Google search term frequency, which indicates that social attention is associated with their underlying quality.

To ensure more consistency for across the different cryptocurrencies, names and tickers, the data is based on results of the following search keywords: “symbol/ticker of the cryptocurrency” + “name of the cryptocurrency” + the term “crypto”. In the case of Bitcoin and Ethereum, this would respectively be: “BTC Bitcoin crypto”, and “ETH Ethereum crypto”.

Ergo, the *Intellectuality* score is the average of the individual z-scores based on the number of patents:

$$Intellectuality = z_{patents}$$

Furthermore, the S*ignificance* score is the average of the individual z-score based on the number of articles:

$$Significance = z_{articles}$$

Safety: As mentioned before, one of the biggest scams that plagues the cryptocurrency market is the pump-and-dump scheme. A low occurrence of these schemes creates for certainty and predictability, which are characteristics for safety. The inverse relationship between volatility and safety is not only known in the cryptocurrency market, but practically in all markets and finance. As a result, the *Safety* score will be measured with the price volatility of the cryptocurrency. The historical pricing data is taken from Yahoo Finance.

In short, the *Safety* score is the average of the individual z-scores based on the inverted volatility:

$$Safety = z_{volatility.}$$

Finally, the three subcomponents are being combined into a quality score, which is again standardized and converted into a single z-score:

$$Quality = z\ (Intellectuality + Significance + Safety).$$

4.1.2 Fixed effects

Besides these three quality subcomponents, the utilization of fixed effects would give a more comprehensive view for the regressions. Asness et al. (2019) use industry and country fixed effects, which are not applicable to cryptocurrencies. Hence, in this paper a “technicality” fixed effect has been formulated and applied, based on the consensus algorithm.

Although there is a certain agreement in the literature that between the most common consensus algorithms, some are better in some aspects than others, there isn’t really an overall quantitative analysis or defining comparison covering the multiple characteristics. However, the paper of Hazari et al. (2019) brings forward a comparative qualitative evaluation of the most common consensus mechanisms. When it comes to energy consumption, scalability and centralization, there is a clear ranking to be formulated, based on the authors comparison table. For every of these three measures, the authors give each consensus mechanism a qualitative score that is presented as positive, neutral and negative. For the technicality fixed effect in this paper, this comparative evaluation is converted into quantitative scores. Cryptocurrencies with a positive rating, get a value of 3. Neutral and Negative each receive a value of

0 and -3, respectively. The *Technicality* score in this paper will be again made out of z-scores of those values regarding energy consumption, scalability and centralization:

$$Technicality = z\,(z_{Energy\ consumption} + z_{Scalability} + z_{Centralization}).$$

Another possibility would be the incorporation of the FCAS, the aforementioned rating in the literature review, into one of the three subcomponents for the creation of the overall quality score. However, the Fundamental Crypto Asset Score is a static variable, and cannot be incorporated into the z-score methodology in this paper. Furthermore, the rating is not available for every cryptocurrency analyzed in this study, so an incorporation for the fixed effect is also not possible. This shortcoming is due to a lack of availability and nature of data though, thus it would be interesting to utilize this rating in future related research.

4.2 Portfolios

The portfolio analysis in this paper relies on two sets of factors, one being the decile sorted portfolios and the other the Quality Minus Junk factor (QMJ).

In the first section of the research section, where the price of quality is analyzed, the paper makes use of ranking decile portfolios based on market capitalization. The second section, where the return of quality is analyzed in an asset pricing model setting, the paper uses 10 ranked quality-sorted portfolios. Here, cryptocurrencies are being assigned to ascending decile portfolios on a 3-monthly basis, based on their quality score.

In addition, the paper uses a Quality Minus Junk factor along with the CAPM and Fama French 3-factor asset pricing models, in order to explain cryptocurrency pricing anomalies. For the QMJ factor construction, the same methodology is used as in the paper of Asness et al. (2019), which in turn is based on the paper of Fama and French (1993). QMJ factors are constructed as the intersection of six value-weighted portfolios formed on size (Big, Medium and Small) and quality (Quality and Junk). After that, cryptocurrencies are assigned to two size-sorted portfolios, based on their market capitalization size, on a 3-monthly basis. The size breakpoint is the median of market capitalization size. The QMJ factor return is the average return on the two high-quality portfolios minus the average return on the two low-quality portfolios, as such:

$$\begin{aligned} QMJ &= \tfrac{1}{2}\,(Small\ Quality + Big\ Quality) - \tfrac{1}{2}\,(Small\ Junk + Big\ Junk) \\ &= \tfrac{1}{2}\,(Small\ Quality - Small\ Junk) + \tfrac{1}{2}\,(Big\ Quality - Big\ Junk) \\ &= \tfrac{1}{2}\,QMJ\ in\ small\ cryptocurrencies + \tfrac{1}{2}\,QMJ\ in\ big\ cryptocurrencies. \end{aligned}$$

4.3 Ex-ante quality forecasts fundamentals

Before commencing the analysis of the price and return of quality with respect to the research question and hypotheses, a compendious forecast testing is done. Asness et al. (2019) also start with this ex-ante quality forecast. Their reasoning behind such a choice is to "show that by selecting high-quality companies (in this paper this would be cryptocurrencies) in the recent past, we succeed in selecting companies that display these characteristics in the future". Furthermore, the authors also argue that predictability of quality is consistent with market efficiency.

In Table 1, cryptocurrencies are sorted into decile portfolios according to their quality rating, on a 3-monthly basis. P1 represents the portfolio with the lowest quality cryptocurrencies, and ascends up to P10, which is the portfolio with the highest quality cryptocurrencies. The table shows the average quality scores at the portfolio formation at time t, along with the average quality scores in the subsequent four years.

The results demonstrate that cryptocurrencies with an overall high-quality rating, tend to keep that high-quality rating up to four years into the future. The same applies to low-quality ratings. In addition, it seems that the range of quality scores diminish year over year, which is mostly explained by the reducing quality score of the highest quality coins in P10. The difference between P1 and P10 remains statistically significant through time. The quality difference between the highest quality portfolio and the second highest, is also considerable. High quality today, has a higher predictive power for high quality in the future. Nevertheless, based on these results, the conclusion is that quality is a persistent attribute.

		P1 (Low)	*P2*	*P3*	*P4*	*P5*	*P6*	*P7*	*P8*	*P9*	*P10 (High)*	*H-L*	*H-L t-stat*
Quality	t	-1.34	-0.06	-0.27	-0.12	-0.04	0.01	0.12	0.48	0.78	4.29	**5.62**	8.51
Quality	t + 1Y	-1.21	-0.19	-0.18	-0.12	-0.08	-0.06	-0.01	0.11	0.41	3.20	**4.41**	8.68
Quality	t + 2Y	-1.14	-0.22	-0.30	-0.14	-0.07	-0.01	0.05	0.12	0.31	2.07	**3.22**	8.93
Quality	t + 3Y	-1.35	-0.44	-0.32	-0.14	-0.06	0.01	0.09	0.21	0.38	2.23	**3.58**	8.90
Quality	t + 4Y	-1.19	-0.23	-0.35	-0.18	-0.06	0.02	0.11	0.17	0.28	1.81	**3.00**	8.99

Table 1: Persistence of Quality Measures

The table shows the average quality scores. Every 3 months, cryptocurrencies are ranked in ascending order on the basis of their quality score. The ranked cryptocurrencies are assigned to one of ten portfolios. Portfolio P1 contains the lowest quality cryptocurrencies, and ascends up to P10, which is the portfolio containing the highest quality cryptocurrencies. The table shows the quality score of each portfolio at the formation time t, up to 4 years in advance, noted by t + 1Y, t + 2Y, t + 3Y, t + 4Y. The sample contains 167 cryptocurrencies and runs from May 2016 to May 2021. H-L is the difference between portfolio P10 and P1. The coefficient is in bold when there is 5% statistical significance.

5. Price of quality cryptocurrencies

The first half of the analysis is designed to either confirm or reject the first null-hypothesis, high-quality cryptocurrencies are relatively cheaper than low-quality cryptocurrencies. In other words, do high-quality cryptocurrencies have lower prices than low-quality cryptocurrencies?

In order to measure if a certain cryptocurrency is relatively expensive or not, a ratio is needed. For this paper, the Network Value-to-Transaction ratio (short: NVT) is used. This ratio measures the efficiency of cryptocurrencies as a medium of exchange (Coelho, 2020). It is calculated by dividing the market cap size of the cryptocurrency by the transaction volume on a certain day of that coin. This ratio is seen as the crypto equivalent of the PE ratio (short for price-earnings ratio). A high PE ratio describes either an overvaluation of a company, or one that is in high growth. Liu & Zhang (2020) explain that a high NVT ratio indicates a higher speculation surrounding the coin, considering that its market cap outpaces the transaction volume. On the other hand, a low NVT ratio indicates a high usage of the coin/token relative to its market cap.

In other words, a high NVT ratio means that a coin is relatively expensive, and vice versa. The authors Liu & Zhang (2020) also mention that the main limitation of this ratio is that it only looks at the medium of exchange aspect of cryptocurrencies, and not the store of value aspect. Nevertheless, even with this shortcoming, the NVT ratio is being used in a number of papers in the cryptocurrency literature as a reliable measure.

The first null-hypothesis could now be rewritten as follows: high-quality cryptocurrencies have a lower NVT ratio than low-quality cryptocurrencies.

5.1 Control variables

The five control variables that will be used in the regression analysis are the following:

Crypto Age: Controlling for the age of cryptocurrencies has been done before. Jahani et al. (2018) uses this variable to research the price volatility of a coin/token. Based on the results, the authors find no significant relationship between the age and price volatility of a cryptocurrency. However, they do find a positive correlation between volume and the coin age. The study of Li et al. (2020) also uses the token age as a control variable to analyze pump-and-dump schemes. Results indicate that the token age is significant and negative in relation with the maximum return of a pump-and-dump event.

The crypto age in this paper is presented as the number of days since the first time the cryptocurrency was publicly available to trade. This data has been retrieved from the website coingecko.com, as this website is seen as a reliable source and used by numerous similar papers.

ICO Funding Dummy: As mentioned before in the literature review, another essential element of the crypto space are ICOs, short for Initial Coin Offerings. This tool of funding has been rapidly increasing, with over 440 ICOs in the first 6 months of 2018 (Cerchiello et al., 2019). The study of Lyandres et al. (2020) highlights the importance of having "skin in the game" by the entrepreneurs and investors. They find that the more involved the investor is in the project, the higher the post-ICO operating performance, coin adoption and financial success of that project.

Based on the literature, having a control variable based on the ICO aspect is necessary. Due to the unsure nature of the amount of funding an ICO has received, this control variable is being used as a dummy variable for this study. In case the cryptocurrency has received some sort of ICO funding, the value equals 1, and 0 otherwise. The data regarding the funding is retrieved from the websites https://www.icodata.io/ico and https://www.coindesk.com/ICO-Tracker.

Nasdaq Closing, *Nasdaq Volume* and *VIX:* The cryptocurrency market has a certain correlation with indices from different stock markets, reported by multiple literature studies. Firstly, there is a negative correlation with the VIX index, otherwise known as the volatility index. This index is a measure for the volatility of the S&P 500. The VIX will be used as a control variable, with the data retrieved from Yahoo Finance. In addition, this paper also will be using the Nasdaq adjusted closing historical prices and volume as controls, also retrieved from Yahoo Finance. The reasoning behind this is due to the evidence found in the literature that cryptocurrency investors are also more likely to invest in the NASDAQ and other technology focused indices and stocks. Hence, there might be a stronger relation between the movement of the NASDAQ and the crypto market.

5.2 Price of quality cryptocurrencies – regression analysis

Now that the explanatory variables, including the controls, have been elucidated, we turn to the actual regression analysis. To see whether a higher quality does indeed demand a lower relative price, meaning a lower NVT ratio, a cross-sectional regression is being run. The dependent variable P is the Log of the NVT ratio, with then the quality score and controls as independent variables, as such:

$$P_i = a + b * Quality_i + Controls_i + e_i$$

When looking at Table 2, it can be perceived that indeed, the higher the quality score, the lower the NVT ration, and thus, relative price. Quality is negative and significant across all four regressions, in relation with the NVT ratio. More precisely, when the quality score rises by 1 unit, the NVT will decrease between 21% and 31%. Furthermore, the results show that the age of the cryptocurrency, the NASDAQ closing price and volume are significant, although with a neutral coefficient. As for the VIX index, it is slightly negative with a coefficient of -0.03, and statistically significant. The ICO Funding Dummy is statistically insignificant in all the regressions.

The adjusted R square is very low, especially in the regressions without the control variables (1 and 3). Based on the adjusted R square of the first regression, it is stated that quality alone only contributes around 2% of the variation of the NVT ratio. Meaning 98% of the variation of the NVT ratio is explained by other variables. Adding the control variables increases the adjusted R square to 12%, which, although a noticeable jump, is still considerably insufficient. Furthermore, it is observed that the technicality fixed effect has practically no impact on the NVT ratio. There are two possible reasons to justify or explain as to why. The first possible reason is that the construction of the technicality component is simply wrong, and/or is focused on the wrong aspects. Another possibility is that the assigned values for the creation of the z-scores are incorrect. It is unclear if the cause is this paper or the paper of Hazari et al. (2019) with its comparative model between the consensus mechanisms. The second reason is that, as mentioned in numerous papers, there is no general agreement to which consensus mechanism is indeed the best or worst. Further research in analyzing the consensus mechanisms and creating a better technicality score might lead to improved results.

	1	*2*	*3*	*4*
Quality	**-0.21**	**-0.29**	**-0.22**	**-0.31**
	(-6.27)	*(-7.89)*	*(6.72)*	*(8.52)*
Crypto Age		**0.00**		**0.00**
		(3.12)		*(-6.23)*
ICO Funding Dummy		-0.11		0.12
		(-1.19)		*(-1.4)*
Nasdaq Closing		**0.00**		**0.00**
		(-12.7)		*(12.75)*
Nasdaq Volume		**0.00**		**0.00**
		(2.45)		*(-2.45)*
VIX		**-0.03**		**-0.03**
		(-4.76)		*(-4.78)*
Adjusted R Square	0.02	0.12	0.02	0.12
Technicality FE			x	x

Table 2: Cross-Sectional Regression, Price of Quality

The dependent variable is the Log of the NVT ratio, gathered on a 3-monthly basis. The explanatory variables are the quality scores ("Quality") and a number of control variables. "Crypto Age" is the number of days since the first time the currency was publicly available to trade. "ICO Funding Dummy" equals 1 in case the coin has received some sort of ICO funding, and 0 otherwise. "Nasdaq Closing" and "Nasdaq Volume" are the adjusted closing historical prices and volume of the NASDAQ exchange. "VIX" is a volatility index of the S&P 500. "Adjusted R Square" is the average of the adjusted R-square of the cross-sectional regressions. The Technicality Fixed Effects are included in regression 3 & 4, noted with an 'x'. Robustness checks of these regressions for the standard errors can be found in the Appendix. The T-statistics are presented in parentheses. The coefficient is in bold when there is 5% statistical significance.

Based on these results, an initial decision of the first null-hypothesis can be made, which is accepting the first null-hypothesis and rejecting the alternative hypothesis. High-quality cryptocurrencies are indeed relatively cheaper than low-quality cryptocurrencies, when looking at the cryptocurrency market as a whole. The deduction is made due to high-quality cryptocurrencies having a lower NVT ratio. This also means that there is less speculation and a higher usage of the coin/token surrounding high-quality cryptocurrencies. It is important to mention that quality has a very limited explanatory power, especially in the case without any control variables.

These results of the regression are based on the cryptocurrency market in its whole, meaning without any sorting. In the next section, the same cross-sectional regression will be run, but using decile market cap size-sorted portfolios. In case of similar results based on these next regressions, with cryptocurrencies in sorted portfolios, it would provide even stronger evidence for accepting the first null-hypothesis.

5.3 Price of quality with market capitalization size-sorted portfolios

In this section, the cryptocurrencies have been split into decile portfolios, according to their market capitalization size. P1 represents the portfolio containing the smallest cryptocurrencies, and P10 the largest.

5.3.1 Descriptive statistics analysis

Before starting the regression analysis on the ten portfolios, having some descriptive statistics could give a broader picture related to the characteristics within each market capitalization size portfolio.

From Table 3, it can be deduced that the larger the average cryptocurrency market cap in a portfolio, the lower the average NVT ratio of that same portfolio. In other words, the smaller the market cap size of the coin or token, the higher the speculative value and lower usage of that coin, which is in agreement with the majority of the literature. Secondly, the quality score also increases slightly in general between portfolios P1 and P9. There is then a big jump in quality score in the largest market capitalization size portfolio, P10. Lastly, crypto age does not really seem to change according to its market cap size, as long as it’s not on the extremes of the market capitalization size spectrum. When looking at the difference in age between the largest cryptocurrencies and smallest, there is a statistically significant difference, with P10 having the oldest and P10 the youngest, new cryptocurrencies.

Besides the descriptive statistics table, there are two figures that provide the same information as Table 3, but in a graphical form. These figures can be found in the appendix. As seen from Figure 1 & 2, there is a clear downward trend line with the average Log of NVT ratio in relation with market cap size, and an upward trend line with the average quality score in relation with the market capitalization size of the coin.

	P1	*P2*	*P3*	*P4*	*P5*	*P6*	*P7*	*P8*	*P9*	*P10*	*H-L*	*H-L t-stat*
Log NVT	185.55	264.76	252.01	193.57	142.69	165.49	120.19	146.57	124.55	52.56	**-133**	*(-7.02)*
Quality score	-0.54	-0.18	-0.19	-0.12	0.00	-0.03	0.01	0.14	0.39	2.08	**2.62**	*(12.17)*
Age	1327.41	444.13	1846.13	1727.36	1525.78	1627.99	1618.68	1706.23	1675.19	1933.87	**606.45**	*(4.81)*

Table 3: Descriptive Statistics Analysis, Price of Quality – decile portfolios

This table presents descriptive statistics results. Cryptocurrencies are split into decile portfolios based on their market capitalization size, with portfolios P1 (smallest market cap size) through P10 (largest market cap size). The descriptors are the average Log NVT, Quality score and Age of the cryptocurrency. The T-statistics are presented in parentheses. The coefficient is in bold when there is 5% statistical significance.

5.3.2 Cross-sectional regressions

After the review of the descriptive statistics, it is time to turn over to the regression analysis of the decile portfolios, ranked by market cap size. The same methodology regarding the regressions has been applied here as in the last section. However, the difference is that, instead of regressing all the data of all the cryptocurrencies together, ten different regressions using ten portfolios are being run. In this section a cross-sectional regression will be run using decile market cap size-sorted portfolios, in order to provide additional potential evidence for accepting the first null-hypothesis. The dependent variable is again the Log of the NVT ratio, with the independent variables still being the quality score and control variables.

From Table 4 it can be deducted that only the quality score of the largest cryptocurrencies has a statistically significant and positive impact on the NVT ratio. This means that an increase of 1 unit of the quality score of a top 10% largest market cap cryptocurrency, corresponds to a 56% increase in the relative price (NVT ratio) in said coin. In other words, the largest cryptocurrencies actually get more relatively expensive, when associated with a higher quality score. The same conclusion would be made about the smallest cryptocurrencies, if the coefficient (1.56) were significant.

No conclusions can be made about other market cap sizes, seeing as the quality score is not statistically significant in the rest of the decile portfolios. While not significant, there could still be the deduction that the majority of the top half-largest crypto portfolios have a negative coefficient in quality, while the bottom smallest crypto portfolios have a positive coefficient. In other words, chances are higher for a top half market cap size cryptocurrency to be less expensive, and vice versa for the bottom half. Once more, it is important to note that none of the quality coefficients between portfolios P1 and P9 are statistically significant. Furthermore, it is clear that virtually none of the control variables have an impact on the NVT ratio, in a market cap size-sorted portfolio case. As a last remark, the adjusted R squared value is substantially higher in the largest market cap portfolio P10. This means that 45% of the variation of the variation of the NVT ratio is explained by quality in that portfolio.

	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10
Quality	1.56	-1.11	0.64	-0.27	1.53	-1.37	-0.12	-0.44	-0.48	**0.59**
	(1.28)	*(-0.89)*	*(-0.61)*	*(-0.19)*	*(0.83)*	*(0.47)*	*(0.92)*	*(-0.36)*	*(-0.46)*	*(2.29)*
Crypto Age	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	(0.04)	*(-0.27)*	*(1.84)*	*(0.86)*	*(-1.11)*	*(1.92)*	*(0.91)*	*(1.52)*	*(0.48)*	*(0.93)*
Nasdaq Closing	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	(-1.65)	*(0.78)*	*(0.01)*	*(-1.58)*	*(-0.68)*	*(1.44)*	*(-1.92)*	*(-1.06)*	*(-1.31)*	*(0.92)*
Nasdaq Volume	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	(1.25)	*(0.88)*	*(-0.16)*	*(-0.82)*	*(0.38)*	*(0.98)*	*(0.77)*	*(-0.82)*	*(1.27)*	*(-0.21)*
VIX	-0.02	0.03	-0.01	0.02	0.00	-0.03	0.00	-0.02	0.01	**-0.05**
	(-0.56)	*(1.27)*	*(-0.4)*	*(-0.25)*	*(-0.04)*	*(0.4)*	*(0.95)*	*(-0.51)*	*(0.21)*	*(-1.99)*
Adjusted R Square	0.02	0.23	0.19	0.16	-0.03	0.08	0.07	0.56	0.06	0.45
Technicality FE	x	x	x	x	x	x	x	x	x	x

Table 4: Cross-Sectional Regression, Price of Quality – decile portfolios

Cryptocurrencies are ranked in ascending order into decile portfolios based on their market capitalization size. The dependent variable is the Log of the NVT ratio, on a 3-monthly basis. The explanatory variables are the quality scores ("Quality") and a number of control variables. "Crypto Age" is the number of days since the first time the currency was publicly available to trade. "Nasdaq Closing" and "Nasdaq Volume" are the adjusted closing historical prices and volume of the Nasdaq exchange. "VIX" is a volatility index of the S&P 500. "Adjusted R Square" is the average of the adjusted R-square of the cross-sectional regression. The Technicality fixed effects are included in all the regression, noted with an 'x'. Robustness check of these regressions for the standard errors can be found in the Appendix. The T-statistics are presented in parentheses. The coefficient is in bold when there is 5% statistical significance.

These results are not in line with the results of the regressions in the previous section, which have led to the acceptance of the first null-hypotheses, "high-quality cryptocurrencies are relatively cheaper than low-quality cryptocurrencies". The market cap size-sorted portfolio results are more ambiguous. On one hand there is a certain difference between the bottom and top half largest cryptocurrencies. Top half cryptocurrencies are less expensive, concurring with the first null-hypothesis. On the other hand, there are outlier results that contest this, namely the ones in portfolio P10.

While accepting the first null-hypothesis is still the decision in this paper, caution is taken, as further research might shed more light into this. Sorting the cryptocurrencies in an alternative way could be one option. Another future road for research is to use a different dependent variable, considering the aforementioned limitations that come with the NVT ratio.

5.4 Price of quality based on quality subcomponents

After analyzing the impact of the quality score on the relative price, both for the total market, as well as for market cap size sorted decile portfolios, this section is dedicated to regressing each of the quality subcomponents. These results are not directly related to any hypothesis, but it is still worthwhile to observe the characteristics of the subcomponents. It is possible that each of the components (*Intellectuality*, *Significance* and *Safety*) have a particularly significant explanatory power and/or coefficient on their own. The cross-sectional regressions have the exact same structure as the one with the overall quality score, as such:

$$P_i = a + b * Intellectuality_i + Controls_i + e_i$$

$$P_i = a + b * Significance_i + Controls_i + e_i$$

$$P_i = a + b * Safety_i + Controls_i + e_i$$

$$P_i = a + b_1 * Intellectuality_i + b_2 * Significance_i + b_3 * Safety_i + Controls_i + e_i$$

It can be derived from Table 5 that each of the three subcomponents do indeed have a somewhat different impact on the NVT ratio. All of the three subcomponents have negative and statistically significant coefficients. Moreover, *Significance* has the highest coefficient of -0.22, followed by *Intellectuality* (-0.15) and *Safety* (-0.11). All three subcomponents on their own are also statistically significant. When the three subcomponents are put together and regressed, the *Intellectuality* component becomes completely insignificant, whereas *Significance* and *Safety* become statistically more significant and have an even more negative coefficient. Additionally, the control variables are practically the same in all regressions, previous section included. The adjusted R square does not, in effect, change throughout each regression, even with the technicality fixed effects included.

	1	2	3	4	5
Intellectuality	**-0.15**			-0.02	-0.02
	(-4.16)			*(0.4)*	*(0.46)*
Significance		**-0.22**		**-0.24**	**-0.24**
		(-5.93)		*(-5.44)*	*(-5.51)*
Safety			**-0.11**	**-0.15**	**-0.18**
			(2.71)	*(3.8)*	*(4.65)*
Crypto Age	**0.00**	0.00	0.00	**0.00**	**0.00**
	(1.96)	*(1.9)*	*(1.39)*	*(2.54)*	*(2.65)*
ICO Funding Dummy	0.11	-0.14	-0.1	0.11	0.11
	(-1.36)	*(-1.69)*	*(-1.26)*	*(-1.28)*	*(-1.32)*
Nasdaq Closing	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**
	(-11.86)	*(-12.08)*	*(-11.31)*	*(-12.02)*	*(-12.2)*
Nasdaq Volume	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**
	(2.48)	*(2.5)*	*(2.39)*	*(2.46)*	*(2.56)*
VIX	**-0.03**	**-0.03**	**-0.03**	**-0.03**	**-0.03**
	(-4.67)	*(-4.68)*	*(-4.6)*	*(-4.69)*	*(-4.62)*
Adjusted R Square	0.10	0.11	0.09	0.11	0.11
Technicality FE					x

Table 5: Cross-Sectional Regression, Price of Quality - subcomponents

The dependent variable is the log of the NVT ratio, on a 3-monthly basis. The explanatory variables are the quality scores of the subcomponents, "Intellectuality", "Significance", "Safety" and a number of control variables. "Crypto Age" is the number of days since the first time the currency was publicly available to trade. "ICO Funding Dummy" equals 1 in case the coin has received some sort of funding, and 0 otherwise. "Nasdaq Closing" and "Nasdaq Volume" are the adjusted closing historical prices and volume of the Nasdaq exchange. "VIX" is a volatility index of the S&P 500. "Adjusted R Square" is the average of the adjusted R-square of the cross-sectional regression. The Technicality fixed effects are included in regression 3 & 4, noted with an 'x'. Robustness check of these regressions for the standard errors can be found in the Appendix. The T-statistics are presented in parentheses. The coefficient is in bold when there is 5% statistical significance.

6. Return of quality cryptocurrencies

The analysis of the excess return of high-quality cryptocurrencies is split into three parts. In the first part, the cryptocurrencies are split into decile portfolios according to their given quality score, with then their returns measured with respect to the excess returns in different asset models. In the second part, the paper measures the excess returns of portfolios that go long in high-quality cryptocurrencies and short in low-quality cryptocurrencies, also with respect to different asset models. In order for this to happen, a QMJ factor is created, short for Quality Minus Junk, which follows the same construction as in the paper of Asness et al. (2019). Finally in the last part, the returns of the QMJ factor are being analyzed during severe bear and bull markets, in order to observe their hedging capabilities.

6.1 Construction

Before analyzing and comparing the excess returns of the quality-sorted decile portfolios with different asset models, it is important to elaborate how the factors of these models are constructed. The two asset models being used are the CAPM one-factor model and the Fama French 3-factor model. These asset models and their factors were intended for stocks, so different variables for the factor's construction should be used for cryptocurrencies in this paper. Factors used for the CAPM and Fama French 3-factor models follow the same construction methodology as the paper of Coelho (2020), considering the author applies these models to a cryptocurrency space.

The Carhart 4-factor model and Fama French 5-factor model are not being used in this paper. The time frame and data range in this research are not extensive enough for a comprehensive capture of the momentum factor for the 4-factor model. This limitation does allow for future research to explore and expand in this aspect. Furthermore, there is the possibility of high collinearity between the *Safety* factor and the momentum factor. The Fama French 5-factor model has not been used due to the high uncertainty and complexity of converting the two additional factors (Robust Minus Weak and Conservative Minus Aggressive) from a stock/firm space to cryptocurrency space. This is the same reason as to why papers such as Coelho (2020) and Pontoh et al. (2019) that use these asset pricing models for cryptocurrencies as well, do not use the Fama French 5-factor model.

The two standard asset pricing models used in this paper are formalized as such:

$$\text{CAPM: } r_t - rf_t = \alpha + \beta^{MKT} * (rm_t - rf_t) + \varepsilon_t$$

$$\text{Fama French 3-factor: } r_t - rf_t = \alpha + \beta^{MKT} * (rm_t - rf_t) + \beta^{SMB} * SMB_t t + \beta^{HML} * HML_t + \varepsilon_t$$

The market factor (MKT) is proxied by the CRIX, which has the purpose of representing the cryptocurrency market movements as accurately as possible. The CRIX, which stands for CRyptocurrency IndeX, is a benchmark for the crypto market. It determines the number of coins included via two information criterions and weights the components based on market cap size, thus mimicking a monthly rebalanced portfolio. Hence, it provides a summary statistic for the cryptocurrency market, as the S&P 500 does for the current state of the US stock market. The data for the computation is being provided CoinGecko (http://data.thecrix.de/#services). Rm is represented by the CRIX market return and Rf is the risk-free rate of that period.

The construction for the SMB (Small Minus Big) and HML (High Minus Low) factors is as follows: the cryptocurrencies in which the market capitalization is above the 90th percentile is considered to have large capitalization (BIG) while the bottom 10th percentile is classified as small capitalization (SMALL). Afterwards each group is further divided into 3 quantiles based on the NVT ratio, with the bottom 30th quantile classified as LOW, the ones between 30th and 70th quantiles

MEDIUM, and the rest above the 70th quantile considered HIGH. The six portfolios are then created through the intersection of those factors which generates the following combinations: SMALL/LOW, SMALL/MEDIUM, SMALL/HIGH, BIG/LOW, BIG/MEDIUM and BIG/HIGH. The abbreviations for these six portfolios are, S/L, S/M, S/H, B/L, B/M and B/H.

Finally, the Small Minus Big factor (SMB) is then determined by calculating the average return of the three SMALL portfolios (S/L, S/M, S/H) minus the average return of the three BIG portfolios (B/L, B/M, B/H). The High Minus Low factor (HML) follows the same sort of construction, with the average return of the two HIGH portfolios (S/H, B/H) minus the average return of the two LOW portfolios (S/L, B/L).

6.2 Quality-Sorted portfolios

As mentioned before, the cryptocurrencies are sorted into decile portfolios based on their quality score, with P1 having the lowest quality score, and P10 the highest. For the main descriptors there is the excess return of the portfolios, the CAPM alpha and the Fama French 3-factor model alpha. The alphas measure the abnormal returns over the risk factors, which translates to the return gained from holding the portfolio, given that the investor would already hold the risk factor portfolios. The alphas therefore show what the risk-adjusted returns are, which is what is needed to draw a conclusion surrounding the second and third null-hypotheses. The excess return is the return minus the US T-bill rate, that is retrieved from the Kenneth French database (mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html). Alpha is the intercept in a time-series regression of 3-monthly excess return.

In this section, the second null-hypothesis is either accepted or rejected: High-quality cryptocurrencies have higher risk-adjusted returns than low-quality cryptocurrencies. The measurement that is observed and used in order to make this choice is the Sharpe Ratio, which measures the risk-adjusted returns. In case high-quality cryptocurrencies have a higher Sharpe Ratio than low-quality cryptocurrencies, the second null-hypothesis is accepted.

As seen from Table 6, the highest quality cryptocurrencies earn 209 basis points less than the lowest quality cryptocurrencies. In other words, a self-financing portfolio that goes long in the highest quality cryptocurrencies and short the lowest quality cryptocurrencies, actually earns a significant negative return. Furthermore, as the quality of the cryptocurrency increases, there seems to be a steady decline in excess return over the T-bill rate. Although most of the results of the first model are significant, the same cannot be said about the CAPM alphas and 3-factor alphas. None of the alphas from the CAPM or Fama French 3-factor models are statistically significant. Nonetheless, there seems to be the same decline in excess return linked with an increase in quality. However, the difference in excess return between the highest quality cryptocurrencies and lowest cryptocurrencies is statistically significant. The highest quality cryptocurrencies earn 176 basis points less than the lowest quality cryptocurrencies in the CAPM model, and 113 basis points less in case of the Fama French 3-factor model.

All these results show the same overall picture though, which is that the lowest quality cryptocurrencies portfolios earn a higher excess return than the highest quality cryptocurrencies portfolios, albeit statistically significant or not. Parenthetically as for some concrete examples, based on given quality score in this paper, some of the highest quality cryptocurrencies are OMG Network, Ripple and Stellar. Some of the lowest quality cryptocurrencies are Gleec, Digital Note and Veritaseum.

Furthermore, the adjusted R squared ranges from 27% to 65%, with an average of 49%. Lastly, it can be seen that the Beta generally decreases, as the average quality of cryptocurrencies in the portfolio increases. This is an expected result, as a lower volatility is linked with higher quality in this study.

The measurement tool used in order to answer the second null-hypothesis and to gauge the performance of the different quality cryptocurrencies portfolio, is the Sharpe Ratio. This ratio measures the excess return over the risk-free rate with the corresponding risk/volatility of that portfolio. The higher the Sharpe Ratio, the greater the investment return is relative to the amount of risk taken. In other words, the higher the Sharpe Ratio, the higher risk-adjusted return.

From the information gathered from Table 6, it can be perceived that the Sharpe Ratio is generally higher for lower quality cryptocurrencies than higher quality cryptocurrencies. Four out of the five lowest quality decile portfolios have a Sharpe Ratio higher than 0.5, whereas all of the highest quality decile portfolios have a Sharpe Ratio lower than 0.5. Hence, even though the variation is higher for the lower quality cryptocurrency portfolios (higher Betas), when adjusted for risk, the excess returns are still higher than of the high-quality cryptocurrency portfolios.

Based on these deductions, the second null-hypothesis, “High-quality cryptocurrencies have a higher risk-adjusted returns than low-quality cryptocurrencies.” is rejected. The Sharpe Ratio gives a good response to this hypothesis. Figure 3, which can be found in the appendix, provides a graphical sense of the trend of the Sharpe Ratio per portfolio. There it can be made even clearer that the lower half of the quality score portfolios have a higher Sharpe Ratio than the top half quality score portfolios.

	P1 (Low)	P2	P3	P4	P5	P6	P7	P8	P9	P10 (High)	H-L	L-H
Excess return	**2.55**	**2.24**	**1.11**	**0.94**	1.64	**0.57**	0.41	**0.37**	**0.56**	**0.46**	**-2.09**	**2.09**
	(2.42)	*(3.07)*	*(3.29)*	*(3.03)*	*(1.21)*	*(2.03)*	*(1.55)*	*(2.09)*	*(2.08)*	*(2.23)*	*(-2.03)*	*(2.03)*
CAPM alpha	1.87	0.74	0.35	0.20	-0.33	-0.06	-0.11	-0.05	0.10	-0.06	**-1.93**	**1.93**
	(1.31)	*(0.97)*	*(1.07)*	*(0.71)*	*(-0.2)*	*(-0.2)*	*(-0.38)*	*(-0.31)*	*(-0.32)*	*(0.26)*	*(-14.96)*	*(14.96)*
3-factor alpha	1.20	0.78	0.27	0.09	-0.42	-0.09	-0.11	-0.06	0.07	-0.08	**-1.28**	**1.28**
	(1.26)	*(1.04)*	*(1.14)*	*(0.5)*	*(-0.33)*	*(-0.56)*	*(-0.56)*	*(-0.6)*	*(0.39)*	*(-0.52)*	*(-2.08)*	*(2.08)*
Beta	2.09	3.81	1.90	1.85	4.97	1.58	1.30	1.07	1.17	1.31	-0.77	
Sharpe Ratio	0.53	0.67	0.75	0.67	0.26	0.42	0.33	0.45	0.43	0.35	-0.18	
Adjusted R2	0.27	0.36	0.56	0.64	0.30	0.61	0.49	0.65	0.47	0.56	0.29	

Table 3: Quality-sorted Portfolios

This table shows the calendar-time portfolio returns. Cryptocurrencies are ranked in ascending order into decile portfolios based on their quality score, on a 3-monthly basis. The portfolios are value weighted and refreshed every 3 months. Excess return is associated with the T-bill rates in the US. Alpha is the intercept in a time-series regression of 3-monthly excess return. The explanatory variables are the returns of the market (MKT), Small Minus Big (SMB), High Minus Low (HML). The sample runs from May 2016 to May 2021. "Beta" is the average sensitivity of the corresponding portfolio. "Sharpe Ratio" measures the excess return over the risk-free rate with the corresponding risk. The T-statistics are presented in parentheses. The coefficient is in bold when there is 5% statistical significance.

An additional noteworthy observation is that Table 6 also gives an indication for the response of the third null-hypothesis: "Going long in high-quality cryptocurrencies and shorting low-quality cryptocurrencies earn significant risk-adjusted returns.". When looking at the difference of the Sharpe Ratio between portfolios P1 and P10, there is a difference of 18 basis points. In other words, going long in the highest-quality cryptocurrencies, and short in the lowest-quality cryptocurrencies, results in a negative risk-adjusted return. However, this deduction is not conclusive, but merely an indication. In the next section, a factor dedicated to the quality that also accounts for the size aspect will be created in order to try to get a verdict for the third null-hypothesis.

6.3 Quality Minus Junk

The results of the previous table indicated that there was an alpha, although not significant, after accounting for the CAPM and Fama French 3-factor models. Hence, there is the possibility that another factor may absorb that alpha. This leads to the creation of the Quality Minus Junk factor, short QMJ. As mentioned before in the Portfolio section, QMJ factors are constructed as the intersection of six value-weighted portfolios formed on size and quality. The size breakpoint is the median of market capitalization size. The QMJ factor return is the average return of the two high-quality portfolios minus the average return of the two low-quality portfolios. In other words, going long on the highest quality cryptocurrencies that are the average of the small and large ones and going short on the lowest quality cryptocurrencies that are the average of the small and large ones. This way, the smaller cryptocurrencies are given a chance to have a bigger representation and give a more complete picture, unlike in the previous section. The QMJ in asset pricing models looks as followed:

$$\text{QMJ one-factor: } r_t - rf_t = \alpha + \beta^{QMJ} * QMJ_t + \varepsilon_t$$

$$\text{QMJ 2-factor: } r_t - rf_t = \alpha + \beta^{MKT} * (rm_t - rf_t) + \beta^{QMJ} * QMJ_t + \varepsilon_t$$

$$\text{QMJ 4-factor: } r_t - rf_t = \alpha + \beta^{MKT} * (rm_t - rf_t) + \beta^{SMB} * SMB_t + \beta^{HML} * HML_t + \beta^{QMJ} * QMJ_t + \varepsilon_t$$

6.3.1 Returns

This section will analyze the returns of portfolios using QMJ factors and also portfolios using different quality subcomponents. Here, the third null-hypothesis: "Going long in high-quality cryptocurrencies and shorting low-quality cryptocurrencies earn significant risk-adjusted returns.", is either accepted or rejected. Again, the Sharpe Ratio is utilized in order to draw a conclusion regarding this decision.

The results in Table 7 show the following deductions. When a portfolio is deployed that goes long in high-quality cryptocurrencies and short in low-quality cryptocurrencies while also accounting for size, that portfolio does not earn a significant alpha in any of the three model cases. In other words, portfolios that use the QMJ factor do not earn significant alphas. After controlling for the excess return over T-bill, there is a positive return, although not significant. When controlling for the CAPM and the Fama French 3-factor model, the alpha even becomes negative.

When the observation switches to the individual quality subcomponents, there is a different story. For both *Intellectuality* and *Significance*, there is a positive and significant alpha, with respect to the excess returns over the T-bills. Twice over, the alphas are relatively very high, with basis points of 75 and 110. These abnormal returns stay positive for *Intellectuality* and *Significance* with respect to the CAPM and Fama French 3-factor models, although not significant. Therefore, the indication here would be that going long in cryptocurrencies that have a high number of patents or articles, and short in cryptocurrencies with a low number of patents or articles on a 3-monthly cycle, leads to portfolios that earn a positive excess return.

Moreover, the Sharpe Ratio is positive for *Intellectuality* and *Significance*. However, for the QMJ factor and especially for the *Safety* subcomponent, the Sharpe Ratio is negative. This is an additional indication that deploying a self-financing portfolio using factors based on the number of articles or patents, creates for a positive excess return. Following these deductions, the argument is made that the subcomponent *Safety* drags down the efficiency and capability of the QMJ factor. In a further section in this paper, the same regression has been run using the QMJ factor which does not account for the *Safety* subcomponent in its quality score.

Another notable observation is the fact that both size factor (SMB) and value factor (HML) are both negative and significant. Thus, each of these factors affect the returns of the QMJ factor negatively. This is a rational outcome considering that high-quality cryptocurrencies tend to have a larger market capitalization size, hence a negative SMB factor. Furthermore, the negative and significant value factor (HML) with respect to the QMJ factor and subcomponents is a direct consequence from the fact that high-quality cryptocurrencies have a lower NVT ratio. This was covered earlier in the first part of the regression analysis, when analyzing the valuation of quality.

Based on the results of Table 7, the third null-hypothesis "Going long in high-quality cryptocurrencies and shorting low-quality cryptocurrencies earn significant risk-adjusted returns.", is rejected. The QMJ factor does not bring forth a significant positive alpha in a deployed portfolio, either on its own or with other asset models, but more importantly, the Sharpe Ratio is negative in these cases. Although this conclusion was anticipated based on the results of the quality-sorted decile portfolios, having a dedicated factor that also takes into consideration the size of the cryptocurrencies indicating the same, is convincing.

	QMJ	*INTELLECTUALITY*	*SIGNIFICANCE*	*SAFETY*
Excess Returns	0.14	**0.75**	**1.10**	-0.04
	(0.35)	*(2.53)*	*(2.71)*	*(-0.19)*
CAPM alpha	-0.08	0.33	0.26	-0.10
	(-0.22)	*(1.04)*	*(0.66)*	*(-0.45)*
3-factor alpha	-0.04	0.24	0.18	-0.04
	(-0.15)	*(1.07)*	*(0.75)*	*(-0.28)*
MKT	0.32	0.40	0.39	-0.02
	(0.69)	*(0.95)*	*(0.8)*	*(-0.07)*
SMB	**-0.75**	**-0.73**	**-1.01**	**-0.45**
	(-4.37)	*(-4.49)*	*(-5.44)*	*(-3.65)*
HML	**-0.47**	**-0.43**	**-0.59**	**-0.32**
	(-4.56)	*(-4.26)*	*(-4.76)*	*(-4.73)*
Sharpe Ratio	-0.03	1.58	1.00	-2.06
Adjusted R2	0.58	0.62	0.35	0.85
F-test	14.84	17.94	7.25	61.50

Table 7: Quality Minus Junk: Returns

This table shows calendar-time portfolio returns. QMJ factors are constructed as the intersection of six value-weighted portfolios formed on size and quality. After that, cryptocurrencies are assigned to two size-sorted portfolios, based on their market capitalization, on a 3-monthly basis. The size breakpoint is the median of market cap size. The QMJ factor return is the average return on the two high-quality portfolios minus the average return on the two low-quality portfolios. Portfolios based on the subcomponents, "Intellectuality", "Significance" and "Safety" are constructed in a similar manner. The explanatory variables are the returns of the market (MKT), Small Minus Big (SMB), High Minus Low (HML). The sample runs from May 2016 to May 2021. The table also shows the average Sharpe Ratio, Adjusted R2 and F-test. The T-statistics are presented in parentheses. The coefficient is in bold when there is 5% statistical significance.

6.3.2 Correlations

This section focuses on the correlation between the returns of the individual quality components; *Intellectuality*, *Significance* and *Safety*. Although there is no direct association between the results and the hypotheses, the additional insights into the subcomponents might still be interesting.

The results on Table 8 show that there is an all-round positive, yet wide-ranging, correlation between the different quality subcomponents when it comes to excess returns over the T-bill rates. Ergo, it seems that in general the higher the quality score of a cryptocurrency in one area, the higher the score will be in a different area. The three subcomponents are also adequately positively correlated with the returns of the overall QMJ factor, with a correlation between 0.27 and 0.55. The high correlation of 0.78 between *Safety* and *Intellectuality* suggests that there is an inverse relation between the number of patents and volatility regarding a certain cryptocurrency. On the other hand, the relatively low correlation of 0.11 between *Significance* and *Intellectually* is also notable. The source of the data of these two subcomponents is the same overarching website, namely Google Patents and Google Articles. One explanation could be that there is a certain delay, meaning the patent is published first, and then followed by the article or paper, or vice versa.

	Returns			
	QMJ	***INTELLECTUALITY***	***SIGNIFICANCE***	***SAFETY***
QMJ	1.00			
INTELLECTUALITY	0.41	1.00		
SIGNIFICANCE	0.27	0.11	1.00	
SAFETY	0.55	0.78	0.20	1.00

Table 8: Quality Minus Junk: Correlations

This correlation matrix table shows the correlation of 3-monthly returns between the QMJ factor and the subcomponents. The QMJ factors are constructed as the intersection of six value-weighted portfolios formed on size and quality. After that, cryptocurrencies are assigned to two size-sorted portfolios, based on their market capitalization, on a 3-monthly basis. The size breakpoint is the median of market cap size. The QMJ factor return is the average return on the two high-quality portfolios minus the average return on the two low-quality portfolios. The subcomponents "Intellectuality", "Significance" and "Safety" all follow the same construction as the QMJ factor. The sample runs from May 2016 to May 2021.

6.3.3 Severe Bear and Bull Markets

Now that the hypothesis analysis has been performed, it might also be interesting to observe if the QMJ factor would be useful for other cases. In this last part of the analysis of the QMJ factor, different scenarios are being run. Due to the long-term nature of the high volatility in the cryptocurrency market, the data has been split up into different periods of 3 months for analysis. The strength of the QMJ factor has been tested under the periods of severe bear and bull markets. Severe bear markets are defined as having a total return in the past 3 months of at least -20%, whereas severe bull markets have a total return of +25% or more in the past 3 months. Noticeable periods that fall into these categories are the crypto crash in early 2018 and the crash in early 2020 due to COVID-19. The extreme bull markets of 2017 and early 2021 are also included in the severe bull market category.

It can be deduced from Table 9, that during severe bear markets, the excess returns of the QMJ factors are negative and significant. This indicates that a portfolio using the QMJ factor only would not be an effective hedging strategy in severe bear markets. This is quite a surprising result, and one that differs greatly from the paper of Asness et al. (2019). Going long in high-quality cryptocurrencies would suggest a safer investing strategy, which should be resilient in severe bear markets. Furthermore, the excess return of the QMJ factor in severe bull markets is higher than that of the CAPM and Fama French 3-factor models, although all insignificant.

The most interesting result though, is that when deploying a portfolio that combines the QMJ factor with the Fama French 3-factor model, it actually earns a positive and significant return of 12 basis points in severe bear markets. Following this deduction leads to the believe that this might be an efficient portfolio management strategy to combat, and even profit from future crashes in the cryptocurrency market. Further research into combining the QMJ factor with asset models containing multiple factors in order to hedge should create for interesting results.

	Returns		
	Excess Returns	CAPM alpha	3-factor alpha
All periods	0.14	-0.08	-0.04
Severe bear markets	**-0.53**	0.10	**0.12**
Severe bull markets	0.73	0.32	0.01
	T-Statistics		
	Excess Returns	CAPM alpha	3-factor alpha
All periods	*(0.35)*	*(-0.22)*	*(-0.16)*
Severe bear markets	*(-11.83)*	*(0.83)*	*(2.21)*
Severe bull markets	*(0.88)*	*(0.24)*	*(0.02)*

Table 4: Quality Minus Junk: Returns in extreme scenarios

This table shows calendar-time portfolio returns in severe bear and bull markets. Severe bear markets are defined as a total return in the past 3 months below -20%, severe bull markets have a total return of +25% in the past 3 months. QMJ factors are constructed as the intersection of six value-weighted portfolios formed on size and quality. After that, cryptocurrencies are assigned to two size-sorted portfolios, based on their market capitalization size, on a 3-monthly basis. The size breakpoint is the median of market cap size. The QMJ factor return is the average return on the two high-quality portfolios minus the average return on the two low-quality portfolios. The explanatory variables are the returns of the market (MKT), Small Minus Big (SMB), High Minus Low (HML). The sample runs from May 2016 to May 2021. The T-statistics are presented in parentheses. The coefficient is in bold when there is 5% statistical significance.

6.3.4 Heteroskedasticity-Robustness checks

To conclude the main research, after analyzing the quality score and Quality Minus Junk factor, a series of robustness checks are performed, starting with a Heteroskedasticity robustness check. While optional, it does make sure that the results are robust to heteroskedasticity, and in turn gives more power to the hypothesis testing ability. The Het-robustness checks have been applied to the sections that analyze the returns of the quality-sorted decile portfolios and QMJ factor, due to their importance in this study.

It is deducted from the tables that these results are in fact robust. Although a couple of results have become marginally significant on the 95% confidence level, the rest of the conclusions remain the same. Generally, the T-values increase slightly under the Het-robustness checks. The full results can be found in the Appendix under section 10.3.

In the next chapter of this paper, a different sort of robustness check will be applied, more specifically in the form of testing alternative arguments surrounding the construction of the quality score.

7. Alternate quality score construction

For the second part of the robustness check, different modifications towards the construction of the quality score will be put to the same tests as in the main research. The quality score used throughout the primary research was composed of three equal weighted subcomponents, based of their respective z-scores, as such:

$$Quality = z\,(Intellectuality + Significance + Safety).$$

In the upcoming sections, three different constructions will be analyzed. The first is the use of market capitalization weighted subcomponents. The second alternate construction is with the incorporation of the *Technicality* z-scores into the quality score. These z-scores were used as fixed effects in the main research. The third alternate construction is regarding the use of only the *Intellectuality* and *Significance* subcomponents.

Afterwards, the returns of both these alternate quality scores and the modified QMJ factor will be analyzed in the same way as in the main research. For all three adjustments of the quality scores there will also be applied a Het-robustness check, for good measure. All these tables are found in the Appendix session, under 10.4, 10.5 and 10.6.

7.1 Market Capitalization Weighted Quality Score

The first adjustment to the construction of the quality score is done towards the weighing aspect of the subcomponents. The z-scores of every subcomponent are this time modified in relation to the market capitalization share of every cryptocurrency, in every time period. To create the general quality scores though, the subcomponents are again equally weighted between them. Subsequently, the same methodology is applied to obtain the returns of the cryptocurrencies and quality-sorted portfolios. The full tables can be found in the appendix under 10.4.

The first noteworthy difference is that the portfolios containing higher quality cryptocurrencies generally have higher excess returns than the portfolios with lower quality cryptocurrencies. This result would have led to a higher chance of accepting the second null-hypothesis. Although this is the complete opposite of the results found in the main research, there still isn't a clear upward trend in excess return in relation with the quality score. When it comes to the correlation between the different subcomponents, there is an overall large and positive correlation between *Safety* and *Significance*, and *Safety* and *Intellectuality*. The low correlation between *Significance* and *Intellectuality* is still present.

Looking at the deployment of a portfolio that utilizes the QMJ factor, there is a certain improvement to be observed. In case of going long on high-quality cryptocurrencies and going short in low-quality cryptocurrencies, when using a quality score that is weighted on market capitalization, there is a significant excess return relative to the T-bills of 95 basis points. The subcomponents *Significance* and *Intellectuality* also earn an excess return of respectively 77 and 74 basis points. These excess returns are remarkably high and statically significant. The same cannot be said for the *Safety* subcomponents, having all insignificant and neutral alphas. Again, the same argument as in the main research is made, that is, that the *Safety* subcomponent drags down the efficiency of the overall quality score, and thus the QMJ factor. Regarding the cases of the CAPM and 3-factor models, there is also no significant alpha. This remains unchanged relative to the principal research.

In extreme cases like severe bull and bear markets, the returns of the QMJ factor are much more volatile and also significant in both cases. Most notable is the 171 basis points of excess returns that the QMJ factor portfolio earns in severe bull markets. In addition, in severe bear markets, the portfolios earn a significant negative alpha. Consequently, there could be the possibility of creating a portfolio that contains both the original QMJ factor, as well as this modified QMJ factor, in order to hedge against both severe bear and bull markets.

Based on these results, it can be deduced that using a quality score that has its subcomponents weighted based on the market capitalization, leads to a different picture compared to the main research. Higher quality cryptocurrencies portfolios do actually earn a higher excess return, but using portfolios containing the QMJ factor creates results that are more volatile in extreme cases. Further research based on this alternative quality score and its hedging capabilities might be interesting, as mentioned before.

7.2 Quality Score with Technicality incorporated

The second variation of the construction of the quality score is the addition of the *Technicality* subcomponent, next to the main three subcomponents. In the main research *Technicality* was used as a fixed effect. The component is constructed with the z-scores of the quantitative rankings of energy consumption, scalability and centralization of every cryptocurrency. The four subcomponents have equal weighting between them, as in the main research. The new quality score will be constructed as following:

$$\textit{Quality} = z\ (\textit{Intellectuality} + \textit{Significance} + \textit{Safety} + \textit{Technicality}).$$

The excess returns and alphas in the different models of quality-sorted portfolios remain practically the same as in the main research, portfolios containing lower quality cryptocurrencies earn a higher excess return than portfolios containing higher quality cryptocurrencies. When deploying a portfolio containing the QMJ factor, the results are generally the same too. The main difference is that a portfolio utilizing only the QMJ factor now earns a significant positive alpha of 95 basis points.

However, multiple differences with the results of the main research can be observed in the extreme scenarios. It is seen that a portfolio utilizing the QMJ factor earns an excess return of 169 basis points relative to the T-bill rate during severe bull markets. This is quite similar to the first mentioned adjustment, the market capitalization weighted quality score. However, in severe bear markets, the QMJ portfolio holds up much better than the two aforementioned constructions of the quality score. This might lead to believe that using a quality score with a technicality subcomponent, would be more efficient as a hedging tool then other constructions of the quality score, when not combined with other asset models. The full tables can be found in the appendix under section 10.5.

These results formulate a more reserved change relative to the main research. There is virtually no change in excess returns in any case, except for the QMJ-only portfolio. However, the performance of the QMJ factor portfolios in both extreme cases is significant.

7.3 Quality Score with only Intellectuality and Significance

The third variation of the quality score construction, concerns the disregard for the *Safety* subcomponent. This leaves a construction of the quality score based only on the *Intellectuality* and *Significance* subcomponents. Furthermore, there is no modification of the z-scores in these two subcomponents, in addition to equal weighing between them. The full tables can be found in the appendix under 10.6.

The new quality score will be constructed as such:

$$\textit{Quality} = z\ (\textit{Intellectuality} + \textit{Significance}).$$

The reasoning behind this alternate construction is due to the fact that throughout the paper, the argument was being made that the subcomponent *Safety* was decreasing the efficiency and capabilities of the QMJ factor in terms of excess return. It was observed that both the QMJ factor and *Safety* subcomponent did not have a significant positive alpha, whereas the *Intellectuality* and *Significance* subcomponents did. The Sharpe Ratios indicated the same.

As a result, the alpha of the new QMJ factor portfolio has increased substantially, relative to the original QMJ factor portfolio. When going long on high-quality cryptocurrencies and going short in low-quality cryptocurrencies, when using a quality score that only accounts for *Intellectuality* and *Significance*, there is a significant excess return relative to the T-bill rate of 101 basis points. However, this is the only significant alpha, even when looking at portfolios utilizing the subcomponents only. Lastly, portfolios using this modified QMJ factor does substantially differ from the results of the main research regarding extreme scenarios.

Based on these results, it can be deducted that besides the excess returns increase of the QMJ only portfolio, the general results are not substantially improved. This is relatively an underwhelming result, in response to the aforementioned argument that was being made throughout the paper.

7.4 Comparison of the results between quality score constructions

Based on all the results of the different versions of the quality score, it is clear that there is no overall "best" version. All four constructions of the quality score have led to strengths and weaknesses in different domains. When looking at the alphas of portfolios that use the QMJ factor only, the quality score construction without the *Safety* subcomponent brings out the highest positive and significant excess return. Portfolios utilizing QMJ factors that are based on market cap weighted quality score, also earn high significant excess returns. However, this construction also leads to the most volatile results in severe bull and bear markets. In these extreme scenarios, portfolios containing only the QMJ factor based on the technicality construction perform the best in severe bull markets, having the highest excess return in such markets while still preserving a somewhat resilience largest resilience against bear markets.

That being said, deploying a portfolio using the Fama French 3-factor model with the original QMJ factor incorporated, actually earns a positive and significant alpha of 12 basis points in severe bear markets. As mentioned before, this is a relatively noteworthy performance result, considering that severe markets are defined in this paper as periods with over a 20% overall return decrease. However, during severe bull markets, the same portfolio has a virtually nonexistent excess return. As a conclusion, the original quality score and QMJ factor, combined with the Fama French 3-factor model, leads to portfolios with very promising hedging capabilities in severe bear markets.

8. Discussion, Limitations & Future Research

The cryptocurrency space is still in its infancy stage. This is reflected in the literature as well, where there is still a lot to explore in future research. Although this paper has aimed to offer a meaningful addition to the literature, there is still an endless number of roads to be taken in order to analyze quality in cryptocurrencies. Furthermore, there are naturally a number of limitations and shortcomings occurring this paper.

8.1 Limitations

The first main limitation of this study is the sample size. There were a total of 167 cryptocurrencies used and studied, which when looking at the total of 4000+ coins (and still growing), is only a fraction. Due to the ease of use and range, the data was gathered from Yahoo Finance. Future research could potentially look into the possibility of developing a code (using API for example) that extracts the data from coinmarketcap.com, coingecko.com or other sources. The sample size problem is a persistent problem in the crypto literature however, due to the limited quantity and access of the complete historical data, especially with the smallest cryptocurrencies. The favorable results for the altcoins in this study, relative to Bitcoin and Ethereum, may be explained by this limitation. In the top 1000 largest market capitalization sizes that were being researched, only the most successful altcoins, and more important, the current ones are encompassed. Altcoins that may have been successful in the past but are currently discontinued, or the ones that have since fallen off, are not taken into account in the study. This means that there is a real possibility of selection bias, which is why it would be compelling to use a dataset that covers the vast majority of all the past and present altcoins, non-existing included.

Another limitation is the data ranges used in the study. Three months may have missed pivotal moments in a very volatile crypto space. A monthly, weekly or daily range would have given much more efficient and precise results towards the creation of the quality score and QMJ factor. Moreover, having a longer time frame in general would also add substantial value. This aspect can be naturally improved upon in the future as time goes by and the cryptocurrency market matures.

A last tangible limitation is one that is also present in the paper of Coelho (2020). It is regarding the use of the Fama French 3-factor model based on the NVT ratio, that proxies the PE ratio. The author concludes that the Fama French 3-factor model does not have a high explanatory power and therefore they do not consider it as a good fit for future applications. The mean adjusted R2 is considerably low and the model has a low predictive power across different portfolios. Moreover, asset pricing models used for stock might not be as efficient for cryptocurrencies. Even though cryptocurrencies are referred to as financial assets, they fundamentally differ from stocks (Liu et al., 2020). The use of more factors, or different asset models could potentially improve upon this limitation, although caution is needed due to the aforementioned potential collinearity and convertibility issues.

8.2 Future research

As for further research, there are a virtually endless number of roads researchers could take. The term quality is a broad term (Asness et al., 2019), especially in an upcoming financial asset class such as cryptocurrencies. As seen from the robustness checks, different constructions of the quality score have a range of implications on the returns of portfolios. An interesting possibility is going more in depth on the technical quality aspect of cryptocurrencies. Future research could construct the quality scores based on the core technology, the team behind the coin/token, the roadmap and/or other qualitative aspects.

As mentioned before, there are companies that are dedicated to analyzing all kind of quality aspects in order to create a straightforward quality rating/score. Two of the most used ratings are the aforementioned FCAS and also Simetri (https://simetri.cryptobriefing.com/). FCAS is a metric to judge the fundamental health of a crypto project, while Simetri gives ratings based on various qualitative and quantitative aspects such as core team and roadmap progress. Another compelling source of collecting data in order to construct the quality score is Intotheblock (https://app.intotheblock.com/). This is a data science company that measures specific actionable signals. Some examples of these are “Concentration by Large Holders”, and “Transactions Greater than $100K”. One limitation is that the company is still in its starting stage, which means that they do not have the information of these signals for a substantial number of cryptocurrencies as of yet.

Lastly, another aspect where future researchers could delve into is the use of the QMJ factor for hedging capabilities. As seen in previous sections, different constructions of the quality score have led to a range of hedging capabilities of portfolios that employ a QMJ factor, both in severe bear markets as bull markets. Future research could also analyze the QMJ portfolio in all kinds of extreme scenarios, not just severe bear and bull markets. Extreme cases like periods of recession/expansion or low/high volatility might lead to interesting results.

9. Conclusion

The aim of this paper was to study whether it is possible to analyze quality and use that data in order to create an efficient investment strategy. The respectable paper of Asness et al. (2019) was a guideline for this paper, seeing as their results and conclusions were vastly promising when applied to companies and stocks. While the goal of applying the same methodology to cryptocurrencies was successful, the results were rather ambiguous.

In order to answer the main research question of this paper, “Do high-quality cryptocurrencies have a lower speculative value and higher risk-adjusted returns than low-quality cryptocurrencies?”, three hypotheses were developed.

The first null-hypothesis is accepted, however with caution, due to the ambiguous results of the second part of that part of the analysis. When analyzing the cryptocurrency market as a whole, high-quality cryptocurrencies are indeed relatively cheaper than low-quality cryptocurrencies. However, when sorting cryptocurrencies according to their market capitalization size, the deduction becomes somewhat uncertain.

Both the second and third null-hypotheses are rejected based on the results of the analysis. High-quality cryptocurrencies do not have higher risk-adjusted returns than low-quality cryptocurrencies. For the testing of the third null-hypothesis, a new Quality Minus Junk factor (QMJ) was created, that goes long in high-quality and short in low-quality cryptocurrencies, while also considering the size of the cryptocurrencies. The results of portfolios using this QMJ factor led to the rejection of the third null-hypothesis, in other words, portfolios going long in high-quality cryptocurrencies and going short in low-quality cryptocurrencies do not earn significant risk-adjusted returns.

Going back to the research question, the answer is two-folded. On one hand, high-quality cryptocurrencies do have lower speculative value. However, this does not translate into higher risk-adjusted returns, seeing as the results of the research of this paper show the opposite.

Besides the analysis regarding the research question and hypotheses, this paper also attempts to study the hedging capabilities of the QMJ factor. Portfolios that use the Fama French 3-factor model in combination with the QMJ factor, have a strong resilience in severe bear markets and thus promising hedging capabilities.

Lastly, alternate construction methodologies of the quality score have given interesting insights into possible future research pathways. It is shown in this paper that small adjustments towards the quality score have large implications for the excess returns of the QMJ portfolio, and portfolio performances during extreme scenarios. Although the specific methodology of the main research has not provided substantial breakthroughs in the quality aspect of the cryptocurrency space, expanding the research very well might.

10. Appendix

10.1 Figures

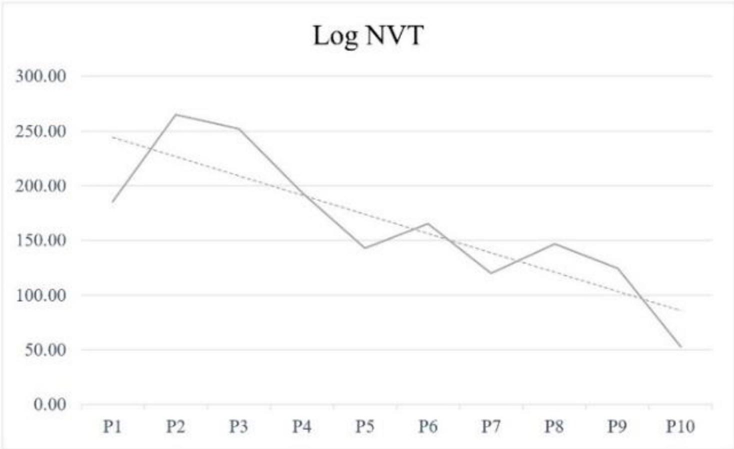

Figure 1

This figure shows the average Log of the NVT ratio of every market cap size-sorted portfolio in a graphical form. P1 represents the decile portfolio containing the smallest market cap size cryptocurrencies, ascending towards P10, the decile portfolio containing the largest market cap size cryptocurrencies. The dotted line is the overall trendline.

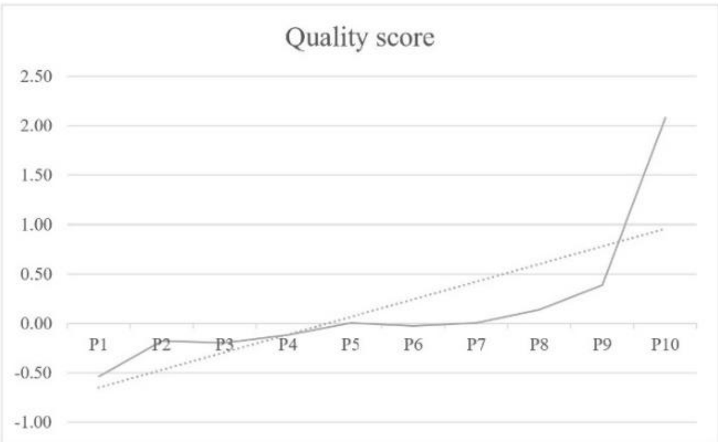

Figure 2

This figure shows the average quality score of every market cap size-sorted portfolio in a graphical form. P1 represents the decile portfolio containing the smallest market cap size cryptocurrencies, ascending towards P10, the decile portfolio containing the largest market cap size cryptocurrencies. The dotted line is the overall trendline.

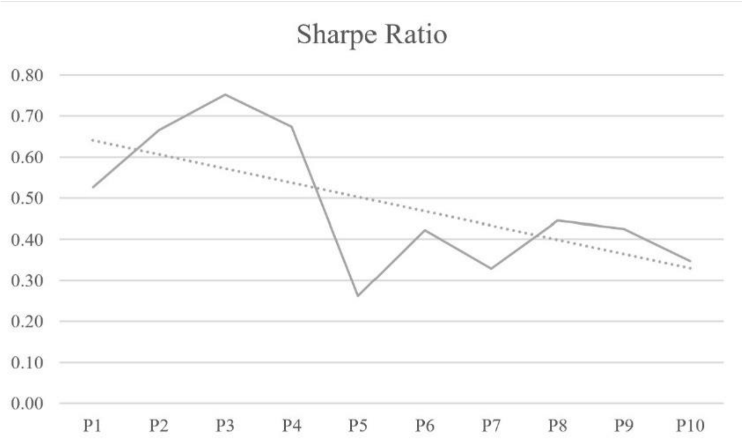

Figure 3

This figure shows the average Sharpe Ratio of the decile portfolios, sorted on their quality score. P1 represents the decile portfolio containing the highest quality score cryptocurrencies, ascending towards P10, the decile portfolio containing the lowest quality score cryptocurrencies.The dotted line is the overall trendline.

10.2 Robustness checks standard errors

	1	2	3	4
Quality	**-0.21**	**-0.26**	**-0.21**	**-0.26**
	(-6.41)	*(-8.21)*	*(6.72)*	*(8.52)*
Crypto Age		**0.00**		**0.00**
		(2.88)		*(-6.14)*
ICO Funding Dummy		-0.11		0.12
		(-1.23)		*(-1.33)*
Nasdaq Closing		**0.00**		**0.00**
		(-12.22)		*(12.85)*
Nasdaq Volume		**0.00**		**0.00**
		(2.43)		*(-2.41)*
VIX		**-0.03**		**-0.03**
		(-4.84)		*(-4.71)*
Adjusted R Square	0.02	0.12	0.02	0.12
Technicality FE			x	x

Table 10: Cross-Sectional Regression, Price of Quality

The dependent variable is the Log of the NVT ratio, gathered on a 3-monthly basis. The explanatory variables are the quality scores ("Quality") and a number of control variables. "Crypto Age" is the number of days since the first time the currency was publicly available to trade. "ICO Funding Dummy" equals 1 in case the coin has received some sort of ICO funding, and 0 otherwise. "Nasdaq Closing" and "Nasdaq Volume" are the adjusted closing historical prices and volume of the NASDAQ exchange. "VIX" is a volatility index of the S&P 500. "Adjusted R Square" is the average of the adjusted R-square of the cross-sectional regression. The Technicality Fixed Effects (FE) are included in regression 3 & 4, noted with an 'x'. The regressions use robust standard errors. The T-statistics are presented in parentheses. The coefficient is in bold when there is 5% statistical significance.

	1	2	3	4	5
Intellectuality	**-0.12**			-0.02	-0.02
	(-4.16)			*(0.4)*	*(0.46)*
Significance		**-0.22**		**-0.24**	**-0.24**
		(-5.93)		*(-5.44)*	*(-5.51)*
Safety			**-0.11**	**-0.15**	**-0.18**
			(2.71)	*(3.8)*	*(4.65)*
Crypto Age	**0.00**	0.00	0.00	**0.00**	**0.00**
	(1.96)	*(1.9)*	*(1.39)*	*(2.54)*	*(2.65)*
ICO Funding Dummy	0.11	-0.14	-0.1	0.11	0.11
	(-1.36)	*(-1.69)*	*(-1.26)*	*(-1.28)*	*(-1.32)*
Nasdaq Closing	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**
	(-11.86)	*(-12.08)*	*(-11.31)*	*(-12.02)*	*(-12.2)*
Nasdaq Volume	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**
	(2.48)	*(2.5)*	*(2.39)*	*(2.46)*	*(2.56)*
VIX	**-0.03**	**-0.03**	**-0.03**	**-0.03**	**-0.03**
	(-4.67)	*(-4.68)*	*(-4.6)*	*(-4.69)*	*(-4.62)*
Adjusted R Square	0.10	0.11	0.09	0.11	0.11
Technicality FE					x

Table 11: Cross-Sectional Regression, Price of Quality - subcomponents

The dependent variable is the log of the NVT ratio, on a 3-monthly basis. The explanatory variables are the quality scores of the subcomponents, "Intellectuality", "Significance", "Safety" and a number of control variables. "Crypto Age" is the number of days since the first time the currency was publicly available to trade. "ICO Funding Dummy" equals 1 in case the coin has received some sort of funding, and 0 otherwise. "Nasdaq Closing" and "Nasdaq Volume" are the adjusted closing historical prices and volume of the Nasdaq exchange. "VIX" is a volatility index of the S&P 500. "Adjusted R Square" is the average of the adjusted R-square of the cross-sectional regression. The Technicality fixed effects (FE) are included in regression 3 & 4, noted with an 'x'. The regressions use robust standard errors. The T-statistics are presented in parentheses. The coefficient is in bold when there is 5% statistical significance.

	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10
Quality	1.56	-1.11	0.64	-0.27	1.53	-1.37	-0.09	-0.44	-0.48	0.59
	(1.29)	*(-0.65)*	*(-0.617)*	*(-0.16)*	*(0.71)*	*(-1.04)*	*(-0.08)*	*(-0.43)*	*(-0.64)*	*(1.97)*
Crypto Age	0.00	0.00	0.00	0.00	0.00	0.00	0.00	**0.00**	0.00	0.00
	(0.03)	*(-0.26)*	*(1.27)*	*(0.84)*	*(-1.23)*	*(1.79)*	*(0.17)*	*(2.09)*	*(0.56)*	*(0.9)*
Nasdaq Closing	**0.00**	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	(-2.41)	*(0.63)*	*(0)*	*(-1.35)*	*(-0.81)*	*(1.62)*	*(-1.83)*	*(-1.43)*	*(-1.38)*	*(0.81)*
Nasdaq Volume	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	(1.32)	*(0.87)*	*(0.16)*	*(0.25)*	*(0.18)*	*(1.15)*	*(0.78)*	*(-0.99)*	*(1.3)*	*(-0.22)*
VIX	-0.02	**0.03**	-0.01	0.02	0.00	-0.03	0.00	-0.02	0.01	**-0.05**
	(-0.87)	*(2.11)*	*(-0.68)*	*(0.51)*	*(-0.3)*	*(-1.16)*	*(-0.06)*	*(-0.62)*	*(0.17)*	*(-2.2)*
Adjusted R Square	0.02	0.23	0.19	0.16	-0.03	0.08	0.07	0.56	0.06	0.45
Technicality FE	x	x	x	x	x	x	x	x	x	x

Table 12: Cross-Sectional Regression, Price of Quality – decile portfolios

Cryptocurrencies are ranked in ascending order into decile portfolios based on their market capitalization size. P1 represents the decile portfolio containing the smallest market cap size cryptocurrencies, ascending towards P10, the decile portfolio containing the largest market cap size cryptocurrencies. The dependent variable is the

Log of the NVT ratio, on a 3-monthly basis. The explanatory variables are the quality scores ("Quality") and a number of control variables. "Crypto Age" is the number of days since the first time the currency was publicly available to trade. "Nasdaq Closing" and "Nasdaq Volume" are the adjusted closing historical prices and volume of the Nasdaq exchange. "VIX" is a volatility index of the S&P 500. "Adjusted R Square" is the average of the adjusted R-square of the cross-sectional regression. The Technicality fixed effects are included in all the regression, noted with an 'x'. The regressions use robust standard errors. The T-statistics are presented in parentheses. The coefficient is in bold when there is 5% statistical significance.

10.3 Hetero-Robustness checks

	P1 *(Low)*	P2	P3	P4	P5	P6	P7	P8	P9	P10 *(High)*	H-L	L-H
Excess return	**2.55**	**2.24**	**1.11**	**0.94**	1.64	**0.57**	0.41	**0.37**	**0.56**	**0.46**	**-2.09**	**2.09**
	(2.42)	*(3.07)*	*(3.29)*	*(3.03)*	*(1.21)*	*(2.03)*	*(1.55)*	*(2.09)*	*(2.08)*	*(2.23)*	*(-2.03)*	*(2.03)*
CAPM alpha	**1.87**	0.74	0.35	0.20	-0.33	-0.06	-0.11	-0.05	0.10	-0.06	**-1.93**	**1.93**
	(2.23)	*(1.69)*	*(1.83)*	*(1.39)*	*(-0.64)*	*(-0.54)*	*(-1.04)*	*(-0.62)*	*(0.64)*	*(-0.75)*	*(-14.96)*	*(14.96)*
3-factor alpha	1.20	0.78	0.27	0.09	-0.42	-0.09	-0.11	-0.06	0.07	-0.08	**-1.28**	**1.28**
	(1.95)	*(1.93)*	*(1.78)*	*(0.62)*	*(-0.69)*	*(-0.81)*	*(-0.79)*	*(-0.71)*	*(0.42)*	*(-0.89)*	*(-2.08)*	*(2.08)*
Beta	2.09	3.81	1.90	1.85	4.97	1.58	1.30	1.07	1.17	1.31	-0.77	
Sharpe Ratio	0.53	0.67	0.75	0.67	0.26	0.42	0.33	0.45	0.43	0.35	-0.18	
Adjusted R2	0.35	0.43	0.60	0.67	0.37	0.64	0.53	0.68	0.51	0.60	0.26	

Table 13: Quality-Sorted Portfolios

This table shows the calendar-time portfolio returns. Cryptocurrencies are ranked in ascending order into decile portfolios based on their quality score, on a 3-monthly basis. The portfolios are value weighted and refreshed every 3 months. Excess return is associated with the T-bill rates in the US. Alpha is the intercept in a time-series regression of 3-monthly excess return. The explanatory variables are the returns of the market (MKT), Small Minus Big (SMB), High Minus Low (HML). The sample runs from May 2016 to May 2021. "Beta" is the average sensitivity of the corresponding portfolio. "Sharpe Ratio" measures the excess return over the risk-free rate with the corresponding risk. "Adjusted R Square" is the average of the adjusted R-square of the cross-sectional regression. The T-statistics are presented in parentheses. The coefficient is in bold when there is 5% statistical significance.

	QMJ	*INTELLECTUALITY*	*SIGNIFICANCE*	*SAFETY*
Excess Returns	0.14	**0.75**	**1.10**	-0.04
	(0.57)	*(2.31)*	*(2.65)*	*(-0.28)*
CAPM alpha	-0.08	**0.33**	0.26	-0.10
	(-0.58)	*(1.96)*	*(1.44)*	*(0.84)*
3-factor alpha	-0.04	0.24	0.18	-0.04
	(-0.25)	*(1.47)*	*(0.96)*	*(0.94)*
Sharpe Ratio	-0.03	1.58	1.00	-2.06
Adjusted R2	0.62	0.66	0.41	0.87

Table 14: Quality Minus Junk: Returns

This table shows calendar-time portfolio returns. QMJ factors are constructed as the intersection of six value-weighted portfolios formed on size and quality. After that, cryptocurrencies are assigned to two size-sorted portfolios, based on their market capitalization, on a 3-monthly basis. The size breakpoint is the median of market cap size. The QMJ factor return is the average return on the two high-quality portfolios minus the average return on the two low-quality portfolios. The explanatory variables are the returns of the market (MKT), Small Minus Big (SMB), High Minus Low (HML). "Sharpe Ratio" measures the excess return over the risk-free rate with the *corresponding risk. The sample runs from May 2016 to May 2021. The T-statistics are presented in parentheses. The coefficient is in bold when there is 5% statistical significance.*

10.4 Market Capitalization Weighted subcomponents

	P1 *(Low)*	P2	P3	P4	P5	P6	P7	P8	P9	P10 *(High)*	H-L	L-H
Excess return	0.42	**1.05**	**0.70**	**0.81**	**0.79**	**2.44**	**1.09**	**0.61**	**1.29**	**0.79**	0.36	-0.36
	(1.63)	*(2.02)*	*(2.42)*	*(2.75)*	*(2.24)*	*(2.06)*	*(2.32)*	*(2.38)*	*(1.99)*	*(2.33)*	*(1.78)*	*(1.78)*
CAPM alpha	0.00	0.32	0.16	0.05	-0.01	0.43	0.27	0.33	0.88	0.15	0.15	-0.15
	(-0.01)	*(0.5)*	*(0.49)*	*(0.2)*	*(-0.04)*	*(0.32)*	*(0.5)*	*(1.04)*	*(1.05)*	*(0.49)*	*(1.28)*	*(1.28)*
3-factor alpha	-0.06	-0.04	-0.04	0.01	-0.04	0.35	0.15	0.30	0.73	0.11	0.17	-0.17
	(-0.21)	*(-0.19)*	*(0.52)*	*(0.05)*	*(-0.13)*	*(0.31)*	*(0.39)*	*(0.98)*	*(0.89)*	*(0.41)*	*(1.4)*	*(1.4)*
Beta	1.08	1.86	1.37	1.92	2.03	5.08	2.08	0.70	1.04	1.61	0.15	
Sharpe Ratio	0.35	0.44	0.52	0.59	0.48	0.45	0.50	0.51	0.43	0.50	0.15	
Adjusted R2	0.27	0.52	0.50	0.71	0.47	0.34	0.41	0.10	0.01	0.45	0.18	

Table 15: Quality-Sorted Portfolios

This table shows the calendar-time portfolio returns. Cryptocurrencies are ranked in ascending order into decile portfolios based on their quality score, on a 3-monthly basis. The portfolios are value weighted and refreshed every 3 months. Excess return is associated with the T-bill rates in the US. Alpha is the intercept in a time-series regression of 3-monthly excess return. The explanatory variables are the returns of the market (MKT), Small Minus Big (SMB), High Minus Low (HML). The sample runs from May 2016 to May 2021. "Beta" is the average sensitivity of the corresponding portfolio. "Sharpe Ratio" measures the excess return over the risk-free rate with the corresponding risk. "Adjusted R Square" is the average of the adjusted R-square of the cross-sectional regression. The T-statistics are presented in parentheses. The coefficient is in bold when there is 5% statistical significance.

	Returns			
	QMJ	***INTELLECTUALITY***	***SIGNIFICANCE***	***SAFETY***
QMJ	1.00			
INTELLECTUALITY	0.54	1.00		
SIGNIFICANCE	0.55	0.13	1.00	
SAFETY	0.84	0.75	0.33	1.00

Table 16: Quality Minus Junk: Correlations

This correlation matrix table shows the correlation of 3-monthly returns between the QMJ factor and the subcomponents. The QMJ factors are constructed as the intersection of six value-weighted portfolios formed on size and quality. After that, cryptocurrencies are assigned to two size-sorted portfolios, based on their market capitalization, on a 3-monthly basis. The size breakpoint is the median of market cap size. The QMJ factor return is the average return on the two high-quality portfolios minus the average return on the two low-quality portfolios. The subcomponents "Intellectuality", "Significance" and "Safety" all follow the same construction as the QMJ factor. The sample runs from May 2016 to May 2021.

	QMJ	INTELLECTUALITY	SIGNIFICANCE	SAFETY
Excess Returns	**0.95**	**0.74**	**0.77**	0.05
	(2.52)	*(2.01)*	*(2.12)*	*(0.23)*
CAPM alpha	0.12	0.17	0.20	-0.06
	(0.32)	*(0.45)*	*(0.55)*	*(-0.23)*
3-factor alpha	0.06	-0.01	0.07	-0.03
	(0.24)	*(1.07)*	*(0.35)*	*(-0.2)*
Sharpe Ratio	0.73	0.74	0.91	-0.38
Adjusted R2	0.38	0.45	0.43	0.78

Table 17: Quality Minus Junk: Returns

This table shows calendar-time portfolio returns. QMJ factors are constructed as the intersection of six value-weighted portfolios formed on size and quality. After that, cryptocurrencies are assigned to two size-sorted portfolios, based on their market capitalization, on a 3-monthly basis. The size breakpoint is the median of market cap size. The QMJ factor return is the average return on the two high-quality portfolios minus the average return on the two low-quality portfolios. The explanatory variables are the returns of the market (MKT), Small Minus Big (SMB), High Minus Low (HML). "Sharpe Ratio" measures the excess return over the risk-free rate with the corresponding risk. The sample runs from May 2016 to May 2021. The T-statistics are presented in parentheses. The coefficient is in bold when there is 5% statistical significance.

	Returns		
	Excess Returns	CAPM alpha	3-factor alpha
All periods	**0.95**	0.12	0.06
Severe bear markets	**-0.74**	**-0.45**	
Severe bull markets	**1.71**	-0.31	-0.12
	T-Statistics		
	Excess Returns	CAPM alpha	3-factor alpha
All periods	*(2.52)*	*(-0.22)*	*(-0.16)*
Severe bear markets	*(-7.42)*	*(-2.08)*	
Severe bull markets	*(2.91)*	*(-0.22)*	*(-0.45)*

Table 18: Quality Minus Junk: Returns in extreme scenarios

This table shows calendar-time portfolio returns in severe bear and bull markets. Severe bear markets are defined as a total return in the past 3 months below -20%, severe bull markets have a total return of +25% in the past 3 months. QMJ factors are constructed as the intersection of six value-weighted portfolios formed on size and quality. After that, cryptocurrencies are assigned to two size-sorted portfolios, based on their market capitalization size, on a 3-monthly basis. The size breakpoint is the median of market cap size. The QMJ factor return is the average return on the two high-quality portfolios minus the average return on the two low-quality portfolios. The explanatory variables are the returns of the market (MKT), Small Minus Big (SMB), High Minus Low (HML). The sample runs from May 2016 to May 2021. The T-statistics are presented in parentheses. The coefficient is in bold when there is 5% statistical significance.

	P1 *(Low)*	P2	P3	P4	P5	P6	P7	P8	P9	P10 *(High)*	H-L	L-H
Excess return	0.42	**1.05**	**0.70**	**0.81**	**0.79**	**2.44**	**1.09**	**0.61**	**1.29**	**0.79**	0.36	-0.36
	(1.63)	*(2.02)*	*(2.42)*	*(2.75)*	*(2.24)*	*(2.06)*	*(2.32)*	*(2.38)*	*(1.99)*	*(2.33)*	*(1.78)*	*(1.78)*
CAPM alpha	0.00	0.32	0.16	0.05	-0.01	0.43	0.27	0.33	0.88	0.15	0.15	-0.15
	(-0.02)	*(1.15)*	*(0.85)*	*(0.4)*	*(-0.08)*	*(0.74)*	*(1.47)*	*(1.47)*	*(1.66)*	*(1.01)*	*(1.28)*	*(1.28)*
3-factor alpha	-0.06	-0.04	-0.04	0.01	-0.04	0.35	0.15	0.30	0.73	0.11	0.17	-0.17
	(-0.39)	*(-0.24)*	*(0.62)*	*(0.07)*	*(-0.35)*	*(0.58)*	*(0.5)*	*(1.3)*	*(1.62)*	*(0.66)*	*(1.4)*	*(1.4)*
Beta	1.08	1.86	1.37	1.92	2.03	5.08	2.08	0.70	1.04	1.61	0.15	
Sharpe Ratio	0.35	0.44	0.52	0.59	0.48	0.45	0.50	0.51	0.43	0.50	0.15	
Adjusted R2	0.27	0.52	0.50	0.71	0.47	0.34	0.41	0.10	0.01	0.45	0.18	

Table 19: Quality-sorted Portfolios - Het-Robustness

This table shows the calendar-time portfolio returns. Cryptocurrencies are ranked in ascending order into decile portfolios based on their quality score, on a 3-monthly basis. The portfolios are value weighted and refreshed every 3 months. Excess return is associated with the T-bill rates in the US. Alpha is the intercept in a time-series regression of 3-monthly excess return. The explanatory variables are the returns of the market (MKT), Small Minus Big (SMB), High Minus Low (HML). The sample runs from May 2016 to May 2021. "Beta" is the average sensitivity of the corresponding portfolio. "Sharpe Ratio" measures the excess return over the risk-free rate with the corresponding risk. "Adjusted R Square" is the average of the adjusted R-square of the cross-sectional regression. The T-statistics are presented in parentheses. The coefficient is in bold when there is 5% statistical significance.

	QMJ	*INTELLECTUALITY*	*SIGNIFICANCE*	*SAFETY*
Excess Returns	**0.95**	**0.74**	**0.77**	0.05
	(2.48)	*(2.05)*	*(2.37)*	*(0.31)*
CAPM alpha	0.12	0.17	0.20	-0.06
	(0.75)	*(0.82)*	*(1.24)*	*(-0.37)*
3-factor alpha	0.06	-0.01	0.07	-0.03
	(0.36)	*(-0.06)*	*(0.4)*	*(-0.24)*
Sharpe Ratio	0.73	0.74	0.91	-0.38
Adjusted R2	0.38	0.45	0.43	0.78

Table 20: Quality Minus Junk: Returns - Het-Robustness

This table shows calendar-time portfolio returns. QMJ factors are constructed as the intersection of six value-weighted portfolios formed on size and quality. After that, cryptos are assigned to two size-sorted portfolios, based on their market capitalization, on a 3-monthly basis. The size breakpoint is the median of market cap size. The QMJ factor return is the average return on the two high-quality portfolios minus the average return on the two low-quality portfolios. Portfolios based on Intellectuality, Significance and Safety are constructed in a similar manner. The explanatory variables are the returns of the market (MKT), Small Minus Big (SMB), High Minus Low (HML). "Sharpe Ratio" measures the excess return over the risk-free rate with the corresponding risk. The sample runs from May 2016 to May 2021. The T-statistics are presented in parentheses. The coefficient is in bold when there is 5% statistical significance.

10.5 Technicality incorporated as subcomponent

	P1 (Low)	P2	P3	P4	P5	P6	P7	P8	P9	P10 (High)	H-L	L-H
Excess return	**2.85**	**0.69**	**1.25**	**1.40**	**0.81**	**0.48**	0.43	0.34	1.65	**0.58**	**-2.27**	**2.27**
	(2.98)	*(2.66)*	*(2.44)*	*(2.16)*	*(2.97)*	*(2.14)*	*(1.82)*	*(1.51)*	*(1.39)*	*(2.39)*	*(-2.49)*	*(-2.49)*
CAPM alpha	1.79	0.26	0.27	0.03	0.12	-0.05	-0.07	-0.13	-0.01	0.06	-1.73	1.73
	(1.51)	*(0.88)*	*(0.49)*	*(0.05)*	*(0.52)*	*(-0.24)*	*(-0.3)*	*(-0.56)*	*(-0.01)*	*(0.23)*	*(1.28)*	*(1.28)*
3-factor alpha	1.35	0.18	0.21	0.10	0.04	-0.07	-0.08	-0.14	-0.13	0.05	**-1.30**	**1.30**
	(1.34)	*(0.74)*	*(0.61)*	*(0.14)*	*(0.21)*	*(-0.51)*	*(-0.61)*	*(-0.96)*	*(-0.12)*	*(0.29)*	*(-11.07)*	*(-11.07)*
Beta	2.67	1.08	2.48	3.47	1.72	1.35	1.27	1.20	4.21	1.31	-1.35	
Sharpe Ratio	0.27	0.52	0.50	0.71	0.47	0.34	0.41	0.10	0.01	0.45	0.18	
Adjusted R2	0.20	0.28	0.40	0.35	0.51	0.61	0.60	0.56	0.35	0.56	0.36	

Table 21: Quality-Sorted Portfolios

This table shows the calendar-time portfolio returns. Cryptocurrencies are ranked in ascending order into decile portfolios based on their quality score, on a 3-monthly basis. The portfolios are value weighted and refreshed every 3 months. Excess return is associated with the T-bill rates in the US. Alpha is the intercept in a time-series regression of 3-monthly excess return. The explanatory variables are the returns of the market (MKT), Small Minus Big (SMB), High Minus Low (HML). The sample runs from May 2016 to May 2021. "Beta" is the average sensitivity of the corresponding portfolio. "Sharpe Ratio" measures the excess return over the risk-free rate with the corresponding risk. "Adjusted R Square" is the average of the adjusted R-square of the cross-sectional regression. The T-statistics are presented in parentheses. The coefficient is in bold when there is 5% statistical significance.

	QMJ	*INTELLECTUALITY*	*SIGNIFICANCE*	*SAFETY*
Excess Returns	0.71	**0.76**	**0.79**	0.02
	(1.61)	*(2.02)*	*(2.14)*	*(0.08)*
CAPM alpha	0.09	0.12	0.16	-0.11
	(0.22)	*(0.35)*	*(0.46)*	*(-0.56)*
3-factor alpha	-0.06	-0.03	0.06	-0.08
	(-0.22)	*(-0.2)*	*(0.27)*	*(-0.59)*
Sharpe Ratio	0.58	0.65	0.83	-1.01
Adjusted R2	0.40	0.50	0.48	0.86

Table 22: Quality Minus Junk: Returns

This table shows calendar-time portfolio returns. QMJ factors are constructed as the intersection of six value-weighted portfolios formed on size and quality. After that, cryptos are assigned to two size-sorted portfolios, based on their market capitalization, on a 3-monthly basis. The size breakpoint is the median of market cap size. The QMJ factor return is the average return on the two high-quality portfolios minus the average return on the two low-quality portfolios. Portfolios based on Intellectuality, Significance and Safety are constructed in a similar manner. The explanatory variables are the returns of the market (MKT), Small Minus Big (SMB), High Minus Low (HML). "Sharpe Ratio" measures the excess return over the risk-free rate with the corresponding risk. The sample runs from May 2016 to May 2021. The T-statistics are presented in parentheses. The coefficient is in bold when there is 5% statistical significance.

	Returns		
	Excess Returns	CAPM alpha	3-factor alpha
All periods	0.71	0.09	0.06
Severe bear markets	**-0.38**	0.06	
Severe bull markets	**1.69**	0.10	-0.01
	T-Statistics		
	Excess Returns	CAPM alpha	3-factor alpha
All periods	*(-1.61)*	*(-0.22)*	*(-0.16)*
Severe bear markets	*(2.14)*	*(0.11)*	
Severe bull markets	*(0.96)*	*(0.16)*	*(-0.02)*

Table 23: Quality Minus Junk: Returns in extreme scenarios

This table shows calendar-time portfolio returns in severe bear and bull markets. Severe bear markets are defined as a total return in the past 3 months below -20%, severe bull markets have a total return of +25% in the past 3 months. QMJ factors are constructed as the intersection of six value-weighted portfolios formed on size and quality. After that, cryptocurrencies are assigned to two size-sorted portfolios, based on their market capitalization size, on a 3-monthly basis. The size breakpoint is the median of market cap size. The QMJ factor return is the average return on the two high-quality portfolios minus the average return on the two low-quality portfolios. The explanatory variables are the returns of the market (MKT), Small Minus Big (SMB), High Minus Low (HML). The sample runs from May 2016 to May 2021. The T-statistics are presented in parentheses. The coefficient is in bold when there is 5% statistical significance.

	P1 *(Low)*	P2	P3	P4	P5	P6	P7	P8	P9	P10 *(High)*	H-L	L-H
Excess return	**2.85**	**0.69**	**1.25**	**1.40**	**0.81**	**0.48**	0.43	0.34	1.65	**0.58**	**-2.27**	**2.27**
	(2.98)	*(2.66)*	*(2.44)*	*(2.16)*	*(2.97)*	*(2.14)*	*(1.82)*	*(1.51)*	*(1.39)*	*(2.39)*	*(-2.49)*	*(-2.49)*
CAPM alpha	**1.79**	0.26	0.27	0.03	0.12	-0.05	-0.07	-0.13	-0.01	0.06	-1.73	1.73
	(2.26)	*(1.33)*	*(1.34)*	*(0.11)*	*(0.89)*	*(-0.49)*	*(-0.84)*	*(-1.47)*	*(-0.03)*	*(0.57)*	*(1.28)*	*(1.28)*
3-factor alpha	1.35	0.18	0.21	0.10	0.04	-0.07	-0.08	-0.14	-0.13	0.05	**-1.30**	**1.30**
	(1.95)	*(1.06)*	*(0.86)*	*(0.37)*	*(0.31)*	*(-0.71)*	*(-0.88)*	*(-1.32)*	*(-0.24)*	*(0.36)*	*(-11.07)*	*(-11.07)*
Beta	2.67	1.08	2.48	3.47	1.72	1.35	1.27	1.20	4.21	1.31	-1.35	
Sharpe Ratio	0.27	0.52	0.50	0.71	0.47	0.34	0.41	0.10	0.01	0.45	0.18	
Adjusted R2	0.20	0.28	0.40	0.35	0.51	0.61	0.60	0.56	0.35	0.56	0.36	

Table 24: Quality-Sorted Portfolios - Het-Robustness

This table shows the calendar-time portfolio returns. Cryptocurrencies are ranked in ascending order into decile portfolios based on their quality score, on a 3-monthly basis. The portfolios are value weighted and refreshed every 3 months. Excess return is associated with the T-bill rates in the US. Alpha is the intercept in a time-series regression of 3-monthly excess return. The explanatory variables are the returns of the market (MKT), Small Minus Big (SMB), High Minus Low (HML). The sample runs from May 2016 to May 2021. "Beta" is the average sensitivity of the corresponding portfolio. "Sharpe Ratio" measures the excess return over the risk-free rate with the corresponding risk. The T-statistics are presented in parentheses. The coefficient is in bold when there is 5% statistical significance.

	QMJ	INTELLECTUALITY	SIGNIFICANCE	SAFETY
Excess Returns	0.71	0.76	**0.79**	0.02
	(1.36)	*(1.9)*	*(2.3)*	*(0.1)*
CAPM alpha	0.09	0.12	0.16	-0.11
	(0.47)	*(0.57)*	*(0.95)*	*(-0.85)*
3-factor alpha	-0.06	-0.03	0.06	-0.08
	(-0.37)	*(-0.2)*	*(0.31)*	*(-0.67)*
Sharpe Ratio	0.58	0.65	0.83	-1.01
Adjusted R2	0.40	0.50	0.48	0.86

Table 25: Quality Minus Junk: Returns - Het-Robustness

This table shows calendar-time portfolio returns. QMJ factors are constructed as the intersection of six value-weighted portfolios formed on size and quality. After that, cryptos are assigned to two size-sorted portfolios, based on their market capitalization, on a 3-monthly basis. The size breakpoint is the median of market cap size. The QMJ factor return is the average return on the two high-quality portfolios minus the average return on the two low-quality portfolios. Portfolios based on Intellectuality, Significance and Safety are constructed in a similar manner. The explanatory variables are the returns of the market (MKT), Small Minus Big (SMB), High Minus Low (HML). "Sharpe Ratio" measures the excess return over the risk-free rate with the corresponding risk. The sample runs from May 2016 to May 2021. The T-statistics are presented in parentheses. The coefficient is in bold when there is 5% statistical significance.

10.6 Quality Score with only Intellectuality and Significance

	QMJ	INTELLECTUALITY	SIGNIFICANCE
Excess Returns	**1.01**	0.72	0.77
	(2.17)	*(1.61)*	*(1.74)*
CAPM alpha	0.08	0.09	0.14
	(0.17)	*(0.19)*	*(0.3)*
3-factor alpha	-0.11	-0.05	0.05
	(-0.43)	*(-0.25)*	*(0.19)*
Sharpe Ratio	0.49	1.58	1.00
Adjusted R2	0.34	0.43	0.38

Table 26: Quality Minus Junk: Returns

This table shows calendar-time portfolio returns. QMJ factors are constructed as the intersection of six value-weighted portfolios formed on size and quality. After that, cryptos are assigned to two size-sorted portfolios, based on their market capitalization, on a 3-monthly basis. The size breakpoint is the median of market cap size. The QMJ factor return is the average return on the two high-quality portfolios minus the average return on the two low-quality portfolios. Portfolios based on Intellectuality and Significance and Safety are constructed in a similar manner. The explanatory variables are the returns of the market (MKT), Small Minus Big (SMB), High Minus Low (HML). "Sharpe Ratio" measures the excess return over the risk-free rate with the corresponding risk. The sample runs from May 2016 to May 2021. The T-statistics are presented in parentheses. The coefficient is in bold when there is 5% statistical significance.

	Returns		
	Excess Returns	CAPM alpha	3-factor alpha
All periods	**1.01**	0.08	-0.11
Severe bear markets	**-0.49**	0.18	
Severe bull markets	0.31	0.16	0.01
	T-Statistics		
	Excess Returns	CAPM alpha	3-factor alpha
All periods	*(2.17)*	*(0.17)*	*(-0.43)*
Severe bear markets	*(-5.34)*	*(0.25)*	
Severe bull markets	*(0.52)*	*(0.17)*	*(0.01)*

Table 27: Quality Minus Junk: Returns in extreme scenarios

This table shows calendar-time portfolio returns in severe bear and bull markets. Severe bear markets are defined as a total return in the past 3 months below -20%, severe bull markets have a total return of +25% in the past 3 months. QMJ factors are constructed as the intersection of six value-weighted portfolios formed on size and quality. After that, cryptocurrencies are assigned to two size-sorted portfolios, based on their market capitalization size, on a 3-monthly basis. The size breakpoint is the median of market cap size. The QMJ factor return is the average return on the two high-quality portfolios minus the average return on the two low-quality portfolios. The explanatory variables are the returns of the market (MKT), Small Minus Big (SMB), High Minus Low (HML). The sample runs from May 2016 to May 2021. The T-statistics are presented in parentheses. The coefficient is in bold when there is 5% statistical significance.

	QMJ	*INTELLECTUALITY*	*SIGNIFICANCE*
Excess Returns	**1.01**	0.72	**0.77**
	(2.12)	*(1.67)*	*(1.98)*
CAPM alpha	0.08	0.09	0.14
	(0.41)	*(0.33)*	*(0.69)*
3-factor alpha	-0.11	-0.05	0.05
	(-0.52)	*(-0.26)*	*(0.23)*
Sharpe Ratio	0.49	1.58	1.00
Adjusted R2	0.40	0.48	0.44

Table 28: Quality Minus Junk: Returns - Het-Robustness

This table shows calendar-time portfolio returns. QMJ factors are constructed as the intersection of six value-weighted portfolios formed on size and quality. After that, cryptos are assigned to two size-sorted portfolios, based on their market capitalization, on a 3-monthly basis. The size breakpoint is the median of market cap size. The QMJ factor return is the average return on the two high-quality portfolios minus the average return on the two low-quality portfolios. Portfolios based on Intellectuality and Significance are constructed in a similar manner. The explanatory variables are the returns of the market (MKT), Small Minus Big (SMB), High Minus Low (HML). "Sharpe Ratio" measures the excess return over the risk-free rate with the corresponding risk. The sample runs from May 2016 to May 2021. The T-statistics are presented in parentheses. The coefficient is in bold when there is 5% statistical significance.

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