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Quantitative Factor Investing Strategies in the Cryptocurrency market

A trading algorithm for long-short single and multi-factor portfolios using a cross-sectional approach

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Preface & Acknowledgements

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ABSTRACT

This paper examines factor investing strategies in the cryptocurrency space. More specifically, the acknowledged factors momentum, value and low-volatility are analyzed utilizing various performance measures. Additionally, this study explores two new factors applicable to the cryptocurrency market, namely; Google query volumes and hash rates. Both created factors have, to the best of my knowledge, not been studied before. To investigate the originality of the two newly proposed factors, a multi-factor regression model is used. To construct the various single and multi-factor portfolios, a daily trading algorithm is developed which determines which cryptocurrencies to short and buy. The results presented in this paper are robust to a variety of specifications. This study finds consistent and significant risk-adjusted return premia for the Google factor. The momentum factor generates better risk-adjusted returns compared to the overall market, yet these results are not consistently significant. Moreover, all created multi-factor portfolios significantly outperform the benchmark portfolios. The other analyzed factor portfolios do not generate excess risk-adjusted returns. Most intriguingly, this paper concludes that the Google factor is a unique systematic driver of return and thus contributes a truly original factor. Moreover, this newly proposed factor presently surpasses all widely recognized factors in terms of risk-adjusted performance.

Keywords: Factor Investing, Portfolio choice, Cryptocurrencies, moving-blocks percentile bootstrap, Algorithmic trading
JEL Classification: G11

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Chapter 1. Introduction & Motivation

In October 2008, a couple of weeks after the U.S. financial system was saved from catastrophe, Satoshi Nakamoto created the first decentralized cryptocurrency: Bitcoin. Nakamoto (2008) introduced a peer-to-peer version of electronic cash, which would later allow for the transfer of online payments without utilizing a trusted third party. He[1] addressed the double-spending problem implemented by financial intermediaries and proposed a solution based on blockchain technology. To authorize transactions without using an intermediary, Nakamoto developed a distributed timestamp server which produces computational proof of the chronological order of transactions. After transactions are authorized, they are stored digitally and are hashed in a blockchain. This continuing chain of hash-based proof-of-work, creates a record that cannot be altered. The blockchain system, based on both cryptography and game theory, could be used by any participant in its network (Nakamoto, 2008, p.2).

After the creation of Bitcoin, other cryptocurrencies have shown an unprecedented growth. As of April 2018, there are 1587 different coins in circulation with a total market capitalization of $422,069,556,820 (CoinMarketCap, 2018). Bitcoin still is the most dominant coin accounting for almost 37% of the cryptocurrency market. Today it is facing more and more competition from other cryptocurrencies. Even though the media mostly focuses on Bitcoin a lot of Altcoins, or better said alternative cryptocurrency coins, have been created to improve what developers perceived as shortcomings of Bitcoin. Moreover, the entry is relatively costless making it easy for developers to capitalize on potential popularity (Gandal & Halaburda, 2014, p.9).

As one would expect, the potential of cryptocurrencies as an investment class is being called into question. Alternative investments such as commodities, real estate, hedge funds and private equity are becoming increasingly popular in portfolio management. Though, unlike other alternative investment opportunities, the fundamental value of cryptos is difficult to grasp. Regardless of whether cryptocurrencies will ever become part of the mainstream financial system, billions of U.S. dollars' worth of cryptos have been traded worldwide with strongly positive returns for a significant number of coins (Chuen, Guo & Wang, 2017, p.15). These positive yields give investors an even higher incentive to comprehend the drivers of cryptos' returns.

Despite the numerous studies conducted on how to estimate returns, a consensus has not been reached. Models such as the Capital Asset Pricing Model (CAPM) and Arbitrage Pricing Theories (APT) have long been criticized and proven to be less robust than hoped. In 1992, Fama and French came to the groundbreaking conclusion that there are characteristics that help predict the return of individual assets. They built a model that consisted of three factors, namely: the market factor (as suggested by the CAPM), a size factor and a value factor. This model, which was later extended with Carhart's (1997) momentum factor, has been highly influential in finance research. Factor investing still is a debated

[1] The true identity of the group or individual called 'Nakamoto' is currently still unknown. For simplicity reasons, Nakamoto is referred to as 'he' during the remainder of this paper.

theory amongst portfolio managers and an increasing amount of literature is emerging. Factors are seen as drivers or characteristics that connect a group of securities and help explain returns within an asset class. Factor investing aspires to gather the risk premia through exposure to the so-called factors. Today the most widely studied factors are value, size, momentum, low-volatility, dividend yield and carry (Bender, Briand, Melas & Subramanian, 2013, p.5).

Due to the growing excitement on this topic, analysts have also started to explore the effectiveness of factors in alternative asset classes. Falkenstein (2009) examined the low-volatility factor across 20 different asset classes, ranging from horse races to movies and from currencies to the bond market. He concluded that the low-volatility anomaly is existing within every single asset class analyzed. A couple of years later, Asness, Moskowitz, & Pedersen (2013) researched the value and momentum factors across eight different markets. They found consistent evidence in favour of momentum and value return premia, present in all markets and asset classes inspected. These findings and co-movement patterns across asset classes and time periods suggest the presence of common global factors. In the years 2009 and 2013 it would have been difficult to incorporate the recently developed asset class: the cryptocurrency market. However, Hubrich (2017) was the first to study the factors carry, momentum and value in the cryptocurrency space. Using a cross-sectional approach, he concludes that the single-factor momentum and carry portfolios provide significant excess returns compared to his benchmark portfolios. Moreover, he shows that the combined portfolio, incorporating all three factors, provides diversification benefits and thus better risk-adjusted returns compared to all the single factor portfolios. Despite Falkenstein's (2009) findings, Hubrich (2017) did not examine the low-volatility factor. Thus, this paper will investigate whether the low-volatility factor can also generate higher risk-adjusted returns in this modern asset class. Additionally, due to Asness et al.'s (2013) discoveries, this study will further examine the effects of the momentum and value factors in the cryptocurrency market. This paper will not incorporate the carry factor because the data on futures and forwards in the cryptocurrency market is at present not available. This study considers the definition of carry used in Hubrich's paper too obscure and ambiguous and will therefore not imitate his translation.

In the last couple of years, new research has focused on more non-traditional factors as well. Preis, Moat, and Stanley (2013) propose the use of substantial new data sources emerging from human interaction with the internet. They suggest that Google query volumes can offer a whole fresh perspective on the behavior of market participants in the stock market. Wang and Vergne (2017) further examine whether this by some called 'buzz factor' surrounding cryptocurrencies can help explain its returns. They also analyze the underlying technology behind the cryptocurrencies and show that the innovation potential embedded in this technology is an essential predictor for crypto returns. Additionally, analysts around the world are analyzing Bitcoin's return drivers and are acknowledging variables ranging from fundamental sources to speculative and technical ones. As an illustration: Kristoufek (2015) investigates the effect of transaction volume, the Chinese market, hash rates and mining difficulty on Bitcoin's price. Hence, most literature on non-traditional factors has either focused on the stock market, Bitcoin's price formation or simple correlations between factors and prices in the cryptocurrency market. It is extremely interesting to discover if investing in portfolios aligned with non-traditional factors can generate higher risk-adjusted returns. Thus, this paper will also incorporate and research some of the non-traditional factors.

Due to the unprecedented growth of the crypto market and its turbulence, it is of utter importance to further research and understand this new asset class. The question addressed in this study is: *Are traditional and non-traditional factors such as value, momentum, low-volatility, hash rates, and Google query volumes applicable to the cryptocurrency market and will investing in these factors provide higher risk-adjusted returns?* Even though the crypto market behaves differently from other financial markets, I expect that factors can help explain and provide excess returns.

In this study, a trading algorithm is created to examine quantitative factor investing strategies in the cryptocurrency market. Eleven different cryptocurrencies, accounting for 73% of the total market, are included in the dataset. The trading algorithm constructs single and multi-factor portfolios based on cross-sectional data and determines which cryptocurrencies to short and buy. Moreover, the algorithm rebalances all portfolios on a daily basis, incorporating prior data only. To analyze the performance of the factor investing strategies, Sharpe ratios, Treynor ratios and Jensen's alpha are compared to two benchmark portfolios. To formally test for the difference in Sharpe ratios between the implemented strategies and our benchmark portfolios, the moving-blocks Künsch (1989) percentile bootstrap method is applied. Moreover, a multi-factor regression model is used to demonstrate the validity and uniqueness of the non-traditional factors created in this research. This way, it can formally be shown whether the returns produced by these non-traditional factor investing strategies are (not) driven by the traditional factors. If the returns of the new factor portfolios remain unexplained in the regression analysis, we can conclude that these created factors are unique systematic drivers of returns. Moreover, if investing in these non-traditional factor portfolios provides higher risk-adjusted returns, this paper can contribute truly original and powerful cryptocurrency factors.

As aforementioned, this paper is one of the firsts to combine both the topics of factor investing and the cryptocurrency market. This study contributes to the limited literature that is currently available in four ways. Firstly, this paper will incorporate additional coins and a larger time frame than adopted in previous research. Secondly, the few preceding papers that focused on factor investing in the cryptocurrency market merely analyzed some of the traditional factors. However, this paper will not only examine the traditional factors but further add and test the validity of new factors. Thirdly, most papers on factor investing test for the presence of factors using linear regression models. Though, in addidion, this paper introduces a trading algorithm that can construct and rebalance all portfolios on a daily basis. Daily rebalancing is, especially in the cryptocurrency market, favorable due to the highly volatile nature of the coins' returns. Lastly, this paper adopts an additional performance analysis that has not been incorporated in the crypto market before. More specifically, Künsch's (1989) moving-blocks percentile bootstrap method is applied, which tests significance in the difference in Sharpe ratios between the factor and benchmark portfolios.

This research demonstrates that the portfolios based on the Google and momentum factor and the portfolios that incorporate a mix of the examined factors, perform (significantly) better in terms of risk-adjusted returns than both implemented benchmark portfolios. The other factor portfolios (value, low-volatility and hash rates) appear to significantly underperform in terms of risk-adjusted returns. Most interestingly, the Google factor is undoubtedly the best performing single-factor strategy. Additionally, the results from the multi-factor regression model (used to determine the originality of the two newly proposed factors) suggest that the Google factor is a truly unique systematic driver of return. Consequently, this study contributes one truly authentic and innovative factor to the crypto market which currently beats all other factors examined in terms of risk-adjusted performance. The results presented in this study are robust to a variety of specifications.

The rest of the paper is structured as follows: Chapter 2 provides adequate background information on both factor investing theories and the cryptocurrency market. Chapter 3 grants insights into the realized data retrieval methods and presents various summary statistics. Chapter 4 carefully describes the methodology implemented to construct and test the various factor portfolios. Chapter 5 presents the results and chapter 6 analyzes the robustness of the preliminary results. Finally, chapter 7 again summarizes this paper's principal findings and describes the main limitations of this study.

Chapter 2. Literature Review

This chapter provides relevant background information on both the cryptocurrency market and factor investing theories. Firstly, in section 2.1, some general knowledge on the cryptocurrency universe is presented. Secondly, in section 2.2, the commonly accepted factor investing theory is discussed. This second section is again subdivided into several subsections, presenting the most significant theories, debates and empirical findings on each factor incorporated in this study.

2.1 The Cryptocurrency Market

Since the creation of Bitcoin in October 2008, a lot of literature has emerged on the topic. Researchers and the media have given a lot of attention to the sudden surge of cryptocurrencies. Analysts focussed on its economics, its underlying technology, its governance, statistics and their price drivers. This section will shortly summarize some of their main findings.

According to Osterrieder, Strika, and Lorenz (2017), "A cryptocurrency is a digital asset designed to work as a medium of exchange using cryptography to secure the transactions and to control the creation of additional units of the currency" (p.58). Cryptocurrencies are perceived as alternative currencies using decentralized systems based on blockchain technology. However, an increasing number of investors buy cryptos chiefly for investment purposes. Osterrieder et al. (2017) identify the extreme risks that regulators, banks, and investors face when investing in this new asset class. They display the heavy risk characteristics from cryptos and advice every crypto investor to be cautious.

As aforementioned, numerous other cryptos have been developed and traded since the inception of Bitcoin as the first decentralized cryptocurrency. Most interestingly, there is one fundamental ingredient that all cryptos share: blockchain technology. Through blockchain technology, a public ledger is created via which a group of agents can agree about the true state of shared data. The public ledger is called 'blockchain' because it is perceived as a chronological chain of blocks. The blocks are filled with both operational and transactional data and are documented by a network of computers. An important feature of blockchain technology is its timestamps, which can be viewed as cryptographic proof of data from previous blocks. Due to these timestamps, it is impossible to adapt the information stored in the blocks without adjusting their digital fingerprint. Altering data would irreversibly break the chain of blocks, making it impossible to modify past validated transactions without being noticed (Catalini and Gans, 2016, p.22).

Though as expected, there are also numerous differences between the various currencies. After the enormous increase in Bitcoin's market capitalization, many alternative cryptocurrencies (known as Altcoins) were developed. Altcoins are Bitcoin-based derivatives, created using Bitcoins' source code which is publicly available on Github (Glaser and Bezzenberger, 2015, p.4). Bitcoin had some shortcomings and Altcoins were developed to address these flaws. Certain Altcoins can lower computational costs, increase the speed of transactions and increase block sizes using different algorithms. Altcoin developers can easily raise money through initial coin offerings (ICOs). Via ICOs, developers can pay for launch and development expenses even before their coin is publicly available on the market (Chuen, Guo, and Wang, 2017, p.10).

The primary reason for Nakamoto (2008) to create an electronic payment system was to avoid mediation and transaction costs and payment uncertainties when doing trades. Nowadays, cryptocurrencies can be used for all sorts of commerce, as long as both traders are willing to transfer or accept cryptos. Though, trading with cryptocurrencies works fairly different from trading with fiat currencies. As an illustration: Let's suppose two traders want to make a trade using cryptos. Trader one wants to buy a specific asset of trader two, costing 5 Bitcoins. To enable this trade, trader one has to announce that he or she wants to transfer 5 Bitcoins to trader two in the Bitcoin network. This announcement is then accompanied by a note, disclosing previous transactional details of trader one. Part of the announcement is encrypted using the private key of trader one, which in turn serves as evidence for the validity of the public message to anyone in the Bitcoin network. If next trader two wants to send cryptos to trader three, he or she also has to publish an announcement signifying that trader two got the 5 Bitcoins from trader one. The Bitcoin network can then identify trader one, two and three by their public keys, serving as IDs. All new trading agreements published to the Bitcoin network are gathered in a sequence of blocks, which we now know acknowledge as blockchain (Böhme, Edelman and Moore, 2015, p.216).

Bitcoins and most other cryptos cannot merely be acquired through doing business with other traders or exchange services. In addition to simply buying coins, one can also obtain Bitcoins and Altcoins through mining. Miners establish the validity of transactions using crypto software that can solve complex math puzzles. Successful miners are paid in cryptos, giving them an incentive to fairly assess the soundness of transaction data. Miners use coin specific systems and face a lot of competition. The individual or group that solves the mathematical puzzle first will receive all the newly issued cryptos while the other miners receive nothing. Each network adapts the difficulty degree of the math problems based on the number of miners added to the network. The more miners and therefore coins generated, the harder it will become to solve the math problems. Moreover, for Bitcoin and some other cryptos, coin supply is limited, and hence miners are rewarded less and less per extra number of blocks (Chuen, Guo, and Wang, 2017, p.8).

For many of us, the underlying technology of cryptos is hard to wrap our heads around. Due to its mystifying nature, a lot of investors are skeptical about the future of cryptocurrencies. Even the acknowledged Nobel-Prize winning economist Robert Shiller has publicly shared his disbelief. On May 30th, 2018, Shiller stated on CNBC news that Bitcoin looks like a bubble that won't be around anymore in 100 years. He believes that this new asset class is mostly a hype that is fuelled by emotions instead of real underlying fundamental value. He did mention that, as expected, he too could be mistaken about this extremely volatile market (Chang, 2018).

Naturally, opposite to the crypto market bears, plenty of bulls firmly believe in the future of this market. Among them is Tim Draper, an acclaimed venture capitalist and founder of Draper Fisher Jurvetson. In April 2018, Draper predicts on CNBC news that Bitcoin is going to multiply 30 times during the upcoming four years (Cheng, 2018).

Throughout the years, many investors joined the debate on the future of cryptocurrencies. However, the only thing that can be said with confidence is that both bulls and bears can never be certain. Hence, for both parties, a deeper analysis of cryptocurrencies as an investment vehicle is greatly valuable.

2.2 Foundations of Factor investing

The first factor investing theory emerged in the 1960's when the Capital Asset Pricing Model was introduced. The CAPM is viewed as the earliest single-factor model and is based on the idea that investors face two different types of risk: systematic and non-systematic risk. Systematic risk or market risk is undiversifiable and is connected to the overall performance of the financial market. Unsystematic risk or idiosyncratic risk is stock specific and can be diversified away. Due the fact that the latter is diversifiable, the CAPM suggests that one factor (the market) drives the returns and risks of all individual stocks (Nielson, Nielsen & Barnes, 2016, p.1).

Naturally, after the inception of the CAPM, analysts criticized the single-factor model for being too insufficient. Scientists stressed the fact that the market is not the only determining factor that drives returns. Hence, in the years that followed, additional factors were researched and proposed (Bender, Briand, Melas & Subramanian, 2013, p.6).

As mentioned in the introduction, a factor is a systematic driver of return and is viewed as a characteristic connecting a group of assets. Some of the most well-known factors are value, size, momentum, low-volatility, dividend yield and carry. This paper incorporates the traditional factors plus some non-traditional factors that apply to the cryptocurrency market. This paper does not incorporate the dividend yield and carry factor because dividend-paying cryptocurrencies are not incorporated in the sample and the data needed to construct the carry factor is not accessible. In the subchapters below, the main findings and theories of all implemented factors are presented. Since literature on factor investing in the cryptocurrency market is extremely limited, theories on factor investing in more explored asset classes are discussed. The methods used to create and design the various factor measures are introduced in the methodology section in chapter 4.

2.2.1 Momentum

Momentum is a well-established trading strategy that refers to persistence in returns: winners are likely to keep winning while past losers are prone to keep losing. To implement this strategy, one buys assets that have been performing well in the past and sells assets that underperform. Momentum is based on several philosophies, some risk-based while others more behavioral based. Risk-based arguments demonstrate that realized and expected returns are highly correlated, which automatically translates into the given definition of momentum. Additionally, behavioral biases side with momentum because theory anticipates that investors rely more on heuristics (Baz, Granger, Harvey, Le Roux and Rattray, 2015, p.6).

Momentum strategies can be implemented in two different ways: as a time-series or cross-sectionally. Time series momentum is a timing strategy which concentrates on a securities' past return. Though, as aforementioned, this paper will perform a cross-sectional analysis of the cryptocurrency market. Therefore, in this study, the cross-sectional momentum definition is applied. Cross-sectional momentum does not merely look at one asset over time; it compares different securities within the same asset class at one point in time. Cross-sectional momentum selects the 'winning' securities. These winners are the assets, or in our case cryptos, that have generated higher returns in the past analyzed time frame compared to their peers (Moskowitz, Ooi, & Pedersen, 2012, p.229).

There is a substantial amount of empirical evidence supporting the momentum factor: In 1993, Jegadeesh and Titman researched several momentum trading strategies in the U.S. stock market using a time frame of 24 years. A particular strategy, which bought stocks with relatively high past 6-months returns and shorted stocks with relatively low past 6-months returns, realized an average compounded excess return of 12.01% per year. They further demonstrated that portfolio returns were highly dependent on the holding and rebalancing time frames implemented in the momentum strategies (Jegadeesh &Titman, 1993, p.70). A couple of years later, Rouwenhorst (1998) studied momentum strategies analyzing over 2190 international stock returns from 12 different European countries. He demonstrated that the international portfolios that included past winners generated higher returns than the portfolios that incorporated the losing stocks. His conclusions, which were drawn in a different market, were comparable to Jegadeesh and Titman's (1993) findings and therefore provide further evidence in favour of the momentum factor. Moreover, as already stated, Asness, Moskowitz, & Pedersen (2013), researched different value and momentum premia across several markets and asset classes. Using a cross-sectional analysis, they also found consistent evidence suggesting momentum return premia present in all markets and asset classes inspected. Lastly, as aforementioned, Hubrich (2017) already studied momentum in the cryptocurrency space. He also adopted a cross-sectional approach and concluded that the single-factor momentum strategy provides significant excess returns compared to his benchmark portfolios.

Due to the above-presented evidence in favour of momentum investing strategies, this study will also investigate whether this so-claimed widespread momentum presence is also existent in the cryptocurrency space. Since this paper incorporates a different dataset, time frame, methodology and different performance measures compared to Hubrich's study, it is interesting to determine whether we encounter similar results. Particularly due to the finding of Asness et al. (2013), suggesting an omnipresence of the momentum factor in all asset classes, I expect that this momentum factor is also present in the cryptocurrency market. Therefore, this paper constructs the following hypothesis:

Hypothesis 1: Momentum investing strategies in the cryptocurrency market generate higher risk-adjusted returns compared to the market index.

2.2.2 Value

According to Bender et al. (2013), the value factor captures excess returns to value securities, which are stocks that are inexpensively priced compared to their fundamental value. The value factor is frequently captured by valuation ratios, such as book-to-price and earnings to price, which identify securities that are under-priced. If an investor chooses to follow this approach, he or she goes long in stocks that are under-priced according to their fundamental value ratio and shorts the securities that are over-priced.

Portfolio managers have been applying value investing strategies for decades. Moreover, this knowledgeable theory has long been explored in finance literature and is now a well-established fundamental factor. It is universally accepted that the value factor has explanatory power for cross-sectional asset returns. These findings are among other things presented in the following literature:

In the 80's, Rosenberg, Reid, and Lanstein (1985) created a so-called book to price strategy. This strategy goes long in stocks that have a high book-value of common equity per share to market price per share (BE/ME) and shorts stocks with low BE/ME ratios. They concluded that U.S. securities' returns where positively related to the value ratio. Chan, Hamao and Lakonishok (1991) researched the cross-sectional predictability of equity returns in Japan using the established book-to-market ratio as one of the explanatory variables. According to their results, this fundamental factor is not just applicable as an explanatory variable for U.S stock returns, but the factor also has significant informative value for Japanese stock returns. One year later, Fama and French (1992) incorporate these findings, giving them an incentive to evaluate the Capital Asset Pricing model critically. Using the cross-sectional regression approach of Fama and Macbeth (1973), they regressed return files on variables that were expected to explain equity returns. Their results suggested that size and particularly value played a determining role in the explanation of the cross-section of securities' returns. They showed that a combination of these two factors absorb the leverage and earnings-to-price effect on stock returns. In 1993, Fama and French again collaborated and introduced their famous three-factor model. This time, they added a default factor and term structure factor. In addition to the asset market, they also analyzed the bond market and demonstrated stochastic links between the two when excluding low-grade corporate bonds from the sample. Using the time-series regression approach of Black, Jensen, and Scholes (1972), they again provide evidence that the proxies used for the size and value risk factors can assist to explain the cross-sectional variation of average securities' returns. In the years to follow, numerous other analysts reached similar conclusions. Finally and most importantly, Hubrich (2017) studied the value factor in the cryptocurrency market. He demonstrated that the single-factor value strategie produced positive yet insignificant alphas compared to his benchmark portfolios. He concluded that the factor was relevant at shorter term holding periods.

Due to the pivotal role of the value factor in finance literature, this factor is also incorporated and tested in this paper. Because this paper includes another dataset, methodology, timespan and diverse and additional performance measures compared to Hubrich's study, it is intriguing to discover whether we encounter similar results. The measure invented by Hubrich (2017) to determine a crypto's value is introduced in the methodology section in chapter 4. However, since this definition is quite original and different from the traditional ratio, it is hard to predict whether investing in this value factor can increase a portfolio's performance. However, because Hubrich did not present any significant evidence in favour of the value factor and due to the deviating nature of the implemented measure, this paper constructs the following hypothesis:

Hypothesis 2: Value investing strategies in the cryptocurrency market do not generate higher risk-adjusted returns compared to the market index.

2.2.3 Low-Volatility

As the name indicates; low-volatility investing implies investing in securities with relatively less volatile return patterns. Since the global financial crisis in 2008, investing in low-volatility stocks has increased in popularity. For many years, investors believed in a risk-return trade-off which suggests that people are compensated for investing in more volatile and therefore riskier stocks. Though, empirical results do not seem to agree with this basic financial principle. Low-volatility portfolios have long outperformed high-volatility portfolios, offering a possible advantageous position for investors (Baker, Bradley & Wurgler, 2011, p.40).

One might wonder why the low-volatility factor is discussed in a research paper on factor investing in cryptocurrencies, an extremely volatile market. However, it has been shown that the volatility factor is present within various different asset classes. Falkenstein (2009) examined the modern theory of risk premiums across 20 different markets. For each asset class, specific measurement characteristics were used. He concluded that the low-volatility anomaly is existent within every single asset class analyzed. Because the cryptocurrency market was highly immature at the time of Falkenstein's research, it is extremely intriguing to discover whether this factor is also present in this new asset class. The main findings on the low-volatility factor in equity markets, are presented in the paragraphs below:

Baker, Bradley and Wurgler (2011) question the low-volatility anomaly using behavioral finance principles. Their behavioral model is built on the assumption that investors are irrational and are therefore willing to use high-volatility stocks as lottery tickets. When entering a lottery, investors are willing to accept a lower expected return in exchange for playing the game and collecting great returns when the stock 'wins'. Baker et al. (2011) sorted various stocks using two different risk measures, namely: low-volatility and beta. They analyzed different portfolio returns using a time frame of 41 years and concluded that regardless of their definition of risk, low-risk stocks consistently outperform high-risk securities.

Alighanbari, Doole, Mrig, and Shankar (2016) investigate two different low-volatility strategies. The first one is purely ranking-based, in which stocks are simply sorted based on their volatility estimate. The second method is optimization-based and accounts for both volatility and correlation effects. Using these two methods, they develop a minimum volatility index using 27 years of data. This index decreased volatility by 30% and outperformed the market by 20 percentage points.

Hsu and Li (2013) generate more ambiguous results. They compare the S&P500 Low Volatility Index and the S&P BMI International Developed Low Volatility Index with the performances of two capitalization-weighted indices. Using a time frame of almost 30 years, they show that the relative performance of a low-volatility index is highly correlated to the overall state of the financial market. During the dot-com bubble, when the market was doing extremely well, low- volatility indices significantly underperformed compared to capitalization-weighted indices. Though, during more stable upward trending markets, low-volatility portfolios did not persistently underperform. Moreover, during financial downturns such as the global financial crisis, low-volatility indices outperformed capitalization-weighted indices. Hence, the (dis)advantages of low-volatility investing rely heavily on the overall state of the market.

Due to these diverging findings, this paper will also test the effectiveness of the proclaimed low-volatility factor. As mentioned above, Hsu and Li (2013) concluded that investing in low-volatility stocks during strong market upturns generate significantly smaller returns. Since crypto prices have appreciated immensely, similar to stock prices during the dot-com bubble, it is intriguing to determine the ambiguous effect of low-volatility investing strategies in the cryptocurrency space. Due to the extremely volatile nature of the cryptocurrency market and due to its bubble-like tendency, the following hypothesis is constructed:

Hypothesis 3: Low-volatility investing strategies in the cryptocurrency market do not generate higher risk-adjusted returns compared to the market index.

2.2.4 Google Query Volumes

During the last decade, the so-called big-data volumes have enlarged immensely. Since the numbers tell the tale, analysts with various specialties have acquired new research opportunities. Preis, Moat, and Stanley (2013) investigate trading behavior in financial markets using google trends. Worldwide, traders make daily investment decisions based on previous information acquired. However, since the emergence of the internet, nearly all information is gathered through online Google searches. Conveniently, Google has made search query data publicly available via their tool 'Google Trends'. Preis et al. (2013) examine the potential of this new data source and assess its explanatory power in the financial market. They analyze changes in Google query volumes for all search terms affiliated to finance. Their results show that search patterns provide meaningful knowledge on future stock market movements, demonstrating some of the possibilities using this new data source.

Kristoufek (2013) also adopts the new data source and tries to quantify the relationship between Bitcoin's price formation and Google or Wikipedia search volumes. Because it is extremely difficult to clarify the return behavior of cryptocurrencies using established economic and financial theories, new methods or models are needed. Kristoufek emphasizes the fact that demand for cryptocurrencies is not motivated by expected macroeconomic development as there are no macroeconomic fundamentals. Though, he claims that investors' faith in the future of the market, or better said investor sentiment, is the most crucial determinant for the price of Bitcoin. He assumes that Google and Wikipedia search volumes are good proxies of investor sentiment and he analyzes the relationship between query data and Bitcoin's price. He concludes that investor sentiment, measured by Google search volumes, and Bitcoin's price are positively correlated.

As demonstrated in the above-discussed papers, the relationship between Google search volumes and stock market returns or Bitcoin's returns have already been examined. However, this paper does not merely want to test whether a positive or negative correlation exists between Google query data and the individual eleven cryptocurrencies in our sample. This study aims to conceive whether a new factor can be acknowledged as a unique systematic driver of crypto returns. Similar to the other quantified definitions implemented, this measure will be introduced in the methodology section in chapter 4. I personally believe that the cryptocurrency market owes much of its success to the irrational behavior of countless investors who experienced the so-called fear-of-missing-out phenomena. Moreover, I believe that this emotional and irrational behavior is partly captured by Google searches. Therefore, the following hypothesis is constructed:

Hypothesis 4: Investment decisions based on the (in this paper created) Google Trends factor can generate higher risk-adjusted returns in the cryptocurrency market compared to the market index.

2.2.5 Hash rates

As stated above, Kristoufek (2013) examined the relationship between Bitcoin's price formation and Google Trends. Two years later, he again analyzed the determinants of Bitcoin prices only now including other untraditional data sources. Particularly, the data stored in blockchain systems could have informative value when predicting the return patterns of Bitcoin. To understand why blockchain information is fruitful, a general understanding of the underlying technology is needed. Thus, a small recap is provided below.

As mentioned in section 2.1, miners are people who establish the validity of transactions by solving complex puzzles. To solve these puzzles, miners use cryptocurrency software that requires computational power. A hash rate, which is expressed as an absolute value, can be interpreted as a measure of computational power. The stronger the required computational power to mine coins, the larger the hash rate (Hayes, 2017, p.1315).

Kristoufek (2015) tries to establish the long-term relationship between hash rates and Bitcoin prices and analyses their correlation. He illustrates the possible effect of hash rates on Bitcoin values. One suggested theory states that larger hash rates (hence rising realized computational power) drives small miners out of the competition. The small miners are unable to afford the rising costs of mining and can therefore no longer acquire cryptocurrencies through mining activities. For that reason, they must resort to other options such as simply purchasing coins via a coin's specific network. This increase in demand would naturally be accompanied with a price increase. Therefore, Kristoufek's theory predicts that hash rates and crypto prices are positively correlated.

This paper does not merely want to test whether a positive or negative correlation exists between certain variables and returns. This study again aims to conceive whether a new, this time more technical factor can be acknowledged as a unique systematic driver of return. The measure used to quantify the factor is proposed in the methodology section in chapter 4. Since a hash rate is a measure of computational power and mining difficulty, higher absolute hash rate numbers imply that it is more difficult to obtain coins through mining. From a psychological point of view, I expect that because these coins are relatively more difficult to acquire, investors want them even more. This increase in demand would consequently increase prices and generate higher returns. Therefore, the following hypothesis is constructed:

Hypothesis 5: Investment decisions based on the (in this paper created) hash rates factor can generate higher risk-adjusted returns in the cryptocurrency market compared to the market index.

Chapter 3. Data

In this section, the data retrieval methods and summary statistics are presented. In total 11 cryptocurrencies are analyzed. These coins were selected based on two criteria, namely: market capitalization and data availability. The cryptocurrencies included in our dataset are Bitcoin, Ethereum, Ripple, Bitcoin Cash, Litecoin, Monero, Dash, Ethereum Classic, Bitcoin Gold, Zcash, and Dogecoin.

3.1 Data Sources and Retrieval Methods

To create the five earlier introduced factors, three different data sources were exploited. Firstly, to construct the traditional momentum, value and low volatility factors, data from the website www.coinmetrics.io is exported. Coinmetrics.io offers daily data on prices, transaction volumes and market cap. From these variables, one can construct the three traditional factors momentum, value and low-volatility. Due to Monero's RingCT (Ring Confidential Transactions) technology, data on daily transaction volumes are not available. Because transaction volumes are needed to construct the value factor, Monero is excluded from the value strategy.

Secondly, to construct the Google factor, search query volumes from the Google Trends tool were exported. Google Trends provides weekly normalized trends data, offering users insights into relative search volumes. The query volumes are indexed to 100, where 100 resembles the maximum number of searches for a specific term and time frame selected. Hence, for each coin, search volumes are values relative to the highest number of queries for that specific coin over a specified time frame. The Google factor can be constructed utilizing these relative search volumes.

Finally, to construct the hash rate factor, data from the website bitinfocharts.com was obtained. The site does not provide export or download tools, but the numerical values were extracted from the source code behind the comparison charts. The desired data can be found between matching double square brackets ([[...]]), each representing a row of hash rates that are separated by a comma. The column names can be found in "labels: [...]". Knowing the source codes' structure, the required information can be extracted using regular expressions (a theoretical computer science theory) to match the known delimiters. For unknown reasons the hash rates from Ripple are not reported, hence this coin is excluded from the hash rate factor investing strategy.

This study implements a time frame from 2014-02-18 to 2018-04-27, thus only available data within this specified period is incorporated. This paper adopted the above-shown start date because this is the first day in history for which returns of at least five coins (Dash, Bitcoin, Litecoin, Ripple, and Dogecoin) are available. For all measures except Google Volume, daily data (including weekends and holidays) is available.

3.2 Summary Statistics

In the following tables and figures, various summary statistics are presented. In table 1 below, the 11 eleven individual cryptocurrencies' abbreviations, total market capitalizations (market price multiplied by the number of coins in circulation) and relative market capitalizations are shown. As can be seen, Bitcoin still is the most dominant coin accounting for almost 38% of the total market. As stated in the introduction, there are currently 1587 different coins in circulation. Though, market movements are mostly determined by a limited number of coins since the five largest coins account for almost 70% of the total market. The total chosen sample represents roughly 73% of the entire cryptocurrency market, making it a valid market proxy.

A visual representation of the evolution of the total market capitalization values from the individual coins is shown in figure 1. As can be seen, the combined market capitalization of the 11 incorporated coins increased immensely in the year 2017. Though, this massive bull run stopped in the beginning of 2018 and consequently prices and market capitalization dropped fiercely. This bearish market behaviour might have been fuelled by certain governments who, at the beginning of 2018, formulated stricter regulating guidelines (Coingecko.com, 2018).

The enormous price appreciation and later depreciation taking place in the years 2017 and 2018 respectively, can be viewed in figure 2. Here, a visual representation of the indexed price levels are displayed over time. The price level of every individual coin is indexed to 100 on the first day all coins included in our sample are traded. Indexing the data at this common date enables us to compare coins with different market values and allows us to determine the growth rates of the 11 coins separately. Figure 2 clearly shows the immense growth rate of Ripple, whose price increased by more than 1500% at the ending of 2017. This particularly strong price increase is possibly the result of ripples relative advantage compared to other coins, offering lower transaction fees and faster transaction speed (ripple.com, 2018).

Table 1: The absolute and relative market capitalizations of the 11 cryptocurrencies.
This table presents parts of the descriptive statistics of the 11 cryptocurrencies that are incorporated in the sample. More specifically, the abbreviation, market capitalization (market price multiplied by the number of coins in circulation), and relative market capitalization of the individual currencies are shown. The market capitalization is expressed in billions of U.S. dollars. The data was extracted from CoinMarketCap.com on the 30th of April, 2018.

Name	Abbreviation	Market Cap (bn USD)	Relative Market Cap
Bitcoin	BTC	153.26	37.76%
Ethereum	ETH	65.90	16.18%
Ripple	XRP	32.42	7.90%
Bitcoin Cash	BCH	22.28	5.70%
Litecoin	LTC	8.21	2.04%
Monero	XMR	3.73	0.93%
Dash	DASH	3.70	0.92%
Ethereum Classic	ETC	2.15	0.54%
Bitcoin Gold	BTG	1.20	0.30%
Zcash	ZEC	1.07	0.26%
Dogecoin	DOGE	0.58	0.14%
Total		304.21	72.66%

Figure 1: A visual representation of the absolute market capitalization values of the 11 cryptocurrencies over time
This figure displays absolute market capitalization values of the eleven individual coins that are included in our sample. Moreover, this graph depicts the evolution of the market capitalization numbers over time. Each colored surface represents the market cap volume of a single coin. Daily market cap data between February 2014 and April 2018 is included, resulting in 1503 daily observation points. Market Cap is expressed in U.S. dollars. The data was extracted from CoinMarketCap.com on the 30th of April, 2018. The absolute values are reported in table 1.

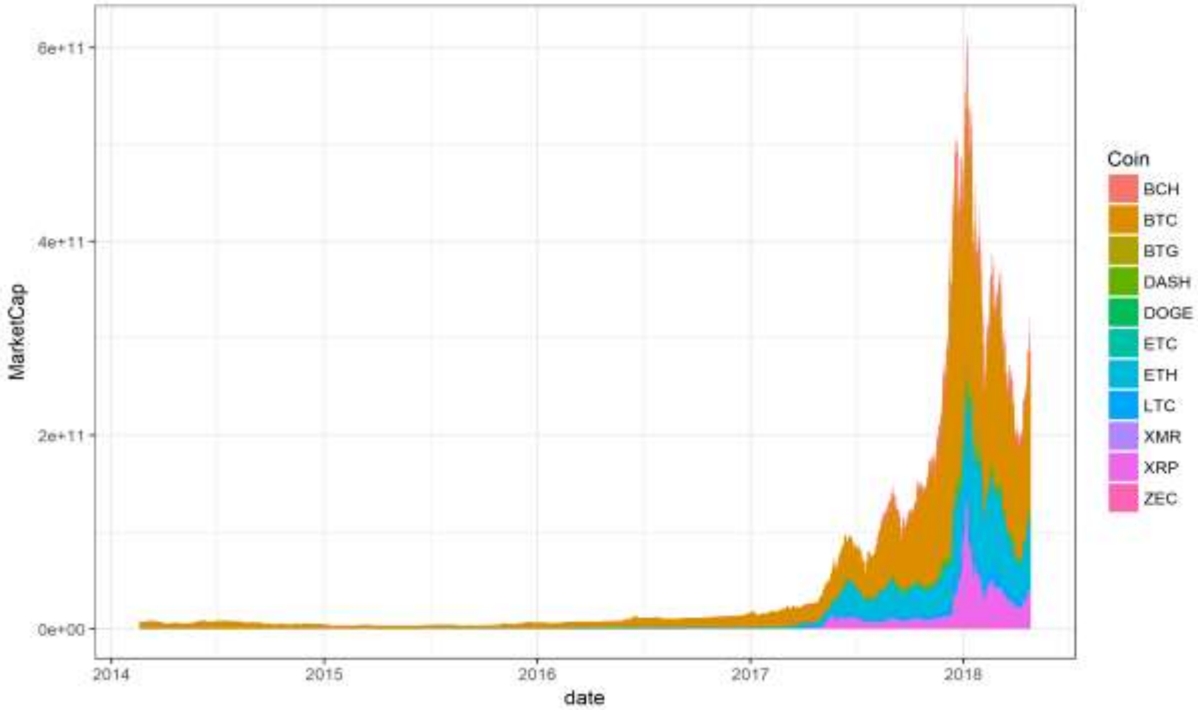
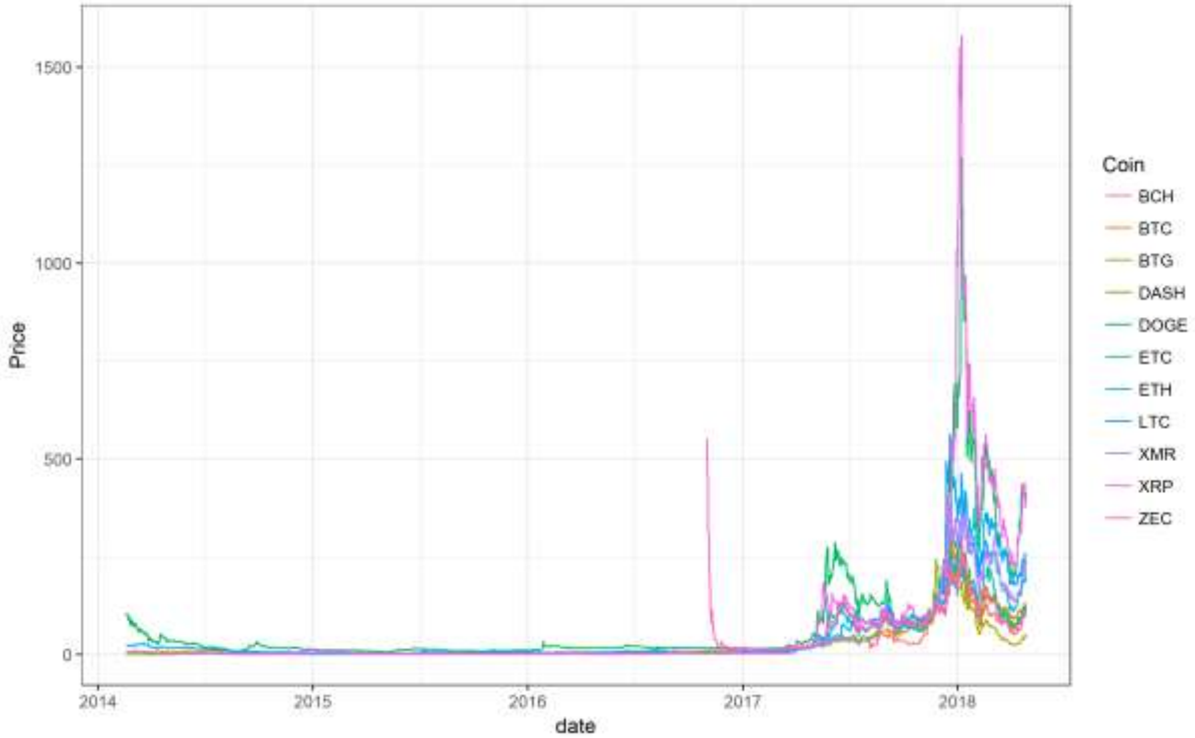


Figure 2: A visual representation of the indexed price levels of the 11 cryptocurrencies over time
This figure displays the indexed price levels of the individual coins over time. The prices of the individual coins are indexed to 100 on the first day all coins included in our sample are traded (16th of November 2017). The displayed time frame ranges from February 2014 to April 2018. The data was extracted from CoinMarketCap.com on the 30th of April 2018.



Additional summary characteristics and return statistics of the individual coins are presented in table 2. One can detect that the first observations that are incorporated in our sample start on February 18th, 2014, the chosen starting date. This date was picked because from that point in time, returns of at least five coins were available. This resulted in a total number of 1530 daily observations. As can be seen, the average daily stock returns vary between 0.26% and 1.04%, which is exceedingly high since these are daily statistics. These extremely high returns are all accompanied with large average daily standard deviations ranging from 3.98% to 12.90%. All skewness measures shown in table 2 are larger than zero. Thus, one can conclude that the distribution of the individual returns is positively skewed. Moreover, looking at the kurtosis measures, one can establish that the individual coins exhibit fat tails. These numbers support Osterrieder et al.'s (2017) findings who examined the statistical properties of cryptocurrencies and assessed the extreme volatile behavior of this new asset class. Finally, in the last row, the mean number of hash rates are presented. As already stated, a hash rate is a proxy for the degree of mining difficulty. Therefore, as shown in table 2, one can conclude that Bitcoin and Bitcoin Cash are two coins that are relatively more difficult to mine. Moreover, Bitcoin Gold, Zcash and Monero are relatively easier to mine.

Table 2: Additional summary characteristics and return statistics from the 11 coins included in our sample.
This table presents additional descriptive statistics of the 11 cryptocurrencies that are incorporated in the sample. More specifically, the starting date, total number of daily observations, distribution statistics and mean number of hash rates of the individual currencies are shown. All data is daily. The return statistics were computed from the data that was extracted from CoinMarketCap.com in April 2018. The hash rate numbers were obtained from Bitinfocharts.com in April 2018.

	BTC	ETH	XRP	BCH	LTC	XMR	DASH	ETC	BTG	ZEC	DOGE
First observation date	18/2/14	10/8/15	18/2/14	3/8/17	18/2/14	24/5/14	18/2/14	27/7/16	16/11/17	1/11/16	18/2/14
Number of daily observations	1530	992	1530	268	1530	1435	1530	640	163	543	1530
Average daily return	0.26%	0.95%	0.55%	1.04%	0.34%	0.62%	0.83%	0.67%	0.26%	0.08%	0.33%
Average standard deviation	3.98%	7.36%	8.54%	11.50%	6.33%	8.05%	9.66%	8.31%	12.90%	9.00%	7.16%
Return skewness	0.15	1.11	7.20	13.81	2.01	1.57	6.99	1.02	2.76	1.14	1.94
Return Kurtosis	5.78	5.58	124.91	5.07	18.51	10.41	113.89	7.05	14.40	8.57	15.32
Mean number of hash rates	3.77E+18	5.15E+13	NaN	1.86E+18	1.72E+13	1.10E+8	2.31E+14	3.49E+12	5.21E+7	2.24E+8	1.34E+13

Chapter 4. Methodology

In this chapter, the steps taken to form the benchmark, and single and multi-factor portfolios are presented. This chapter is organized as follows: First, the quantified definitions of the various factor measures are introduced. Second, the formation of the two benchmark portfolios, that serve as a market index proxy for the cryptocurrency space, is discussed. After the establishment of the factor specific measures and benchmark portfolios, the trading algorithm that is designed to form the various portfolios is presented. The algorithm first creates the single-factor portfolios based on the five factors researched in this paper. The weights of the individual coins are determined using both equal weighting and equal volatility weighting techniques, resulting in the construction of 5x2 single-factor portfolios. After the construction of the two benchmark portfolios and the ten single-factor portfolios, three multi-factor portfolios are created. Moreover, since this study aims to reveal whether these new factors can be acknowledged as unique systematic drivers of returns, a regression analysis is performed. Lastly, a proper performance analysis is introduced in order to formally test the different investment strategies. This paper incorporates three risk-adjusted performance measures, namely: Jensen's alpha, the Treynor ratio and the Sharpe ratio. Additionally, to formally test for the difference between the Sharpe ratios of the 13 originated factor strategies and the benchmark portfolios,the moving-blocks Künsch (1989) percentile bootstrap method is applied.

4.1 The Factor Measures

This paper does not aim to create factor investing strategies best applicable to the cryptocurrency market. Though, it aims to establish whether consistent factor return premia exist in the cryptocurrency space using its most conventional and straightforward measures. Consequently, using other (perhaps in this market superior) factor measures could generate higher risk-adjusted returns.

4.1.1 The momentum Measure

Commonly for momentum, a time-frame of 12 months is used to analyze the past cumulative raw monthly returns on the securities. Due to the availability of daily data, the shorter time frame and the extremely volatile behavior of returns this paper will define momentum based on weekly returns. Hubrich (2017) addresses the high volatile behaviour of cryptocurrencies. He claims that, even though the time frame of crypto returns is substantially shorter than the time frame of stock returns, the sample contains enough significant variation to draw robust conclusions.

The quantified definition of the momentum of currency i at time t is given by the following equation:

$$M_{i,t} = \frac{1}{7}\sum_{j=1}^{7} r_{i,t-j}$$

Where $M_{i,t}$ is the computed momentum of coin i at time t, $r_{i,t-j}$ is the return of currency i at time $t-j$, and j is the timestep in days. Since cryptocurrencies are traded every single day of the week, momentum is defined as the average return generated over the previous 7 days.

4.1.2 Value Measure

In equity markets, the value factor is commonly captured through valuation ratios such as the book value of common equity to market price. For cryptocurrencies it is more difficult to establish their intrinsic value. This makes it harder to ascertain whether the coin is fairly priced. Hubrich (2017) addresses this challenge and stresses that the value factor should have mean-reverting tendencies, implying that the factor should contain a fundamental variable that is comparable to market values. The dollar-valued on-chain transaction volume satisfies this criteria. This volume is calculated as the sum of all transaction outputs that belong to the blocks mined on a specific day. Transaction outputs are certain amounts of cryptocurrencies that are sent from one trader to another. They are sent together with a set of rules that can decipher the output. Thus, this transaction volume reveals a lot about the economic activity of a certain cryptocurrency.

Hubrich derived his ideas and value metric from the website coinmetrics.io. Coinmetrics was the first to introduce the Network Value to Transactions (NVT) ratio, where the network value amounts to the total market value of all tokens that are currently in circulation per cryptocurrency and the transaction element refers to the above-mentioned dollar-valued on-chain transaction volume. Naturally, one would expect that a high dollar transaction volume implies greater economic activity for a certain currency. This implies that a low raw NVT ratio corresponds to a relatively undervalued cryptocurrency (Coinmetrics.io, 2018).

To validate this measure, one assumption must be made. Even though cryptocurrencies store transactions in logs that are dispersed across a network of engaging computers, transaction volumes are hard to retrieve. This is because the logs record both spent and unspent outputs. Unspent outputs are perceived as amounts that traders have in their ‘wallets’ but have not yet been used for actual transactions. Unspent outputs are still regarded as transactions since it is never possible for traders to send a fraction of their transactions received. For example: If trader one receives 10 Bitcoins and later wants to transfer 5 Bitcoins to trader two, the actual spent amount for trader one would normally amount to 5. Yet, it is not possible for cryptocurrency traders to arbitrarily decide how much cryptos to transfer out of their wallets. Trader one can only transfer 10 Bitcoins as a whole, of which 5 Bitcoins are sent to trader 2 and the other 5 Bitcoins are sent (back) to trader 1. Unfortunately, it is impossible to distinguish the different transactions from another and determine which part is change.

Thus, even though commonly one would say 5 Bitcoins are traded, the outputs amount to 10. Therefore, the dollar-valued on chain transaction volume always overestimates the true transaction volume. In order to validate this metric, the following assumption must be made:

The spent to unspent output ratio is similar for all cryptocurrencies

Based on this assumption, the NVT measure is a valid proxy for value.

Equal to the momentum factor, the value factor is also based on prior weeks' data. The quantified definition of the value measure for currency i at time t is therefore given by the following equation:

$$\mathrm{NVT_{it}} = \frac{\mathrm{Network\ Value_{it}}}{\frac{1}{\mathrm{j}}\sum_{\mathrm{j}=1}^{7}\mathrm{Dollar-value\ on\ chain\ transaction\ volume_{i,t-j}}}$$

Where the $\mathrm{Network\ Value_{it}}$ stands for the total market value of all coins in circulation for cryptocurrency i at time t and the denominator represents the average dollar-valued on chain transaction volume of the past 7 days for cryptocurrency i.

4.1.3 Volatility Measure

The volatility measure applied in this paper is based on the method used for the creation of the S&P500 Low Volatility Index. This index evaluates the returns of some of the least volatile securities from the S&P500. The index is created in two steps:

1. The selection of the securities based on their conditional volatility levels
2. The allocation of the individual weights for the selected low-volatility securities

Hence, the S&P500 Low Volatility index is a long-only portfolio that (every time the portfolio is rebalanced) goes long in the least volatile securities. Because this paper implements a long-short approach, both the least and most volatile coins are selected. To create the low-volatility factor for the cryptocurrency market, two consecutive steps have to be followed:

Firstly, the conditional volatility is computed for every coin i at time t. The conditional volatility is defined as the weekly rolling standard deviation of coin i's daily price returns. This measure is, similar to the momentum and value factor measures, based on prior week's data. The following equation shows the quantified definition of the conditional volatility:

$$\text{Volatility}_{it} = \sqrt{\frac{\sum_{i=1}^{N}(X_{it} - \overline{X}_i)^2}{N-1}}$$

Where X_{it} and $\overline{X}_i$ stand for the return of cryptocurrency i at time t and the weekly average return of cryptocurrency i, respectively. Moreover, since it is possible to trade cryptos every day of the week, N amounts to 7.

Secondly, similar to methodology applied for the construction of the S&P500 index, the coins are ranked based on the inverse of the conditional volatilities in descending order. Again, since this paper incorporates a long-short approach, the top 30th percentile and bottom 30th percentile are selected. According to the low-volatility theory, one goes long (short) in the coins that are present in the top (bottom) 30th percentile.

4.1.4 Google Trends Measure

To the best of my knowledge, this study is the first to create a long-short single-factor portfolio based on a Google factor. As mentioned in chapter 3, the data is obtained from the Google Trends tool which provides users with insights on the frequency of specific search terms. Google Trends provides weekly data so if this were the only factor examined in the paper, it would have been more logical to develop a trading algorithm that rebalances portfolios weekly. However, because all other single-factor portfolios are rebalanced daily, this portfolio is (for simplicity reasons) also rebalanced daily. Most importantly, the three multi-factor portfolios (which are also rebalanced daily) incorporate the single-factor portfolios. Therefore, to avoid unnecessary complexity in the algorithm, the Google portfolio is also rebalanced daily. Though in practice, this results in a weekly rebalanced portfolio, since the underlying values do not change.

The incorporated factor measure is constructed in a relatively arbitrary way since there is no other research this study can base the Google measure on. Though, because this paper perceives search volumes as a proxy for investor sentiment, I expect that a growth in query volumes for a specific coin exemplifies more interest in this coin. Rising interest drives op prices in financial markets. Hence, the algorithm buys coins of which the number of Google searches increases and shorts the currencies for which the number of Google query volumes decreases. One might perceive this approach as a modified momentum strategy that now analyzes Google search terms instead of returns. The past winners are the coins receiving more interest and the past losers are the coins losing interest of the general public.

4.1.5 Hash Rate Measure

This study is (to the best of my knowledge) the first to create a long-short single-factor portfolio based on hash rate values. Because hash rates proxy mining difficulty, larger absolute hash rate values signify a rising degree of mining difficulty. This paper assumes that when coins become more difficult to mine, small miners will no longer be able to afford the (mining) costs. Hence, this study expects that small miners will pursue alternative methods to acquire cryptos and thus buy crypto coins through their network. This increase in demand will in turn push up prices. Therefore, the trading algorithm buys coins that have hash rate values larger than the median of all coins and shorts cryptos with hash rate values below the median of all coins. Unfortunately, there is no record on the hash rate values from Ripple. Thus, this coin is excluded from the hash rate factor investing strategy.

4.2 Construction of the Benchmark Portfolios

In this paper, cryptocurrencies are perceived as a new asset class. Since you cannot compare apples and oranges, portfolio returns and performance measures are not compared to market or stock returns. For that reason, the constructed factor portfolios' performance will be compared to two different benchmark portfolios. Currently, a representative cryptocurrency index called the CRIX is available and serves as a benchmark for the crypto market. Unfortunately, the index is created almost six months after our implemented start date. If we would like to compare the performances of the various factor portfolios to the performance of the CRIX, we would have to drop 10% of our data. Because this paper already analyzes a relatively short time frame, it is unwise to drop more data. For that reason, two benchmark portfolios are created and one of them will serve as a market proxy. This way, available and informative data does not have to be dropped. The created benchmark portfolios are solely invested in the eleven cryptocurrencies that are incorporated in our sample. Hence, the total chosen sample represents roughly 73% of the entire cryptocurrency market, making it a valid market proxy. Both benchmarks are derived from Hubrich's (2017) paper.

Benchmark 1: The equally weighted Benchmark

As the name implies, equal weights are allocated to all coins available in the sample on each rebalancing date. In the upcoming regression analyses, this benchmark portfolio will be used as a market proxy.

Benchmark 2: The Capitalization Weighted benchmark

Weights are proportional to the market value of each specific cryptocurrency on every rebalancing date. As an illustration: If on a certain rebalancing date Bitcoin accounts for 50% of the total market capitalization, 50% of the weights will be allocated to this coin. This second benchmark portfolio will be adopted as a second reference point to compare all factor portfolios with.

4.3 The Trading Algorithm for the single-factor portfolios

In this sub-section, the daily trading algorithm that constructs the single-factor portfolios is presented. The portfolios are rebalanced daily due to the extremely volatile nature of cryptocurrencies. As stated before, the algorithm creates five single-factor portfolios based on the factors researched in this paper. The weights of the individual coins are determined using both equal weighting and equal volatility weighting techniques, resulting in the construction 5x2 single-factor portfolios. As the name suggests, the equally weighted portfolios assign equal weights to all coins that are being bought or shorted. The equal volatility weighted portfolio assigns weights based on the volatility of the individual coins. The weights are determined using the below-shown formula:

$$\mathrm{w_{it}} = \frac{\frac{1}{\mathrm{Volatility_{it}}}}{\sum_{j=1}^{N} \frac{1}{\mathrm{Volatility_{jt}}}}$$

Where $\mathrm{w_{it}}$ represents the weight of cryptocurrency i at time t, j represents all the other individual coins bought or shorted at time t and N stands for the total number of cryptocurrencies bought or shorted at a specific point in time.

The algorithm that constructs the 5x2 single-factor portfolios is shown below. Note that this algorithm is executed on a daily basis and calculations are based on prior week's data. Since all factors are based on prior week's data the algorithm starts trading on the 8th day of our implemented time frame.

4.3.1 Momentum

Algorithm for the Equal Weighted Momentum Portfolio

1. Determine the weekly momentum of all available currencies
2. Take a long position in the cryptocurrency with the highest momentum
3. Take a short position in the cryptocurrency with the lowest momentum
4. Repeat steps 2 and 3 until all coins are selected

Algorithm for the Volatility Weighted Momentum Portfolio

1. Determine the weekly momentum of all available currencies
2. Take a long position in the cryptocurrency with the highest momentum
3. Take a short position in the cryptocurrency with the lowest momentum
5. Repeat steps 2 and 3 until all coins are selected
4. Assign equal volatility weights to all the individual long and short positions

4.3.2 Value

Algorithm for the Equal Weighted Value Portfolio

1. Determine the weekly Network Value to Transaction ratio (NVT) for each available coin in the sample
2. Z-score each NVT ratio longitudinally, constructing a normalized variable
3. Take a long position in the cryptocurrency with the lowest NVT ratio
4. Take a short position in the cryptocurrency with the highest NVT ratio
5. Repeat steps 3 and 4 until all coins are selected

Algorithm for the Equal Volatility Weighted Value Portfolio

1. Determine the weekly Network Value to Transaction ratio (NVT) for each available coin in the sample
2. Z-score each NVT ratio longitudinally, constructing a normalized variable
3. Take a long position in the cryptocurrency with the lowest NVT ratio
4. Take a short position in the cryptocurrency with the highest NVT ratio
5. Repeat steps 3 and 4 until all coins are selected
6. Assign equal volatility weights to all the individual long and short positions

4.3.3 Low- Volatility

Algorithm for the Equal Weighted Low-Volatility Portfolio

1. Calculate the volatility of the prior week's return of each available cryptocurrency in the sample
2. Rank the coins based on the inverse of their volatility in descending order
3. Go long in the coins that are positioned in the highest 30^{th} percentile
4. Short the coins that are positioned in the lowest 30^{th} percentile

Algorithm for the Equal Volatility Weighted Low-Volatility Portfolio

1. Calculate the volatility of the prior week's return of each available cryptocurrency in the sample
2. Rank the coins based on the inverse of their volatility in descending order
3. Go long in the coins that are positioned in the highest 30^{th} percentile
4. Short the coins that are positioned in the lowest 30^{th} percentile
5. Assign equal volatility weights to all the individual long and short positions

4.3.4 Google Trends

Algorithm for the Equal Weighted Google Trends Portfolio

1. Determine the growth rates of the Google search terms for each specific coin in the sample
2. Take a long position in the cryptocurrencies that have positive growth rates
3. Take a short position in the cryptocurrencies that have negative growth rates

Algorithm for the Equal Volatility Weighted Google Trends Portfolio

1. Determine the growth rates of the Google search terms for each specific coin in the sample
2. Take a long position in the cryptocurrencies that have positive growth rates
3. Take a short position in the cryptocurrencies that have negative growth rates
4. Assign equal volatility weights to all the individual long and short positions

4.3.5 Hash Rates

Algorithm for the Equal Weighted Hash Rates Portfolio

1. Place all available hash rate values in ascending order and determine the median
2. Take a long position in the coins that are present in the top half
3. Take a short position in the coins that are present in the bottom half

Algorithm for the Equal Volatility Weighted Hash Rates Portfolio

1. Place all available hash rate values in ascending order and determine the median
2. Take a long position in the coins that are present in the top half
3. Take a short position in the coins that are present in the bottom half
4. Assign equal volatility weights to all the individual long and short positions

4.4 *The formation of the multi-factor portfolios*

This section describes the establishment of the three multi-factor portfolios. All multi-factor portfolios are based on (some of) the 5x2 single-factor portfolios and 2 benchmark portfolios. Hence, a total of 12 different single-factor portfolios can be blended. Again, the algorithm rebalances all multi-factor factor portfolios on a daily basis. In this paper, the following three multi-factor portfolios are developed:

1. *The Equal Weighted Multi-Factor Portfolio*
   This portfolio incorporates all 12 earlier established portfolios. The weights of the included single-factor portfolios are determined using the known equal weighting method. Hence, the algorithm assigns equal weights to all 12 factor portfolios.

2. *The Equal Volatility Weighted Multi-Factor Portfolio*
   This portfolio also includes all 12 individual portfolios. The weights of the included single-factor portfolios are now determined using the equal volatility weighting method. Thus, the weights of the 12 individual portfolios are based on the inverse of the computed weekly volatilities of the individual portfolios.

3. *The Sharpe Multi-Factor Portfolio*
   This portfolio incorporates 9 out of 12 individual factor portfolios. The portfolios that obtained the nine best Sharpe ratio values based on prior week's data are incorporated in this multi-factor portfolio.

4.5 *Regression Analysis to test the untraditional factors*

This paper introduces two new factors which, to the best of my knowledge, have not been analyzed before. However, to identify whether these two factors are indeed new and different from the earlier established factors, a regression analysis will be performed. Via a regression analysis, it can formally be shown whether these new factors are unique systematic drivers of returns. In total two different time series regressions, testing the two possibly original factors, are performed. More specifically, the portfolio returns of the new factors are regressed on the portfolio returns of the market proxy and the traditional factors. For this regression the equal weighted factor portfolios and market proxy are used. The quantified definition of the two separate time series regressions is shown below:

$$\mathrm{Google}_t = \alpha + \beta_1(\mathrm{Market}_t - r_f) + \beta_2\mathrm{MOM}_t + \beta_3\mathrm{Value}_t + \beta_4\mathrm{LowVol}_t + \epsilon_t$$

$$\mathrm{Hashrates}_t = \alpha + \beta_1(\mathrm{Market}_t - r_f) + \beta_2\mathrm{MOM}_t + \beta_3\mathrm{Value}_t + \beta_4\mathrm{LowVol}_t + \epsilon_t$$

If the variation in returns of the market proxy and traditional factor investing strategies fail to explain the variation in returns of the new factor portfolios, one can conclude that these new factors are unique systematic drivers of returns. Moreover, if investing in these non-traditional factor portfolios provides better risk-adjusted returns, this paper can contribute two truly original and valuable cryptocurrency factors.

4.6 Performance Analysis

To analyze and judge the performance of the several implemented strategies this paper will include various measures for risk-adjusted returns. Merely screening average annualized returns would give a distorted picture since coin prices appreciated immensely up until 2017. Moreover, due to the highly volatile nature of crypto returns, it is more approriate to compare performances based on measures that incorporate risk. Therefore, the performances of the 13 established factor portfolios are measured in terms of their Sharpe ratio, Treynor ratio and Jensen's alpha.

1. *Jensen's alpha*

Jensen's alpha, developed by Michael Jensen (1968), is a measure that demonstrates whether (factor) portfolios are earning approriate returns compared to the levels of systematic risk they are bearing. Jensen derived this measure from a direct application of the CAPM, which is defined as:

$$\overline{r_i} = r_f + \beta_i(\bar{r}_m - r_f)$$

Where $\bar{r}_i$ represents the required return of security i, r_f stands for the risk free rate, β_i represents the beta of security i with respect to the market and $\bar{r}_m$ stands for expected market return. The idea behind the CAPM is that investors are compensated for both the time value of money and systematic risk. As mentioned in chaper 2, investors in the CAPM are not compensated for idiosyncratic risk since (according to this model) stock specific risk is diversifiable. The risk free rate is added to compensate investors for the time value of money. Beta is added as a measure for systematic risk and demonstrates how portfolio returns respond to changes in returns of the market portfolio.

Based on the CAPM, Jensen's alpha was developed to measure the average difference between a portfolio's required return and actual return. Hence, alpha is the intercept in the time series regression of a portfolio's excess returns on the market portfolio's excess returns, as shown below:

$$r_{it} - r_f = \alpha + \beta_i(r_{mt} - r_f)$$

Where r_{it} represents the annualized return of portfolio i at time t, r_f represents the risk free rate, β_i stands for the beta of portfolio i, r_{mt} represents the annualized return of the market portfolio at time t and α (alpha) is the intercept of the regression. In the above-shown expression, alpha is interpreted as a systematic risk-adjusted performance measure. A positive alpha implies that portfolio i outperforms the market proxy portfolio. In this paper the three-month treasury bill rate is used as an approximation for the annual risk-free rate. More specifically, the average of the risk free rate over the implemented time frame (2014-02-18 to 2018-04-27) is utilized. The three-month treasury bill rates were extracted from the fred.stlouisfed.org website. Because t-bill rates are annualized, the daily return time series of the portfolios are also annualized. The annualized return at time t is computed as the daily return at time t multiplied by 365, since cryptocurrencies can be traded every day of the year.

Normally, the risk free rate is subtracted from long-only portfolios to adjust for the time value of money. However, in this paper 13 long-short portfolios are incorporated thus one might consider not to subtract the risk free rate from the portfolio's return. Though, this study takes a conservative approach in return calculation since shorting in the crypto market is not common. This paper therefore assumes that short positions are fully collateralized and that the collateral is not rewarded with the risk free rate.

2. *The Treynor ratio*

The Treynor ratio, as developed by Jack Treynor (1966), is defined as follows:

$$\text{Treynor Ratio} = \frac{\bar{r}_i - \mathrm{r_f}}{\beta_\mathrm{i}}$$

Where $\bar{\mathrm{r}}_\mathrm{i}$ stands for the average annualized return of portfolio i, $\mathrm{r_f}$ represents the risk free rate, and β_i represents the beta of portfolio i. The average annualized return is again computed by multiplying the average daily return with 365. Thus, the Treynor ratio describes the excess return one receives compared to the systemtic risk one bears on his or hers investment.

3. *The Sharpe ratio*

The Sharpe ratio, as designed by William F. Sharpe (1966), is simular to the Treynor ratio and is defined as follows:

$$\text{Sharpe Ratio} = \frac{\bar{\mathrm{r}}_\mathrm{i} - \mathrm{r_f}}{\sigma_\mathrm{i}}$$

Where $\bar{r}_i$ and $\mathrm{r_f}$ again stands for the average annualized return of portfolio i and the risk free rate respectively, and σ_i stands for the portfolio's volatility. Hence, the Treynor ratio and Sharpe ratio both measure excess returns in comparison to risk proxies. However, the Sharpe ratio compares excess returns to total risk instead of merely systematic risk.

To determine if factor investing strategies in the cryptocurrency market provide better risk-adjusted returns, we are going to compare the Sharpe ratios, Treynor ratios and Jensen's alpha of the 13 factor exposed portfolios to the risk-adjusted performance ratios of the two benchmark portfolios. If the alpha of our factor portfolios is postive and if the Sharpe and Treynor ratios of the factor based portfolio strategies are higher than the Sharpe and Treynor ratios of the benchmark portfolios, one can assume that factor investing generates better risk-adjusted returns compared to the crypto market as whole. Though, this study will also formally test for the difference in Sharpe ratios between the implemented factor strategies and the benchmark portfolios. The most commonly adopted method to test for the difference in Sharpe ratios is the well-established test of Jobson and Korkie (1981). However, this method is only applicable when returns exhibit thin tails. This is not the case for cryptocurrencies as shown in table 2 and 3 from this paper. This study therefore incorporates a more applicable bootstrap approach, namely the moving-blocks (Künsch, 1989) percentile bootstrap method.

Bootstrapping is a method used to simulate a probability distribution for a statistic. It is a widely recognized method through which we can determine the robustness of our findings. For time series data, a moving-blocks bootstrap is preferred, as it accounts for (possible) autoregressive relations. In short; This method divides the time series in a number of blocks, randomly selects a number of these blocks (with replacement) and fuses them together to obtain a new time series on which the (bootstrapped) statistic is calculated. This process is repeated a sufficient number of times to obtain an empirical distribution function (EDF). Using the percentile bootstrap approach, the central 95% percentile is selected as the 95% confidence interval for the statistic.

More formally stated: To construct a confidence interval for the Sharpe ratio of a portfolio with returns time series $\{x_t\}, t = 1, \dots, N$, with N as the length of the time series, we denote b as the number of observations in a block and M as the number of bootstrap iterations. Let B_j denote block j, with observations $x_j, \dots, x_{j+b-1}$ and B the set of all $N - b$ blocks. Then bootstrapping a confidence interval for the Sharpe ratio of a portfolio is done as follows:

For i in 1 to M:

1. Select N/b blocks from B with replacement, such that a total of approximately N points is selected
2. Combine the selected blocks to obtain a bootstrapped time series $x*$
3. Calculate Sharpe ratio i based on $x*$

The M bootstrapped Sharpe ratio's form the empirical distribution function of the Sharpe ratio of the portfolio. The mean of the bootstrapped statistics is the estimate. The 95% confidence interval for this estimate starts at the 2.5% percentile and ends at the 97.5% percentile. Moreover, to formally show that there is a significant difference between the Sharpe ratios of the factor portfolios and benchmark portfolios, an empirical distribution function of the difference in Sharpe ratios is created. Hence, the resampling technique again produces multiple estimates of the Sharpre ratio for a specific combination of time periods of a specific portfolio. Though this time, the Sharpe estimate of the benchmark portfolio over the same time period is subtracted. Once we obtained the empirical distribution function of the difference in Sharpe ratios between factor portfolio i and the benchmark portfolio, we can determine whether the difference is significantly larger than 0.

This study will not formally test for the difference in Treynor ratios since (due to some extremely close to zero, negative and insignificant betas) the ratios provided via the bootstrapping process were unreasonably large in more than 5% of the samples.

Chapter 5. Results

In this chapter, the risk-adjusted performance measures of the various constructed factor portfolios are examined. This chapter is sub-divided into four parts. In the first sub-section, a table containing the return statistics of the various portfolios will be presented. This way, a preliminary picture of the portfolios' performance in terms of returns and volatility can be constructed. In the second sub-section, a table including the three risk-adjusted performance measures (the Treynor ratio, Sharpe ratio and Jensen's alpha) is displayed. This way, a preparatory result regarding the relative risk-adjusted performances of the factor portfolios can be formulated. The third sub-chapter presents the results of the moving-blocks percentile bootstrap test. After analysing the bootstrap test results, we can draw statistically significant conclusions on whether the difference in Sharpe ratios between the benchmark portfolios and factor portfolios is significantly different from zero. Lastly, the results from the linear regression analysis that tests the originality of the two newly proposed factors are presented.

5.1 Return statistics

Table 3 depicted below, presents several descriptive return statistics of the 15 implemented portfolios. One does not need to inspect comparative return statistics of factor portfolios implemented in equity markets to conclude that the displayed return statistics in table 3 are immensely large and volatile. The total generated return over the entire implemented time frame (computed with daily compounding) varies between 494,806.0% and -97.6%. The two single-factor portfolios momentum and especially Google produced substantially large returns. The third column reports the uncompounded average annualized returns of the 15 individual portfolios. Here, the extraordinary return performance of both Google portfolios can also be examined. In fact, the Google portfolios are the only strategies that produce larger average annualized returns than the two benchmark portfolios. The other 8 single-factor portfolios and the three multi-factor portfolios exhibit lower annualized returns. Moreover, both value portfolios, the equally weighted hash rate portfolio and equally weighted volatility portfolio generate negative mean annualized returns. However, all single-factor portfolios that generate lower annualized returns than the two benchmark portfolios also exhibit substantially lower volatility values. Particularly the multi-factor portfolios exhibit much lower annualized volatility levels. Hence, the final risk-adjusted return measures remain ambiguous for now. Finally, the last two columns report the skewness and kurtosis of the portfolio returns. As can be seen, most single-factor portfolios and all multi-factor portfolios exhibit positive skewness. This is a welcome portfolio characteristic since positive skewness entails that returns increase quickly yet decrease slowly, which is a desirable feature for investment managers. Moreover, one can observe that all portfolios exhibit high kurtosis which is expected since the crypto market is still developing. This indicates a relatively high probability of producing extreme returns, which in turn increases the risk level.

Table 3: Return statistics of the 15 constructed portfolios

This table presents the return statistics of the 2 benchmark, 10 single and 3 multi-factor portfolios. More specifically, the 15 created portfolios are displayed in the first column where Bench1 and Bench2 represent the equally weighted and market capitalization weighted benchmark portfolios, respectively. The abbreviations shown after the underscore of the 13 factor portfolios (_EW & _VW) reveal which specific weighting technique is applied to construct the portfolios. Accordingly, EW stands for equally weighted and VW stands for Volatility weighted. The abbreviations depicted before the underscore of the single-factor portfolios represent a particular factor, where GOH stands for Google, HSR stands for hash rates, MOM stands for momentum, NVT represents the value factor and VOL the volatility factor. Finally, MIX resembles the multi-factor portfolios which are introduced in section 4.4, and the MIX_SRP represents the multi-factor Sharpe portfolio. The other columns report the total return generated over the entire implemented time frame, the mean annualized return (mean daily return multiplied with 365), the annualized volatility (the mean daily volatility multiplied with $\sqrt{365}$), the skewness of the annualized returns and kurtosis of annualized returns. The total return is calculated with daily compounding. For all other measures the uncompounded return statistics are shown. The sample period spans from 2014-02-25 to 2018-04-27.

Portfolios	Total return over period	Mean annualized return	Annualized Volatility	Skewness of returns	Kurtosis of returns
Bench1	18,777.8 %	162.61%	84.89%	0.0687	5.2853
Bench2	7,790.5%	132.39%	73.15%	-0.1957	5.2009
GOH_EW	494,806.0%	237.74%	81.43%	1.2966	11.9508
GOH_VW	183,444.30%	206.51%	71.49%	1.1118	9.3877
HSR_EW	-87.97%	-43.82 %	37.66%	-0.9299	4.7792
HSR_VW	188.58%	31.01%	33.02%	0.0325	8.5352
MOM_EW	17301.74%	136.07%	48.27%	1.0296	19.3697
MOM_VW	1653.31%	76.32%	38.47%	2.2407	39.5617
NVT_EW	-50.88%	-10.32%	37.17%	1.1774	15.4495
NVT_VW	-81.75%	-34.90%	33.60%	-4.8984	88.7478
VOL_EW	-97.56	-72.11%	57.44%	-1.7208	16.2156
VOL_VW	80.64%	26.96%	51.35%	2.4851	29.1414
MIX_EW	1593.73%	70.71%	22.14%	0.9378	4.8583
MIX_SRP	6447.05%	104.78%	27.90%	1.3046	7.3098
MIX_VW	713.51%	52.09%	17.49%	0.8996	7.7023

5.2 Performance Measures

Table 4 depicted below, presents the three risk-adjusted performance measures of the 13 factor portfolios and two benchmark portfolios. In the second to fourth columns, the time series regression results of the factor portfolios' excess returns on the market's excess returns are depicted. Jensen's alpha is presented in the second column and resembles the amount of excess annualized return obtained by investing in a factor portfolio instead of the market portfolio. Thus, alpha is perceived as a factor (risk-adjusted) return premium. A positive alpha implies that investing in a single or multi-factor portfolio generates higher risk-adjusted returns compared to investing in the market portfolio. Beta (β_i) is displayed in column 3 and represents the level of systematic risk factor portfolio i bears in comparison to the market as whole. When analyzing column two, one can see that the alphas of the different portfolios vary between -43.04% and 226.93%. However, in order to draw valid conclusions, the associated t-statistics of the individual alphas must be studied. If the coefficients of the independent variables have corresponding t-statistics that are larger than |1.96|, we can conclude (α=5%) that the coefficients significantly differ from zero. Because we would like to draw statistically significant conclusions, we only interpret the alphas that are significantly different from zero. As can be seen, the only portfolio that obtained a significantly negative alpha is the volatility weighted value portfolio. This implies that investing in this value portfolio generates worse risk-adjusted returns than simply investing in the market portfolio. However, both Google portfolios, both momentum portfolios and all multi-factor portfolios produce statistically significant positive alphas. Moreover, the alphas obtained are excessively high. The Google portfolios are again most noteworthy producing immense alphas of almost 227%. This implies that on average, an equal weighted single-factor Google portfolio generates 227% excess risk-adjusted returns compared to the market portfolio. When summarizing the results stated above, we can conclude that according to Jensen's alpha, momentum, Google and all multi-factor portfolios generate higher risk-adjusted returns compared to the market. Another notable encounter is displayed in column three, which presents the beta coefficients of the implemented portfolios to the market. In equity markets, a negative beta is rarely detected. However, as shown in column four, the beta coefficients of the equal weighted hash rates and low-volatility portfolios are significantly negative. In the fourth column, the adjusted-R^2 of the several regressions are depicted. As can be seen, the percentage of variation in the single-factor portfolios' returns that is explained by the market is very small. The percentage of variation in returns of the multi-factor portfolios that can be explained by the variation in returns of the market portfolio is much larger. This is a very logical finding since the market portfolio is included in all multi-factor portfolios, thus it is partly explaining itself.

The last two columns display the other two risk-adjusted performance measures: the Sharpe ratio and Treynor ratio. For now, we will compare both ratios of the factor portfolios to the ratios of the benchmark portfolios. Later, we will analyze the results of the moving-blocks percentile bootstrap test to see if the difference in Sharpe ratios between the benchmark portfolios and factor portfolios is significantly different from zero. As aforementioned, the bootstrap method to test for the difference in Treynor ratios was not attainable.

As shown below, the Sharpe ratios obtained from the two benchmark portfolios are quite large, signifying that the market already offers a substantial amount of excess returns compared to the overall risk an investor is bearing on his or her investment. However, when detecting which portfolios produce larger Sharpe ratio values than both benchmark portfolios, we again identify the same portfolios. More specifically, both Google portfolios, momentum portfolios and all multi-factor portfolios generate higher Sharpe ratios than both benchmark portfolios. Most noteworthy, the Sharpe multi-factor portfolio generates a Sharpe ratio of 3.74, a ratio which is approximately two times as high as the Sharpe ratio of the benchmark portfolios. This multi-factor portfolio was created by selecting the nine best performing portfolios in terms of Sharpe ratios every day. Thus, the fact that this blended portfolio performs best in terms of Sharpe ratios is plausible.

When analyzing the last column, which displays the Treynor ratios, we again conclude that the earlier mentioned portfolios (the Google portfolios, momentum portfolios and multi-factor portfolios) produce better risk-adjusted returns than both benchmark portfolios. Moreover, both hash rate portfolios and the equally weighted volatility portfolio seem to generate larger Treynor ratios than the benchmark portfolios. Though, we must be careful; The Treynor ratios from the equal weighted hash rates and low-volatility portfolios are incoherently high. Furthermore, the corresponding Sharpe ratios of these single-factor portfolios are negative and thus suggest that a risk-less asset would have performed better than the factor portfolios. However, these contradictory findings can be explained by the encountered negative betas in column three. Due to the negative betas the sign (which should have been negative) of the Treynor ratio flipped and became positive. Thus, when betas are negative, a negative large Treynor ratio indicates that the portfolio performed well. Though in our case, the large positive Treynor ratios (which are accompanied with negative betas) indicate that the portfolios underperformed in terms of risk-adjusted returns compared to a risk-less asset.

In conclusion, we find that according to all three risk-adjusted performance measures both Google portfolios, both momentum portfolios and all multi-factor portfolios perform better than both implemented benchmarks. According to the Treynor measure, the volatility weighted hash rates portfolio also generates higher (systematic) risk-adjusted returns. This is a peculiar finding, since the Sharpe ratio of the portfolio underperforms compared to the Sharpe ratios of the benchmark portfolios. Nevertheless, Sharpe ratios are adjusted to total risk instead of systematic risk. However, alpha also measures excess returns adjusted to market risk and is therefore very comparable to the Treynor ratio. Though, the alpha of the specified portfolio is not significantly different from 0 according to the reported t-statistic in column two. Since we cannot draw any statistically significant conclusions from the Treynor ratios we will adhere to the findings suggested by Jensen's alpha. Hence, for now, we conclude that the Google, momentum and multi-factor portfolios consistently outperform the market.

Table 4: A risk-adjusted performance analysis of the 15 implemented portfolios
This table presents the results from the three incorporated risk-adjusted performance measures. More specifically, the 15 created portfolios are shown in the first column where Bench1 and Bench2 represent the equally weighted and market capitalization weighted benchmark portfolios, respectively. The abbreviations shown after the underscore of the 13 factor portfolios (_EW & _VW) reveal which specific weighting technique is applied to construct the portfolios. Accordingly, EW stands for equally weighted and VW stands for Volatility weighted. The abbreviations depicted before the underscore of the single-factor portfolios represent a particular factor, where GOH stands for Google, HSR stands for hash rates, MOM stands for momentum, NVT represents the value factor and VOL the volatility factor. Finally, MIX resembles the multi-factor portfolios which are introduced in section 4.4, and the MIX_SRP represents the multi-factor Sharpe portfolio. Columns 2 to 4 report the intercept (alpha), alpha's t-statistic and Adjusted R^2 of the linear regression of the 14 (13 factor portfolios + Bench2) annualized portfolio returns on the market's portfolio return. In this regression Bench1, the equally weighted market portfolio serves as a market proxy. Therefore, no regression results are depicted in the first row. In columns 5 and 6, the Sharpe ratios and Treynor ratios of the 15 established portfolios are depicted. The sample period spans from 2014-02-25 to 2018-04-27.

Portfolio	**Jensen's Alpha**		**Beta**		**Adjusted R Squared**	**Sharpe ratio**	**Treynor Ratio**
Bench1	X		X		X	1.9105	1.6217
Bench2	18.54%	(0.8681)	0.6993	(27.9648)	0.6583	1.8038	1.8868
GOH_EW	226.93%	(5.8625)	0.0640	(0.9630)	0.0038	2.9144	37.0765
GOH_VW	195.01%	(5.6732)	0.0682	(1.1720)	0.0059	2.8826	30.2202
HSR_EW	-14.83%	(-0.8897)	-0.1815	(-10.4173)	0.1668	-1.1753	2.4390
HSR_VW	18.87%	(1.1917)	0.0721	(4.2862)	0.0338	0.9258	4.2372
MOM_EW	114.34%	(5.3658)	0.1313	(3.3333)	0.0527	2.8098	10.3323
MOM_VW	71.39%	(4.0638)	0.0277	(0.9753)	0.0031	1.9726	27.3858
NVT_EW	-30.10%	(-1.8359)	0.1193	(4.6683)	0.0736	-0.2894	-0.9019
NVT_VW	-43.04%	(-2.8762)	0.0474	(2.0232)	0.0137	-1.0519	-7.4506
VOL_EW	-31.90%	(-1.3187)	-0.2507	(-6.3561)	0.1367	-1.2631	2.8941
VOL_VW	-7.84%	(-0.3603)	0.2119	(6.1178)	0.1221	0.5165	1.2518
MIX_EW	43.11%	(5.2031)	0.1674	(17.6400)	0.4117	3.1740	4.1969
MIX_SRP	76.12%	(6.6832)	0.1741	(9.5779)	0.2800	3.7405	5.9950
MIX_VW	34.51%	(4.6764)	0.1057	(11.6997)	0.2624	2.9527	4.8882

5.3 Results of the moving-blocks percentile Bootstrap test

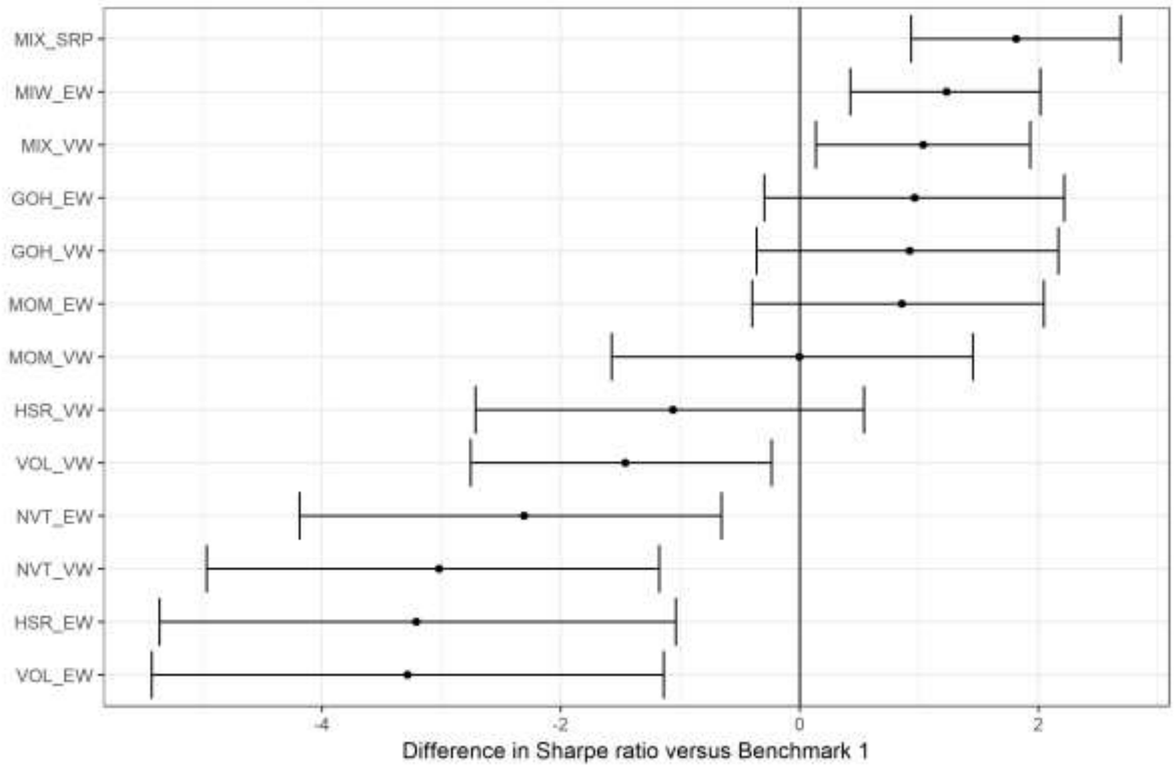
Up until now, alpha is the only performance measure for which we can draw statistically significant conclusions. However, to increase the robustness of our preliminary results, this section will identify whether the Google, momentum and multi-factor portfolios also significantly outperform the benchmark portfolios in terms of their Sharpe ratios.

The moving-blocks percentile bootstrap method was used for two main reasons. First, it enabled us to simulate the probability distribution of the 15 different Sharpe ratios. From these obtained empirical distribution functions, 15 confidence intervals were derived. The confidence intervals of all portfolios can be found in table A1 in appendix A. Second, we obtained the empirical distribution function of the difference in Sharpe ratios between factor portfolio i and the benchmark portfolio. These results are presented in the scatter plots depicted in figure 3 and 4 below. After analyzing both figures we can determine whether Sharpe ratios of the factor portfolios significantly differ from the Sharpe ratios of both benchmark portfolios.

In both figures below, a scatter plot with error bars is presented. The scatter plots depict the difference in Sharpe ratios between the 13 factor portfolios and the benchmark portfolios. Via this scatter plot we can clearly display the estimated values obtained from the empirical distribution functions of the difference in Sharpe ratios. The dots on the lines reflect the average bootstrapped Sharpe ratio and thus our estimate. The lines represent the 95% confidence interval and give a general idea of how precise the estimate is. In figure 3 (4), the difference in Sharpe ratios between the 13 factor portfolios and the equal weighted (market capitalization weighted) benchmark is shown. The y-axis displays the 13 factor strategies, the x-axis displays the difference in Sharpe ratios between a specific factor portfolio and the benchmark. If there is no difference between the examined Sharpe ratios, the dot (the average bootstrapped Sharpe ratio) will lay on the the vertical line at x = 0. If the dot of a specific portfolio is on the right (left) side of the vertical line, the difference in Sharpe ratios is positive (negative). We will first analyze the results in figure 3.

Figure 3: A scatter plot with error bars depicting the difference in Sharpe ratios between the 13 factor portfolios and benchmark 1

This scatter plot displays the difference in bootstrapped Sharpe ratios (obtained from the empirical distribution function) between the 13 factor portfolios and the equal weighted benchmark portfolio. The y-axis displays the 13 factor strategies. The abbreviations shown after the underscore of the 13 factor portfolios (_EW & _VW) reveal which specific weighting technique is applied to construct the portfolios. Accordingly, EW stands for equally weighted and VW stands for Volatility weighted. The abbreviations depicted before the underscore of the single-factor portfolios represent a particular factor, where GOH stands for Google, HSR stands for hash rates, MOM stands for momentum, NVT represents the value factor and VOL the volatility factor. Finally, MIX resembles the multi-factor portfolios which are introduced in section 4.4, and the MIX_SRP represents the multi-factor Sharpe portfolio. The x-axis displays the difference in Sharpe ratios between a specific factor portfolio and the first benchmark portfolio. The dots on the lines reflect the average bootstrapped Sharpe ratio and thus our estimate for the difference. The lines represent the 95% confidence interval of the difference.



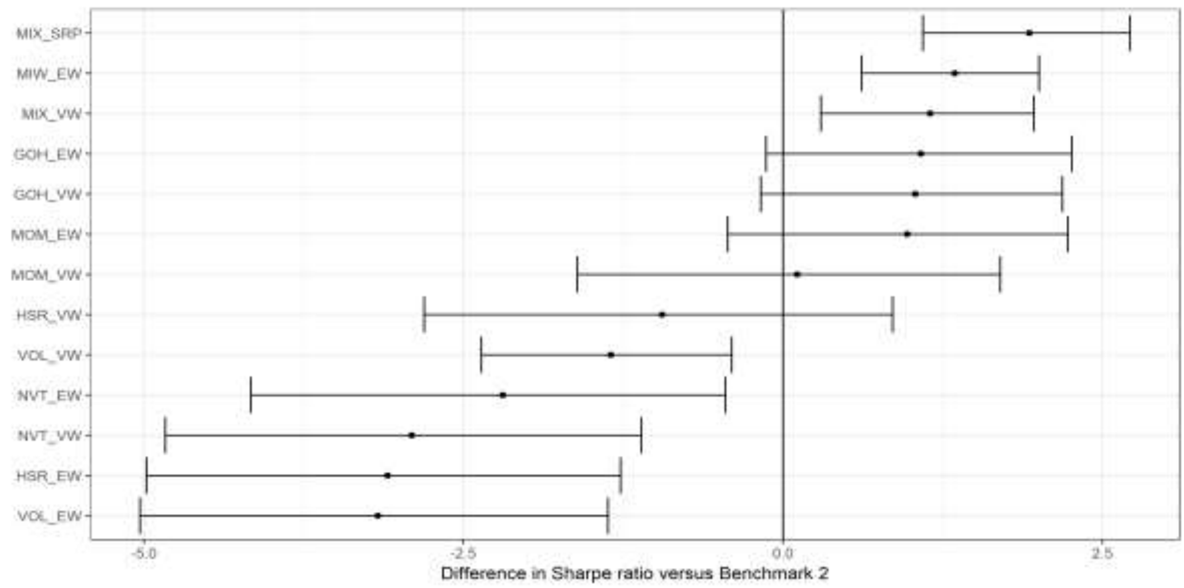
As depicted, there are three portfolios whose Sharpe ratios are significantly larger than the Sharpe ratio of the equal weighted benchmark portfolio, namely the three multi-factor portfolios. Moreover, the estimated Sharpe ratios of both Google portfolios and the equal weighted momentum portfolio also appear to be larger than the Sharpe ratio of the benchmark portfolio. However, this difference is not statistically significant when maintaining 95% confidence level. Furthermore, the difference in Sharpe ratios between the volatility weighted momentum portfolio and the benchmark portfolio appears to be zero. The estimated Sharpe ratios of all other factor portfolios are smaller than the Sharpe ratio of the benchmark.

The results presented in figure 4 are quite similar. Though the positive differences in Sharpe ratios between the factor portfolios and the benchmark portfolio are amplified. Thus, it seems that the market capitalization weighted benchmark underperforms in terms of Sharpe ratio compared to the equal weighted benchmark. Nevertheless, similar to our previous findings, one can conclude that the three multi-factor portfolios generate significantly higher Sharpe ratios compared to the second benchmark portfolio. Moreover, the estimated Sharpe ratios of both Google portfolios and both momentum portfolios appear to be larger than the estimated Sharpe ratio of the second benchmark portfolio. Though, the difference is (again) not statistically significant when maintaining a 95% confidence level. The difference in Sharpe ratios between the other factor portfolios and the second benchmark is again negative.

Summarizing the above mentioned findings, one can conclude that the multi-factor portfolios perform significantly better in terms of Sharpe ratios than the benchmark strategies. Moreover, both Google and momentum strategies seem to outperform the benchmark portfolios as well. Though, the realized difference in Sharpe ratios is not statistically significant when maintaining a 95% confidence interval. The other factor portfolios significantly underperform in terms of risk-adjusted returns. The results from the bootstrap test are therefore appropriately in line with the conclusions drawn in section 5.2.

Figure 4: A scatter plot with error bars depicting the difference in Sharpe ratios between the 13 factor portfolios and benchmark 2

This scatter plot displays the difference in bootstrapped Sharpe ratios (obtained from the empirical distribution function) between the 13 factor portfolios and the market capitalization weighted benchmark portfolio. The y-axis displays the 13 factor strategies. The abbreviations shown after the underscore of the 13 factor portfolios (_EW & _VW) reveal which specific weighting technique is applied to construct the portfolios. Accordingly, EW stands for equally weighted and VW stands for Volatility weighted. The abbreviations depicted before the underscore of the single-factor portfolios represent a particular factor, where GOG stands for Google, HSR stands for hash rates, MOM stands for momentum, NVT represents the value factor and VOL the volatility factor. Finally, MIX resembles the multi-factor portfolios which are introduced in section 4.4. The x-axis displays the difference in Sharpe ratios between a specific factor portfolio and the second benchmark portfolio. The dots on the lines reflect the average bootstrapped Sharpe ratio and thus our estimate. The lines represent the selected 95% confidence interval.



After analyzing the results presented in section 5.1, 5.2 and 5.3, we can conclude the following: Indisputably, the multi-factor portfolios appear to significantly outperform the benchmark portfolios in terms of risk-adjusted returns. The Google and momentum portfolios significantly outperform the benchmark portfolios according to Jensen's alpha. Moreover, the obtained Sharpe and Treynor ratios of these single-factor portfolios are substantially higher. Though, according to the bootstrap's test for difference in Sharpe ratios, the ratios do not significantly (α=5%) differ from 0. The other factor portfolios (value, low-volatility and hash rates) appear to produce lower risk-adjusted returns compared to the two benchmark portfolios. We therefore accept our first, second, third and fourth hypotheses, and reject the fifth hypothesis.

5.2 *Regression results*

As promised, this paper will also identify whether the two newly proposed factors Google Trends and hash rates are indeed different from the earlier established factors. To test whether these untraditional factors are unique systematic drivers of returns, a regression analysis was performed. More specifically, the returns of the equal weighted Google portfolio and hash rate portfolio were regressed on the portfolio returns of the market proxy and the traditional factors. The regression results are depicted in table 5 below.

We will first analyze the originality of the Google factor. As shown below, the coefficients (and their corresponding t-statistics) of the various independent variables are shown in columns three to six. A large and significant regression coefficient indicates a strong dependence between the newly proposed Google factor and the specific factor portfolio. If the coefficients of the independent variables have corresponding t-statistics that are larger than |1.96|, we can conclude (α=5%) that the coefficient significantly differs from zero. However, as depicted below, none of the regression coefficients in the first row are statistically significant. This indicates that the market, momentum, value and low-volatility factor portfolios do not drive the returns of our Google portfolio. Moreover, the reported adjusted R^2 of the regression analysis is extremely small (0.011). This implies that only 1.1% of the variation in returns of the Google portfolio can be explained by the variation in returns of the market, momentum, value and low-volatility portfolios. Moreover, as shown in the regression results, the Google strategy maintains a highly significant and positive alpha of 0.62%. This indicates that the Google strategy provides excess returns that cannot be explained by the market or traditional factor portfolios. Therefore, this paper concludes that the Google factor is a unique systematic driver of return. This is an extremely exhilarating finding, since the Google factor has proven be the best performing single-factor strategy in terms of all implemented risk-adjusted performance measures. Thus, this paper contributes a new steady-performing factor to the cryptocurrency market which currently surpasses all traditional factors in terms of risk-adjusted performance.

In the third row depicted in table 5 below, the regression results of the returns of the hash rate portfolio on the portfolio returns of the market proxy and the traditional factors are presented. This time we encounter very different results. As shown below, the regression coefficients of the market, value and low-volatility portfolios are statistically significant (α=5%). This means that the betas of these specific portfolios significantly differ from zero. Thus, we can conclude that the hash rate factor strategy has a large dependence on the market, the value and low-volatility strategies. The hash rate factor can therefore not be viewed as a unique systematic driver of return.

Table 5. A regression analysis to test for the originality of the Google and hash rate factors
This table presents the results of two linear time series regressions. More specifically, the portfolio returns of the two newly proposed factors (Google and hash rates) are regressed on the portfolio returns of the market (column 3), momentum (column 4), low-volatility (column 5) and value (column 6). For the regression the equal weighted factor portfolios and market proxy were used. The t-statistics of the estimates are reported in parenthesis. The adjusted R^2 is depicted in the last column.

Portfolio	Intercept	Market	MOM_EW	VOL_EW	NVT_EW	Adj.R^2
Google Hits	0.0062	0.0412	0.1344	-0.0132	0.0793	0.011
	(5.1964)	(0.6767)	(0.792)	(-0.1137)	(0.4701)	
Hash rates	-0.0007	-0.1656	-0.0508	0.1622	0.1956	0.250
	(-1.4167)	(-8.1216)	(-1.1051)	(4.0045)	(2.9876)	

Chapter 6. Robustness Check

In this chapter the robustness of the inference that two single-factor portfolios (Google and momentum) and all implemented multi-factor portfolios generate better risk-adjusted returns than the implemented benchmark portfolios is discussed. Our prior results are already persuasive since three different performance measures have been implemented. As shown in table 4, all three performance measures indicate that the above-mentioned portfolios generate better risk-adjusted. The robustness of our preliminary findings was further enhanced using the moving-blocks percentile bootstrap method. The results of the bootstrap analysis, which tests for the difference in Sharpe ratios, suggested that the multi-factor portfolios performed significantly better in terms of Sharpe ratios than both benchmark strategies. Moreover, the equal weighted momentum and both Google strategies seemed to outperform the benchmark portfolios as well.

However, to further increase the robustness of our findings, we will analyze the results of the three performance measures over three different time frames. Since the inception of Bitcoin and the surge of the other cryptocurrencies, a lot of developments in the crypto market have taken place. As shown in figure 2, the market experienced both up and downturns during the last couple of years. From the beginning of our time frame to the end of 2016, price levels remained relatively stable. However, in 2017 price levels appreciated immensely and the market experienced a transitory bull run. Though, since Januari 2018, price levels have collapsed and the total market capitalization of cryptos depreciated. Thus, this paper will investigate whether the previously determined well-performing portfolios still outperform the benchmark portfolios during these different market conditions. Our time frame is split into three periods; the first interval contains all data from our start date (18-02-2014) until the end of 2016 (31-12-2016), the second period includes all data from the year 2017 thus from 01-01-2017 to 31-12-2017, the last time frame incorporates all available data from 2018 thus from 01-01-2018 to 27-4-2018. Tables 6, 7 and 8 present the results of the risk-adjusted performance analysis over the three different timespans. The tables are structured similarly to table 4. Hence, the second to fourth columns present the time series regression results of the factor portfolios' excess returns on the market's excess returns, and the last two columns depict the Sharpe and Treynor ratio. We will first analyze the performance of the factor portfolios during the first sub-period, thus using a time frame from 18-02-2014 to 31-12-2016. The results are depicted in table 6 below.

As shown in table 6, a considerable number of alphas significantly differ from zero when maintaining a 5% confidence level. Most interestingly, the only factor portfolios that again obtain positive and significant alphas are the (by now familiar) Google, momentum and multi-factor portfolios. Particularly the Google portfolios generate incredibly high excess returns of approximately 120% (volatility weighted) and 155% (equal weighted). During this period, the equal weighted hash rates portfolio and both volatility portfolios appear to significantly underperform compared to the market portfolio. Thus, the hash rates and volatility portfolios are (according to Jensen's alpha) performing quite differently during this shorter time span. Though, similar to the results depicted in table 4, the adjusted-R^2 of the regression analysis on the factor portfolios is again very small and sometimes even negative. This indicates that the variation in returns of our market proxy fail to explain the variation in returns of our factor portfolios. Moreover, when examining the displayed Sharpe ratios in column 5, we can again conclude that the Google, momentum and multi-factor portfolios are the only strategies that produce larger Sharpe ratio values than both benchmark portfolios. The other factor portfolios seem to underperform in terms of Sharpe ratios. Additionally, the presented Treynor ratios suggest similar outcomes. Though we must stress to carefully analyze column 6, since negative betas flip the signs of the corresponding Treynor ratios. Interestingly, we find that all Treynor ratios that exhibit opposite signs from the equivalent Sharpe ratios are accompanied with negative betas. All in all one can conclude, that within this specified time frame, the same factor portfolios (Google, momentum and all multi-factor portfolios) persistently outperform the benchmark portfolios.

Table 6: A risk-adjusted performance analysis of the 15 established portfolios, incorporating a time frame from 18-02-2014 to 31-12-2016

This table presents the three incorporated risk-adjusted performance measures. More specifically, the 15 created portfolios are shown in the first column where Bench1 and Bench2 represent the equally weighted and market capitalization weighted benchmark portfolios, respectively. The abbreviations shown after the underscore of the 13 factor portfolios (_EW & _VW) reveal which specific weighting technique is applied to construct the portfolios. Accordingly, EW stands for equally weighted and VW stands for Volatility weighted. The abbreviations depicted before the underscore of the single-factor portfolios represent a particular factor, where GOH stands for Google, HSR stands for hash rates, MOM stands for momentum, NVT represents the value factor and VOL the volatility factor. Finally, MIX resembles the multi-factor portfolios which were introduced in section 4.4, and the MIX_SRP represents the multi-factor Sharpe portfolio. Columns 2 to 4 report the intercept (alpha), alpha's t-statistic and the Adjusted R^2 of the linear regression of the 14 (13 factor portfolios + market capitalization weighted benchmark portfolio) annualized portfolio returns on the market's portfolio return. In this regression Bench1, the equally weighted market portfolio, serves as a market proxy. Therefore, no regression results are displayed in the first row. In columns 5 and 6, the Sharpe ratios and Treynor ratios are depicted. The sample period spans from 18-02-2014 to 31-12-2016.

Portfolio	**Jensen's Alpha**		**Beta**		**Adjusted R Squared**	**Sharpe ratio**	**Treynor Ratio**
Bench1	X		X		X	0.9378	0.6458
Bench2	-0.85%	(-0.0359)	0.6438	(14.4542)	0.5645	0.6905	0.6327
GOH_EW	154.93%	(3.2220)	0.0165	(0.1289)	-0.0008	1.8514	94.5263
GOH_VW	119.45%	(2.9569)	0.0353	(0.3395)	0.0002	1.7262	34.5168
HSR_EW	-44.42%	(-2.0400)	-0.1984	(-6.0215)	0.1244	-1.4828	2.8850
HSR_VW	31.37%	(1.5986)	0.0119	(0.4524)	-0.0003	0.9881	26.9332
MOM_EW	112.12%	(4.1288)	0.0908	(1.3595)	0.0165	2.4934	12.9904
MOM_VW	72.20%	(3.7655)	-0.0053	(-0.1341)	-0.0009	2.1623	-135.9182
NVT_EW	-4.17%	(-0.2117)	0.1878	(4.2362)	0.1238	0.2172	0.4237
NVT_VW	-17.50%	(-1.1680)	0.1289	(5.0439)	0.1099	-0.3442	-0.7122
VOL_EW	-60.23%	(-2.1288)	-0.3834	(-7.0266)	0.2321	-1.5531	2.2167
VOL_VW	-53.03%	(-2.1551)	0.1152	(2.4797)	0.0349	-1.0877	-3.9577
MIX_EW	25.82%	(2.5426)	0.1369	(9.8797)	0.2330	1.7771	2.5317
MIX_SRP	45.75%	(3.5101)	0.1216	(5.3994)	0.1230	2.2532	4.4085
MIX_VW	21.24%	(2.3632)	0.0984	(7.0365)	0.1691	1.6782	2.8040

Table 7 below presents the performance of the various factor portfolios in 2017. As shown below almost all portfolios (including the benchmark portfolios) performed extremely well according to all three performance measures. The benchmark portfolios obtained extremely generous Sharpe (Treynor) ratios, indicating that the market already offered a substantial amount of excess returns compared to the overall (systematic) risk an investor bore on his or her investment. This is a plausible discovery since prices in the cryptocurrency market appreciated fiercely during the implemented time frame. Though, it is interesting to determine whether the Google, momentum and multi-factor portfolios still outperform the already well-performing benchmark portfolios in terms of risk-adjusted return. As can be seen, the Google, equal weighted momentum and multi-factor portfolios continue to consistently outperform the benchmark portfolios according to Jensen's alpha. Though, this time the volatility weighted momentum portfolio does not seem to significantly outperform the benchmark portfolio since its corresponding t-statistic is 1.5143. Moreover, contradicting the results from the first analyzed sub-period, the equally weighted hash rate portfolio generates statistically significant excess (instead of lower) returns compared to the market proxy. Furthermore, both value portfolios appear to significantly underperform in terms of risk-adjusted returns. Examining the last two columns, we again discover that the Google and multi-factor portfolios produce larger Sharpe ratios than the benchmark portfolios yet (while still performing well) the momentum portfolios produce lower Sharpe ratios than the benchmark portfolios.

Though, the performance measure of Jack Treynor is again in line with our main results presented in chapter 5, as both Google, momentum and all multi-factor portfolios exhibit significantly larger Treynor ratios. Summarizing the above findings we can conclude that during the year 2017, the Google, the equal weighted momentum portfolio, and all multi-factor portfolios generated significantly larger risk-adjusted returns than both benchmark portfolios. The volatility weighted momentum portfolio appears to produce better, yet not significantly better, risk-adjusted returns. Moreover, in this bull market, the value factor seemed to significantly underperform in terms of risk-adjusted returns compared to the market proxy.

Table 7: A risk-adjusted performance analysis of the 15 established portfolios, incorporating a time frame from from 01-01-17 to 31-12-17

This table presents the three incorporated risk-adjusted performance measures. More specifically, the 15 created portfolios are shown in the first column where Bench1 and Bench2 represent the equally weighted and market capitalization weighted benchmark portfolios, respectively. The abbreviations shown after the underscore of the 13 factor portfolios (_EW & _VW) reveal which specific weighting technique is applied to construct the portfolios. Accordingly, EW stands for equally weighted and VW stands for Volatility weighted. The abbreviations depicted before the underscore of the single-factor portfolios represent a particular factor, where GOH stands for Google, HSR stands for hash rates, MOM stands for momentum, NVT represents the value factor and VOL the volatility factor. Finally, MIX resembles the multi-factor portfolios which were introduced in section 4.4, and the MIX_SRP represents the multi-factor Sharpe portfolio. Columns 2 to 4 report the intercept (alpha), alpha's t-statistic and Adjusted R^2 of the linear regression of the 14 (13 factor portfolios + market capitalization weighted benchmark portfolio) annualized portfolio returns on the market's portfolio return. In this regression Bench1, the equally weighted market portfolio, serves as a market proxy. Therefore, no regression results are displayed in the first row. In columns 5 and 6, the Sharpe ratios and Treynor ratios are depicted. The sample period spans from 18-02-2014 to 31-12-2016.

Portfolio	Jensen's Alpha		Beta		Adjusted R Squared	Sharpe ratio	Treynor Ratio
Bench1	X		X		X	4.8601	4.9958
Bench2	94.37%	(1.6640)	0.6884	(18.566)	0.6376	4.9497	6.3667
GOH_EW	320.50%	(4.0461)	0.2196	(2.7036)	0.0803	5.4866	19.5927
GOH_VW	312.68%	(3.9323)	0.1934	(2.2671)	0.0648	5.3456	21.1640
HSR_EW	69.36%	(2.4589)	-0.1755	(-7.066)	0.2422	-0.5014	1.0428
HSR_VW	-33.10%	(-1.0436)	0.1341	(4.9008)	0.1475	0.9520	2.5277
MOM_EW	117.57%	(2.6104)	0.2179	(3.4319)	0.1654	4.1402	10.3928
MOM_VW	66.29%	(1.5143)	0.0926	(1.7293)	0.0310	2.1690	12.1541
NVT_EW	-89.07%	(-2.5070)	0.0523	(1.6001)	0.0146	-1.5405	-12.0430
NVT_VW	-98.06%	(-2.6442)	-0.0502	(-1.1564)	0.0083	-2.5015	24.5332
VOL_EW	17.50%	(0.3473)	-0.2142	(-2.8647)	0.0978	-1.2871	4.1786
VOL_VW	64.14%	(1.3464)	0.3085	(4.8371)	0.1926	3.0380	7.0750
MIX_EW	70.18%	(4.1740)	0.2056	(13.098)	0.6113	6.4025	8.4098
MIX_SRP	125.84%	(4.4055)	0.2495	(7.3485)	0.5025	6.9325	10.0386
MIX_VW	53.77%	(3.5674)	0.1347	(9.6588)	0.4532	5.8967	8.9887

Lastly, the performance of the factor portfolios using all available data from 2018 is analyzed. Since (as shown figure 2) price levels dropped immensely, it is interesting to reveal whether the Google, momentum and multi-factor portfolios still produce generous excess risk-adjusted returns. As shown in table 8 depicted below, according to Jensen's alpha, both Google and all multi-factor portfolios again outperform the market portfolio. Most noteworthy, the Google portfolios generate unseen and inimaginable excess risk-adjusted returns compared to the market proxy, displaying alphas of 312.27% and 348.26%. This is personal record for the Google portfolios, implying this particular strategy also performs extremely well during market downturns. The momentum portfolios do not produce alphas that are significantly different from 0, meaning that they do not significantly outperform the market proxy. However, according to the Sharpe and Treynor ratios both Google, momentum, low-volatility and all multi-factor portfolios produce larger risk-adjusted returns. Thus, interestingly and contradictory to our previous findings, both low-volatility portfolios also seem to outperform the market. This discovery is in line with Hsu and Li's (2013) findings which were discussed in chapter 2. They concluded that the low-volatility factor was highly dependent on the overall state of the market and showed that this factor only outperformed other factors during financial downturns. Examining the below-depicted results, it appears that this paper can draw similar conclusions. However, according to Jensen's alpha the volatility strategies do not significantly outperform the market. Lastly, this study again likes to stress that one must carefully analyze column 6 since negative betas flip the signs of the corresponding Treynor ratios.

In conclusion, we find that after analyzing all three risk-adjusted performance measures using three different implemented time frames, both Google portfolios and all multi-factor portfolios significantly outperform the market proxy. These findings are robust to several different market conditions. Moreover, according to the Sharpe (Treynor) ratio, both momentum portfolios offer larger excess returns in relation to the overall (systematic) risk an investor bears on his or her investment. However, the portfolios do not seem to perform significantly better when compared to both benchmark portfolios. Additionally, the value portfolios seem to significantly underperform when the market exhibits bullish behavior. Lastly, the low-volatility portfolios seem to outperform the benchmark portfolios when the market exhibits bearish behavior.

Table 8: : A risk-adjusted performance analysis of the 15 established portfolios, incorporating a time frame from 01-01-2018 to 27-04-2018

This table presents the three incorporated risk-adjusted performance measures. More specifically, the 15 created portfolios are shown in the first column where Bench1 and Bench2 represent the equally weighted and market capitalization weighted benchmark portfolios, respectively. The abbreviations shown after the underscore of the 13 factor portfolios (_EW & _VW) reveal which specific weighting technique is applied to construct the portfolios. Accordingly, EW stands for equally weighted and VW stands for Volatility weighted. The abbreviations depicted before the underscore of the single-factor portfolios represent a particular factor, where GOH stands for Google, HSR stands for hash rates, MOM stands for momentum, NVT represents the value factor and VOL the volatility factor. Finally, MIX resembles the multi-factor portfolios which were introduced in section 4.4, and the MIX_SRP represents the multi-factor Sharpe portfolio. Columns 2 to 4 report the intercept (alpha), alpha's t-statistic and the Adjusted R^2 of the linear regression of the 14 (13 factor portfolios + market capitalization weighted benchmark portfolio) annualized portfolio returns on the market's portfolio return. In this regression Bench1, the equally weighted market portfolio, serves as a market proxy. Therefore, no regression results are displayed in the first row. In columns 5 and 6, the Sharpe ratios and Treynor ratios are depicted. The sample period spans from 01-01-18 to 27-4-18.

Portfolio	Jensen's Alpha		Beta		Adjusted R Squared	Sharpe ratio	Treynor Ratio
Bench1	X		X		X	-0.2248	-0.2962
Bench2	5.81%	(0.1098)	0.8397	(31.5737)	0.9272	-0.1660	-0.2270
GOH_EW	348.26%	(3.4681)	-0.1529	(-2.1219)	0.1060	5.9069	-23.0795
GOH_VW	312.27%	(3.1316)	-0.1281	(-1.7829)	0.0733	5.3404	-24.6773
HSR_EW	-15.89%	(-0.4155)	-0.1707	(-8.3879)	0.4716	-0.3324	0.6346
HSR_VW	9.41%	(0.2228)	0.1044	(4.5286)	0.2194	0.2185	0.6055
MOM_EW	9.62%	(0.1721)	0.0525	(1.9839)	0.0404	0.2572	1.5356
MOM_VW	-3.70%	(-0.0646)	-0.0231	(-0.7462)	0.0006	-0.0951	1.3043
NVT_EW	-9.97%	(-0.2104)	0.1011	(3.7984)	0.2097	-0.4529	-1.2823
NVT_VW	9.49%	(0.2048)	0.0593	(2.2420)	0.0779	0.2898	1.3036
VOL_EW	89.79%	(1.4257)	-0.0109	(-0.3710)	-0.0069	2.6489	-82.6139
VOL_VW	71.40%	(1.1447)	0.2372	(8.9680)	0.4542	1.3953	2.7138
MIX_EW	68.87%	(2.9029)	0.1590	(9.7535)	0.7280	2.6169	4.0345
MIX_SRP	99.98%	(2.5891)	0.1387	(5.0020)	0.4265	3.4459	6.9122
MIX_VW	49.11%	(2.2491)	0.0608	(4.6598)	0.3003	3.2691	7.7817

Chapter 7. Conclusion & Discussion

This study examined factor investing strategies in the cryptocurrency market. More specifically, the effects of investing in the traditional factors momentum, value and low-volatility on portfolios' risk-adjusted returns have been analyzed utilizing various performance measures. Moreover, two newly proposed factors (Google query volumes and hash rates) have been created which, to the best of my knowledge, have not been studied before. To construct the various single and multi-factor portfolios a trading algorithm was developed that determines which cryptocurrencies to short and buy. The algorithm rebalanced all portfolios on a daily basis, incorporating prior data only. The performance of the 13 developed factor portfolios (5x2 single-factor portfolios plus 3 multi-factor portfolios) has been examined based on three risk-adjusted performance measures (Jensen's alpha, the Sharpe ratio and Treynor ratio). Additionally, to further increase the robustness of our findings, the moving-blocks percentile bootstrap method was used to test for the difference in Sharpe ratios between the factor portfolios and benchmark portfolios. Furthermore, additional robustness checks were added through which we could evaluate the performance of the various factor portfolios during several different market conditions. Lastly, a multi-factor regression model was implemented to investigate the originality of the two newly created factors.

The results suggested by the various performance measures and robustness checks are reasonably compatible. When including the entire dataset, all three risk-adjusted performance measures agree that both Google portfolios, both momentum portfolios and all multi-factor portfolios perform significantly better than both implemented benchmark portfolios. The best performing single-factor strategy is, without doubt, the Google factor which produces significant alphas of 195% (volatility weighted) and 227% (equal weighted). Though the moving-blocks percentile bootstrap approach, which tests for the difference in Sharpe ratios between the factor and benchmark portfolios, presented slightly different outcomes. According to the test results, the multi-factor portfolios significantly (α = 5%) outperform both benchmark portfolios which is in line with our preliminary conclusion. Moreover, both Google and momentum strategies seem to generate higher risk-adjusted returns, yet the difference in Sharpe ratios between those factor portfolios and the benchmark portfolios is not statistically significant. The other factor portfolios (value, low-volatility and hash rates) appear to significantly underperform in terms of risk-adjusted returns. Finally in chapter 6, the robustness of the inference that the Google, momentum and multi-factor portfolios generate better risk-adjusted returns than the implemented benchmark portfolios was further examined. In this final robustness check, the results suggested by the three risk-adjusted performance measures were evaluated under three different market conditions. Three different time frames captured the evolution of the cryptocurrency market when price levels were stable, when price levels were appreciating (bull market), and when price levels were depreciating (bear market). The results from this concluding robustness analysis suggested that both Google portfolios and all multi-factor portfolios significantly surpassed the performance of the market proxy under several different market conditions. Additionally, similar to our preparatory conclusion, the Sharpe (Treynor) ratios of both momentum portfolios suggest that the momentum strategy provides larger excess returns in relation to the overall (systematic) risk an investor bore on the investment. Nevertheless, the momentum portfolios did not perform significantly better during every distinct timespan. All in all we can conclude, that both Google portfolios and all multi-factor portfolios generate significantly higher risk-adjusted returns than the benchmark portfolios. The momentum portfolios appear to outperform the benchmark portfolios as well, though these results are not always significant. The other single-factor portfolios (significantly) underperform in terms of risk-adjusted returns compared to both benchmark portfolios. Lastly, the results from the multi-factor regression analyses (which identified if the Google and hash rates factors are unique systematic drivers of returns) suggested that Google is a truly original factor. Though, the hash rate factor turned out to have a large dependence on the market, value, and low-volatility portfolios and is therefore not identified as a new driver of return. Nevertheless, due to the establishment of the Google factor, this paper contributes one new and truly original steady-performing factor to the cryptocurrency market which currently surpasses all other examined factors in terms of risk-adjusted performance.

As aforementioned, this study investigated the traditional factors momentum, value, and low-volatility because those particular factors have been proven to work across a variety of different asset classes (Asness, Moskowitz, & Pedersen, 2013; Falkenstein, 2009). However, the results presented in this paper are not in line with the conclusions drawn in existing literature. More specifically, this paper can not establish a clear presence of the value and low-volatility factors in the cryptocurrency market. Evidence in favour of the value factor in equity markets has been presented by numerous analysts, as specified in chapter two. Morover, Hubrich (2017) already analysed the effects of this established factor in the cryptocurrency market and encountered postive yet insignifcant alphas. Though, according to the various performance measures and robustness checks implemented in this paper, the value strategy (sometimes significantly) underperforms in terms of risk-adjusted returns compared to our benchmark portfolios. Our findings on the effectiveness of the low-volatility factor are in agreement with the results presented by Hsu and Li (2013). Though, they contradict the findings of numerous other analysts and specifically the discovery from Falkenstein (2009) who suggested a global presence of the volatility factor within every asset class. The low-volatility factor appears to underperform when analyzing the entire time frame, however in bear markets (table 8) this factor appears to perform surprisingly well. On the contrary, our findings on the validity of the momentum factor appear to be in line with existing literature. As specified in chapter two, previous literature presented evidence in favour of momentum investing strategies. Additionally, this paper concludes that the momentum factor is present and effective in the cryptocurrency market. However, according to the various implemented robustness checks, the momentum portfolios do not perform significantly better compared to the market proxy. Since this study is (reportedly) the first to construct and introduce Google and hash rates factor portfolios, we can not compare our results to findings from existing literature.

This paper encountered several limitations. Firstly, despite the availability of daily data, our implemented time frame is fairly short. Moreover, due to the rapid evolution of the cryptocurrency universe, this study presumes that the results presented might no longer be applicable in a couple of years. Secondly, the factor measures and definitions incorporated in this paper were chosen relatively arbitrarily. As aforementioned, this study did not aim to construct factor investing strategies best applicable to the cryptocurrency market. Though, it aimed to determine whether consistent factor return premia exist in this new asset class utilizing its most acknowledged measures. Consequently, using different (perhaps in this market superior) factor measures could have generate higher risk-adjusted returns. Thirdly, this study did not incorporate the recognized cryptocurrency index called the CRIX. Since the CRIX was created six months after our implemented start date, we created our own benchmark portfolios of which one (the equal weighted benchmark portfolio) served as a market proxy in multiple regression analyses. This way, we did not have to drop available and informative data from our already brief sample. However, incorporating an acknowledged index when (in the future) more data is available is recommended. Fourthly and most importantly, this paper did not incorporate the fees associated with cryptocurrency transactions when testing the various factor strategies. The fees charged by cryptocurrency exchanges are exchange, currency and time specific and are presently remarkably high. The results presented in this study are therefore more theoretical than practical in nature. As a result, an algorithm that rebalances all portfolios on a daily basis is in practice not recommended due to these (currently) high transaction costs. Lastly, I would like to stress that the findings presented in this paper should not be interpreted as a recommendation for investors in the cryptocurrency market. Alternatively, these results simply suggest a presence of factor return premia in the cryptocurrency space.

Based on the above-stated limitations, this paper proposes three main suggestions for further research; Firstly, new literature will benefit from a deeper analysis into the various different factor measures applicable to cryptocurrency market. As stated above, the measures were chosen relatively arbitrarily. Thus, altering the number of coins to short or buy, or altering the duration of the analyzed time spans at every rebalancing date will consequently alter the performance of the portfolios. This way, measures best applicable to the crypto market can be incorporated through which higher risk-adjusted returns can be generated. Secondly, I recommend for an additional and more practical analysis of factor investing in the cryptocurrency market. After analyzing the extraordinary theoretical performance of the Google and multi-factor portfolios, it is intriguing to determine whether those well-performing strategies can still generate excess risk-adjusted returns after accounting for transaction costs. Because transaction costs in the crypto market are currently high, I suggest for a new trading algorithm which rebalances all portfolios less frequently. Though, because of the extremely volatile nature of cryptocurrencies, the performance of these less frequently rebalanced portfolios will remain ambiguous. Lastly, due to the exceptional performance of the (in this paper established) Google factor, it is appealing to explore the effect of this original factor in other asset classes.

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Appendix A

Confidence Intervals of the Bootstrapped Sharpe ratios

Table A1: The confidence Intervals of the Sharpe ratio estimates of the 15 implemented portfolios
This table presents the confidence intervals of the 15 bootstrapped Sharpe ratios. The 15 strategies are displayed in the first column where Bench1 and Bench2 represent the equally weighted and market capitalization weighted benchmark portfolios, respectively. The abbreviations shown after the underscore of the 13 factor portfolios (_EW & _VW) reveal which specific weighting technique is applied to construct the portfolios. Accordingly, EW stands for equally weighted and VW stands for Volatility weighted. The abbreviations depicted before the underscore of the single-factor portfolios represent a particular factor, where GOG stands for Google, HSR stands for hash rates, MOM stands for momentum, NVT represents the value factor and VOL the volatility factor. Finally, MIX resembles the multi-factor portfolios which are introduced in section 4.4. The confidence intervals is obtained from the simulated empirical distribution function. The 95% confidence interval for the estimate (mean which is depicted in column 5) starts at the 2.5% percentile and ends at the 97.5% percentile, which are depicted in the second and seventh column respectively. The 90% confidence interval for the estimate (mean) starts at the 5% percentile and ends at the 95% percentile, which are depicted in the third and fifth column, respectively. The median of the 15 different distribution functions is displayed in the fourth column.

Portfolio	2.5%	5%	50%	Mean	95%	97.5%
Bench1	0.6474	0.8409	1.9887	2.0048	3.2195	3.4581
Bench2	0.6066	0.7818	1.8662	1.8955	3.0892	3.3353
GOH_EW	1.9582	2.1060	2.9412	2.9592	3.8569	4.0369
GOH_VW	1.9096	2.0801	2.9088	2.9154	3.7610	3.9277
HSR_EW	-2.3427	-2.1762	-1.2270	-1.2196	-0.2432	-0.0151
HSR_VW	-0.0674	0.0933	0.9331	0.9268	1.7532	1.8985
MOM_EW	1.8826	2.0361	2.8516	2.8438	3.6148	3.7499
MOM_VW	0.9822	1.1450	1.9868	1.9767	2.7907	2.9424
NVT_EW	-1.3283	-1.1890	-0.3242	-0.3227	0.5415	0.7014
NVT_VW	-1.8876	-1.7607	-1.0593	-1.0359	-0.2526	-0.0737
VOL_EW	-2.3772	-2.2117	-1.3051	-1.2958	-0.3421	-0.1830
VOL_VW	-0.8172	-0.5977	0.5491	0.5392	1.6511	1.8346
EW_MIX	2.0011	2.1855	3.2224	3.2244	4.2646	4.4629
MOM_MIX	2.6284	2.8262	3.8140	3.8118	4.7981	4.9887
VW_MIX	1.8684	2.0649	3.0360	3.0332	3.9914	4.1622

Table 5 above displays the confidence intervals of the bootstrapped Sharpe ratios. These confidence intervals are used to determine the precision of our estimates. The 95% confidence interval for this estimate starts at the 2.5% percentile and ends at the 97.5% percentile. The smaller the displayed confidence interval the more precise our estimate is. Thus, it appears that the bootstrapped Sharpe ratio estimates of our momentum portfolios are most accurate. Moreover, both benchmark portfolios exhibit the largest confidence intervals implying that their estimated Sharpe ratios are less precise.