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Commodity Futures and Cryptocurrencies: Same-Same but Different

An empirical study across the two asset classes to determine which market characteristics influence risk-based and behavioural-based anomalies

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Preface and Acknowledgements

Abstract

In recent years, various studies started questioning the validity of market anomalies and which characteristics influence their appearance among asset classes. This study analyzes a set of factors found to be significant by past literature for the commodity future and the cryptocurrency markets. Furthermore, the work presents two new investment strategies based on coin popularity and the relation between temperature and commodity prices. Based on an original comparison between these asset classes, the study finds that the presence of institutional investors and the possibility to short leads to a prevalence of risk-based factors such as *Skewness*, *Carry,* and *Kurtosis*. These factors appear to be priced in the commodity cross-sectional returns. Conversely, a high proportion of retail investors and short-selling constraints (characteristics of the cryptocurrency market) stimulate behavioral-based anomalies such as *Max Return, Momentum, and Seasonality-effects*. Cryptocurrency cross-sectional return also prices simple risk measures such as Volume volatility or liquidity, which do not emerge for commodity futures. Control for false-positive does not change the results significantly; conclusions are approximately the same after applying four p-value adjustments. Outcomes do not change after subsample analyses. Lastly, the investigation proves that the classical equity factor model struggles to explain returns. Conversely, although some anomalies' alphas remain significant, a market-specific 3-factor model remarkably increases the quality of the results.

Introduction

After Moskowitz's paper on diversification and modern portfolio theory, published in 1952, an entire world of literature has tried to explain and predict cross-sectional stock returns. Among others, William Sharpe (1964) and John Lintner (1965) published one of the first papers on the Capital Asset Pricing Model. The CAPM was realized to price financial securities and determine the level of return an investor should expect when buying a particular asset. Even though successful, the model was also based on solid and unrealizable assumptions[1]. The use of the CAPM still takes place in financial areas nowadays – such as in companies' equity cost rates – but the model lost its power in forecasting expected yield. It turned out market return was not the only risk investors had to bear when investing in a stock. Other risk factors were founded to explain the cross-sectional equity return. One of the most remarkable articles was written by Fama & French (1993). The authors argued that the cross-sectional equity return could be explained by a 3-factor model using the market return, a factor for companies' size, and a factor for companies' over-/under- valuation. The day the paper was published marked the birth of a vast strain of literature, which is still evolving today and developed across periods and asset classes.

Today, hundreds of anomalies have been documented; however, whether these are driven by reward for risk, investors' biases or data mining has become an up-to-date question. A recent paper published by Harvey, Lui, and Zhu (2016) suggest a new approach for evaluating the significance of the analysis, mining the consistency of part of this vast literature. After analyzing more than 300 anomalies in the stock market, the authors discovered that depending on the p-value correction applied, 25 to 50% of the anomalies turn out to be insignificant. The persistency and trustworthiness of many factors started to falter and became a relevant topic for the finance literature. This work aims to contribute to that.

Baltussen et al. (2021) and Tharann et al. (2019) take a multi-asset class approach, testing which factors are priced, in different markets. The former study investigates Commodity and Equity market, while the latter paper performed an extensive study across time and assets, analyzing 24 global factor premiums across the four major existing asset classes[2]. A problem remains to be solved. Each instrument in the financial industry is characterized primarily by its features, but also by the characteristics of the market in which it is traded. Although this can be estimated, it remains unexplained whether the anomalies appearance is due to the asset characteristics itself, or the environment that influences investment decisions.

[1] In specific: (i) it requires companies' full-spread information, comprehensively and immediately integrated into prices (ii) market agents are entirely rational and risk-averse, seeking the maximum utility from their investments.

[2] Equity, Bond, Currency, and Commodity

To this extent, this study uses simple portfolio construction with a fixed rebalancing period[3], to replicate the central anomalies for two assets, theoretically close but practically far, namely Commodity and Cryptocurrency. At first glance, the decision might not ring a bell, but it has a central explanation. From a purely theoretical point of view, commodities and cryptocurrencies can be seen as similar (if not equal) instruments. They share the following characteristics: (I) absence of cash flow; (II) prices, at least theoretically, driven by pure demand and supply; (III) single specific use in the real economy; (IV) change in supply requires investments and time; (V) No specific link with other financial variables (such as interest rate for currencies and bonds). Furthermore, according to the commodity futures trading commission (CFTC), bitcoin, the sized token[4] in the market, is considered a commodity under the Commodity Exchange Act[5]. Even though it is not official yet, in the view of Heath P. Tarbert – Commissioner and former Chairman and Chief Executive of CFTC[6] - Ether will follow the same fate. In addition, Ripple Labs[7] has taken the position that XRP, its digital token, is a commodity.[8] Lastly, according to an article published on TronWeekly.com[9], Cardano[10] might become a currency in the future, but so far, it is still considered a commodity.

Now, the assumption does not have to be misunderstood. This study is not attempting to say the price of commodity futures and the price of cryptocurrency are driven by the same forces. Today, Cryptocurrency are widely used for speculation purposes, and each coin's "true value" is hardly calculable, and it usually does not reflect market price. However, in an efficient market, where information is perfect, complete, and fully available, and investors, as rational, instantaneously transmit the news into prices, the movement of both assets should be driven by the same factors. Explained from another point of view, the technique to find out the fair price of Gold should be approximately the same as the procedure to calculate bitcoin's price. Because of the theoretical similarities, but mostly thanks to the highly different influences and purposes that drive investment decisions in each market, this represents an exciting and maybe unique comparison occasion.

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[3] Monthly for Commodity Futures and Weekly for Cryptocurrency

[4] Although Token, Coin and Crypto represent three different things in the Cryptocurrency universe, they will be used as synonym in this study

[5] https://www.cftc.gov/PressRoom/PressReleases/8051-19

[6] Commodity Futures Trading Commission

[7] American Technology company that developed the Ripple payment protocol and exchange network. Ripple is in the top 10 cryptocurrencies for market capitalization

[8] https://www.jdsupra.com/legalnews/to-register-or-not-to-register-a-common-5100117

[9] https://www.tronweekly.com/will-cardano-ada-turn-into-currency-or-remain-commodity/

[10] The 9th cryptocurrency for capitalization. Data update up to 04/05/2022

To summarize the research questions:

1. *Which are the prominent anomalies in the commodity futures (cryptocurrency) market? How many of these remain consistent even after a p-value adjustment?*

2. *Can these returns be explained by pre-existent factors models?*

3. *Having stated that these two assets are fundamentally similar, which are the market conditions that stimulates risk-based or behavioral-based factors?*

This thesis replicates the most famous documented irregularities present in both markets. Compared with stocks, there are only a few mimicable factors, primarily due to the assets themselves. Unlike a company share, commodity and cryptocurrency prices do not reflect balance sheets or cash flows. Their value is (or should) mainly driven by demand and supply and by their employment in the real economy. A detailed explanation of which anomalies are replicated is provided in the Data section. Factors used are similar for both instruments, yet some characteristics differentiate one from the other. As an original contribution of this thesis, additional strategies considering climate change[11], a new liquidity measure, and coins popularity, are performed.

Whenever multiple tests are performed, there is a risk of discovering false positives.[12] To solve the problem, this study deploys the three p-value corrections proposed by Harvey et al. (2016)[13] and an additional measure developed by Wilson (2018). These adjustments provide an understanding of whether the majorly documented irregularities in the Commodity and the Cryptocurrency markets are, in fact, significant or just driven by intense data mining. Given that the p-value corrections depend on the number of tests, this analysis studies the same amount (21) for both market. Pre-adjustment long-short portfolios report significant results in 9 out of 21 factors at a 5% level and 5 out of 21 factors at a 1% level for the commodity market. Similarly, 10 out of 21 long-short portfolios turned out to be significant at a 5% level for Cryptocurrency, while 9 of them remain as such at a 1% threshold.

As expected, Bonferroni is the most conservative measure that leads to only one discovery at a 1% level for Commodity. The statistical factors are four for Cryptocurrency.[14] Holm reports similar results for both. For both markets, BHY is the correction that leads to the highest number of discoveries, doubling the amount respect to the first two adjustments at a 1% level. A combined analysis that considered all

[11] Inspired by Taşkin D. et al. (2021), which studied the relationship between global climate change and the commodity price, finding positive significant results for industrial commodities and precious metals.
[12] Rejected hypothesis that should not, leading you to trust that the hypothesis is true when, in reality, it is not
[13] Bonferroni, Holm and BHY
[14] At 5% level remained significant 3 and 7 strategies for respectively Commodity and Cryptocurrency.

the anomalies together (42) leads to slightly but not wildly different results. Wilson harmonics mean p-value proves that at least one of the factors is undoubtedly different from 0. The conclusion holds a 1% level for Cryptocurrency and at a 5% level for commodities when the analysis excludes the most significant strategies.

In general, for Commodity, *Carry* seems robust to any correction and standard level of significance[15], while *Momentum* turns insignificant for Bonferroni and Holm at a 1% level. The same result is founded for the *3-Weeks Momentum* in Cryptocurrency. *Google Trend, Liquidity, Transaction Volume, and Standard Deviation of Dollar Volume* are robust to any adjustments and any ordinary level of significance; however, the last three present an elevated level of correlation. Pre-adjustment, risk-based factors such as *Skewness, Kurtosis,* and *LongRatio* are statistically different from 0 for Commodity while not for Cryptocurrency. On the contrary, behavioral-based factors such as *Max Price, Price*, and *Seas* are statistically different from zero for Cryptocurrency while not for Commodity. Based on the results, we can conclude that cryptocurrency anomalies are driven mainly by people's biases, while in the Commodity market, agents price some risks deemed non-relevant when exchanging coins.

The paper tests the robustness of the results in several dimensions. Two separate one-factor models are run, using both the equity market return and the specific-asset market return[16]. This is also the case for the 3- and 5-factor models from Fama & French (1993, 2015) and for a specific 3-factor model for Commodity and Cryptocurrency. In light of the evidence, results are poor for the first four regressions. Nevertheless, the BGR model (Commodity) and the ASM model (Cryptocurrency) can almost entirely explain the strategies' abnormal returns. Specifically, only alphas from Skewness and Long-Ratio remain significant at 5% and 10% levels for commodity, while the ASM model cannot explain *Liquidity, Google Trend, Transaction Volume,* and *Standard Deviation of Dollar Volume*.[17]

This study also performs two subsample analyses, one per market. The Commodities sample is restricted to the period 2004-2022. Indeed, the volumes of trading activity in commodity futures markets increased substantially from 2003.[18] Table E1 in Appendix E shows the result of this study. Generally, no meaningful changes in terms of the significance of mean return are displayed. *LongRatio* changes marginally (only significant at 10% after 2003) while *Kurtosis* is statistically equal to 0 (in the entire sample, it is significant at 10%). The opposite fate happened to Size.

On the contrary, the Cryptocurrency sample is restricted up to 2021. This decision is taken because the market's percentage of institutional investors has severely increased since last year. According to the

[15] This analysis considers 10%, 5% and 1% level.
[16] A specification of which market return is utilized is given in the Data Section.
[17] Note that the factors used as independent variables in the regression are excluded. Specifically, these are Carry and Momentum for Commodity, 3-Weeks Momentum, and Size for Cryptocurrency.
[18] According to Barclays Capital, the level of investment in commodities by institutional investors increased from $ 18 billion in 2003 to $250billion in 2010. They run a survey of over 250 institutional investors.

findings, relevant changes are not documented; in specific, only 1- and 4- weeks *Momentum* became less significant[19], while 2-Month *Reversal* is now robust at 5%. The rest of the Factors do not differ from the whole sample in terms of significance and magnitude. Considering that the percentage of Retail investors moved from 80% in 2018 to roughly 32% in 2022[20], we can infer that these new market actors did not change the investment style applied in the market. A more specific study could investigate the differences in strategies deployed by financial institutions because, based on these results, they decided to enter from a purely speculative point of view. Unfortunately, this investigation goes behind the purpose of this study.

The last part of this work compares the results found from a market-efficiency point of view, controlling how many anomalies persist in each market, and which type (behavioral or risk) factors prevail. According to Hollstein et al. (2021), Commodity futures are fundamentally easier to short than stocks due to the formers being derivates. Similarly, the authors state that institutional operators in the market represent a much higher fraction of investors. Conversely, the cryptocurrency market is represented by a more significant proportion of retail investors and an implicit impossibility to short coins. This dualism allows to contribute to the existing literature with an original approach.

Because of these two flanks of the coins, the analysis can shed light on the characteristics that make a market prone to certain factors (if any) and which qualities push an environment closer or farther from efficiency. To this extent, institutional investors, though their better understanding of the market, tend to: (i) make behavioral anomalies disappear and, (ii) rationally price risk-based ones (Such as *Skewness*, *Kurtosis*, et cetera). Conversely, behavioral biases strategies are more pronounced in Cryptocurrency, where most investors are retail. The only priced risks are those that can easily be computed. Short selling constraints also play a role. In markets where such constraints are stronger (Cryptocurrency), investors are less willing to act as arbitrageurs and therefore let the mispricing persist. Moreover, when these opportunities can be easily exploited (commodity), the only strategies that remain significant are those that reward a priced risk. An exception concerns *Momentum* and *Reversal* for the Future market. This study finds evidence that institutional investors encourage over- and under-reaction, trying to get the best out of it.

The rest of this study is organized as follows; Section II introduces theoretical concepts and a description of how the thesis contributes to the existing literature. Section III presents the data used.

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[19] It is provided a possible explanation in section V.IV about why trend following strategies should increase when institutional investors enter the market.

[20] According to an article by George Steer (Morgan Stanley research) published in the Financial Times, Retail investors represented roughly 80% of the total daily volume on Coinbase in 2018, while today, that proportion is set to 32%. The level decreased significantly (specifically after Q4 – 2020), but it is still above the share of retail investors in other markers (For the U.S. stock, this is around 10%).
https://www.ft.com/content/12b80e7f-047d-4273-8766-226b5d91a1fc

Section IV introduces the applied methodology, while section V shows the main empirical results of the strategies, the p-value adjustments, robustness checks, and the market efficiency implications. In conclusion, Section VI explains the main conclusions, suggesting limitation, and possible improvement.

Relevance of the subject

The efficient market hypothesis (EMH) argues that information is instantaneously embedded in prices, and, because of the randomness of the market, investors cannot do achieve, in the long term, positive and significant alphas. Moreover, because of transaction costs, passive portfolios should always be more performing than active strategies. The presence of anomalies in the cross-sectional return represents a possibility to make a profit without bearing any risk and it goes against EMH. Although they sometimes look not robust to out-of-sample analyses or different periods, their existence has been widely documented. Anomalies can be the result of inadequate asset-pricing models or market inefficiencies.

The most relevant market inefficiencies documented are transaction costs, information asymmetries, short-selling constraints, and irrationalities. Liu (2010) studied how the transaction costs influences efficiency. He showed that double-listed stocks[21], which could not exploit the deregulation of one of the two countries, reported prices less prone to follow asset-pricing models. The paper links this issue with the impossibility of reducing transaction costs. Similarly, three years before, the same author[22] uncovered that the efficiency of the price discovery process could be improved with a reduction in transaction costs. Li (2020) documented that asymmetry in information can increase equity misevaluation, and that the analyst coverage has proved to harm equity mispricing. Furthermore, Mayers and Maijuf (1984) link superior manager information with firms' investment opportunities. According to the study, if stocks are issued to finance an investment, it is rational to believe that the stock price will fall.

This study does not focus on the first two points, but it instead analyses how short-selling constraints and irrationality can affect mispricing and, more precisely, anomalies. The literature on irrationality is vast and does not take sides on one side. Even though noise traders are considered a source of mispricing, it is not clear yet between institutional and individual investors who act as smart and noise ones. On the one hand, papers such as Blonski et al. (2016) or Barber et al. (2000) studied how individual investors become less performing when they need to deal with great mathematical reasoning ability[23] and how households performed poorly in individual investments during the period 1991 to 1996. On the other hand, Simonovska et al. (2019), documented that retail investors in Thailand systematically outperformed institutional ones thanks to the ability of the formers to focus on small stocks.

[21] A double-listing represents any security that is traded on two or more different exchanges. Companies do so because of several benefits, one above all is the increased liquidity

[22] Liu (2007); "*Securities Transaction Tax and Market Efficiency: Evidence from the Japanese Experience.*"

[23] As it happens with financial investments

As far as noise traders are concerned, the prevalence of institutional on one side and retail on the other allows to draw conclusions about which type of investor is the greater contributor to mispricing. If the Commodity market presents a higher number and more robust anomalies, we can argue that institutional investors, even if only marginally, contribute or incentivize mispricing. The vice versa conclusion can be drawn for the Cryptocurrency and retail investors. Similarly, the distinction can be made between risk-based or behavioral-based factors.

Because of these similarities, a second investigation can be constructed. Short selling allows investors to take the opposite position and exploit arbitrage opportunities, correcting market's mispricing. Taking a short position is not always possible; it can involve several risks and be expensive. In this regard, Commodity Futures are derivative contracts requiring substantially less effort than equity's. With Future contracts, no marginal account exists, and it only requires placing the order (sell) and find a counterpart. According to Walter Sledz, director of Sales at NinjaTrader, the level of liquidity and required margins also influences the ease with which you can short Futures[24].

The situation is not the same in Crypto market. Short selling is mainly restricted to a small number of sized coins, operating in unregulated markets, and having a considerably smaller number of guarantees. As an example, several centralized exchanges indeed allow to take short positions; however, short-selling constraints do not only concern technical possibilities. Barberis et al. (2003) identify three types of risks that investors face when acting as arbitrageurs: (i) fundamental risk, namely the risk that the investor might be wrong about its analysis and its position. Cryptocurrencies have been in place for a few years now, and their price and real implication in the economy is still unknown. Therefore, define a fundamental value for cryptos is extremely more complex than for Commodities; (ii) Noise Trader Risk, namely the risk that the mispricing will get worse or last as long as the investor is forced to leave the market before the market corrects. As stated above, the investor' concentration in the cryptocurrency market is much higher the commodity one. Small-sized investors prevail in defining coin prices and the mispricing is impossible to correct when upcoming news influences markets; (iii) Transaction costs, namely the risk that keeping the position open will cost more than the profit earned by applying long-short strategy. This part is not considered in this study since forecasting the average transaction costs, differentiating by investor's size, would require hardly accessible data and would improve only marginally.

Several papers have already studied the presence of anomalies in both cryptocurrencies and commodities. As far as the former is concerned, we can highlight Hollstein et al. (2021), which extensively examined anomalies such as *Size, Jump risk, Momentum, Skewness, and Volatility of Volatility*. Such anomalies have been initially studied for the equity market and then replicated for the

[24] https://www.youtube.com/watch?v=38N4aJl0N7g

commodity one. To this extent, Fama & French (1993) proposed the Size factor. Cremers et al. (2015) examined the aggregate Jump and Volatility[25] risk in the cross-section of stock returns. Jagedeesh & Titman (1993) first theorized the Momentum anomaly, and lastly, Baltussen et al. (2018) studied the Volatility-of-Volatility factor. Specifically for Commodity, Szymanowska et al. (2013) replicate past studies differentiating between spot and term premia. Basu D. et al. (2013) studied the risk-premia linked to the Hedging Pressure, while Yang (2013) and Bakshi et al. (2019) investigated the risk-premia linked to the term structure. This paper contributes to the existing literature in various ways. Firstly, by applying different p-value adjustments to stress the factor's robustness. Furthermore, it takes a new approach to test the liquidity factor. The latter was firstly studied by Amihud (2002) on the stock market and further replicated by Hollstein et al. (2021) on the commodity one. With the Amihud measure, the strategy turned out to be insignificant, and this thesis takes a new approach to investigate it. Lastly, a new anomaly is developed based on the climate change effect on commodity prices.

The literature is sensibly less extensive but growing as far as cryptocurrencies are concerned. Liu et al. (2019) explore the cryptocurrency market's cross-sectional returns, highlighting several significant factors. Yang (2019) replicated more than 20 stock return anomalies, and Dong et al. (2022) pointed out the effect of liquidity on the significance of anomalies. Paper such as Caporale and Plastun (2019), Long et al. (2020), and Susana et al. (2020) investigated the overreaction effect and the cross-sectional seasonality effect, respectively. This thesis casts novel insights on the validity of the literature, enclosing several single studies in a unique work. In addition, p-value corrections are applied to test for robustness. Moreover, the paper develops a new strategy based on the popularity of each coin over time.

Regarding the market efficiency implication, the literature is vast and concentrated around the equity market. Fama (1998) studied the persistence of the long-term effect of anomalies, concluding that we cannot entirely reject the EMH since most of the irregularities are not robust to out-of-sample analysis. However, different articles focused instead on finding an explanation for anomalies' existence. It is worth mentioning Wouters (2006), who deeply analyzed the style investing[26] and the related anomalies.[27] Subsequently, Latif et al. (2012) shed light on the validity of the EMH and explanations for the to-date well-tested anomalies. Yang (2017) proved that the source of abnormal returns originates from financing constraints, while Engelberg et al. (2018) focused on the investor's expectation as a mispricing explanation. Lastly, studies by Brunnermeier et al. (2014), Stein (2009), and Chen et al. (2020) analyzed the relationship between institutional investors and market efficiency. This paper can

[25] In Hollstein et al. (2021) paper, this factor turned out to be insignificant

[26] Investment style is The method and philosophy followed by an investor when (s)he selects assets for a portfolio is called Investment Style. It bases on different factors such as risk preference, geographic area, growth vs. value orientation, and market cap.

[27] He focused on the Value factor, analysts' earnings forecasts effect, popularity style, and size-prima.

help understand which elements influence risk-based and behavioral-based factors through an original comparison between markets.

In general, this paper can be helpful for retail and institutional investors who want to pursue active strategies. Moreover, it sheds light on new asset allocation opportunities (popularity for crypto, liquidity, and climate change for commodities) that, to the best of my knowledge, nobody tested in this way before. Lastly, considering the technological revolution characterizing the financial industry is rational to believe that new assets, contracts, or instruments will be born in the future. Knowing which peculiarities influence the deviation of prices from their fundamentals will be a value-added for this literature.

Data

Data for both cryptocurrency and commodity are collected from sources mentioned in past literature, using daily closing prices to build weekly cryptocurrency returns and monthly commodity returns.

a. Commodities

The sample contains 31 commodity futures[28] with a period that ranges from 05/01/1980 to 05/01/2022. Forty years of data could not be found for each future; however, a minimum of 10 years is always preserved. Every time series is denoted in U.S. Dollar. The closing, high, and low price are collected from the Bloomberg Finance Database. Data regarding contracts' open interest and spot prices[29] are gathered from the Global Financial Data (also known as GDF). In contrast, data regarding the hedging pressure[30] are piled up from the Commodity Futures Trading Commission (CFTC). The temperature anomaly series come from by the Global Historical Surface Temperature Anomalies (HadCRUT4)[31]. Lastly, those price series that could not be found on the previous resources are downloaded from Eikon & DataStream.

The 31 commodity futures indexes are the following:

Aluminum, Brent Crude Oil, Cocoa, Coffee, Copper, Corn, Cotton, Feeder Cattle, Gold, Heating Oil, Lean Hogs, Live Cattle, Lumber, Milk, Natural Gas, Oats, Orange Juice, Palladium, Platinum, Rough Rice, Silver, Soybean Meal, Soybean Oil, Soybeans, Sugar, Wheat, WTI Crude Oil, Ethanol, Soybean Crush, Nickel, Cobalt.

b. Cryptocurrencies

The sample contains 89 coins from 01/01/2015 up to 01/05/2022. Only tokens that still exist today[32] with at least $100mln of market capitalization are collected. All the price series have been gathered from Yahoo Finance[33]. Conversely, data regarding Market Capitalization and transaction amounts comes from Coinmetrics. The former was created to publish data on major public blockchains and make cryptocurrency market research easier. Unfortunately, because of either internal policy of too

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[28] To avoid future contract maturity and price irregularity, each future return is rolled on the first notice day, following the procedure suggested by the Bloomberg Finance Database. Every price series is split-adjusted, and the commodity futures is held with a fixed maturity. To this extent, the strategies presented in this study yield only the commodity futures spot and not the premia linked to the term structure. The First notice day is when an investor who has acquired a futures contract may be obligated to physically deliver the contract's underlying commodity. The first notification day varies per contract and is also subject to exchange regulations.

[29] For a more detailed explanation of the Spot series please consult the Global Financial Database

[30] Defined by Basu et al. (2013) as the propensity of market participants to be net long.

[31] Met Office Hadley Centre observations datasets

[32] The only exception is Luna, involved in a scandal that drove the price close to zero a few weeks after the data collection. To this extent, in data 05-27-2022, the coin founders decided to implement a hard fork in Terra’s blockchain, renaming the old Luna coin as Luna Classic and issuing a new cryptocurrency called Terra Classic.

[33] Volume and Close, Opening, High, Low price

early birth of the coin, the latter website does not provide data for each of the 89 coins. In any case, analyses have not been affected by it. In addition, a popularity index metric is collected, representing the relative interest (based on Google clicks) regarding each token. Data are provided by the Google Trend website.

The previously mentioned 89 coins are:

1. *Bitcoin (BTC), Ethereum (ETH), BNB (BNB), Cardano (ADA), Dogecoin (DOGE), Ripple (XRP), Polkadot (DOT), Wrapped Bitcoin (WBTC), Cronos (CRO), Polygon (MATIC), Litecoin (LTC), TRON (TRX), Hainlink (LINK), Bitcoin cash (BCH), Uniswap (UNI), FTX Token (FTT), UNUS SED LEO (LEO), Algolrand (ALGO), Stellar (XLM), Ethereum Classic (ETC), Monero (XMR), Internet Computer (ICP), Decentraland (MANA), Tezos (XTZ), Aave (AAVE), Zcash (ZEC), Maker (MKR), Bitcoin SV (BSV), Huobi Token (HT), Neo (NEO), Quant (QNT), Curve DAO Token (CRV), Dash (DASH), Basic Attention Token (BAT), Kyber Network Crystal v2 (KNC) (81*), NEM (XEM) (88*), Decred (DCR), Compound (COMP) (90*), Synthetix (SNX), Gnosis (GNO), PAX Gold (PAXG), OMG Network (OMG), Serum (SRM), Bitcoin Gold (BTG), 1INCH Network (1INCH), renBTC (RENBTC), SushiSwap (SUSHI), UMA (UMA), Polymath (POLY), Ren (REN), DigiByte (DGB), Perpetual Protocol (PERP), Powerledger (POWR, Ripple (XRP), Solana (SOL), Terra (LUNA), Avalanche (AVAX), Shiba Inu (SHIB), NEAR Protocol (NEAR), ApeCoin (APE), Cosmos (ATOM), Filecoin (FIL), Hedera (HBAR), VeChain (VET), Elrond (EGLD), The Sandbox (SAND), Theta Network (THETA), Fantom (FTM), THORChain (RUNE), PancakeSwap (CAKE), Klaytn (KLAY), Axie Infinity (AXS), EOS (EOS), Flow (FLOW), Helium (HNT), The Graph (GRT), IOTA (MIOTA), Waves (WAVES), Convex Finance (CVX), BitTorrent (BTT), eCash (XEC), Stacks (STX), Kusama (KSM), Nexo (NEXO), Harmony (ONE), Chiliz (CHZ), Celo (CELO), Gala (GALA), Zilliqa (ZIL), OKB (OKB), Enjin Coin (ENJ), Loopring (LRC)*

Although they respected the criteria, stable coins such as Tether or Binance Cash are deliberately excluded. They are pegged to the US dollar and would not have fit in the analysis. The fact they behave almost wholly as a currency was mining the basing assumption for which cryptocurrencies, from a merely theoretical point of view, are relatively like commodities futures.

Kenneth French's website provides additional data concerning Fama&French Factors[34] and the risk-free rate[35]. Lastly, the Bloomberg Commodity Index and Bloomberg Galaxy Crypto Index are selected as the market return for the two assets. They Both come from the Bloomberg Finance Database.

[34] Equity Market return, Size, Value, Profitability, and Investment policy
[35] 1-Month Treasury Bill

I. *Summary Statistics*

Table 1 provides a statistical overview of the Commodities. Several Futures, such as *Coffee*, *Cocoa*, *Corn*, and *Wheat*, have annualized negative mean excess returns over the studied period. An explanation is found in the considered period. Most of the series started in May 1980, right after the commodity shock that particularly inflated prices in early 1970. In fact, the same annualized mean excess returns, considering the period 1990-2022, report sensibly higher results, and most of the negative series turn either positive or significantly less negative.

Table 3 and Table 5 report summary statistics for the studied factors. Table 3 shows the correlation among different anomalies, while Table 5 reports mean return, standard deviation, maximum, and minimum value results[36]. As we can see, only a few – expected – variables display a correlation higher than 0.2. Most cases concern similar anomalies such as *Momentum* and *Reversal* or *Size* and *Value*. As far as the factors are concerned, *5-year Reversal* and *Momentum* present the lowest and the highest average magnitude (Respectively -1.35% and 1.81% per month). Note that every portfolio is constructed in the same way[37]; A negative return, if significant, can be turned positive, taking the opposite position. Similarly, *3-year Reversal* and *Overreaction* have the highest and the lowest standard deviation, respectively. In conclusion, *Momentum* scored the highest monthly return, while *Carry* scored the lowest.

Table 2 shows summary statistics for the cryptocurrency market. Unlike before, it does not report the single coin-specific results since the number is remarkably higher than commodity futures. To this extent, a yearly based summary table is provided. Over the past eight years, the sample has reported only two years of negative returns and overall positive performance; the standard deviation level is higher than for commodity. Table 4[38] and Table 6 show summary statistics for the studied factors (correlation and performance statistics). Unlike above, the correlation among anomalies is higher, and, in some cases, it touches values above 0.5. Nevertheless, this is not a surprising result. Most variables are derived from price information only, and it is logical to believe that they have common forces that drive them. Interestingly, the two liquidity measures[39] present a lower correlation than what STD[40] and LIQ have. An in-depth analysis is shown in Appendix A.

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[36] The correlation table does not report January Effect, Temperature anomaly (1 and 2), Week-Of-The-Year, and Christmas, since it was not applied the same portfolio construction, but only studied whether the factor displays a fixed effect over the sample studied.

[37] Factor = Port3 -Port1, where P3 is the portfolio that encloses the commodities with the highest value in that metric, and P1 is the portfolio that encloses the commodities with the lowest one

[38] Table 4a provides the correlation among all factors except Google Trend. For the former, it is provided a different table4b since the portfolio construction is monthly rebalanced, and factors are transformed accordingly.

[39] One is performed according to Danyliv et al. (2014), while the second is computed as the number of daily transactions for each coin.

[40] Standard deviation of dollar volume

Momentum appears to be the variable with the highest magnitude, while liquidity measures report the lowest one. Note that, for Cryptocurrency, the reported data are at a weekly frequency and should be converted monthly before any comparison. *Max Price* is the variable with the highest variability - with a 12,75% weekly standard deviation - while *Overreaction* is the least volatile. Interestingly, *Skewness* and *Overreaction* have scored the highest and the lowest returns in the sample studied; however, as indicated later in the study, none of them turned out to be significant for cryptocurrencies.

Research Methodology

I. Portfolio Construction

To investigate if the selected factors are priced in the cross-sectional cryptocurrencies and commodity futures returns, this work examines the performance of 32 unique strategies. Most of them have already been tested as significant in past literature. However, to try additional risks priced in the marker (or a reinterpretation of an existing one), original investigations are also proposed. Appendix B provides a detailed explanation of the methodology applied for each factor[41].

In addition, several models are used to test the ex-ante transaction cost profitability of the long-short portfolios. These are: (i) the Capital Asset Pricing Model (CAPM), both with the equity market return and the specific asset market return. (ii) The Fama & French 3- and 5-factor models. The *Momentum* factor is calculated instead of the *Value* factor since not replicable for the cryptocurrency market. (iii) an additional 3-factor model with asset-specific factors. Section III of the Empirical Result chapter provides further details on the implementation. For both assets the fully-collateralized excess return is computed, following Koijen et al. (2013) as:

$$er_{t+1} = \left(\frac{F_{t+1} - F_t}{F_t}\right) - r_t^f$$

Where P_t and P_{t+1} are the market prices of the assets respectively today and tomorrow, while r_t^f is the 1-month treasury bill rate provided by the Kenneth French website. Most of the anomalies are replicated for both asset classes, but specifically for the commodity market:

Momentum Factor, Equity Size Factor, Seasonality Effects (January effect, Week-of-the-year, Christmas effect), Historical Skewness, Historical Kurtosis, 3-Years Reversal, 5-Years Reversal, Carry, Systematic Effect of Hedging Pressure, Value, Standard Deviation of the Volume, Overreaction, Betting-Against-Beta, Liquidity, Temperature Anomaly, Seas, Max Price Measure and Max Measure

On the contrary, for the cryptocurrency market:

1-2-3-4 Weeks Momentum, Max Price Measure, Max Measure, Standard Deviation of Dollar volume, Seas[42], Idiosyncratic Volatility, Size, Overreaction, Popularity Trend, Historical Skewness, Historical Kurtosis, 2-Month Reversal, 6-Months Reversal, 18-Months Reversal, Liquidity, Price and Betting-Against-Beta

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[41] Since some factors are replicated for both markets, the methodology is explained only once in the section that belongs to the asset used by the original paper. In short, Overreaction comes from an article that used a Cryptocurrency sample and will therefore be explained in that section.

[42] Weekly cross-sectional seasonality effect

Even though papers such as Baltussen et al. (2018) and Cremers et al. (2015) analyzing options data demonstrated the significance of Volatility-of-Volatility and the Jump factors, this study does not replicate them. They concern an instrument (Options) that, practically, only exists for the commodity market[43]. It might have attached the final comparison.

The portfolio formation is always the same, and it follows past literature. At the beginning of each month (week for cryptocurrency), assets are sorted based on the selected factor's value. The long-short portfolio is formed on the difference between the last and the first quantile. In most cases, it concerns the 90th and the 10th percentile. Specific data are not always available, and sometimes a five quantiles division is needed[44]. Portfolios are rebalanced every month (week) for the commodity futures (cryptocurrency), tracking the excess return of the strategy.

[43] I am aware that some exchanges allow buying and selling options written on cryptocurrencies. However, these only concern a few coins, and the Data collection would have implied several troubles since they are not directly available.

[44] Consult Appendix F for a list of which factors are p10-p1 and which are p5 – p1

II. P-hacking in financial literature

Almost fifty years ago, the first paper testing the Capital Asset Pricing Model was published, stating that the market beta was a satisfying explanator for the cross-sectional expected return. From that date on, hundreds of papers were published studying patterns in the cross-sectional returns. If, on the one hand, a t-statistics of 2.0 was considered a satisfying cutoff for factor significance, the assumption does not hold anymore today. Harvey, Liu, and Zhu, in 2016, tested more than 300 papers to v validate their results' significance. Among several findings, the authors generated the idea that most literature conclusions were driven by data mining rather than rational economic theory. After initially suggesting a new threshold $t > 3$, the authors incentivized further research to adjust the significance level for multiple tests.

HLZ's paper is just one of the vast literature that tries to remedy the p-hacking[45] problem that flows through academic research. For example, in 2017, Harvey published a study explaining how the financial-academic industry is pushed toward a p-hacking approach. Insignificant papers are less likely to be published by renowned financial journals, leading researchers not to submit works with "marginal" results. Similarly, in some studies, the data collecting process is so time-consuming that the risk of not finding a meaningful result is too high. Another paper by Daniele Fanelli in 2010 analyzed thousands of articles across industries to see how many of these reported positive conclusions for the tested hypothesis. The author divides the disciplines into "hard" and "soft"[46], discovering that the "soft" disciplines are more likely to show results that support the initial hypotheses (and vice versa). In particular, the odds of reporting a positive result are around five times higher for a paper published in Psychology and Economics than in Space Science.

To account for this problem, this thesis applies four p-value corrections, employing the three-validity methods explained by Harvey and adding a fourth one developed by Daniel J. Wilson in 2018. Among other reasons, the latter model presents some computational advantages using the harmonic mean p-value. Methodologies are gathered from the original works.

Whenever we test a hypothesis in statistics, this is subject to two error specifications: (i) Type I Error, which occurs when we reject a hypothesis when it is true, and (ii) Type 2 Error, when we do not reject a hypothesis when it is false. Intuitively, which of the two magnitudes should be minimized represents a tradeoff. If we want to avoid Type I error, we can decrease the significance level (and vice versa). However, such a procedure will increase the likelihood of not rejecting an assumption when that is true.

[45]There are several opinions on what p-hacking is, but generally, it happens when a researcher investigates many relationships only reporting the significant results.

[46] According to the paper's definition, data and theories speak more for themselves (such as Space Science) in hard disciplines. On the contrary, soft ones are those where scientists' prestige, political beliefs, and other non-cognitive factors play a more significant role in all decisions made in research

There is no strict answer to which error Type should be avoided; a balanced combo is always preferred. Nevertheless, Type I is generally considered worse. It is more damaging to reject what is true than to keep what is not.

Type 1 error can be controlled by the Family-wise Error Rate (FWER) and the False Discovery Rate (FDR). The latter is defined as the probability of finding at least one Type I error, regardless of the number of tests performed. Bonferroni and Holm's adjustments (the first two methods proposed) ensure that FWER does not exceed the pre-determined threshold of significance α.

$$FWER = P_r\left(N_{0|r} \geq\ 1\right)$$

On the contrary, the former measure is defined to estimate the proportion of false discoveries among all. Empirically:

$$FDR = E[FDP]$$

Where FDP[47] is defined as

$$FDP\ = \begin{cases} N_{0|r} & if\ \ R\ >\ 0 \\ 0 & if\ \ R\ =\ 0 \end{cases}$$

FDR is less stringent than the FWER measure since it allows the probability to grow in the proportion of the number of tests. Both FWER and FDR are essential and widely applied in scientific research. Which is the best one depends on the specific case. Here below are proposed measures that control for both, more in specific Bonferroni, Holm, and Wilson for the FWER and BHY for FDR.[48]

a. Bonferroni

Each test is adjusted in the same way by Bonferroni. It multiplies the original p-value by the number of tests M, then compares the modified p-value to the threshold value.

$$P_i^{Bonferroni} = \min\ [\,M\ \times\ P_i, 1\,]$$

[47] FDP stands for the false discovery proportion

[48] The procedure that follows is taken from the original papers (Harvey et al. (2016) for the first three and Wilson (2018) for the last one.

For each test, it rejects any hypothesis with $P_i^{Bonferroni} \leq \ \alpha_i$ Where α_i is the level of significance that we select[49]. Even though it is one of the most widespread corrections in the statistical literature, Bonferroni is usually considered too rigorous. The number of tests performed affects how a result is interpreted and applies the same correction to all the p-values. For example, in cases where several tests are performed, it might be considered too stringent.[50]

b. Holm

Holm's measure applies the following p-value adjustment:

$$P_i^{Holm} = \min\left[\max_{\mathrm{j\leq i}}\ \{\ (M-j+1)p_j\}, 1\right]$$

It firstly sorts the p-value in an ascendant order ($p_1 \leq p_2 \leq \cdots \leq p_M$), associated with their relative null hypothesis ($H_1 \leq H_2 \leq \cdots \leq H_M$). Once applied the adjustment, the minimum level for *k* is identify such that $P_i^{Holm} < \ \alpha_i$ Now, all the null hypotheses $H_1 \ldots H_{(k-1)}$ are rejected but not from H_k onwards[51]. Because fewer rigorous obstacles are applied to the $(k-1)_{th}$ *P-values*, more discoveries are made under Holm's adjustment than under Bonferroni's modification.[52]

c. BHY Adjustment

The procedure is like Holm's method, However BHY starts with the largest p-vale and move to the smallest one. It orders the original p-values in ascendant order such that $p_1 \leq p_2 \leq \cdots \leq p_M$ Furthermore, it set k as the maximum order such that $P_b \leq \frac{b}{M \times c(M)} \propto_d$ and it reject the null hypotheses for $H_1 \leq H_2 \leq \cdots \leq H_k \ but\ not\ H_{k+1} \ldots H_M$[53]

Specifically, the p-value is defined according to the following system:

[49] Note that the original paper uses a different specification modifying the level of significance α and not directly the p-value. The specification is the following: $Pvalue \geq \frac{\propto_w}{M}$ [49]. Although different in computation, they lead to the same result.

[50] A more exhaustive description of the Bonferroni's correction is available at Harvey et al. (2016)

[51] Note that also in this case, the original paper takes the opposite approach inflaming the level of significant (alpha). The test is rejected if it accomplishes the following inequality: $P_b > \frac{\propto_w}{M+1-b}$. Although different in computation, they lead to the same result.

[52] A more exhaustive description of the Holm's correction is available at Harvey et al. (2016)

[53] To be coherent with the two previous methods I test basing on the new p-value (P_i^{BHY}) but the outcome is exactly the same as controlling the old p-value with the new level of significance.

$$P_i^{BHY} = \begin{cases} P_m & if \quad i = M \\ \min[\, P_{(i+1)}^{BHY}, \dfrac{M \times c(M)}{i} p_i \,] & if \quad i \leq M-1 \end{cases}$$

In this case, c(M) is a function that control the generality of the tests and it depends by the total number of tests performed. It can assume various specification but, in this study, it will be defined as:

$$c(\mathrm{M}) = \sum_{j=1}^{M} \frac{1}{j}$$

the choice of c(M) can influence the rate of discovery, which will decrease if the value of the function increases. The choice for this study follows the approach of Harvey et al (2016). The current specification of c(M) makes it valid under any form of dependence between the p-value. In a different situation, where all the tests are independent, a value of c(M) = 1 could have been assumed[54]

d. Wilson Adjustment

Initially created for genetic determinants of disease in genome-wide association studies, the Wilson correction can control for the Familywise error rate in dependent tests using the generalized central limit theorem.[55] The goal of the method is to derive the null distribution for the mean maximized likelihood ratio using a classical equivalent to the model-average Bayes factor.

The indication of the formula in the paper is slightly different, here it is reported a simplified[56] version:

$$P_i^{Wilson} = \min\left[\frac{n}{\sum_{i=1}^{n} 1/p_i}, 1\right]$$

Unlike Bonferroni, which is typically defined as too stringent when the number of tests grows, The HMP allows for tight control of the FWER while avoiding both simulation studies and overly strict Bonferroni correction. This benefit grows when tests are non-independent. It performs tests not on the single p-value but a group, investigating their joint statistical significance. It is similar to Fisher's method[57] but does not require independency among tests. Wilson Harmonic mean p-value has two

[54] A more exhaustive description of the procedure is available in Harvey et al (2016) paper

[55] For further details, please consult the original paper from Wilson (2018)

[56] Simplified in term of readability. The output of the formula is the same as the one indicated in the original study.

[57] Fisher, R. A. (1992).

interpretations: (i) direct reading as an approximation of the true p-value (ii) a method to transform it into an asymptotically exact p-value. This study uses the first approach.

e. Discussion on the p-value correction method

Although the previous methods fit this research, they were initially designed to be applied in different fields than Economics and Finance, environments where the number of tests is way above the amount studied here. To this extent, a deeper analysis of the weakness and the strength of each correction could clarify which is the one that could better satisfy our purpose. In general, when the number of tests increases (and vice versa), FWER is less preferred since it controls for even one false discovery happening among the entire sample. A common standard to define a "large sample" still needs to be found. Additional remarks should address the dependency structure of tests. Although both HMP and BHY are proved to be persistent in correlation among statistics, Bonferroni and Holm need further specification. They could lack discovery power when there is dependence on tests. The definition of a dependent structure could undoubtedly improve this analysis. Unfortunately, this goes beyond the purpose of the study.

Empirical Results

As indicated above, every month (week), we sort the commodities (cryptocurrencies) into three portfolios[58] according to the studied factor. The return of the 3–1 portfolio is calculated as the difference between the return of portfolio 3 (greatest exposure on the factor) and portfolio 1 (lowest exposure on the factor). The net investment of the strategy is zero. Most of the findings follow the previous literature and represent additional proof of their persistence over time. Moreover, this is one of the few related studies that captured the commodity price shocks after the Covid-19 pandemic and the Ukraine war.

I. Commodity Future Strategies

Following the approach by Hollstein et al. (2021), this research is based on the most conservative position, employing fully collateralized futures holdings. To this extent, the return of the 3–1 portfolio is specified as:

$$R_i = \frac{1}{2} * (R_3) - \frac{1}{2} * (R_1)$$

Where R_i is the return of the strategy *i*, while R_3 and R_1 are the returns of Portfolio 3 and Portfolio 1, respectively. The remaining 50% of the investment earns the risk-free rate and acts as collateral. The results for such strategies are reported in the following sections, divided by the asset class. Table 7A[59] reports the portfolios' mean return.

3- and 5-Year Reversal: The strategy that sells the commodities with the poorest 36-month (60-month) performance and buys the commodities with the best 36-month (60-month) performance yield a negative mean return of -7.19% p.a. (-7.96% p.a.). Both horizons are significant at the 5% level.

This finding is inconsistent with Hollstein et al. (2021), that found a positive mean return of 2.36% p.a. (2.26%). However, there is a vast literature that documents the long-term reversal across markets. De Bondt & Thaler (1985) obtained a negative mean return of -25% for a 3-year holding period, Antoniou et al. (2003) documented positive profits for contrarian strategies in the London stock exchange, and Zaremba et al. (2021) studied the long-run reversal effect from 1265 to 2017 in commodity returns. They found robust negative results, also across subsamples and subperiods.

Betting-Against-Beta: Forming a portfolio according to the commodity historical market beta yields an insignificant mean return of 0.38% p.a. This factor seems not to be priced in the cross-sectional return of the commodity futures market. This result partially agrees with Baltussen et al. (2021), who

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[58] If not for isolated cases in which not enough commodities/crypto were available to calculate the factor, the portfolio is divided into three categories: the bottom 10%, the central 80%, and the top 10% (10(80)100)
[59] Note that the Table reports monthly results while the value here is indicated as annualized.

found a weakly significant positive Sharpe ratio for the BAB factor in the commodity market. However, when the analysis was expanded to the whole selection (1800-2016), the latter turned out to be insignificant.

Carry: A zero-investment portfolio generated by the difference between a contango, and a back-warded portfolio generates a mean significant return of -6.13%. This result is consistent with Bakshi et al. (2019), which reported a positive mean return of 16.85% p.a. Note that to be coherent in the analysis, this study performs the portfolio as P3 – P1 while the original paper takes an opposite approach (P1-P4). Note that, although results are lower in terms of mean return, they also present a significant lower standard deviation (9,51% p.a. against the 23,08 p.a. scored by the original paper).

As discussed later, the Carry factor – which incorporates the slope of the future curve – takes part in the BGT model and is crucial to explaining the cross-sectional factor returns.

Kurtosis: The portfolio of commodities constructed on their Historical Kurtosis reports a weakly significant mean return of 4.09% p.a. The result agrees with Fernandez-Perez et al. (2018) and Amaya et al. (2015). They find significant positive results for commodity and equity.

Kurtosis has been to be also proved by Hollstein et al. (2021). In their analysis, the alpha was significant in 3 out of 7 cases after performing a multiple-testing threshold. It seems that investors price this risk in the commodity market.

Long Ratio: Sorting commodities according to their average hedging pressure, taking a long (short) position in those with the highest (lowest) value yield a significant negative mean return of -3.62% p.a. This result is consistent with Basu and Miffre (2013). They slightly differentiate the analysis sampling the commodities by different ranking and holding periods. However, averaging their results over the analyses, they reached a significant positive mean return of 5.63%.

As for the *Carry* case, the original study took a Low-High approach; this work takes the opposite for consistency with the methodology. The mean return is significant at the 5% level, and, as discussed later, all the tested alphas are at least weakly significant.[60] It looks that commodities with the lowest average hedgers' hedging pressure overperform the commodities with the highest one.

Liquidity: Forming a zero-investment portfolio sorting according to the Danyliv et al. (2014) liquidity measure yields a yearly negative insignificant mean return of -2.02%. This result goes along with Hollstein et al. (2021) but in contrast with Szymanowska et al. (2014). The latter found a significant negative return of -9.40% using a different sample (1986-2010).

[60] At 10% level for BGR alpha and F&F 5-Factors model, while at 5% for F&F 3-Factors model, CAPM and Commodity CAPM

Interestingly, performing the same analysis for that period delivers a -5.05% mean return which is significant at the 10% level[61]. After further subsamples analyses, this factor's validity appears sensible to the timespan and how liquidity is calculated. Intuitively, the level of trading in commodity futures markets has remarkably increased over the last 20 years, and the risk linked to liquidity, also considering the prevalence of institutional investors, could have disappeared[62]

Max Price (Commodity): The long-short strategy based on sorting the commodities by the maximum price of the past month delivers a weakly significant negative mean return of -3.64% p.a. The result appears to be significant only at the 10% level, and the alpha is explained by both the equity market return and the commodity one.

Consulting the literature, it seems that nobody has tested this anomaly for the commodity market before, primarily considering that the usual MAX Measure – Firstly implemented by Bali et al. (2011) - involves the returns and not the price itself. No comparison with past literature can be made in this case.

Max Return (Commodity): Going long a portfolio with the highest return during the previous 12 months, and going short a portfolio with the lowest one, yields a significant negative mean return of -5,71% p.a.

Bali et al. (2011) found a similar result for the equity market with a negative but significant return. On the contrary, in a working paper presented by Hollstein et al. (2021), the Max measure is not priced in the cross-sectional commodity market but in the equity one. They give as possible explanation the overweighted bias of investors that creates the Max anomaly in the equity market, but not in the Commodity one.

Momentum: Following the past 1-year return, going long on commodities that best performed and short on those that did worst yields a positive significant mean return of 10.85% p.a. The result is in line but substantially higher than Hollstein et al. (2021) and Gorton et al. (2013), which documented respectively 7.44% p.a. and 5,97% p.a.

The magnitude of these results appears to be different. An explanation takes place in Moskowitz et al. (2012) that documented the momentum smile. Considering that Hollstein's paper restricts its sample up to December 2015, it could not capture the 2020 crisis and mainly the 2022 commodity price surge. The latter events have increased the variability and, according to Moskowitz's paper, the return too.

[61] This is an unreported analysis

[62] According to Barclays Capital, the level of investment in commodities by institutional investors increased from $18 billion in 2003 to $250billion in 2010. They run a survey of over 250 institutional investors.

Overreaction: The original paper studied two manifestations of the phenomenon: (i) the counter-reaction movements after an overreacted day differ from those after standard days (ii) Price movements following overreacted days in the direction of the overreaction vary from those following standard days. Since the paper reported unprofitable results from the first strategy, this study put only in place the "same-movement reaction effect." Going long (short) on those commodities that reported an abnormal positive (negative) return in a given month, delivers a weakly significant mean return of -0.61% p.a. Both the classical CAPM and the Commodity-CAPM can explain it. Although the initial study was performed in the cryptocurrency market, this result agrees with Caporale et al. (2019), that documented a non-significant mean return.

Size: Sorting the commodities according to the Fama&French Equity Size factor, taking a long (short) position in the sized commodities reports an insignificant mean return of -2.06%. There is vast literature on this risk factor. Fama&French (1993, 2015) found it to be significant and complementary to other well-known anomalies, such as value. Amel-Zadeh (2011) found a decisive momentum factor across size portfolios in the German Equity Market. On the contrary, Keim (1983) suggested that half of the "size return" is explained by the January effect for 1963-1979. As far as this analysis is concerned, it does not appear to be priced in the commodity one.

Standard Deviation of Dollar Volume: Going long a portfolio with the highest volume standard deviation on going short a portfolio with an opposite position delivers an insignificant mean return of -0.44% p.a. Similarly, in the case of *Max Price*, the literature spoke little about this anomaly in the commodity market. On the contrary, Chordia et al. (2001) studied this factor for equity, finding a negative mean excess return. Their result is not affected after the F&F factors adjustments.

It is worth mentioning that Chordia's analysis took place almost 20 years ago. Repeating the tests for the subsample 1980-2000, turns the factor be significant at the 10% level. Additional tests with older horizons could be performed to check whether the strategy has lost magnitude over time.

Seasonality Effects: This research studies different seasonality and fixed effects that proved significant in the commodity market to past literature. These are *Week-of-the-Year, Christmas,* and *January.*

January effect: Controlling for the cross-sectional January effect in the commodity market report an insignificant positive return of 0.25% p.a. This result does not agree with Qadan et al. (2019), which reported a general positive significance yield for the January effect.

Christmas Effect: Controlling for the cross-sectional Christmas effect in the commodity market report an insignificant negative return of 0,5% p.a. Also, in this case, the result does not agree with Qadan et al. (2019), which reported a general positive Christmas effect.

It is worth mentioning that for both factors, the sample considered by the paper is significantly smaller and includes a reduced number of years. In addition, Chang (1988) investigated the January effect in Commodity markets during different samples and, although significant from 1966 to 1971, its magnitude decreased over time, disappearing for the last two subsamples (1978-1981 and 1982-86).

Week-of-the-year: a significant positive effect of magnitude 1.60% p.a. is encountered for Week 51 of the year. This result agrees with Forgas (1995), for which investor mood can be attributed to the underlying mechanism capable of explaining part of the abnormal returns observed in the market. This outcome is based on the psychological theory that a boost in investor mood lowers risk aversion, allowing people to take on greater danger. To this extent, the week across Christmas is rational to believe that people will be in a better mood to respect the rest of the year, and therefore more prone to take risks.

Seas: Going long a portfolio in commodity futures with the highest average Seas[63] and short a portfolio in coins with the lowest average Seas yield an insignificant mean return of -0,2% p.a. Unlike previous anomalies, Seas is calculated on a daily base horizon and not with monthly returns. However, the portfolio is still rebalanced every month.

Besides Long et al. (2020), who tested this factor for the cryptocurrency market, no other literature reports the study for the commodity market.

Skewness: The portfolio constructed by sorting the commodities according to their Historical Skewness reports a significant negative return of -6.41% p.a. The result agrees with Fernandez-Perez et al. (2018) and Amaya et al. (2015), which found significant negative results for commodity and equity, respectively.

Although the return of Fernandez-Perez is lower (-8.01%), the Sharpe Ratios of the two strategies are almost the same, scoring a -0.80 for this study and -0.78 for Fernandez-Perez's paper.

Temperature anomaly: The distinction between the first temperature attempt and the second one is described in detail in the Appendix B. However, in simple terms, the first attempt follows a study from Taskin et al. (2021) who discovered that the temperature anomaly series could predict future price indexes. On the contrary, the second attempt interest a study published by the European Environment Agency that highlights which commodities are majorly exposed to climate change and which are less. The idea is that if specific goods risk being less producible in the future because of the effects of climate change, this should be reflected in their price. Which commodities take part in each group is explained in Appendix C.

Temperature 1: Controlling for the fixed effect of industrial and precious metal commodities yields a non-significant positive return of 0,019% p.a. Since the timespan started in 1980, it is rational to believe

[63] Average same-weekday return

that climate change impact was not widely considered a risk at that time. However, replicating the study for a shorter interval, starting from 2015[64], reports a non-significant mean return of 1,18% p.a. Even in this case, no fixed effect can be linked to those futures.

Temperature 2: Controlling for the fixed effect linked to those agriculture commodities that, according to the report aired by the European Environment Agency, will be more affected by climate change, delivers a monthly significant mean return of -6.03% p.a. This result does not align with the previous hypothesis since it looks like more at-risk commodities yield a lower return. In this regard, a paper published by Makkonen et al. (2021) discovered a significant positive (negative) impact between temperature anomaly and soybean, corn, and cocoa (soybean, corn, cotton, and coffee). They used a quantile regression approach.

A further and more specific investigation could better explain this fixed effect. The same analysis for 2015-2022 is run as in the previous case. Although the magnitude of the effect increases (9.3% p.a.), the value is now only significant at the 10% level.

Value: The strategy that goes long (short) on a portfolio with the highest (lowest) magnitude in the value factor yields an insignificant positive return of 1.38% p.a. It looks like the commodity cross-sectional return does not price the value factor. This result is consistent with Hollstein et al. (2021), which found an insignificant mean return of 0.44% p.a.; however, both do not agree with Asness et al. (2013), which found a significant positive return of 6.3% for a non-collateralized portfolio position.

[64] This is the year the Paris Climate Change Agreement entered into force.

II. Cryptocurrency Strategies

As far as the cryptocurrencies are concerned, Table 8A reports the portfolios' mean returns. Most findings follow the previous literature and represent additional proof of their persistence over time. In the cryptocurrency case, though, the number of existing investigations is sensibly smaller, and this thesis can participate in the expanding world of analyses regarding this disruptive asset class.

1-2-3-4 Weeks Momentum: Sorting commodities on their past 1-2-3-4 Weeks return, going long on coins that best performed and going short on coins that did worst, yield a positive significant mean return for all different horizons. *1-* and *4-week Momentum* appears to be the least significant (only at 10%), returning 0.88% and 0.78% p.w., respectively. *2-Week Momentum* yields a positive mean return of 0.9% p.w and emerges significant at the 5% level. Lastly, *3-Week Momentum* is the strongest, with a mean weekly return of 1.67%.

These results agree with Liu et al. (2019). They found the highest and most significant returns for *2-* and *3-weeks Momentum*. Yang (2019) also found similar results in terms of sign and significance; however, the magnitude is considerably different since he used daily rebalancing in his analysis. It is possible to agree that Momentum is robust across time and samples and has a significant positive return for short horizons. The strategy turned out to be insignificant for a timespan longer than four weeks.

Why this factor, although simple to compute, still exist across different asset class is a reason for studying. De Long, Shleifer, Summers, and Waldmann (1990a) proposed an explanation based on the noise trader risk. In their model, overconfident noise investors move the price and generate a considerable amount of risk. Therefore, fundamental traders and Arbitrageurs are reluctant to enter the market and let the mispricing persist. This theory looks even more believable for Cryptos than other asset classes, considering the prevalence of retail investors operating in the market.

2- 6- 18-Months Reversal: A portfolio going long the coins with the best 2- 6- 18- Months past performance and going short the coins with the worst one generates varied but always insignificant results.

The *2-* and *18-Months reversal* yield a weekly mean return of 0.9% and 0.005%, respectively. On the contrary *6-Month reversal* render a weekly mean return of -0.2%. These results agree with Yang (2019), that found insignificant results for the short-term reversal at monthly frequency. On the contrary, Dong (2022) discovered significant positive results when analyzing mean return only. The author also points out that the market factor alone could explain the result.

In addition, Dong (2022) replicated the analysis in a market-reduced liquidity environment. Although this used to increase the power of several anomalies, it does not happen for short-term reversal that turns insignificant. Unlike the equity market, where short-term price reversal has been widely proved (Jegadeesh & Titman (1990)), it seems not to be priced in the cryptocurrency cross-sectional return.

Betting-Against-Beta: Forming a portfolio according to the coins' historical market beta yield an insignificant mean return of 0.22% p.w. Although with an opposite sign, Yang (2019) reports little results for this factor. *Betting-Against-Beta* seems not to be priced in the cross-sectional return of the cryptocurrency market.

Google Trend: Going long (short) a portfolio with the highest (lowest) google popularity value at Month t-2 yield a significant monthly mean return of -9.67%.

To the best of my knowledge, nobody applied such a measure to the cryptocurrency market before, and to any other asset class. The Google Trend index should be a proxy to estimate each coin's sentiment. Barberis et al. (1998) proposed a model to calculate investor sentiment and how its impact leads market agents to over-and under-react to certain news. The Google Trend values serves as a simplified proxy for it. Considering that most of the coins in the analysis were born no more than 2/3 years ago, an increase in their popularity is likely associated with positive news that attracted investor attention. The more investors, the higher the gain, creating a short-term loop of newly attracted buyers and returns. To this extent, papers such as De Bondt et al. (1989) and Piccoli et al. (2017) documented systematic price reversal for stocks with large long-term profits/losses and how investor sentiment drives individual stock prices to severe market fluctuations. Their discoveries showed how people overreact to positive news, creating a long reversal effect in asset prices.

When a coin is particularly sought on Google, the number of investors willing to buy it increases remarkably. However, once the dust has settled, investors either concretize their gain or decide to leave the market. Together they make the price fall. Further analyses were also performed with different look-back periods; for 1 and 3 months the strategy remained significant at 1%.

Kurtosis: The portfolio constructed according to the coins' Historical Kurtosis reports a positive insignificant mean return of 0.48% p.w. Even in this case, the result agrees with Liu (2019), that found a weekly negligible mean return of 0.6%.

Kurtosis has been proved to be priced across different markets (Fernandez-perez et al. (2017) for the commodity and Amaya et al. (2015) for the equity); however, it seems not to be the same in the cryptocurrency cross-sectional return.

Idiosyncratic Volatility (Res): The long-short strategy based on sorting the coins by their idiosyncratic Volatility yields an insignificant negative mean return of -0.15% p.w.

This result does not agree with Yang (2019) and Dong (2022), which report positive and significant returns. However, Yang also reports that the strategy effect decreases (to insignificant) for the subsample 2016-2017, and its alpha is statistically equal to 0 when regressed on market return and a size factor. Unfortunately, Dong does not provide such metrics. *Idiosyncratic Volatility* was also found to be insignificant for commodities by Hollstein et al. (2021), in contrast with what Ang et al. (2006b) discovered for the equity market.

Liquidity: Forming a zero-investment portfolio sorting according to the Danyliv et al. (2014) liquidity measure yields a negative significant mean return of -2.68% p.w. Literature has always focused on testing this anomaly using Amihud (2002) measure and rarely on the cryptocurrency market. In this regard, Liu (2019) found an insignificant positive mean return of 2.6% p.w. applying Amihud's measure.

The latter criterion was designed to control the equity market and might not be appropriate for such a volatile and unpredictable assets such as cryptocurrencies[65]. On the contrary, Danyliv's measure was instead theorized to calculate what liquidity could mean from a trader's perspective and could be a better fit for this environment.

Max Price (Cryptocurrency): The long-short strategy based on sorting the coins by the maximum price of the past 26 weeks delivers a significant negative mean return of -2.4% p.w. This result agrees with Liu (2019), which found a significant negative mean of -4.1% p.w. Even though the magnitude of the factor appears to be lower, the Max anomaly is significant at the 1% level, while in Liu's paper is only significant at 5%.

Max Return (Cryptocurrency): Going long a portfolio with the highest return during the previous 26 weeks, and going short a portfolio with the lowest one, yield an insignificant mean return of -0.45% p.w. At first sight, this result seems in contrast with Yang (2019), which found, with daily rebalancing, a positive significant mean return. However, the author's sample starts in January 2009 up to July 2018, and the effect becomes weaker and insignificant for the subsample 2017-2018. It could be the case that the magnitude of this anomaly decreased over time and was too feeble for the period (2015-2022) analyzed in this work.

Overreaction: As for the commodity case, it is only replicated the "same-movement reaction effect." Going long (short) on those coins that reported an abnormal positive (negative) return a specific week delivers an insignificant mean return of 0.37% p.w. This result agrees with Caporale et al. (2019), that report a non-significant mean return.

Price: The long-short strategy-based sorting the coins by the logarithm of the past week's price delivers a significant negative mean return of -2.34% p.w. This outcome is similar to Liu et al. (2019), which revealed a significant mean return of -3.9% p.w.

Even though it is persistent across studies, it presents a positive correlation equal to 0.95 with the Maximum Price factor. Unfortunately, Liu et al. (2019) do not report such a table, but I reckon the two factors are also highly connected in their results.

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[65] Table 9 reports the average standard deviation for both the commodity index[65] and a value-weighted index composed of Bitcoin and Ethereum. The calculation includes only these two coins since they account for almost 70% of the total cryptocurrency market capitalization. Data are provided by Coinmarketcap.com in data 06-10-2022.

Seas: Going long a portfolio in coins with the highest average Seas[66] and short a portfolio in coins with the lowest average Seas yield a significant mean return of -0,25% p.w. Unlike previous anomalies, Seas is calculated on a daily base horizon and not with weekly returns. The portfolio is still rebalanced every week. This result is in contrast with past literature. Indeed, although always significant, Long et al. (2020) reported a positive mean return of 0.31% per day for the equal-weighted portfolio.

Size (Market Cap): Sorting the cryptocurrencies according to their market capitalization, taking a long (short) position in the (less) sized coins, reports a significant mean return of -2,2% p.w. Yang (2019) reported a similar result in term of sing and significance, with a weekly mean magnitude of -3,4%. On the contrary, Dong (2022) found a positive but insignificant yield with daily rebalancing.

The result also gets along with what Banz (1981) found in the equity market for which smaller firms have, on average, higher risk-adjusted returns.

Skewness: The portfolio constructed by sorting the cryptocurrencies according to their Historical Skewness reports a positive insignificant mean return of 0.29% p.w. The result agrees with Liu (2019), that finds positive but insignificant results of 0.5% p.w.

Skewness has been proved to be priced across different markets (Fernandez-perez et al. (2017) for the commodity market and Amaya et al. (2015) for the equity market); however, it seems not to be the same in the cryptocurrency cross-sectional return.

Standard Deviation of Dollar Volume: Going long a portfolio with the highest volume standard deviation and going short a portfolio with an opposite characteristic delivers a significant mean return of -2.43% p.w.

Dong (2022) report a significant mean monthly return of -27.35%, while Liu et al. (2019) report a weekly significant mean return of -3%. This factor appears to be priced in the cryptocurrency cross-section return. More interestingly, as it will be explained later in detail, this anomaly cannot be explained by any of the selected factor models.[67]

Transaction volume: The portfolio constructed by sorting the cryptocurrencies according to the daily number of transactions reports a negative significant mean return of – 1.8% p.w. The number of daily transactions can be seen as a measure of liquidity for each coin. To this extent, the least liquid coins have, on average, a higher return.

Since both Dong (2022) and Yang (2019) study a factor linked to the volume traded, concluding in a negative significant mean result, it could be argued that the transaction volume is just a proxy for the volume level of each coin. However, regressing token's volume on number of transactions (and vice versa) reports an R^2 of just 1.04%. The two metrics are also feebly correlated (0.1018).

[66] Average same-weekday return
[67] Capm, Fama&French 3- and 5- Factor models, Cryptocurrency-CAPM, Cryptocurrency 3-factor model.

III. Cross-sectional asset return

The following chapter explores whether a few factors explain cryptocurrency and commodities' cross-sectional returns, investigating whether the strategies' alpha remains significant. Consult Table 7B and Table 8B for a complete overview of the results.

The study initially implements the most well-known models used to explain the cross-sectional equity returns; these are: (i) one-factor model with the equity market return. (ii) Fama&French 3-Factor model. Additionally to the market factor, it includes *Size* and *Value* (iii) the Fama&French 5-Factor model, which encloses Profitability and Investment. Newey & West (1987) robust standard errors are calculated to correct for heteroskedasticity. As it will be explained more in detail during this chapter, these models struggle to explain the cross-sectional returns since they were born to describe equity market anomalies. To this extent, the paper serves two additional "personalized" models for each asset class.

Equity CAPM:

Regressing the portfolios on the equity market returns delivers poor results for both the cryptocurrency and the commodity market. As expected, there is little predictor power in equity indexes. More specifically, only *1-week, 4-weeks momentum,* and *Overreaction*'s alphas turned insignificant for the cryptocurrency market (the strategies' mean returns were, however, only significant at a 10% level). MAXP for commodities had the same fate, and MAXR alpha is now significant at 10% and not at 5%. All the other values remained significant.

3- and 5-Factor Model:

Results do not change remarkably from the one-factor model. Indeed, besides MAXR that turned insignificant with both 3- and 5- factor models, no other alpha turned out to be insignificant for commodities. it looks like the efficiency of Fama & French's models is reduced with commodity and cryptocurrency.

These results generally agree with Hollstein et al. (2021). They tested several anomalies in the commodity market, and both 3- and 5- Factor models performed poorly across factors. As far as cryptocurrencies are concerned, the outcome is close to Liu et al. (2019), which found that these models cannot account for the cross-sectional returns in the market. In addition, all the factors' signs remain unchanged after the regressions; hence the average return always goes in the same direction as their alphas.

The little results discovered incentivized new factor model approaches, more specific for the assets themselves. To this extent, this research implemented three additional investigations: (i) A one-factor model with specific-market returns for both assets. As far as commodities are concerned, the latter is represented by the Bloomberg Commodity Index. The fund contains 23 commodity futures indices spread between six sectors. Similarly, the Bloomberg Galaxy Crypto Index[68] serves as such for cryptocurrency. The latter is a value-weighted benchmark created to evaluate the performance over time of the most sized coins traded in USD. (ii) BGR-model, proposed by Bakshi et al. (2019) for commodities. They argued that a model of just three factors could have explained the cross-sectional commodity returns. One that captures the average excess return in the market (AVG), one that captures the slope of the futures curve (CARRY), and one that captures the Momentum effect (CMOM). The names come on behalf of the creators of this model[69]. (iii) ASM-model, the three-factor approach suggested by Liu et al. (2019) for cryptocurrency. It is composed of a cryptocurrency market factor (CAVG), a cryptocurrency size factor (CSIZE)[70], and a cryptocurrency momentum factor (CMOM). Considering that the correlation among 1-,2-,3-, and 4- weeks *momentum* is elevated[71], only the *3-weeks momentum* is used as an explanatory factor since the most significant. Liu et al. (2019) do not adequately name this model; for simplicity, it will be called ASM[72]. Results are shown in Table 7B (For Commodity Futures Regressions) and Table 8B (for Cryptocurrency Regressions).

One-Factor model with specific market return:

Explaining the factors' alphas with the specific market return does not provide remarkably better results. Specifically, the only added explanatory power in the MKT factor since it appears to be significant only at the 5% level and not at 1%[73].

[68] The Bloomberg Galaxy Crypto Index (BGCI) contains, in order of relevance: BTC, ETH, ADA, SOL, AVAX, DOT, MATIC, ATOM, LTC, LINK, UNI, and BCH. Data updated in June 2022.

[69] It was initially theorized by Bhardwaj, Gorton and Rouwenhorst (2014). However, they had not adequately tested the model but instead stated it could capture trading patterns in the commodity market. Bakshi, Gao Bakshi, and Rossi (2014) have also proposed an approximately identical model. The "BGR" name can then refer to both working papers.

[70] It differs from the market cap factor since, in this case, the long leg of the portfolio represents 30% of the smallest coin while the short leg represents 30% of the biggest ones. The MKT factor was using a 10%-10% approach,

[71] Check Table 11 in the Graph-Table section

[72] ASM stands for *Average, Size, Momentum*

[73] All other alphas turned insignificant with the equity market factor are also explained by this model.

3-Factor Model for Commodity:

A model that incorporates the commodity futures' market return, the slope of the futures curve, and a *momentum* factor largely increases the results. Specifically, it can explain the abnormal returns for *Kurtosis*, *3*- and *5- Years Reversal*, *Overreaction*, *Maximum Price*, *and Maximum Return*[74].

Only two factors – *Skewness* and *Long-Ratio* - remain significant after this control, each at a 5% level. The Skewness result does not agree with Hollstein et al. (2021), where, although resistant to all equity factor models, it appears to be explained by the BGR model. As far as Long-Ratio is concerned, the original paper from Basu et al. (2013) does not provide results for Fama & French or BGR regressions. Although additional studies could be performed, in light of the evidence, it appears to be priced in the cross-sectional commodity return. Additional improvement effects are on the R^2. The average variability explained by the 5-Factor model is around 1%, while the BGR explains around 8% of the cross-sectional return.

3-Factor Model for Cryptocurrency:

A model incorporating the coins' market return, the coin size, and a *momentum* factor increases the results extensively. In addition to the previous models, the ASM allows explaining *Price*, *Maximum Price*, and *Market Capitalization*.[75] The Cross-sectional return appears to price *Liquidity*, *Transaction Volume*, *Google Trend*, *Standard Deviation of Dollar Volume* (STD), and *Seas*. Although *Liquidity* and *Transaction Volume* are highly correlated and might capture the same effect, this is not entirely the case. The correlation among the two factors is equal to 0.62, which is high but notably lower than *Liquidity* and STD, which is equal to 0.84.

Including the liquidity factor in the model increases its explanatory power. *Transaction Volume* and STD alphas are insignificant with this 4-factor model[76]. On the contrary, *Google Trend* and *Seas* still appear significant[77]. To this extent, the factor could be added when explaining the variables premia in the market. This hypothesis also agrees with Dong (2022). They studied that the liquidity funding (modeled with the federal fund rate[78]) in the market is negatively correlated with the liquidity of the

[74] Note that those mean returns that turned out insignificant in the first place are excluded from this list and explained by this model. Moreover, Temperature and Seasonality's effects are also not considered. Similarly, Momentum and Carry are also kept out since they are part of the explanatory variable. However, their returns cannot be explained using a two-factor model (AVG + MOM to explain CARRY and AVG + CARRY to explain MOM). The analysis is unreported

[75] As in the commodity case, those alphas that the previous model explained are excluded by this list. They are explained by this model too.

[76] Please check Appendix A for the results

[77] Check Appendix D for the results

[78] Reporting the definition of bankrate.com: "*The interest rate at which banks and other depository institutions lend money to each other, usually on an overnight basis. The law requires banks to keep a certain percentage of their customer's money on reserve, where the banks earn no interest on it. Consequently, banks try to stay as close to the reserve limit as possible without going under it, lending money back and forth to maintain the proper level*"

assets, and 13 out of the 14 analyzed anomalies increase their magnitude in a period of low liquidity. The R^2 value is vastly improved here too. The F&F 5-Factor model justifies around 2%, while the ASM has an average explanation of 17,5%.

IV. Controls on Factor significance

One of the original values of this study is to investigate whether the significance of the factors is resistant to P-Value adjustments. In the methodology section, there is a detailed explanation of how they are implemented. Since the correction output depends on the number of tests performed, this study selects an equal number of factors[79] , namely 21 each. Moreover, an investigation is repeated, considering all the anomalies together (42 in total) to better compare asset classes.

Table 11 displays the outcomes of the mixed correction, while Table 12 and Table 13 describe the single analyses. Lastly, Table 14 shows the percentage of strategies that remained significant after the control compared with the initial p-value threshold.

Bonferroni and Holm:

Bonferroni is generally considered too stringent by literature – precisely when the number of tests is elevated - and several times, it induces the non-rejection of hypotheses that similar adjustment would not. When considering the Commodity Future market, only *Momentum*, *Carry*, and *Week-of-the-Year* remains significant at 10% after the adjustment[80], while only *Carry* is resistant at a 1% significance level. In the Cryptocurrency market, the situation is a bit different. Although the pre-adjustment number of significant factors is close to the commodity case, cryptocurrencies show greater and more resistant magnitudes. At the 1% level, four anomalies appear robust to Bonferroni. From a different point of view, 44% of pre-adjustment significant anomalies remained as such. For the Commodity Future market, they represent only 20%. The percentage is also higher for $\alpha = 0{,}05$ and $\alpha = 0{,}10$.

As far as Holm is concerned, the situation remains approximately the same, with only one more finding in the commodity market for $\alpha = 10\%$ and one additional for the cryptocurrency (both at $\alpha = 5\%$ and 10%). It could be shown that all the discoveries that happened under Bonferroni appear under Holm too, while the opposite is not valid. The difference increases if the number of tests grows, and in our case (21 for the single analysis and 42 for the combined one) is not that evident.

Studying all the anomalies together generally decrease the number of findings (because of the increased number of tests). For each asset, Table 15 displays the number before and after the correction. The effect seems homogeneous among the significance levels and more pronounced when $\alpha = 0.05$.

[79] For example, the Week-Of-The-Year effect involves 52 tests; however, only the most significant one is included

[80] These are also significant at the 5% level.

BHY:

BHY is considered the least invasive adjustment and usually leads to the highest number of discoveries. It controls for the False Discovery Rate (FDR) and not the Family-wise Error Rate (FWER). Under BHY, for the commodity market, the study discovers nine significant factors at the 10% level but only two at 1%. *Carry*, and *Momentum* are the isolated cases robust enough to resist such a threshold. Conversely, cryptocurrencies are less affected. Almost 90% of the factors remained significant at 1% after the correction. The number of discoveries is double compared to the precedent adjustments. At the 10% and 5% levels, BHY's findings are similar to Bonferroni and Holm.

Wilson:

Although three correction above perform well when the analyzed tests are independent, they can fall short when the considered hypotheses are not self–reliant. We can solve the problem using the Wilson criteria, which differ slightly in terms of logic and mathematics. It investigates if at least one of the tested hypotheses has a significant outcome and if any null hypotheses should be rejected. The harmonic mean p-value indicates that at alpha percent, we have no cause to reject any of the null hypotheses at alpha percent; hence we have no significant results in our p-value selection. This value is equal to 0.00154 and 0.00015 for Commodity and Cryptocurrency, respectively. To this extent, we can state that at least one of the tests is significantly different from 0 and should therefore be rejected. For the combined study, the Harmonic P-value is equal to 0,0002778. Even in this case, the same conclusion can be drawn.

It might be argued that this analysis falls apart since some factors have been proved significant by several studies and then should undoubtedly be considered as such. The conclusion that at least one factor is statistically significant adds nothing to the previous literature. Therefore, the test is repeated, not including those factors that took part in both the BGR and the ASM models as well as those that remained significant at a 1% level after Bonferroni Adjustment.[81] Table 16 shows the results. It reveals that at least one test is significant for the cryptocurrency and the combined sample with an $\alpha = 0.01$. The same conclusion can be reached for the commodity with a 5% confidence level.

[81] Google Trend, Liquidity, Standard Deviation of the Dollar Volume and Transaction Volume.

V. *Final Discussion on Market Efficiency:*

The literature on asset' expected returns has changed dramatically over time. From the first CAPM studies[82] - whose purpose was to explain the whole expected return - to hundreds of papers that evidenced factors that can, although partially, explain the cross-sectional return. The documented factors can be divided into risk-based and behavioral-based. The formers suggest that abnormal returns exist because investors hold financial risks that cannot be captured by the market factor.[83] On the contrary, behavioral-based anomalies arise from biases in investor psychology.

Risk-based factors can still go along with the efficient market hypothesis, for which markets leave no space for riskless rewarded positions. In fact, in an entirely rational and efficient scenario, all the excess return is derived from a risk that the market, as efficient, is pricing. The situation is more complicated for behavioral anomalies. Latif et al. (2011) state that efficient markets struggle to explain behavioral-linked anomalies observed across asset returns.[84]

The study shows that several factors look priced in the cryptocurrency and commodity cross-section returns. They classify one asset more as prone to risk-based and one as more prone to behavioral-based anomalies. After the BHY p-value correction[85], at a 5% significance level, *Momentum*, *Skewness, Carry, Week-of-the-Year, and Reversal5Y,* are still significant for commodity. On the other side, results suggest that the strategies of *3-weeks Momentum*, *MarketCapitalization*, *MaxPrice*, *Price*, *Standard Deviation of Dollar Volume, Seas, Google Trend, Liquidity,* and *Transaction Volume* produce significant returns for cryptocurrency.

Skewness and *Carry* represent a rewarded risk for the investors. The first anomaly incorporates people's preference to have positively skewed returns (Bali et al. (2017a)) and the second one incorporates the risk embedded in the futures curve. Pre-adjusted p-values for *Kurtosis* and *LongRatio* are also statistically different from zero. *Momentum*, (*Max*) *Price*, *Seas, and Google Trend* do not incorporate any risk; existent behavioral biases can instead explain them. (*Max*) *Price* can probably be linked to the reviewed concept of anchoring (Tversky and Kahneman (1974)) and people's tendency to overweight the probability of events ((Barberis & Huang, 2008)). *Google Trend* and *3-Weeks Momentum* seems to explain in the Overreaction bias and the investors' sentiment.[86] *Seas* finds its motivation in sentiment (Hirshleifer, Jiang, and Meng 2020)) and trading patterns within a population (Bogousslavsky (2016))[87].

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[82] The model was independently introduced by Treynor (1961) and Sharpe (1964) following a working paper by Markowitz (1952) on portfolio optimization and diversification.
[83] A simple example is provided by Fama & French (1993) with size and value factors. The first factor prices the illiquidity risk of small companies, while the second factor states that value stocks yield higher returns than growth stocks.
[84] simple examples are Momentum anomaly and market overreaction.
[85] Here, it is considered the adjustment made on the two samples singularly and not the combined sample.
[86] Check the anomaly in the result section for a more detailed explanation.
[87] These two papers are part of the motivation that Long et al. (2020) gave for the existence of the Seasonality effect in the cross-sectional return of cryptocurrency.

Besides *MarketCapitalization*, which could be linked to the Fama & French Size-Factor, risk-based anomalies are entirely connected to liquidity and volatility (STD, LIQ, TRV). Considering the record share of retail investors operating in the cryptocurrency market, it is rational to believe that they will require a return for baring volatility[88] and a return for the uncertainty surrounding coins liquidity. Even before adjusting the p-values, risk-based factors such as *Skewness*, *Kurtosis*, or *Betting-Against-Beta*, turned out to be insignificant. It could be said that institutional investors, through their better understanding of the market, tend to make behavioral anomalies disappear and rationally price risk-based ones (Such as *Skewness*, *Kurtosis*). Coherently, behavioral biases are more pronounced in Cryptocurrency, where most investors are retail, and short-selling constraints decrease arbitrageurs' power. As mentioned before, the only risk-based strategies that still work in the crypto market are those that can easily be computed by people.

Two knots remain to untie, namely *Momentum* and *Reversal*. Considering that there is no risk embedded in past return, the existence of people's irrationality the force that drives their existence. Brunnermeier et al. (2004) found that hedge funds heavily invested in technology stocks during the dot.com bubble, although aware of it, and they also reduced some positions right before the stock's downfall. Similarly, Cremers & Pareek (2009) proved that equities with a higher proportion of short-term institutional investors have more pronounced *Momentum* and *Reversal* returns. They lie, knowing they are lying. From what arose from the subsample analysis on cryptocurrency, the entrance of institutional (and theoretically well-informed) investors into the market did not lower the magnitude of the tested anomalies.

What can be concluded from it? Financial institutions represent the most knowledgeable form of investor is out of the discussion, but this does not mean they will act in favor of people's wellbeing. Their power in the cryptocurrency market is still limited, allowing (and exploiting) several behavioral-based anomalies to persist across samples and periods. However, with Commodity Futures, the situation changes. Risk-based factors dominate the scene,[89] leaving little room for behavioral ones. The only survivals are those that majorly benefit institutional investors[90].

Conversely, retail agents are exposed every day to several signals and have little capacity to process them all. For example, Miller (1956) proved that, as human beings, we could only operate 7 ± 2 information simultaneously. To put this in perspective, the average number of tweets per hour containing Bitcoin is approximately 12.000.[91] Because of that, retail's investment decisions are based

[88] Note that, according to table 9, the standard deviation of returns is significantly higher in the cryptocurrency market than in the commodity one.
[89] Note that Jump Risk and Volatility-of-Volatility are also priced in the commodity cross-sectional return. For the reasons stated in the "*Relevance of the subject*" section, this study does not replicate them; however, they represent additional proof of risk-based anomaly in the market.
[90] Momentum and Reversal
[91] Data updated on 06/16/2022 from Tweetbinder.com

on easily readable and accessible information, such as past prices, market capitalization, but also level of volatility and liquidity.

Conclusion and Discussion

This paper studied which market anomalies remain significant after p-value adjustments for the Commodity and Cryptocurrency market, analyzing the characteristics that emphasize risk- or behavioral-based factors. Using more than 30 of the most traded Commodity Futures and more than 80 of the sized coins in the market, 21 strategies have been performed for both assets. The majority of the strategies has been documented by past literature before, but some original contributions are presented. Approximately half of the tested strategies turned out to be significant at the 5% level; however, the Cryptocurrency cross-sectional return appears to be more resilient to the p-value corrections rather than Commodity Futures. Results do not significantly differ when considering subsamples. As expected, Bonferroni reports the lowest number of findings. However, thanks to Wilson's harmonic p-value calculation, we can state that at least one of the strategies has a return that is certainly different from zero. Results hold even when the most powerful strategies are excluded.

Commodity futures investors appear to price predominantly risk-based factors such as *Skewness, Carry,* and *Hedging Pressure (LongRatio)*. Conversely, Crypto investors let more space to behavioral-based strategies, with significant results for 2- and 3- *Weeks Momentum, Max Price, and Popularity*. The former market's agents also appear to price risks for which information is readily available, such as *Standard Deviation of Dollar Price* and *Liquidity*. The 1-, 3- and 5- Factor models generally perform poorly when explaining the returns of these strategies; however, excellent results are discovered when using a specific 3-factor model. In fact, only a few alphas remain unexplained. From a market-efficiency point of view, institutional investors and accessible short-selling appear to push behavioral mispricing away and preserve only rewards for risks. The exception is made for Trend-Following strategies such as *Momentum* and *Reversal*. In line with the previous literature, it appears that financial institutions try to increment and exploit over- and underreaction in the market to maximize their profit, making the trend following strategies one of the most robust. Retail investors and the implicit impossibility to short create a perfect environment for asset mispricing. The cryptocurrency market looks dominated by behavioral biases and only easily readable risks.

Even though the study presents various tests, there are several areas of improvements. Firstly, it excludes option-related factors for an easier comparison between the two markets, since such a contracts barely exist for Cryptocurrency. Examples are Volatility-of-Volatility or Jump Risk[92], found to be priced in the Commodity Futures cross-sectional return. If options are more common for cryptocurrencies in a couple of years, a study replicating and comparing both could be an added value for this research.

Moreover, this study mainly focuses on those strategies found to be significant by past literature, excluding those whose returns were not statistically different from zero. However, it is not rare that

[92] Studied by Baltussen et al. (2018) and Cremers et el. (2015), respectively

literature results are not aligned with each other. A project that investigates additional factors that exist but, in the past, appeared not to be priced, could be a critical value-added for this work. An additional improvement could be the consideration of transaction costs. Even though Hollstein et al. (2021) state that results are robust to their inclusion, this study does not consider them at all. A fair estimation could be made for Commodity Futures, but this would be hardly applicable for cryptocurrency. The presence of several centralized and decentralized exchanges makes it challenging to collect data and estimate the average expense that an investor could face. Lastly, an additional investigation could concern *Temperature anomaly* and *Popularity* (GT), which, to the best of my knowledge, are presented here for the first time. First, even though this study reports insignificant results, it is rational to believe that the market will start pricing the environmental change risk. The same analysis, replicated in 5 to 10 years, could give remarkably different results.

Moreover, because data is hardly findable, only the strategy based on the Granger Causality test could be performed. However, new and more innovative evaluation methods might better capture this effect, and who knows, maybe already find it significant. In this regard, further analysis embedding the evaluation approach proposed by Makkonen et al. (2021), analyzing more in specific each commodity future, could give insight into how this risk can benefit portfolio management techniques. On the contrary, Popularity is one of the most robust strategies founded in the cryptocurrency market. Any combination of the other factors cannot explain its return, and the monthly yield associated with this strategy is one of the highest. In this regard, a deeper investigation of the reason behind its strength and of the elements, market conditions, or biases, that drives it could allow for a better understanding of this remarkable strategy.

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Table 1: Summary Statistics – Monthly Commodity Excess Returns

This table reports the summary statistics of commodity future monthly excess return. The value of Mean, Standard Deviation (SD), Max, Skewness, and Kurtosis are annualized.

Commodity	Mean	SD	Max	Skewness	Kurtosis
Aluminum	-.00468	.05639	0.148368	.00551	3.328014
Brent Oil	.005106	.103806	0.420803	-1.169691	11.948465
Cobalt	.004111	.090494	0.305706	-.581732	8.545801
Cocoa	-.00407	.087268	0.298475	.190629	3.67889
Coffee	-.004523	.101577	0.405848	.366601	4.730057
Copper	.000149	.073239	0.298943	-.454502	7.251277
Corn	-.002048	.081158	0.371058	-.306967	5.52914
Cotton	-.002886	.08793	0.260940	-1.710287	15.651155
Ethanol	.012309	.091712	0.298853	-.026142	4.528903
Feeder Cattle	-.002774	.044014	0.144836	-.359077	4.935843
Gold	-.00181	.04812	0.173727	-.070882	4.722257
Heating Oil	.003366	.107817	0.477115	-.317156	6.742421
Live Cattle	-.003567	.050991	0.130242	-.652135	5.402163
Lean Hogs	-.000932	.107143	0.340171	-.246762	4.368199
Lumber	.001201	.114777	0.460053	-.072225	6.018088
Milk	.000526	.099648	0.607031	.000519	9.927054
Natural Gas	.001542	.150235	0.486205	-.113701	3.955329
Nickel	.003759	.099845	0.319259	.004469	3.30837
Oats	-.000915	.09689	0.653577	.613922	6.884387
Orange Juice	-.003013	.090706	0.503161	.478867	4.837138
Palladium	.004007	.091457	0.379095	-.231038	5.13586
Platinum	-.001225	.064015	0.285605	-.541773	6.863021
Rough rice	-.0081	.071504	0.379299	.360942	5.339869
Soybean Crush	-.002163	.320223	1.763589	-.85588	18.137064
Silver	-.003307	.085458	0.267029	-.05549	4.337271
Soybean Meal	-.000384	.072321	0.263470	.202701	3.842587
Soybean Oil	-.004195	.073386	0.353413	.13111	5.012475
Soybean	-.003255	.066921	0.233600	-.18149	4.114048
Sugar	-.011651	.103656	0.505552	.193848	5.056911
Wheat	-.002411	.080025	0.352798	.140296	4.216607
WTI	-.000744	.102653	0.609777	-.655383	12.603495

Table 2: Summary Statistics – Yearly Cryptocurrency Excess Returns

This table reports the summary statistics of cryptocurrency's weekly excess return. The value of Mean, Standard Deviation, and Average Volume are annualized. "Number of coins" indicates the number of cryptocurrencies present in the sample in that year.

Year	Number of Coins	Average Return	Standard Deviation	Average Volume (mil)
2015	10	27,151%	112,765%	21,5
2016	15	51,156%	52,862%	47,2
2017	35	826,531%	217,040%	554
2018	47	-179,822%	152,663%	290
2019	62	-13,337%	100,025%	690
2020	85	108,917%	131,154%	1060
2021	88	164,725%	154,478%	1670
2022	89	-193,279%	99,508%	1500
Full	89	44,443%	137,961%	1090

Table 3: Commodity Futures Factors Correlation

This table shows the cross-sectional average correlation of factors for the commodity futures market. From the analysis, the variables related to fixed effects (Week-of-the-year, Christmas, January, and Temperature (1 and 2)) are excluded from the calculation because of the different computation techniques.

Commodity Factors Correlation

Variables	MAXP	SKW	KUR	SIZE	SEAS	LR	Y3REV	Y5REV	BAB	LIQ	MAXR	CARRY	MOM	OVER	STD	VAL
MAXP	1.000															
SKW	0.043	1.000														
KUR	0.033	-0.030	1.000													
SIZE	0.272	0.111	0.079	1.000												
SEAS	-0.091	0.010	-0.017	-0.115	1.000											
LR	-0.022	0.128	-0.081	0.046	-0.104	1.000										
Y3REV	-0.036	0.109	-0.012	0.000	0.072	-0.070	1.000									
Y5REV	-0.039	0.126	0.115	0.082	0.037	-0.039	0.456	1.000								
BAB	-0.250	-0.045	-0.171	0.010	-0.003	-0.038	0.103	-0.010	1.000							
LIQ	-0.068	-0.047	-0.005	0.109	-0.064	0.098	-0.038	0.011	-0.012	1.000						
MAXR	-0.023	0.012	-0.194	-0.178	0.029	-0.068	0.389	0.356	0.096	-0.033	1.000					
CARRY	-0.015	-0.091	-0.060	0.154	-0.013	0.035	-0.006	-0.023	0.004	0.059	-0.010	1.000				
MOM	0.009	-0.207	0.046	-0.008	-0.033	-0.013	-0.557	-0.500	-0.085	0.023	-0.414	0.029	1.000			
OVER	0.069	-0.030	-0.022	0.061	-0.019	0.009	0.070	0.052	0.034	0.018	0.098	0.038	-0.079	1.000		
STD	0.005	0.012	-0.065	0.396	-0.164	0.250	0.021	0.035	0.146	0.365	-0.056	0.134	-0.031	-0.008	1.000	
VAL	-0.067	0.057	-0.010	0.208	-0.013	0.143	-0.044	0.019	-0.084	-0.120	-0.015	0.467	-0.029	0.056	0.118	1.000

Table 4a: Cryptocurrency Factors Correlation

This table shows the cross-sectional average correlation of factors for the cryptocurrency market. The only variable excluded is Google Trend since it was computed via monthly returns. A separated table is provided later in the document.

Cryptocurrency Factors Correlation

Variables	MOM2	MOM3	MAXP	STD	SEAS	MKT	LIQ	TRV	PRC	MOM1	MOM4	RES	MAXR	M2REV	M6REV	M18REV	OVER	SKW	KUR	BAB
MOM2	1.000																			
MOM3	0.495	1.000																		
MAXP	-0.128	-0.215	1.000																	
STD	-0.182	-0.243	0.178	1.000																
SEAS	0.041	-0.044	0.112	-0.059	1.000															
MKT	0.038	-0.119	0.324	0.407	0.026	1.0(														
LIQ	0.075	0.183	-0.255	-0.822	-0.006	-0.450	1.000													
TRV	0.091	0.127	-0.086	-0.617	-0.069	-0.579	0.640	1.000												
PRC	-0.088	-0.155	0.947	0.206	0.124	0.341	-0.255	-0.129	1.000											
MOM1	0.680	0.210	-0.127	-0.140	0.000	0.108	0.051	0.047	-0.095	1.000										
MOM4	0.076	0.515	-0.002	-0.245	-0.147	-0.007	0.153	0.086	0.033	0.128	1.000									
RES	0.224	0.231	-0.316	-0.371	0.017	-0.223	0.385	0.220	-0.297	0.070	0.207	1.000								
MAXR	0.152	0.051	-0.228	0.100	-0.176	0.042	-0.076	-0.104	-0.202	0.124	0.035	0.558	1.000							
M2REV	-0.009	-0.366	-0.027	0.141	-0.123	0.167	-0.145	-0.133	-0.083	-0.061	-0.562	-0.102	-0.082	1.000						
M6REV	-0.146	-0.523	0.112	0.137	-0.139	0.009	-0.098	0.008	0.068	-0.189	-0.571	-0.164	-0.118	0.468	1.000					
M18REV	-0.024	-0.437	0.056	0.066	0.067	0.093	-0.061	0.028	0.019	-0.117	-0.413	0.055	0.114	0.338	0.536	1.000				
OVER	0.012	0.187	-0.127	-0.136	-0.169	-0.188	0.190	0.077	-0.097	0.039	0.263	0.150	0.007	-0.097	-0.109	-0.085	1.000			
SKW	-0.097	-0.154	-0.091	0.002	-0.085	-0.099	0.018	0.048	-0.096	-0.061	-0.055	-0.189	-0.402	0.051	0.177	0.117	0.093	1.000		
KUR	-0.093	0.046	-0.102	-0.455	-0.209	-0.367	0.529	0.405	-0.135	-0.097	0.035	0.154	-0.278	-0.057	0.012	-0.060	0.048	0.273	1.000	
BAB	0.066	0.083	-0.377	-0.148	-0.012	-0.254	0.172	0.140	-0.350	-0.100	0.064	0.557	0.422	0.038	-0.088	0.030	0.017	0.001	0.162	1.000

Table 4b: Google Trend Correlation

This table shows the cross-sectional average correlation of Google Trend with the other factors for the cryptocurrency market.

Variables	GT
MOM2	-0.066
MOM3	0.034
MAXP	-0.345
STD	-0.194
SEAS	-0.092
MKT	0.040
LIQ	-0.009
LIQ2	0.149
PRC	-0.282
MOM1	-0.065
MOM4	-0.003
RES	0.039
MAXR	0.064
M2REV	-0.155
M6REV	0.065
M18REV	0.002
OVER	0.131
SKW	-0.063
KUR	-0.161
BAB	0.146

Table 5: Statistics – Commodity Futures Factors

This table recaps the summarized statistics of the factors used in this thesis for the futures commodity market. Mean, Standard Deviation, Max and Min are considered monthly, while the Sharpe Ratio is annualized. The formula used is the following: $SR_i = \left(\frac{Mean_i}{SD_i}\right) * \sqrt{12}$ *where* SR_i *is the yearly Sharpe Ratio for the factor i*

Commodity Anomaly	Mean	SD	Sharpe Ratio	Max	Min
MAXP	-0,00303	0,04262	-0,49255	0,15591	-0,1247
SKW	-0,00534	0,04649	-0,7958	0,17014	-0,2739
KUR	0,00341	0,04802	0,491986	0,26465	-0,3457
SIZE	-0,00172	0,03261	-0,36543	0,14679	-0,1315
SEAS	-0,00017	0,00314	-0,37509	0,01194	-0,0188
LR	-0,00302	0,03027	-0,69122	0,08345	-0,125
Y3REV	-0,00599	0,06451	-0,64331	0,23854	-0,3743
Y5REV	-0,00663	0,05825	-0,78857	0,23114	-0,3485
BAB	0,00032	0,064	0,034641	0,25522	-0,3286
LIQ	-0,00168	0,04278	-0,27208	0,14721	-0,1638
MAXR	-0,00476	0,06318	-0,52197	0,34571	-0,375
CARRY	-0,00511	0,02747	-1,28879	0,12258	-0,082
MOM	0,00904	0,06262	1,000175	0,35864	-0,1903
OVER	-0,00051	0,01438	-0,24572	0,10089	-0,1853
STD	-0,00037	0,04782	-0,05361	0,14728	-0,3252
VAL	0,00115	0,03928	0,202837	0,20843	-0,136

Table 6: Statistics – Cryptocurrency Factors

This table shows the summarized statistics of the factors used in this thesis for the cryptocurrency market. Mean, Standard Deviation, Max and Min are considered weekly, while the Sharpe Ratio is annualized. The formula used is the following: $SR_i = \left(\frac{Mean_i}{SD_i}\right) * \sqrt{52}$ *where* SR_i *is the yearly Sharpe Ratio for the factor i.*

Cryptocurrency Anomaly	Mean	SD	Sharpe Ratio	Max	Min
MOM2	0,00993	0,07753	0,92359	0,35812	-0,32717
MOM3	0,01675	0,08103	1,49063	0,47848	-0,23668
MAXP	-0,02407	0,12775	-1,35868	0,32074	-0,8434
STD	-0,02435	0,09995	-1,75678	0,27146	-0,41811
SEAS	-0,00255	0,01508	-1,21938	0,0465	-0,05176
MKT	-0,02162	0,10844	-1,4377	0,33277	-0,52449
LIQ	-0,02682	0,09742	-1,98524	0,25783	-0,4256
TRV	-0,01769	0,07959	-1,60277	0,23593	-0,34657
PRC	-0,0234	0,12756	-1,32283	0,32074	-0,8434
MOM1	0,0085	0,08434	0,72675	0,33048	-0,46075
MOM4	0,00783	0,08427	0,67002	0,24508	-0,34537
RES	-0,0015	0,11985	-0,09025	0,34179	-0,53168
MAXR	-0,00449	0,10006	-0,32358	0,34184	-0,42558
M2REV	0,00924	0,1086	0,61354	0,38707	-0,31539
M6REV	-0,00229	0,10451	-0,15801	0,27543	-0,37127
M18REV	0,00005	0,107	0,00337	0,32374	-0,36106
OVER	0,00371	0,03619	0,73924	0,10576	-0,09017
SKW	0,00286	0,10491	0,19659	0,86308	-0,20521
GT[93]	-0.09674	0.11643	0,30608	0,15909	-0,45239
KUR	0,00484	0,11403	0,12859	0,51036	-0,56059
BAB	0,00224	0,12562	0,92359	0,55078	-0,49431

[93] All the values related to this factor are expressed per month.

Table 7A: Commodity Futures Factor– Mean Returns

*This table shows the results for the portfolio sorts. Each month, commodity futures are sorted into three portfolios based on the value indicated in the first row. Portfolio P3 (P1) carries the futures with the highest (lowest) value of the respective value. Portfolios are rebalanced monthly. "Mean Return" indicates the average excess return that the strategy reported over the studied sample, while on parenthesis is indicated the Standard Error. ***, **, *, indicate significance at the 1%, 5%, and 10% level, respectively.*

Commodity Future Portfolio Returns

		Momentum			**Skewness**			**Kurtosis**	
	P1	P3	P3 – P1	P1	P3	P3 – P1	P1	P3	P3 – P1
Mean Return	-0,01504***	0,0030349	0,0090374***	-0,001608	-0,012287***	-0,0053393***	-0,0063085	0,0005091	0,0034088
	(0,0026)	(0,0055)	(0,0028258)	(0,0030174)	(0,0034205)	(0,0020769)	(0,0029004)	(0,0037925)	(0,0021452)
		Size			**Liquidity**			**Carry**	
	P1	P3	P3 – P1	P1	P3	P3 – P1	P1	P3	P3 – P1
Mean Return	-0,00028	-0,003729*	-0,0017249	0,0004027	-0,002955	-0,0016788	0,0004369	-0,0097868***	-0,0051119***
	(0,0023784)	(0,0023252)	(0,0014542)	(0,0029135)	(0,0036671)	(0,0019404)	(0,0022594)	(0,0027638)	(0,0012261)
		Long Ratio			**Value**			**Temperature 1**	
	P1	P3	P3 – P1	P1	P3	P3 – P1	P1	P3	P3 – P1
Mean Return	0,001392	-0,004653**	-0,0030226**	-0,0029026	-0,000606	0,0011483	-	-	0,00019115
	(0,0025427)	(0,0021849)	(0,0014719)	(0,0029094)	(0,0036888)	(0,0018535)	-	-	(0,0009468)
		Temperature 2			**January**			**Week-of-the-Year**	
	P1	P3	P3 – P1	P1	P3	P3 – P1	P1	P3	P3 – P1
Mean Return	0.0016129	-0.003506*	-0,0027371*	-	-	0,0001033	-	-	0,0006621***
	-	-	(0,0011256)	-	-	(0,0015881)	-	-	(0,0002145)
		Christmas			**Max Price**			**Max Return**	
	P1	P3	P3 – P1	P1	P3	P3 – P1	P1	P3	P3 – P1
Mean Return	-	-	-0,0002135	0,0010172	-0,005039**	-0,0030279*	-0,0019786***	-0,0113256	-0,0047582**
	-	-	(0,0001122)	(0,0029622)	(0,0030118)	(0,0018984)	(0,0032282)	(0,0047874)	(0,0028687)
		Reversal3Y			**Reversal5Y**			**Std Dev of Dollar Volume**	
	P1	P3	P3 – P1	P1	P3	P3 – P1	P1	P3	P3 – P1
Mean Return	0,0014976	-0,104728**	-0,0059852**	0,0031147	-0,01014**	-0,0066271**	0,0000611	-0,0006876	-0,0003744
	(0,0035363)	(0,0050014)	(0,0029853)	(0,0036336)	(0,0047137)	(0,0027678)	(0,0031149)	(0,0037944)	(0,00215165)
		Overreaction			**Betting-against-Beta**			**Seas**	
	P1	P3	P3 – P1	P1	P3	P3 – P1	P1	P3	P3 – P1
Mean Return	-0,0042814**	0,0003733	-0.0005143*	-0,0030737	-0,002436	0,0003188	0,0003423***	0,0000902	-0,0001739
	0,0009545	(0,0009725)	(0,0006393)	(0,0026139)	(0,0053713)	(0,002977)	(0,0001398)	(0,0002337)	(0,00014065)

Table 7B: Commodity Futures Factor– Alpha significance

*The table reports the results of the portfolios' alphas. The construction technique is the same as before. The table reports the monthly alpha estimated based on the CO-CAPM (with commodity market return), the CAPM (with equity market return), the Fama & French (1993) 3-factor model, the Fama & French (2015) 5-Factor model, and the BGR model theorized by Bakshi et al. (2019). The robust Newey & West (1987) standard errors are presented in parenthesis. ***, **, *, indicate significance at the 1%, 5%, and 10% level, respectively.*

Commodity Future Regressions

	Momentum	**Skewness**	**Kurtosis**	**Size**	**Liquidity**	**Carry**	**Long Ratio**	**Betting-Against-Beta**
Co-CAPM Alpha	0,0090288***	-0,0053614***	0,00342705	- 0,001777	0,0017224	0,0051162***	-0,0030711**	0,0003554
	(0,0028318)	(0,0020798)	(0,0021506)	(0,0014493)	(0,0019413)	(0,00122959	(0,0014772)	(0,0029814)
CAMP Alpha	0,0088981***	-0,005341***	0,00336455	- 0,0017773	0,0016148	0,00496265***	-0,0028644**	0,0004935
	(0,0028377)	(0,0020873)	(0,0021553)	(0,0009576)	(0,0019454)	(0,00122065)	(0,0014686)	(0,002987)
3-Factor Alpha	0,0087303***	-0,0052802***	0,003313	-0,001889	-0,0017124	0,00508805***	-0,0029187**	0,0004171
	(0,0028535)	(0,0020981)	(0,0021587)	(0,0014643)	(0,0019543)	(0,00122515)	(0,0014785)	(0,0030042)
5-Factor Alpha	0,0083778***	-0,0053107***	0,0033983	-0,0020187	-0,0015802	0,00499865***	-0,0028865**	0,0002602
	(0,0028471)	(0,0021112)	(0,0021719)	(0,0014706)	(0,0019652)	(0,00123185)	(0,0014794)	(0,0030207)
BGR alpha	-	-0,0046452**	0,0030547	-0,0013247	-0,0017518	-	-0,0028851*	0,0018355
	-	(0,0020485)	(0,0021691)	(0,0015044)	(0,0019996)	-	(0,0015016)	(0,0028596)

	Value	**Max Price**	**Max Return**	**Reversal3Y**	**Reversal5Y**	**Std. Dev. of Dollar Volume**	**Overreaction**	**Seas**
Co-CAMP Alpha	0,0011852	-0,002837	-0,0047549*	-0,0060073**	-0,0067252**	-0,0004077	-0,0005144	-0,006279
	(0,0018555)	(0,0018956)	(0,0025742)	(0,0029906)	(0,0027657)	(0,00214445)	(0,0003427)	(0,0026024)
CAMP Alpha	0,0011692	-0,0029688	-0.0045403	-0,0060406**	-0,0065543**	-0,0003574	-0,0003885	-0,0061039
	(0,0018596)	(0,0019074)	(0,00258385)	(0,0030009)	(0,002783)	(0,00215815)	(0,0003264)	(0,00260345)
3-Factor Alpha	0,0011649	-0,003066	-0,0044315	-0,0061633**	-0,0065416**	-0,00215815	-0,0004963	-0,006041
	(0,0018715)	(0,0019172)	(0,0028889)	(0,0030182)	(0,0027958)	(0,0006765)	(0,0006475)	(0,00261525)
5-Factor Alpha	0,0013762	-0,0029298	-0,0044244	-0,0061103**	-0,0063987**	-0,0021539	-0,0005159	-0,0062017
	(0,0018794)	(0,0019207)	(0,0028992)	(0,003029)	(0,0027822)	(0,0006482)	(0,0006515)	(0,0026177)
BGR alpha	0,0039941	-0,0034468	-0,0017185	-0,0021416	-0,0024489	0,0021654	-0,0002623	-0,0063363
	(0,0015967)	(0,0019618)	(0,0025169)	(0,0025937)	(0,0024635)	(0,001185)	(0,000568)	(0,00251005)

Table 8A: Cryptocurrency Factor Results – Mean Returns

*This table shows the results for the portfolio sorts. Each week, cryptocurrencies are sorted into three portfolios based on the value indicated in the first row. Portfolio P3 (P1) carries the futures with the highest (lowest) value of the respective value. Portfolios are rebalanced weekly. "Mean Return" indicates the average excess return that the strategy reported over the studied sample, while on parenthesis is indicated the Standard Error. ***, **, *, indicate significance at the 1%, 5%, and 10% level, respectively.*

Cryptocurrency Portfolio Returns

		3-Weeks Momentum			**Skewness**			**Kurtosis**	
	P1	P3	P3 – P1	P1	P3	P3 – P1	P1	P3	P3 – P1
Mean Return	-0,0018886	0,014857*	0,0167456***	0,006607	0,0094648	0,002864	0,0090125	0,0138487	0,0048363
	(0,0093554)	(0,0098521)	(0,0053312)	(0,0090833)	(0,0113842)	(0,0068875)	(0,0107501)	(0,0109562)	(0,0074862)
		Market Cap			**Liquidity**			**Transaction Volume**	
	P1	P3	P3 – P1	P1	P3	P3 – P1	P1	P3	P3 – P1
Mean Return	0,0237245**	0,0021079	-0,0216166***	0,0264587***	-0,0003608	-0,0268195***	0,021564***	0,0028531	-0,0187109***
	(0,0105093)	(0,0087266)	(0,00711995)	(0,0096402)	(0,0084055)	(0,0063824)	(0,0089817)	(0,0087535)	(0,0051472)
		1-Week Momentum			**2-Weeks Momentum**			**4-Weeks Momentum**	
	P1	P3	P3 – P1	P1	P3	P3 – P1	P1	P3	P3 – P1
Mean Return	0,0031527	0,011649	0,0084963*	0,0008805	0,010814	0,0099335**	0,0011482	0,0089749	0,0078267*
	(0,0094095)	(0,0094584)	(0,0055371)	(0,0098061)	(0,0095438)	(0,0051013)	(0,0090716)	(0,0099085)	(0,0055565)
		Idiosyncratic Volatility			**Price**			**Google Trend**	
	P1	P3	P3 – P1	P1	P3	P3 – P1	P1	P3	P3 – P1
Mean Return	0,0067843	0,0052819	-0,0015024	0,0221346**	-0,0012697	-0,0234044***	0,0691094*	-0,0276251	-0,0967345***
	(0,0086067)	(0,0113738)	(0,0078684)	(0,0122988)	(0,0078217)	(0,008339)	(0,0446316)	(0,0381778)	(0,016303)
		Std Dev of Dollar Volume			**Max Price**			**Max Return**	
	P1	P3	P3 – P1	P1	P3	P3 – P1	P1	P3	P3 – P1
Mean Return	0,0235961***	-0,0007516	-0,0243477***	0,0229931**	-0,0010773	-0,0240704***	0,0079636	0,0034701	-0,0044935
	(0,0091908)	(0,008334)	(0,0065478)	(0,012368)	(0,0078251)	(0,008351)	(0,0089919)	(0,0104946)	(0,0065551)
		Reversal2M			**Reversal6M**			**Reversal18M**	
	P1	P3	P3 – P1	P1	P3	P3 – P1	P1	P3	P3 – P1
Mean Return	-0,0024754	0,006764	0,0092394	0,0014974	-0,0007976	-0,002295	0,0142072*	0,0142617	0,0000546
	(0,0095151)	(0,0095474)	(0,0072243)	(0,0094741)	(0,0092573)	(0,007264)	(0,010704)	(0,011302)	(0,0085669)
		Overreaction			**Betting-against-Beta**			**Seas**	
	P1	P3	P3 – P1	P1	P3	P3 – P1	P1	P3	P3 – P1
Mean Return	0,0003733	-0,0042814**	0,0037109	0,0088315	0,0110691	0,0022377	-0,0009476	0,0027327***	-0,0025519***
	(0,0025193)	(0,0023553)	(0,00123812)	(0,008152)	(0,0116484)	(0,0082471)	(0,0013766)	(0,001063)	(0,0010284)

Table 8B: Cryptocurrency Factor Results – Alpha significance

*The table reports the results of the portfolios' alphas. The construction technique is the same as before. The table reports the monthly alpha estimated based on the CO-CAPM (with cryptocurrency market return), the CAPM (with equity market return), the Fama & French (1993) 3-factor model, the Fama & French (2015) 5-Factor model, and the ASM model according to by Liu et al. (2019). The robust Newey & West (1987) standard errors are presented in parenthesis. ***, **, *, indicate significance at the 1%, 5%, and 10% level, respectively*

Cryptocurrency Regressions

	3 – Weeks Momentum	**Skewness**	**Kurtosis**	**Market Cap**	**Liquidity**	**Transaction Volume**	**1-Week Momentum**
Co-CAPM Alpha	0,0173355***	0,0019823	0,0050277	-0,028301**	-0,0257677***	-0,0172693***	0,0079997
	(0,0053701)	(0,006567)	(0,0073712)	(0,0068813)	(0,0061574)	(0,0051361)	(0,0054226)
CAMP Alpha	0,016216***	0,0025356	0,0043039	-0,0217432***	-0,026727***	-0,0180036***	0,0091093
	(0,0053701)	(0,0069598)	(0,0075571)	(0,0071668)	(0,0064493)	(0,0052507)	(0,0055618)
3-Factor Alpha	0,0169178***	0,0022703	0,0022703	-0,0220366***	-0,0266209***	-0,0177614***	0,0092434*
	(0,0053862)	(0,0069591)	(0,0069591)	(0,0071767)	(0,0064356)	(0,0052397)	(0,005577)
5-Factor Alpha	0,0159769***	0,0022828	0,0022828	-0,0217815***	-0,02487***	-0,0174285***	0,0088893
	(0,005358)	(0,0068498)	(0,0068498)	(0,0072347)	(0,0062667)	(0,0052796)	(0,0055424)
BGR alpha	-	-0,0013328	-0,0013328	-0,0084835	-0,0178276***	-0,0086703**	0,005984
	-	(0,0059864)	(0,0059864)	(0,0052127)	(0,0056701)	(0,0039831)	(0,0051144)
	2-Weeks Momentum	**4-Weeks Momentum**	**Idiosyncratic Volatility**	**Price**	**Google Trend**	**Standard Deviation of Dollar Volume**	**Max Price**
Co-CAMP Alpha	0,0101009**	0,0074141	-0,0007861	-0,0220676***	-0,0941264***	-0,0235911***	-0,0225995***
	(0,0050256)	(0,0054035)	(0,0076746)	(0,0078932)	(0,0157527)	(0,0063916)	(0,0078794)
CAMP Alpha	0,010631	0,0076569	-0,0009365	-0,024017***	-0,096259***	-0,0248116***	-0,024732***
	(0,0051348)	(0,0056016)	(0,0079459)	(0,0084195)	(0,0167908)	(0,0066061)	(0,0084298)
3-Factor Alpha	0,01039**	0,008261	-0,0008281	-0,0236736***	-0,1012545***	-0,0247623***	-0,024454***
	(0,0051682)	(0,005615)	(0,0079799)	(0,008461)	(0,0204566)	(0,0066222)	(0,0084673)
5-Factor Alpha	0,0097312*	0,007273	-0,0035977	-0,0228595***	-0,0871636***	-0,0242752***	-0,0232104***
	(0,0052003)	(0,0055784)	(0,007813)	(0,0084386)	(0,0196193)	(0,0066231)	(0,008442)
BGR alpha	0,004528	-0,0021647	-0,0063174	-0,0083741	-0,0934867***	-0,0157988***	-0,0085971
	(0,0045179)	(0,0047091)	(0,007435)	(0,0068958)	(0,0148672)	(0,0058399)	(0,0069486)
	Max Return	**Reversal2M**	**Reversal6M**	**Reversal18M**	**Overreaction**	**Betting-Against-Beta**	**Seas**
Co-CAMP Alpha	-0,003607	0,0091648	-0,0023291	0,0013624	0,0028295	0,003419	-0,0025153**
	(0,0063622)	(0,007199)	(0,0075345)	(0,0084452)	(0,0023158)	(0,0080092)	(0,0010239)
CAMP Alpha	-0,0042559	0,009795	-0,0023291	0,000561	0,0038922	0,0017932	-0,0025277**
	(0,0066255)	(0,0072744)	(0,0073545)	(0,0086947)	(0,0023971)	(0,0083119)	(0,001043)
3-Factor Alpha	-0,0039947	0,0103988	-0,0019801	0,0012336	0,004119	0,0023033	-0,0024925**
	(0,0066433)	(0,0073142)	(0,0074052)	(0,0087253)	(0,0024247)	(0,0083635)	(0,0010426)
5-Factor Alpha	-0,0051672	0,0098678	-0,0032239	0,0017953	0,0036109	0,0005772	-0,00251**
	(0,0065313)	(0,0072712)	(0,0072738)	(0,008676)	(0,0024396)	(0,0082904)	(0,0010568)
BGR alpha	-0,005095	0,0009385	-0,0014201	-0,0095041	0,0006558	0,000444	-0,0025272**
	(0,0062296)	(0,0066721)	(0,0063529)	(0,0079167)	(0,002477)	(0,0081967)	(0,0010857)

Table 9: Cryptocurrency and Commodity indices volatility

This table reports the average volatility for the commodity (monthly) and cryptocurrency (weekly) index. For cryptocurrency, it is represented by a market-capitalization-weighted index between bitcoin and Ethereum only since they represent around 70% of the total market (June 2022). The commodity index is the same implied for the CO-CAPM regression in commodity futures.

Standard Deviation

Year	*Btc + Eth*	*Commodity Index*
2017	.16969	.013223
2018	.133342	.012583
2019	.091096	.012368
2020	.11021	.019738
2021	.111915	.018217
2022	.07695	.03182

Table 10: 1-2-3- and 4-Weeks Momentum Correlation

This table shows the cross-sectional average correlation of 1-,2-,3- and 4-weeks moment in the cryptocurrency market.

Variables	MOM1	MOM2	MOM3	MOM4
MOM1	1.000			
MOM2	0.622	1.000		
MOM3	0.233	0.442	1.000	
MOM4	0.213	0.092	0.569	1.000

Table 11a: Combined P-Value Adjustment

This study represents the P-value correction in the combined study for the commodity future factors. "Mean" and "Standard Error" are monthly. T-stat and P-value present value before any change. Bonferroni, Holm, and BHY represent the new p-value after the corresponding adjustment. Rank H (Rank B) indicates the descending (ascending) order position of the p-value in the total ranking of the strategy when considering all 42 portfolios. Note that also Panel B (next page) needs to be considered to understand the table fully.

Panel A: Commodity Futures

Anomaly	Mean	Std.Error	T-stat	P-value	Bonferroni	Holm	BHY	Rank H	Rank B
Momentum	0,0090	0,0028258	3,198	0,0007	0,0294	0,0259	0,0049	37	6
Skewness	-0,0053	0,0020769	-2,571	0,0052	0,2184	0,1612	0,0182	31	12
Kurtosis	0,0034	0,0021452	-1,589	0,0563	1	1	0,1126	22	21
Size	-0,0017	0,0014542	-1,186	0,1181	1	1	0,17715	15	28
Liquidity	-0,0017	0,0019404	-0,865	0,1937	1	1	0,280531034	14	29
Carry	-0,0051	0,0012261	-4,169	0,00009	0,00378	0,0036	0,00189	40	2
LongRatio	-0,0030	0,0014719	-2,054	0,0203	0,8526	0,5481	0,0532875	27	16
Value	0,0011	0,0018535	-0,620	0,2679	1	1	0,340963636	10	33
Temperature1	0,0002	0,0009468	0,200	0,840	1	1	0,860487805	2	41
Temperature2	-0,0027	0,0011256	-2,430	0,015	0,63	0,42	0,042	28	15
January	0,0001	0,0015881	0,070	0,948	1	0,948	0,948	1	42
Week-of-the-Year (51)	0,0007	0,0002145	3,090	0,002	0,084	0,068	0,009333333	34	9
Christmas	-0,0002	0,0001122	-1,900	0,057	1	1	0,108818182	21	22
MaxP	-0,0030	0,0018984	-1,595	0,0557	1	1	0,11697	23	20
MaxR	-0,0048	0,0028687	-1,659	0,0489	1	1	0,108094737	24	19
Reversal 3Y	-0,0060	0,0029853	-2,005	0,0228	0,9576	0,5928	0,056329412	26	17
Reversal 5Y	-0,0066	0,0027678	-2,394	0,0085	0,357	0,2465	0,0255	29	14
StdPriceVolume	-0,0004	0,0021517	-0,174	0,431	1	1	0,489243243	6	37
Overreaction	-0,0005	0,0006393	-0,805	0,2107	1	1	0,29498	13	30
Betting-Against-Beta	0,0003	0,0029774	0,107	0,4574	1	1	0,505547368	5	38
SEAS	-0,0002	0,0001407	-1,236	0,109	1	1	0,168777778	16	27

Table 11b: Combined P-Value Adjustment

This study represents the P-value correction in the combined study for the cryptocurrency factors. "Mean" and "Standard Error" are weekly. T-stat and P-value present value before any change. Bonferroni, Holm, and BHY represent the new p-value after the corresponding adjustment. Rank H (Rank B) indicates the descending (ascending) order position of the p-value in the total ranking of the strategy when considering all 42 portfolios. Note that also Panel A (previous page) needs to be considered to understand the table fully.

Panel B: Cryptocurrency

Anomaly	Mean	Std.Error	T-stat	P-value	Bonferroni	Holm	BHY	Rank H	Rank B
1-Week Momentum	0,00850	0,0055371	1,535	0,0631	1	0,631	0,110425	10	12
2-Weeks Momentum	0,00993	0,0051013	1,947	0,0264	0,5544	0,3168	0,05544	12	10
3-Weeks Momentum	0,01675	0,0053312	3,141	0,001	0,021	0,017	0,0042	17	5
4-Weeks Momentum	0,00783	0,0055565	1,409	0,0802	1	0,7218	0,129553846	9	13
Max Return	-0,00449	0,0065551	-0,686	0,2469	1	1	0,34566	7	15
Max Price	-0,02407	0,008351	-2,882	0,0022	0,0462	0,033	0,0066	15	7
Price	-0,02340	0,008339	-2,807	0,0027	0,0567	0,0378	0,0070875	14	8
StdPriceVolume	-0,02435	0,0065478	-3,719	0,0001	0,0021	0,0019	0,0007	19	3
Seas	-0,00255	0,0010284	-2,481	0,0069	0,1449	0,0897	0,0161	13	9
Idiosyncratic Vol (Res)	-0,00150	0,0078684	-0,191	0,4244	1	1	0,469073684	3	19
Size (MKT)	-0,02162	0,00711995	-3,036	0,0013	0,0273	0,0208	0,00455	16	6
Overreaction	0,00371	0,0023812	1,559	0,0603	1	0,6633	0,115118182	11	11
Google Trend	-0,09673	0,016303	-5,934	0,000009	0,000189	0,000189	0,000189	21	1
Skewness	0,00286	0,0068875	0,416	0,339	1	1	0,418764706	5	17
Kurtosis	0,00484	0,0074862	0,646	0,2595	1	1	0,34059375	6	16
2mreversal	0,00924	0,0072243	1,279	0,1011	1	0,8088	0,15165	8	14
6mReversal	-0,00230	0,007264	-0,316	0,6238	1	0,6238	0,6238	1	21
18mReversal	0,00005	0,0085669	0,006	0,4975	1	0,995	0,522375	2	20
Liquidity	-0,02682	0,0063824	-4,202	0,00009	0,00189	0,0018	0,000945	20	2
Transaction Volume	-0,01769	0,0051472	-3,386	0,0004	0,0084	0,0072	0,0021	18	4
Betting-Against-Beta	0,00224	0,0082471	0,271	0,3932	1	1	0,458733333	4	18

Table 12: Commodity P-value Adjustment

This study represents the P-value correction in the single study for the commodity future factors. "Mean" and "Standard Error" are monthly. T-stat and P-value present value before any change. Bonferroni, Holm, and BHY represent the new p-value after the corresponding adjustment. Rank H (Rank B) indicates the descending (ascending) order position of the p-value in the total ranking of the strategy when considering all the 21 portfolios.

Commodity	*Mean*	*Std.Error*	*T-stat*	*P-value*	*Bonferroni*	*Holm*	*BHY*	*Rank H*	*Rank B*
Momentum	*0,00903735*	*0,002826*	*3,1981*	*0*	*0,0147*	*0,014*	*0,0074*	*20*	*2*
Skewness	*-0,00533925*	*0,002077*	*-2,5708*	*0,01*	*0,1092*	*0,0936*	*0,0273*	*18*	*4*
Kurtosis	*0,0034088*	*0,002145*	*-1,589*	*0,06*	*1*	*0,6193*	*0,1075*	*11*	*11*
Size	*-0,00172485*	*0,001454*	*-1,1861*	*0,12*	*1*	*0,9448*	*0,1772*	*8*	*14*
Liquidity	*-0,00167875*	*0,00194*	*-0,8652*	*0,19*	*1*	*1*	*0,2712*	*7*	*15*
Carry	*-0,00511185*	*0,001226*	*-4,1691*	*0*	*0,00189*	*0,00189*	*0,0019*	*21*	*1*
LongRatio	*-0,0030226*	*0,001472*	*-2,0536*	*0,02*	*0,4263*	*0,3045*	*0,0609*	*15*	*7*
Value	*0,00114825*	*0,001854*	*-0,6195*	*0,27*	*1*	*1*	*0,3309*	*5*	*17*
Temperature1	*0,00019115*	*0,000947*	*0,2*	*0,84*	*1*	*1*	*0,882*	*2*	*20*
Temperature2	*-0,00273705*	*0,001126*	*-2,43*	*0,02*	*0,315*	*0,24*	*0,0525*	*16*	*6*
January	*0,00010325*	*0,001588*	*0,07*	*0,95*	*1*	*0,948*	*0,948*	*1*	*21*
Week-of-the-Year (51)	*0,0006621*	*0,000215*	*3,09*	*0*	*0,042*	*0,038*	*0,014*	*19*	*3*
Christmas	*-0,0002135*	*0,000112*	*-1,9*	*0,06*	*1*	*0,57*	*0,0998*	*10*	*12*
MaxrcP	*-0,00302785*	*0,001898*	*-1,5949*	*0,06*	*1*	*0,6684*	*0,117*	*12*	*10*
MaxRet	*-0,0047582*	*0,002869*	*-1,6586*	*0,05*	*1*	*0,6357*	*0,1141*	*13*	*9*
Reversal 3Y	*-0,0059852*	*0,002985*	*-2,0049*	*0,02*	*0,4788*	*0,3192*	*0,0599*	*14*	*8*
Reversal 5Y	*-0,0066271*	*0,002768*	*-2,3944*	*0,01*	*0,1785*	*0,1445*	*0,0357*	*17*	*5*
StdPriceVolume	*-0,00037435*	*0,002152*	*-0,174*	*0,43*	*1*	*1*	*0,5028*	*4*	*18*
Overreaction	*-0,0005143*	*0,000639*	*-0,8045*	*0,21*	*1*	*1*	*0,2765*	*6*	*16*
Betting Against Beta	*0,0003188*	*0,002977*	*0,1071*	*0,46*	*1*	*1*	*0,5055*	*3*	*19*
SEAS	*-0,00017385*	*0,000141*	*-1,2359*	*0,11*	*1*	*0,9765*	*0,1753*	*9*	*13*

Table 13: Cryptocurrency P-value Adjustment

This study represents the P-value correction in the combined study for the cryptocurrency factors. "Mean" and "Standard Error" are weekly. T-stat and P-value present value before any change. Bonferroni, Holm, and BHY represent the new p-value after the corresponding adjustment. Rank H (Rank B) indicates the descending (ascending) order position of the p-value in the total ranking of the strategy when considering all the 21 portfolios.

Cryptocurrency	*Mean*	*Std.Error*	*T-stat*	*P-value*	*Bonferroni*	*Holm*	*BHY*	*Rank H*	*Rank B*
1-Week Momentum	*0,0084963*	*0,005537*	*1,5345*	*0,06*	*1*	*0,631*	*0,1104*	*10*	*12*
2-Weeks Momentum	*0,0099335*	*0,005101*	*1,9472*	*0,03*	*0,5544*	*0,3168*	*0,0554*	*12*	*10*
3-Weeks Momentum	*0,0167456*	*0,005331*	*3,141*	*0*	*0,021*	*0,017*	*0,0042*	*17*	*5*
4-Weeks Momentum	*0,0078267*	*0,005557*	*1,4086*	*0,08*	*1*	*0,7218*	*0,1296*	*9*	*13*
Max Return	*-0,0044935*	*0,006555*	*-0,6855*	*0,25*	*1*	*1*	*0,3457*	*7*	*15*
Max Price	*-0,0240704*	*0,008351*	*-2,8823*	*0*	*0,0462*	*0,033*	*0,0066*	*15*	*7*
Price	*-0,0234044*	*0,008339*	*-2,8066*	*0*	*0,0567*	*0,0378*	*0,0071*	*14*	*8*
StdPriceVolume	*-0,0243477*	*0,006548*	*-3,7185*	*0*	*0,0021*	*0,0019*	*0,0007*	*19*	*3*
Seas	*-0,0025519*	*0,001028*	*-2,4813*	*0,01*	*0,1449*	*0,0897*	*0,0161*	*13*	*9*
Idiosyncratic Vol (Res)	*-0,0015024*	*0,007868*	*-0,1909*	*0,42*	*1*	*1*	*0,4691*	*3*	*19*
Size (MKT)	*-0,0216166*	*0,00712*	*-3,0362*	*0*	*0,0273*	*0,0208*	*0,0046*	*16*	*6*
Overreaction	*0,0037109*	*0,002381*	*1,5585*	*0,06*	*1*	*0,6633*	*0,1151*	*11*	*11*
Google Trend	*-0,0967345*	*0,016303*	*-5,9335*	*0*	*0,000189*	*0,000189*	*0,0002*	*21*	*1*
Skewness	*0,002864*	*0,006888*	*0,4158*	*0,34*	*1*	*1*	*0,4188*	*5*	*17*
Kurtosis	*0,0048363*	*0,007486*	*0,646*	*0,26*	*1*	*1*	*0,3406*	*6*	*16*
2mreversal	*0,0092394*	*0,007224*	*1,2789*	*0,1*	*1*	*0,8088*	*0,1517*	*8*	*14*
6mReversal	*-0,002295*	*0,007264*	*-0,3159*	*0,62*	*1*	*0,6238*	*0,6238*	*1*	*21*
18mReversal	*0,0000546*	*0,008567*	*0,0064*	*0,5*	*1*	*0,995*	*0,5224*	*2*	*20*
Liquidity	*-0,0268195*	*0,006382*	*-4,2021*	*0*	*0,00189*	*0,0018*	*0,0009*	*20*	*2*
Transaction Volume	*-0,0176916*	*0,005147*	*-3,3857*	*0*	*0,0084*	*0,0072*	*0,0021*	*18*	*4*
Betting-Against-Beta	*0,0022377*	*0,008247*	*0,2713*	*0,39*	*1*	*1*	*0,4587*	*4*	*18*

Table 14: Summary of Significant Factors after Corrections

This table presents the number of significant factors for the commodity and cryptocurrency markets. "Initial N° of Significant" represents the number of strategy's returns statistically different from 0 before any correction. "N° Significant Bonferroni/Holm/BHY" reports the same metrics based on the replated adjusted p-value. "%" is the percentage of strategies that remained significant after the adjustment.

Panel A: Commodity Futures - Number of Significant Factors

	Initial N° of Significant	N° Significant Bonferroni	%	N° Significant Holm	%	N° Significant BHY	%
N° of Sign 10%	12	3	25%	4	33%	9	75%
N° of Sign 5%	9	3	33%	3	33%	5	56%
N° of Sign 1%	5	1	20%	1	0,2	2	40%

Panel B: Cryptocurrency - Number of Significant Factors

	Initial N° of Significant	N° Significant Bonferroni	%	N° Significant Holm	%	N° Significant BHY	%
N° of Sign 10%	13	9	69%	9	69%	10	77%
N° of Sign 5%	10	7	70%	8	80%	9	90%
N° of Sign 1%	9	4	44%	4	44%	8	89%

Panel C: Combined

	Initial N° of Significant	N° Significant Bonferroni	%	N° Significant Holm	%	N° Significant BHY	%
N° of Sign 10%	25	10	40%	11	44%	18	72%
N° of Sign 5%	19	7	37%	8	42%	15	79%
N° of Sign 1%	14	4	29%	4	29%	10	71%

Table 15: Number of Discoveries for Individuals and Combined Corrections

The table shows the number of significant factors differentiating between the single and the combined correction. "Combined" is the number of significant factors when analyzing the 42 portfolios together. "Single Sum" represents the combined amount between the numbers of significant strategies resulting from a single correction in the two markets. "Difference" is defined as Single Sum – Combined. Finally, "Commodity %" ("Crypto") highlights the percentage of significant commodity (crypto) factors over the total.

		Combined	Single Sum	Difference	Commodities	Commodity %	Crypto	Crypto %
Bonferroni	N* of Sign 10%	10	11	-1	3	27%	8	73%
	N* of Sign 5%	7	10	-3	3	30%	7	70%
	N* of Sign 1%	4	5	-1	1	20%	4	80%
Holm	N* of Sign 10%	11	13	-2	4	31%	9	69%
	N* of Sign 5%	8	11	-3	3	27%	8	73%
	N* of Sign 1%	4	5	-1	1	20%	4	80%
BHY	N* of Sign 10%	18	19	-1	9	47%	10	53%
	N* of Sign 5%	15	14	1	5	36%	9	64%
	N* of Sign 1%	10	9	1	1	11%	8	89%

Table 16: Wilson Harmonic P-value For the Full and the Reduced Sample

The table shows the value for the Harmonic mean p-value under Wilson's (2019) approach. "Full Sample" indicates the value calculated over all the portfolios. "Reduced Sample" does not consider the factors belonging to the specific 3-factor model (BGR for commodity and ASM for cryptocurrency), which turned out to be significant at 1% after Bonferroni adjustment. The Wilson p-value indicates the probability of finding at least one significant factor among those studied.

	Full Sample	*Reduced Sample*
Wilson Commodity	0,001541713	0,01756773
Wilson Cryptocurrency	0,000152646	0,005962588
Wilson Combined	0,000277788	0,009154158

Appendix and Tables

Appendix A: In depth analysis on STD, LIQ and TRV factors. Alpha significance, Correlation and R^2

As the result section explains, these strategies appear robust to all the explanatory models applied. However, they also present a high level of correlation among each other. This Appendix describes an additional model to see whether the three strategies explain each other. This result would suggest that they capture a similar effect in the market.

Table A1:

Alphas significance after adjusted ASM Model

Commodity Anomaly	STD	LIQ	TRV
STD	-	-0,00075	-0,00970*
LIQ	-0,00574*	-	-0,01185**
TRV	-0,00342	-0,00230	-

Note: The table reports the alphas and the significance of the strategy after running the modified ASM Model. The latter is specified as following:

$$R^i = \propto^i + \beta^i_{mkt} MKT + \beta^i_{size} SIZE + \beta^i_{mom} MOM + \beta^i_x X$$

Where X represents each factor on the column. For each Anomaly, two additional regressions are run, adding once at a time the remaining factor as an explanatory variable

Although all significant from the previous regressions, the factors here seem to capture a similar effect in the cross-sectional cryptocurrency return. *Transaction volume*'s alpha is insignificant for the two additional regressions, which makes sense considering the high level of correlation among the two factors.

The second result for which LIQ remains significant, at least at 10%, is less obvious, even after these explanatory variables are added. It looks that the investors consider coins' liquidity as an essential factor before putting money in them. On the contrary, *Standard Deviation of Dollar Price* seems to be captured by a liquidity factor. For future purposes, it might be helpful to consider a model that assesses *Liquidity* together with *Momentum*, *Size,* and *Market Return*.

Table A2:

Correlation Table for Liquidity, Transaction and Standard Deviation Factors

Anomaly Correlation	STD	LIQ	TRV
STD	1,0000		
LIQ	0,8411	1,0000	
TRV	0,6054	0,6178	1,0000

Table A3:

R^2 Values for both the ASM model and the Modified one

Commodity Anomaly	STD	LIQ	TRV
STD	-	0,7145 (0,1894)	0,3789 (0,1894)
LIQ	0,7251 (0,2192)	-	0,4116 (0,2192)
TRV	0,5164 (0,3688)	0,5243 (0,3688)	-

The table reports the R^2 of the regression after running the modified ASM Model. The latter is specified as following:

$$R^i = \propto^i + \beta^i_{mkt} MKT + \beta^i_{size} SIZE + \beta^i_{mom} MOM + \beta^i_x X$$

Where X represents each factor on the column, for each Anomaly, two additional regressions are run, adding the remaining factor as an explanatory variable once at a time. In parenthesis is indicated the R2 of the original ASM model.

Including additional variables can remarkably increase the level of variance of the dependent variable explained. On the one hand, the effect on *Transaction Volume* is high but not even close to the magnitude of the remaining two strategies. TRV started from an adequate level (around 37%), while LIQ and STD scored almost half of it. The modified ASM model performs better in the last two cases than TRV. Once again, LIQ and STD appear to capture a similar effect in the cross-sectional return.

Appendix B: Variable specific methodology

a. Commodities Specific Variables

3-Years Reversal: (De Bondt & Thaler, 1985) It is defined as the excess return of a long-short monthly rebalanced portfolio, sorting commodity futures by their average excess return over the last 36-months.

5-Years Reversal: (De Bondt & Thaler, 1985) It is defined as the excess return of a long-short monthly rebalanced portfolio, sorting commodity futures by their average excess return over the last 60-months

Betting-against-beta*: (Frazzini and Pedersen. (2014)* It is defined as the excess return of a long-short monthly rebalanced portfolio, sorting commodity futures by their 36-Month Beta. Following the approach taken by Frazzini and Pedersen, it does not directly estimate the Beta, but it calculates it in two steps. The formula is the following:

$$\hat{\beta}_i^{ts} = \hat{\rho}\frac{\hat{\sigma}_i}{\hat{\sigma}_m}$$

Where ρ is the estimated correlation between the commodity and the market returns while σ_i and σ_m are the estimated volatilities for the commodity and the market. The paper takes this approach and not a direct estimation for reasons linked to the different estimation horizons and the data timeframe[94]

Carry: Bakshi et al. (2019), it is defined as the excess return of a long-short monthly rebalanced portfolio that goes short on the commodities that are most backwardated (lowest $\ln(y_t)$) and long on those that are most in contango (highest $\ln(y_t)$)[95]. The original paper defines $y_t = F_t^1 / F_t^0$ as the slope of the futures curve.

Equity Size Factor*:* (Fama&French, 1993) It is defined as the excess return of a long-short monthly rebalanced portfolio, sorting commodity futures by their market capitalization. In this case, data for the Open Interest of each asset are collected, and the factor is defined as:

$$Size_{i,t} = OpenInterest_t \times Price_t$$

Historical Skewness*:* (Amaya et al., 2015 & Cox(2010)) It is defined as the excess return of a long-short monthly rebalanced portfolio, sorting commodity futures by their Historical Skewness. The measure is calculated following Cox (2010) and with a 12 months' time horizon.

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[94] For a detailed explanation, please consult the original paper

[95] Note that Bakshi's paper goes long (short) in the most Backwardated (Contango) Commodity futures. For consistency with the portfolio construction, I take the opposite approach.

***Historical Kurtosis**:* (Amaya et al., 2015 & Cox(2010)) It is defined as the excess return of a long-short monthly rebalanced portfolio, sorting commodity futures by their Historical Kurtosis. The measure is calculated following Cox (2010) and with a 12 months' time horizon.

Liquidity: (Danyliv et al. (2014) It is defined as the excess return of a long-short monthly rebalanced portfolio, sorting commodity futures by their Liquidity value. Initially studied by Amihud (2002) it was found insignificant by Hollstein et al. (2021). However, Danvlin et al. Proposed a new measure from a trader perspective. The indicator aims to answer the question: "*What amount of money is needed to create a daily single unit price fluctuation of the stock?"*[96]

To do so, they proposed the following equation:

$$Liquidity = Log\left(\frac{Consideration}{Price\ Range}\right) = Log\left(\frac{V_t * P_{close}}{P_{High,T} - P_{Low,T}}\right)$$

Where V_t is the total volume traded the day before, P_{close} is yesterday's closing price, while P_{High} and P_{Low} are the highest and the lowers price registered in the trading session the previous day.

To this extent, the factor consists of a portfolio that takes a long position in the less liquid commodities and a short position in the most liquid ones.

Momentum: (Bakshi et al. (2019)) It is defined as the excess return of a long-short monthly rebalanced portfolio, sorting commodity futures by their 12-months mean returns.

***Systematic Effect of Hedging Pressure**: Basu et al. (2013)* It is defined as the excess return of a long-short monthly rebalanced portfolio, sorting commodity futures by their hedging pressure. For the thesis purpose, *hedging pressure* is defined as the number of long contracts divided by the total number of contracts in each commodity.

***Seasonality Effect**:* (Qadan et al. 2019): Although several seasonality effects are proven to be prices among asset classes, the work replicates the analysis for three of the most famous ones: the *January Effect*, *Christmas Effect*, and *Week-of-the-Year Effect*. For all of them, the idea is to run a regression to see whether returns differ significantly with respect to the rest of the year. For *January*, it is tested whether these are higher (or lower) during this month. For Christmas Effect, this work tests whether returns are higher (or lower) on the first and the second trading day after the holidays. For W*eek-of the-year*[97] it is tested if a specific Week during a year reports persistent higher or lower returns over

[96] Citation from the paper

[97] Documented by Levy and Yagil (2012)

time. Regressions are taken from Qadan et al. (2019). The model is the same for each fixed effect (data and periods are those that change):

$$R_t = \propto_i * D_i + \partial_i * R_{t-1} + \varepsilon_t$$

Where R_t is the excess return of the asset, while $\propto_i$ is the coefficient of the Dummy variable that incorporates the Seasonality Effect.

***Temperature anomaly**:* This factor has never been tested before. Since climate change directly affects commodity production, the aim is to see whether this risk is priced in the cross-sectional return.

This article investigates whether certain commodities futures, being more exposed to climate change, have significantly increased their price more than less-affected commodities from 1990 to today. If this is the case, the specific assets should have yielded a fixed positive significant return during this period.

The study takes two approaches to select which commodities are more exposed. Firstly, Taskin et al. (2021) studied that the Global Historical Surface Temperature Anomaly series have positive predictive power over Industrial commodities and precious metal prices. They put the Granger causality test in place and found significant positive results for those two indexes.

The second approach is restricted to a subsample following a report published by the European Environment Agency in March 2020: "Consequences of global climate change and their impact on Europe – A view on agriculture commodities." Among other things, they explained which agricultural goods are more exposed to climate change and less diversifiable (and vice versa).

Since *Temperature* is studied as a fixed effect, the regression is the same of the seasonality one:

$$R_t = \propto_i * D_i + \partial_i * R_{t-1} + \varepsilon_t$$

Where R_t is the excess return of the asset, while $\propto_i$ is the coefficient of the Dummy variable that takes value equal to 1 if the commodity belongs to the controlled sample and 0 otherwise.

Value: (Asness et al. 2013) It is defined as the excess return of a long-short monthly rebalanced portfolio, sorting commodity futures by their Value Factor. The former is defined as the ratio of the log of average daily futures prices from 4.5 to 5.5 years ago to the current log futures price.

b. *Cryptocurrencies Specific Variables.*

Such as in the previous case, the same portfolio construction methodology is applied. The only difference is the weekly rebalancing horizon, following the approach of Liu et al. (2019). The paper does not specify why it takes this horizon, but two conclusions can be drawn. First, the recursive higher volatility in the cryptocurrency probably requires a more frequent rebalancing horizon. Secondly, some anomalies appear significant only for short periods (such as *Momentum*).

The only case it is used a monthly rebalancing is for the Popularity anomaly. Indeed, data from Google Trend can be collected only monthly for the needed period.

Moreover, several papers only perform factors based on price, volume, and market capitalization information. The reason is that accounting or financial data for coins are hardly collectible or unsuitable. Nevertheless, the situation is similar for the commodities and does not create distinct differences in tested factors.

1-2-3-4 Weeks Momentum: (Liu et al. (2019)): It is defined as the excess return of a long-short weekly rebalanced portfolio, sorting coins by their 1, 2, 3 and 4 weeks mean returns. Some papers replicate this factor also for longer horizons; however, the strategy does not look to be profitable.

Google Trend*:* It is defined as the excess return of a long-short monthly rebalanced portfolio, sorting coins based on the monthly popularity index at t-2 relative to the analysis period. Unfortunately, knowing which coin will have the maximum popularity in advance is impossible. Thus, the strategy follows a "Short-term reversal approach." Differently from the former, the evaluated metrics are not past excess return but the search interest. The provided interest index span from a score of 100 (indicating the highest search frequency) to a score of 0 (indicating that not enough data was found for the term).

Idiosyncratic volatility (Res): (Ang et al. (2006) It is defined as the excess return of a long-short weekly rebalanced portfolio, sorting coins by the idiosyncratic volatility of their returns. Following the approach of the paper, the market return is considered when calculating return residuals.

$$R_{i,d} = \propto_i + \beta_i * R_{m,d} + \varepsilon_{i,d}, \qquad d = 1, \dots, D_t$$

Where $\varepsilon_{i,d}$ is the idiosyncratic return for the cryptocurrency I on day *d*, while D_t is the number of trading days in week *t.* Once calculated the error terms, the factor is defined as:

$$Res_{i,t} = \sqrt{Var(\varepsilon_{i,d})}, \qquad d = 1, \dots, D_t$$

Market Capitalization: (Liu et al. (2019): It is defined as the excess return of a long-short weekly rebalanced portfolio, sorting coins by market capitalization. In this case, the metrics incorporate the sum value in USD of the current coin supply.

Max Price Measure: (Liu et al. (2019): It is defined as the excess return of a long-short weekly rebalanced portfolio, sorting coins by their max price factor. The latter is defined as the maximum price of the portfolio formation week

Max Measure: (Bali et al. 2011): It is defined as the excess return of a long-short weekly rebalanced portfolio, sorting coins by max factor. The latter is defined as the maximum excess return in a given week.

Price: (Liu et al. 2019): It is defined as the excess return of a long-short weekly rebalanced portfolio, sorting coins by their price.

Standard Deviation of Dollar Volume*:* (Chordia, Subrahamanyam & Anshuman, 2001)[98] It is defined as the excess return of a long-short weekly rebalanced portfolio, sorting coins by their standard volatility of the weekly dollar trading volume.

Seasonality in the Cross-section of Cryptocurrency returns (SEAS): (following Keloharju, Linnainmaa, and Nyberg (2016): It is defined as the excess return of a long-short weekly rebalanced portfolio, sorting coins by their weekly cross-sectional seasonality effect. The idea behind this is that the average same weekday return in the past is positively correlated with future performance. For example, if you are planning to invest on a specific day of the week, you should check if the latter delivered high returns in the past.

According to the approach of the paper, the measure is calculated as follows:

$$SEAS_{i,t} = \frac{1}{20}\left(R_{i,t-7} + R_{i,t-14} + \cdots + R_{i,t-140}\right)$$

Where 7, 14… ,140 are the number of days, and R_i is the log-return of the cryptocurrency *i*.

Overreaction: (Caporale 2019) It is defined as the excess return of a long-short weekly rebalanced portfolio, buying (selling) coins if they delivered an abnormal positive (negative) return the previous week[99]. Following the methodology of the paper, returns are calculated as follows:

$$R_t = \frac{(High_i - Low_i)}{Low_i} \times 100\%$$

Where R_i is the percentage weekly return, and High (Low) is the maximum (minimum) price of the week *i*.

The paper decided to use high (low) instead of the standard open (close) price to capture the amplitude of the movement during the trading session. It also helps to capture the overreaction adequately.

[98] The original paper calculated the measure with daily volumes, because of data availability, here a weekly approach is taken

[99] The same anomaly for the commodity futures market is rebalance monthly.

After calculating the returns, to determine which coins have overreacted, this inequality is followed:

$$R_i > (\overline{R_n} + k \times \delta_n)$$

Where R_n is the average weekly return for the period n, while k and δ_n are respectively the number of standard deviations which identify the overreaction and the standard deviation of weekly returns for the period n.

The paper explains the different approaches to define in detail, concluding that the most appropriate value is 1. Once identified which coins overreacted in a certain period, a position of the same sign[100] for the following week is taken, testing whether this strategy can yield higher than the market average.

***Transaction Volume**:* It is defined as the excess return of a long-short weekly rebalanced portfolio, sorting coins by their number of weekly transactions.

[100] If the overreaction was in an upper (lower) direction, a long (short) position on the coin is taken for the following week.

Appendix C: Specific Commodity Futures per each Temp Factor:

Temp1:

Aluminum, Cobalt, Copper, Gold, Palladium, Platinum, Silver and Nickel. In the study's sample, they represent the Commodities belonging to the Precious Metal and Industrial categories.

Temp2:

Cocoa, Coffee, Rough Rice and Wheat. The sample is restricted since the paper was identifying some agriculture products which are at risk although not traded in the Commodity Future Markets (such as Palm oil or exotic fruit)

Appendix D: Google Trend and Seas results with the adjusted ASM model

Table D1:

Google Trend and Seas Results with Liquidity Factor

Commodity Anomaly	GT	SEAS
Panel A: Classical ASM Model		
Alpha	-0,0941***	-0,00253**
R^2	0,0586	0,0193
Panel B: Adjusted ASM Model		
Alpha	-0,08746***	-0,00273**
R^2	0,0732	0,0250

The table reports the R^2 of the regression after running the modified ASM Model. The latter is specified as following:

$$R^i = \propto^i + \beta^i_{mkt}MKT + \beta^i_{size}SIZE + \beta^i_{mom}MOM + \beta^i_{liq}LIQ$$

For both Anomaly, two additional regressions are run adding the Liquidity Factor.

The table shows the results of a modified ASM Model containing the Liquidity Factor as an explanatory variable. The prototype improves in both cases in terms of variability explained; however, not in a remarkable way. The effect on the significance and the magnitude of the alpha can be considered null. It seems like these factors cannot be described by any of the performed strategies (in unreported regression, none of the other portfolios could better explain GT and SEAS).

Table D2:

Google Trend and Seas Results Regressed upon each other

Commodity Anomaly	GT	SEAS
Panel A: Additional ASM Model		
Alpha	-0,0901***	-0,0062
R^2	0,0782	0,0571

The table reports the R^2 of the regression after running the modified ASM Model. The latter is specified as following:

$$R^i = \propto^i + \beta^i_{mkt}MKT + \beta^i_{size}SIZE + \beta^i_{mom}MOM + \beta^i_{y}Y$$

For both Anomaly an additional regression is run, adding the GT Factor when SEAS is the dependent variable and vice versa.

Unlike before, the table shows that the alpha of SEAS, although consistently robust before, appears not significant anymore when the *Google Trend* is included in the analysis. The opposite is not true. Even in this case, a deeper analysis of the background effects that cause GT, which appears robust to any control, can be an exciting point for further analysis.

Appendix E: Subsample Analysis

Table E1:

Commodity Future Portfolio Significance after 2003

Commodity Future Portfolio Returns (2004-2022)

	Momentum	Skewness	Kurtosis	Size	Liquidity	Carry	Long Ratio
Mean Return	0,014908***	-0,00713***	0,001709	-0,002786*	0,000048	-0,00402***	-0,002862*
	(0,003938)	(0,002714)	(0,00317)	(0,002048)	(0,002919)	(0,00164)	(0,002023)
	Value	**Temperature 1**	**Temperature 2**	**January**	**Week-of-the-Year**	**Christmas**	**Max Price**
Mean Return	0,0001758	0,0003823	-0,005474**	0,004532	0,001836***	0,000328	-0,002349
	(0,002447)	(0,001894)	(0,002251)	0,001187	(000624)	(0,000061)	(0,002574)
	Max Return	**Reversal3Y**	**Reversal5Y**	**Std Dev of Dollar Volume**	**Overreaction**	**Betting Against Beta**	**Seas**
Mean Return	-0,00952**	-0,01033***	-0,01020***	0,001919	-0,001265	0,003956	-0,0002124
	(0,00444)	(0,00404)	(0,004029)	(0,003367)	(0,0013218)	(0,004393)	(0,000196)

Table E2:

Cryptocurrency Future Portfolio Significance before 2021

Cryptocurrency Portfolio Returns (2015-2020)

	3-Weeks Momentum	Skewness	Kurtosis	Market Cap	Liquidity	Transaction Volume	1-Week Momentum
Mean Return	0,016107***	0,000185	0,00880	-0,021877***	-0,026618***	-0,17885***	0,00867
	(0,006405)	(0,009078)	(0,00900)	(0,009012)	(0,007963)	(0,006672)	(0,006838)
	2-Weeks Momentum	**4-Weeks Momentum**	**Idiosyncratic Volatility**	**Price**	**Google Trend**	**Std Dev of Dollar Volume**	**Max Price**
Mean Return	0,009307*	0,007976	-0,008651	-0,018400**	-0,081416***	-0,024006***	-0,018968**
	(0,006359)	(0,006889)	(0,009520)	(0,010601)	(0,017222)	(0,008342)	(0,01069)
	Max Return	**Reversal2M**	**Reversal6M**	**Reversal18M**	**Overreaction**	**Betting Against Beta**	**Seas**
Mean Return	-0,007635	0,014775**	-0,009816	0,007305	0,003369	0,001244	-0,0020707*
	(0,007738)	(0,008512)	(0,00954)	(0,01011)	(0,002774)	(0,010302)	(0,0013212)

Appendix F: List of factors divided by portfolio percentile selection

Portfolio Percentile For each Commodity Factor:

A 90-10 portfolio approach is implied for: MOM, SKW, KUR, LIQ, LR, VAL, MAXP, MAXR, 3YREV, 5YREV, STD, OVER, BAB and SEAS

An 80-20 portfolio approach is implied for: CARRY, SIZE

Portfolio Percentile For each Cryptocurrency Factor:

A 90-10 portfolio approach is implied for: MAXR, MAXP, PRC, STD, SEAS, RES, MKT, SKW, KUR, 2MREV, 6MREV, 18MREV, LIQ, TRV, BAB

An 80-20 portfolio approach is implied for: MOM1, MOM2, MOM3, MOM4, GT