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Bachelor Thesis in Financial Economics

Cross-Sectional Momentum Effects in Statistical Arbitrage Techniques

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Abstract

This thesis examines whether cross-sectional momentum exists in cryptocurrency statistical arbitrage strategies, in an endeavour to mitigate financial risk arising from investing in other, more traditional assets. Congruent with the principal methodology implemented in equity momentum literature, said strategies are constructed from a selection of the seven largest cryptocurrencies by market capitalisation. While the cross-sectional analysis indicates negative returns for all statistically significant relative strength rules, the risk-adjusted average returns of the multifactor asset pricing models furthermore yield similar outcomes. These results thus allude to a clear and significant dominance of the contrarian effect at high-frequency intervals, over both (a) the momentum effect and (b) the considered benchmark portfolios.

Key Words: Cryptocurrencies, Statistical Arbitrage Strategies, Cross-Sectional Analysis, Factor Investing, Momentum Effect, Contrarian Effect.

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I. Introduction

In the wake of the revolutionary blockchain technology, shortcomings of traditional payment networks could become the inefficiencies of a bygone era. Cryptocurrencies, digital assets founded in said innovation, serve as mediums of exchange; belonging to a transaction mechanism in which records of individual coin ownership, creation, and transfer are stored in a decentralised, distributed ledger. Within cryptocurrency systems, the balance and integrity of these ledgers is upheld by a community of mutually distrustful parties, who through cryptographic techniques, validate transactions (Brito & Castillo, 2013). Managed by these peer-to-peer networks, cryptocurrency exchanges lack centralised points of vulnerability present in central banking systems and digital currency, and thus provide a more secure alternative to conventional payment mechanisms.

The momentum effect in financial markets, unearthed by Jegadesh & Titman (1993), is a phenomenon that enables investors to temporarily earn abnormal returns when holding and shorting stocks, with high and low historical cumulative yields respectively. The existence of this empirically observed tendency - for an asset's historical price inertia to solely warrant its future return trend - is a direct violation of the efficient-market hypothesis, as corresponding strategies can consistently "beat the market", in a manner independent of fundamental analysis. The appearance of momentum is frequently attributed to cognitive biases observed in investor crowd behaviour such as overreaction, underreaction, or the disposition effect, all of which exhibit an antipersistent nature (Daniel et al., 1998). Therefore, as momentum dissipates, asset price distortions eventually cease to exist (the reversal effect), and thus lead to mispricings that contrarian strategies aim to exploit through holding long positions in stocks with historically poor performances and shorting high historical cumulative return equities to gain positive excess returns (Aravind, 2016). While the momentum effect has been extensively investigated in the context of traditional financial assets, consider Rouwenhorst (1998) and Menkhoff et al. (2012), the only recent emergence of the cryptocurrency market has left empirical literature on the latter, regarding price movement characteristics, rather limited.

The application of equally-weighted cross-sectional momentum strategies is explored by Liu and Tsyvinski (2019) who ascertain that zero-investment momentum strategies with weekly look-back periods generate approximately three percent excess weekly returns (2.7%, 3.3%, 4.1%, and 2.5% for one-, two-, three-, and four-week momentum respectively). Chu et al. (2019) furthermore extend the research scope to an hourly frequency and find that it is theoretically possible to profitably adapt the simple strategy to short-term financial data - with passive investing strategies logging cumulative returns of over 300% nearing the end of the considered period. While the aforementioned investigations, among others, have identified the existence of both a long- and short-term momentum effect in cryptocurrency markets, as of present no literature has been published regarding cryptocurrency momentum as a statistical arbitrage strategy (one that bets on the likelihood that mean reversion occurs at a per-second or hourly frequency). Despite the facts that (a) cryptocurrency exchanges currently do not offer short-selling functions with coin-fiat pairs, and (b) transaction times required in high-frequency trading may be too small for current cryptocurrency networks, the inevitable development of blockchain technology could enable these trading strategies in the future. In turn, this has led to the following research question:

"Does the usage of cross-sectional cryptocurrency price momentum as a statistical arbitrage strategy yield profitable returns?"

The motivation behind this thesis is to contribute to existing literature by not only examining whether high-frequency momentum trading is profitable in cryptocurrency markets, but also if it represents a feasible option to mitigate risk in financial portfolios. These aims furthermore resemble the scientific and social relevance of the paper.

The contents of this investigation are organised as follows. Section II sheds light on existing literature relating to the momentum effect in both traditional assets and cryptocurrencies. In Section III, the data used for the analysis is thoroughly examined; Section IV outlines the methodology that will be employed; Section V details the results relating to the cross-sectional and multifactor analysis; Section VI then provides a discussion of the results and relates these to the findings of said literature; Section VII concludes the thesis and additionally expresses its limitations.

II. Literature Review

I. Existing Literature on Momentum in Traditional Asset Markets

Price momentum strategies, frequently referred to as relative strength rules, garnered unprecedented attention following the findings of Jegadeesh and Titman (1993). While momentum investing had been the focal point of a substantial body of earlier academic literature - most notably Levy (1967) - surrounding market efficiency, claims concerning its ability to, on average, yield abnormal returns were routinely attributed to distortions in statistical analysis. However, given the success of various mutual funds in the Grinblatt and Titman (1991) sample and the predictive power of Value Line rankings, Jegadeesh and Titman (1993) express significant skepticism regarding these conclusions - citing the former examples as suggestive evidence of price momentum's ability to generate abnormal returns after all. In an endeavour to reconcile their hypothesis with the contemporary academic debate, Jegadeesh and Titman (1993) examine the performance of momentum strategies over 3- to 12-month horizons in the New York Stock Exchange (NYSE) from 1965 to 1989. The considered strategies select stocks based on their respective returns over the preceding 1, 2, 3, or 4 quarters, and are thereafter examined for varying holding periods of 1 to 4 quarters - giving a total of 16 iterations. More specifically, at the start of each month t, securities are sorted (in ascending order) according to their returns over the past J months, and then divided into ten decile portfolios on the basis of said ranking - labelling the top- and bottom-decile portfolios as “losers" and “winners" respectively. In each month t, the momentum strategy subsequently buys the winner - while shorting the loser-portfolio, and holds this position for K months (commonly referred to as a J-month/K-month strategy). To avoid the bid-ask spread effects and price pressure, documented in Lehmann (1990), Jegadeesh and Titman (1993) furthermore examine a second set of 16 strategies that differ from the former by skipping a week between the portfolio formation and holding periods. The results of this paper document that investment strategies which buy past winners and sell past losers generate significant positive returns over 3- to 12- month holding periods. The strategy that the authors examine in most detail, namely the *MOM(6,6)*, is able to realise an average compounded excess return of 12.01% per year. While the authors indicate that the relative strength profits are unattributable to lead-lag effects caused by delayed stock price reactions to common factors, the evidence is however compatible with delayed price reactions to firm-specific information. They furthermore note that when the returns of identical relative strength strategies are examined over a 36 month holding period, nearly half of the excess return generated in the first year after portfolio formation dissipates in the two years that follow.

Although Jegadeesh and Titman (1993) document that relative strength strategies induce statistically significant abnormal returns over medium-term horizons, it cannot be ruled out that these return patterns are simply the outcome of an intra-market anomaly. While Asness et.al (1996) and Richards (1997) recognise this concern and provide compelling evidence regarding the existence of the momentum phenomenon in national (US) market indices, Rouwenhorst (1998) further widens the scope of return pattern investigations to an international context. Utilizing an identical procedure to Jegadesh and Titman (1993), Rouwenhorst attempts to discern whether international return continuation within, and across, markets exists at the individual stock level - using a sample of 2,190 stocks from 12 European countries during the period 1978 to 1995. According to the author, the "European evidence is remarkably similar to findings for the US by Jegadeesh and Titman (1993)", stating that a medium-term internationally diversified relative strength portfolio earns a monthly return of approximately one percent. Upon further inspection, Rouwenhorst additionally reveals that, in isolation, all national market indices in the sample experience momentum effects - suggesting that the results of Jegadeesh and Titman (1993) are unlikely to be caused by chance.

Contrary to the extensive literature on relative strength strategies in the cross-section of equity markets, prior to the publication of Menkhoff et. al (2012), investigations pertaining to the existence of currency momentum were predominantly rooted in time-series analysis of single exchange rates[3]. Whilst these studies indicate that momentum investing as a technical trading rule is temporarily profitable, Menkhoff et. al (2012) attempt to extend the domain of pre-existing research to foreign exchange (FX) markets - the natural laboratory for examining the economic anatomy of currency momentum profits. Primarily populated by sophisticated professional investors, FX markets exist in the absence of natural short-selling constraints [4] and hence exhibit higher levels of liquidity, vast transaction volumes and low transaction costs relative to regular stock markets. Consequently, considering FX markets should therefore significantly increase the difficulty of generating consistent excess returns from relative strength strategies according to Menkhoff et. al (2012). To evaluate the validity of their hypothesis, the paper explores the performance of 48 currencies (relative to the USD) in the sample period stretching from January 1976 to January 2010. Congruent with the methodology implemented in equity market literature, the authors employ a *J*-month/*K*-month momentum strategy with formation and holding periods of either 1, 3, 6, 9, or 12 months. They show that momentum strategies yield abnormally positive excess annualized returns of approximately 8%. Strategies that employ longer holding periods also generate higher returns consistently. It is also important to note that their currency momentum profits are highly time varying.

While cross-sectional momentum effects in medium-term foreign exchange rate returns appear to be robust, Raza et. al (2014) investigate whether these relative strength strategies also prove successful over short-term horizons. To explore the return dynamics of said investment schemes, the authors consider weekly exchange rate data pertaining to 63 emerging and developed market currencies, from November 1997 to July 2013. On par with the procedure adopted by Menkhoff et. al (2012), they construct portfolios (with 1-4 week look-back and holding periods) that take up long and short positions in the 20% most appreciated and depreciated currencies, relative to the U.S. dollar. In contrast to short-term reversal effects, documented in equity market literature, Raza et. al (2014) find strong evidence favouring the existence of short-term cross-sectional momentum in FX markets. More explicitly, out of the 16 *J*-week/*K*-week strategies considered, 15 yield statistically significant positive mean returns (ranging from 1.84% to 8.60% on an annualised basis) - suggesting that the hypothesis of reversal can be rejected in favour of momentum in weekly currency returns. The magnitude of momentum returns are furthermore directly proportional to the length of the look-back period, with annualised excess returns climbing by as much as 6.28% when the look-back period increases from one to three weeks for $K=1$ strategies.

II. Existing Literature on Momentum in Cryptocurrency Markets

Owing to the inception of Bitcoin, cryptocurrencies have accumulated significant attention in academic literature. While they are embedded in a fundamentally new technology, whose potential is currently ambiguous, these assets fulfil functions analogous to other, more traditional instruments - warranting questions pertaining to investor and market valuations of current and future cryptocurrency prospects. Aspiring to uncover the nature of said assets, Liu and Tsyvinski (2018) investigate the aggregate relationships between three major cryptocurrencies and standard asset classes - in addition to examining the driving factors behind their market activity in the short-term. Despite popular narratives claiming correspondence between returns of cryptocurrencies and traditional instruments (insinuating dual compensation by conventional risk factors), the authors find compelling evidence regarding distinct risk-return tradeoffs between the two. Instead, upon turning to cryptocurrency specific factors that mirror predictors of stocks, currencies, and commodities, Liu and Tsyvinski (2018) observe that only price momentum and investor attention are capable of forecasting the radically different asset class. In reference to the former, the authors find statistically significant evidence favouring time-series momentum at daily and weekly frequencies for all three coins - with the top and bottom quintiles of Bitcoin returns achieving average yields up to 11.22 and 2.60 percent respectively (at the optimal one-week formation horizon). Irrespective of a less pronounced effect for Ethereum, relative to Bitcoin and Ripple, Liu and Tsyvinski (2018) nevertheless confirm the existence of relative strength rules in cryptocurrency markets - but then with a discernably higher mean and standard deviation of returns than those for traditional asset classes.

In striving to establish a set of empirical regularities specific to cryptocurrency markets, Liu and Tsyvinski (2019) extend the outlook of their aforementioned investigation to a cross-sectional analysis. More specifically, through utilizing standard asset pricing tools they examine whether the characteristics deemed important in equity returns are moreover exploitable in a cryptocurrency setting. From those factors explaining cross-sectional stock returns - compiled by Feng et al. (2017) - Liu and Tsyvinski (2019) analyse the performance of 25 variables (based only on price and market information) for coins with market capitalizations exceeding one million dollars, from 2014 until 2018. Each week cryptocurrencies are sorted into quintile portfolios - according to their value as calculated in the context of a specific factor - for which the average excess returns over the risk-free rate in the subsequent week are calculated. Drawing from this factor-specific portfolio construction, Liu and Tsyvinski (2019) then form a long-short strategy corresponding to the difference between the fifth and first quintiles respectively. They find that statistically significant zero-investment momentum strategies with one-week lookback periods generate, on average, excess weekly returns of approximately three percent (2.7%, 3.3%, 4.1%, and 2.5% for one-, two-, three-, and four-week holding periods respectively).

Per restricting their parameters of inquiry solely to contemporary mediums of exchange, Rohrbach et al. (2017) investigate the nature of cross-sectional and longitudinal momentum effects in traditional fiat- and crypto-currency markets. Diverging from the *J*-month/*K*-month methodology adopted by the vast majority of asset momentum literature, Rohrbach et al. (2017) instead employ a geometric Brownian Motion algorithm - presented by Baz et al. (2015) - to evaluate the dynamics of financial asset returns and generate trade signals. To examine momentum effects in these assets, the authors consider 16 USD-denoted foreign currency exchange rates and the seven largest cryptocurrencies by market capitalization (provided the coins have a minimum data history of two and a half years) - for sample periods stretching to the present date from 1974 and 2017 respectively. While the results documented in Rohrbach et al. (2017) indicate that momentum investing was only profitable for G10 currencies until the 2008 financial crisis, for emerging market currencies strategy proves effective to date - logging longitudinal and cross-sectional annualized returns of 2.48% and 1.13% with Sharpe ratios of 0.586 and 0.253. Furthermore, contrary to the findings of Liu and Tsyvinski (2018, 2019), the authors additionally observe that the magnitude of annualized momentum returns in cross-sectional portfolios (56.94%) significantly outweigh those of their longitudinal counterpart (42.02%) - all while possessing Sharpe ratios of 1.48 and 1.68. They reason that the disparity in momentum returns between assets is attributable to investor compensation for the additional risk taken to hold them - explaining why emerging market currencies and cryptocurrencies both have better performances than those belonging to the G10 subset.

The rise to prominence of algorithmic neural networks in cryptocurrency trading, as mentioned in Rohrbach et al. (2017), has led to a resurgence of explorations pertaining to traditional investment strategies; among which Chu et al. (2019), who investigate whether the application of relative strength rules to high-frequency financial data can consistently generate positive returns, akin to those documented in the foregoing papers. In addition to their active portfolios that generate trade signals based on exponential moving average models of coin returns, the authors also implement a passive strategy - one similar to that of Liu and Tsyvinski (2019). The latter is furthermore divided into two different types, namely one with variable weights and the other with fixed ones. Here the varied weights "mirror the share of the live market capitalisation corresponding to a specific cryptocurrency on the first day of every month", while the fixed-weight approach simply aims to create a zero-cost portfolio (Chu et al., 2019). Analagous to Rohrbach et al. (2015), the authors use hourly prices of the top seven cryptocurrencies (by market capitalization), from February to August of 2017 (under the assumption that these have continually existed throughout the considered period). Chu et al. (2019) find that when using active strategies they are able to achieve cumulative log returns of approximately 0.4. Intriguing is the fact however, that their passive strategies significantly outperform their active counterpart, yielding cumulative returns of over 300% towards the end of the sample period. Interesting to note is the authors' observation that the monthly varying weights outperforms the fixed weight approach during the sample period. In light of this evidence, the authors conclude that it is theoretically possible to successfully apply this simple strategy to a high frequency setting. While the authors mention that, in their current capacity, cryptocurrencies cannot be sold short at scale, they argue that the reality of these strategies becoming more readily available as cryptocurrency markets develop, seems increasingly plausible. However, they do note that the extensive time frame required to validate transactions of some cryptocurrencies may present a problem when trading on shorter intervals than those presented in their analysis.

III. Data

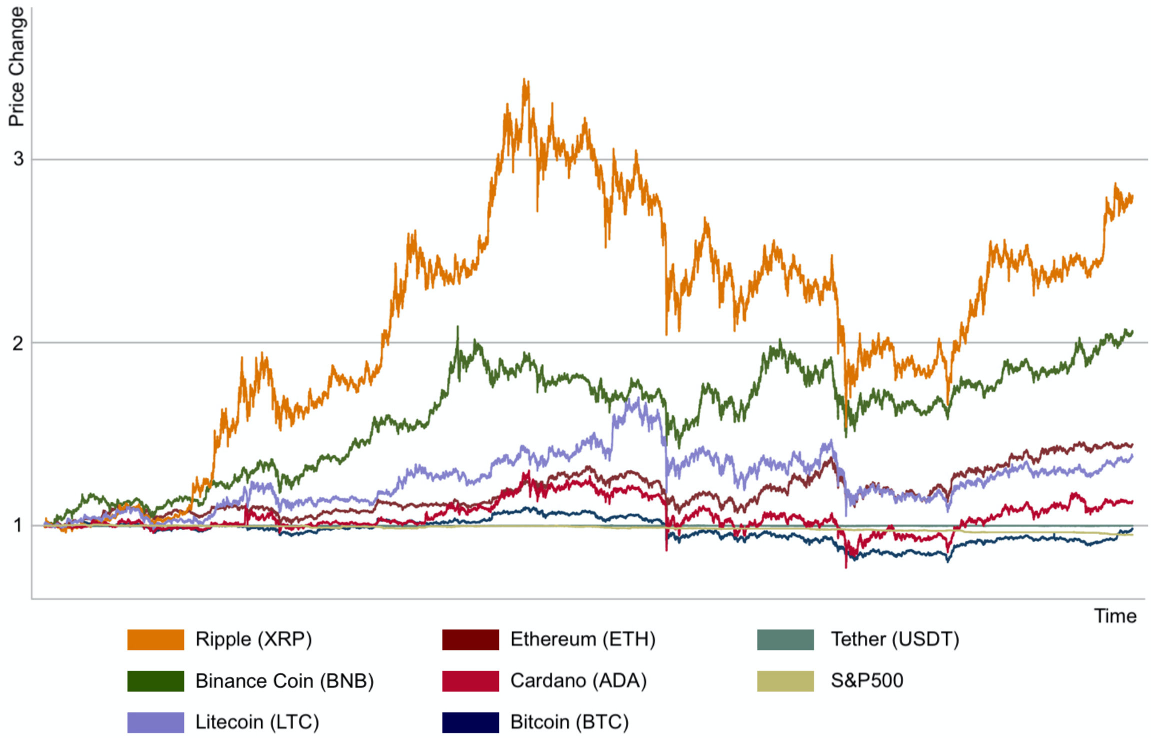
To examine the existence of high-frequency momentum strategies in cryptocurrencies, the data employed for this investigation is of an intraday, or more specifically a per-minute, nature. Considering the microscale hereof, the utilised data sample exhibits a significantly shorter time horizon as compared to Rohrbach et al. (2017) and Chu et al. (2019), namely one month. Commencing at 00:00 on April 1st 2021, the samples selected for all relevant financial instruments contain 43,200 observations, which will subsequently terminate at May 1st 00:00. Similar to Rohrbach et al. (2017), the relative strength strategies are composed of the seven largest cryptocurrencies by market capitalization (provided the coins have a minimum data history of two and a half years), which are: Bitcoin (BTC), Ethereum (ETH), Binance Coin (BNB), Ripple (XRP), Tether (USDT), Cardano (ADA), and Litecoin (LTC). As this set covers approximately 85% of the total market capitalisation at the inception of the dataset, it is reasonable to assume that it provides an adequate representation of market demand for cryptocurrencies. Polkadot (DOT) was initially included in the analysis, however due to anomalies in its price data, it was removed in favour of Litecoin (LTC). For the aforementioned coins, historical OHLC (Open/High/Low/Close) data from multiple cryptocurrency exchanges is retrieved from CryptoDataDownload to quote a weighted average price in the international market. Furthermore, in an endeavour to compare the performance of the considered momentum strategies to a proxy of the traditional asset "market portfolio", data on the S&P500 market index (of comparable intervals) was obtained from Dukascopy - an online trading service provider. An equity market comparison is made as Liu and Tsyvinski (2018) claim that the Sharpe ratios of cryptocurrencies are most comparable to those of stocks in the short term - despite citing distinct risk-return tradeoffs between assets.

Prior to in-depth statistical analysis the indexed hourly exchange rates of the relevant financial instruments are briefly examined in Figure 1. Here, the first exchange rate for each asset at 00:00 on April 1st 2021 is normalised to a value of one, after which the following prices are all adjusted relative to this value - enabling an examination of the true variation in asset rates (independent of absolute monetary values). Over the considered period, Ripple, Binance Coin, Litecoin, and Ethereum show a general increase in exchange rate value, whereas the other assets tend to fluctuate around their initial value. The largest increases in indexed prices are observed in Ripple and Binance Coin, while their smallest counterparts are

Tether and the S&P500. As will be illustrated momentarily, these trends are also reflected in the values belonging to the coefficient of variation, presented in Table 1.

Figure I:

Indexed Prices of Relevant Assets



* Historical OHLC data made available by CryptoDataDownload and Dukascopy.

Table I:

Summary Statistics

Summary statistics of the per-minute exchange, relative to the USD, of Bitcoin (BTC), Ethereum (ETH), Binance Coin (BNB), Ripple (XRP), Tether (USDT), Cardano (ADA), Litecoin (LTC), and the S&P500 from 00:00 on the 1st of April 2021 to 00:00 on the 1st of May 2021, exclusive.

Statistic	BTC	ETH	BNB	XRP	USDT	ADA	LTC	SP500
Minimum	47,030	1,886	300.8	0.5489	0.9938	0.9189	192.8	3,981
Q1	54,700	2,099	408.2	1.007	1.000	1.192	224.4	4,092
Median	57,610	2,218	509.6	1.304	1.001	1.226	249.0	4,141
Mean	57,110	2,273	484.7	1.210	1.001	1.255	245.7	4,130
Q3	59,620	2,431	552.8	1.412	1.002	1.311	264.4	4,177
Maximum	64,830	2,801	634.0	1.965	1.007	1.557	335.2	4,210

Skewness	-0.3340	0.6535	-0.5580	-0.3123	-0.07420	0.5946	0.3367	-0.7554
Kurtosis	2.600	2.496	2.067	2.333	5.646	2.930	2.968	2.566
SD	3707	224.3	85.81	0.3490	7.656 e^{-04}	0.09781	28.36	56.66
Variance	1.370e^{+07}	50,290	7,364	0.1218	5.862 e^{-07}	0.009567	804.3	3,211
CV	6.491	9.868	17.70	28.84	0.07648	7.794	11.54	0.01372
Range	17,800	915.0	333.2	1.416	0.01320	0.6381	142.4	85.00
IQR	4,920	332.0	144.6	0.4050	0.002000	0.1190	40.00	229.0

* Historical OHLC data made available by CryptoDataDownload and Dukascopy.

Table 1 presents an analysis of the summary statistics of the per-minute exchange rates of the seven selected currencies relative to the USD. Upon inspection it can be observed that, with exception to the minimum, the smallest and largest values for the first quartile, median, mean, third quartile, and maximum are all given by Tether and Bitcoin respectively. Specifically for cryptocurrencies, these values can be perceived as a measure of popularity, where market demand is an increasing function of their magnitudes. Furthermore, in terms of skewness, five of the eight instruments exhibit negative values. All eight assets additionally display leptokurtic distributions as well, implying that the hourly exchange rates are a subset of a peaked distribution that possesses thick tails - indicating increased investment risk as return distributions deviate from normality. The standard deviations and variances of the majority of considered assets are moreover generally significantly large with exceptions of Ripple, Tether, and Cardano; while the largest belong to Bitcoin and Ethereum respectively, which non-coincidentally are the two most frequently traded cryptocurrencies on the market.

IV. Methodology

Employing a methodology similar to that of Jegadeesh and Titman (1993) and Chu et al. (2019) - this investigation examines various short-term strategies to assess whether cross-sectional momentum effects exist in cryptocurrency markets. The considered strategies select coins with regard to their respective returns over look-back periods *(J)* of 5, 10, 15, 20 or 30 minutes, and subsequently retain said currencies for holding-periods *(K)* of similar time intervals - amassing a total of 25 iterations. More explicitly, cryptocurrencies are first ranked (on a per-minute frequency) according to their returns over the past *J* minutes - in descending order - after which the three best and worst historically performing coins are assigned to the "winner" and "loser" portfolios respectively. Given the lagged return portfolios, individual momentum strategies then buy the "winner" and short the "loser", to create a zero-cost strategy, and furthermore hold this position for *K* minutes. Formulaically, the return of a particular momentum strategy's investment portfolio, $R_p^{(J,K)}$, is calculated as indicated below:

$$R_p^{(J,K)} = \sum_{i=1}^{3} \frac{1}{3} \cdot R_{i(j)}^{+k} - \sum_{i=5}^{7} \frac{1}{3} \cdot R_{i(j)}^{+k} \qquad \textbf{(1)}$$

While the ranking cryptocurrencies are assigned (based on their look-back period performance) is depicted by *i*, their ensuing returns over the holding period are illustrated by $R_{i(j)}^{+k}$. Furthermore, due to the exclusion of the median return among the coins, to obtain a zero-cost strategy, the sum of returns in both the "winner" and "loser" portfolio are divided by the number of cryptocurrencies in them, namely: three. The results of the cross-sectional analysis for each strategy will subsequently be evaluated against the first hypothesis:

H_1: The strategy MOM(J,K) generates statistically significant positive returns.

Following the cross-sectional analysis of short-term cryptocurrency momentum, the risk-adjusted average returns (α) of the considered strategies will be calculated. This measure - referred to as Jensen's alpha - indicates whether the return of a financial instrument is in excess of its theoretical expected rate of return, postulated by the Capital Asset Pricing Model (CAPM). The relationship between α and CAPM can be expressed as follows:

$$E(R_p) \ = \ R_f + \beta_p[E(R_m) - R_f] \quad \textbf{(2)}$$

$$\alpha_p = R_p^{(J,K)} - [R_f + \beta_p(R_m - R_f)] \quad \textbf{(3)}$$

The equation outlined in (2) is that of the CAPM. Here, $E(R_p)$ represents the expected return of a financial asset, while $E(R_m)$ and R_f are the expected rate of return of the market index and the associated risk free rate respectively. The term β_p, however, is a measure of the volatility - an asset's nondiversifiable or systematic risk - relative to the market. If an asset, in the context of CAPM, exhibits a beta greater/lower than 1, then this suggests that its returns on average move more/less than one-to-one with that of the market portfolio. Integrating all relevant aspects into CAPM then stipulates that the expected, risk adjusted, return of an asset should equal the sum of (a) the risk free rate and (b) the product of the asset's systematic risk and the market risk premium. Upon closer inspection of equation (3) per contra, the association becomes clear; given that α_p is statistically significant, a corresponding positive value would imply that the asset performs structurally better than its expected returns established by CAPM - hence generating excess returns for the associated risk level.

Furthermore, as Fama and French (1992) show in their three-factor model, the alpha belonging to an asset can moreover be quantified relative to benchmarks other than CAPM. Hence, in an endeavour to determine the risk adjusted average returns of the considered momentum strategies, eight factors are utilised. In light of the possibility that the returns of said strategies could solely exist due to extreme return patterns documented in one or more cryptocurrencies, the intra-hour returns belonging to Bitcoin, Ethereum, Binance Coin, Ripple, Tether, Cardano, and Litecoin will be employed as independent variables. In addition to the aforementioned factors, the return of the S&P500 (an equity market proxy) is also regarded as a benchmark - specifically to investigate inter-asset return similarities. While returns generated by the momentum strategies, $R_{pt}^{(J,K)}$, are treated as dependent variables, the factors specific to cryptocurrencies and the equity market are used as regressors - as such, the following regression is performed for each momentum strategy:

$$R_{pt}^{(J,K)} = \alpha_{p,MF} + \beta_{p,EMR} \cdot R_{EMR,t} + \beta_{p,BTC} \cdot R_{BTC,t} + \beta_{p,ETH} \cdot R_{ETH,t} + \beta_{p,BNB} \cdot R_{BNB,t} \quad \textbf{(4)}$$
$$+ \ \beta_{p,XRP} \cdot R_{XRP,t} + \beta_{p,USDT} \cdot R_{USDT,t} + \beta_{p,ADA} \cdot R_{ADA,t} + \beta_{p,LTC} \cdot R_{LTC,t} + \varepsilon_{pt,MF}$$

The equation above explains the return of the momentum strategies at time t. Important to note, is the alpha $\alpha_{p,\,MF}$ which indicates the average return of said strategies in excess of the considered benchmarks. While $\beta_{p,\,EMR}$ is the measure of the strategy's return volatility relative to that of the equity market ($R_{EMR,\,t}$), the other betas represent the measure of risk arising from exposure to the seven cryptocurrency factors ($R_{ticker,t}$). Furthermore, $\varepsilon_{pt,\,MF}$is the error term at time t belonging to the different regressions.

To identify whether the momentum strategies earn enough for the risks that they are exposed to, the alphas will be evaluated against the null hypothesis that its inherent value is zero, namely: H_0: $\alpha_{MF} = 0$. This hypothesis is furthermore tested against its alternative, more specifically that it differs from zero - implying that two-tailed critical values must be applied for analytical purposes. If the outcome of the t-test indicates that the alpha of a momentum strategy is positive and significant, then the portfolio is generating profits in excess of the returns it ought to yield for the level of risk it bears. Under the assumption that alpha equals or is less than zero, the strategy earns too little and is hence inefficient (Jensen, 1968). The results of the multifactor analysis for each strategy will subsequently be evaluated against the second hypothesis:

H_2: The risk-adjusted return of strategy MOM(J,K) is significant and positive.

V. Results

The following section explores the cross-sectional analysis results of the different relative strength rules. From the information presented in Table 2, it is noticeable that the vast majority of short-term momentum strategies generate negative returns. More specifically, given that they yield statistically significant non-zero returns at the 95% confidence interval, all considered strategies report losses. Interesting to note though, is that of all examined look-back periods, only the 20-minute lagged return base exhibits insignificant return patterns, namely in *MOM(20,5), MOM(20,10),* and *MOM(20,15).* Upon differentiating between momentum strategies according to their look-back period, it can be observed that those containing smaller *J*-values, on average, display the most statistically significant losses. Under primary scrutiny here are *MOM(5,5)*, *MOM(5,10),* and *MOM(10,5)*, which possess t-statistics of -13.33, -12.36, and -10.63, with corresponding hourly volatilities of 1.2%, 8.0%, and 12% respectively. Accounting for the risk-free rate of return - the average interest rate on a three-month U.S. Treasury bill over the period - this comes down to individual hourly Sharpe ratios of -0.064, -0.059, and -0.051 (the highest in the sample). Through substituting the common denominator of analysis to holding periods however, a more curious pattern presents itself; given a particular holding period, the statistical significance of average momentum returns appear to be inversely related to the look-back period up to and including *J=20,* after which the significance increases again. Irrespective of the statistical significance, this implies that as the *J*-value increases up to 30 for a given holding period, the average portfolio returns tend to decrease.

While these results, upon initial review, might seemingly indicate that there is no intra hour cross-sectional price momentum in cryptocurrency markets, drawing conclusions from this information alone might be insufficient. Returning to the summary statistics in Table 1, it can be seen that the coefficients of variation (CV) belonging to the relevant cryptocurrencies vary significantly, with Ripple and Tether listing differences of nearly 29 points. This suggests that if the level of dispersion around the mean, or volatility, is significantly greater for one asset than the other, the profitability of momentum strategies could be entirely due to the return pattern of one cryptocurrency. Nevertheless, Table 2 contains an overview of the cross-sectional results of the zero cost portfolios, for all 25 momentum strategies (an overview of the long- and short-only portfolios is furthermore included in Appendix 1).

Table II:

Descriptive Statistics of Relative Strength Portfolios

The relative strength portfolios are constructed according to the J-minute lagged returns of the seven largest cryptocurrencies, by market capitalization, and held for K minutes. The combination of formation- (J) and holding-periods (K) for the different strategies are indicated in the first column. The cryptocurrencies are classified - in descending order - on the basis of their J-minute lagged returns, after which a zero-investment portfolio is formed that buys/sells the three highest/lowest historical return performers (referred to as “Winners” and “Losers” respectively). The average, hourly-adjusted returns of these portfolios are first presented in the third column. Similar adjustments are made for the standard deviation and standard error of said portfolios. The t-statistic and corresponding p-value, which highlight the probability of the average portfolio return belonging to a zero-mean probability distribution, are presented in columns seven and eight. Furthermore, to compute the Sharpe Ratio the average interest rate on a three-month U.S. Treasury bill over the period is used as a risk-free rate proxy. The sample period spans from April 1st to May 1st, 2021.

MOM(J,K)	Observations	Average Return (%)	SD (%)	Sharpe Ratio	Standard Error	T-Statistic	P-Value
MOM(5,5):	43,225	-0.7585	11.83	-0.06411	0.05690	-13.33	0.000
MOM(5,10):	43,220	-0.4783	8.045	-0.05947	0.03870	-12.36	0.000
MOM(5,15):	43,215	-0.2499	6.469	-0.03861	0.03112	-8.03	0.000
MOM(5,20):	43,210	-0.1987	5.564	-0.03573	0.02676	-7.424	0.000
MOM(5,30):	43,200	-0.1938	4.528	-0.04280	0.02179	-8.895	0.000
MOM(10,5):	43,220	-0.6128	11.99	-0.05116	0.05765	-10.63	0.000
MOM(10,10):	43,220	-0.2601	8.131	-0.03201	0.03911	-6.65	0.000
MOM(10,15):	43,215	-0.1579	6.487	-0.02436	0.03121	-5.06	0.000
MOM(10,20):	43,210	-0.1828	5.452	-0.03268	0.02623	-6.97	0.000

MOM(10,30):	43,200	-0.1852	4.534	-0.04084	0.02181	-8.49	0.000
MOM(15,5):	43,215	-0.2490	12.09	-0.02059	0.05818	-4.28	0.000
MOM(15,10):	43,215	-0.08133	8.168	-0.009980	0.03929	-2.07	0.019
MOM(15,15):	43,215	-0.09856	6.525	-0.01515	0.03139	-3.14	0.001
MOM(15,20):	43,210	-0.1618	5.606	-0.02885	0.02697	-6.00	0.000
MOM(15,30):	43,200	-0.1474	4.539	-0.03248	0.02184	-6.75	0.000
MOM(20,5):	43,210	0.04914	11.74	0.004199	0.05648	0.87	0.808
MOM(20,10):	43,210	0.01277	8.044	0.001606	0.03870	0.33	0.629
MOM(20,15):	43,210	-0.04311	6.356	-0.006786	0.03057	-1.41	0.079
MOM(20,20):	43,210	-0.3317	22.03	-0.01505	0.1060	-3.13	0.009
MOM(20,30):	43,200	-0.1076	4.536	-0.02370	0.02183	-4.93	0.000
MOM(30,5):	43,200	-0.3913	12.32	-0.03175	0.05929	-6.60	0.000
MOM(30,10):	43,200	-0.2043	8.442	-0.02418	0.04062	-5.03	0.000
MOM(30,15):	43,200	-0.1529	6.705	-0.02282	0.03226	-4.74	0.000
MOM(30,20):	43,200	-0.1568	5.758	-0.02722	0.02770	-5.66	0.000
MOM(30,30):	43,200	-0.1475	4.631	-0.03186	0.02228	-6.62	0.000

[*] These portfolios are constructed utilizing historical OHLC data made available by CryptoDataDownload.

Once the return distributions of the momentum strategies had been identified, a multifactor analysis could be conducted to calculate the risk-adjusted average returns (Jensen's alpha) of the corresponding portfolios. Momentum returns are regressed against the returns of an equity market proxy and the seven considered cryptocurrencies. While the former is included to compare inter-asset return patterns, the latter controls for the possibility that momentum effects exist solely due to extreme return patterns documented in one or two coins. While observing the contents of Table 3, it can be established that the predominance of alphas are (a) significant at the 99% confidence interval, and (b) negative. Similar to the aforementioned exceptions, only *MOM(20,5)* and *MOM(20,10)*, exhibit positive alphas - however due to their statistically insignificant nature ($p > 0.05$), akin to *MOM(20,15)* and *MOM(15,10)*, no further information can be drawn from these samples. Intriguing however, is the fact that all relative strength strategies - except for those with look-back periods of *J=20* - yield slightly higher risk-adjusted average returns as compared to their non-adjusted counterparts.

Furthermore, while not necessarily statistically significant in every regression, for some momentum portfolios, the generated returns can be explained by movements in the S&P500. Noteworthy is the fact, that in all those cases, β_{EM} takes on negative values - indicating that high frequency momentum strategies move in a direction opposite to the stock market. When turning to cryptocurrency-specific factors however, the pattern seems to be less pronounced. While Cardano (ADA) and Litecoin (LTC) are negative and statistically significant in all regressions at the 99% confidence level, all other coins exhibit varying characteristics. These cryptocurrencies might explain movements in one momentum strategy, but not in the other, or indicate correlations of different signs for different dependent variables. Nonetheless, considering that the majority of portfolios generate negative alphas, the results hence imply that these momentum strategies are incapable of compensating for the risk exposure to the equity market and various cryptocurrencies - instead suggesting the existence of contrarian strategies at a high frequency.

Table III:

Multifactor Model of Risk-Adjusted Momentum Strategy Returns

The momentum portfolios are constructed according to the J-minute lagged returns of the seven largest cryptocurrencies, by market capitalization, and held for K minutes. The combination of formation- (J) and holding-periods (K) for the different strategies are indicated in the first column. The cryptocurrencies are classified on the basis of their J-minute lagged returns, after which a zero-investment portfolio is formed that buys/sells the three highest/lowest historical return performers. The average, per holding period return, of these portfolios are presented in the second column. Following this, the performance of said momentum strategies are regressed against the returns of the S&P500 (EM), Bitcoin (BTC), Ethereum (ETH), Binance Coin (BNB), Ripple (XRP), Tether (USDT), Cardano (ADA), and Litecoin (LTC). The models yield alphas (describing the investment's ability to beat the regressed variable), betas (measuring the strategy's systematic risk as compared to the regressed variable), and R^2 values (the proportion of fluctuations in contrarian strategies explainable by the regressed variable). Furthermore, the numbers in parentheses represent the t-statistic corresponding to $H_0: \beta_x = 0$. The sample period spans from April 1st to May 1st, 2021.

CON(J,K)	Average Return (%)	α_{MF} (e^{-02})	β_{EM}	β_{BTC}	β_{ETH}	β_{BNB}	β_{XRP}	β_{USDT}	β_{ADA}	β_{LTC}	R^2
MOM(5,5):	-0.06343 (13.33)	-0.06182 (-13.10)	-0.3713 (-2.22)	0.1592 (3.98)	-0.08059 (-2.87)	0.01540 (1.04)	-0.01932 (-2.33)	0.03981 (0.45)	-0.2180 (-15.21)	-0.1104 (-13.10)	0.0206
MOM(5,10):	-0.07987 (12.36)	-0.07566 (-11.77)	0.009747 (0.06)	0.2637 (6.75)	-0.1883 (-6.85)	-0.003335 (-0.23)	-0.01413 (-1.74)	-0.4366 (-3.81)	-0.1091 (-7.22)	-0.1196 (-7.91)	0.0071
MOM(5,15):	-0.06254 (8.03)	-0.06172 (-7.96)	0.1483 (0.76)	-0.1428 (-3.68)	0.01533 (0.56)	0.02609 (1.89)	0.02550 (3.14)	0.07508 (0.56)	-0.1524 (-9.87)	-0.1156 (-7.60)	0.0158
MOM(5,20):	-0.06627 (7.42)	-0.06495 (-7.28)	0.005045 (0.03)	-0.07058 (-1.83)	-0.01612 (-0.58)	-0.004696 (-0.34)	0.03212 (3.94)	0.02214 (0.15)	-0.1340 (-8.61)	-0.06060 (-3.95)	0.0092
MOM(5,30):	-0.09693 (8.90)	-0.09671 (-8.85)	-0.3839 (-2.36)	-0.1189 (-3.03)	-0.06114 (-2.19)	0.02801 (2.08)	0.04359 (5.30)	0.1522 (0.85)	-0.1152 (-7.23)	-0.0300 (-1.92)	0.0068

MOM(10,5):	-0.05121 (10.63)	-0.04815 (-10.20)	-0.7430 (-4.45)	0.2920 (7.30)	-0.1250 (-4.45)	-0.001549 (0.10)	0.002857 (0.34)	-0.2240 (-2.53)	-0.3216 (-22.43)	-0.1906 (-12.80)	0.0427
MOM(10,10):	-0.04340 (6.65)	-0.04032 (-6.28)	-0.3860 (-2.38)	-0.01503 (-0.39)	-0.7829 (-2.85)	0.02745 (1.93)	0.04928 (6.06)	-0.09154 (-0.80)	-0.2493 (-16.52)	-0.1830 (-12.12)	0.0356
MOM(10,15):	-0.03949 (5.06)	-0.03783 (-4.91)	-0.6013 (-3.09)	-0.1309 (-3.39)	-0.07234 (-2.65)	0.03372 (2.45)	0.08601 (10.64)	0.1120 (0.84)	-0.2344 (-15.27)	-0.1540 (-10.19)	0.0309
MOM(10,20):	-0.06097 (6.97)	-0.06069 (-6.80)	-0.6619 (-4.14)	-0.2147 (5.56)	-0.03731 (-1.35)	0.008374 (0.62)	0.09891 (12.14)	0.3061 (2.02)	-0.2056 (-13.22)	-0.08322 (-5.42)	0.0219
MOM(10,30):	-0.09266 (8.49)	-0.09070 (-8.32)	-0.6213 (-3.83)	-0.02493 (-0.64)	-0.1614 (-5.80)	0.04674 (3.48)	0.07538 (9.19)	0.4246 (2.37)	-0.2095 (-13.18)	-0.02642 (-1.70)	0.0142
MOM(15,5):	-0.02077 (4.28)	-0.01881 (-3.99)	-0.5984 (-3.58)	-0.02246 (-0.56)	-0.03971 (-1.41)	0.05416 (3.65)	0.03046 (3.67)	0.1181 (1.34)	-0.3782 (-26.40)	-0.2126 (-14.28)	0.0590
MOM(15,10):	-0.01356 (2.07)	-0.01038 (-1.62)	-0.5704 (-3.54)	-0.06692 (-1.72)	-0.04108 (-1.50)	0.01774 (1.26)	0.05692 (7.03)	0.1590 (1.40)	-0.3214 (-21.41)	-0.1853 (-12.34)	0.0489
MOM(15,15):	-0.02465 (3.14)	-0.02282 (-2.97)	-0.7481 (-3.86)	-0.1760 (-4.56)	-0.02788 (-1.02)	0.01633 (1.19)	0.09261 (11.48)	0.1952 (1.46)	-0.2734 (-17.83)	-0.1719 (-11.39)	0.0401
MOM(15,20):	-0.05395 (6.00)	-0.05336 (-5.99)	-0.4349 (-2.72)	-0.2342 (-6.08)	-0.05068 (-1.84)	0.01000 (0.74)	0.09050 (11.13)	0.5271 (3.49)	-0.2461 (-15.84)	-0.06929 (-4.52)	0.0284
MOM(15,30):	-0.07375 (6.75)	-0.07207 (-6.65)	-0.2225 (-1.38)	-0.05110 (-1.32)	-0.1178 (-4.26)	0.07096 (5.32)	0.06006 (7.36)	0.3465 (1.94)	-0.3216 (-20.35)	-0.04591 (-2.97)	0.0280
MOM(20,5):	0.004096 (-0.87)	0.005350 (1.15)	-0.8279 (-5.03)	0.08453 (2.14)	-0.03383 (-1.22)	0.06877 (4.69)	0.01578 (1.93)	0.2717 (3.12)	-0.2399 (-16.98)	-0.1515 (-10.32)	0.207

MOM(20,10):	0.002129 (-0.33)	0.002070 (0.33)	-0.5836 (-3.64)	-0.05329 (-1.38)	0.008726 (0.32)	0.01409 (1.00)	0.08288 (10.30)	0.3840 (3.39)	-0.1864 (-12.49)	-0.1050 (-7.03)	0.0118
MOM(20,15):	-0.01078 (1.41)	-0.01223 (-1.60)	-0.8414 (-4.37)	-0.03116 (-0.81)	-0.05373 (-1.98)	0.008495 (0.62)	0.1113 (13.88)	0.2512 (1.89)	-0.1205 (-7.92)	-0.07337 (-4.89)	0.0073
MOM(20,20):	-0.02768 (3.13)	-0.03140 (-3.55)	-0.6294 (-3.97)	-0.04397 (-1.15)	-0.05422 (-1.98)	0.04375 (3.24)	0.1113 (13.77)	0.3806 (2.53)	-0.1765 (-11.43)	-0.02118 (-1.39)	0.0075
MOM(20,30):	-0.05380 (4.93)	-0.05804 (-5.30)	-0.3526 (-2.16)	0.07391 (1.88)	-0.07604 (-2.72)	0.08814 (6.54)	0.07875 (9.56)	0.3508 (1.95)	-0.2137 (-13.39)	-0.04567 (-2.92)	0.0072
MOM(30,5):	-0.03267 (6.60)	-0.02987 (-6.27)	-0.5527 (-3.28)	0.01495 (0.37)	-0.1450 (-5.11)	-0.009128 (-0.61)	0.005512 (0.66)	0.4492 (5.03)	-0.3968 (-27.42)	-0.1626 (-10.82)	0.0768
MOM(30,10):	-0.03393 (5.03)	-0.02962 (-4.55)	-0.3069 (-1.87)	0.08536 (2.16)	-0.1543 (-5.54)	-0.02878 (-2.00)	0.05721 (6.94)	0.4714 (4.06)	-0.4486 (-29.33)	-0.1430 (-9.35)	0.0729
MOM(30,15):	-0.03824 (4.74)	-0.03335 (-4.27)	-0.3240 (-1.65)	0.06021 (1.54)	-0.1733 (-6.27)	-0.009426 (-0.68)	0.08171 (9.98)	0.2409 (1.78)	-0.4409 (-28.36)	-0.1457 (-9.52)	0.0696
MOM(30,20):	-0.05231 (5.66)	-0.04927 (-5.50)	0.1114 (0.69)	-0.03583 (-0.92)	-0.1709 (-6.16)	0.01387 (1.01)	0.1045 (12.78)	0.4517 (2.97)	-0.4548 (-29.12)	-0.1175 (-7.63)	0.700
MOM(30,30):	-0.07378 (6.62)	-0.07302 (-6.72)	-0.4385 (-2.71)	-0.05710 (-1.47)	-0.2291 (-8.26)	0.03457 (2.58)	0.1155 (14.12)	0.5419 (3.03)	-0.4390 (-27.69)	-0.05185 (-3.34)	0.0594

[*] These portfolios and regressions are constructed utilizing historical OHLC data made available by CryptoDataDownload and Dukascopy.

VI. Discussion

I. Comparing Results to Existing Literature

While Rohrbach et al. (2017) show that cross-sectional 24-hour strategies could generate cumulative returns of approximately 1.2 over a one and a half year period, Chu et al. (2019) extend their analysis to higher frequency price data. The authors consider two types of cross-sectional strategies, namely active and passive portfolios - where the former and latter produce trade signals based on (a) an exponential moving average model of coin returns, and (b) the return of cryptocurrencies in the foregoing period, respectively. Given the incompatibility of active portfolios with the methodology used in this investigation, comparative figures will be drawn from passive strategies instead - which rely on fixed time periods as opposed to rolling windows. Chu et al. (2019) furthermore compute two types of passive strategies - one with variable weights and the other with fixed ones. Here, the varied weights "mirror the share of the live market capitalisation corresponding to a specific cryptocurrency on the first day of every month", while the fixed-weight approach simply aims to create a zero-cost portfolio (Chu et al., 2019). Interesting to note is the authors' observation that the monthly varying weights outperforms the fixed weight approach during the sample period. Even more intriguing is the fact that the returns for both momentum strategies are positive, increasing, and statistically significant - yielding cumulative returns of over 300% towards the end of the sample period. To more effectively compare results with Chu et al. (2019), this thesis initially employs an hourly momentum strategy for the considered data set (Appendix 2 & 3).

Contrary to the findings of Chu et al. (2019) however, it can be noticed that the *MOM(60,60)* strategy, on average, gives rise to per-holding period returns of -0.13%. Expressed in cumulative terms, at 00:00 May 1st 2021 the strategy has effectively reduced the portfolio value to a mere 20% of the capital invested at inception. While Chu et al. (2019) discuss the possibility that the effectiveness of their strategies could have been "amplified by the fact that during [their sample], the whole cryptocurrency market was considered to have been in a bull market state", evidence provided by Cheng et al. (2019) might instead imply that the general existence of the momentum effect is attributable to individual coin bullishness. More specifically, in their investigation Cheng et al. (2019) find that while long-term (monthly) bullishness is directly proportional to the magnitude of momentum trends in Bitcoin and Ethereum, these sustained price increases lead to stronger contrarian characteristics in Ripple instead. Given the significant bullishness of Ripple in this sample, as opposed to the sub-par performance of Bitcoin and Ethereum (Figure 1), it is possible that the contrarian effect dominated the strategies. Meanwhile, the exorbitant yields of Bitcoin and Ethereum compared to the relatively mediocre returns of Ripple, documented in the Chu et al. (2019) sample, could alternatively enable the momentum effect to prevail in theirs.

Given the highly negative returns across the relevant strategies in Table 2, there is moreover significant evidence favouring reversals rather than momentum over shorter term horizons as well. Quantitative, analytical approaches to trading, such as those depicted in this thesis, embody statistical arbitrage strategies that employ mean reversion analysis to mitigate financial risk. As the returns among cryptocurrencies are highly correlated (Appendix 4), short-term deviations will tend to assume a temporary nature, after which they are likely to converge back together. Both momentum and contrarian strategies therefore bet on the likelihood that the divergence between said assets will not only persist, but widen further in the future. Even though the results encapsulated in Table 2 might initially propose that crowd behaviour among investors can lead to exploitable mispricings, the results of Cheng et al. (2019) might instead suggest that the contrarian returns are only temporary. While, as of yet, there is no academic research indicating that relative sample-cryptocurrency bullishness determines whether the cross-sectional momentum or contrarian effect dominates the intra-hour strategy, it is at least plausible that it may. Nevertheless, regardless of a possible crowding out effect, in the considered sample 88% of the strategies yield negative returns at the 0.05 significance level - signalling a strong contrarian return pattern.

Digressing from the cross-sectional momentum returns established by Chu et al. (2019), the discussion turns to the results of the multifactor asset pricing model. Similar to Liu and Tsyvinski (2018), the results in Table 3 indicate, additional to sizeable equity market betas, large (negative) and statistically significant alphas - for the vast majority of momentum portfolios. While this analysis does not imply that high-frequency momentum in both cryptocurrency and equity markets behave in similar fashion, it does enable us to conclude that equity market risk factors influence the return pattern of cryptocurrency momentum. More specifically, in all regressions where generated portfolio returns can be explained by movements in the S&P500, β_{EM} takes on negative values - indicating that high frequency momentum strategies move in a direction opposite to the stock market, and can instead act as a form of insurance for when the market performs poorly.

Unfortunately, akin to those in Rohrbach et al. (2017) and Chu et al. (2019), the sample selection technique used in this thesis may cast doubt on the aforementioned results. As stipulated in section III, coins only qualify for inclusion in the relative strength strategies if they have a minimum data history of two and a half years - however according to Brown et al. (1995) this method of data selection does not account for potential survivorship bias. In particular, said approach selects cryptocurrencies under the assumption that they have survived the entire sample period, hence failing to consider the possibility that a coin may cease to exist somewhere along the way. Instead, the solution to this problem would require all existing cryptocurrencies (10,945) to be examined at a per-minute frequency from 00:00 on April 1st to 00:00 on May 1st 2021 (CoinMarketCap, 2021). Irrespective of the fact that the computational power required herefore is not realistically attainable for a Bachelor Thesis, the presence of survivorship bias within the sample, although not definite, may lead to spurious results.

II. Transaction Costs

Although the conclusions drawn from this investigation have significant implications for cryptocurrency trading in a high-frequency setting, it should be noted that the associated trading mechanisms in practice are limited relative to those for more traditional assets. Namely, as mentioned in Chu et al. (2019), under the assumption that exchanges do offer short selling functions, they very infrequently offer this option with cryptocurrency-fiat pairs - thus erecting a significant obstruction in the practical implementation of the cross-sectional momentum strategies. Transaction times may furthermore present an additional problem. While various solutions have been proposed regarding the unpleasant scalability situation that arises in cryptocurrencies due to restrictions in their blockchain - as of yet, even in major networks, transaction times are not small enough to support intra-hour trading. Given these technical network impediments, there is no reliable course of action to determine the true transaction costs accompanied by trading cryptocurrencies at this scale - causing them not to be taken into account in the investigation.

VII. Conclusion

I. Summary of Relevant Findings

This thesis has analysed one of the oldest financial trading strategies, namely relative strength rules, in the context of a high-frequency cryptocurrency market setting. In attempting to establish whether the momentum effect dominates the sample, the minute-by-minute closing prices of the top seven cryptocurrencies (by market capitalisation) are utilised, from 00:00 on April 1st 2021 until 00:00 on May 1st of the same year. Following the initial analysis of cross-sectional momentum strategy returns, this paper then employs a multifactor asset pricing model to evaluate their associated risk-adjusted returns. The results here indicate that it is theoretically impossible to profitably apply momentum as a statistical arbitrage technique, instead alluding to the existence of exploitable contrarian opportunities on the short-term. Accordingly, the answer to the research question of whether the usage of cross-sectional cryptocurrency price momentum as a statistical arbitrage strategy yields profitable returns in this sample is a resounding no.

More specifically, from Table 2 it is noticeable that, given that they yield statistically significant non-zero returns at the 95% confidence interval, all considered momentum strategies generate losses. However, through classifying strategies according to (a) their look-back periods, and (b) their holding periods, curious patterns present themselves. While the former differentiation indicates that strategies containing smaller J-values, on average, display the most statistically significant losses, the latter shows that the statistical significance of average momentum returns appear to be inversely related to the look-back period. These results do not only imply that minimizing both J and K would yield the most profitable and significant contrarian return pattern, but also suggest that their corresponding Sharpe Ratios are higher. Given this revelation, inverting the process applied in *MOM(5,5)*, *MOM(5,10)*, and *MOM(10,5)* come under primary scrutiny, for their contrarian counterparts would possess t-statistics of 13.33, 12.36, and 10.63 respectively, with hourly adjusted returns of 0.76%, 0.48%, and 0.61%. This therefore indicates that the first hypothesis of this investigation, namely that the momentum strategies generate statistically significant positive returns, is proven to be false. Following the identification of cross-sectional return distributions, the associated risk-adjusted returns belonging to the momentum strategies are calculated. From the contents of Table 3, it can be established that the predominance of alphas are (a) significant at the 99% confidence interval, and (b) negative. This furthermore signifies that returns cannot be solely explained by return movements in the considered benchmarks, and that the contrarian equivalents would generate profits in excess of the returns they ought to yield for the level of borne risk - providing resounding evidence in favour of contrarian price reversals at high frequencies. In light of the statistically significant negative risk-adjusted returns for all relevant strategies, the second hypothesis is also rejected. Whereas these momentum strategies would generally only be valuable as a form of insurance against stock market declines, including their contrarian counterpart to a primarily equity-based portfolio however would actually decrease risk - as all significant equity betas would lie within the range of 0-1 (Table 3).

Despite these results indicating the existence of price reversals in the sample, it is important to note that the findings of Cheng et al. (2019) suggest that these contrarian returns may only be temporary. More specifically, the authors allude to the possibility that the magnitude of a cryptocurrency's recent historical bullishness can give rise to either contrarian or momentum characteristics, depending on the coin of interest. While, as of yet, there is no academic research indicating that relative sample-cryptocurrency bullishness determines whether the cross-sectional momentum or contrarian effect dominates the intra-hour strategy, it is at least plausible that it may.

II. Limitations and Potential Further Research

While the initial results indicate clear potential for contrarian statistical arbitrage techniques, there are various limitations of the research that must be taken into account. The first to note is the sample period of the dataset. Although, upon initial glance there might seem to be a considerable amount of observations per cryptocurrency (namely 43,200), the micro-scale of investing in this thesis implies that this only accounts for one month. Despite the selection of a larger dataset being infeasible for a Bachelor Thesis, this characteristic still limits the relevance of the results, for the dominance of the contrarian effect might simply have been an aberration when considering a larger time frame. Related to the computational power restriction, is the other limitation that the analysis could potentially be subject to survivorship bias, thus yielding spurious results. The only possible solution to this problem would be to include all existing cryptocurrencies in the momentum strategies, however due to the lack of computational power, this was not a realistic option for a Bachelor Thesis.

Furthermore, as was mentioned previously, there is a limitation in the applicability of the results postulated by this thesis on actual cryptocurrency markets. Whether it be cross-sectional contrarian or momentum strategies, both are dependent on their ability to go short in a winner/loser portfolio. However, as of yet it is impossible to short-sell a lot of cryptocurrencies, indicating that these strategies are currently impractical. Given that various solutions have been proposed regarding the scalability issues of cryptocurrencies, future developments might see this short-selling constraint removed. As such, the analysis of high-frequency price reversals is still relevant, given its potential profitability in the future.

An additional limitation is that transaction costs are not considered as relevant in this investigation. As the magnitude of trading costs in cryptocurrency exchanges are a positive function of the amount of transactions made, there is no reliable way to account for these as the presence of high-frequency investing would, as the name suggests, realise a significant influx in costs (Chu et al., 2019).

Further research into the existence of contrarian statistical arbitrage strategies in cryptocurrencies, could therefore focus on eradicating the potential survivorship bias by employing a dynamic sample - one that has a changing amount of coins considered. The analysis could additionally span a time horizon of a year in order to account for the possibility of contrarian effects being an outlier.

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Appendix 1:

Overview of Long- and Short-Only Portfolios

The relative strength portfolios are constructed according to the J-minute lagged returns of the seven largest cryptocurrencies, by market capitalization, and held for K minutes. The combination of formation- (J) and holding-periods (K) for the different strategies are indicated in the first column. The cryptocurrencies are classified - in descending order - on the basis of their J-minute lagged returns, after which a zero-investment portfolio is formed that buys/sells the three highest/lowest historical return performers (referred to as "Winners" and "Losers" respectively). The average, hourly-adjusted returns of these winner (long) and loser (short) portfolios are first presented in the third column. Similar adjustments are made for the standard deviation of said portfolios. The t-statistic and corresponding p-value, which highlight the probability of the average portfolio return belonging to a zero-mean probability distribution, are presented in columns seven and eight.

MOM(J,K)	Observations	Portfolio	Average Return (%)	SD (%)	T-Statistic	P-Value
MOM(5,5):	43,225	Long	-0.1873	13.09	-2.97	0.003
		Short	0.5752	14.47	8.26	0.000
MOM(5,10):	43,220	Long	0.07114	9.103	-0.92	0.358
		Short	0.3219	9.916	9.22	0.000
MOM(5,15):	43,215	Long	0.09726	1.671	8.85	0.000
		Short	0.2963	6.984	9.58	0.000
MOM(5,20):	43,210	Long	0.09654	6.459	3.13	0.002
		Short	0.2912	6.874	8.96	0.000
MOM(5,30):	43,200	Long	-0.1077	5.212	3.85	0.000
		Short	0.5079	5.497	11.01	0.000

MOM(10,5):	43,220	Long	0.06518	12.79	-1.75	0.080
		Short	0.3260	14.66	7.20	0.000
MOM(10,10):	43,220	Long	0.1132	8.915	1.52	0.129
		Short	0.2714	10.07	6.73	0.000
MOM(10,15):	43,215	Long	0.1029	7.266	3.24	0.001
		Short	0.2861	8.049	7.01	0.000
MOM(10,20):	43,210	Long	0.09968	6.403	3.34	0.001
		Short	0.2852	6.931	8.58	0.000
MOM(10,30):	43,200	Long	0.08449	5.206	3.98	0.000
		Short	0.3345	5.535	10.71	0.000
MOM(15,5):	43,215	Long	0.1638	12.73	1.38	0.168
		Short	0.2447	14.92	4.66	0.000
MOM(15,10):	43,215	Long	0.1482	8.844	3.85	0.000
		Short	0.2470	10.20	4.99	0.000
MOM(15,15):	43,215	Long	0.1169	7.200	4.28	0.000
		Short	0.2790	8.124	6.32	0.000
MOM(15,20):	43,210	Long	0.1226	6.326	3.84	0.000

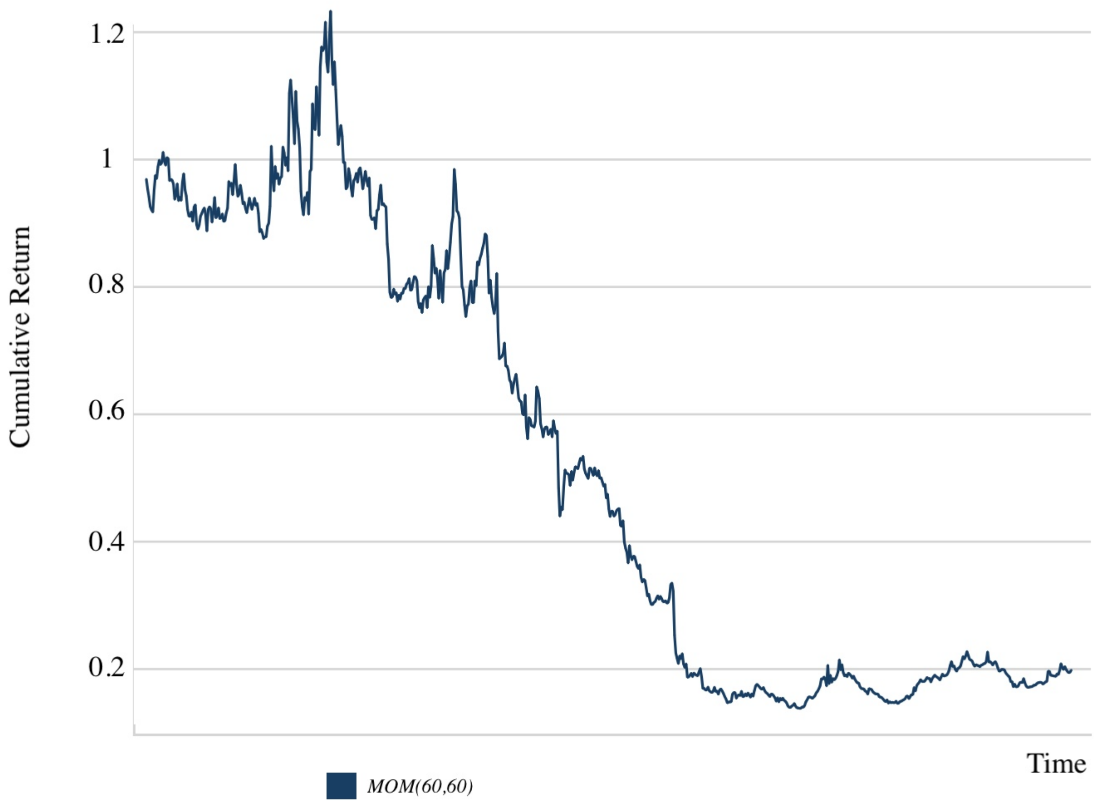
		Short	0.2704	6.986	8.30	0.000
MOM(15,30):	43,200	Long	0.2635	5.108	4.99	0.000
		Short	0.2134	5.625	9.99	0.000
MOM(20,5):	43,210	Long	0.2265	13.07	4.19	0.000
		Short	0.2140	14.09	3.15	0.002
MOM(20,10):	43,210	Long	0.1990	9.251	5.09	0.000
		Short	0.2345	9.609	4.63	0.000
MOM(20,15):	43,210	Long	0.1653	7.558	5.25	0.000
		Short	0.2487	7.600	6.41	0.000
MOM(20,20):	43,210	Long	0.1502	6.622	5.19	0.000
		Short	0.2580	6.611	7.82	0.000
MOM(20,30):	43,200	Long	0.02442	5.300	5.89	0.000
		Short	0.4173	5.351	10.02	0.000
MOM(30,5):	43,200	Long	0.1065	12.38	0.41	0.682
		Short	0.3105	15.14	5.73	0.000
MOM(30,10):	43,200	Long	0.1228	8.684	2.55	0.011
		Short	0.2760	10.39	6.21	0.000

MOM(30,15):	43,200	Long	0.1219	3.020	8.45	0.000
		Short	0.2790	8.337	6.88	0.000
MOM(30,20):	43,200	Long	0.1260	6.119	4.14	0.000
		Short	0.2738	7.213	8.04	0.000
MOM(30,30):	43,200	Long	-0.04028	4.979	5.26	0.000
		Short	0.4398	5.748	9.90	0.000

[*] These portfolios are constructed utilizing historical OHLC data made available by CryptoDataDownload.

Appendix 2:

Cumulative In-Sample Return of *MOM(60,60)*



* Historical OHLC data made available by CryptoDataDownload.

Appendix 3:

Cross-Sectional Return Pattern of *MOM(60,60)*

The relative strength portfolios are constructed according to the 60-minute lagged returns of the seven largest cryptocurrencies, by market capitalization, and held for 60 minutes. The cryptocurrencies are classified - in descending order - on the basis of their J-minute lagged returns, after which a zero-investment portfolio is formed that buys/sells the three highest/lowest historical return performers. The average, hourly returns of this strategy are first presented in the second column, and corresponding standard deviations in the third. The t-statistic and corresponding p-value, which highlight the probability of the average portfolio return belonging to a zero-mean probability distribution, are presented in columns four and five.

Observations	Average Return (%)	SD (%)	T-Statistic	P-Value
43,140	-0.1296%	3.031	-8.88	0.000

* Historical OHLC data made available by CryptoDataDownload.

Appendix 4:

Correlations Between Hourly Cryptocurrency Returns

Correlegram of hourly returns of Bitcoin (BTC), Ethereum (ETH), Binance Coin (BNB), Ripple (XRP), Tether (USDT), Cardano (ADA), and Litecoin (LTC) from 00:00 1st of April 2021 to 00:00 1st of May 2021, exclusive.

	BTC	**ETH**	**BNB**	**XRP**	**USDT**	**ADA**	**LTC**
BTC	1	0.7145	0.6693	0.5835	0.2723	0.6183	0.5692
ETH	0.7145	1	0.5823	0.5132	-0.1717	0.4922	0.6885
BNB	0.6693	0.5823	1	0.5236	0.1669	0.5170	0.4925
XRP	0.5835	0.5132	0.5236	1	0.5236	0.4614	0.4649
USDT	0.2723	-0.1717	0.1669	0.5236	1	0.2581	-0.1757
ADA	0.6183	0.4922	0.5170	0.4614	0.2581	1	0.4122
LTC	0.5692	0.6885	0.4925	0.4649	-0.1757	0.4122	1

* Correlegram is constructed utilizing historical OHLC data made available by CryptoDataDownload.