Factor Structure of Cryptocurrencies[*]

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Abstract

We investigate the cross-section asset-pricing patterns of major cryptocurrencies from 2017 to 2021. We show that the basis, momentum, and basis momentum factors earn statistically significant excess returns, a result consistent with the commodity futures literature. We document meaningful evidences that contrast the future returns within the factor structure. Daily factor returns are statistically and economically much stronger than weekly factor returns. Monthly factor returns are non-significant.

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1. Introduction

Cryptocurrency has attracted a significant attention from both the academia and the industry in the last decade. Increasingly more firms have started accepting it as a legit investment product and a valid payment. According to a 2020 survey conducted by HSB[1], more than 1/3 of small-medium businesses in the US accept bitcoin. Some large corporations, such as Microsoft[2] and Facebook[3], have also made massive investments in their own cryptocurrency-related products, obtaining a toehold in this new industry. Against this backdrop, a number of researches in the academia has established a set of empirical regularities for cryptocurrencies. Liu and Tsyvinski (2018) uncovered empirical evidence that cryptocurrency returns are exposed to network factors, which were theoretically derived in Pagnotta and Buraschi (2018) and Cong et al. (2019). Makarov and Schoar (2020) found that a common component of signed volume can explain up to 85% of the variation in bitcoin returns. Liu et al. (2019) identified three common priced factors, i.e., cryptocurrency market, size, and momentum, in the cryptocurrency market. Yet, no research has been conducted regarding the cryptocurrency futures market. There are at least two reasons to analyse the returns of cryptocurrency futures empirically. First, we can draw (dis)similarity with other asset classes, which diversify the risk for their portfolio. Second, a growing number of firmsholds cryptocurrencies strategically. By obtaining the empirical pattern ofcryptocurrency futures, we can evaluate the effectiveness of using cryptocurrency futures as a hedging instrument.

In this paper, we provide the evidence on the stylized facts of returns of cryptocurrency futures. Our sample consist of 13 largest coins that have futures contracts available for trading on OKEx, the world-leading cryptocurrency derivatives market by volume. The sample period spans from the beginning date when cryptocurrency futures take off on OKEx (i.e., November 2017) to March 2021.

The literature on the traditional commodity futures market document a set of risk factors that explain the cross-section of commodity futures returns. Among the factors uncovered by past researches (e.g., Erb and Harvey, 2006, Miffre and Rallis, 2007, Yang, 2013, and Boons and Prado, 2019), we choose to investigate the three most

[1] https://www.munichre.com/hsb/en/press-and-publications/press-releases/2020/2020-01-15-one-third-of-small-businesses-accept-cryptocurrency.html

[2] https://news.microsoft.com/en-gb/2018/03/21/microsoft-azure-helps-nivaura-launch-worlds-first-blockchain-based-investment-product/

[3] https://www.ft.com/content/cfe4ca11-139a-4d4e-8a65-b3be3a0166be

persistent and commonly documented factors—basis, momentum, and basis-momentum. We find that some factor-driven trading strategies of traditional commodity futures are equally profitable in the cryptocurrency futures market.

Specifically, a long-short portfolio formed based on cross-sectional signals regarding the basis and basis-momentum generates statistically significant excess returns, with returns mainly coming from the long position and remaining robust after considering transaction costs. However, such profitability vanishes as we increase our holding length from one day to one month, a result contrasts the commodity futures literature which consider the holding length to be at least one month (e.g., Erb and Harvey, 2006; Szymanowska et al., 2014). Furthermore, a portfolio that follows a momentum strategy does not appear to earn statistically significant returns across different holding lengths, another result divergent from the traditional commodity futures evidence.

Next, we investigate whether the profitability of any factor-driven trading strategies can be explained by other factors. Specifically, after forming long-short portfolios based on any factor, we run a spanning regressions by regressing the return series of this strategy against that of other strategies. An equal-weighted cryptocurrency futures market index is included to control for the futures market risk premium. If the alpha in such regressionsbecome statistically insignificant after including the return series of a long-shortportfolio in the regression, and if the beta of this newly added return series is significant, then we conclude that the profitability of our regressand strategy is subsumed by this newly included factor-driven strategy. Similar approaches have been employed in the past studies to examine which equity risk factors are significant in explaining the time variation of expected equity returns (Barillas and Shanken, 2017; Fama and French, 2018). We show that the profitability of basis-momentum portfoliosthat trade futures can be explained by the profitability earned by trading on basis signals. Such a correlation is the strongest when we have shorter holding lengths and look-back periods. Given that the basis-momentum signal is constructed in a way equal to change in the basis over time, rather than a summation of the change in basis and a measure of average curvature used in (Boons and Prado, 2019), our result impliesthat, when the holding length is one day and look-back period is five days, thehistorical basis value does not help predict cryptocurrency futures returns after conditioning on the contemporaneous basis value. However, as holding length become one week and look-back period is five weeks, the cryptocurrency basis-momentum returns now appear to negatively predicted by momentum profitability and have a return component orthogonal to our factors. When we increase holding length to one month and look-back period to five months, the basis-momentum profitability has almost vanished, only marginally dependent on basis returns. Furthermore, portfolios constructed based on momentum and basis signals tend to provide at least some excessreturns that are orthogonal to other factors. In addition, the cryptocurrency futures market index both co-move only insignificantly with return of our portfolios formed according to every signal type.

Moreover, the momentum portfolio that trade futures with one-day holding length does not earn statistically significant return given its insignificant alpha and coefficients of other factors for all six specifications. Returns earned on portfolios that trade futures (based on futures momentum with one-week holding length) also appear to be negatively associated with the basis-momentum profitability. This can be caused by mechanism of how basis momentum signals are constructed according Equation 3. However, such negative correlation between basis momentum and momentum is only statistically significant when we focus on portfolios with five weeks of look-back period. This potentially indicates that, in the intermediate term, there is a larger cross-sectional variation amongst futures momentum. The reason could be that five weeks may be approximate the amount of time needed for an information to transmit through the cryptocurrency market, according to the behavioural finance literature (e.g., Hong and Stein, 1999).

Finally, as a robustness check, we document the correlation structure of signal rankings across portfolios. As expected, the signal rankings in our cryptocurrency basis portfolio tend to highly positively correlated with those in our basis-momentum portfolio. They seem to be unrelated with those in portfolio utilizing momentum signals. The signal rankings in the momentum portfolio are found to have a moderate negative correlation with those in the basis-momentum portfolio.

2. Data and Methodology

We gratefully acknowledge data support from GrandLine Technologies®, a systematic market-neutral hedge fund trading mid-frequency statistical arbitrage strategies on crypto derivatives. The data source is 1Token®, a crypto-finance institutional software provider.

We collect traded data of 12 cryptocurrencies (ADA, BCH, BSV, BTC, DOT, EOS, ETC, ETH, LINK, LTC, TRX, XRP) from OKEx®. It was launched in July 2017 and since then has developed into one of the world's largest cryptocurrency exchanges. OKEx is the most liquid exchange in terms of daily trading volume for future contracts in the past few years. In this paper, we collect close prices in the minute-level frequency for each coin's futures markets from 13 Nov 2017 to 31 Mar 2021 and resample them as daily, weekly, and monthly frequency. The time-series of cryptocurrency futures market index is collected by taking equally-weighted average ofreturns of the futures contract on each day in our sample period. We only consider Current Quarter (CQ) future contracts, which does not require frequent rolling-over. It has been rolled at 16:00 (UTC+8) on the last Friday for each end of quarter. The cryptocurrency futures market index is constructed as an equally-weighted average return of all cryptocurrency futures contracts that we have data on the corresponding day.

Following Boons and Prado (2019), we calculate our "basis", "momentum", and "basis-momentum" signals using the following formula, respectively:

$$\text{Basis: } B_t = (S_t - F_t^{CQ})/F_t^{CQ} \approx s_t - f_t^{CQ} \tag{1}$$

$$\text{Momentum: } \prod_{k=t-J}^{t} (1 + R_{fut,k}^{CQ}) - 1 \tag{2}$$

$$\text{BasisMomentum: } \prod_{k=t-J}^{t} (1 + R_{S,k}) - \prod_{k=t-J}^{t} (1 + R_{fut,k}^{CQ}) \tag{3}$$

$$\approx \sum_{k=t-J}^{t} (r_{S,k}) - \sum_{k=t-J}^{t} (r_{fut,k}^{CQ})$$

$$= \sum_{k=t-J}^{t} (s_k - s_{k-1}) - \sum_{k=t-J}^{t} (f_k^{CQ} - f_{k-1}^{CQ})$$

$$= (s_t - s_{t-J-1}) - (f_t^{CQ} - f_{t-J-1}^{CQ})$$

$$= B_t - B_{t-J-1}$$

where S_t denotes the spot price on day t, J our choice of signal-identification months,

F_{t-1}^{CQ} the futures price on day $t-1$, $R_{fut,k}^{CQ} = \frac{F_k^{CQ}}{F_{k-1}^{CQ}} - 1$ the return obtained from holding the CQ contract from day $k-1$ to day k. The lower cases denote their log-transformed version. In this study, we consider four different look-back periods, i.e., 1, 3, 5, and 7 days. However, for brevity, we only discuss in more detail results obtained based on setting look-back periods as 5 days. Results obtained from utilizing other look-back periods lead to the same conclusion as the results we presented in the paper. We also look at other choices of holding length, i.e., one week and one month. When the holding length is one week (month), the unit of look-back period will be automatically changed to weeks (months). Note that, given the data limit, we can only utilize the CQ futures contracts to establish our basis-momentum portfolio. As a result, our basis-momentum measure becomes the difference between the contemporaneous basis and a historical basis depending on our look-back period.

To construct the cryptocurrency factor portfolios, based on look-back period J, we calculate the ranking by all coins based on their sorting characteristics at the beginning of every day (week, or month) and calculate the equal-weighted portfolio returns consist of top 3, middle 3, and bottom 3 coin futures contracts.[4] They are respectively denoted as the "high" portfolio, "med" portfolio, and "low" portfolio. Then, the factor-mimicking portfolio returns are calculated from taking long position on the top portfolio and short position on the bottom portfolio, that is a "high-low" or "long-short" portfolio. In order to compute excess return that we will use when running spanning regressions, we need additionally risk-free rates. We use 1-Month Treasury Constant Maturity Rate as our proxy for the risk-free rate[5]. This rate will be adjusted according to the holding length we look at. For example, when we look at strategies with one-day holding length, our daily risk-free rate is calculated as the monthly rate divided by 30. The excess factor portfolio returns, when used in spanningregressions, are computed as the difference between the long-short portfolio return andthe risk-free rate. The excess return of the cryptocurrency market indices is the difference between the return of the cryptocurrency index and the risk-free rate.

[4] The actual number of coins in each portfolio may differ from 3 depending on the number of available coins we have on the portfolio formation day. For example, on 14 November 2017, we have futures data for five coins, so our top, middle, and bottom portfolios, respectively, comprise of one, two, and one coins. A detailed description can be found in Table 2.

[5] https://fred.stlouisfed.org/series/DGS1MO

3. Main Results

In this section, we investigate the profitability of each factor-driven strategy, which, respectively, follows basis, (futures) momentum, and basis-momentum signals. We start with looking at the raw return earned by each portfolio under each strategy, including long-only, short-only, and long-short portfolios. We then consider whether the profitability is associated with high tail risks and is sensitive to transaction costs. Next, we examine whether the three cross-sectional cryptocurrency return predictors that we have identified can be spanned by each other. Inspired by Fama and French (1996), we perform regressions for each factor-driven portfolio (excess) returns which subsequently add in more factors. A statistically significant alpha would imply that the profitability associated with the current factor cannot be subsumed bythe factors we just added in. We regress returns of factor long-short portfolios that trade futures (spots) only against other factor portfolios that trade futures. For brevity, we only present regression results for a fixed look-back period of 5. The results obtained from employing other look-back period within the same measurement of time(i.e., day, week, and month) lead to the same conclusion. We first consider results for portfolios that hold securities for one day, then those that hold for one week, and finally those that hold for one month. The computation of excess returns of our factor-mimicking portfolios and market indices is discussed in Section 2.

Before commenting on factor-specific performance, we first take a look at our benchmark portfolios. From the results of benchmark portfolios, BTC portfolios have better performance than equal-weighted portfolios with futures instrument. Based on Table 4d, BTC portfolio has a higher annualized return (106.51%) than Equally Weighted portfolio (101.15%), a higher average return (0.29%) than equally weighted portfolio (0.28%), a higher t-statistics (2.11) than equally weighted portfolio (1.78), and a higher Sharpe ratio (1.13) than equally weighted portfolio (0.95). To put their relative profitability into perspective, exhibited in Figure 2, one dollar invested in an equal-weighted portfolio that comprises of futures will be worth about 4 dollars by the end of sample period, March 2021. One dollar invested in the BTC futures will allow an investor to accumulate at least 8 dollars from the investment.

3.1 Basis Factor

According to Table 4a, the high basis portfolio with one-day holding length exhibits the highest annualized returns of 262.00% compared with the medium portfolio (111.62%) and the low portfolio (-64.53%). The similar descending trend from high to medium and medium to low portfolio trading futures appears in all categories of statistics, ranging from t-statistics, Sharpe ratio, win/loss ratio and maximum drawdown. Our results remain robust to considering transaction cost, as shown in the right column under each summary statistics category in Table 4a. One dollar invested in a basis-driven high-low portfolio that trade futures since November 2017 will be, net of transaction cost, worth above 100 dollars by March 2021, as shown in Figure 1. Furthermore, we are interested in checking whether the profitability of this basis strategy remains if we rebalance our portfolio based on a different frequency, such as every week or month. In Table 5, we report the t-statistics of annualised returns of high-low portfolios rebalancing daily, weekly, and monthly. A glimpse at the first rowshows that the profitability of trading on basis diminishes as we rebalance our portfolioless frequently. Specifically, while the annualised return of weekly portfolios remains statistically significant, it is not for monthly portfolios.

Next, we examine whether profitability of the basis portfolio could be explained by other factors utilising a set of spanning regressions. We also distinguish by different holding lengths when constructing portfolios. The regression results are displayed in Table 6a, where we control for cryptocurrency futures market risk proxy and the risk premium induced by trading on momentum and basis momentum. Model (1) contains results of portfolios constructed using one-day holding length, whereas Model (2) and

(3) contain results using one-week and one-month holding lengths, respectively. The table shows that, irrespective of the rebalancing frequency, the strategy's profitability can be explained by the risk premium of basis momentum to a significant extent. Either the momentum premium or the Crypto futures index does not provide significant explanatory power in explaining the basis portfolio returns. Most importantly, the basisstrategy generates a statistically significant alpha when our rebalancing frequency is less than one month. The R-squared of around 0.30 across all three columns indicates that risk premium of momentum and basis momentum together with cryptocurrency futures market proxy jointly provide a good approximation of the basis profitability over time.

Amongst the traditional asset classes, such stocks and foreign currencies, a number of literatures has identified the explanatory power of liquidity risk exposure on the profitability of basis, momentum, and basis momentum strategies (e.g., Asness et al., 2013; Boons and Prado, 2019. For example, Boons and Prado (2019) argue that the basis-momentum effect arises because imbalances in the supply of and demand for futures contracts that materialize within and across futures curves when the market-clearing ability of speculators and financial intermediaries is impaired, which ismore likely to occur in the event of illiquidity shock. Hence, we now investigate the sensitivity of the excess returns of basis-based portfolio to controlling other market factors and the liquidity risk premium. We first consider the cryptocurrency market, which is proxied by the average excess return of the cryptocurrency securities. We also take into account the possibilities that risk premium in the cryptocurrency market may be similarly related to the global equity and futures market as the traditional commodity market (Asness et al., 2013). Then, we control for the liquidity risk premium, which encompasses a return series of a long-short portfolio created by sorting based on Amihud (2002) measure. The regression results are displayed in Table7a. Results in Model (1)-(2) show that, when trading futures contracts with one-day holding length, the basis-driven strategies earn statistically significant returns that are not explained by all different market proxies and risk premium induced by other risk factors (i.e., liquidity risk, momentum, and basis momentum) with significant positive constant terms across models. Such a significant outperformance remains intact if we change our holding length from one day to one week, as displayed in Model (3)-(4). Furthermore, trading on a monthly basis will not significantly outperform the market, as illustrated in Model (5)-(6). Finally, basis-driven risk premium is shown to be related positively to the global futures market and negatively to the global equity market. While the former finding is consistent with Asness et al. (2013), the latter is not.

3.2 Momentum Factor

Much literature of commodity futures has documented a strong momentum effect among traditional futures contract (e.g., Erb and Harvey, 2006, Shen et al., 2007). Eyeballing Table 4b shows that the high momentum portfolio rebalanced daily exhibits the highest annualized returns (161.38%) compared to the medium portfolio (63.26%) and the low portfolio (73.75%). The high momentum portfolio also enjoys a significantly higher Sharpe ratio (1.25) than the medium portfolio (0.59) and the low portfolio (0.64). The difference in performance between the medium and the low portfolios are, however, not discernible by looking at the raw summary statistics in Table 4b. We, then, investigate the profitability of executing a zero-cost momentum strategy by taking a long position in the high portfolio and a short position in the low portfolio. Looking at the third row of Table 4b demonstrates that the return of such a strategy is 87.63%, only marginally higher than that of medium or low portfolios. The profitability of this zero-cost strategy is also not statistically significant given a t-statistics of 1.69 as shown in the fourth column. The indifference in the performance persists when we consider alternative holding lengths, as shown in Table 5. Its Sharpe ratio and maximum drawdown, however, do improve compared to medium or low portfolios. The above results stay unchanged after accounting for transaction costs as shown in the right column under each summary statistics category in Table 4b. One dollar invested in a basis-driven high-low portfolio since November 2017 will be, net of transaction cost, worth only 2 dollars by March 2021, as shown in Figure 1.

Next, Table 6b exhibits the spanning regression results with respect to high-low portfolios that trade futures based on momentum signals. Consistent with our summary statistics, the momentum portfolio does not earn statistically significant return given its insignificant alpha and coefficients of other factors for all three rebalancing frequencies. The fact that the momentum profitability tends to be negatively correlated with the basis-momentum profitability could be caused by how basis momentum signals are constructed according to Equation 3.

We now examine the sensitivity of the excess returns of momentum-based portfolio to controlling other market factors and the liquidity risk premium. We consider the same market proxies and illiquidity risk factor as discussed in the preceding sub-section. Consistent with our initial conclusion, Table 7b shows that trading cryptocurrency futures based on momentum signals does not generate statistically significant excess return. Finally, when investigating the coefficients of our market proxies, we find that the momentum strategy with one-day holding horizon tends to produce returns that are positively associated with the global futures market, a result in line with Asness et al. (2013). The profitability of monthly momentum strategies is shown to positively covary with the liquidity risk and basis risk premium. However, such a correlation becomes non-existent when looking at alternative choices of holding lengths.

3.3 Basis Momentum Factor

The basis momentum is a newly identified factor, found to effectively capture the commodity spot premium, term premium, and liquidity risk (Boons and Prado, 2019; Szymanowska et al., 2014). Table 4c exhibits summary statistics for futures portfolios based on basis momentum signals. We find that the high basis-momentum portfolio exhibits the highest annualized returns (218.39%) compared to medium portfolios (81.41%) and low portfolio (-14.34%). The similar descending trend from high to medium and medium to low portfolios with trading spot and futures appears in all categories of statistics, ranging from t-statics, Sharpe ratio, to maximum drawdown. The profitability of a zero-cost trading strategy, executed by taking a long position in the high portfolio and taking a low position in the low portfolio, appears outstanding with annualized returns of 232.73%. Conclusions remain robust after accounting for transaction costs as shown in the right column under each summary statistics title in Table 4c. However, the profitability of basis momentum strategy is not robust to longer holding length such as one week and one month, as presented in the final four rows in Table 5. One dollar invested in a basis-driven high-low futures portfolio since November 2017 will be, net of transaction cost, worth around 20 dollars by March 2021, as shown in Figure 1.

Moreover, according to 7c, we find that the profitability of the one-day futures portfolio that trade on basis-momentum will no longer earn statistically significant excess return once the basis factor is included in the regression, indicating that the basis momentum returns are subsumed by basis returns. Given that the basis-momentum signal is constructed in a way equal to change in the basis over time,rather than a summation of the change in basis and a measure of average curvature used in (Boons and Prado, 2019), our result implies that, when the holding length is one day and look-back period is five days, the historical basis value does not help predict cryptocurrency futures returns after conditioning on the contemporaneous basis value. The cryptocurrency future market index and MSCI returns do not contribute to explaining the basis-momentum portfolio returns. Then, when looking at weekly returns and increase our look-back period to five weeks, we find that the returns earnedon basis momentum tend to significantly negatively correlated with the returns earned on momentum, as illustrated in Model (3) and (4). The basis returns continue playing a significant role in explaining positively the basis momentum returns. After we partial out factor-related effects, the basis momentum strategy tends to earn significantly negative excess returns. When choosing a look-back period of five months and a holding length of one month, as shown in Model (5) and (6), we find that the basis momentum profitability almost vanishes completely, leaving only a minor positive correlation with basis returns. Finally, the liquidity risk premium does not contribute to explaining the variation in basis momentum returns across time, whereas the GSCI returns only help predict (negatively) the variation when we rebalance our portfolio on a daily basis.

Taken together, the significant positive correlation between basis momentum returns and basis returns across different look-back periods is expected given how basis momentum is constructed based on Equation 3. The finding of a negative correlation between basis momentum and futures momentum also complements our results regarding the determinants of momentum returns. The fact that such a negative correlation is the strongest when we look five weeks back could suggest that, in the intermediate term, there is a larger cross-sectional variation amongst futures momentum, rather than spot momentum. Furthermore, the significantly negative alphas earned by a basis momentum strategy with five-week look-back period, irrespective of trading futures or spot, may imply that, when the basis gap has been closed up at an abnormally faster rate for a long time (e.g., five weeks), futures contracts have the tendency to experience a reversal afterwards. However, such an effect is not prominent when we consider a longer period of time, such as five months in our case.

4. Extended Analysis: Signal Ranking Correlation

In the last section, we show that, irrespective of trading futures or spot, there appears tobe a significant positive correlation between the profitability of the basis portfolio and that of the basis-momentum portfolio. If such a positive correlation is driven by the similar coin composition of the two portfolios, then we should expect that the two portfolios' respective signal rankings must be highly positively correlated as well. Furthermore, especially in the intermediate term, the returns realized from basis-momentum portfolios are inclined to co-move negatively with the returns realized from momentum portfolios. It is therefore expected that the signal rankings inthe momentum portfolio are negatively associated with the rankings in thebasis-momentum portfolios. In addition, our previous findings that momentum profitability tends to be unexplained by the profitability of basis strategy should indicatea close-to-zero correlation between basis signals and momentum signals across time.

In Table 8, we display a coloured signal ranking correlation matrix that compares the signal rankings pairwise across different portfolios. The results in this Table 8 confirm our previous conjecture. Specifically, irrespective of the choice of look-back period and holding length, we found highly positive correlation in signal rankings, hence coin turnovers, between basis and basis-momentum portfolios. Except when the look-back period is seven months, the basis momentum signal rankings, on average, are negatively correlated with the momentum signal rankings across holding lengths and look-back periods. Finally, the momentum signals tend to be uncorrelated with basis signal across holding lengths and look-back periods, indicating that the basis factor and momentum factor are driving a cryptocurrency return in two different dimensions.

5. Conclusion

We find that cross-section returns of cryptocurrency futures can be analysed using standard asset pricing tools. We show that constructing zero-cost portfolios that trade futures based on signals including basis, momentum, and basis momentum can earn statistically significant excess returns, a result consistent with traditional commodity futures literature (e.g., Miffre, 2016). More specifically, trading futures based on basis and basis momentum signals will generate more excess returns compared to trading on (futures) momentum signals. Trading spot based on basis will still be able to realize significant profit. Compared to trading futures, trading spot based on momentum produce greater profitability compared to trading based on basis momentum.

Moreover, we document some stylized facts on the cross-section of cryptocurrencies that can be used to assess and develop theoretical models. First, the significant excess returns earned on zero-cost factor-driven portfolios mainly come from long positions, implying that the observed excess returns are more likely to be attributed to compensation for risk rather than financial market microstructure restrictions. Second,when the basis is high in real terms (after a series of rises in spot prices or drops in futures prices), the spot contract will experience a large increase in price, whereas the futures contract will try to catch up at a faster rate aiming to restore the current (arguably abnormally) high basis to the historical level. This catch-up process will result in a wider basis over time, following a period of high basis values.

Third, in the intermediate term, there is a larger cross-sectional variation amongst futures momentum, possibly attributed to that five weeks may be the approximate amount of time for an information to transmit through the cryptocurrency market (Hong and Stein, 1999). Finally, we find that the profitability of those factor-driven strategies, especially those purely comprised of long positions, all drop sharply as we increase our holding length and look-back period. When we increase our holding length to be one month, any profitability is gone. This draws stark contrast with the traditional asset pricing evidence regarding the equity market, where the minimal length of holding is often one month, and statistically significant returns mostly concentrate in those portfolios that hold at least one month.

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Figure 1. Daily long-short portfolio cumulative sum returns

This figure shows the cumulative sum of the long-short portfolio returns generated respectively by a) basis, b) momentum, and c)basis-momentum factor strategy with futures instrument. The long-short (or, high-low) portfolioís formed based on taking a long position in the high portfolio and a short position in the low portfolio. The high portfolio indicates portfolios constructed based on trading the cryptocurrency futures contracts with the highest signals. The low portfolio indicates portfolios constructed based on trading the cryptocurrency futures contracts with the lowest signal. The medium portfolio indicates portfolios constructed based on trading the cryptocurrency futures contractswhich do not appear in either high or low portfolios. All portfolios reported in this table take5 look-back periods. The holding length is one day. Signal ranges from basis, momentum, and basis momentum which are, respectively computed using Equation 1, 2, and 3. This tableincorporates both the result without trading cost (indicated by the blue line) and the result withtrading cost (indicated by the orange line). We consider all cryptocurrencies in various periodsshowed in the table 1. Our sample period is from 13 November 2017 to 31 March 2021.

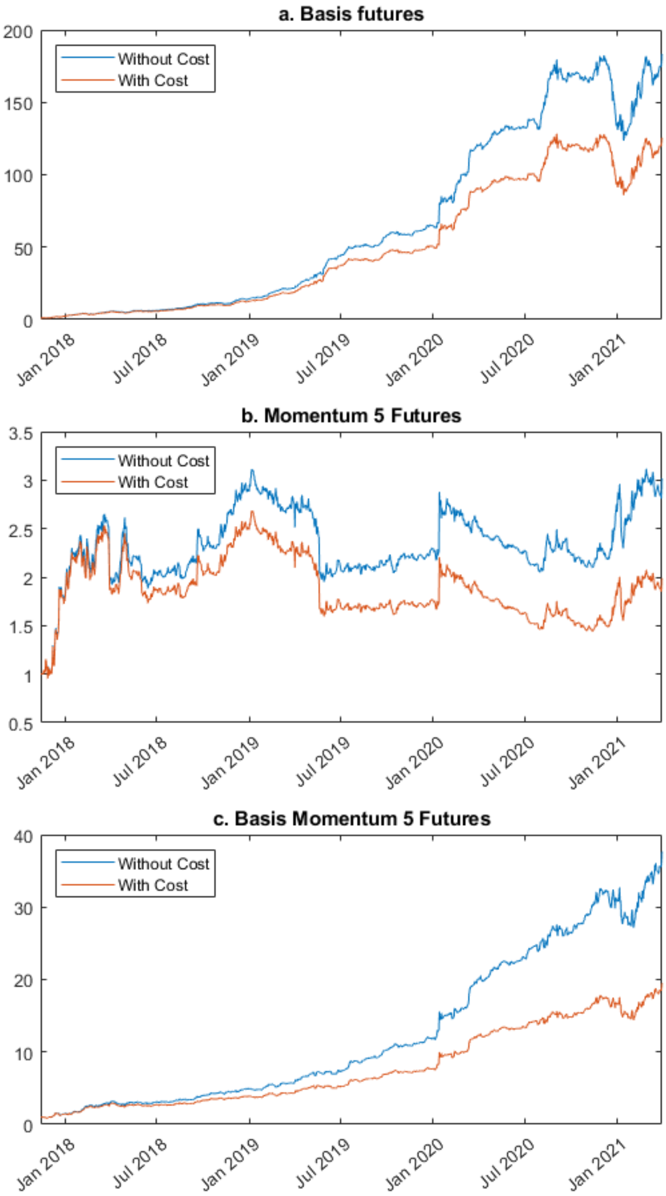

Figure 2. Benchmark daily returns cumulative sum returns

This figure shows the cumulative sum daily returns of the benchmark portfolios. Subfigure a demonstrates the equally weighted portfolio with futures instrument; subfigure b demonstrates the BTC portfolio with futures instrument. For equal weighted portfolio, we use all cryptocurrencies in the table 1. Our sampleperiod is from 13 November 2017 to 31 March 2021.

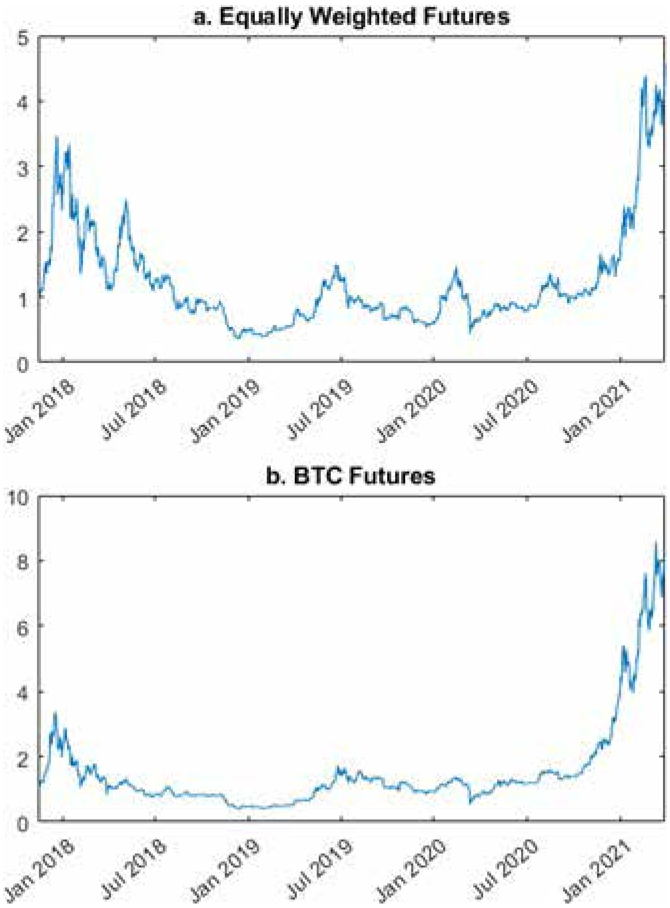

Table 1: Studied cryptocurrency's introduction

This table displays cryptocurrencies studied in thisresearch along with their initial date in our data.

No.	Cryptocurrency Name	Initial Date in Our Data	Average Daily Trading Volume ($mil)
1	Ethereum (ETH)	2017-11-13	31.100
2	Litecoin (LTC)	2017-11-13	11.262
3	Bitcoin (BTC)	2017-11-13	10.281
4	Bitcoin Cash (BCH)	2017-11-13	9.717
5	Ethereum Classic (ETC)	2017-11-13	4.171
6	EOS	2018-04-02	33.994
7	Ripple (XRP)	2018-04-02	.711
8	Bitcoin SV (BSV)	2019-05-24	2.719
9	TRON (TRX)	2019-05-24	0.711
10	Polkadot (DOT)	2020-09-11	3.266
11	Chainlink (LINK)	2020-08-02	2.521
12	Cardano (ADA)	2020-08-02	1.045

Table 2. Number of cryptocurrencies in each period and trading rules

This table displays cryptocurrencies in different period andthe corresponding high, medium, and short portfolios' composition. For example, during 13 July 2011 to 1 April 2018, we have5 cryptocurrencies. Accordingly, we put one cryptocurrency in high portfolio, three cryptocurrencies in medium portfolio, and one cryptocurrency in low portfolio based on the ranks of cryptocurrencies generated by our trading strategy.

Starting Date	Ending Date	Cryptocurrencies	High	Medium	Low
2017-11-13	2018-04-01	BCH, BTC, ETC, ETH, LTC (5)	1	3	1
2018-04-02	2018-11-15	BCH, BTC, ETC, ETH, LTC, EOS, XRP (7)	2	3	2
2018-11-16	2018-12-28	BTC, ETC, ETH, LTC, EOS, XRP (6)	2	2	2
2018-12-29	2019-05-23	BCH, BTC, ETC, ETH, LTC, EOS, XRP, BSV (8)	3	2	3
2019-05-23	2020-08-01	BCH, BTC, ETC, ETH, LTC, EOS, XRP, BSV, TRX (9)	3	3	3
2020-08-02	2020-09-10	BCH, BTC, ETC, ETH, LTC, EOS, XRP, BSV, TRX, LINK, ADA (11)	4	3	4
2020-09-11	2021-03-31	BCH, BTC, ETC, ETH, LTC, EOS, XRP, BSV, TRX, LINK, ADA, DOT (12)	4	4	4

Table 3. Cryptocurrencies daily returns summary statistics

Table 3 shows the summary statistics ofthe Futures returns of 12 cryptocurrencies. The sample period of each cryptocurrency starts from its own date but ends at the same date on March 31st, 2021. The statistics include the minimum,5%, 25%. 50%, 75%, 95%, and the maximum value of the Index return.

Cryptocurrency	Mean	Min	5%	25%	50%	75%	95%	Max
BTC	0.0029	-0.4839	-0.0667	-0.0162	0.0023	0.0218	0.0802	0.3265
ETH	0.0030	-0.4767	-0.0839	-0.0240	0.0012	0.0297	0.0938	0.2998
BCH	0.0022	-0.5405	-0.0952	-0.0286	-0.0003	0.0296	0.1061	0.4352
LTC	0.0019	-0.4864	-0.0983	-0.0234	0.0022	0.0290	0.0986	0.3898
ETC	0.0029	-0.4575	-0.0887	-0.0281	0.0001	0.0307	0.1017	0.4473
XRP	0.0016	-0.4726	-0.0964	-0.0242	0.0013	0.0271	0.0991	0.3565
EOS	0.0021	-0.4456	-0.0848	-0.0232	0.0004	0.0240	0.0878	0.5631
TRX	0.0044	-0.5005	-0.0946	-0.0253	-0.0005	0.0254	0.0962	1.4604
BSV	0.0032	-0.4873	-0.0902	-0.0251	0.0019	0.0312	0.1049	0.4539
LINK	0.0082	-0.2152	-0.1011	-0.0372	0.0026	0.0492	0.1408	0.2831
ADA	0.0118	-0.1829	-0.0953	-0.0258	0.0057	0.0387	0.1431	0.3437
DOT	0.0133	-0.1425	-0.0842	-0.0303	0.0037	0.0420	0.1268	0.3629

Table 4. Portfolio returns summary statistics

This table documents summary statistics of returns generated by our three different tradingstrategies (i.e., basis, momentum, and basis momentum) and the benchmark portfolios. The high portfolio indicates portfolios constructed based on trading the cryptocurrency futures contracts with the highest signals. The low portfolio indicates portfolios constructed based on trading the cryptocurrency futures contracts with the lowest signal. The medium portfolio indicates portfolios constructed based on trading the cryptocurrency futures contracts which do not appear in either high or low portfolios. The high-low portfolio is formed based on taking a long position in the high portfolio and a short position in the low portfolio. Signal ranges from basis, momentum, and basis momentum which are, respectively computed using Equation 1, 2, and 3. All portfolios reported in this table take 5 look-back periods. The holding length is one day. Crypto Market (equally weighted) indicates a strategy that invest equalamount of capital in each cryptocurrency every day and buy and hold for a certain period. BTC indicates investing in BTC by using simple buy and hold strategy. The trading period is from 13 November 2017 to 31 March 2021. Cryptocurrencies invested are informedin Table 1. This table displays annualized daily returns, the average returns, and t-statistics, Sharpe ratio, win rate, win/loss ratio, and maximum drawdown of return series of each portfolio. Here, we take the riskless interest rate as 1.68% per year, which is the averagevalue of one-month T-bill rate.

(a) Basis Futures Portfolios

Portfolio	Annualized Return (%)		Average Return (%)		T-stats		Sharpe Ratio		Win Rate		Win/Loss Ratio		Maximum Drawdown (%)	
High	262.00	251.38	0.72	0.69	4.17	4.00	2.25	2.16	0.56	0.56	1.46	1.44	64.09	67.13
Medium	111.62	98.33	0.31	0.27	1.91	1.68	1.02	0.90	0.52	0.52	1.15	1.10	87.86	89.90
Low	-64.53	-79.67	-0.18	-0.22	-1.03	-1.28	-0.58	-0.71	0.48	0.48	0.80	0.79	99.88	99.92
High-Low	326.58	304.03	0.89	0.83	7.07	6.60	3.83	3.57	0.61	0.60	1.31	1.28	55.82	57.42

(b) Momentum Futures Portfolios

Portfolio	Annualized Return (%)		Average Return (%)		T-stats		Sharpe Ratio		Win Rate		Win/Loss Ratio		Maximum Drawdown (%)	
High	161.38	149.23	0.44	0.41	2.32	2.14	1.25	1.16	0.51	0.51	1.21	1.17	89.39	90.69
Medium	63.26	48.19	0.17	0.13	1.12	0.85	0.59	0.45	0.52	0.52	1.01	0.98	92.20	94.31
Low	73.75	59.80	0.20	0.16	1.20	0.97	0.64	0.51	0.51	0.51	1.03	0.99	95.90	96.42
High-Low	87.63	62.79	0.24	0.17	1.69	1.21	0.91	0.64	0.49	0.48	1.06	1.02	64.25	77.35

(c) Basis Momentum Futures Portfolios

Portfolio	Annualized Return (%)		Average Return (%)		T-stats		Sharpe Ratio		Win Rate		Win/Loss Ratio		Maximum Drawdown (%)	
High	218.39	198.33	0.60	0.54	3.41	3.10	1.85	1.68	0.53	0.52	1.53	1.45	77.03	79.42
Medium	81.41	62.15	0.22	0.17	1.40	1.07	0.75	0.57	0.53	0.53	1.05	1.01	93.70	94.70
Low	-14.34	-33.00	-0.04	-0.09	-0.23	-0.53	-0.14	-0.31	0.49	0.49	0.86	0.84	99.30	99.55
High-Low	232.73	193.54	0.64	0.53	5.17	4.31	2.80	2.33	0.58	0.55	1.44	1.35	46.38	46.87

(d) Benchmark Portfolios

Portfolio	Annualized Return (%)	Average Return (%)	T-stats	Sharpe Ratio	Win Rate	Win/Loss Ratio	Maximum Drawdown (%)
Crypto Market (Equally Weighted)	101.15	0.28	1.78	0.95	0.53	1.08	68.18
BTC	106.51	0.29	2.11	1.13	0.53	1.00	75.05

Table 5: Matrix of T-Statistics Across Portfolios

This table displays a matrix of t-statistics for average returns of futures portfolios with different signal type, look-back period, and holding length. *** p < 0.01, ** p < 0.05, * p < 0.1

	Holding Length: One Day				Holding Length: One Week				Holding Length: One Month			
Portfolio	High	Medium	Low	High-Low	High	Medium	Low	High-Low	High	Medium	Low	High-Low
(Basis, CQ, 1)	4.17***	1.91*	-1.03	7.08***	2.65***	1.73*	0.37	3.35***	1.55	1.49	1.13	0.40
(Momentum, CQ, 1)	1.94*	1.50	1.55	0.80	1.99**	1.18	1.46	1.14	0.87	1.09	1.32	-0.59
(Momentum, CQ, 3)	2.25**	1.46	1.10	1.74*	1.85*	0.97	1.19	0.91	1.16	1.54	0.95	0.32
(Momentum, CQ, 5)	2.32**	1.12	1.20	1.69*	1.18	0.82	0.81	0.56	1.47	1.10	1.13	0.59
(Momentum, CQ, 7)	1.85	1.48	1.47	0.73	0.96	1.35	0.52	0.73	1.10	1.40	0.85	0.14
(Basis Momentum, CQ, 1)	3.86***	1.07	0.39	5.28***	2.04**	1.93*	0.35	2.76***	0.93	1.28	1.02	-0.50
(Basis Momentum, CQ, 3)	2.93***	1.27	0.40	3.40***	1.78*	1.57	0.62	1.83	1.60	1.15	1.35	0.08
(Basis Momentum, CQ, 5)	3.41***	1.40	-0.23	5.17***	0.68	1.30	0.65	-0.07	1.46	1.16	0.91	1.08
(Basis Momentum, CQ, 7)	3.65***	0.99	0.43	4.78***	1.46	0.83	0.90	0.82	1.73	1.01	0.99	1.29

Table 6. Spanning Regression of Futures Portfolios Formed Based on Basis

This table reports regression results regarding the returns of portfolios that trade futures based on three different signals with varying holding lengths. The signals are, respectively, basis, momentum, and basis momentum. The holding length ranges one day, one week, to one month. In Panel (a), the dependent variable is the returns of "high-low basis" portfolio, which is constructed as a long-short futures portfolio based on the contemporaneous basis. Basis is computed using Equation 1. In Panel (b), the dependent variable is the returns of "high-low mom" portfolio, which is constructed as a long-short futures portfolio based on the momentum values. Momentum (of futures) is computed using Equation 2. In Panel (c), the dependent variable is the returns of "high-low basis mom" portfolio, which is constructed as a long-short futures portfolio based on the momentum values. Momentum (offutures) is computed using Equation 2. Model (1) of each panel report results for portfolios with one-day holding length,Model (2) report with one-week holding length, and Model (3) report with one-month holding length. All "high-low basis" portfolio is constructed as shorting \$0.5 in the short portfolio and investing \$0.5 in the long portfolio. Risk-free rates, proxied by the one-month T-bill rate, are subtracted from all my dependent and independent variables. The risk-free rate is adjusted according to the holding length of our strategies. The t-statistics presented underneath each estimate are calculated using standard errors clustered in the time dimension. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

(a) Dependent Variable: High-Low Basis Futures Portfolio

	(1)	(2)	(3)
VARIABLES	Daily	Weekly	Monthly
Crypto Market Index	-0.00985	-0.0196	-0.184
	(-0.887)	(-0.657)	(-1.669)
high-low momentum	0.0924	0.255*	0.136
	(1.525)	(1.928)	(1.082)
high-low basis momentum	0.560***	0.521***	0.698***
	(9.441)	(3.906)	(2.934)
Constant	0.00230***	0.0114***	-0.000680
	(4.374)	(3.496)	(-0.0364)
Observations	1,219	150	35
R-squared	0.311	0.248	0.357

(b) Dependent Variable: High-Low Momentum Futures Portfolio

	(1)	(2)	(3)
VARIABLES	Daily	Weekly	Monthly
Crypto Market Index	0.0166	-0.00185	0.150
	(0.917)	(-0.0484)	(0.957)
high-low basis	0.166	0.330*	0.261
	(1.400)	(1.800)	(1.163)
high-low basis momentum	-0.0813	-0.441***	-0.271
	(-0.573)	(-2.961)	(-0.856)
Constant	0.000402	-0.00203	-0.00132
	(0.534)	(-0.609)	(-0.0575)
Observations	1,219	150	35
R-squared	0.018	0.140	0.075

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(c) Dependent Variable: High-Low Basis Momentum Futures Portfolio

VARIABLES	(1) Daily	(2) Weekly	(3) Monthly
Crypto Market Index	0.0120	-0.0345	0.0941
	(1.144)	(-1.088)	(1.427)
high-low basis	0.540***	0.409***	0.383*
	(7.974)	(3.386)	(2.023)
high-low momentum	-0.0436	-0.267***	-0.0771
	(-0.558)	(-3.097)	(-1.166)
Constant	0.000711	-0.00755***	0.00463
	(1.273)	(-3.039)	(0.339)
Observations	1,219	150	35
R-squared	0.304	0.285	0.276

Table 7. Sensitivity of Portfolio Profitability to Liquidity Risk Exposure

This table reports regression results regarding the returnsof futures portfolios based on either of basis, momentum, and basis momentum signals. The holding length varies from oneday, one week, to one month. The dependent variables for Panel (a), (b), and (c) are, respectively, the returns of "high-lowbasis" portfolio, "high-low mom" portfolio, and "high-low basis mom" portfolio. The signals of basis, momentum, and basis momentum are, respectively computed using Equation 1, 2, and 3. Model (1)-(2) of each panel report results for portfolioswith one-day holding length, Model (3)-(4) report with one-week holding length, and Model (5)-(6) report with one-monthholding length. The independent variables are proxies for illiquidity risk factor ("Illiquidity Factor"), market risk factors, including the average cryptocurrency futures returns ("Crypto Market Index"), MSCI returns ("MSCI"), and GSCI returns("GSCI"). The illiquidity risk factor encompasses a return series of a long-short portfolio which is created by sorting basedon Amihud (2002) measure. Risk-free rates, proxied by the one-month T-bill rate, are subtracted from all my dependent andindependent variables. The t-statistics presented underneath each estimate are calculated using standard errors clustered inthe time dimension. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

(a) Dependent Variable: High-Low Basis Futures Portfolio

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Daily	Daily	Weekly	Weekly	Monthly	Monthly
Crypto Market Index	-0.00420	-0.0175	0.0354	-0.0454	0.217	-0.212
	(-0.140)	(-0.777)	(0.324)	(-0.754)	(0.612)	(-1.274)
MSCI	-0.173*	-0.0733	-0.0586	-0.183	0.512	0.288
	(-1.748)	(-0.930)	(-0.290)	(-1.039)	(0.413)	(0.344)
GSCI	5.42e-05***	6.84e-05***	-0.0496	0.106	-0.356	0.427
	(13.82)	(16.33)	(-0.201)	(0.628)	(-0.370)	(0.648)
Illiquidity Factor	0.0416	-0.000727	-0.0527	0.131	-0.205	-0.397
	(0.442)	(-0.0110)	(-0.282)	(0.968)	(-0.564)	(-1.475)
high-low momentum		0.0909		0.263**		0.205
		(1.512)		(2.008)		(1.153)
high-low basis momentum		0.561***		0.540***		0.747***
		(9.496)		(4.269)		(3.047)
Constant	0.00852***	0.00469***	0.0293***	0.0236***	0.0147	0.0187
	(6.675)	(4.437)	(3.628)	(3.497)	(0.344)	(0.493)
Observations	1,229	1,219	155	150	40	35
R-squared	0.006	0.315	0.004	0.270	0.053	0.528

(b) Dependent Variable: High-Low Momentum Futures Portfolio

VARIABLES	(1) Daily	(2) Daily	(3) Weekly	(4) Weekly	(5) Monthly	(6) Monthly
Crypto Market Index	0.0321	0.0350	0.0258	0.00547	-0.0559	0.0332
	(0.885)	(0.970)	(0.266)	(0.0690)	(-0.178)	(0.107)
MSCI	-0.145	-0.142	-0.226	-0.0386	2.155*	1.949*
	(-1.470)	(-1.460)	(-0.942)	(-0.190)	(1.728)	(1.932)
GSCI	2.90e-05***	1.77e-05**	0.0501	0.0135	-0.576	-0.732
	(5.024)	(1.981)	(0.209)	(0.0662)	(-0.825)	(-1.256)
Illiquidity Factor	0.0386	0.0368	-0.0569	-0.111	0.415	0.546***
	(0.273)	(0.275)	(-0.360)	(-0.946)	(1.646)	(2.844)
high-low basis		0.164		0.346*		0.418**
		(1.387)		(1.869)		(2.226)
high-low basis momentum		-0.0837		-0.450***		-0.249
		(-0.595)		(-3.057)		(-0.899)
Constant	0.00201	0.00121	0.00927	-0.000925	-0.0105	-0.0192
	(1.395)	(0.785)	(1.186)	(-0.137)	(-0.242)	(-0.487)
Observations	1,225	1,219	150	150	35	35
R-squared	0.005	0.020	0.007	0.150	0.213	0.282

(c) Dependent Variable: High-Low Basis Momentum Futures Portfolio

VARIABLES	(1) Daily	(2) Daily	(3) Weekly	(4) Weekly	(5) Monthly	(6) Monthly
Crypto Market Index	0.0198	0.0231	-0.128**	-0.0758	0.0666	0.142
	(0.673)	(1.049)	(-2.006)	(-1.340)	(0.646)	(1.619)
MSCI	-0.155	-0.0679	0.393**	0.346**	-1.554	-1.197
	(-1.564)	(-0.870)	(2.344)	(2.281)	(-1.356)	(-1.316)
GSCI	-2.96e-05***	-5.77e-05***	0.0173	-0.0233	0.423	0.0951
	(-5.983)	(-10.73)	(0.0942)	(-0.158)	(0.614)	(0.212)
Illiquidity Factor	0.0653	0.0457	-0.0516	-0.104	-0.00949	0.167
	(0.560)	(0.516)	(-0.603)	(-1.183)	(-0.0556)	(0.906)
high-low basis		0.540***		0.420***		0.456***
		(8.031)		(3.695)		(2.748)
high-low momentum		-0.0447		-0.266***		-0.0745
		(-0.582)		(-3.076)		(-1.448)
Constant	0.00608***	0.00170	-0.00454	-0.0120**	0.0282	0.0103
	(4.834)	(1.518)	(-0.673)	(-2.385)	(0.920)	(0.418)
Observations	1,219	1,219	150	150	35	35
R-squared	0.008	0.308	0.058	0.314	0.117	0.419

Table 8. Signal Ranking Correlation Matrix Across Portfolios

This table exhibits the ranking correlation matrix across portfolios that are formed based on different signal type (i.e., basis,momentum, and basis-momentum), holding length, and look-back period (k). Specifically, on each day, a signal value is calculated for each cryptocurrency. Signals are ranked toform portfolios, such as the High-Low portfolio constructed based on taking a high position in coins with highest signals and a Low position in coins with lowest signals. We can then calculate the correlation between the signal rankings across two portfolios on each day, for a given holding length. The chart below reports the time-series average of such correlation.

(a) Daily Correlation

Strategy	(Mom, 1)	(Mom, 3)	(Mom, 5)	(Mom, 7)	(Basis)	(Basis Mom, 1)	(Basis Mom, 3)	(Basis Mom, 5)	(Basis Mom, 7)
(Mom, 1)	1.000	0.429	0.323	0.283	-0.079	-0.330	-0.190	-0.159	-0.134
(Mom, 3)		1.000	0.628	0.508	-0.057	-0.102	-0.277	-0.181	-0.137
(Mom, 5)			1.000	0.719	-0.035	-0.059	-0.125	-0.236	-0.162
(Mom, 7)				1.000	-0.015	-0.052	-0.087	-0.122	-0.212
(Basis)					1.000	0.235	0.259	0.284	0.297
(Basis Mom, 1)						1.000	0.402	0.341	0.307
(Basis Mom, 3)							1.000	0.509	0.435
(Basis Mom, 5)								1.000	0.559
(Basis Mom, 7)									1.000

b) Weekly Correlation

Strategy	(Mom, 1)	(Mom, 3)	(Mom, 5)	(Mom, 7)	(Basis)	(Basis Mom, 1)	(Basis Mom, 3)	(Basis Mom, 5)	(Basis Mom, 7)
(Mom, 1)	1.000	0.448	0.339	0.293	-0.018	-0.224	-0.097	-0.083	-0.068
(Mom, 3)		1.000	0.647	0.518	-0.005	-0.056	-0.177	-0.135	-0.058
(Mom, 5)			1.000	0.732	0.001	-0.043	-0.095	-0.134	-0.082
(Mom, 7)				1.000	-0.017	-0.058	-0.094	-0.119	-0.149
(Basis)					1.000	0.289	0.337	0.418	0.384
(Basis Mom, 1)						1.000	0.389	0.333	0.281
(Basis Mom, 3)							1.000	0.508	0.385
(Basis Mom, 5)								1.000	0.572
(Basis Mom, 7)									1.000

c) Monthly Correlation

Strategy	(Mom, 1)	(Mom, 3)	(Mom, 5)	(Mom, 7)	(Basis)	(Basis Mom, 1)	(Basis Mom, 3)	(Basis Mom, 5)	(Basis Mom, 7)
(Mom, 1)	1.000	0.470	0.406	0.303	0.103	-0.092	-0.033	-0.007	0.015
(Mom, 3)		1.000	0.652	0.527	-0.018	-0.133	-0.039	-0.090	0.130
(Mom, 5)			1.000	0.722	-0.004	-0.110	-0.114	-0.041	0.051
(Mom, 7)				1.000	0.012	-0.072	-0.075	-0.109	0.034
(Basis)					1.000	0.383	0.430	0.356	0.331
(Basis Mom, 1)						1.000	0.266	0.220	0.308
(Basis Mom, 3)							1.000	0.436	0.295
(Basis Mom, 5)								1.000	0.319
(Basis Mom, 7)									1.000