Risk-Return Relation of Cryptocurrency Carry Trade

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Abstract

This paper comprehensively examines the risk-return relation of cryptocurrency carry trade using realistic borrowing and lending interest rates. We find significant violations of the uncovered interest rate parity in the cryptocurrency market. The cross-sectional carry trade strategy yields an annualized return of 46.71% and a Sharpe ratio of 0.77. Unlike fiat-currency carry trade which is vulnerable to crash risk, the cryptocurrency carry trade is resistant to the cryptocurrency market crashes in 2018 and 2021. We show that the crypto-carry trade returns cannot be explained by established risk factors from fiat currencies or cryptocurrencies. We find that geopolitical risk explains a substantial amount of the carry returns.

JEL Classification:
Keywords: Cryptocurrency, Carry trade, Uncovered interest rate parity, Geopolitical risk

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1 Introduction

Cryptocurrency has emerged as a new investment vehicle in recent years, offering novel opportunities to investors. This study explores the relation between risk and return in the cryptocurrency carry trade. Previous research on fiat currencies shows that carry trade can deliver positive returns by leveraging the differential in interest rates between low- and high-yielding currencies. The study by Koijen et al. (2018) broads the scope of the carry trade concept to other asset classes and finds that this strategy delivers positive returns in global equity, commodity, bond, options, and other markets. Examining the cryptocurrency carry trade not only expands our understanding of the carry trade but also reveals new investment prospects for investors. Furthermore, understanding the risk-based drivers of cryptocurrency carry returns sheds light on how cryptocurrency differs from traditional assets in terms of return determination and assists investors in managing their portfolio risk more effectively.

We begin our examination by assessing the validity of the uncovered interest rate parity (UIP) hypothesis in the cryptocurrency market (Keynes, 1923). To do so, we employ the UIP regression methodology outlined by Fama (1984) and examine the interest rate differential between cryptocurrency and US Dollar, as defined by Koijen et al. (2018). Our findings reveal that this carry factor has a positive impact on cryptocurrency's excess returns in the time-series, indicating that UIP does not hold in the cryptocurrency market. Both the observed interest rate and the futures-implied interest rate of cryptocurrency are tested to validate the UIP hypothesis, ultimately confirming its violation in the cryptocurrency market.

The empirical tests of UIP provide evidence in support of a positive return for a time-series carry trade between cryptocurrency and US Dollar. Next, we explore the returns generated by a time-series carry trade between stablecoins and US Dollar. This popular trading strategy involves borrowing US dollars, exchanging them for stablecoins, which are pegged to the US dollar, and depositing them in online platforms to earn a higher interest rate. We utilize two widely-used stablecoins, DAI and USDT(tether), in our examination of the carry trade returns between stablecoins and U.S. Dollar. Our findings show that this strategy generates an annualized return of approximately 9% with a Sharpe ratio as high as 3.47.

We subsequently examine the performance of cross-sectional carry trade beyond the stablecoins. We observe that by going long on cryptocurrencies with high interest rates and shorting those with low interest rates, cross-sectional carry trade can generate substantial positive carry returns. We categorize the cryptocurrencies in our sample based on their carry, dividing them into three equal groups. We hold each portfolio for one week and rebalance it at the end of each week.[1] The carry return is calculated as the return of the highest-interest cryptocurrencies minus the return of the lowest-interest group. This strategy results in an annualized mean carry return of 46.71%, a standard deviation of 60.68%, and a Sharpe ratio of 0.77.

We then compare the performance of the carry portfolio with that of a passively constructed, equally weighted (EW) cryptocurrency portfolio. By scaling the carry portfolio to match the volatility of the EW portfolio, we demonstrate that the carry portfolio not only delivers more consistent performance, but also withstands the significant market downturns that occurred in 2018 and 2021.

Further examination shows that the carry trade premium of cryptocurrencies cannot be solely attributed to the three-factor model of Liu et al. (2022), downside or volatility risk. Instead, the geopolitical risk from Caldara and Iacoviello (2022) seems to play a major role in driving the carry return. This is a departure from the conventional understanding of carry trade risk in fiat currency markets. Once the impact of geopolitical risk is taken into account, the risk-ajusted alpha of cryptocurrency carry trade turns negative.

Our study is related to carry literature which focuses on fiat-currencies. Our research demonstrates that the drivers of carry returns in fiat currencies and cryptocurrencies are vastly distinct. Past studies have indicated that carry trade in fiat currency markets generates substantial positive returns (Burnside et al., 2011; Lettau et al., 2014; Lustig et al., 2011). This positive carry premium is attributed to various types of risks, such as

[1] We follow the practice in Cong et al. (2022) to do this. Since weekly interest rate data for the U.S. Dollar is not available on weekends, we rebalance the portfolio on Fridays.

carry trade risk (Lustig et al., 2011), global equity market volatility (Lustig et al., 2011), downside risk (Lettau et al., 2014), global foreign exchange volatility risk (Menkhoff et al., 2012), peso-event risk (Burnside et al., 2011), jump risk (Lee and Wang, 2019), among others. However, our findings suggest that the positive carry trade return of cryptocurrency can be explained by geopolitical risk factors as noted by Caldara and Iacoviello (2022), but a significant negative portion of the carry return remains unaccounted for, which differs from the carry trade of fiat currency.

Our paper is the most comprehensive study on the risk-return relation of cryptocurrency carry trade to our knowledge. Several papers also investigate the cryptocurrency carry trade, but neither the scope nor the coverage of these studies are comparable to ours. Specifically, we differ from existing cryptocurrency carry studies in the following aspects. First, we use realistic borrowing and lending interest rates from a major online trading platform for all cryptocurrencies. Cong et al. (2022) use staking reward rate as a proxy for cryptocurrency interest rate.[2] However, many cryptocurrencies, such as Bitcoin, cannot be staked so that they cannot be included in their sample. Some studies use crypto-derivatives to infer interest rates, such as perpetual swaps (Franz and Schmeling, 2021) and futures contract (Christin et al., 2022).[3] Crypto-derivatives suffer from liquidity issues (Greene and McDowall, 2018; Kumar, 2022), especially when the underlying token has a smaller market share. Moreover, Franz and Valentin (2020) show that the spot and derivatives market for cryptocurrencies are segregated and conventional economic parities are often violated. Second, instead of focusing on a few ad hoc tokens (Christin et al., 2022), our study includes over 40 cryptocurrencies. Our cryptocurrency universe consists of all actively traded currencies from the Bitfinex platform with non-trivial borrowing and lending rates, including major tokens like Bitcoin, Etherium as well as stablecoins like USDT and DAI. Third, we conduct a risk factor analysis of the cryptocurrency carry trade from an asset-market view. Existing studies propose explanations from other than

[2]Staking reward is earned when investors lock their cryptocurrency for a certain period to help verify transactions on the Blockchain system or maintain the safety of the network (Chitra, 2020).

[3]The strategy in Christin et al. (2022) is to short the perpetual futures of Bitcoin and long Bitcoin as a hedge. Therefore, their strategy is actually an arbitrage strategy based on deviations of covered interest rate parity. However, the carry trade strategy in our paper is an arbitrage strategy based on deviations of uncovered interest rate parity.

the risk-based perspective. For example, Cong et al. (2022) propose that the positive carry return comes from transaction convenience. Franz and Schmeling (2021) suggest that the carry return is caused by capital insufficiency and speculation with high leverage. We show that the carry trade returns cannot be explained by established risk factors from either fiat currencies (Lustig et al., 2011) or cryptocurrencies (Liu et al., 2022). We find that geopolitical risk explains a substantial amount of the carry returns.

The rest of the paper is organized as follows. Section 2 describes the data. Section 3 examines whether UIP condition holds in the time-series in cryptocurrency markets. Section 4 investigates the carry trade strategy of cryptocurrencies. Section 5 investigates the possible economic explanations for the carry return. Section 6 provides the results of robustness check. Section 7 concludes.

2 Data

The cryptocurrency interest rate data was obtained from the Bitfinex platform, which operates as a peer-to-peer lending and borrowing platform for cryptocurrencies. The interest rate in this study is the observed deposit and lending rate of cryptocurrencies on the Bitfinex platform.[4] Bitfinex was selected as the source of cryptocurrency interest rate data due to its status as the largest exchange providing interest rates for Bitcoin through a limit order book (Franz and Valentin, 2020). The sample period was limited to October 2016 to December 2021, as the data on interest rates from Bitfinex is considered reliable only after October 2016 (Franz and Valentin, 2020).

We obtain data on the interest rates of 46 cryptocurrencies from the Bitfinex platform.[5] The deposit rate of a cryptocurrency is equal to 0.85 multiplied by the borrowing

[4]Investors can conduct margin trading on the Bitfinex platform, which allows them to trade cryptocurrencies with leverage by borrowing cryptocurrencies from others. The interest rate we use is the borrowing and lending rate of their funding. It should be noted that this interest rate differs from the staking reward rate, as described by Cong et al. (2022). The latter refers to the rewards received by investors for locking their cryptocurrency for a set period in order to validate transactions and enhance network security, as stated in Chitra (2020)

[5]We can collect data on interest rates for 49 cryptocurrencies in total from the Bitfinex platform, including 4 stablecoins. However, following Cong et al. (2022), we remove the observations in the first week after the cryptocurrencies were first launched because Cong et al. (2022) propose that there are abnormal fluctuations in cryptocurrency prices at this period. After this filter, there are 46 cryptocurrencies left in the sample.

rate of the cryptocurrency.[6] The interest rate from Bitfinex is at hourly frequency. To mitigate the impact of outliers, we employ a precautionary measure of replacing hourly interest rates that exceed the 99th percentile of historical observations with their preceding value. We then calculate the daily interest rate by taking the volume-weighted average of hourly observations, as per Franz and Valentin (2020). The final daily interest rate was utilized to calculate the monthly and weekly interest rates by multiplying it by 30 and 7, respectively.

The summary statistics of the annualized interest rate, calculated as the daily rate multiplied by 365, are displayed in Table 1. Table 1 shows that the annualized interest rates for Bitcoin and Ethereum were 8.13% and 6.00%, respectively.

[Insert Table 1 Here]

We collect daily spot prices of 46 cryptocurrencies from coinmarketcap.com as per Liu et al. (2022). To ensure accuracy, we eliminate the first-week observations following the launch of each cryptocurrency as suggested by Cong et al. (2022), who posit abnormal fluctuations in cryptocurrency prices occur during this period. We also replace outliers, observations larger than the 99th percentile or smaller than the 1st percentile, with the previous value. Table 2 presents a summary of daily log price changes ($\log P_2 - \log P_1$) of cryptocurrencies.

[Insert Table 2 Here]

We acquire the monthly interest rate of the U.S. Dollar from Federal Reserve Economic Data (FRED) and the weekly interest rate of the U.S. Dollar from the OptionMetrics database. We source the market, size, and momentum factors of cryptocurrencies from Liu et al. (2022), the geopolitical risk data from Caldara and Iacoviello (2022), and the VIX data from the Bloomberg database.

We gather data on Bitcoin and Ethereum futures in the Chicago Mercantile Exchange (CME) from the Bloomberg database. Our sample period for Bitcoin extends from December 2017 to May 2022, while for Ethereum, it covers February 2021 to May 2022. To ensure high-quality data, we exclude futures prices with missing or zero trading volume

[6] The reason is that the fund providers have to pay a fee equal to 15% of the interest they earned if the funding is not opened with a hidden offer.

and observations with bid-ask spread larger than 10% of the mid-price. Spot prices for Bitcoin and Ethereum in Section 6 are sourced from Yahoo Finance to expand the sample period.

3 Revisit UIP Condition

In this section, we examine the validity of the Uncovered Interest Rate Parity (UIP) in the cryptocurrency market by utilizing the regression method introduced by Fama (1984). The significance of testing the UIP lies in the fact that the profitability of the time-series carry trade strategy is contingent upon its violation. The UIP, originally proposed by Keynes (1923), suggests that a currency with a higher interest rate is expected to depreciate relative to a currency with a lower interest rate. Hence, investors should not be able to earn a profit by borrowing the low-interest currency and investing in the high-interest currency. The interest rate differential between any pair of currencies cannot predict the currency excess returns. In light of this, we test whether the interest rate differential between cryptocurrency and U.S. Dollar can predict the log excess return of cryptocurrency. We conduct our analysis in both the spot market and the futures market. In the spot market, we first perform UIP regression on each of the 42 cryptocurrencies in our sample obtained from the Bitfinex platform.[7] We then conduct a panel regression that includes all 42 cryptocurrencies to test the UIP condition. In the futures market, Section 6.2 uses the futures implied interest rate differential of Bitcoin and Ethereum to test the robustness of our findings.

The UIP regression in the spot market of cryptocurrencies is as follows:

$$r_{t+1} = \alpha + \beta(i_t^c - i_t^{USD}) + \epsilon_{t+1}\,. \tag{1}$$

where r_{t+1} is the log excess return of a cryptocurrency from time t to time t+1. i_t^c and i_t^{USD} are the interest rates of the cryptocurrency and U.S. Dollar from time t to time

[7] It is worth noting that we exclude stablecoins from our analysis, as their prices are pegged to assets such as the US Dollar, Euro, or gold, and as such, their interest rates are not expected to predict their excess returns.

$t+1$, respectively. In line with the methodology presented in Fama (1984), the return and interest rate differential in our regression are expressed as percentage points. The log excess return of the cryptocurrency is defined as in Lettau et al. (2014):

$$r_{t+1} = i_t^c - i_t^{USD} + \Delta s_{t+1} \,. \tag{2}$$

where s_t is the log price of the cryptocurrency in terms of the U.S. Dollar. The calculation of this excess return involves borrowing U.S. Dollars, exchanging them for Bitcoin, depositing the funds on online platforms to earn interest, and measuring the resulting return. As per the uncovered interest rate parity (UIP) hypothesis, the excess return should be negligible since the appreciation or depreciation of cryptocurrencies is determined by the relationship between their interest rate with that of the U.S. Dollar. If the cryptocurrency's interest rate is higher, it is expected to depreciate, and vice versa, rendering it unprofitable to borrow U.S. Dollars and invest in cryptocurrencies. Hence, the β estimates in regression equation (1) should approach zero, indicating that $i_t^c - i_t^{USD}$ cannot predict the future excess returns of cryptocurrencies.

We evaluate the relationship between interest rate differential and cryptocurrency excess returns using both weekly and monthly returns. The sample period for our analysis is October 2016 to December 2021, a span of approximately five years. To increase the number of observations, we perform the analysis at a daily frequency. The process of calculating the monthly and weekly returns at a daily frequency involves simulating a daily carry trade strategy. On each day, we borrow US Dollars, exchange them for a cryptocurrency, deposit the cryptocurrency on the Bitfinex platform for one month (or one week), exchange the cryptocurrency back to US Dollars, and repay the loan. This process is repeated daily, yielding monthly (or weekly) excess returns at a daily frequency.

Table 3 shows the results of the UIP regression with monthly returns for each of the 37 cryptocurrencies.[8] The results of our regression analysis indicate that the estimates of β are significantly positive for 9 cryptocurrencies, implying that an increase in their

[8] Initially, there are 42 cryptocurrencies in our sample (not including stablecoins). However, 5 of them, Compound, Elrond, Maker, Polygon, and SHIBA INU are excluded in Table 3 since the observations of monthly returns for these 5 cryptocurrencies are not enough to do the regression.

interest rates relative to the U.S. Dollar is associated with an appreciation in their value, leading to an increase in their future excess returns. This finding suggests a violation of the UIP condition for these cryptocurrencies. For 7 cryptocurrencies, the estimates of β are significantly negative, indicating that an increase in their interest rates relative to the U.S. Dollar results in a larger depreciation of their value, leading to a decrease in their excess returns. This result also indicates a violation of the UIP condition for these cryptocurrencies. It is noteworthy that many popular cryptocurrencies, including Bitcoin, Ethereum, Litecoin, and Solana, all exhibit deviations from the UIP principle. Meanwhile, the estimates of β are insignificant for 21 cryptocurrencies, implying that there is insufficient evidence of a violation of the UIP condition among these cryptocurrencies.

[Insert Table 3 Here]

Table 4 shows the results of UIP regression with weekly returns for each individual cryptocurrency. There are 40 cryptocurrencies in this test.[9] The estimates of β for 10 cryptocurrencies are significantly positive, 3 are significantly negative, and 27 are insignificant.

[Insert Table 4 Here]

The results in Table 5 demonstrate that when all 42 cryptocurrencies are considered together in the panel regression, the estimates of β are significantly positive.[10] In particular, the regression model that accounts for both individual and time fixed effects, and with monthly returns, shows that a 1% increase in the interest rate differential is associated with a 1.55% increase in the future excess return of the cryptocurrency. These findings indicate that the UIP condition does not hold in the 42 cryptocurrency universe.

[Insert Table 5 Here]

In summary, the results from our analysis demonstrate that the uncovered interest rate parity (UIP) hypothesis is not upheld in the cryptocurrency market. Specifically,

[9] SHIBA INU and Maker are not included here. For SHIBA INU, there are not sufficient observations to do the regression using Newey-West standard error with 3 lags. For Maker, the interest rate varies too little, whereas the price is too volatile, so that the absolute value of the coefficient is estimated to be extremely large (-124,917.2), which is not reasonable. Therefore, we do not include Maker, either.

[10] We don't include the 4 stablecoins in the test because their prices are pegged to some other assets such as U.S. Dollar, Euro or gold so that the price changes are not supposed to be predicted by the interest rate differential.

the interest rate differential between cryptocurrency and the U.S. Dollar can positively predict future excess returns of cryptocurrencies. An increase in the interest rate of a cryptocurrency or a decrease in the interest rate of the U.S. Dollar is associated with an appreciation of the cryptocurrency against the U.S. Dollar. Conversely, a decrease in the interest rate of a cryptocurrency or an increase in the interest rate of the U.S. Dollar is associated with a depreciation of the cryptocurrency, resulting in a decrease in its excess return. In addition, Section 6.2 also performs a robustness check by testing the UIP hypothesis in the futures market of Bitcoin and Ethereum. The results indicate that UIP is violated in the Bitcoin futures market, but there is insufficient evidence of UIP violation in the Ethereum futures market.

4 Carry Trade

In this section, we explore the implementation of various forms of carry trade strategies using cryptocurrencies. The carry trade strategy involves borrowing currencies with low interest rates and investing in currencies with high interest rates. Section 4.1 examines the time-series carry trade between stablecoins and the U.S. Dollar, a popular investment strategy among investors. Meanwhile, section 4.2 focuses on the cross-sectional carry trade in the cryptocurrency universe.

4.1 Time-series Carry Trade between Stablecoins and U.S. Dollar

In practice, investors often implement a carry trade strategy of borrowing U.S. Dollars, exchanging them for stablecoins pegged to the U.S. Dollar, and depositing the stablecoins on online platforms to earn a profit as the interest rates of stablecoins are usually higher than those of the U.S. Dollar. This constitutes a carry trade between stablecoins and the U.S. Dollar, and in this subsection, we investigate the profitability of this strategy.

The described carry trade strategy focuses on two stablecoins, USDT (Tether) and Dai, both of which are pegged to the U.S. Dollar. The direction of the trade depends on whether the interest rate of the U.S. Dollar is higher or lower than the lending and deposit rate of the stablecoins. When the interest rate of the U.S. Dollar is lower than the interest rate of depositing a stablecoin, the strategy involves borrowing U.S. Dollar, exchanging it for a stablecoin, and depositing it on the Bitfinex platform for a specific period of time, either one month or one week. If the interest rate of the U.S. Dollar is higher than the interest rate of borrowing the stablecoin, we execute the trade in reverse by borrowing the stablecoin, exchanging it into U.S. Dollar, and depositing U.S. Dollar. If the interest rate of the U.S. Dollar falls between the two, no trade is conducted. The strategy aims to generate a monthly or weekly carry return, which is calculated at a daily frequency.

The return of the strategy for each situation is calculated as follows,

$$r_{t+1} = \begin{cases} i_t^{c-dep} - i_t^{USD} + \Delta s_{t+1} & i_t^{c-dep} > i_t^{USD} \\ i_t^{USD} - i_t^{c-borw} - \Delta s_{t+1} & i_t^{USD} > i_t^{c-borw} \\ 0 & i_t^{c-dep} \leq i_t^{USD} \leq i_t^{c-borw} \end{cases}$$

where i_t^{c-dep} and i_t^{c-borw} are the deposit rate and borrowing rate of a stablecoin, respectively.

Table 6 shows the results.[11] The monthly carry return and weekly carry return for both USDT and Dai are significantly positive at 1 % level. As expected, almost all carry returns come from the interest rate differential, since the peg between the U.S. Dollar and stablecoins is largely maintained during the sample period. This strategy offers a very high Sharpe ratio. For example, the annualized carry return of USDT calculated from the monthly return is 9.067%, and the Sharpe ratio is as high as 3.469. The result confirms the profitability of the carry strategy between stablecoins and the U.S. Dollar.

[Insert Table 6 Here]

[11] The means, standard deviations and Newey-West standard errors (Newey and West, 1987) are annualized and in percentage points. The Sharpe ratios are annualized and in real numbers. Annualized mean is the mean of monthly (weekly) return multiplied by 12 (52). Annualized standard deviation is the standard deviation of monthly (weekly) return multiplied by $\sqrt{12}$ ($\sqrt{52}$). Annualized Sharpe Ratio is the ratio of the annualized mean and annualized standard deviation.

4.2 Cross-sectional Carry Trade

In this subsection, we investigate the cross-sectional carry trade within the 42 cryptocurrency universe.[12] The strategy involves going long on cryptocurrencies with high interest rates and shorting cryptocurrencies with low interest rates. We adopt two methods to construct the cross-sectional carry portfolio: 1) ranking the cryptocurrencies by their carry ($i_t^c - i_t^{USD}$) and dividing the universe into three equal groups, with the carry return being the difference in return between the highest (group 3) and lowest carry group (group 1); 2) a method introduced by Asness et al. (2013) that involves using the weight determined by the rank of carry for each cryptocurrency to form the carry trade portfolio. The weight for each cryptocurrency is calculated as $w_t^i = z_t(rank(c_t^i) - \frac{N_t+1}{2})$, where w_t^i is the weight of cryptocurrency i at time t in the portfolio, c_t^i is the carry of the cryptocurrency at time t, N_t is the total number of cryptocurrencies at time t, and z_t is a scalar that ensures the total weight of long positions is 1 and the total weight of short positions is -1. A cryptocurrency with a high carry will receive a high weight, and if its carry falls below the bottom 50th percentile, it will receive a negative weight (for shorting).

We rank cryptocurrencies by carry and construct the carry portfolio at the end of each week (Friday), holding for one week and rebalancing the carry portfolio next Friday. The return of an individual cryptocurrency is calculated as follows. If a cryptocurrency is in the long position,

$$r_{t+1} = i_t^{c-dep} - i_t^{USD} + \Delta s_{t+1}\,. \tag{3}$$

If a cryptocurrency is in the short position,

$$r_{t+1} = i_t^{USD} - i_t^{c-borw} - \Delta s_{t+1}\,. \tag{4}$$

where i_t^{c-dep} and i_t^{c-borw} are the interest rate of depositing and borrowing the cryptocurrency, respectively. s_t is log price of the cryptocurrency.

In the first method for forming the cross-sectional carry portfolio, we calculate the

[12]We don't include stablecoins in this test for the same reason as that in section 3.

average return, interest rate differential, and price change for each group by taking the equal-weighted average of the individual cryptocurrencies within the group. The carry return is found by subtracting the return of the group with the lowest carry from the return of the group with the highest carry. For the second method, the carry return is computed as the weighted average return of all cryptocurrencies, based on the weight determined by the rank of carry for each cryptocurrency as described by Asness et al. (2013).[13] As suggested by Cong et al. (2022), we exclude the observations from the first week after the launch of each cryptocurrency, due to the presence of abnormal price fluctuations during this period.

Table 7 shows the results. The mean, standard deviation, and Sharpe ratio are annualized and reported in percentage points.[14] We multiply the weekly mean by 52 and weekly standard deviation by $\sqrt{52}$ to calculate the annualized mean and standard deviation. The Sharpe ratio is the annualized mean excess return divided by the annualized standard deviation of excess return. The returns are quite large and volatile compared with those of fiat currencies reported in Table 1 of Lustig et al. (2011).

For the first method of constructing the cross-sectional carry portfolio, the cryptocurrencies appreciate on average for all three groups. The level of appreciation grows as the carry increases from group 1 to group 3, with group 3 seeing the largest appreciation of 74.11% per year. The average carry for each group is -0.13%, 2.87%, and 18.99%, respectively. The excess return for each group is the sum of its carry and price appreciation, with group 3 having the highest excess return of 93.102% due to its highest carry and appreciation. The average excess returns for groups 1 and 2 are 46.39% and 60.14% respectively. This indicates that carry can predict the excess return of cryptocurrencies in the cross-section, with higher carry leading to higher excess return. The carry return, or the difference between the excess return of group 3 and group 1, is 46.71% per year and significant at the 5% level. The annualized standard deviation is 60.67%, and the

[13]For cryptocurrencies with negative weight, we take its absolute value when calculate the weighted average return because Equation (4) already takes the negative sign into account.

[14]In method 1, since all cryptocurrencies in Group 1 are in a short position, we use Equation (4) to calculate the returns. We report the negative value of the returns, price change, and interest rate differential of Group 1 to make an easier comparison with those of Group 2 and Group 3, in which the cryptocurrencies are all in the long position.

annualized Sharpe ratio is 0.770. The difference in carry between groups 1 and 2 is small, so the difference in their excess returns is only 13.744%, which is not significant at the 10% level.

[Insert Table 7 Here]

Using the second method, the mean annualized carry return is 35.911%, significant at the 10% level. The return of the carry portfolio $r_{carry} = \sum w^j r^j = \sum_{w^j>0} w^j r^j - \sum_{w^j<0} |w^j| r^j$. It means that cryptocurrencies with high carry have a larger return than those with low carry, consistent with the previous result that carry can positively predict excess returns of cryptocurrencies in the cross-section.

The average price change of the carry portfolio is 16.032% every year, about half of the carry return. The price change of the carry portfolio is the weighted average price change of cryptocurrencies with high carry minus the weighted average price change of those with low carry: $\Delta s = \sum w^j \Delta s^j = \sum_{w^j>0} w^j \Delta s^j - \sum_{w^j<0} |w^j| \Delta s^j$. It means that the cryptocurrencies with higher carry on average appreciate to a larger degree than those with lower carry, which is consistent with the result using the first method.

The carry of the portfolio, $C = \sum w^j C^j = \sum w^j (i^j - i^{USD})$, is the weighted average of carry of each cryptocurrency. According to Koijen et al. (2018), the carry of the portfolio is the weighted average carry of cryptocurrencies with high carry minus the weighted average carry of cryptocurrencies with low carry: $C = \sum w^j C^j = \sum_{w^j>0} w^j C^j - \sum_{w^j<0} |w^j| C^j > 0$. The carry of the portfolio is 19.879%. Therefore, about half the carry return comes from the difference in price appreciation between high-carry cryptocurrencies and low-carry cryptocurrencies, and about half the carry return comes from the difference in weighted-average carry between high-carry cryptocurrencies and low-carry cryptocurrencies.

In summary, the results find that carry trade can yield profits in cryptocurrency markets, and that carry is a reliable predictor of excess return across all groups, regardless of the method used to build the carry portfolio.

To further explore the properties and characteristics of the cross-sectional carry return, we compare it with the return of a passive equal-weighted portfolio (EW portfolio) constructed with the cryptocurrency universe, as Koijen et al. (2018) did in their study. To make a fair comparison, we also apply the method in Koijen et al. (2018) to scale the carry portfolio (constructed with the first method) by the ratio of the volatility of the carry portfolio to that of the EW portfolio to make sure that the two portfolios have the same volatility in magnitude.

The summary statistics presented in Table 8 indicate that the standard deviation for both the carry return and the equal-weighted portfolio return is 90.62% per annum, as expected. The carry portfolio exhibits a higher average annual return of 69.76%, approximately 7% greater than the equal-weighted portfolio return. Furthermore, the carry return is positively skewed, implying a lower risk of significant decline compared to the equal-weighted portfolio return, which is negatively skewed and exposes investors to heightened crash risk. The Sharpe ratio of the carry return is also superior to that of the equal-weighted portfolio return. This supports the findings documented in Koijen et al. (2018) that the carry portfolio, in most cases, has a higher Sharpe ratio and is less susceptible to crash risk than the equal-weighted portfolio.

[Insert Table 8 Here]

Figure 1 depicts the cumulative returns of the carry portfolio and the equal-weighted (EW) portfolio. Over the sample period, the carry return demonstrates a steady upward trend, albeit with a few slight dips around 2018 and the start of 2021. On the other hand, the EW return is characterized by more pronounced fluctuations, particularly around 2018 and 2021. Of particular interest is the behavior of the two returns in the face of cryptocurrency market crashes. The carry return shows a moderate decline prior to the 2018 crash, but manages to withstand the impact of the bear market. On the other hand, the EW return exhibits a sharp surge before the 2018 crash and suffers a significant decline during the crash. Similar patterns are observed before and during the 2021 crash. The results are consistent with the findings in Table 8, which showed that the carry return is positively skewed, meaning it is less susceptible to crash risk. Conversely, the EW return is negatively skewed, making it more vulnerable to crash risk.

[Insert Figure 1 Here]

5 Explainations for Carry Trade Return

The cross-sectional carry trade of cryptocurrencies has produced significant positive returns. We examined the reasons for this outcome and found that the cryptocurrency factors of the market, size, momentum, downside risk, and volatility risk as discussed in Liu et al. (2022) could not account for the carry premium.[15] Conversely, the geopolitical risk factor discussed in Caldara and Iacoviello (2022) appears to contribute to the positive carry premium. However, after including geopolitical risk as a variable, the average unexplained excess return (α) became significantly negative.

The study by Liu et al. (2022) identifies three risk factors for cryptocurrencies: market, size, and momentum. They demonstrate that these factors can effectively explain the abnormal returns of various cryptocurrency trading strategies. In this analysis, we examine the ability of the cryptocurrency three-factor model to account for the abnormal return of the cryptocurrency carry strategy. Specifically, we perform a time-series regression analysis to assess the relationship between the carry return and the three factors,

$$r_t^{carry} = \alpha + \beta_1 cmkt_t + \beta_2 csize_t + \beta_3 cmom_t + \epsilon_t \,. \tag{5}$$

We use the cross-sectional carry return from section 4.2 (method 1). Following Lustig et al. (2011), we use return in levels instead of log return for the regression.[16]

The results of the time-series regression, presented in Panel A of Table 9, indicate that the average weekly carry return is 0.014 when no risk variables or factors are included. Upon the inclusion of the cryptocurrency three factors proposed by Liu et al. (2022), none of the factor coefficients are statistically significant, and the α even increases from 0.014 to 0.015 and remains significant. This suggests that the cryptocurrency three-factor model cannot fully explain the carry return.

The following passage examines other potential explanations for the positive carry return observed in cross-sectional cryptocurrency trading strategies. Firstly, the impact

[15] Although the volatility risk shares common time-series variation with the carry return, but the α remains significantly positive and becomes even larger than the mean carry return.

[16] Both the cross-sectional carry return in this paper and cryptocurrency three factors from Liu et al. (2022) are at a weekly frequency.

of downside risk on the carry return is analyzed. Based on the methodology presented by Henriksson and Merton (1981), a regression model is run, incorporating the cryptocurrency market factor from Liu et al. (2022) to measure market return in the cryptocurrency market and the downside risk factor,

$$r_t = \beta_0 + \beta_{mkt} r_{m,t} + \beta_{down} max\left\{0, -r_{m,t}\right\} + \epsilon_t$$

The results, as shown in Table 9, indicate that the coefficient of the downside risk is not significant, implying that the carry return is relatively insensitive to downside risk, consistent with the findings in Section 4.2. Furthermore, the residual return (α) remains significant at the 10% level and increases in magnitude. Thus, downside risk does not explain the positive carry return.

Next, the potential impact of volatility risk is evaluated. The weekly changes in VIX are used to proxy for volatility risk. The results, as depicted in Table 9, show that the coefficient of volatility risk is negative (-0.002) and significant at the 5% level, but the average unexplained return (α) remains significant at the 5% level and increases in magnitude. This suggests that, although volatility risk shares some time-series variation with the carry return, it does not explain the positive carry premium.

[Insert Table 9 Here]

Finally, we examine the effect of geopolitical risk as proposed by Caldara and Iacoviello (2022) on the carry return. Caldara and Iacoviello (2022) provides several measurements related to geopolitical risk, from which we select six, namely, recent geopolitical risk (GPR), recent geopolitical risk threats (GPRT), recent geopolitical risk acts (GPRA), historical geopolitical risk (GPRH), historical geopolitical risk threats (GPRHT), and historical geopolitical risk acts (GPRHA). As these risk variables are reported at a monthly frequency, we compound the weekly carry return into monthly returns. The regression model is expressed as follows:

$$r_t^{carry} = \alpha + \beta A_t + \epsilon_t, , \tag{6}$$

where A_t represents GPR, GPRT, GPRA, GPRH, GPRHT or GPRHA. The results are presented in Panel B of Table 9. Without the inclusion of explanatory variables, the monthly carry return is estimated to be 0.049, significant at the 5% level. Upon the addition of different measurements of geopolitical risk, the coefficients of geopolitical risk are found to be significantly positive for GPRA, GPRH, and GPRHA, yet resulting in significantly negative α values. These results suggest that geopolitical risk plays a role in explaining the positive carry return.

These results, where the risk-adjusted alpha becomes negative after adjusting for geopolitical risk, may help explain why the cryptocurrency carry portfolio exhibits only a slightly higher mean return and Sharpe ratio compared to the equal-weighted portfolio, as depicted in Table 8. This is in contrast to the findings of Koijen et al. (2018) who observe that carry portfolios generally offer much higher mean returns and Sharpe ratios compared to equal-weighted portfolios across most asset classes, as displayed in Table 2 of their paper. The negative risk-adjusted alpha may also help explain the fact that we get a Sharpe ratio (0.770) of the cryptocurrency carry portfolio, lower than those documented in Cong et al. (2022) and Franz and Schmeling (2021) (1.62 and 1.24, respectively).

The results in our study are consistent with Cong et al. (2022) and Franz and Schmeling (2021) that UIP is violated in cryptocurrency markets and that that there is a significantly positive return of the cryptocurrency carry strategy. However, We propose that the economic explanation of the positive cryptocurrency carry return is different from those in Cong et al. (2022) and Franz and Schmeling (2021), as discussed in the introduction. The difference may come from the practice that we use a different proxy for the interest rates of cryptocurrencies. It is still not conclusive what is the best proxy for cryptocurrency interest rate, and the carry return derived from different proxies of interest rate might have different economic meanings.

In conclusion, our findings demonstrate that the cross-sectional carry strategy produces a significantly positive carry return. Despite the efforts to explain this return through the cryptocurrency three-factor model introduced by Liu et al. (2022), downside risk and volatility risk, they were found to be insufficient. However, the positive carry return is better explained by geopolitical risk as proposed by Caldara and Iacoviello (2022). Nonetheless, a significant negative component of the carry return remains unexplained.

6 Robustness Check

6.1 UIP Regression in the Futures Market of Cryptocurrency

In this section, we perform the UIP regression in the futures market. In other words, we use the futures implied interest rate differential between cryptocurrency and the U.S. Dollar instead of the observed interest rate differential. Bitcoin and Ethereum are the only two cryptocurrencies for which futures markets are available.

The UIP regression equation is as follows:

$$r_{t+1} = \alpha + \beta c_t + \epsilon_{t+1} \,. \tag{7}$$

where r_{t+1} is the log excess return of cryptocurrency in the futures market, namely the excess return of a long position in the cryptocurrency futures. c_t is the futures implied interest rate differential between cryptocurrency and U.S. Dollar, namely carry defined in Koijen et al. (2018). If UIP holds, the estimate of β should be 0, which means that carry cannot predict the excess return of cryptocurrency.

Following Fama (1984), futures implied interest rate differential, is calculated as follows:

$$c_t = s_t - f_t \,. \tag{8}$$

where s_t is the log spot price of cryptocurrency in terms of U.S. Dollar and f_t is the log futures (expires at t+1) price of cryptocurrency in terms of U.S. Dollar. If covered interest rate parity (or CIP) holds, it should be equal to $i_t^c - i_t^{USD}$. Therefore, c_t is the futures implied interest rate differential between Bitcoin and U.S. Dollar.[17]

[17]Following Koijen et al. (2018), when we calculate carry, we use linearly interpolate to estimate prices of futures which will expire in 1 month (1 week).

Following Fama (1984), the log excess return of cryptocurrency in the futures market is calculated as follows:

$$r_{t+1} = s_{t+1} - f_t \,. \tag{9}$$

This is the return of taking a long position in the futures contract of crytocurrency, and also an analogy of the return when investors take a long position of cryptocurrency and a short position of U.S. Dollar in the spot market.[18] When we calculate the return, we assume that $s_{t+1} = f_{t+1}$ at maturity, so we use f_{t+1} instead of s_{t+1} in Equation (9).[19] As we did in Section 3, we do the test with monthly returns and weekly returns at a daily frequency. Following Fama (1984), r_{t+1} and c_t in regression Equation (7) are in percentage points.

The results of the regression analysis are presented in Table 10. For Bitcoin futures, both the monthly and weekly returns demonstrate significant positive estimates of β, indicating that the implied interest rate differential (carry) in the futures market can positively predict the future excess return of Bitcoin. A 1% increase in the monthly (weekly) carry is found to be associated with a 1.66% (0.91%) increase in the monthly (weekly) excess return of Bitcoin futures in the following period. On the other hand, the results for Ethereum futures exhibit positive but insignificant estimates of β for both monthly and weekly returns. These findings indicate that the Uncovered Interest Parity (UIP) hypothesis does not hold in the Bitcoin futures market, and the carry factor has a significant impact on predicting the excess return of Bitcoin futures in the time series. However, the evidence for UIP violation in the Ethereum futures market remains insufficient.

[Insert Table 10 Here]

[18] The reason can be seen from the formula of the excess return of taking a long position in cryptocurrency futures: $r_{t+1} = s_{t+1} - f_t = \Delta s_{t+1} + s_t - f_t$. If CIP holds, we replace $s_t - f_t$ by $i_t^c - i_t^{USD}$ and get the same formula as the excess return of Bitcoin in the spot market (Equation 2).

[19] We roll over 2 days before the date of the last trade of the futures contract because the Bitcoin futures contract becomes less liquid after that.

7 Conclusion

The findings of this study suggest that the cryptocurrency carry portfolio provides investors with unique investment opportunities, as it is able to withstand periods of cryptocurrency market crashes while still delivering a steadily rising cumulative return. To further understand the risk-return dynamics of this strategy, we investigate the impact of various existing risk factors on the cryptocurrency carry return. Our results suggest that geopolitical risk is a significant factor in explaining the positive carry return, but that a negative risk-adjusted carry return still persists, warranting further investigation in future research.

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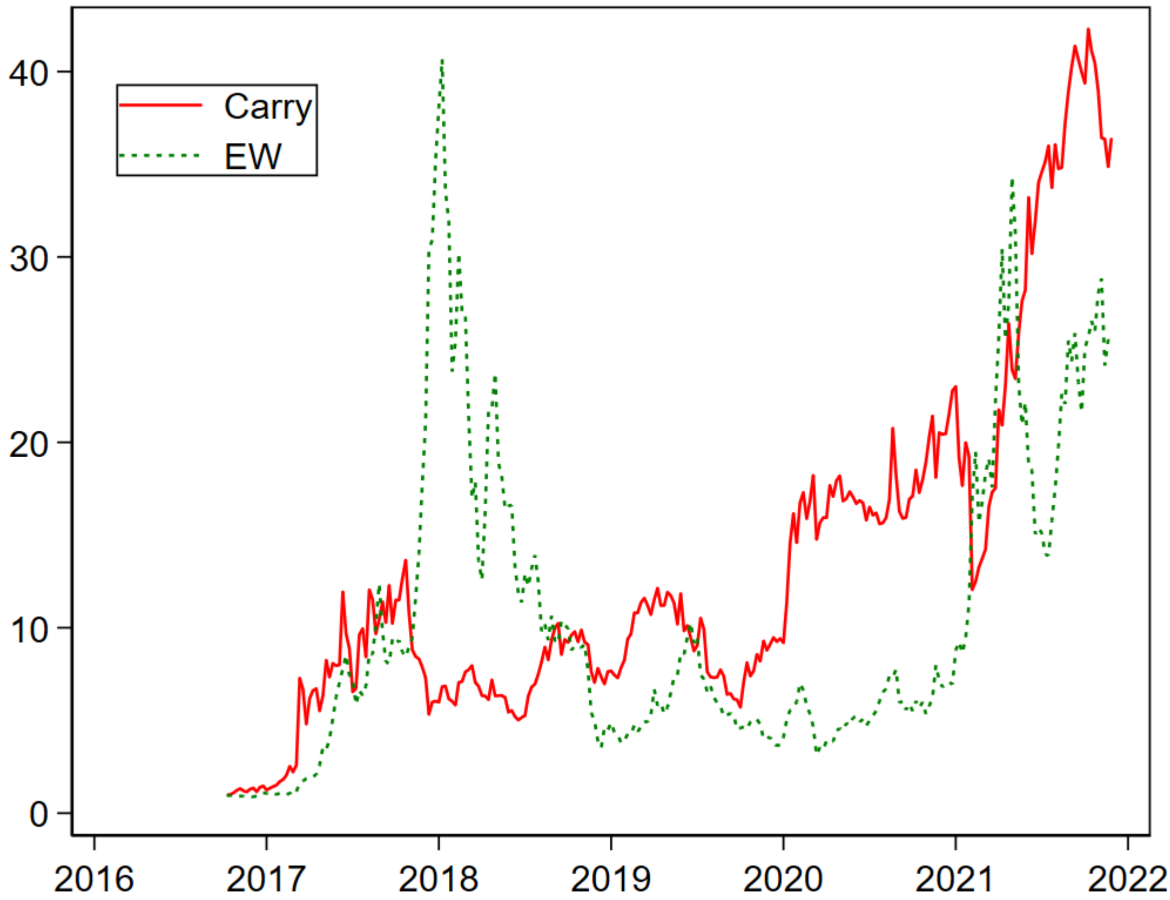
Figure 1: Cumulative Returns of Carry Portfolio and Passive Equal-weighted Portfolio



This figure plots the cumulative return of the carry portfolio and that of the passive equal-weighted (EW) portfolio. The cumulative return (vertical axis) is in real number (not percentage points). The carry portfolio is constructed with method 1 in section 4.2 and scaled to have the same volatility as the EW portfolio. The sample period is Oct. 2016 to Dec. 2021.

Table 1: Summary Statistics of Interest Rates

currency	0x	Algorand	Avalanche	Axie Infinity	Bitcoin	Bitcoin Cash	Bitcoin Gold	Bitcoin SV	Cardano	Chainlink	Compound	Cosmos
Start	17oct2018	03mar2020	05aug2021	25oct2021	03oct2016	17feb2021	27dec2017	21dec2018	03sep2020	25aug2020	10nov2021	26feb2020
mean %	5.915	7.115	22.126	184.508	8.129	0.791	16.851	7.782	16.925	4.184	115.084	7.032
sd %	0.426	0.541	1.125	2.273	0.489	0.245	1.050	0.406	2.012	0.467	4.084	0.719
min %	0.000	0.000	0.000	89.240	0.000	0.000	0.000	0.000	0.000	0.000	36.504	0.000
p25 %	1.732	0.471	4.949	146.768	2.086	0.000	3.325	2.351	0.505	0.016	47.420	0.133
Median %	3.343	3.733	12.198	195.168	4.929	0.000	9.116	5.726	1.606	1.126	75.210	0.832
p75 %	6.702	9.077	36.504	215.184	9.351	0.000	22.399	9.503	7.071	3.176	198.423	10.025
max %	53.556	61.446	85.241	248.198	44.546	34.239	113.241	37.351	154.829	50.736	209.547	73.043
skewness %	316.418	263.082	113.342	-45.967	202.424	612.691	198.728	178.219	261.263	331.819	21.080	293.569
kurtosis %	1506.883	1066.316	343.586	233.490	677.872	3945.451	731.590	623.548	846.944	1411.302	113.204	1193.880

currency	Dai	Dash	Dogecoin	EOS	Elrond	Ethereum	Ethereum Classic	FTX Token	Fantom	Filecoin	IOTA	Litecoin
Start	23jul2020	16mar2017	04may2021	10jul2017	28oct2021	03oct2016	03oct2016	06mar2020	22oct2021	23nov2020	03jul2017	03oct2016
mean %	13.233	7.990	9.721	6.605	165.340	6.001	9.692	25.978	80.895	49.335	1.221	6.075
sd %	1.601	0.577	0.931	0.781	2.603	0.290	0.817	2.012	3.349	2.995	0.192	0.471
min %	0.000	0.000	0.309	0.000	36.504	0.143	0.000	0.000	36.504	0.000	0.000	0.000
p25 %	0.935	1.465	0.654	0.133	155.295	1.998	0.666	0.463	44.745	7.033	0.000	1.146
Median %	5.329	3.802	1.876	0.748	179.021	4.242	2.945	6.109	54.846	24.317	0.253	3.205
p75 %	8.150	10.596	7.895	5.425	191.571	8.039	11.892	36.922	78.415	73.141	0.789	7.061
max %	155.030	75.354	92.458	92.841	238.168	26.769	91.792	173.592	251.551	226.749	41.833	61.417
skewness %	340.657	294.259	244.944	379.581	-111.529	146.956	277.960	166.456	198.194	145.338	658.825	340.671
kurtosis %	1384.968	1348.090	843.542	1882.713	387.424	480.785	1210.410	482.352	546.831	433.403	5641.180	1699.418

currency	Maker	Metaverse ETP	Monero	Neo	OMG Network	Polkadot	Polygon	SHIBA INU	Santiment Network	Solana	Stellar	SushiSwap
Start	09nov2021	20oct2017	15mar2017	18sep2017	04aug2017	27aug2020	26oct2021	11nov2021	18sep2017	01jun2021	19aug2019	20jan2021
mean %	32.545	11.695	5.187	14.009	6.038	6.264	172.235	15.598	8.918	18.499	5.255	25.860
sd %	0.762	1.519	0.366	0.990	0.560	1.262	3.149	0.749	1.282	1.480	0.647	1.454
min %	0.000	0.000	0.000	0.000	0.000	0.000	36.394	2.948	0.000	0.054	0.000	3.928
p25 %	36.504	0.000	1.199	2.207	0.266	0.000	113.441	4.524	0.000	1.856	0.133	8.474
Median %	36.504	0.962	2.797	6.483	1.610	0.068	207.753	7.652	0.314	8.461	0.696	15.416
p75 %	36.504	7.461	6.412	17.673	5.817	0.376	215.099	30.490	5.648	23.884	3.192	29.496
max %	54.089	185.582	46.895	117.309	57.544	145.348	234.054	36.504	207.965	166.931	83.997	133.679
skewness %	-150.755	401.412	326.886	241.151	266.243	478.770	-74.857	56.883	514.804	291.502	375.471	211.728
kurtosis %	454.130	2069.404	1654.035	973.716	1007.514	2553.609	213.505	148.698	3436.562	1251.473	1847.097	704.523

currency	TRON	Tether	Tether EURt	Tether Gold	Tezos	Uniswap	XRP	Zcash	pNetwork	yearn.finance		
Start	02sep2020	21dec2018	01oct2021	14feb2020	15aug2019	30sep2020	05jul2017	20dec2016	08jul2020	11nov2020		
mean %	10.798	11.911	18.101	3.754	11.428	12.897	2.929	4.594	8.542	23.030		
sd %	0.934	0.460	1.074	0.939	0.951	0.873	0.290	0.453	0.859	1.351		
min %	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	2.267		
p25 %	0.000	6.255	3.585	0.000	0.421	0.594	0.133	0.189	0.000	3.060		
Median %	1.998	10.864	3.597	0.000	5.329	3.741	0.666	1.321	0.621	14.113		
p75 %	14.338	14.656	30.722	0.000	12.011	25.831	3.010	4.206	11.591	37.044		
max %	103.822	50.738	65.939	141.785	123.173	80.536	44.497	56.199	122.320	122.167		
skewness %	221.668	184.239	108.111	564.441	305.122	160.344	370.018	320.668	317.585	175.416		
kurtosis %	819.463	773.437	272.581	3592.310	1451.416	563.788	2043.601	1433.196	1623.736	648.236		

This table provides summary statistics of annualized interest rates of 46 cryptocurrencies in our sample. The data is from Bitfinex platform. All statistics are in percentage points. The end date of sample for most cryptocurrencies are Nov. 30, 2021, for other cryptocurrencies the sample ends 1 day earlier or later. Annualized mean is daily mean multiplied by 365. Annualized standard deviation is daily standard deviation multiplied by $\sqrt{365}$.

Table 2: Summary Statistics of Daily Price Change

currency	0x	Algorand	Avalanche	Axie Infinity	Bitcoin	Bitcoin Cash	Bitcoin Gold	Bitcoin SV	Cardano	Chainlink	Compound	Cosmos
mean%	0.033	0.445	2.353	0.157	0.351	-0.115	-0.153	0.044	0.891	0.181	-1.239	0.442
sd%	7.131	8.469	9.924	5.045	4.921	7.394	7.796	7.486	7.548	7.602	5.862	8.572
min%	-46.005	-57.990	-21.007	-8.871	-46.473	-43.461	-37.667	-56.029	-30.111	-46.602	-9.077	-49.288
p25%	-3.804	-3.965	-3.626	-2.763	-1.590	-2.877	-3.250	-2.714	-3.175	-3.952	-5.949	-3.424
Median%	0.022	0.317	1.849	0.667	0.255	0.481	0.000	0.000	0.393	0.510	-2.871	0.500
p75%	3.514	4.857	8.555	3.045	2.556	3.293	2.850	2.562	4.025	4.847	2.660	4.236
max%	44.044	41.331	24.644	12.069	22.512	42.082	71.658	58.449	27.944	20.687	10.761	36.991
skewness%	4.534	-60.538	1.987	28.289	-69.794	-34.258	126.370	60.135	41.246	-92.748	40.202	-56.257
kurtosis%	874.469	1040.692	310.528	267.465	1172.668	1406.204	1794.609	2078.381	509.184	721.143	237.694	832.092
currency	Dai	Dash	Dogecoin	EOS	Elrond	Ethereum	Ethereum Classic	FTX Token	Fantom	Filecoin	IOTA	Litecoin
mean%	-0.015	0.059	-0.633	0.071	2.250	0.447	0.287	0.224	-0.764	0.241	0.122	0.310
sd%	0.389	7.149	9.091	8.236	9.382	6.771	7.344	5.534	9.354	8.498	8.340	6.974
min%	-1.961	-46.546	-49.617	-50.323	-13.436	-55.071	-50.779	-32.175	-15.268	-42.616	-50.555	-44.901
p25%	0.000	-2.906	-4.714	-2.992	-1.677	-2.350	-2.692	-2.505	-6.682	-3.449	-3.481	-2.615
Median%	0.000	0.000	-0.246	0.000	0.657	0.050	0.000	0.031	-1.962	-0.245	0.000	0.000
p75%	0.000	3.254	2.867	3.102	2.861	3.202	3.065	3.174	2.342	3.608	3.802	2.801
max%	1.961	39.959	24.094	43.944	34.510	39.140	45.768	29.559	20.018	45.873	64.367	53.980
skewness%	-94.883	-18.041	-115.913	-6.506	199.752	5.809	5.569	-24.459	82.138	53.247	56.364	56.568
kurtosis%	1403.777	936.687	1001.026	922.744	835.630	1067.430	981.499	873.447	316.997	1091.396	1023.187	1312.629
currency	Maker	Metaverse ETP	Monero	Neo	OMG Network	Polkadot	Polygon	SHIBA INU	Santiment Network	Solana	Stellar	SushiSwap
mean%	-0.459	-0.277	0.201	0.054	0.105	0.602	0.118	-0.385	0.029	1.502	0.268	0.044
sd%	4.294	10.082	6.899	7.578	8.583	8.441	6.804	9.785	9.053	8.010	7.033	8.526
min%	-7.255	-101.163	-53.418	-45.391	-45.379	-47.697	-8.311	-11.650	-81.001	-31.825	-36.004	-29.096
p25%	-3.731	-3.754	-2.746	-3.716	-3.922	-3.822	-4.692	-4.645	-3.704	-3.587	-2.789	-5.051
Median%	-0.601	-0.317	0.066	0.000	0.000	0.523	-1.711	-3.473	0.000	1.670	0.164	0.000
p75%	2.969	3.254	3.357	3.732	3.933	5.145	3.636	4.174	3.695	5.860	3.197	4.417
max%	6.276	105.990	51.087	47.567	54.165	28.283	19.081	16.753	51.551	32.983	55.932	36.430
skewness%	11.670	30.056	-31.401	-6.545	35.940	-42.998	112.857	83.293	-16.986	13.230	121.547	19.143
kurtosis%	200.454	2819.731	1325.021	874.628	816.786	718.025	379.943	270.478	1387.436	593.981	1488.928	446.893
currency	TRON	Tether	Tether EURt	Tether Gold	Tezos	Uniswap	XRP	Zcash	pNetwork	yearn.finance		
mean%	0.329	-0.003	-0.041	0.029	0.261	0.567	0.124	0.147	0.125	0.192		
sd%	7.500	0.405	0.468	0.996	7.778	8.501	7.796	7.538	9.720	7.184		
min%	-38.342	-1.980	-0.881	-4.830	-60.547	-40.333	-55.040	-53.941	-41.428	-33.510		
p25%	-3.038	0.000	0.000	-0.405	-2.994	-4.468	-2.729	-3.277	-5.015	-3.762		
Median%	0.347	0.000	0.000	0.079	0.000	0.675	-0.037	-0.023	0.000	0.531		
p75%	3.342	0.000	0.000	0.532	3.822	5.407	2.658	3.763	3.962	3.996		
max%	46.205	1.980	0.881	3.747	32.994	32.293	62.668	64.995	59.660	28.820		
skewness%	46.178	-6.436	-4.691	-58.578	-112.712	1.278	91.077	22.571	92.424	-12.868		
kurtosis%	1050.339	925.379	349.308	591.082	1266.852	553.676	1784.723	1147.269	943.450	592.997		

This table reports summary statistics of daily change in log prices ($logP_2 - logP_1$) of the 46 cryptocurrencies in our sample ($logP_2 - logP_1$). All prices are close prices. All statistics are in percentage points. The data is from the website coinmarketcap.com. Sample period for each cryptocurrency is the same as that in Table 1.

Table 3: UIP Regression (monthly return)

	0x	Algorand	Avalanche	Axie Infinity	Bitcoin	Bitcoin Cash	Bitcoin Gold
β	-15.352***	4.891	1.883	3.726***	8.641***	-19.305***	3.156
	(2.856)	(4.110)	(4.067)	(0.204)	(1.971)	(6.603)	(2.364)
α	7.201***	9.649***	39.538***	-43.109***	3.426**	2.374	-5.107*
	(2.468)	(2.949)	(9.720)	(2.836)	(1.399)	(4.303)	(2.816)
N	793	431	60	5	1,319	183	1,000
	Bitcoin SV	Cardano	Chainlink	Cosmos	Dash	Dogecoin	EOS
β	-12.586***	-2.241**	-4.161	-4.112*	7.997***	-7.694***	-2.470
	(3.920)	(1.024)	(3.077)	(2.180)	(2.105)	(2.089)	(2.002)
α	8.243**	25.749***	7.774**	14.725***	-1.602	-3.435	3.231
	(3.312)	(3.973)	(3.405)	(3.434)	(2.024)	(4.940)	(2.288)
N	746	302	309	421	1,207	129	1,125
	Ethereum	Ethereum Classic	FTX Token	Fantom	Filecoin	IOTA	Litecoin
β	13.333**	-1.263	0.660	1.043	2.075	4.335	12.719***
	(5.725)	(1.039)	(1.040)	(2.795)	(1.648)	(6.738)	(3.080)
α	5.375**	7.736***	8.260***	-29.546*	3.478	3.083	2.615
	(2.231)	(2.089)	(2.785)	(11.765)	(6.197)	(2.311)	(1.918)
N	1,325	1,324	308	6	241	1,130	1,325
	Metaverse ETP	Monero	Neo	OMG Network	Polkadot	Santiment Network	Solana
β	1.810	-1.562	-0.409	5.951**	-0.863	3.563	3.835*
	(1.118)	(2.999)	(1.294)	(2.386)	(0.823)	(2.353)	(1.983)
α	-5.605**	5.030***	2.213	-0.409	16.409***	-0.325	32.697***
	(2.572)	(1.809)	(2.238)	(2.257)	(4.301)	(2.809)	(8.862)
N	1,047	1,207	1,075	1,106	307	1,076	110
	Stellar	SushiSwap	TRON	Tezos	Uniswap	XRP	Zcash
β	-0.499	4.991**	3.447	4.199*	-5.490	5.706	1.605
	(1.487)	(2.083)	(2.932)	(2.342)	(3.376)	(5.617)	(3.675)
α	7.051***	-8.684*	7.462**	4.188	21.261***	2.713	2.277
	(2.605)	(4.407)	(3.573)	(2.731)	(5.828)	(2.067)	(1.722)
N	575	203	303	577	283	1,098	1,269
	pNetwork	yearn.finance					
β	-10.504***	1.620					
	(2.652)	(1.296)					
α	8.284	1.280					
	(5.109)	(2.898)					
N	344	251					

This table reports the results of UIP regression for each cryptocurrency with monthly interest rates and monthly returns. The regression equation is $r_{t+1} = \alpha + \beta(i_t^c - i_t^{USD}) + \epsilon_{t+1}$. Following Fama (1984), the return and interest rate differential in the regression are in percentage points. Newey-West standard errors are reported in parentheses. ***, ** and * indicates that $p < 0.01$, $p < 0.05$ and $p < 0.1$, respectively. There are 37 cryptocurrencies in tatal in this test. We do not include stablecoins here. Compound, Elrond, Maker, Polygon and SHIBA INU are not included either since the observations of monthly returns for these cryptocurrencies are not enough to do the regression. The data of cryptocurrency interest rates is from Bitfinex platform. The data of cryptocurrency prices is from the website coinmarketcap.com. The data of one-month US interest rate we use is the market yield on US Treasury securities at 1-month constant maturity, quoted on an investment basis, not seasonally adjusted, from FRED. The sample period is Oct. 2016 to Dec. 2021. The estimates of β for 9 cryptocurrencies are significantly positive, for 7 cryptocurrencies are significantly negative, and for 21 cryptocurrencies are insignificant.

Table 4: UIP Regression (weekly return)

	0x	Algorand	Avalanche	Axie Infinity	Bitcoin	Bitcoin Cash	Bitcoin Gold	Bitcoin SV
β	-4.602	-5.389	8.507	5.008	15.392***	-36.850	1.974	-12.469
	(6.363)	(10.058)	(11.779)	(3.033)	(3.375)	(30.571)	(2.737)	(7.935)
α	0.692	2.541*	9.072*	-11.191	0.085	0.308	-0.984	1.752
	(1.034)	(1.482)	(4.562)	(9.830)	(0.554)	(1.739)	(1.087)	(1.314)
N	781	435	75	22	1,279	196	977	736
	Cardano	Chainlink	Compound	Cosmos	Dash	Dogecoin	EOS	Elrond
β	-2.633	-18.929***	3.334**	-14.993***	14.712**	-9.926*	-3.503	-6.519
	(1.905)	(6.441)	(1.050)	(5.018)	(6.862)	(5.145)	(3.646)	(3.931)
α	5.325***	2.225	-11.108***	3.789**	-1.119	-1.283	0.854	27.958**
	(1.607)	(1.476)	(2.029)	(1.583)	(0.901)	(2.374)	(0.891)	(10.863)
N	309	316	10	430	1,174	143	1,097	17
	Ethereum	Ethereum Classic	FTX Token	Fantom	Filecoin	IOTA	Litecoin	Metaverse ETP
β	24.718**	-1.143	0.993	3.062*	3.015**	-1.579	11.887**	1.826
	(9.604)	(2.164)	(1.627)	(1.719)	(1.400)	(19.064)	(5.586)	(2.228)
α	0.350	1.682**	1.154	-8.535	-0.269	0.771	0.652	-1.391
	(0.809)	(0.845)	(1.294)	(6.069)	(2.590)	(0.943)	(0.761)	(1.048)
N	1,286	1,286	311	23	246	1,101	1,286	1,021
	Monero	Neo	OMG Network	Polkadot	Polygon	Santiment Network	Solana	Stellar
β	6.368	-1.906	4.832	-2.052	1.839	11.374**	11.038**	-4.375
	(6.331)	(2.300)	(5.929)	(1.493)	(3.240)	(4.863)	(5.215)	(4.555)
α	0.744	0.888	0.151	2.848*	-4.402	-1.082	3.961	1.680
	(0.752)	(0.934)	(1.019)	(1.703)	(9.353)	(1.039)	(3.281)	(1.160)
N	1,174	1,049	1,078	314	21	1,050	124	573
	SushiSwap	TRON	Tezos	Uniswap	XRP	Zcash	pNetwork	yearn.finance
β	4.839	2.894	2.443	3.698	14.608*	-3.174	-5.171	1.476
	(5.918)	(3.822)	(3.031)	(6.398)	(8.278)	(6.435)	(7.766)	(3.463)
α	-1.231	1.236	0.880	2.169	0.365	1.047	1.644	0.361
	(2.507)	(1.577)	(1.239)	(1.972)	(0.860)	(0.763)	(2.072)	(1.471)
N	215	310	575	291	1,072	1,231	351	259

This table reports the results of UIP regression for each cryptocurrency with weekly interest rates and weekly returns. The regression equation is $r_{t+1} = \alpha + \beta(i_t^c - i_t^{USD}) + \epsilon_{t+1}$. Following Fama (1984), the return and interest rate differential in the regression are in percentage points. Newey-West standard errors are reported in parentheses. ***, ** and * indicates that $p < 0.01$, $p < 0.05$ and $p < 0.1$, respectively. The test includes 40 cryptocurrencies in total. SHIBA INU is not included because there are not sufficient observations to do the regression using Newey-West standard error with 3 lags. Maker is not included because the interest rate of Maker varies too little, whereas the price is too volatile, so that the coefficient is extremely large (-124,917.2), which is not reasonable. The data of cryptocurrency interest rates is from Bitfinex platform. The data of cryptocurrency prices is from the website coinmarketcap.com. The data of one-week (7 days) US interest rate is from OptionMetrics. The sample period is Oct. 2016 to Dec. 2021. The estimates of β for 10 cryptocurrencies are significantly positive, for 3 cryptocurrencies are significantly negative, for 27 cryptocurrencies are insignificant.

Table 5: UIP Panel Regression

	Individual fixed effects	Time fixed effects	β	N
Monthly Return	X	X	1.550***	24,526
			(0.348)	
	X		1.335***	24,526
			(0.461)	
		X	1.413***	24,526
			(0.326)	
Weekly Return	X	X	1.729***	24,257
			(0.614)	
	X		2.256***	24,257
			(0.807)	
		X	1.618***	24,257
			(0.493)	

This table reports the results of panel regression for the UIP tests with all 42 cryptocurrencies in our sample (stablecoins are not included). The regression equation is $r_{j,t+1} = \alpha_j + \beta(i^c_{j,t} - i^{USD}_t) + \gamma_t + \epsilon_{j,t+1}$. α_j is individual fixed effect and γ_t is time fixed effect. Newey-West standard errors are reported in parentheses. ***, ** and * indicates that $p < 0.01$, $p < 0.05$ and $p < 0.1$, respectively. The data of cryptocurrency interest rates is from Bitfinex platform. The data of cryptocurrency prices is from the website coinmarketcap.com. The data of one-month US interest rate we use is the market yield on US Treasury securities at 1-month constant maturity, quoted on an investment basis, not seasonally adjusted, from FRED. The data of one-week (7 days) US interest rate is from OptionMetrics. The sample period is Oct. 2016 to Dec. 2021.

Table 6: Time-series Carry Trade between Stablecoins and U.S. Dollar

	USDT		DAI	
Portfolio	month	week	month	week
	Price Change: Δs		Price Change: Δs	
Mean	-0.324	-0.614	-1.284	0.316
Std	1.786	3.117	2.055	3.368
	$i^c - i^{USD}$		Carry	
Mean	9.391	9.429	11.974	11.155
Std	2.072	0.989	7.813	3.598
	Carry Return		Carry Return	
Mean	9.067	8.815	10.690	11.470
	(0.499)	(0.991)	(2.333)	(2.160)
Std	2.614	3.206	7.340	4.014
SR	3.469	2.750	1.456	2.857

This table reports the results of time-series carry trade between stablecoins (USDT and Dai) and U.S. Dollar. Total carry return, price change and interest rate differential (carry) are reported. Means, standard deviations and Newey-West standard errors (in parentheses) are annualized and in percentage points. Sharpe Ratios are annualized and in real numbers. Annualized mean is the mean of monthly (weekly) return multiplied by 12 (52). Annualized standard deviation is the standard deviation of monthly (weekly) return multiplied by $\sqrt{12}$ ($\sqrt{52}$). Annualized Sharpe Ratio is the ratio of the annualized mean and annualized standard deviation. We use monthly (weekly) carry return at daily frequency to increase the number of observations. The sample period of USDT is Dec. 2018 - Nov. 2021. The sample period of DAI is Jul. 2020 - Nov. 2021. For USDT, the monthly and weekly carry return are significantly positive at 1%. For DAI, the monthly and weekly carry return are significantly positive at 1%.

Table 7: Cross-sectional Carry Trade

	Method 1			Method 2
Portfolio	1	2	3	
		Price Change: Δs^j		Δs
Mean	46.525	57.267	74.113	16.032
Std	95.390	92.651	102.726	51.892
		$i^j - i^{USD}$		C
Mean	-0.131	2.872	18.989	19.879
Std	0.261	0.504	1.705	1.815
		$r^j = i^j - i^{USD} + \Delta s^j$		
Mean	46.394	60.138	93.102	
Std	95.442	92.743	102.829	
SR	0.486	0.648	0.905	
		High minus Low: $r^j - r^1$		r_{carry}
Mean		13.744	46.708	35.911
		(17.206)	(23.378)	(21.065)
Std		44.917	60.675	51.843
SR		0.306	0.770	0.693

This table reports the summary statistics of cross-sectional carry trade portfolios within our cryptocurrency universe. We report the portfolio returns r, price change Δs and interest rate differential $i^j - i^{USD}$ (or carry C) for each portfolio. The universe includes 42 cryptocurrencies in total, not including stablecoins because the prices of stablecoins are pegged to other assets (U.S. Dollar, euro, gold etc.) so that interest rates are not supposed to predict their price change. We use weekly returns (at weekly frequency rather than daily frequency) and weekly interest rates. Means, standard deviations and Newey-West standard errors (in parentheses) are annualized and in percentage points. Sharpe Ratios are in real numbers. Annualized mean is the weekly mean multiplied by 52. Annualized standard deviation is the weekly standard deviation multiplied by $\sqrt{52}$. Annualized Sharpe Ratio is the ratio of the two terms. The sample period is Oct. 2016 to Dec. 2021. We use two methods to construct the carry portfolio. In method 1, we firstly rank the cryptocurrencies by their carry, and then split them equally into three groups (some groups might have 1 more than other groups if the total number is not divisible by 3). In method 2, we use the method introduced by Asness et al. (2013). Specifically, we use the weight determined by their carry for each cryptocurrency to construct the carry portfolio: $w_t^i = z_t(rank(c_t^i) - \frac{N_t+1}{2})$. In method 1: $r^3 - r^1$ is significant at 5% level, whereas $r^2 - r^1$ is not significant. In method 2, the carry return is significant at 10% level.

Table 8: A Comparison between Carry Portfolio and Passive Equal Weighted Portfolio

	N	Mean	Std	Skewness	Kurtosis	SR
Carry	268	69.757	90.616	1.773	19.351	0.770
EW	268	62.746	90.616	-0.101	3.703	0.692

This table reports the summary statistics of the return of the carry portfolio and that of the equal-weighted portfolio. Mean and Standard deviation are in percentage points. N, Skewness, Kurtosis and SR are in real numbers. The sample period is Oct. 2016 to Dec. 2021. Carry portfolio is constructed with method 1, and scaled to have the same volatility as the equal weighted portfolio for comparison. Specifically, firstly we get the ratio of carry portfolio volatility and equal weighted portfolio volatility, and then we divide carry return by the ratio.

Table 9: Regression Results of Carry Return on Risk Factors and Risk Variables

Panel A: Cryptocurrency Three Factors, Downside Risk and Volatility Risk

	α	cmkt	csize	cmom	downside	volatility	Adj.R^2
Carry Return	0.014**						
	(0.007)						
Carry Return	0.015**	-0.017	-0.048	0.219			0.042
	(0.006)	(0.083)	(0.032)	(0.152)			
Carry Return	0.018*	-0.050			-0.091		-0.009
	(0.011)	(0.116)			(0.173)		
Carry Return	0.015**					-0.002**	0.001
	(0.007)					(0.001)	

Panel B: Geopolitical Risk

	α	GPR	GPRT	GPRA	GPRH	GPRHT	GPRHA	Adj.R^2
Carry Return	0.049**							
	(0.023)							
Carry Return	-0.0841	0.0015						0.0199
	(0.0819)	(0.0010)						
Carry Return	0.0252		0.0002					-0.0153
	(0.0935)		(0.0009)					
Carry Return	-0.0989**			0.0022***				0.1040
	(0.0485)			(0.0008)				
Carry Return	-0.1314*				0.0026**			0.0536
	(0.0716)				(0.0011)			
Carry Return	-0.0193					0.0007		-0.0061
	(0.0829)					(0.0009)		
Carry Return	-0.0952**						0.0029***	0.1157
	(0.0471)						(0.0011)	

This table presents the regression results of cross-sectional carry return ($r_3 - r_1$) on risk factors or risk variables. Following Lustig et al. (2011), we use return in levels instead of log return to do the regression. Regression coefficients, Newey-West standard errors (in parentheses) and Adj.R^2's are reported. ***, ** and * indicates that $p < 0.01$, $p < 0.05$ and $p < 0.1$, respectively. Panel A presents the results for the crypto three factors from Liu et al. (2022), downside risk and volatility risk. Sample period is Oct. 2016 - Jul. 2020 because the data of cryptocurrency three factors is only available until July 2020. We use weekly change in VIX to proxy for volatility risk. Data of VIX is from Bloomberg database. Both the cross-sectional carry return and explanatory variables are at weekly frequency. Panel B presents the results for Geopolitical risk from Caldara and Iacoviello (2022). GPR, GPRT, GPRA, GPRH, GPRHT and GPRHA stand for recent GPR, recent GPR threats, recent GPR Acts, historical GPR, historical GPR threats and historical GPR acts, respectively. Sample period is from Oct. 2016 to Nov. 2021.

Table 10: UIP Regression in the Futures Market

	BTC		ETH	
	Month	Week	Month	Week
β	1.658**	0.909***	0.866	0.773
	(0.758)	(0.297)	(1.479)	(0.688)
α	8.307***	1.105	-0.929	-1.576
	(1.947)	(0.741)	(3.507)	(1.681)
N	610	629	180	199

This table presents the results of UIP regression in the futures market. The regression equation is $r_{t+1} = \alpha + \beta c_t + \epsilon_{t+1}$. $r_{t+1} = s_{t+1} - f_t$ is the log return of holding cryptocurrency futures. $c_t = s_t - f_t$ is the carry of the cryptocurrency, or futures implied interest rate differential between the cryptocurrency and U.S. Dollar. Newey-West standard errors are reported in parentheses. ***, ** and * indicates that $p < 0.01$, $p < 0.05$ and $p < 0.1$, respectively. The sample period for Bitcoin futures is Dec. 2017 to May. 2022. The sample period for Ethereum futures is Feb. 2021 to May. 2022.