Downloaded from https:;/academic.oup.comfraps/article/12/3/667/6543623 by Des Moines University - Osteopathic Medical Center useron 19 October 2022



**The Review of Asset Pricing Studies** SFS

**The Cross-Section of Cryptocurrency Returns**

**Nicola Borri**

LUISS University,Italy

**Kirill Shakhnov**

School of Economics,University of Surrey,UK

At a given point in time,bitcoin prices are different on exchanges located in different countries,or against different currencies.While existing literature attributes the largest price differencesto frictions,like market segmentation,tradingplatforms advertize howto execute trades based on this infomation.We provide a novel risk-based explanation of these price differences for a sample containing the most reputable exchanges and after accounting for all transaction costs and limitations to trade.Bitcoin prices for more ex- pensive pairs are riskier because they depreciate more in bad times for cryptocurrency investors,when aggregate liquidity and investor sentiment are lower.(JEL G12,G14, G15,F31).

Received January26,2021;editorialdecision December 1,2021 by Editor Jeffrey Pontiff. Authorshave furnished an Internet Appendix,whichis available on the OxfordUniversity Press Web sitenext to the link to the final published paper online.

Investors buy bitcoins on a multitude of exchanges located in different coun- tries and against different currencies.At one point in time,and in a friction- less world where investors could trade instantaneously across exchanges,the bitcoin price,converted in a common currency,should be the same every- where and for any currency pair.Instead,large differences exist in bitcoin prices across exchanges located in different countries or for different currency pairs.Investorsknow these differences and discuss them extensively on cryp- tocurrency and investment social platforms.

Common explanations for these large and persistent price differences,or

*bitcoin discounts,are limits to arbitrage and market inefficiency (Makarov*

and Schoar(2019) ).According to these explanations,and because of the enormous arbitrage opportunities available,cryptocurrency markets are



We thank Bob Chirinko,Sergei Kovbasyuk,Gabriele Zinna,Paolo Santucci de Magistris,Aleh Tsyvinski, Yukun Liu,Paolo Porchia and seminar and conferenceparticipants at LUISS,EIEF,Crypto Valley Conference on Blockchain Technology,Technische Universitat Berlin,Bankof Italy,University of Navara,ICEF (HSE), CFE-CFStatistics 2018,CFE-CFStatistics 2019.Aleksandr Schneider provided excellent research assistance. Some of the material in this paper previously circulated underthe tite "Cryptomarket Discounts".Send cor- respondence to Nicola Borri,nborri@luissit.

*The Review ofAsset Pricing Snadies 12(2022)667-705*

O The Author(s)2022.Published by Oxford University Press on behalfof The Society for Financial Studies. All rights reserved.For permissions,please email:journals.permissions@oup.com

<https://doi.org/10.1093/rapstu/raac007> Advance Acess publication 7March 2022

*Review of Asset Pricing Shudies /v 12n32022*

Downloaded from https:; /lacadem ic.oup.com/raps/art ic le/12/3/667/6543623 by Des Moines Un ivers ity - Osteopath ic Medical Center user on 19 October 2022

highly inefficient.While various frictions and the opacity of many exchanges can explain the largest differences in bitcoin prices,we document significantly smaller differences,but economically significant,also in a sample where these frictions are likely to be small,and for the most reputable exchanges.This casts doubts over the possibility that these stories alone could provide a comprehensive explanation.In this paper,after accounting for all the trans- action costs,we show that these arbitrage-like opportunities are not riskless and then propose a novel explanation that relates deviations in bitcoin prices to aggregate risk in cryptocurrency markets.As cryptocurrency markets be- come more mature,limits to arbitrage stories are likely to play a lesser role. Instead,we show that the risk-based explanation of bitcoin discounts applies also to the more recent sample.

With the rapidly growing importance of bitcoin and bloomingof dozens of new cryptocurrencies,it becomes crucial to study the efficiency and structure of cryptocurrency markets.We focus on bitcoin because it was the first cryptocurrency,and it currently accounts for two-thirds of the total market capitalization and one-third of the trading volume,and then extend our analysis to a larger set of cryptocurrencies.

We carefully select the sample of exchange-currency pairs to minimize the impact of various frictions,like market segmentation,data reliability and liquidity;then,we form portfolios to isolate the possible common compo- nents,and accommodatethe large time variation in the number of exchanges and currencies pairs.We select exchanges based on several indicators of “quality”,including ratings,web traffic data,and liquidity.For example, the exchanges in our sample are not among those singled out for “fake vol- ume and/or noneconomic wash trading”in a widely circulated report by Bitwise,the creator of the first crypto index fund(Bitwise(2019 )). Furthermore,we use the capital control index constructed by Fernández et al.(2016) to select exchange locations and currency pairs available to in- ternational investors and we drop illiquid pairs.While this strategy dramat- ically reduces the number of exchanges and pairs in our sample,it canaddress the issue of data quality and market segmentation.Our baseline sample runs from May 2015to May 2021 and,thus,includes the two boom-bust cycles for cryptocurrencies of 2017 and 2020.

We take the perspective of investors that observe bitcoin discounts and form portfolios according to two investable strategies.The first,which we refer to as the cross strategy,is based on the persistence of discounts and is designed to buy bitcoin using a benchmark exchange-currency pair and to sell bitcoin using relatively “expensive”exchange-currency pairs.The second, which we refer to as the within strategy,is based on the mean-reversion of discounts and is designed to buy bitcoin using relatively“cheap”exchange- currency pairs and to sell bitcoin at a later date using the same pair.

*The Cross-Section ofCryptocurrency Retarns*

Downloaded from [https://academic.oup.com/raps/article/121 23 by Des Moines University - Osteopathic Medical Center user on 190ctober 2022](https://academic.oup.com/raps/article/12123byDesMoinesUniversity-OsteopathicMedicalCenteruseron190ctober2022)

The first portfolio contains the pairs with the smallest average discounts (i.e.,the“cheapest”pairs),while the last portfolio the pairs with the largest average discounts (i.e.,the more“expensive”pairs).For both strategies,we obtain a large,and significant,cross-section of excess returns before trans- action costs.Specifically,for cross portfolios,the average excess return of a long/short strategy that goes long in the last portfolio and short in the first portfolio is equal to 181 basis point per day.Similarly,for within portfolios, the average excess return of the long/short strategyis equal to 127 basis points per day.Although these returns are extremely large,theyare mostly absorbed by transaction costs,which significantly reduce average returns by approxi- mately 50 basis points for each of the cross portfolios and by 90 basis points for each of the within portfolios.In fact,the within returns are not statistically significant after accounting for all the transaction costs and fees.In contrast, the cross returns after transaction costs are smaller but significantly larger than zero.Since the within portfolio returns are negative after transaction costs,we concentrate our attention on net returns for cross portfolios.These results highlight the importance ofstudying net returns and one of the con- tributions of this paper is to use detailed data on transaction costs to distin- guish gross and net returns.

To account for transaction costs,we collect data on withdrawal,deposit, margins,and trading fees for all the exchanges in thesample,and on bid/ask spreads for a subset of 33 pairs for which we are able to collect reliable data. We document a large heterogeneity in bid/ask spreads across exchanges, currency pairs,and time.We further extend the sample of bid/ask spreads using the estimates from predictiveregressions of bid/ask spreads on intraday price volatility and trading volume and,for robustness,using the methodol- ogies proposed by Roll(1984)and Abdi and Ranaldo (2017).

The average net excess return of a long/short cross strategy that goes long in the last portfolio and short in the first portfolio is equal to 31 basis points per day for a daily (non-annualized)Sharpe ratio of 13%.As a reference over the same period and frequency,the Sharpe ratio of bitcoin returns is equal to approximately 6%,and the Sharpe ratio of U.S.market excess returns is approximately equal to 4%.Bid/ask spreads are responsible for most of this reduction.To roughly estimate the contribution of the different transaction costs,we note that withdrawalanddeposit fees are typically small and lump sum and the average trading fee is 15 basis points per trade. Investors pay these costs twice for the within strategy,but only once for the cross strategy.This is because in the cross strategy,one of the two trades always involves the benchmark pair,the dollar-to-bitcoin pair onthe Kraken exchange,for which these costs are negligible,especially for larger investors. Bid/ask spreads bite particularly long/short strategies,as they require four trades to be completed.However,we find that the short leg of the strategy does notcontribute much to the overall returns.Then,investors could reduce transaction costs by executing only the long leg.

*Review of Asset Pricing Shudies /v12n32022*

Downloaded from https:; /lacadem ic.oup.com/raps/art ic le/12/3/667/6543623 by Des Moines Un ivers ity - Osteopath ic Medical Center user on 19 October 2022

Both strategies are risky because investors,in order to form portfolios by bitcoin discounts,must transfer balances across exchanges and,then,buy and sell bitcoin at different times.The latter assumption captures the uncer- tain waitingtimes required by the architecture of both the blockchain (i.e.,the time required for the proof-of-work)and the exchanges (i.e.,the number of confirmations from the blockchain required to settle the transfers of balan- ces),which imply that pure,instantaneous,arbitrage strategies are not imple- mentable.Investors in the cross and within strategies face risksdue to delays, possibly related to thespeed oforder execution and the inability to trade on a particular exchange due to a temporary shut down,along with the high vol- atility and low liquidity of cryptocurrencies.

Weestimate a two-factor model to identify the common factors that could explain this cross-section.The first factor,which we call as the Bitcoin factor, is the crypto counterpart of the dollar factorfrom the currency risk premiums literature( Lustig and Verdelhan(2011)).The second factor,which we call the bitcoin carry factor,or CarryBtc,is the return spread between the last and first portfolios and is highly correlated with the second principal component of cross portfolio returns.We find that CarryBic explains a large fraction of the cross-sectional variation in portfolio returns.

We show that these returns compensate investors for taking on more ag- gregate risk in cryptocurrency markets.Bitcoin prices for more“expensive” pairs depreciate morein bad timesfor cryptocurrencyinvestors,when aggre- gate liquidity and investor sentiment about bitcoin are lower.The basic fi- nance logic we use for any other asset can be applied to cryptocurrencies.If an asset offers low returns when investors'marginal utility is high,it is risky, and then investors require a compensation through a positive excess return. We identify bad times for investors by projecting Carrybie on a large set of crypto and noncrypto factors.We find that CarryBtc is unrelated to non- crypto factors,but that a large fraction of its variation is significantly and positively related to bitcoin aggregate liquidity risks,which we proxyfor with the innovations to the mean bid/ask spreads on all pairs and the aggregate Amihud (2002)illiquidity measure;to bitcoin sentiment,which we proxy for with changes in the Google Trend index for the query “bitcoin”and with bitcoin momentum.Formal tests show that CarryBtcis a relevant factor in the time series and the cross-section of portfolio returns both in sample and out of sample.For the latter,we split the bitcoin pairs in our sample into two nonoverlapping groups and show that the CarryBtcrisk factor obtained from the first group is priced in the cross-section of portfolio returns of the second group.

We evaluate the robustness of our results along several dimensions.First, we consider all transaction costs,like trading and margin fees,and show that the cross-section of portfolio returns remains large and significant,but trade size can substantially reduce portfolio returns.Second,we show that the cross and within strategies are implementable by building factor-mimicking

*The Cross-Section of Cryptocurrency Returns*

Downloaded from https:/lacadem ic. ( by Des Moines University - Osteopathic Medical Center useron 19 October 2022

portfolios of the long/short portfolios using two methodologies.The first admits long-only positions on the available assets in order to address the concern that investors could not short some of the pairs in our sample. The second additionally admits a short position on the bitcoin-to-dollar pair on Kraken that was available to all investors throughout the sample. Third,we show that our results are robust to a slower,weekly,frequency of rebalancing to address the concern that a daily rebalancing could not be implementable because,for example,of the time required to execute a trade ona givenexchange or the convertibility in fiat currencies and the transfer of balances across exchanges.Fourth,we find that our results hold in a more recent sample,since 2018when crypto“came of age.”Fifth,weshowthat our results extend to samples that include other crypto-to-crypto pairs,like ethereum-to-bitcoin,or only crypto-to-fiat pairs,like ethereum-to-euro,pro- viding a broader view on this new asset class.Note that,while governments can use domestic legislation to restrict flows offiat currencies across borders they have few instruments to restrict flows of cryptocurrencies.

This paper contributes to the recent and growing literature on empirical asset pricing of cryptocurrencies.One strand of the literature studies the risk- return characteristics of cryptocurrencies,typically considering returns be- fore transaction costs.Liu and Tsyvinski(2021) find that only crypto-specific risk factors,like investors'attention and momentum,can explain the time- series risk-return relation for cryptocurrencies.Liu,Tsyvinski,and Wu (forthcoming)show that the cross-section of returns for a large set of cryp- tocurrencies is explained by three crypto-specific factors,unrelated to tradi- tional risk factors.These factors are unrelated to CarryBic,which,thus, contains additional pricing information.A second strand of the literature studies the efficiency and pricing of cryptocurrencies. Makarov and Schoar (2019)use bitcoin price differences across exchange-currency pairs to study the efficiency of cryptocurrency markets.In a small sample of pairs charac- terized by small bid/ask spreads,they document large arbitrage opportunities across exchanges in different locations and explain them withcapital controls and weak financial institutions.In acompanion paper,we expand Makarov and Schoar's sample to include all the fiat and cryptocurrencies and decom- pose the variability in bitcoin prices in components associated with,in order of importance,time,location of the exchanges,and currency pair(Borri and Shakhnov (2018)). Krückeberg and Scholz(2020),instead,attribute these price differences to market ineffciencies and untapped arbitrage opportuni- ties.This paper builds a bridge between these two strands of the literature:it accounts forall the transaction costs and limitations totrade,and provides a

Yermack (2013),Velde (2013),and Dwyer (2015)are excellent primersthat describe the functioning of the blockchain and cryptocurrencies.Cataliniand Gans(2016),Biais et al.(2019),Cong,He,and Li(2020),and Ma, Gans,and Tourky (2018) analyze from the perspective of economic theory howblockchain technologyand cryptocurrencies willinfluence the rate and direction of innovation and the incentives and equilibria behind the “proof of work”protocols.

*Review of Asset Pricing Shudies /v 12n32022*

Downloaded from https:; /lacadem ic.oup.com/raps/art ic le/12/3/667/6543623 by Des Moines Un ivers ity - Osteopath ic Medical Center user on 19 October 2022

risk-based explanation of bitcoin price differences across exchanges,currency pairs,and time.This paper is also related to the large finance literature on market efficiency and anomalies as well as limits to arbitrage.Some papers argue that market inefficiencies can explain differences in the prices of ho- mogenous assets,others attribute them to differences in risk.Examples of the former,are Lee,Shleifer,and Thaler(1991);Chen,Kan,and Miller(1993)for closed-end funds; Lamont and Thaler(2003) for tech stock carve-outs; Gagnon and Karolyi(2010) for cross-listed stocks,such as ADRs; Burnside (2011)for the forwardpremium;and Du,Tepper,and Verdelhan

(2018) for the deviations from the covered interest parity.Examples of the latter are Cochrane (2002)for tech stock carve-outs;Krishnamurthy(2002) for on the run and off the run bonds;and Lustig and Verdelhan(2007)for the forward premium.Pontiff(1996) and Tuckman and Vila(1992) argue that idiosyncratic risks limit arbitrage opportunities.This paper is the first to propose a risk-based explanation for bitcoin price differences across liquid fiat-to-bitcoin pairs traded on exchanges located in countries with no capital controls.

**1.Bitcoin Portfolios**

To investigate how far a risk-based explanation can go in explaining bitcoin price differences in different markets and against different currencies,we take the perspective ofinvestors who form portfolios according to two strategies based on the persistence or mean-reversion ofbitcoin discounts.By forming portfolios,we accommodate the large time-variation in the number of exchanges and currencies pairs and isolate common factors.For both strat- egies,we obtain a large and significant cross-section ofreturns before trans- action costs.In this section,we focus ona samplein which frictions are small, containing the most liquid pairs and exchanges located in countries with limited constraints for foreign investors and satisfying a set of constraints in terms of“quality.”Section 3 accounts for execution risks,additional trans- action costs,and different samples.

**1.1 Building portfolios**

1.1.1 Data. Investors can trade bitcoin and other cryptocurrencies in two types of exchanges.The first,referred to as crypto-to-crypto exchanges,are exchanges on which only cryptocurrency pairs are traded (i.e.,bitcoin for ethereum),and where investors can deposit and withdraw only cryptocur- rencies;the second,referred to as fiat-to-crypto exchanges,are instead exchanges where investors can trade fiat currencies for cryptocurrencies (i.e.,U.S.dollar for bitcoin),and deposit and withdraw both fiat and cryp- tocurrencies.While the second type of exchanges is subject to country regu- lations,for example,U.S.-based fiat-to-crypto exchanges are registered as a

Downloaded from https:l lacadem ic.oup.com r raps/article/ by Des Moines Un ivers ity - Osteopath ic Medical Center useron 19 October 2022

money service business with the Financial Crimes Enforcement Network of the U.S.Department of Treasury,the first type of exchanges is mostly unregulated,a point that has recently raised concerns about their reliability (Bitwise (2019);Gandal et al.(2018)and risk of price manipulation using pump-and-dump schemes (Li,Shin,and Wang (2020).2

The two types of exchanges also differ in the number of currency pairs traded:while investors can trade many,often in the hundreds,crypto-to- crypto currency pairs on crypto-to-crypto exchanges,they can trade only a few,mostly fiat-to-crypto,currency pairs on fiat-to-crypto exchanges.The majority of transactions takes place on exchanges that function like standard equity markets where investors submit buyand sell orders that are cleared by a centralized order book.Instead,other exchanges offer order-matching services and match buyers'and sellers'orders when they overlap.Finally, note that all exchanges operate 24/7,including Saturdays,Sundays,and hol- idays,and use the UNIXtime-stamp to track time and ensure the immediate comparability of market prices.

We start by collecting daily bitcoin price and volume data for allexchanges and currency pairs available on the CryptoCompare website (https://crypto- compare.com/),a leading source of cryptocurrency trading data.In our base- line analysis,werestrict our sample along several dimensions in orderto focus on reliable exchanges and currency pairs that are likely to be available to foreign investors.

First,we only consider fiat-to-crypto pairs on fiat-to-crypto exchanges (e.g.,the dollar-to-bitcoin pair on Coinbase,but not the ether-to-bitcoin pair on Coinbase),because of the lower reliability of crypto-to-crypto exchanges.In what follows,we treat each fiat-to-crypto currency pair on a given exchange as a different asset.For example,we treat the dollar-to- bitcoin pairon Coinbase and the dollar-to-bitcoin pair on Krakendifferently. Similarly,the dollar-to-bitcoin and euro-to-bitcoin pairs,both on Coinbase, are also different assets.

Second,we consider only fiat-to-crypto exchanges that satisfy several indi- cators of“quality,”including ratings and web traffic data produced by

Third,to focus on pairs likely available to foreign investors,we include in the sample only pairs that satisfy both of the two following criteria to min- imize the role of restrictions to capital flows.The exchanges must be located in one of the following countries:Australia,Canada,Denmark,the Eurozone,Hong Kong,Israel,Japan,Poland,Switzerland,the U.K.,and

²According to the report by Bitwise(2019),95%of thevolumein CoinMarketCap is fake and/or noneconomicin nature.While this claim has not been independently verified,it is reasonable to assume that exchanges have an incentiveto appear at thetop of the lists used by media organizations to attract listing fees from ICOs and altcoins.We note that all the exchanges described in the report as fabricating data are crypto-to-crypto exchanges and,thus,not in our sample of bitcoin-to-fiat pairs. Li, Shin , and Wang (2020)argue that pump- and-dump schemes ocur mostly on crypto-to-crypto exchanges,last onlyfew minutes,and that fiat-to-crypto exchanges,like Bittrex,banned them.In Section B.I of the Internet Appendix,we report various “quality” indicators,for each exchange in the baseline sample (see Table A3 ).

*Review of Asset Pricing Shudies /v 12n32022*

Downloaded from https;/lacadem ic.oup.com/raps/art ic le/12/3/667/6543623 by Des Moines Un ivers ity - Osteopath ic Medical Center user on 19 October 2022

the U.S.The fiat currencies must be one ofthe following:Australian dollar, Canadian dollar,Danish krone,euro,Hong Kong dollar,Israeli shekel Japanese yen,Polish zloty,Swiss franc,British pound,the U.S.dollar.We select this set of countries and currencies based on the tightness in capital controls with respect to the United States using the capital control index constructed by Fernández et al.(2016).

Fourth,we compute U.S.dollar prices for all fiat-to-bitcoin pairs using daily spot rates from WM/Reuters and available on Datastream.For this reason,we exclude nonbusiness days because of the unavailability of spot rates.Fifth,to focus on the most liquid pairs,we consider the following additional restrictions.We exclude pairs with less than 30 days of observa- tions;pairs traded on peer-to-peer platforms,which typically have very low volume;pairs with an average daily bid/ask spread larger than 2%;and observations corresponding to the 5-day average of daily volume smaller than 10 bitcoins

Our baseline sample runs from May 26,2015,to May 25,2021.The start- ing date of the sample depends on the availability of a minimum number of pairs to build portfolios and the possibility of shorting the dollar-to-bitcoin pair.Our raw sample contains 258 fiat-to-bitcoin pairs,while our baseline sample contains,at most,68 pairs traded on 29 exchanges.Table 1 contains descriptive statistics of the baseline sample.The number of exchanges and currency pairs increases over time because pairs enter and exit the sample as new exchanges open and close,and new pairs are introduced.Specifically,we start with ll pairs traded on 16 exchangesand end with 68 pairs traded on 29 exchanges.Over the sample,the daily median trading volume increased from US$250,000 to approximately US$7.5 million.This corroborates the view that cryptocurrency markets have become more mature:despite the large increase in the number of pairs,the median trading volume did not decline. In the same period,the bitcoin price increased from approximately US$430 to aboutUS$38,000 in May 2021.

1.1.2 Bitcoin discounts.Investorscan trade bitcoin in a setofm=1,...,M markets (i.e.,exchanges),using a set of j=1,...,J currencies. ;denotes the units of currency j=1,...,J required to buy one bitcoin in market m (e.g.,euros for bitcoin on Bitfinex).We take the perspective of U.S.dollar- based investors trading bitcoin in these markets and currencies.S denotes the spot exchange rate expressed in units of currency jper U.S.dollar(e.g.,euro per dollar).The U.S.dollar price of one bitcoin in market mand currency jis



(1)

If investors could trade instantaneously across exchanges and in the ab- sence of frictions,according to the law of one price they should get the same

The Cross-Section ofCryptocurrency Returns

**Table 1**

**Baseline sample**

All fiat-to-crypto #exchanges #pairs

Daily volume USD millions) median

Daily volume (BTC)

p10 p90

Price (Kraken) USD per BTC

Baseline

#exchanges #pairs

median

Year

431.31 960.77 1.4402.20 3.691.90 7,168.30 28.959.20 38,388.10

16

18

25

39

47

68

68

26

31

48

81

82

82

82

2015

2016

2017

2018

2019

2020

2021

15,998.13 8,510.73 24.788.88 14.266.37 4,713.13 8,404.77 7,273.81

0.25 0.55 43.52 3.60 1.15 5.44 7.63

589.98 662.24 .085.81 951.13 157.08 251.92 165.71

2.09 17.44 17.61 28.29 10.92 10.13 10.28

11

12

15

21

26

29

29

41

51

86

149

152

152

152

Thetaberepotsdesipie tatistcsforthe basiesample.Foreachof the vasfrom2015t02021 wereporthe biconpriceinU.S.dolarson theKraken exchange(the benchmark air, the median dailyolumeinmilions of US.dolarsand n unitsobicoin;thenumber ofavailabechangsandpais.For hevolume expresedi bitcoins,weatsoreport hel0thand9o0nh perentlevalues tespecively,pl0 andp90).The lastwocolumms report he toal mmberofavilabexchangsand paisinthesamplecontaningllthefatocrypto pairsaftereliminating per-to-per and iliuid exchanges.Descripie statstic are for th last avilabe day ofeach year.For 2021,the ae for thelast day of the samplein May25,2021.Data are fom the Cryptocompare website(https://cryptocompare.com/)and Thomson Reuters.

675

2Z0Z Jaq0106l uo Josn Jou8o eoipew 0ypedolso-4IsIeNiun suIow soa kq εz98tS9/299/8/Zvopwesde./uoodnoopuopese/:sday woy pepeolumO

*Review of Asset Pricing Shudies /v 12n32022*

Downloaded from https:;/lacadem ic.oup.comf raps/art ic le/12/3/6 23 by Des Moines Un ivers ity - Osteopath ic Medical Center useron 19 0ctober 2022

dollars per bitcoin in each market m and currency j.In fact,there exist large, persistent,and time-varying price differences across both markets and cur- rencies,and over time (see,e.g.,Makarov and Schoar(2019);Borri and

Shakhnov(2018)).3

We write the price in market m=1,the Kraken exchange,and currencyj= 1,the U.S.dollar,as the numeraire.This choice is motivated by the fact that Kraken is one of the oldest exchanges,launched in September 2013,with large bitcoin trading volume and low transaction costs.In addition,Kraken is one of the first exchanges to introduce margin trading and the possibility of short-selling the dollar-to-bitcoin pair.At a given point in time,we define the bitcoin discount in market m and currency jas

(2)

If Dmj<0,then investors get a smaller number of dollars per bitcoin in market m and currency j than in the reference market.On the contrary,if Dmj>0,then investors get a larger number of dollars per bitcoin in market mand currency jthan in the reference market.Finally,when Dm,=0,invest- ors get the same number of bitcoins in market mand currency jas they get in the reference market.

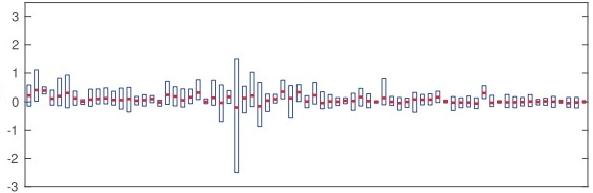
Figure 1 summarizes some of the properties of the bitcoin discounts for the pairs in oursample.Specifically,the top panel plots the median discount (red mark),along with the 25th and 75th percentiles (blue box)and the bottom panel.The bottom panel reports the half-life for each pair,where the latter captures the time it takes for a shock to dissipate by 50%and is estimated using an autoregressive process of order 1 on discounts.Discounts are,on average,different from zero and usually positive and volatile.For the average pair,almost 17%of the daily observations have discounts larger than 1%in absolute value.Within the same market,discounts are time varying and can be positive and negative and can reach absolute values of 30%.Finally, discounts are persistent and mean-reverting with a mean (median)half-life of0.98(0.48)days.According to standard augmented Dickey-Fuller tests,we reject the null of unit root for all pairs at standard significance levels.

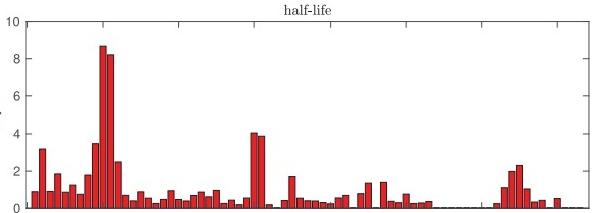
1.1.3 Bitcoin excess returns.We assume investors can borrow at the dollar risk-free rate R and use lowercase letters the log of any variable (i.e., x=log(X)).We consider the following two strategies based on observed bitcoin discounts.The first is a cross strategy that exploits the persistence

³Given thecurrent blockchain technology,a minimum 10-minute wait for confirmation in the bitcoin blockchain is hardcoded into the program,and exchanges typically require more than oneconfirmation before deposit cryptocurrencies in investor's accounts.Therefore,unless investors have the possibility to buy and short-sell bitcoin and keep balances indifferent exchanges,theycannot trade instantaneously acrossexchanges.However, short-sllingis not possible in allexchanges and maintaining balances impliesinventorycosts.For these reasons, although higher-frequency (i.e,intraday)data are available,wedo notuse themin the construction of returns.

Downloaded from https:; /lacadem ic.oup.com/raps/art ic le/12/3/667/6543623 by Des Moines Un ivers ity - Osteopath ic Medical Center user on 19 October 2022

*Dm.*





days

**Figure 1**

**Bitcoin discounts**

Thetop panel of the figure presents aboxplot of bitcoindiscounts(Dm)for all the pairs in the baselinesample. For eachbox,the central redmark represents the median discount,and the bottom and top edgesof the box represent the 25thand 75th percentiles.The bottom panel presents a bar plot where each barcorresponds to the half-life of one of the pairs in the baseline sample.To measure the half-life,we run an autoregressive procss of order 1 on discounts:the half-life is equalto log(0.5)/log(p),where pisthe persistence parameter,and captures the time it takes for a shock to dissipate by 50%.Note that according to standard augmented Dickey-Fuller tests,we reject the null of unit root for all pairs at standard significance levels.Daily data come from the

Cryptocompare website (https://eryptocompare.com)and Thomson Reuters for the period May 26,2015,to May 25,2021.

of bitcoin discounts.The second is a within strategy,based on the mean reversion of bitcoin discounts

Figure 2 exemplifies the timing of the cross strategy using data for the bitcoin-to-euro pair on Bitfinex for May 8,2019.At time t,an investor observes a discount D₁=4.22%for the bitcoin-to-euro pair traded on Bitfinex.She then borrows one U.S.dollarat the risk-free rate to buy bitcoin using the benchmark bitcoin-to-dollar pair on Kraken.Note that,for the investor to complete the transaction,she first needs to deposit the initial dollar amount on the Kraken exchange (or she must have an existing bal- ance).The investor then transfers her bitcoin balance to a different exchange, in the example Bitfinex.In Figure 2,the transfer,which could take up to 24 hours before confirmation,is represented by the vertical dashed line.At time t +1,the investor first trades bitcoins for euros on Bitfinex and then exchanges euros for U.S.dollars on the foreign exchange market.Finally,the investor

Downloaded from https;/lacadem ic.oup.com/raps/art ic le/12/3/667/6543623 by Des Moines Un ivers ity - Osteopath ic Medical Center user on 19 October 2022

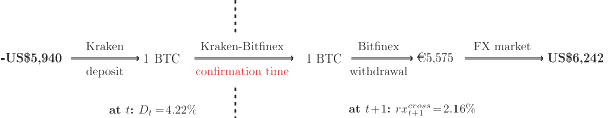


Figure 2

Cross strateg

This figure exemplifies the timing of a crass strategy.Attimet,theinvestor buys bitcoins with U.S.dollars in the referencemarket,that is Kraken,using the benchmark bitcoin-to-dollar pair.For the investor to complete the transaction,she first needs to deposit the initial dollar amount onthe Kraken exchange(or shemust have an existing balance).The investor then transfers her bitcoin balance to a different exchange (Bitfinex in the figure). The transfer could take up to 24 hours before confirmation.At time t+1,the investor first trades bitcoins for euros on Bitfinex,and then exchanges euros for U.S.dollars at the spot rate on the foreign exchange(FX) market.Because of theuncertainty around the confirmation time,we make the conservative assumption of a period to be equal to 1 day.The figureis based on data for t equal to May 8,2019,when the discount associated with the bitcoin-to-europair on Bitfinex was equal to 4.22%.The resultant daily crass return was equal to 2.16%.

pays back the initial loan plus any accrued interest.The daily return of the cross trade in this example is equal to 2.16%.

Cross excess returns,expressed in U.S.dollars,are then



(3)

=Pm,z+1-s₄1-Pi,,-r,

where pm;and ;are,respectively,the (log)prices of pair jin market m expressed in dollars and units of currency j,and s is the (log)spot exchange rate in units ofcurrencyjper dollar (see Equation 1).Note that,for the cross strategy,the transaction at time talways occurs using the benchmark dollar- to-bitcoin pair on Kraken.Despite some similarities with an arbitrage strat- egy,this is actually a risky trade.In fact,investors are exposed to the risk of price changes during the transfer of bitcoins from Kraken at time t to market m at time t+1(in the figure Coinbase).In addition,investors are further exposed to the exchange rate risk att+1,with theexception of trades against other dollar-to-bitcoin pairs.

Because of the uncertainty around the confirmation time,we make the assumption of a period to be 1 day and we show that results are robust to a slower weekly frequency.The exchange Kraken advertises an average con- firmation time of 1 hour.However,according to data we collect from the data provider <https://www.blockchain.com>,the confirmation time varies over time:the 99th percentile of the average confirmation time for a given day is approximately equal to 24 hours,and the average is equal to one hour.

The within strategy is a standard buy-and-hold investment for a particular pair jtraded on a givenexchange m withaholding period of one day.Within excess returns,expressed in U.S.dollars,are then

*The Cross-Section ofCryptocurrency Returns*

Downloaded from <https://academic.oup.com/raps/article/12/3/667/6543623>

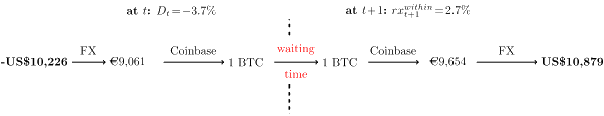


Figure 3

*Within strategy*

This figure exemplifies the timing of a within strategy.At time t,theinvestor buys bitcoinswith U.S.dollars using the bitcoin-to-euro pair on Coinbase.For the investor to complete the transaction,she first needs to deposit the initial dollar amount on the Coinbase exchange(or she must have an existing balance).At timet+ 1,the investor first trades bitcoins for euros on Coinbase,and then exchanges euros for U.S.dollarsat the spot rate on the foreignexchange(FX)market.Becauseof the uncertainty around the execution time,we make the conservative assumption of a period to beequal to l day.Thefigureis basedondata for requal to July 14,2019, when the discount assocated with thebitcoin-to-euro pair on Coinbase was equalto-3.77%.The resultant daily within return was equal to 2.7%.



(4)



Figure 3 exemplifies the within strategy using data for the bitcoin-to-euro pair on Coinbase for July 14,2019.At time t,an investor observes a discount D₁=-3.7%for the bitcoin-to-euro pair traded on Coinbase.She then bor- rows one U.S.dollar at the risk-free rate,exchanges it to euros on the foreign exchange market to buy bitcoin using the bitcoin-to-euro pair on Coinbase.

At time t+1,the investor first trades bitcoins for euros on Coinbase,and

by

Des

then exchanges euros for U.S.dollars on the foreign exchange market.The

Moines Un ivers ity - Osteopath ic Medical

daily return of the within trade in this exaple is equal to 2.7%.

In the construction of returns for both strategies,we need to account for the possibility of exchange shutdowns:that is the fact that investors cannot complete their desired trade att+1 because of the nonavailability of a given fiat-to-bitcoin pair.Temporary shutdowns are relatively frequent,for exam- ple,because of distributed denial-of-service attacks(DDos)or software mal- function.We make the assumption that investors,in case of a shutdown,can sell their bitcoins at the median price prevailing at t+1 across all pairs.In Section 3 we consider additional execution risks and evaluate the robustness ofour assumption.

Center user on 190ctober 2022

1.1.4 Bid and ask prices.We obtain daily bid-ask spreads data from Bitcoinity for a subset of 33 fiat-to-bitcoin pairs in our sample.In addition, we estimatebid and ask prices for all the remaining fiat-to-bitcoin pairs using the predicted values from the following panel regression:

BAmj,1=α;+y,+B(L)vmj,z+A(L)hlm,j,+fm,j,t (5)

*Review of Asset Pricing Shudies /v 12n32022*

Downloaded from https:l/academ ic.oup.com/raps/art ic le/12/3/66716543623 by Des Moines Un ivers ity- Osteopath ic Medical Center useron 19 October 2022

where B(L)and A(L)are fifth-order lag polynomial,v is the log trading volume in bitcoins,hl is the lag of the high-low spread,and x;and y,are currency and time fixed effects.⁴Returns net of bid-ask spreads are



(6)



(7)

where  is the bid-ask spread for market m and currency j,and we assume that theprice without transaction costs is halfway between the bid and ask prices.

1.1.5 Portfolios.At the end of each day t,investors form two sets of seven portfolios sorted by bitcoin discounts Dm,jz.Portfolios are ranked from the lowest negative to the highest positive bitcoin discount.For the first set of portfolios,investors use the cross strategy.For the second set of portfolios, investors use the within strategy.These strategies are implementable,in the sense that they are based on signals available to all investors.To execute a cross strategy investors must transfer crypto and fiat currencies across exchanges.The within strategy,on the other hand,requires transfers of cryp- tocurrencies only to adjust balances.In fact,we note that the cross strategy is popular among cryptocurrency investors,and websites like https://bitsgap. com/arbitrage-tool/or https://arbismart.com/offer the possibility to identify in real-time the largest discounts and immediately start cross trades.

In the cross strategy,investors always start at time t by buying bitcoin using the benchmark pair.Recall that negative (positive)discounts refer to pairs that have a low (high)price relative to the benchmark.Portfolio 1,then, groups the returns from selling,at time t+1,the pairs with the lowest discounts at time t (i.e.,the“cheapest”pairs),while portfolio 7 groups the pairs with the highest discounts at time t(i.e.,the more“expensive”pairs).In the within strategy,investors buy and hold one pair for 1 day.Portfolio 1, then,groups the returns from investing in the pairs with the lowestdiscounts while portfolio 7in the pairs with the highest discounts.

4 The (within)-R²of our pand estimation is 20%,and most ofthe coefficients are significant at standard confi- dence levels.Specifically,higher trading volume and lower high-low spread areassociated with smaller bid/ask spreads.Brauneis et al.(2021)argue that low frequency liquidity measures,for example based on high and low prics,are good estimates of actual liquidity measured with high-frequency indicators.Section BII ofthe Internet Appendix presents estimates of bid/ask spreads using alternative estimators based on daily high, low,and close prics.Note that while the bid-ask spreads for the most liquid pairs in our sample are smal and consistent with other studies(Dyhrbergetal,2018),those for theless liquid pairs are an order ofmagnitude larger.Finally,some exchanges do not offer a limit order book,but only a matchingof buy/sell orders.For these exchanges our bid/askestimates are a proxy of liquidity,as theydo not explicitly post bid/ask prices.

*The Cross-Section of Cryptocurrency Returns*

Downloaded from https:l lacadem ic.oup.com raps/art ic le/1; by Des Moines University - Osteopathic Medical Center user on 19 0ctober 2022

For both sets of portfolios,we compute the bitcoin excess returns rXk;x+1 for portfolio k by taking the average of the bitcoin excess returns in each portfolio k:



The total number of pairs in our portfolios varies over time.We have a total of 11 assets at the beginning of the sample in May 2015,and 64 at the end of the sample in May 2021.The maximum number of pairs attained during the sample is 64.Note that we start building portfolios in May 2015 because of the availability of a minimum number ofpairs and the possibility of shorting bitcoin on Kraken,our benchmark exchange.

1.2 Returns to bitcoin speculation for a U.S.investor

Table 2 offers a quick snapshot of the properties of the two sets of seven portfolios sorted by bitcoin discounts.For each portfolio k,we report the average and standard deviation of discounts (panel A);cross returns (panel B);and within returns (panel C).For returns,we also report the average of long/short returns.For cross returns,the long/short returns correspond to a high-minus-low strategy that goes long in portfolio 7 and short in portfolio 1 (i.e.,7-1).For within returns,the long/short returns correspond to a low- minus-high strategy that goes long in portfolio 1 and shortin portfolio 7(i.e., 1-7).For returns,we also report standard errors,computed by bootstrap, and Sharpe ratios computed as the ratio of mean to standard deviation of daily excess returns.All moments are daily,and Sharpe ratios are not annualized.5

Panel A reports the average bitcoin discounts.Portfolio 1 contains pairs with the largest negative discounts and portfolio 7 pairs with the largest positive discounts.Recall that when discounts are negative (positive),invest- ors get a smaller (larger)number of dollarsper bitcoin than they would in the case ofthe benchmark pair on Kraken.Across the seven portfolios,discounts increase monotonically from -97 basis points to 152 basis points per day.

Panel B shows that,by sorting pairs by their discounts,we obtain a mono- tonic increasing cross-section of gross and net cross returns.Specifically, gross excess returns increase,across the seven portfolios,from 14 basis points to 153 basis points per day.Standard deviations of excess returns are similar across portfolios so that we also obtain a cross-section of Sharpe ratios. Specifically,daily Sharpe ratios increase from 3%to 32%.The standard errors indicate thatfor allportfolios average returns are significantly different

⁵In Section F.VIII and FIⅡ of the Internet Appendix,we show that theproperties of the bitcoin portfolios are robust to smaller and larger numbers of portfoliosand provideevidence of no clustering of subsets of the pairs in any portfolio using the k-means dustering test.

*Review ofAsset Pricing Shudies /v 12n32022*

Downloaded from htps:/lacadem ic.oup.com/raps/art ic le/12/3/667/6543623 by Des Moines Un ivers ity - Osteopath ic Medical Center useron 19 October 2022

**Table 2**

**Bitcoin portfolios:U.S.investor**

Portfolio 1 2 3 4 5 6 7 Long/short

A.Discounts

-0.97 1.41

1.52 1.82

-0.08 0.59

0.51 0.94

0.08 0.62

0.26 0.73

Mean SD

-0.28 0.66

B.Cross returns 7-1

Mean SD

SE SR

Mean SD

SE SR

Mean SD

SE SR

0.14 4.67 0.12 0.03

-0.23 4.69 0.12 -0.05

1.15 4.92

0.13

0.23

0.39 4.58 0.12 0.09

0.16 4.58 0.12 0.03

0.68 4.64 0.12 0.15

Gross returns

0.66 4.66 0.11

0.45 4.62 0.12 0.10

0.55 4.64 0.12 0.12

0.86 4.64 0.12 0.19

0.14

Returns net of bid/ask

0.35 4.67 0.12 0.08

0.62 4.65

0.12

0.13

0.26 4.62

0.12

0.06

0.46 4.66 0.12 0.10

C.Within returns

Gross returns

0.53 0.47 0.40 0.35

4.66 4.65 4.65 4.59

0.12 0.12 0.12 0.12

0.11 0.10 0.09 0.08

1.53 4.77 0.11 0.32

1.10 4.79 0.13 0.23

0.03 4.49 0.11 0.01

1.39 2.22 0.06 0.62

0.58 2.29 0.06 0.25 1-7

1.12 2.14 0.06 0.52

Returns net of bid/ask

0.22 0.14 0.07 -0.07

Mean SD

SE SR

0.27 4.65 0.11 0.06

-0.77 4.63 0.12 -0.17

-0.37 2.19 0.05 -0.17

0.47 4.89 0.13 0.10

4.67 4.69 4.65 4.62

0.12 0.13 0.12 0.12

0.05 0.03 0.01 -0.01

Thistablereports,for each portfolio k=1...,7,the mean,and standarddeviation for the average discounts (panelA);the mean(Mecan),standarddeviation(Sid),standard error (SD),and Sharpe ratio (SR)forthe cross returns (panel B)and for the within returns(panel C).Standard errors areby bootstrap,and Sharpe ratios are computed as ratios of daily means to daily standard deviations and are not annualized.Only for returns,the table reports the mean,standard deviation,standard error,and Sharpe ratio for long/short excess returns, defined as the returns of a zero-cost strategy that goes long in portfolio 7 and short in portfolio 1 for cross returns;and long in portfolio 1 and short in portfolio 7 for within returns.For both the cross and within investment strategies,we consider both gross and net returns.Portfolios are constructedby sorting assets into sevengroups at timetby theirdiscounts Dmjp.The first portfolio contains the pairs with the lowest negative discounts.The last portfolio contains the pairs with the highest positive discounts.Data are from the Cryptocomparewebsite (https:/cryptocompare.com)and Thomson Reuters.The sample period is May 26, 2015,to May 25,2021.

from zero as theyare more than two standard errors from zero.⁶A zero-cost high-minus-low strategythat goes long in portfolio 7 and short in portfolio 1 produces large and statistically significant excess returns of approximately 139 basis points

For many pairs,bid/ask spreads are not negligible.In fact,net returns are 37 basis points smaller for the first portfolio,and almost 43 basis points smaller for the last portfolio.The average return of the long/short strategy is substantially smaller after accounting for transaction costs and approxi- mately equal to 59 basis points for a Sharpe ratio of 26%.Net long/short



6 Wereject the null of equal returns,at standardsignificance levels,for the corner portfoliosusing Newey and West(1986) heteroscedasticity and autocorrelation consistentstandarderrors.In addition,we also find that the Patton and Timmermann (2010) tests for a monotonic relationship(MR and MR)reject the null of fat or weakly decreasing pattern against the alternative of strictly increasing pattern.

*The Cross-Section of Cryptocurrency Returns*

Downloaded from https:l lacadem ic.oup.com raps/art ic le/1 , by Des Moines University- Osteopathic Medical Center useron 19 October 2022

returns are not simply equal to the difference between the corner portfolios' net returns.As back of the envelope calculation,consider that long/short net returns are instead equal to the long/short gross returns net of the difference between the averages of the gross andnet returns of the corner portfolios (i.e., 1.39-(1.53-1.10)-(0.14+0.23)=0.59).To go short in portfolio 1, investors must be able to short bitcoin on Kraken,our benchmark exchange. Kraken introduced margin trading and the possibility to open short positions starting on May 5,2015,thus at the beginning ofour sample.At the time of this writing,several of the exchanges in our sample offer margin trading,but in 2015,investors could short bitcoin only on Kraken and Bitfinex.?In Section 3,we will show that the mean long/short return remains positive and statistically different from zero also after accounting for exchange and margin fees.

Panel C of Table 2 shows that,by sorting pairs by their discounts,we also obtain a monotonic decreasing cross-section of gross and net within returns. Specifically,gross returns decrease,across the seven portfolios,from 115 basis points to 3 basis points per day.However,net returns are negative or not statistically different from zero for all portfolios,except for the first and the second.In fact,while the gross long/short average return is equal to 112 basis points per day,the corresponding average net return is equal to-37 basis points per day.Therefore,the within strategy is not economically prof- itable.Further,in order to implement the long/short within strategy over time,investors need to be able not only to transfer either bitcoin or fiat currency across exchanges but to short pairs on all exchanges.The latter is not always possible.Alternatively,for the shortposition,investors couldkeep balances of fiat currencies on all exchanges;for the long position,investors could keep balances of bitcoin on all exchanges.These balances would grow over time,exposing investors to inventory costs related to changes in bitcoin and fiat currency prices.

For both the cross and within long/short strategies,the long position accounts for most of the return,while the contribution of the short position is negligible.This is important for two reasons.First,as discussed above, short positions are not available on all exchanges or for the entire sample. Second,the short position accounts for one-half of the transaction costs and, additionally,requires the payment of margin fees (see also Table 7). Therefore,we consider the net returns from the long/short strategies ascon- servative estimates of the returns available to investors.Although the daily Sharpe ratios associated with the cross and within long/short strategies are large,in Section3 we highlight that the Sharpe ratio associated witha realistic portfolio,with a relatively small fraction invested in the crypto asset and the

Alternatively,investors could hold balanceson allexchanges.Specifically,for the short position,investors could keep balances of fiat on all exchanges and bitcoinon Kraken.Atthe endofeach period,investors should adjust their balances by transferring bitcoin to Kraken

*Review of Asset Pricing Shudies /v 12n32022*

Downloaded from [https://academic.oup.com/raps/article/12/3/667/6543623 by Des Moines University - Osteopathic Medical Center user on 190ctober 2022](https://academic.oup.com/raps/article/12/3/667/6543623byDesMoinesUniversity-OsteopathicMedicalCenteruseron190ctober2022)

rest in the U.S.equity market,is only marginally higher than the market Sharpe ratio.In the Internet Appendix,we further show that our results are robust with respect to several extensions:Section F.IV considers a larger sample that includes nonbusiness days;Section F.V considers the average returns of factor-mimicking portfolios of the long/short cross and within strategies that are likely to be available to investors;and Section F.VI presents the results for a slower weekly frequency of rebalancing.

**2.Common Factors in Bitcoin Returns**

We have uncovered two different cross-sections of bitcoin excess returns related to strategies based on observed bitcoin discounts.After accounting for transaction costs,portfolio within returns are not statistically different from zero.These returns,then,are likely evidence of frictions that prevent investors from absorbing price differences across markets and pairs.In con- trast,we have found a significant cross-section of portfolio cross returns after accounting for transaction costs.The latter is a popular strategy among investors and facilitated by trading platforms that advertize bitcoin discounts.

In this section,we show that the large cross-section of cross portfolio returns captures the compensation that investors demand to bear aggregate risk in cryptocurrency markets.Differences in portfolio cross returns are matched by covariances with just two risk factors:the bitcoin return on Kraken(BtcKraken),and the excess return form a long/shortzero-coststrategy that goes long in the last portfolio and short in the first (i.e.,7-1).We refer to this second factor as CarryBtc The first factor is a levelfactor that captures the returns ofinvesting in bitcoin using the benchmark pair,thatis the dollar- to-bitcoin pair on Kraken,and is the crypto counterpart of the Dollar factor in the currency risk premium literature (Lustig and Verdelhan (2011)).The second is aslope factor that explains the cross-section of portfolio returns.We show that CarryBtc is related to bitcoin aggregate liquidity and sentiment, while it is not related to traditional risk factors,like the Fama and French

(1993)factors for equity markets.Note thatin this section we always consider portfolio returns net of bid/ask spreads,and not gross returns.In Section 3 we additionally account for exchange trading and margin fees.

**2.1 Results**

We construct a two-factor model.The first factor,denoted by BtCKraken,is simply the return of an investment in the bitcoin-to-dollar pair on Kraken, our benchmark pair.The second factor,denoted by CarryBic captures the excess returns of a zero-coststrategy that goes longin portfolio 7and short in portfolio 1.These factors are highly correlated with the first two principal components of portfolio returns.

Downloaded from [https://academic.oup.com/raps/article/12/3/667/6543623 by Des Moines University - Osteopathic Medical Center user on 190ctober 2022](https://academic.oup.com/raps/article/12/3/667/6543623byDesMoinesUniversity-OsteopathicMedicalCenteruseron190ctober2022)

**Table 3**

**Descriptive statistics:Risk factors**

Mean SD Skew Kurt VaR₁% Corr(PC,x) Corr(PC₂,x)

Carryp BICKrak Cros8

2.30 4.63 4.53

0.59 0.35 0.42

46.92 9.75 10.41

0.07 0.99 1.00

0.87 -0.03 -0.00

-4.03 -12.81 -12.60

-1.14 -0.07 -0.03

The table reports mean(Mean),standard deviation(SD),skewness (Skev),kurtosis (Kurr),value at risk with confidence 1%(VaR₁%),and correlation coefficients with respect to the first two principal components for Carys Bicratenand Cross(Corr(PC,x),withi=1,2 and x=Cary,Bic,Cross).Carryne denotes the excess returnsofa zero-cost cros strategy that goeslongin portfolio 7and short in portfolio 1.BIcka denotes the returns of investing in bitcoinsusing the benchmark dollar-to-bitcoin pair on the Kraken exchange.Cross denotes the returnsfor an investor that goes longin all hecross portfolios.Allreturns arenet of bid/ask spreads. Daily data come from the Cryptocompare website (https://cryptocompare.com)and Thomson Reuters for the period May 26,2015,to May 26,2021

Table 3 presents descriptive statistics for these two risk factors,as well as a third factor,denoted by Cross,which is the average excess returns across all seven cross portfolios.The average return on CarryBtcis equal to0.59%per day.CarryBtc returns are also volatile (2.30%),negatively skewed(-1.14), and have a very large kurtosis (46.92).The mean return on BtcKraken is ap- proximately one-half the mean return on CarryBtc,with a larger standard deviation.Therefore,while the Sharpe ratio of CarryBic is approximately

equal to 26%,the Sharpe ratio of BtcKraken is approximately 9%.CarryBic is highly correlated with the second principal component (0.87)extracted from portfolio returns,while BtcKraken is highly correlated with the first prin- cipal component (0.99).Note how Cross is de facto the first principal com- ponent,and therefore is highly correlated with BtCKraken.

Table 4 reports the asset pricing results obtained using two procedures applied to the portfolios sorted on bitcoin discounts:a generalized method of moments estimation (GMM)applied to linear factor models,following Hansen(1982) ,and a two-state OLS estimation following Fama and MacBeth (1973),henceforth FMB (see Section E in the Internet Appendix for details on the estimation procedures).

2.1.1 Cross-sectional regressions. The top panel of the table reports esti- mates of the market prices of risk λand thestochastic discount factor(SDF) loadingsb,the adjusted R²,root-mean-square error(RMSE),and the p-value of a x²test for the null that all the cross-sectional prices errors are zero (in percentage points).The first risk factor,BtcKraken,has an estimated risk price of 13 basis points (GMM₂),compared with a sample mean of32 basis points.

All portfolios have a beta close to one with respect to this first factor.As a result,the first factor explains none of the cross-sectional variation in port- folio returns.This is why the standard errors on the risk price estimates are large.For example,the GMM standard error is 15 basis points.While the BtcKraken factor does not explain any of the cross-sectional variation in

Downloaded from https:l/academ ic.oup.com/raps/art ic le/12/3/667/6543623 by Des Moines Un ivers ity- Osteopath ic Medical Center useron 19 October 2022

**Table 4**

**Asset pricing:U.S.investor**

*A.Risk prices*

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | 2B | λCarryjs | bBi | bcr R² | | RMSE | x²(%) |  |
| GMM₁ GMM₂ FMB  Mean 8.e. | 0.29  [0.17]  0.13  [0.15]  0.29  [0.12]  0.32  [0.12] | 1.51  [0.28]  1.68  [0.21]  1.51  [0.07]  0.59  [0.16] | 0.87  [0.77]  0.05  [0.69]  0.86  [0.56] | 28.84 [5.43] 32.05 [4.06] 28.83 [1.26] | 94.07  98.80  92.58 | 0.08  0.18  0.08 | 0.05  0.12  0.00 |  |
| Portfolio |  |  |  | B.Factor betas | |  |  |  |
|  | k | R² | | z²(α) | p-value | (% |
| 2  3  4  5  6  7  All | -0.31  [0.05]  -0.15  [0.03]  -0.05  [0.03]  -0.04  [0.07]  0.09  [0.03]  0.21  [0.04]  0.50  [0.07] | 0.95  [0.01]  0.96  [0.01]  0.97  [0.01]  0.97  [0.01]  0.98  [0.01]  0.97  [0.01]  0.96 [0.01] | -0.39 [0.07] -0.01 [0.02] -0.01  [0.02]  0.13  [0.09] 0.10 [0.04]  0.18  [0.05]  0.49 [0.09 | 92.39  95.89  96.80 95.45 96.93  95.47  94.05 | | 614.49 | 0.00 |  |

PanelA reportsresults from GMMand Fama and MacBeth(1973)asset pricing procedureson the seven bitcoin portfolios sorted with respect to bitcoindiscounts.Market prices of riskλ,theadjustedR²,the root-mean-square error(RMSE),and the p-values of z²tests on pricing errors are reported in percentage points.b denotes the vector of factor loadings.Allexcess returns are multiplied by 100.Shanken(1992)-correctedstandard errors are reported in parentheses.Wedo not indudea constant in thesecond step of the FMB procedure.Panel Breports OLS estimates of the factor betas.R²s andp-values arereported in percentage points.The standard errors in brackets are Neweyand West(1986)standard errors computedwith the optimal mumber of lags according to Andrews(1991).The z²test statistic dv-¹a tests the nul that all intercepts are jointly zero.This statistic is constructed from theNewey and West(1986)variance-covariancematrix (onelag)for the system of equations (see Cochrane (2009).Daily data come from the Cryptocompare website (https://cryptocompare.com)and Thomson Reuters.The sample period is May 26,2015,to May 26,2021.

expected returns,it is important for the level of the average returns.The market price of risk of the second factor,CarryBic is equal to 168 basis points per day.This means that an asset with a beta of one on the CarryBic,and a beta of zero on the first factor,earns a risk premium of 1.68%per day.The GMM standard error ofthe risk price is 21 basis points.The FMB standard erroris only 7basis points.So,the riskprice is more than two standard errors from zero,and highly statistically significant.

Although pricing errors are small(the RMSEis just 18 basis points)and the adjusted R²is approximately 98%,we cannot reject the null that all pricing errors are zero,as p-values are around 12%.In Section F of the Internet Appendix ,we show that CarryBic is a priced risk factor also in

*The Cross-Section ofCryptocurrency Retarns*

Downloaded from [https://academic.oup.com/raps/article/12/3 3623 by Des Moines University - Osteopathic Medical Center user on 190ctober 2022](https://academic.oup.com/raps/article/12/33623byDesMoinesUniversity-OsteopathicMedicalCenteruseron190ctober2022)

portfolios at weekly frequency,and in a shorter sample starting in January 2018,after the bitcoin frenzy of 2017.In addition,we show that the market price of CarryBtc risk is time varying,and in particular,it is higher in bad times for financial markets,when the VIX volatility index is high.

2.1.2 Time Series Regressions. The bottom panel of Table 4 reports the intercepts (denoted by a)and the slope coefficients (denoted by β)obtained by running time-series regressions of each portfolio'sexcess returns Rxkona constant and the BtcKraken and CarryBic factors.The first column reports a's estimates in percentage pointsper day.The point estimates are small but statistically different from zero,particularly in the corner portfolios.As a result,the null that the as are jointly zero is rejected at standard significance levels.This indicates that the true factor structure possibly contains more than two factors.In fact,a principal component analysis(see Table A7in the Internet Appendix)indicates that the third component,which captures cur- vature,has a contribution to the total variance similar to that ofthe second component and could contribute to explain differences in the expected returns of corner and middle portfolios.We do not include this additional risk factor due to the small number of portfolios.Further,the as might capture the effect of possible frictions that we were not able to eliminate despite the restrictions on the sample and the use of portfolios.The second and third columns of the same panel report the estimated βs for the BtcKraken and CarryBtc factors.The βs on the BtcKraken factor are similar across port- folios and close to one,while the βs on the CarryBic factor increase from -0.39 for the first portfolio to 0.49 for the last portfolio (i.e.,portfolio 7).

A natural interpretation of our results is that portfolios with higher comovement with CarryBte are riskier exactly because,on average,have high returns in good times for cryptocurrencyinvestors,when CarryBicexcess returns are large,and low returns in bad times,when CarryBic excess returns are small.On the contrary,BtCKraken is a level factor that explainsthe average excess return but does not price the cross-section of returns.In the next paragraph,we show that CarryBtc return is lower in bad times for crypto investors,when bitcoin liquidity and sentiment are lower

2.1.3 What risks. We investigate whether standard noncrypto factors can span the CarryBte and BtcKraken factors,as well as the Cross factor Specifically,Table 5 presents the results of contemporaneous linear regres- sions of the return of each factor on a large set of crypto and noncrypto factors.We report Newey and West(1986) standard errors in brackets.

Panel A groups the crypto factors that we choose among crypto specific factors and the crypto counterparts of the“currency zo0,”thatis risk factors that have been proposed to explain the cross-section of currency returns. BtCKraken and CarryBic are the crypto counterparts of the Dollar and Carry

*Review of Asset Pricing Shudies /v 12n32022*

Downloaded from https:l/academ ic.oup.com/raps/art ic le/12/3/667/6543623 by Des Moines Un ivers ity- Osteopath ic Medical Center useron 19 October 2022

**Table 5**

**Disconnect between crypto and noncrypto factors**

CarryB BiCknakcn Cross

|  |  |  |  |
| --- | --- | --- | --- |
| α | 2.924  [0.298] | 0.11  [0.510]  A.Crypto factors | 0.324 [0.090] |
| BiCKrak | 0.02  [0.020] |  | 0.960 [0.010] |
| CarrYB |  | 0.09  [0.083] | 0.06  [0.022] |
| MOMrabcn | 0.634 | 0.02 | 0.094 |
| [0.123 | [0.200 | [0.029] |
| MOM | 0.254  [0.059] | -0.10 [0.066] | -0.024 [0.009] |
| Volsc | 0.87 | 5.470 | 0.32 |
| [0.576] | [1.877] | [0.192] |
| Liquidity | -35.28  [19.624] | 3.45  [4.255] | 5.58 [5.101] |
| BidAsk | -0.84  [0.484] | 0.31  [0.566] | -0.35 [0.142] |
| AGoog | 0.01  [0.007] | -0.01  [0.015] | 0.00  [0.003] |
| DDoS | -0.114 [0.017] | -0.01  [0.029]  B.Noncrypto factors | -0.024 [0.005] |
| MKT | -0.04  [0.125] | -0.28 [0.334] | 0.04 [0.039] |
| SMB | -0.01 | 0.29 | -0.02 |
| [0.127] | [0.306] | [0.045] |
| HML | -0.12 | 0.14 | 0.02 |
| [0.111] | [0.267] | [0.041] |
| MOM | -0.07 [0.088] | 0.01  [0.194] | -0.01 [0.030] |
| CarrVFX | -0.00  [0.139] | -0.15 [0.296] | 0.06  [0.041] |
| Gold | -0.03 | 0.36 | -0.01 |
| [0.093] | [0.182] | [0.030] |
| △Vie | -0.00 | -0.05 | 0.00 |
| Adj.R²(% | [0.014] | [0.052] | [0.005] |
| 23.706 | 3.107 | 97.340 |
| F(%) | 0.000 | 1.174 | 0.000 |

This tablepresentsthe results of contemporaneous linar regressions of Carr ync,Btckakon,and Cross returns on

different noncrypto and crypto factors.Carrypeis the excess return of a zero-Cost cross strategy longin portfolio 7and short inportfolio 1;Crass is the return of a strategy long in all cross pairs.Portfolios are sorted by bitcoin discounts.BIcKakenis thereturn of the dollar-to-bitcoin pair on Kraken.Panel A groups the crypto factors,and panel B the noncrypto factors.Thecrypto factors are:the bitcoin(BiCxralan),carry(Carrynn),and two mo- mentum(MOMkaken MOMm)factors;the global FX volatility factor of Menkhoff etal.(2012a )for cryptos (Volse);the meanof Amihud (2002)'s illiquidity (Liquidity)and innovations to the bid/ask spread (BidAsk) across all pairs;the change in the Google Trend index for the query “bitcoin”(△Goog);the fraction ofinactive exchanges (DDoS).MOMRnkenis the cumulated bitcoin return over the previous 30 days(up to period t-2); MOMne is the return of a zero-cost strategy long (short)in a portfolio containing the pairs with the highest (owest)cross return in the previous 30 days.The noncrypto factors are:the Fama and French(1993) three equity factors(MKT,SMB,HML);the Carhart (1997) equity momentum factor(MOM);the currency carry trade(Carryx)factor,proxied by the return of the Deutsche Bank G10 currency carry trade ETF;the logprice changes for the GoldBullion (Gold),and the CBOE VIXvolatlity index(△Vix).The last row reports the p- values (in percentages)of an F-test onall coefficientsequal to zero (exdluding the constant).Dailydata come from theCryptocompare website(https://cryptocompare.com),Thomson Reuters,Bloomberg.Google,and the Kenneth French data library for the period May 26,2015,to May 26,2021.

*The Cross-Section ofCryptocurrency Retarns*

Downloaded from https://academ ic.oup.comf raps/art ic le/12 23 by Des Moines University - Osteopathic Medical Center useron 19 0ctober 2022

factors for currencies (see Lustig,Roussanov,and Verdelhan(2011)). MOMkraken and MOMpic are two crypto momentum factors.MOMkraken is the cumulated return of the dollar-to-bitcoin pair on Kraken over the previous 30 days.To construct MOMBtc,we first sort all pairs by the cross return in the previous 30 days and then consider the return of the zero-cost strategy long(short)the portfolio containing the pairs with the highest (low- est)past return.The latter is the crypto counterpart of the momentum factor for currencies proposed by Menkhoff,Sarno,Schmeling,and Schrimpf (2012b).The momentum factors can be interpreted in terms of investor sen- timent or overreaction channel (see Liu and Tsyvinski (2021)for cryptocur- rencies or Nicholas,Shleifer,and Vishny (1998)for equities).We further consider an increase in the Google Trend index for the query“bitcoin”on

*all geographical areas(△Goog)as proxy for investor sentiment,as it is asso-*

ciated with a greater interest for bitcoin.Liu and Tsyvinski(2021)consider this factor a proxy for investors'attention.Furthermore,we consider several proxies foraggregate crypto liquidity:VolBiccontains the crypto counterpart of the innovations to the global FX volatility factor of Menkhoff et al. (2012a);Liquidity and BidAsk are,respectively,the mean of the Amihud (2002)illiquidity indicator and the innovations to the bid/ask spread across all pairs.Finally,we consider the fraction of daily inactive exchanges(DDoS) as a proxy for bitcoin counterparty risk.

Panel B groups the noncrypto factors.Weconsider the standard Fama and French (1993) three factors(MKT,SMB,HML)and the Carhart(1997) momentum factor(MOM)for equities.In addition,we also include a proxy for the currency carry trade (CarryFx);the log price changes for the Gold Bullion (Gold);the CBOE VIX volatility index(△Vix).MKT,SMB,HML, and MOM are risk factors commonly used to price various types of assets, like equities and bonds,and are from the Kenneth French's website.Gold, like other precious metals,is considered a store of value,and a popular nar- rative considers cryptocurrencies an alternative to these precious metals.△ Vix captures movements in aggregate liquidity and investors'risk aversion. Data on gold prices and the VIX index are from Datastream.We proxy the currency carry trade factor with the return of the Deutsche Bank G10 cur- rency carry trade ETF,whose prices we obtain from Bloomberg.

We summarize our results as follows.First,we find that CarryBie,as well as BtcKraken,is unrelated to noncrypto factors,a finding that echoes Liu and

Tsyvinski (2021) results for aggregate bitcoin returns.Second,while it is difficult to relate BtcKraken returns to observable factors (excluding Volptc), we find thata sizeable fraction of the time-seriesvariation in CarryBicreturns can be explained by different crypto factors.Specifically,we find that CarryBic is lower when momentum returns are lower;when bitcoin liquidity risk is higher (i.e.,when the Amihud (2002)illiquidity measure and the inno- vations to the average bid/ask spread are higher).In addition,CarryBtc returns tend to be lower when the Google Trend index is lower,although

*Review of Asset Pricing Shudies /v12n32022*

Downloaded from [https://academic.oup.com/raps/article/12/3/667/6543623 by Des Moines University - Osteopathic Medical Center user on 190ctober 2022](https://academic.oup.com/raps/article/12/3/667/6543623byDesMoinesUniversity-OsteopathicMedicalCenteruseron190ctober2022)

this effectis estimated imprecisely.Further,CarryBie returns tend to be lower when the fraction of inactive exchanges is larger.These results highlight the fact that CarryBic returns are risky because they are high (low)in good (bad) times for bitcoin investors.Differently from what Menkhoff et al.(2012a ) show for currencies,we find that Carrybicreturns are not significantly related to innovations in global volatility.Because it is difficult to disentangle vola- tility and liquidity effects,the latter result might be explained by the fact that the two liquidity factors already capture the effect of global volatility.The significant relation between CarryBie return and the measure of counterparty risk(DDoS)is related to the technological evolution ofthe infrastructure of crypto exchanges and will probably diminish or disappear as a risk factor when the market is more mature.For CarryBtc,the adjusted R²is approxi- mately equal to 30%,in comparison to the adjusted R²for BtcKraken of 3.6%, and the intercept(a)is large and significantly different from zero at standard confidence levels.These results are robust with respect to a different window in the construction of the momentum factors.Finally,we confirm that Cross is fully explained by the bitcoin return.

Liu,Tsyvinski,and Wu (forthcoming)identify three crypto factors that price the cross-section of cryptocurrencies.The three factors are a cryptocur- rency market factor(CMKT),a cryptocurrency size factor (CSMB),and a cryptocurrency momentum factor(CMOM)and areonly available at weekly frequency.8They argue that the momentum effect is concentrated among the large coins and is consistent with recent theories of investors'overreaction; that the size effect is mainly concentrated among the smallest coins and is interpreted as an illiquidity premium;while the market factor is simply the bitcoin return.In Table Al1 (Section F of the Internet Appendix ),we show that CarryBtcis not spanned by either the cryptocurrency size factor(CSMB) or the cryptocurrency momentum factor (CMOM).Instead,we interpret CarryBie as a proxy for good times in crypto currency markets.In particular, we showthat CarryBiereturn is higher at times ofhigher liquidity andinvestor sentiment.

**3.Robustness**

In this section,we consider several extensions.First,we report additional characteristics of the bitcoin portfolios.Second,we carefully consider all transaction costs,like trading,margin and exchange fees.Third,we discuss Sharpe ratios for realistic portfoliosincluding crypto and non crypto assets. Fourth,we consider alternative samples with more pairs,like additional fiat and crypto currencies.Fourth,we consider execution risk,that is the risk that a transaction is not executed within the range of recent market prices

We are grateful to Yukun Liu for sharing the data on the thre factors,which are only available at weekly frequency.We interested readers to Liu,Tsyvinski,and Wu (forthcoming for details about the construction of the three factors and their interpretation.

*The Cross-Section ofCryptocurrency Retarns*

Downloaded from [https://academic.oup.com/raps/article/12/ 623 by Des Moines University - Osteopathic Medical Center useron 19 0ctober 2022](https://academic.oup.com/raps/article/12/623byDesMoinesUniversity-OsteopathicMedicalCenteruseron190ctober2022)

observed by investors.Sixth,we consider the properties of portfolios with a slower weekly rebalancing.

The main takeaway of this section is that CarryBicreturns remain large and significant after accounting for all transaction costs and in more recent sam- ples,or samples containing additional fiat-to-bitcoin,crypto-to-bitcoin and crypto-to-fiat pairs,and in portfolios rebalanced weekly.However,execution risk and trade size could substantially reduce CarryBtc returns

We further test the robustness of our results by considering an out-of- sample experiment using two randomly selected subsamples from our data. We use the CarryBtcfactor extracted from one random subsample to success- fully price the cross-section of portfolio returns obtained using the second random sample.

**3.1 Additional characteristics**

Table 6 presents additional characteristics of the bitcoin portfolios sorted by discounts.We find that corner portfolios,that is portfolios with the largest positive or negative discounts,are characterized,on average,by lower liquid- ity and higher counterparty risk.

A lower trading volume and higher bid/ask spreads and intraday volatility indicate lower liquidity;a smaller wallet size,larger fraction of inactive pairs, and a lower rating (measured by the exchange grade points assigned by CoinMarketCap),indicate higher counterparty risk.The wallet size of an exchange not onlycaptures the supply of bitcoins (i.e.,the number of bitcoins in circulation on a particular exchange)but also provides a measure of assets for an exchange,similar to deposits for a financial institution.

We consider as additional indicators of counterparty risk the mean frac- tion of inactive pairs and exchange rating for each portfolio.The fraction of inactive pairs is the average number of pairs not available at time t+1,but in which investors could have invest at time t.As a back-of-the-envelope cal- culation,consider that the average number of pairs per portfolio is equal to six.Therefore,when the fraction ofinactive pairs for a given portfolio isequal to 1%,there is one inactive pair in that portfolio every 16 days (1/(6×1%)≈16).the Cryptocompare website (https://cryptocompare. com)assignsa ratingto different exchanges,summarized by the grade points, where a higher number corresponds to a more reliable exchange.

The high/low spread,defined as the difference between the high and low daily bitcoin prices as a fraction of their average,also indicates a higher risk for investors because of the higher intraday volatility.The average degree of capital controls,measured by the overall restriction index ka from Fernández et al.(2016) ,is an indicator of the frictions that might prevent investors to

*Review ofAsset Pricing Shudies /v 12n32022*

Downloaded from htps:/lacadem ic.oup.com/raps/art ic le/12/3/667/6543623 by Des Moines Un ivers ity - Osteopath ic Medical Center useron 19 October 2022

**Table 6**

**Bitcoin portfolios:additional characteristics**

Portfolio 1 2 3 4 5 6 7

Mean SE

Mean SE

Mean SE

Mean SE

Mean SE

Mean SE

Mean SE

Mean SE

3.49 0.19

0.37 0.01

6.07 0.15

98.25 2.69

0.86 0.14

47.26 0.24

0.12 0.36

-0.05 0.01

5.19 0.19

0.24 0.01

5.82 0.13

111.49 2.94

0.13

0.05

50.04 0.21

0.10 0.29

-0.05 0.01

Volume (btc thousands)

|  |  |  |
| --- | --- | --- |
| 5.31 0.19  Bid-ask 0.19  0.01  High-low  5.79 0.18 | 4.84  0.19  spread(%)  0.20 0.01  spread (%)  5.76 0.13 | 4.45 0.24  0.20 0.01  5.80 0.15 |

Wallet (btc thousands)

|  |  |  |
| --- | --- | --- |
| 110.94 2.98  Fraction of 0.16  0.08  Exchange 51.24  0.19  Capital 0.09 | 111.90 3.03  inactive 0.13  0.05 | 99.10 3.03  pairs(%) 0.20 0.06 |
| grade points  51.40 51.21  0.18 0.19  control index  0.10 0.10 | |

0.24 0.23 0.21

Exchange rate growth (%)

0.03 0.01

-0.00

0.01

-0.03 0.01

4.18 0.21

0.24 0.01

5.71 0.13

94.91 2.84

0.15

0.05

49.66 0.21

0.12 0.27

0.03 0.01

2.90

0.11

0.43 0.01

6.01 0.14

94.67 2.35

0.50 0.09

45.95

0.16

0.14 0.26

0.03 0.01

This table reports additional characteristics oftheseven portfolios sorted by bitcoin discounts.The addtional characteristicsaretrading volume (in thousands of bitcoins);bid/ask spread (in percentage);high/lowspread (in percentage);wallet size(in thousands of bitcoins);fraction of inactive pairs (in percentage);exchange grade points;and capital control indexandexchange rate growth(in percentage).Ateach point in time t,and for each portfoliok,wecompute the equally weighted averagefor each characteristic.Each panel reports mean,standard deviation and standard eror by bootstrap estimated over the sampleMay 26,2015,to May 25,2021.The high/ lowspread is the difference betweenthe high and low daily bitcoin pricesas afraction of their average.Details on the definition ofinactive pairs and walle sizeare in Section 3.Daily data come fromthe Cryptocompare website (https://cryptocompare.com)andThomson Reuters.The exchange grade points are from the Cryptocompare and are constant for each exchange throughout the sample (a higher number corresponds to a more rehable exchange).Thecapital control indexistheoverall restriction index ka from Fernández etal.(2016)(kais equal to 0.125 for the United States in 2019;a higher number is associated to more restrictions).Exchange wallets are manually obtained from Walletexplorer.Note that the ka is available at anmual frequency up to 2019.For the sample since 2019,we fix ka to the last available values.

execute their trades.With respect to both of these measures,we do not find significant differences across portfolios.9

Finally,we observe that by sorting pairs by their discounts we obtain an increasing cross-section of average exchange rate growth (i.e.,the change in the value of fat currencies with respect to the dollar).Note that the average exchange rate growth is negative and significant for portfolio 1 (i.e.,a dollar depreciation),and positive and significant for portfolio 7(i.e.,a dollar ap- preciation).Although economically small,the effect of the change in the exchange rate further increases the risk of the long/short strategy.For



9 As reference,ka is equal to 0.13 for the United Statesat the end of 2019,and the averagevalue acrossthe seven portfolios is equal to 0.11 (lower values correspond to looser capitalcontrol levdls).

*The Cross-Section ofCryptocurrency Retarns*

Downloaded from https:; /lacadem ic.oup.com/raps/art ic le/12/3 323 by Des Moines University - Osteopathic Medical Center user on 190ctober 2022

example,an investorlong in portfolio 7,on average,exchanges fiat currency for dollars at a lower rate.

**3.2 Transaction costs**

We now show how the returns of the two investment strategies change after accounting for all transaction costs,that is bid/ask spreads and trading fees To roughly estimate the impact of transaction costs,note that themean daily bid/ask spread is 27 basis points (Table 6),and the average trading fee is 15 basis points per trade (Table A3 in Section B.I of the Internet Appendix ). Investors pay these costs twice for the within strategy,but only once for the cross strategy.This is because the cross strategy always involves one of the two trades on the benchmark pair,the dollar-to-bitcoin pair on the Kraken exchange,for which these costs are negligible.

In what follows,we carefully consider the heterogeneity in bid/ask spreads across portfolios;the market depth;and all trading and margin fees that can potentially affect returns.We focus on both the cross and within strategies and only on the long/short returns.Recall that,for cross investors,the long/ short strategy goes short in the first portfolio,with the most negative dis- count.On the contrary,for within investors,the long/short strategy goes short in the last portfolio,with the most positive discount.Bitcoin investors must additionally pay deposit and withdrawal fees to the exchanges;trading fees and margin fees when entering short positions.

Table 7 documents the impact of the different transaction costs on the long/short returns.The left side of the table refers to cross returns,while the right side refers to within returns.Panel A reports gross average portfolios returns,and panels B to E report average portfolio returns for different specifications of the transaction costs.

Panel B reports the average portfolio returns net of bid/ask spreads,where thebid/ask spreads are those for the subset of 33 pairsforwhich we were able to collect data on Bitcoinity.As highlighted in the discussion of Table 2,bid/ ask spreads have a differential impact across portfolios.Specifically,average returns decrease more for corner portfolios.Panel C additionally accounts for trading fees,which uniformly lower returns by 37 basis points for cross portfolios and by 67 basis points for within portfolios.After accounting for bid/ask spreads,net returns of long/short within strategies are negative.For this reason,in what follows we focus on the impact of additional transaction costs and frictions only on cross portfolios.

To evaluate the likelyimpact of trading feeson the croSs-section of portfolio returns,we manually collect current trading fees for all the exchanges in our sample.For all exchanges,except Kraken,we fix trading fees to 0.15%,which corresponds tothe median taker trading fee.Taker fees are charged to invest- ors who absorb liquidity with market orders,as opposed to maker fees,which are charged to investors who provide liquidity by placing limit orders.

Downloaded from https:l/academ ic.oup.com/raps/art ic le/12/3/667/6543623 by Des Moines Un ivers ity- Osteopath ic Medical Center useron 19 October 2022

**Table 7**

**Bitcoin portfolios:Long/short returns**

Cross returns long/short:rai+1-rx'+1 Within returns long/short:rxi+1-rx+

Portfolio 2-1 3-1 4-1 5-1 6-1 7-1 1-7 2-7 3-7 4-7 5-7 6-7

|  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Mean SE | 0.25 0.12 | 0.30 0.12 | A.Gross returns | | | | | | | | | 0.32 0.12 |
| 0.40 0.12 | 0.51 0.11 | 0.72 0.12 | 1.39 0.11 | 1.12 0.13 | 0.65 0.12 | 0.50 0.12 | 0.44  0.12 | 0.37  0.12 |
| B.Net o bid-ask | | | | | | | | |
| Mean SE | -0.16 0.04 | -0.07 0.04 | 0.02 0.12 0.29 0.90 0.26 0.04 -0.04 -0.12 -0.20  0.05 0.05 0.05 0.06 0.05 0.03 0.03 0.04 0.03  C.Trading fees &net of bid-ask | | | | | | | | | -0.32 0.03 |
| Mean SE | -0.53 0.04 | -0.44 0.04 | -0.35 -0.25 -0.08 0.53 -0.41 -0.63 -0.7 1  0.06 0.05 0.05 0.06 0.05 0.03 0.03  D.Net oftrading fees &bid-ask (synthetic) | | | | | | | -0.79 0.03 | -0.87 0.03 | -0.99  0.03 |
| Mean SE | -0.73 0.04 | -0.63 0.04 | -0.53 -0.43 -0.27 0.21 -1.04 -1.24 -1.29  0.05 0.05 0.05 0.06 0.06 0.04 0.04  E.Net of trading fees &bid-ask (10 bte depth) | | | | | | | -1.36 0.04 | -1.44 0.03 | -1.57 0.03 |
| Mean SE | -1.98 0.07 | -1.81 0.07 | -1.74 -1.72  0. 08 0.06 | | -1.69  0.07 | -1.29  0.07 | -3.67  0.06 | -2.97  0.04 | -2.88  0.04 | -3.01 0.04 | -3.24 0.03 | -3.66 0.03 |

This table reports the mean and standarderrors for thereturns on long/short cros and within portfolios.For

cross portfolios,thelong/shortstrategy goes long in portfolio k=2,..,7and short in the first portfolio.For withinportfolios,the long/short strategy goes longin portfoliok=1,...,6 and short in the last portfolio.Panel A corresponds to gross portfolioreturns.Panel B to returns net of bid/ask spreads for thesubsample of bitcoin- to-fiat pairs for which we obtained bid/ask spreads from https:/ldata.bitcoinity.org.Panel C to returns that additionally account for trading fees.Pane D toreturns net of sywthetic bid/ask spreads and trading fees.The synthetic bid/ask spreads are generated for all the bitcoin-to-fiat pairs using thepredicted values from panel regressions of the availablebid/ask spreads on the historical market data.Panel Ecorresponds toreturns net of trading fes and bid/ask spreads at themarket depth of 10 bitcoins.Daily data come from the Cryptocompare website(https://cryptocompare.com),Bitcoinity,and Thomson Reuters for the periodMay 26,2015,to May25, 2021.

Therefore,we implicitly assume investors post their offers,which are,then executed within the horizon of one day.For the exchanges in our sample,the conservative estimates for the median taker and maker fees are,respectively, 0.25%and 0.15%.These values are calculated based on maximum fees for investors,but exchanges typically employ an asymmetric pricing model with fee discounts in order to incentivize higher levels of trading activity.As for Kraken,we fix the trading fee to 0%,which corresponds to the current fee charged to investors with total orders larger than US$10 million in a month. Our choice ismotivated by the factthat,for thecrossstrategy,investors always start on Kraken,so that we should expect a large number of orders in a given month on this exchange.Table A3 in the Internet Appendix presents detailed information on trading fees for all exchanges.Finally,we fix the margin fee required to maintain a short position on Kraken to 0.07%,which corresponds to the current opening fee plus the roll-over positions for 24 hours.

After accounting for both bid/ask spreads and trading fees,long/short returns for portfolio 7 are positive and statistically different from zero, and,as for our baseline portfolios,the Patton andTimmermann(2010) tests reject the null of flat or weakly decreasing pattern against the alternative of the strictly increasing pattern.Since measures of the historical bid/ask spreads are not available for all our pairs,in panels B and C,we use gross

*The Cross-Section ofCryptocurrency Retarns*

Downloaded from https://academ ic.oup.comf raps/art ic le/12r 3623 by Des Moines University - Osteopathic Medical Center useron 19 0ctober 2022

returns based on all available pairs,while bid-ask spreads are based on the subsample of available pairs.In panel D,we generate synthetic bid/ask spreads for all the pairs estimating the panel described in Equation (5).We find that,also in this case,the long/short returns for the last portfolio are positive and statistically significant.

Finally,panel E reports average returns net of trading fees and bid/ask spreads at the market depth of 10 BTC (approximately US$300,000 at the end of the sample),to account for sizeable trading positions.In this case, returns for all portfolios are large and negative.Therefore,the size of trades matters:once we account for market depth,returns become large and neg- ative at orders larger than US$300,000,which correspond to approximately 6%ofthe daily median trading volume and is five times larger than the 10th percentile.Market depth introduces a constraint on the maximum trade size to obtain non-negative expected returns,which influences the likelihood that large investors would engage in this trade and the opportunity for investorsto fully absorb bitcoin price differences.

**3.3 Sharpe ratios and crypto shares**

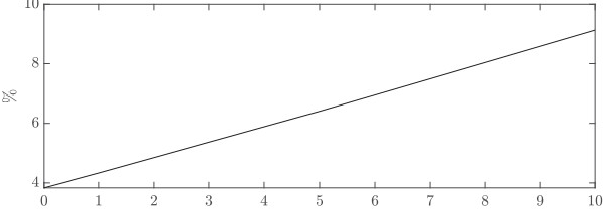
In Table 2,we presented the properties of seven portfolios sorted by bitcoin discounts for two strategies,that is the cross and within strategies.In our discussion,we highlighted the very large Sharpe ratios associated with these portfolios,even after accounting for bid/ask spreads.Specifically,we docu- mented a daily Sharpe ratio of 26%for the long/short cross strategy,and of 17%for the long/short within strategy.These figures are large compared,for example,with the Sharpe ratio of the U.S.equity market over the same period (i.e.,approximately 4%).

Because the typical investor does not have all of her wealth invested in these strategies,a more meaningful comparison for the risky proxy calculation is probably to consider an investor who holds a relatively small fraction of her portfolio in crypto assets,and the restin traditional assets,for examplethe U.S. equity market. Figure 4 illustrates this comparison by reporting the daily Sharpe ratios of portfolios with a weight w that goes from 0%to 10%in the long/short crypto strategy,and with a weight 1-w in the U.S.equity market portfolio.The figure illustrates asimple point:investing a small fraction of your aggregate portfolio in the long/short strategies would increase the portfolio Sharpe ratio only marginally.For example,for the cross strategy,a portfolio witha weight of 1%incrypto would be associatedwitha Sharpe ratioof 4.3%.

**3.4 Alternative samples**

Table 8 documents the average portfolio discounts and net cross and within returns for alternative samples.All samples end on May 25,2021,while the starting dates differ as we will describe below.

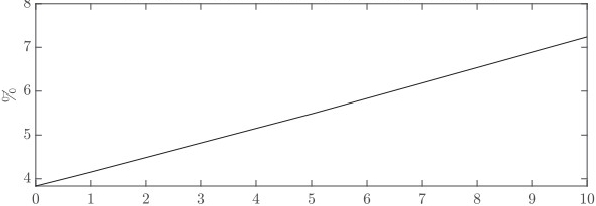
Downloaded from https:l/academ ic.oup.com/raps/art ic le/12/3/667/6543623 by Des Moines Un ivers ity- Osteopath ic Medical Center useron 19 October 2022



Sharpe ratios long/short cross and equity market

crypto share(%)

Sharpe ratios long/short within and equity market



crypto share(%)

**Figure 4**

**Sharpe ratios and crypto shares**

**This figure plots the Sharpe ratio**s associatedwith portfoliosinvestedwitha weightw that goes from0%to 10% in the long/short crypto strategy,and with a weight 1-w inthe U.S.equity market portfolio.The top pane corresponds to the crass strategy and the bottom panel corresponds to the within strategy.Daily data come from theCryptocompare website (https://cryptocompare.com)and Thomson Reuters.The sample period is May 26,2015,to May 25,2021.

Panel A,for convenience,summarizes the baseline results also reported in Table 2.Panel B considers a shorter sample for the same pairs;the sample starts on January 2,2018,when crypto“came of age”and after the bitcoin frenzy of 2017.Also in this sample,cross net returns increase monotonically from the last to the first portfolio.The average long/short return is 46 basis points per day,statistically different from zero at conventional levels and very close to the value obtained in the longer sample.Similarly to the baseline sample,within portfolio net returns decrease from portfolio 1 to portfolio 7, but are negative for all portfolios.

Panel C considers a sample that includes a larger set of the fiat-to-bitcoin pairs available on the Cryptocompare website (https://cryptocompare. com).10 Also in this sample,cross net returns are monotonically increasing from the last to the first portfolio.Returns are,on average,higher than in the

10 The sampleincludes 146 pairsfor 15 fat-to-bitcoinpairs traded on 81 exchanges located in 27 countries around the world.The additional fiat currenciesare Brazilian real,Chinese yuan,Hong Kong dollar,Korean won, Mexican peso,Russian ruble,Singapore dollar,Ukrainian hrywnia.

*The Cross-Section ofCryptocurrency Retarns*

Downloaded from https:l/academ ic.oup.com/raps/art ic le/12/3/667/6543623 by Des Moines Un ivers ity- Osteopath ic Medical Center useron 19 October 2022

**Table 8**

**Bitcoin portfolios:alternative samples**

Porifolia 1 2 3 4 5 6 7 Long/short

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  |  | A.Baselne sample |  |  |
|  |  | Discounts |  |  |
| Mean | -0.97 -0.28 -0.08 | 0.08 0.26 0.51 | 1.52 |  |
| SE | 0.04 0.02 0.02 | 0.02 0.02 0.02 | 0.05 |  |
| Mean | -0.23 0.15 0.26 | Cross net returns  0.35 0.46 0.62 | 1.10 | 0.59 |
| SE | 0.12 0.11 0.11 | 0.12 0.12 0.12  Withi nct returns | 0.12 | 0.06 |
| Mean | 0.46 0.26 0.22 | 0.14 0.07 -0.07 | -0.77 | -0.37 |
| SE | 0.12 0.12 0.12 | 0.12 0.12 0.11  B.Baseline sample,since 2018 | 0.12 | 0.06 |
| Mean | -0.75 -0.18 -0.05 | Discounts  0.06 0.18 0.37 | 1.16 |  |
| SE | 0.03 0.01 0.01 | 0.01 0.01 0.02 | 0.05 |  |
| Mean | -0.47 -0.01 0.07 | Cro8s net returns  0.11 0.13 0.27 | 0.74 | **0.46** |
| SE | 0.17 0.17 0.16 | 0.17 0.16 0.16  Within net returns | 0.18 | **0.05** |
| Mean | -0.06 -0.04 -0.04 | —0.10 -0.22 —0.29 | -0.69 | **-0.56** |
| SE | 0.17 0.16 0.16 | 0.17 0.17 0.16  C.All fial-to-bitcoin pairs Discounts | 0.15 | **0.04** |
| Mean | -1.94 -0.39 -0.02 | 0.25 0.61 1.29 | 4.31 |  |
| SE | 0.05 0.02 0.02 | 0.02 0.03 0.04 | 0.09 |  |
| Mean | -0.97 0.10 0.35 | Cross net returns  0.47 0.71 1.16 | 3.94 | **4.36** |
| SE | 0.12 0.12 0.12 | 0.12 0.12 0.12 | 0.16 | **0.13** |
| Mean | 0.80 0.34 0.26 | Withi nct returns  0.09 —0.06 -0.36 | -0.72 | **-0.04** |
| SE | 0.12 0.12 0.12  D.Al/crypto-10-bitcoi pairs | 0.12 0.12 0.11 | 0.15 | **0.10** |
| Mean | -2.95 -0.43 -0.14 | Discounts  -0.02 0.08 0.26 | 1.91 |  |
| SE | 0.11 0.02 0.00 | 0.00 0.00 0.01 | 0.05 |  |
| Mean | -0.28 -0.02 0.26 | Cross gross returns  0.62 0.52 0.17 | 0.71 | **0.99** |
| SE | 0.32 0.15 0.19 | 0.33 0.27 0.18  Wihin gross returns | 0.21 | **0.13** |
| Mean | 3.10 0.42 0.43 | 0.79 0.48 -0.09 | -0.97 | **4.07** |
| SE | 0.40 0.16 0.21 | 0.42 0.33 0.18  E.All cryptO-10-fiat pairs | 0.24 | 0.11 |
| Mean | -2.03 -0.52 -0.20 | Discounts  0.03 0.32 0.81 | 2.94 |  |
| SE | 0.05 0.02 0.02 | 0.01 0.02 0.03  Cross gross returns | 0.07 |  |
| Mean | -0.00 0.42 0.46 | 0.55 0.69 1.08 | 2.13 | **2.13** |
| SE | 0.13 0.13 0.13 | 0.13 0.14 0.13  Within gnoss returng | 0.13 | 0.13 |
| Mean | 2.13 0.93 0.65 | 0.50 0.37 0.26 | -0.71 | **2.84** |
| SE | 0.15 0.15 0.14 | 0.15 0.13 0.13 | 0.14 | 0.11 |

This table reports,for each potfolio jand different samples,the means and bootstrap standard errors of the average discountsand cross and within returns for portfolios sorted by bitcoin discounts.All samples end on May 25,2021.The long/shortreturns are in bold.Pane A corresponds to the baseline sample and aperiod starting May 26,2015.Panel B considers thesame pairs over a shorter period starting January 2,2018.PanelC considers a sample that indudes a larger set of the fiat-to-bitcoin pairs available on the Cryptocompare website(https:// cryptocompare.com)for a period starting May26,2015.PanelDand Econsider,respectively,asample containing 411 crypto-to-bitcoin pairs and 274 crypto-to-fiatpairs(exduding bitcoim)for a period starting March 31,2016. The crypto pairs in panels Dand Eare ADA,BCH,DOGE,EOS,EIC,ETH,LTC,XLM,XMR,and XRP. Thefiat pairs in panel Eare AUD,CAD,CHF,EUR,GBP,JPY,PLN,and USD.All returns,with theexception of those of Panel D and E,are net of bid/askspreads.All returns are in umits of dollars per bitcoin except those reportedin panelDwhich are inunits of ETHper bitcoinand paned Ewhich areinunits of dollarsperETH.Daily data come from the Cryptocompare website (https:/cryptocompare com),Bitcoinity,and Thomson Reuters.

*Review of Asset Pricing Shudies /v 12n32022*

Downloaded from [https://academic.oup.com/raps/article/12/3/667/6543623 by Des Moines University - Osteopathic Medical Center user on 190ctober 2022](https://academic.oup.com/raps/article/12/3/667/6543623byDesMoinesUniversity-OsteopathicMedicalCenteruseron190ctober2022)

baseline sample and the mean long/short return is equal to 436 basis points per day and statistically different from zero.However,these large returns are most likely not attainable.In fact,this sample includes pairs from countries with restrictions on capital fows,limiting investors'ability to transfer money in,and out of,some of the exchanges.Although some of the capital control measures are likely to bite more retail than large investors (Baba and Kokenyne,2011 ),they are likely to make the cross strategy difficult to im- plement.Further,according to various quality indicators some of the exchanges are less reliable and some of the pairs are associated with lower trading volume.Similarly to the baseline sample,within returns decline monotonically from the first to the last portfolio,and the long/short return is negative and not statistically different from zero after accounting for bid/ ask spreads.

Panel D considers a sample containing several crypto-to-bitcoin pairs for a period starting on March 31,2016,when data for a number of pairs sufficient to build portfolios are available.Specifically,we include 411 pairs traded on 87 exchanges for 10 of the most-traded cryptocurrencies against bitcoin. For each crypto-to-bitcoin pair,we select from the Cryptocompare website (https://cryptocompare.com)the exchange-pairs corresponding to the top 20 in terms of trading volume as of May 2021,and compute prices and returns measured in units of ETH per bitcoin,and discounts with respect to the ethereum-to-bitcoin pair on Kraken.We focus on gross returns because of the unavailability of the historical bid/ask spreads for most of the pairs.Even though transferring cryptocurrencies,as opposed to fiat currencies,should be less restrictive from the perspective of domestic regulations of international flows,we document a large cross-section of discounts,from-2.95%on the first portfolio to 1.91%on the last portfolio.Also for this sample,we find evidence of economically large increasing cross returns and decreasing within returns.The mean return on the long/short strategies is positive,statistically different from zero,and larger thanfor the bitcoin pairs.Thisis not surprising as these returns are before transaction costs,which are likely to be larger for crypto pairs different from bitcoin,because these pairs tend to be less liquid. However,because of the unavailability of the historical bid/ask spreads for most of the pairs,we could not test this conjecture.

Finally,panel E considers a sample containing 274 crypto-to-fiat pairs, excluding bitcoin,for a period starting on March 31,2016,when data for a number of pairs sufficient to build portfolios are available.Specifically,we consider the same cryptocurrencies included in the sample from panel D and the following eight fiat currencies:Australian dollar,Canadian dollar,Swiss franc,Euro,British pound,Japanese yen,Polish zlot,and U.S.dollar.These pairs are traded on 29 exchanges and we compute prices and returns



11 The 10 cryptocurrencies are cardano (ADA),bitcoin cash (BCH),dogecoin (DOGE),EOS,ethereum cash (ETC),ethereum(ETH),litecoin (LTH),stellar(XLM),monero(XMR),and ripple (XRP)

Downloaded from [https://academic.oup.com/raps/article/12/3/667/6543623 by Des Moines University - Osteopathic Medical Center user on 190ctober 2022](https://academic.oup.com/raps/article/12/3/667/6543623byDesMoinesUniversity-OsteopathicMedicalCenteruseron190ctober2022)

**Table 9**

**Execution risks**

*portfolios*

*Within*

portfolios

Cross

|  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Porfolio 1 | 2 | 3 | 4 | 5 | 6 | 7 | 1 | 2 | 3 | 4 | 5 | 6 | 7 |

A.Baseline gross retuns

Mean 0.140.390.450.550.660.861.531.150.680.530.470.400.350.03

SE 0.120.120.120.120.110.120.110.130.120.120.120.120.120.11

B.Sell at zero price when exchangeshutdowns

Mean -0.730.260.290.420.460.711.030.260.550.370.350.200.20-0.46

SE 0.180.130.140.130.130.130.160.190.130.140.130.140.130.15

C.Sell at low price of the day

Mean -3.30-2.88 -2.74 -2.67-2.55-2.33-1.69-2.35-2.61 -2.66-2.74-2.80-2.81-3.13

SE 0.110.110.110.110.110.100.110.110.110.110.110.110.110.11

D.Sell at mean low/high price of the day

Mean -1.58-1.25-1.15-1.06-0.95-0.73-0.08 -0.60-0.96-1.06-1.14-1.20-1.23-1.55

SE 0.110.100.100.110.100.110.110.110.100.110.100.100.110.11

This table reports,for each portfolioj,the mean crass and within returns,and correspondingstandard errors by bootstrap,for the seven portfolios sorted by bitcoin discounts.Panel A reports the baseline gross returns.In panelB,we assume that investorsalways close theirtrades ata price of zeroif apair available at time r then drops out ofthe sample att+1.In panel C,we assume thatinvestorsdose their trades att+1 always at thelowest price of the day for a given exchange-currency pair.In panelD,weassume that investorsclose their trades att+ 1 always at themeanbetweenthe dosing and the lowestprice of the day.Allreturns arebefore transaction costs. Dailydata come from the Cryptocompare website (https://cryptocompare.com)and Thomson Reuters.The sample period is May 26,2015,to May 25,2021.

measured in units of dollar per ETH and discounts with respect to the ethereum-to-dollar pair on Kraken.Also in this sample,we find a large croSs-section of discounts,from-2.03%on the first portfolio to 2.94%on the last portfolio,which is matched by an increasing cross-section of cross returns and a declining cross-section of within returns.The mean return on the long/short strategies is positive,large and statistically different from zero, although we note that returns are before transaction costs because of the unavailability of the historical bid/ask spreads for most of the pairs.

**3.5 Execution risk**

Bitcoin investors are exposed to different forms of execution risks.While all investors face the risk that they cannot execute a transaction within the range of market prices observed before sending their orders,cross investors face additional risks related to the transfer of balances across exchanges.

Table 9 documents the effect of different forms of execution risk.In our baseline analysis,when a pair is available at time t,but not at time t+1,we assume that investors close their trade at the median closing price across all pairs.We referto this situation as an“exchange shutdown.”These eventscan be temporary,for example because ofa software malfunctioning or denial-of- service attack,or permanentin case of bankruptcy.While panel A reports the baseline cross and within portfolio returns,and panel B documents average returns under the more conservative assumption that investors mustsell their balance at a zero price (i.e.,fora-100%return).In thiscase,average returns

Downloaded from https:; /lacadem ic.oup.com/raps/art ic le/12/3/667/6543623 by Des Moines Un ivers ity - Osteopath ic Medical Center user on 19 October 2022

are lower.For cross portfolios,the average return on portfolio 7 remains highly significant.In contrast,for within portfolios,the average return on portfolio 1 becomes not statistically different from zero. Table A6 in Section Dof the Internet Appendix reports estimates of the returns forinvestors who had their balances stuck in an exchange because of a long shutdown.Under the assumption thatinvestors sell their balance at the price of the day in which the exchange finally reopens,we show that returns are,on average,slightly negative.l²

The definition of excess returns from Equation(3) relies on the assumption of near-instant speed ofexecution at daily closing prices.Completing a trade requires the time to transfer bitcoins across exchanges and to execute a trade within the exchange.It is difficult to exactly quantify these amounts of time, as they both depend on the type ofinvestor(i.e.,retail or hedge fund)and the state of the network.The time required by the bitcoin blockchain to transfer bitcoins across exchange wallets depends on the congestion of the network and has recently ranged anywhere between 10 minutes to 24 hours.On the other hand,trade execution within an exchange is much faster,with only 3.95%of trades taking longer than one second to be executed for the largest exchanges (Krückeberg and Scholz (2020),but with delays for some of the exchanges(e.g.,Bitfinex's average order execution delay is 156milliseconds). Panels C and D report returns under different scenarios.Panel C assumes thatinvestors always sellat the lowest price of the day for a given pair.In this case,we obtain a cross-section of both cross and within returns,but the av- erage returns are large and negative for all portfolios,dropping by an average of325 basis points.Returns reported in panel D are based on the assumption that investors always sell at the average price between the high and the low price of the day for a given pair.In this case,all portfolio returns are negative and the average return drops by 162 basis points.In sum,our results indicate that bitcoin execution risk can significantly lower thereturns to investors and contributes to explain bitcoin price differences acrossexchanges and currency pairs.The effects of execution risk are likely to play a smallerrole in the future as the technological infrastructure of exchanges evolves to reduce these risks.13



12 Moore and Christin(2013) find that,by early 2013,45%of bitcoin exchanges had dosed,and many of the remaining markets were subject to frequent outages andsecurity breaches,while Vasekand Moore (2015) document several denial-of-service attacks against cryptocurrency exchanges.In our sample,on a given day, approximately 14%of the pairs are not available (se Figure All in the Internet Appendix).The numbers reportedin Table 6correspondto thefractionof pairs active at time t,but not at timet+1.Finally, Table A5in the Internet Appendix lists critical events for the largest cryptocurrency exchanges.

13 In the InternetAppendix,wepresent additional evidence about execution risk.Section FXI shows that pairs in the corner portfolios are less liquid,asmeasured by theAmihud(2002)illiquidity measure.For the spot currency market,Ranaldo and Santucci de Magistris (2019)show that violations of the triangular arbitrage parity are more likely for lesliquid pairs.Section G shows that corner portfolios arealso associated with higher idiosyn- cratic risk,which couldmotivate an alternative explanation for thedocumented cross-sction of returns based on costly arbitrage and idiosyncratic risk(Pontiff,1996).

Downloaded from https:l/academ ic.oup.com/raps/art ic le/12/3/667/6543623 by Des Moines Un ivers ity- Osteopath ic Medical Center useron 19 October 2022

**Table 10**

**Bitcoin portfolios:U.S.investor (weekly frequency)**

Portfolio 1 2 3 4 5 6 7 Long/short

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
|  |  |  | A.Discounts |  |  |
| Mean | -1.00 | -0.26 | -0.04 0.12 0.31 0.57 | 1.60 |  |
| SD | 1.63 | 0.65 | 0.54 0.57 0.79 1.02  B.Cross returns | 1.71 | 7-1 |
| Mean | 2.14 | 2.22 | Gross returns  2.45 2.46 2.59 2.77 | 3.22 | 1.08 |
| SD | 11.04 | 10.73 | 11.43 11.00 10.98 11.00 | 10.95 | 1.80 |
| SE | 0.62 | 0.61 | 0.67 0.65 0.63 0.61 | 0.62 | 0.10 |
| SR | 0.19 | 0.21 | 0.21 0.22 0.24 0.25  Returns net of bid/ask | 0.29 | 0.60 |
| Mean | 1.77 | 1.99 | 2.26 2.28 2.39 2.54 | 2.80 | 0.27 |
| SD | 11.10 | 10.72 | 11.39 11.01 11.01 11.02 | 11.02 | 1.95 |
| SE | 0.63 | 0.62 | 0.64 0.61 0.64 0.63 | 0.62 | 0.11 |
| SR | 0.16 | 0.19 | 0.20 0.21 0.22 0.23  C.Within returns | 0.25 | 0.14 1-7 |
| Mean | 3.19 | 2.49 | Gross returns  2.49 2.34 2.27 2.19 | 1.62 | 1.56 |
| SD | 11.12 | 10.76 | 11.40 10.96 10.91 10.90 | 10.75 | 2.60 |
| SE | 0.65 | 0.62 | 0.63 0.62 0.63 0.61 | 0.63 | 0.15 |
| SR | 0.29 | 0.23 | 0.22 0.21 0.21 0.20  Returns net of bid/ask | 0.15 | 0.60 |
| Mean | 2.50 | 2.07 | 2.16 2.04 1.91 1.79 | 0.83 | 0.08 |
| SD | 11.16 | 10.81 | 11.38 10.97 10.95 10.93 | 10.87 | 2.34 |
| SE | 0.65 | 0.62 | 0.66 0.63 0.62 0.64 | 0.61 | 0.12 |
| SR | 0.22 | 0.19 | 0.19 0.19 0.17 0.16 | 0.08 | 0.04 |

This table reports,for each portfolio,the mean and standard deviation for bitcoindiscounts;the excess cross returns,and the high-minus-low returns from a zero-cost strategy 7-1;and the excess within returns,and the high-minus-low returns from a zero-cost strategy 1-7.For returns,we also report standard errors by bootstrap andgross and net returns.We divideeach year into 52weeks.Thefirst week of the year consists of the first 7days of the year.Thefirst 5l weeks of the year consist of 7 days each and the last week of the year consists of thelast 8days of the year.For both the crass and within returns,the holding period isequal to 5 days,because weexdude nonbusiness days,like Saturdays and Sundays.Transaction costs indudebid-ask spreads,but do not include trading,margin,and exchangefees.Portfolios are constructed by sorting assets into seven groups at time t by their discounts.The first portfolio contains assets withthe lowest negative discounts.The last portfolio contains assets with the highest positive discounts.Weeklydata come from the Cryptocomparewebsite(https://crypto- compare.com)and Thomson Reuters.The sample period is May 27,2015,to May 20,2021.

**3.6 Weekly rebalancing**

In our baseline analysis,we consider a period of 1 day and form daily bitcoin portfolios.One reason of concern is the implementability of the cross and within strategies at the daily frequency.For example,the time to execute a trade on a given exchange,and the convertibility in fiat currencies and the transfer of balances across different exchanges,might put a constraint on the rebalancing frequency.On the other hand,a slower frequency ofrebalancing might reduce transaction costs (i.e.,bid/ask spreads and trading fees),thereby substantially reducing daily returns.In this section,we show that our results also hold at a lower frequency of trading.

We leave the details about the construction of the weekly portfolios to Section F.VIin the Internet Appendix and present here the properties of the weekly portfolios (see Table 10).Panel A reports the average bitcoin dis- counts.The mean discounts increase monotonically from-100 basis points

*Review of Asset Pricing Shudies /v12n32022*

Downloaded from https:; /lacadem ic.oup.com/raps/art ic le/12/3/667/6543623 by Des Moines Un ivers ity - Osteopath ic Medical Center user on 19 October 2022

for the first portfolio to 160 basis points for the last portfolio.We start with the description of cross portfolio returns (panel B).Similarly to the sample at the daily frequency,also at the weekly frequency excess returns increase monotonically across portfolios:gross returns increase from approximately 214 basis points to 322 basis points per week.The long/short 7-1 average return,before transaction costs,is equal to 108 basis points.Accounting for the bid/ask spread reduces the average long/short return by approximately 81 basis points.The net average long/short return is equal to 27 basis point,and is statistically different from zero (the standard error is equal to 11 basis points).To facilitate the comparison with the portfolios at daily frequency, we recall that the average net long/short return at the daily frequencyis equal to 59 basis points per day and,thus,one order of magnitude larger than the average net long/short return at the weekly frequency (i.e.,27/5=5.4 basis points per day,where 5 is the number of days in the holding period).PanelC considers within returns.Also,in this case,we qualitatively replicate the results of the portfolios at daily frequency.Specifically,we obtain a mono- tonically decreasing cross-section of portfolio gross and net returns.Note that the average portfolio net returns are positive for all portfolios,while the average net long/short within return is equal to 8 basis points per week,but not statistically different from zero.

**3.7 Out-of-sample**

We investigate whether our results hold out-of-sample by constructing two nonoverlapping randomselected groups of approximately the same size from the universe of pairs of the baseline sample.First,we form portfolios sorted by bitcoin discounts for each of the two groups.Because of the lower number of pairs per group,we now form only five portfolios.We obtain a monoton- ically increasing cross-section of cross net returns in both samples (see Table A12 in Section F of the Internet Appendix).Second,we construct the CarryBicfactor from portfolio returns of the first group,and repeat the asset pricing exercise using as test assets the portfolios of the second group.Note that,as the portfolios are formed using two nonoverlapping sets of pairs, CarryBic is constructed from pairs that are different with respect to those contained in the portfolios used as test assets.Specifically,CarryBtcis now the return from a zero-cost strategy that goes long in portfolio 5 and short in portfolio I from the first sample.We find that the estimate for the market price of the CarryBicfactor is significant and similar to the one weobtain in our baseline asset pricing estimation.The full asset pricing results are reportedin Table A13 in Section Fofthe Internet Appendix.

Downloaded from htps:/lacadem ic.oup.com raps lat ic le/12/3/66716543623 by Des Moines Un ivers ity - Osteopath ic Medical Center useron 19October 2022

**4.Conclusions**

Common explanations of the large bitcoin price differences across exchanges and currency pairs are limits to arbitrage and market efficiency,as argued in the influential paper by Makarov andSchoar(2019).Accordingto this view, cryptocurrencies are not a“normal”asset class.In this paper,we propose a more balanced view and show that while there are some arbitrage-like op- portunities,they are not riskless.

We propose a novel risk-based explanation of bitcoin price differences and carefully account for all the transaction costs and limitations to trade.Bitcoin prices for more“expensive”pairs depreciate more in bad times for crypto- currency investors,when aggregate liquidity is lower and more uncertain,and investor sentiment about bitcoin is lower.Available returns compensate investors for taking on more aggregate risk.

We identify common risk factors in the data by building portfolios sorted on bitcoin past price deviations.By forming portfolios we can focus on the common components in bitcoin returns,accommodate variations in the number of exchanges and currencies pairs,and average out idiosyncratic risks.A two-factor model explains a large fraction of the cross-sectional variation in portfolio returns.Therefore,our results support the conclusion that the documented cross-section of returns represents compensation for risk,and is not just a measure of the inefficiency of cryptocurrency markets

**References**

Abdi,F.,and A.Ranaldo.2017.A simple estimation of bid-ask spreads from daily close,high,and low prices

*Review ofFmancial Shudies 30:4437-4480.*

Amihud,Y.2002.Ⅲiquidity and stock returns:cross-sectionand time-serieseffects.Jounal ofFimancial Markets 5:31-56.

Andrews,D.W.1991.Heteroskedasticity and autocorrelation consistent covariancematrix estimation.

*Econometric 59:817-858.*

Baba,C,A.Kokenyne.2011.Effectiveness of capital controls in selcted emerging markets in the 20005. Working Paper,IMF.

Biais,B,C.Bisiere,M.Bouvard,and C.Casamatta.2019.The blockchain folk theorem.Review ofFinancial

*Snudies 32:1662-1715.*

Bitwise.2019.Presentation to the U.S.Securitiesand ExchangeCommission.BitwiseAsset Management. Borri,N.,and K.Shakhnov.2018.Cryptomarket discounts.Working Paper,LUISS University

Brauneis,A,R.Mestel,R.Riordan,andE.Theissen.2021.How to Measure the Liquidity of Cryptocurrency

*Markets?Jounal of Banking &Fmance 124:106041.*

Burnside,C.2011.The cross section of foreign currency risk premia and consumptiongrowth risk:Comment.

*American Economic Review 101:3456-76.*

Carhart,M.M.1997.Onpersistence in mutual fund performance.Journal of Finance 52:57-82

Catalini,C.,andJ.S.Gans.2016.Somesimpleeconomics of the blockchain.NBER Working Paper No.24242.

*Review of Asset Pricing Shudies [v 12n32022*

Downloaded from https; l lacadem ic.oup.com r raps lart ic le/12/3/66716543623 by Des Moines Un ivers ity- Osteopath ic Medical Center user on 19 October 2022

Chen,N.-f,R.Kan,and M.H.Miler.1993.Are the discounts onclosed-end funds a sentiment index?Jourmal

*ofFnance 48:795-800.*

Cochrane,J.H.2002.Stocks as money:convenience yield and thetech-stock bubble.NBER Working Paper 8987.

——— .2009.Asset Pricing,revisededition.Princeton,NJ:Princeton University Press.

Cong.L W.,Z.He,and J.Li.2020.Decentralized mining in centralized pools.Review ofFinancialShudies

34:1191-235.

Du,W,A.Tepper,and A.Verdelhan.2018.Deviations from covered interest rateparity.Jourmal of Fncmce 73:915-957.

Dwyer,G.P.2015.Theeconomics of Bitcoin and similar privatedigital currencies.Joural ofFinancial Stability 17:81-91.

Dyhrberg.A.H,S.Foley,and J.Svec.2018.Howinvestibleis Bitcoin?Analyzing the liquidity andtransaction

*costs of Bitcoin markets.Economics Lettlers 171:140-143.*

Fama,E.F,andK.R.French.1993.Common risk factors in the returns on stocks and bonds.Jounalof

*Financial Economics 33:3-56.*

Fama,E.F,and J.D.MacBeth.1973.Risk,return,and equilibrium:Empirical tests.Jounal ofPolitical

*Economy 81:607-36.*

Fernández,A,M.W.Klein,A.Rebuci,M.Schindler,and M.Uribe.2016.Capitalcontrol measures:A new

dataset.IMF EcomomicReview April:548-574.

Gagnon,L,and G.A.Karolyi.2010.Multi-market trading and arbitrage.Jounal of Fincncial Economics

97:53-80.

Gandal,N,J.Hamrick,T.Moore,andT.Oberman.2018.Price manipulation in the Bitcoinecosystem.Journal

*of Monetary Ecomomics 95:86-96.*

Hansen,L.P.1982.Large sampleproperties of generalized method ofmoments estimators.Econometrica:

*Journal of the EconometricSociely 50:1029-1054.*

Krishnamurthy,A.2002.The bond/old-bond spread.Journal of FncancialEconomics 66:463-506.

Krūckeberg,S.,andP.Scholz2020.Decentralized efficiency?Arbitrage in bitcoinmarkets.Financial Analysts

*Journal 76.*

Lamont,O.A,and R.H.Thaler.2003.Can the market addandsubtract?Mispricing in techstock carve-ous.

*Journal of Political Economy 111:227-268.*

Lee,C,A.Shleifer,and R.H.Thaler.1991.Investor sentiment and the closed-end fund puzle.Jourmal of

*Fnance 46.75-109.*

Li,T,D.Shin,and B.Wang.2020.Cryptocurrency pump-and-dump schemes.Working Paper,University of

Florida.

Liu,Y,and A.Tsywinski.2021.Risks andreturnsof cryptocurrency.Review of Financial Shudies 34:2689-2727. Liu,Y.,A.Tsyvinski,and X.Wu.Forthcoming.Common risk factors incryptocurrency.Journal of Fimcmce.

Lustig,H,N.Roussanov,and A.Verdelhan.2011.Common risk factors in currency markets.Review of

*Financial Shudies 24:3731-77.*

Lustig,H,andA.Verdelhan.2007.The cross sectionofforeign currency risk premia and consumption growth

risk.Ameriaan Economie Review 97:89-117.

 — .2011.The cross-section of foreign currency risk premia and consumption growth risk:Reply.Amerian

*EconomicReview 101:3477-500.*

*The Cross-Section ofCryptocurrency Returns*

Downloaded from https:; /lacadem ic.oup.com/raps/art ic le/12/3/667/6543623 by Des Moines Un ivers ity - Osteopath ic Medical Center user on 19 October 2022

Ma,J,J.S.Gans,and R.Tourky.2018.Marketstructure inbitcoin mining.NBER WorkingPaper.

Makarov,L,and A.Schoar.2019.Trading and arbitragein cryptocurrency markets.Journal of Fnancial

*Economics 135:293-319.*

Menkhoff,L,L.Sarmo,M.Schmeling,and A.Schrimpf.2012a.Carry trades and global forcign exchange

*volatility.Journal ofFmance 67:681-718.*

*-.2012b.Currency momentum strategies.Journalof Financial Economics 106:660-84.*

Moore,T,and N.Christin.2013.Beware the middleman:Empirical analysis of Bitcoin-exchange risk.In

*International Conferenceon Financial Cryptograply cand Data Security,25-33.New York:Springer.*

Newey,W.K,and K.D.West.1986.A simple,positive semi-definite,heteroskedasticity and autocorrelation-

consistent covariance matrix.Econometrica 55.703-708

Nicholas,B.,A.Shleifer,and R.Vishny.1998.A model of investor sentiment.Jourmal of Fmancial Economics 49:307-343.

Patton,A.J,and A.Timmermann.2010.Monotonicityin asset returns:New tests with applications to the term structure,the CAPM,and portfolio sorts.Jounalof Financial Economics 98:605-625.

Pontiff,J.1996.Costly arbitrage:Evidence from closed-end funds.Qucrterly.Jouanal of Economics111:1135-51.

Ranaldo,A,andP.Santucide Magistris.2019.Trading volume,illiquidity and commonalities in FX markets. Research Paper,University of St.Gallen

Roll,R.1984.Asimple implicit measure of theeffective bid-ask spread inanefficient market.Jouanalof Fncnce 39:1127-39.

Shanken,J.1992.On the estimation of beta-pricing models.Review of Financial Studies 5:1-33.

Tuckman,B.,and J.-L.Vila.1992.Arbitrage with holding costs:A utility-based approach.Jounal of Fncnce 47:1283-1302.

Vasek,M.,and T.Moore.2015.There's no free lunch,even using Bitcoin:Tracking the popularity and profits of

*virtual currency scams.In Imternational Conference on FmancialCryptograplyaid Data Securiy,44-61.New*

York;Springer

Velde,F.2013.Bitcoin:A primer.Chicago Fed Letter.

Yermack,D.2013.Is Bitcoin areal currency?An economic appraisal.NBERWorking Paper 19747.