Arbitrage in the Market for Cryptocurrencies*

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Abstract

Arbitrage opportunities in markets for cryptocurrencies are well-documented. In this paper, we confirm that they exist; however, their magnitude decreased greatly from April 2018 onward. Analyzing various trading strategies, we show that it is hardly possible to exploit existing price differences since then. We discuss and test several mechanisms that may be responsible for the increased market efficiency and find that, particularly, informed trading is correlated with a reduction in arbitrage opportunities.

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1 Introduction

Cryptocurrencies have gained considerable importance in the investment domain. There is now sizeable market capitalization and trading volume. Despite this, arbitrage opportunities can be observed again and again. For example, the recent implosion of the crypto exchange FTX, the third largest crypto exchange at the time, has again strained the confidence in crypto markets. In this connection, the share price of the Grayscale Bitcoin Trust (GBTC), which has a market capitalization of approximately USD 10.5 billion and owns 3.5% of the world's bitcoin, dropped to a 39% discount relative to the value of its holdings. The price drop emerged because frightened investors tried to withdraw their funds, and created arbitrage opportunities in the crpyto market. In line with this observation, recent papers have documented substantial arbitrage opportunities, which sometimes persist over weeks (Borri and Shakhnov, 2022; Kroeger and Sarkar, 2017; Makarov and Schoar, 2020; Pieters and Vivanco, 2017). Nevertheless, as cryptocurrency markets have become more mature and competitive in recent years, with, for example, an increasing number of institutional investors, two natural and important questions arise: How have market inefficiencies, in particular arbitrage opportunities, evolved, and if they have changed, what are the drivers of this development? In this paper, we address these questions by providing a long-term analysis of price deviations and the drivers of their evolution.

In recent years, price deviations in the crypto market may have changed for several reasons. Increased competition between exchanges—or market fragmentation (O'Hara and Ye, 2011)—may have led to reduced trading costs and improved latency for traders. As a result, exploiting arbitrage opportunities has become cheaper and less risky. Thus, more investors may decide to engage in exploiting arbitrage opportunities, yielding more efficient pricing. In addition, the number of professional investors has increased in recent years. PwC (2021) reports that a large number of hedge funds who engage in the crypto market apply arbitrage trading strategies. In a similar vein, retail investors may also be more aware of arbitrage opportunities and exploit them. A series of websites such as bitsgap, tokenspread, and cryptohopper have emerged that explicitly collect information on mispricing and allow for more informed (retail) trading. Both a larger number of institutional investors and a larger number of informed retail investors may contribute to more efficient pricing between exchanges. Such an argument is consistent with the observation from the asset pricing literature that many pricing anomalies vanish after they have been documented in the academic literature (McLean and Pontiff, 2016). In addition, changes in investors' funding liquidity may influence arbitrage opportunities (Brunnermeier and Pedersen, 2008; Gârleanu and Pedersen, 2011). Cheaper funding opportunities may make it more attractive to exploit price deviations. Finally, the amount of news may influence arbitrage opportunities. Here, the expectation is that more intensive news coverage will improve the extent and speed with which prices adapt.

To address our research questions, we first successfully replicate previous findings about the existence of price deviations (Makarov and Schoar, 2020). In the next step, we extend the analysis to a horizon of five years from the beginning of 2017 to the end of 2021. This time period is considerably longer than previous studies. Our results show that arbitrage opportunities in the cryptocurrency market have decreased significantly over time. We find that price deviations hardly exist since April 2018, which is the end of the time period analyzed by Makarov and Schoar (2020). Estimating the returns of a cross-platform arbitrage strategy, we demonstrate that the reduction in arbitrage opportunities is not merely a statistical finding but that, in fact, arbitrage opportunities fail to generate meaningful returns in the more recent time period. Finally, we turn to the drivers of this evolution. Our analysis indicates increased institutional engagement and informed trading to be related to lower price deviations. We also find a positive relation between funding liquidity and price deviations. Moreover, we can show that price deviations are related to volatility and liquidity. We do not find evidence in favor of the notion that competition between exchanges or market fragmentation has significantly contributed to changes in arbitrage opportunities over time.

Our paper is linked to different strands in the literature. It follows up on recent research on the price building and arbitrage potential of cryptocurrencies (e.g., Borri and Shakhnov, 2022; Brauneis et al., 2019; Dyhrberg, 2020; Kroeger and Sarkar, 2017; Makarov and Schoar, 2020; Pieters and Vivanco, 2017). In this literature, Liu and Tsyvinski (2018) find that risk and return characteristics of cryptocurrencies are distinct from those of traditional assets. Other studies document arbitrage opportunities in the crypto market. Our study contributes to this literature by studying the evolution of arbitrage in the cryptocurrency market over time. The trading strategy analysis of our paper also links to the literature that studies the potential success of crypto trading strategies (Lintilhac and Tourin, 2017). More generally, our paper is also related to the literature on arbitrage in general and the limits thereof (e.g., Akram, Rime, and Sarno, 2008; Beschwitz and Massa, 2020; DeLong et al., 1990; Gromb and Vayanos, 2002, 2018) and to studies that analyze arbitrage empirically (e.g., Froot and Dabora, 1999; Rosenthal and Yong, 1990). Our paper is also related to the literature that explores the market for cryptocurrencies as a payment or transaction device and that focuses on the blockchain technology in general (e.g., Böhme et al., 2015; Ciaian, Rajcaniova, and Kancs, 2019; Pagnotta and Buraschi, 2018). Several studies (Cong, He, and Li, 2021; Easley, O'Hara, and Basu, 2019; Huberman, Leshno, and Moallemi, 2021) analyze mining fees and the miners' incentives, while others focus on investors' trading behavior (Hasso, Pelster, and Breitmayer, 2019; Jain, McInish, and Miller, 2019; Pelster, Breitmayer, and Hasso, 2019). Dyhrberg, Foley, and Svec (2018) analyze the investability of bitcoin by investigating transaction costs and liquidity of bitcoin.

The remainder of the paper is structured as follows. Section 2 explains the data. We provide some descriptive statistics in Section 3. Section 4 estimates arbitrage indices and documents the price discrepancies of different cryptocurrencies between exchanges. In Section 5, we implement a cross-platform strategy and determine the profitability of arbitrage strategies in crypto markets. Section 6 focuses on the determinants of price deviations and their evolution over time. The final section concludes.

2 Data

We focus on the three largest cryptocurrencies by volume, bitcoin (BTC), ether (ETH), and ripple (XRP), because these currencies show longevity on the cryptocurrency market, are available almost everywhere, and thus come with the highest possible liquidity. Similar to most other cryptocurrencies, they can be traded with fiat currencies on fiat-to-crypto-exchanges or with other cryptocurrencies on crypto-to-crypto exchanges. In contrast, other cryptocurrencies are available only for a limited time-period, are far less mature, and oftentimes can only be traded on specific exchanges, and hence, they are much less suited for arbitrage.

For each cryptocurrency, we consider their corresponding fiat and tether (USDT) trading pairs. Tether represents the most popular stable coin, both by market capitalization and volume.[1] We consider currency pairs of both fiat-to-crypto and crypto-to-crypto exchanges. Fiat-to-crypto exchanges differ from crypto-to-crypto exchanges in several ways. The access to fiat-to-crypto exchanges is often geographically limited and the exchange subject to local regulations. For example, U.S.-based exchanges fall under the regulatory scope of the Bank Secrecy Act (BSA) and must report to the Financial Crimes Enforcement Network (Hyatt, 2021). Even though may fiat-to-crypto exchanges operate in multiple countries, depending on the country and the exchange, an investor may not be able to trade with all fiat currencies offered. Kraken, for example, offers all customers access to various fiat currencies, regardless of one's location (Kraken, 2019), whereas Coinbase only offers specific currencies depending on the location (Coinbase, 2022). Importantly, each fiat-crypto pairing is traded independently and has its own order book, thus opening the door for potential price deviations even within an exchange. Hence, each pair can be considered a unique asset. On the other hand, crypto-to-crypto exchanges are geographically less limited but do not allow the conversion of cryptocurrencies to fiat currencies. They are less tightly regulated. Prior literature classifies them as less reliable, because these exchanges are, for example, accused reporting fake trades and volumes.[2] Crypto-only exchanges also have higher risks for pump-and-dump schemes (Li, Shin, and Wang, 2021). In general, as they operate based on stable coins, crypto-to-crypto exchanges do not have to establish genuine fiat banking connections (Griffin and Shams, 2020). However, some exchanges create separate entities, which are compliant to local regulations. For example, Binance—considered to be the largest exchange in the world by trading volume—launched a separate exchange Binance.US for the American market in 2019.

We obtain tick-level trade data from Kaiko. Kaiko is considered one of the leading providers for crypto market data and is commonly used in empirical studies (see, e.g., Makarov and Schoar, 2020). Kaiko collects data through APIs directly from exchanges. The trade data includes the timestamp of each trade, the execution price, the quantity of the trade, and an indicator of whether the trade was sell or buy initiated by the taker side. In crypto exchanges, a distinction is made between a "maker" and a "taker." Makers create liquidity by placing bid and ask orders, while takers take liquidity out of the order book by closing these orders.

Following Makarov and Schoar (2020), we begin our sample in 2017. Earlier, only limited data were available and the cryptomarket was still very illiquid. We start with 41 exchanges that are covered by Kaiko. These are ACX, BTC-Alpha, Bibox, BigONE, Binance, Bit-Z, BitBay, BitFlyer, BitForex,

[1]Tether is issued by Tether Holding Limited, and according to the company, each tether token (USDT) is hedged with one U.S. dollar with the aim that tether holds the U.S. dollar parity. So-called stable coins have gained a lot of importance in the cryptocurrency market over the last years. Stable coins allow investors to hold funds on crypto-to-crypto exchanges without exposing themselves to the high volatility of cryptocurrencies. As of early March 2022, around 80% of the daily volume of cryptocurrencies was traded via stable coins (CoinMarketCap, 2022b).

[2]Several exchanges conduct wash trades to pretend higher liquidity and trading volume with the aim of gaining popularity. According to Bitwise (2019), 95% of the reported volume on CoinMarketCap in March 2019 was fake. Similarly, Cong et al. (2021) argue that 70% of the volume from unregulated exchanges was fake volume during several months in 2019.

Bitbank, Bitfinex, Bithumb, Bitlish, Bitso, Bitstamp, Bittrex, BtcTurk, CoinEx, CoinMate, Coinbase, Coincheck, Coinfloor, EXX, ErisX, Gemini, HitBTC, Huobi, Itbit, Korbit, Kraken, KuCoin, LMAX, OkCoin, OkEX, Poloniex, Quoine, TheRockTrading, Upbit, Yobit, ZB, and Zaif. We do not include exchanges that operate via a broker, as these exchanges are subject to different fee structures with high and sometimes opaque fees. This makes it unfeasible to implement arbitrage strategies.

We then apply a few data filters. First, we require exchanges to fulfill the minimum quality criteria of the leading crypto data providers, CoinMarketCap (2022c) and Cryptocompare (2021). Exchanges have to transparently reflect price information and adhere to regulations and laws applicable to them. We argue that exchanges that do not fulfill such requirements are not feasible to implement arbitrage strategies, because investments via these exchanges are potentially very risky. We filter BtcTurk, BitForex, Bibox, BTC-Alpha, CoinMate, TheRockTrading, EXX, and Yobit based on this criterion. Second, we require that each exchange has operated for at least two years (equal to 40%) of our sample period. This requirement is related to the first requirement, as investors do not have reliable information on the quality of an exchange that has just started its operation. ACX, ErisX, LMAX, and Bitlish do not fulfill this two-year requirement. ACX, ErisX, and Bitlish additionally only provide very limited liquidity. Third, we omit Chinese exchanges (Bit-Z, Huobi, and OkCoin) because of multiple government interventions during our sample period, ultimately leading to a ban of cryptocurrencies in September 2021 (John and Wilson, 2021). These filter criteria yield a sample of 18 fiat-to-crypto and 10 crypto-to-crypto exchanges (see Table A.1). For the fiat-to-crypto exchanges, we consider the most liquid fiat currencies and obtain 129 different assets.[3] We summarize the effects of our filter criteria in Figure A.1.

We carefully clean the trade data, and remove obvious data errors. The early data (i.e., 2017–2019) denominates cryptocurrencies on Bitfinex in U.S. dollar (USD) and other fiat currencies, and includes tether (USDT) pairs starting March 2019. However, according to Alexander and Dakos (2020), cryptocurrencies denominated in USD on Bitfinex were actually denominated in USDT prior to the exchange, officially making the distinction between tether and fiat currencies in March 2019. In support of this notion, Griffin and Shams (2020) argue that Bitfinex's public statements in this regard are ambiguous, and that prices at that time were significantly closer to USDT-quoted prices than to USD. Thus, we consider Bitfinex prices denominated in fiat as USDT-quoted prices until the official distinction in spring 2019. We also use exchanges status pages to identify data errors and remove them.[4]

We use hourly exchange rates from Bloomberg to convert prices of fiat pairs. As the cryptocurrency market—compared to the foreign currency market—is always open, we use the next available

[3] Note that Bitfinex and Bittrex count towards both fiat-to-crypto and crypto-to-crypto exchanges.

[4] See, for example, `https://blog.bitbank.cc/tag/maintenance/` for Bitbank, `https://status.bitflyer.com/` for bitFlyer, `https://bitfinex.statuspage.io/` for Bitfinex, `https://status.btcturk.com/` for BtcTurk, `https://status.bitpay.com/` for BitPay, `https://status.coinbase.com/` for Coinbase, `https://status.gemini.com/` for Gemini, `https://status.huobigroup.com/` for Huobi, `https://status.paxos.com/` for ItBit, `https://status.kraken.com/` for Kraken, `https://status.korbit.co.kr/` for Korbit, `https://status.lmax.com/` for LMAX, `https://www.okcoin.com/status` for Okcoin, `https://www.okx.com/status` for OkEX, `https://status.bitso.com/` for Bitso, `https://bigone.zendesk.com/hc/en-us/sections/900000046383-Other-Announcement?page=1#articles` for BigONE, and `https://support.bithumb.pro/hc/en-us/sections/360010889734-Others` for BitGlobal.

exchange rate when the foreign currency market is closed. For prices denominated in USDT, we use the USD-to-USDT price from CoinMarketCap (2022d), which is an average of USD-to-USDT prices from multiple exchanges, for conversion purposes.

3 Summary statistics

We begin our analysis with some summary statistics. First, we report statistics on the volume-weighted prices of each exchange on an hourly basis. We calculate volume-weighted prices by multiplying each transaction-price with its volume, and dividing the sum by the total volume of that hour. We also calculate the hourly bid-ask spreads for each exchange and currency, using the indicator of whether a trade was sell or buy initiated. The indicator identifies the highest bid/lowest ask order(s) at the time of the trade. As the trade data from Itbit does not include a correct trade direction indicator, we apply the algorithm of Lee and Ready (1991) to determine the trade direction of Itbit currency pairs.[5] Similarly, the raw data lacks correct trade identifiers for most of April 2021 for all exchanges and crypto-currency pairs. Again, we apply the algorithm of Lee and Ready (1991) to determine the trade direction.

Table 1 presents descriptive statistics of the price premium, the trading volume (in millions of U.S. dollars), and the bid-ask spreads (in basis points) of all exchanges, sorted by their geographic location. The price premium quantifies the percentage price difference of one exchange with respect to the average price of all exchanges in a given hour. We separately calculate price premiums for crypto-only exchanges and for fiat-to-crypto exchanges, and we list crypto-only exchanges separately because they are not subject to geographic restrictions. We estimate bid-ask spreads using the difference between successive bid and ask orders, and aggregate the result hourly. We combine the U.S. and Europe into one region because their main currencies can usually be traded in both regions. For brevity, we only present the main currency-pair for exchanges that allow investors to trade multiple currency-pairs.

Table 1

Interestingly, South Korean exchanges show significantly higher prices for all three cryptocurrencies compared to the other crypto-to-fiat exchanges. Thus, South Korean exchanges drive the average price premiums. The South Korean exchanges also have a higher standard deviation of price premiums, indicating greater price movements. This phenomenon has been documented before and is commonly referred to as the "kimchi premium." As a result of the financial crisis following 2008, South Korea introduced capital export restrictions in 2010 that limit the capital outflow to USD 50,000 per person per year (Choi, Lehar, and Stauffer, 2022). Furthermore, trading on South Korean exchanges is only allowed for South Korean citizens (Ramirez, 2018). Due to these restrictions, the South Korean cryptocurrency market is an isolated market and prevents arbitrageurs from exploiting price differences.

[5] According to Lee and Ready (1991) and Abdi and Ranaldo (2017), this rule correctly classifies trades in more than 90% of the cases.

In general, price deviations of exchanges within a region are, on average, more similar within regions than compared to other regions. For example, exchanges from the U.S./Europe tend to generally have lower price premiums compared to the exchanges from other regions—ignoring tether exchanges. In the U.S./Europe region, the price premiums of BitBay and Coinfloor significantly differ from other exchanges. Notably, these exchanges also have significantly smaller trading volumes and come with a higher bid-ask spread, indicating that low liquidity may hinder efficient price formation.

Price premiums on tether exchanges are in a different category and feature significantly smaller price differences compared to fiat-to-crypto exchanges. One exception are the prices on HitBTC, which differ considerably from other crypto-only exchanges. As expected, the tether exchanges have significantly higher trading volumes and lower bid-ask spreads.

Overall, price deviations within an exchange are similar for BTC, ETH, and XRP, as long as the relative trading volume of a cryptocurrency is not too low. We summarize that a first inspection of price premiums highlights significant price differences in particular among fiat-to-crypto exchanges. On the other hand, crypto-only exchanges show more consistent pricing patterns—and a higher trading volume. Thus, price premiums could be related to the regional focus of exchanges and their trading volume.

Figure 1 shows the evolution of the average prices, daily volumes, and bid-ask spreads over time, separately for the fiat-to-crypto and tether-to-crypto exchanges. For bid-ask spreads of fiat pairs, we additionally distinguish between all pairs and the ten most liquid pairs. While the prices of bitcoin and ether have risen sharply over our sample period, ripple has not returned to its all-time high from early 2018. The volumes of all currency-pairs have continuously increased over time. The evolution of average bid-ask spreads shows a more ambiguous pattern. While bid-ask spreads for tether exchanges and the most liquid fiat pairs have steadily declined, some fiat pairs remain at a higher level, and the average bid-ask spread stabilizes after 2018. Interestingly, the spreads of liquid fiat pairs and tether pairs are at a very similar level as of 2019 and are developing in a similar pattern.

Figure 1

4 Price deviations

We start the formal analysis of price differences of cryptocurrencies across exchanges by studying simple arbitrage opportunities (e.g., Shkilko, Van Ness, and Van Ness, 2008). We illustrate such arbitrage opportunities in Figure 2. The inside bid of one trading venue, here venue X, is larger than the inside ask of another trading venue, here venue Y. As a result, investors can exploit price differences across exchanges—as long as they are able to trade on both exchanges.

Figure 2

We study whether such instances can be found in our data. First, for every five-second interval, we obtain the highest bid (in USD) for a given cryptocurrency across all exchanges in our data. Next, we obtain the lowest ask (in USD) for the same cryptocurrency across all exchanges in the same five-second interval. The difference between these two constitutes the largest possible arbitrage opportunity at that point in time. A negative difference indicates that no arbitrage opportunities are available. In line with the notion that being able to make economic profits by trading (see the efficient-market-hypothesis definition of Jensen, 1978) is highly relevant we require that all quotes come with a volume of at least .5 in our main analysis. Quotes with less contracts may constitute price differences that seem attractive on the face of it, but do not allow investors to make meaningful trading profits of them.

We show the evolution of simple arbitrage opportunities over time in Figure 3. Panel A shows that—for the most part—arbitrage opportunities are available in the crypto market. Some arbitrage opportunities are only available for a brief period of time. These spikes can be explained, for example, by flash crashes or hacker activities at individual exchanges (Sensoy, Akyildirim, and Söylemezgil, 2021) or pump and dump activities (Li, Shin, and Wang, 2021). Other arbitrage opportunities are more pervasive and continue to be available for a longer period of time. The figure also illustrates that both types of arbitrage opportunities seem to decline over time.

In Panels B and C of Figure 3, we vary the minimum volume requirement. Varying the minimum volume has only marginal effects on the arbitrage index. Overall, the alternative volume requirements do not alter our main conclusion.

We additionally provide several variants of the figure that apply the various exchange filter criteria one by one in Figure A.1 in the Appendix. Including the filtered exchanges increases available arbitrage opportunities over time, but does not affect the time trend in a meaningful way. Omitting Chinese exchanges yields reduced arbitrage opportunities in particular during the first part of our sample, but less so in the later part of the sample period. Overall, the figure indicates that not one filter, but rather the combination of filters reduces arbitrage opportunities significantly.

Figure 3

In fact, the literature provides established arbitrage indices to quantify such arbitrage opportunities (see, e.g., Makarov and Schoar, 2020). Next, we estimate the index proposed by Makarov and Schoar (2020) to allow for a comparison of our findings with the existing literature. This index captures the maximum price difference between exchanges over time. Every hour, we divide the highest price by the lowest price and aggregate the result on a daily basis using volume-weighted averages to reduce intraday volatility.

Panel A of Figure 4 shows the evolution of the index for bitcoin from 2017 to 2021. Overall, the pattern of the arbitrage index between January 2017 and March 2018 is almost identical to the patterns documented in Makarov and Schoar (2020). Our amplitude is slightly lower, as we study volume-weighted prices at the hourly level, while Makarov and Schoar (2020) aggregate prices every minute. The intra-hourly volatility leads to slightly higher price differences. We find meaningful arbitrage opportunities, with values above 5% for almost the entire sample period. Several periods indicate significantly higher price discrepancies, for example in mid-2017, late 2017, mid-2019, and in spring 2021. Table 2 shows yearly averages of the arbitrage indices, for BTC, ETH, and XRP.

Figure 4 and Table 2

As documented in Table 1, the South Korean exchanges appear to exhibit a significant price premium compared to other exchanges. Given the nature of the arbitrage index (i.e., based on maximum price differences) and these institutional restrictions, we recalculate the arbitrage index without using South Korean exchanges. The resulting index shows fewer spikes and a considerably lower level. Annual averages decrease monotonically from 5.2% in 2017 to 2.7% in 2021.

Next, we estimate a third index that excludes the crypto-only exchanges with tether and Bitfinex. The existing literature considers crypto-only exchanges less reliable because many of them are associated with price manipulation and fake volumes (Borri and Shakhnov, 2022; Li, Shin, and Wang, 2021). At the same time, investors can trade on these exchanges without geographical and time restrictions, and using cryptocurrencies only allows investors to move funds faster (moving fiat currencies usually takes longer on crypto exchanges). Thus, the price discovery and arbitrage opportunities could be different on these exchanges. Similar concerns (lower reliability and more manipulations) hold for Bitfinex, which has been involved in various controversies and allegations.[6] Consequently, we also remove Bitfinex for the last index.

The omission of crypto-only exchanges and Bitfinex further reduces the arbitrage index to an average of 1.018. While price differences are lower between 2017 and 2019, price differences in 2020 and 2021 are mostly the same. Although there are isolated price dispersions between 2019 and 2021, the arbitrage index shows that the average maximum price difference between exchanges was only 1.1% after 2019 compared to 2.8% from 2017 to 2018.

For the arbitrage indices of ETH and XRP (Panels B and C), we find patterns and averages that are in line with BTC, albeit slightly higher. The higher level may be explained by the lower liquidity of ETH and XRP, compared to BTC. As documented in Table 1, the trading volumes of ETH and XRP currency pairs are significantly lower and the bid-ask spreads are higher.

Last, as the arbitrage index only considers the minimum and maximum price across all exchanges, we further divide the index into geographic components. Taking a look at individual regions

[6] Leaked documents in 2017 suggested that the owners of Tether Limited and Bitfinex are the same, manipulating prices and laundering money through Bitfinex (Popper, 2017). It seems that price manipulations of BTC took place on Bitfinex by the issuing of an abnormal amount of tethers to buy bitcoins (Griffin and Shams, 2020). The Commodity Futures Trading Commission (CFTC) fined Tether Holding Limited in October 2021 for making untrue or misleading statements in connection with USDT, addressing the concern that USDTs were not fully backed. Similarly, the CFTC fined Bitfinex for illegal, off-exchange transaction with USDT and BTC (CFTC, 2021a). At the same time, it remains unclear in which currency prices were quoted prior to spring 2019 and how the transition has proceeded (Alexander and Dakos, 2020; Griffin and Shams, 2020). Finally, it is known that between 2017 and (at least) 2019, customers were not able to withdraw fiat currencies from the exchange. Consequently, investors fled into cryptocurrencies to be able to withdraw their funds (Floyd and De, 2018; Haig, 2017; Martinez, 2019). The CFTC arrived at the conclusion "that since at least in or about November 2017, identified non-ECP U.S. persons were not permitted to withdraw fiat or stablecoin" (CFTC, 2021b, October 15, 2021). As a result, cryptocurrency prices on Bitfinex rose excessively numerous times, and arbitrageurs were unable to take advantage of these price premiums (21Shares, 2019; Haig, 2017; Madeira, 2017).

and exchanges allows us to study the source of the price inconsistencies. Investors are (often) not allowed to trade on specific fiat-to-crypto exchanges depending on their location. These barriers may reduce the exploitation of price differences, as circumventing these barriers is costly. Figure 5 shows the arbitrage indeces of the three cryptocurrencies divided into the regions of the U.S./Europe, Japan, and South Korea. In addition, we include the tether-based exchanges. We only estimate an arbitrage index when at least three exchanges are available in our data. The regional split highlights that geographic characteristics or the type of exchange have an important impact on price discrepancies. Moreover, while the isolated view of the tether- and Japanese-based exchanges show low average price deviations (below three basis points) from 2019 onwards, the exchanges of the U.S./Europe and South Korea regions still exhibit significant price deviations.

Figure 5

Overall, our findings in this section indicate significant arbitrage opportunities on the crypto market—in line with Makarov and Schoar (2020). However, our findings also indicate that the arbitrage opportunities seem to have reduced over time. In the next section, we first study explicit investment strategies that exploit these arbitrage opportunities before we shed more light on the evolution of arbitrage opportunities over time in Section 6.

5 Cross-platform trading strategy

Section 4 shows declining but still persistent price differences across exchanges over recent years. In this section, we ask whether these price differences can be exploited using a simple cross-platform trading strategy following Borri and Shakhnov (2022). The goal is to quantify potential returns of a trading strategy, to examine the relation between the arbitrage strategy and bid-ask spreads and transaction costs, and to explore practical limitations. Importantly, we require that the arbitrage strategy can actually be implemented given the institutional environment.

In general, cross-platform strategies can be implemented with simultaneous transactions or with transactions that have a slight time difference. Obviously, one would prefer the simultaneous strategy to minimize the risk of price changes while having an exposure. However, the simultaneous strategy requires that arbitrageurs always hold balances on all exchanges to be able to immediately trade on price deviations. This is necessary because depositing fiat currencies on crypto exchanges can take several days. If arbitrageurs cannot or do not want to hold balances on multiple exchanges at the same time—for example, because of arising opportunity costs, or because they are concerned about the reliability of an exchange (see, e.g., the FTX bankruptcy)—investors have to transfer funds between exchanges when arbitrage opportunities arise. The duration of this transfer is determined by the confirmation times of the blockchain and creates a small time difference between arbitrage transactions that exposes the arbitrageur to price risk.[7] Importantly, these confirmation times vary

[7]Each cryptocurrency transaction needs to be confirmed by miners, and depending on the demand for transactions that require confirmation, confirmation times change and increase with high transaction volumes. Note that this only

over time and differ between cryptocurrencies; compared to bitcoin, ether and ripple have rather short confirmation times that exhibit less time variation. We plot the average confirmation times for blockchain transactions between January 2017 and December 2021 in Figure A.2 in the Appendix. The average confirmation time for bitcoin is about two hours during the sample period. Consequently, we assume an unconditional confirmation time of two hours for our analysis. We discuss the impact of conditional confirmation times in Section 5.3. In general, investors can choose to offer higher transaction fees as additional compensation for miners, which prioritizes a transaction. However, this option is not available on most exchanges. As a result, the non-simultaneous arbitrage strategy is not risk-free. The arbitrageur is subject to price risk while her funds are transferred between exchanges.

We restrict the analysis in this section to fiat-to-crypto pairs for bitcoin and ether, which allow for consistent arbitrage strategies that promise the largest returns. We omit Ripple because the coin is available only on some exchanges during the sample period, making a consistent arbitrage strategy infeasible for long stretches of time. In addition, price differences across crypto-only pairs are lower (see Table 1), while at the same time a zero-cost strategy would imply more transaction steps and consequently more fees. Thus, arbitrage strategies on crypto-only pairs are less profitable. We also exclude South Korean exchanges because of existing capital flow constraints. As a result of the capital flow constraints, systematic international trading of cryptocurrencies using South Korean exchanges is limited, and a trading strategy cannot be implemented in a meaningful way. Finally, we exclude all assets from Bitfinex due to the withdrawal issues discussed above. Again, these restrictions prevent the implementation a successful arbitrage strategy.

5.1 Methodology

Considering the institutional environment of cryptocurrency trading, we begin the arbitrage trading strategy on Kraken. Kraken is the only exchange that reliably allows investors to short cryptocurrencies over our sample period. Taking short positions in cryptocurrencies is necessary to implement a long–short strategy. In addition, Kraken is a large, reliable, and strongly regulated exchange with low transaction fees, making it attractive to pursue arbitrage strategies via the exchange. Considering various exchange closures over time (Christin and Moore, 2013), making use of a reliable crypto exchange to start one's arbitrage strategies is important. Thus, starting the arbitrage strategy on Kraken allows us to study a strategy that can in fact be implemented.

While taking a short position is not necessary to implement the long leg of an arbitrage strategy, the additional restriction for the long leg has only limited impact on the returns of the strategy because prices on Kraken are typically on the low end of the spectrum (see Table 1); only four pairs have lower average bitcoin prices. For ether, we find two pairs with a lower price. We provide additional support for this notion when we estimate price discounts in Table 3. In addition, trading costs are typically inversely related to the trading volume on an exchange (see below). Thus, keeping one exchange constant allows us to realize lower transaction costs. Hence, we opt for consistency between the long and the short leg of the strategy. Figure A.3 in the Appendix shows the evolution of the arbitrage

refers to off-exchange transactions; within-exchange transactions are not written on the blockchain. Exchanges function like banks and control the balance of investors.

index of Makarov and Schoar (2020), with the restriction used for the arbitrage strategy here; we consider maximum price deviations relative to Kraken. Overall, the evolution of the index is similar to the index in Figure 4.

Without additional loss of generalizability, the investor first borrows U.S. dollars at the risk-free rate and deposits them on the Kraken exchange.[8] At time t, she buys bitcoins on Kraken and transfers them to another exchange on which she sells them at the given rate at time $t+1$. Finally, she withdraws the fiat money from the exchange. In case the cryptocurrency on the second exchange is listed in another fiat currency than U.S. dollars, she exchanges back to U.S. dollars via a regular foreign exchange market and repays the initial loan. We illustrate the cross-platform strategy in Figure 6.

Figure 6

We first estimate price discounts to the Kraken-USD pair by dividing the price of exchange e and currency c by the U.S. dollar price on Kraken:

$$D_{e,c} = \frac{Price_{e,c}}{Price_{Kraken,USD}} - 1 \tag{1}$$

We summarize price discounts in Table 3. A negative discount indicates that the cryptocurrency is cheaper compared to the Kraken-USD pair. A positive discount indicates a higher price compared to the Kraken-USD pair. Note that the comparison between exchanges has to be treated with caution, as we do not consider the time series in this table. As a result, pairs that are only available during the most recent years, when price differences in the crypto market are smaller, appear cheaper than pairs that are available over the entire time period and were subject to larger price deviations at the beginning of the sample period.

Table 3

Interestingly, non-USD pairs from exchanges that also have cryptocurrencies quoted in USD are more expensive than their USD pairs. For example, the EUR and GBP pairs from Coinbase and Quoine/Liquid have larger discounts to Kraken-USD prices than the USD pairs on those exchanges. Again, this may be explained with institutional aspects leading to market fragmentation, as U.S. investors are only allowed to trade cryptocurrencies denominated in USD on selected exchanges, for example on Coinbase.

Turning to the arbitrage strategy, we calculate the cross returns as the relative difference of the price of the exchange e with the fiat currency c at time $t+1$ and the price of the U.S. dollar pair on

[8] Starting with a different currency would require the investor to first exchange the fiat currency to USD. However, in this case, the investor could potentially waive the last step of the strategy, which is to exchange the fiat currency to USD.

Kraken at time t. Last, we subtract the risk-free interest rate R^f for the initial loan:

$$r_{e,c,t+1} = log(Price_{e,c,t+1}) - log(Price_{Kraken,USD,t}) - log(R_t^f) \tag{2}$$

We form seven portfolios and sort them from lowest negative to highest positive discount $D_{e,c}$. Thus, portfolio 1 consists of the lowest-priced pairs compared to the benchmark price on Kraken, and portfolio 7 contains the highest-priced pairs. For each portfolio k, the average returns $r_{k,t+1}$ are calculated as:

$$r_{k,t+1} = \frac{1}{N_k} \sum r_{e,c,t+1} \tag{3}$$

Based on these portfolios, we estimate the returns to a zero-cost high-minus-low strategy that goes long in portfolio 7 (largest discounts) and short in portfolio 1 (lowest discounts).

We next consider trading costs and fees.[9] Account management and depositing fiat/cryptocurrencies on exchanges is mostly free of charge. Exchanges charge transaction fees for buying and selling cryptocurrencies that are usually divided into maker fee and taker fee. Given that "makers" create liquidity by placing limit orders, while "takers" consume liquidity using market orders, taker fees are always higher than maker fees. For the cross-platform strategy, we only consider taker fees in order to ensure an efficient execution of the strategy. These fees are inversely related to the trading volume of an investor in the previous 30 days. Table A.2 in the Appendix lists the highest and lowest possible fees together with the fees that result from a trading volume of 1 million USD over the previous 30 days.

In addition, exchanges typically charge transaction fees for withdrawals. While fiat currencies can usually be withdrawn for negligible amounts, cross-exchange transactions of cryptocurrencies require fees to the miners. Most exchanges pay the mining fees and deduct a flat fee. Since the withdrawal fees are lump sums, they are neglected. Given that we abstract from withdrawal fees, the practical implementation of the arbitrage strategy is likely to incur larger costs than we estimate. In addition to the mentioned withdrawal fees, cross-border trading may also cause additional fees if one does not have a bank account in each jurisdiction. Hence, actual returns to the arbitrage strategies are most likely lower than our estimated returns.

Following the withdrawal, the fiat currency has to be converted into USD, causing additional fees if it is not already in USD. According to Ramadorai (2008), those fees are approximately three basis points for institutional investors. Note that retail investors may incur higher fees. For the taker fees on Kraken, we take the lowest possible transfer fee of ten basis points, which is the fee that is

[9]While exchange-related fees may have changed over time, our research on the current fees comes to similar conclusions as previous studies on earlier time periods (Borri and Shakhnov, 2022; Makarov and Schoar, 2020). As a result, we assume constant fees for the entire sample period. This is also in line with Bianchi, Babiak, and Dickerson (2022) who apply a fixed cost of 30 (40) basis points for a long (short) side of an investment strategy to approximate trading frictions in liquidity provision over a similar sample period.

obtained for a trading volume of more than USD 10 million in the previous 30 days. Since we always trade on this exchange, we can assume to reach high trading volume on Kraken. For holding a short position, Kraken charges an opening fee of 0.01% and a rollover fee of 0.01% every four hours. Since we assume a confirmation time of two hours and cryptocurrencies have to be transferred twice via exchanges to close the position, we set these fees to two basis points.

5.2 Results

Table 4 summarizes the discounts (Panel A) and returns (Panels B to F) of the seven portfolios. Part A of the table focuses on bitcoin; Part B focuses on ether. We begin by discussing part A. The last column shows the return of the long–short strategy. We estimate portfolio returns considering various transactions fees. First, the gross returns (Panel B) correspond to the returns of the portfolios, without accounting for any costs. For the returns net of bid/ask (Panel C), we assume that the prices are halfway from the respective bid-ask spreads. Additionally, we take the above discussed transaction costs into account (Panels D to F).

Table 4

Panel A shows that the discounts range from –35 basis points for portfolio 1 to 100 basis points for portfolio 7. The gross returns in Panel B are slightly lower but overall very similar to the discounts. Returns are positive for portfolios 3 to 7, and all portfolios suffer from a relatively high standard deviation of gross returns, indicating a high variability of the returns. Portfolios with larger returns, on average, also show a higher volatility of returns. The long–short strategy considering gross returns results in an average return of 104 basis points.

Including bid-ask spreads in the calculation leads to a reduction of 3 to 7 basis points of the returns, depending on the portfolio (Panel C). The returns of the extreme portfolios seem to have reduced more. Accordingly, the return of the zero-cost strategy falls to 93 basis points; thus, the bid-ask spreads account for 11 basis points. Note that the net of bid-ask returns of the zero-cost strategy is no longer the difference of the extreme portfolios, but the gross long–short return minus the changes due to the bid-ask spreads of the extreme portfolios.

Panels D to F additionally take the other transaction fees into account. We use three different taker fees, since these can vary substantially depending on the trading volume. First, we consider the minimum transaction costs in Panel D. These costs are unavoidable without special exchange arrangements. Note that such minimum trading costs, at least on average, are unrealistic, as the trading volumes (on each exchange) would usually have to be in the tens of millions each month to realize such low transaction costs. Assuming such costs, the mean returns of portfolios 1 to 4 are negative, and the return of the long–short strategy amounts to 46 basis points, indicating a reduction of 47 basis points compared to the gross returns. The returns of all portfolios have decreased with similar magnitude, which suggests that the different fees of the exchanges do not explain higher price discounts.

Considering that minimum transaction costs do not seem realistic considering the necessary trading volume to realize these fees, we additionally calculate the returns with fees that would apply to a trading volume of USD 1 million over the 30 preceding days (Panel E). Such transaction costs reduce the return of the portfolios considerably, yielding a net return to the long–short strategy of (only) 25 basis points. Thus, relative to the net return accounting for bid-ask spreads, the transaction costs have a total impact of 68 basis points on the long–short strategy. Portfolios 1 through 7 indicate that this return is mainly driven by the long position in portfolio 7. As the price on Kraken compared to other exchanges is low, on average (Table 3), the short position does not lead to a positive return, on average.

Finally, for completeness, we also calculate the returns with maximum transaction costs (Panel F). Such transaction costs would occur for trading volumes in the low thousands over the previous 30 days. Maximum transaction costs make the long–short strategy unattractive and yield negative returns. The comparison between Panels D, E, and F highlights that the trading volume of an arbitrageur has a crucial impact on her returns. Exploiting arbitrage opportunities is only profitable for investors who trade frequently and in high volumes, thus realizing relatively low transactions costs. In the remaining analysis, we assume taker fees that are valid for a trading volume of USD 1 million over the previous 30 days.

Next, we consider the evolution of returns over time and plot rolling 100-day average returns in Figure 7. Part A focuses on bitcoin; Part B shows the returns for ether. Panel A shows the discounts of portfolios 1 and 7 and the average discounts. Price differences and discounts decrease over time. Consistent with the arbitrage index excluding South Korean and crypto-only exchanges (Figure 4), we find higher price deviations, in particular, in mid-2017, late 2017, and late 2018.

Figure 7

Panel B shows the gross returns together with the daily bitcoin returns. We include bitcoin returns as a proxy for the overall crypto market returns. Large bitcoin returns may influence the gross returns of the arbitrage strategy because the selling-leg of the strategy is implemented "only" two hours after observation of the discounts. In line with Panel A, the differences between the extreme portfolios become substantially smaller from 2019 onward. Overall, the magnitude of the gross returns is very similar to the magnitude of the discounts. Thus, the price movement of bitcoin has seemingly just a minor impact on the magnitude of the gross returns. Further, the gross returns indicate that the short position of portfolio 1 has only a limited impact on the overall return of the 7-1 long–short strategy. The returns mostly come from the long position in portfolio 7, which is consistent with the results from above and the observation that the Kraken exchange shows comparatively low prices.

Panel C shows the net returns and highlights the impact of bid-ask spreads and transaction costs on gross returns, while Panel D shows the gross and net returns of the 7-1 long–short strategy. Even though transaction costs substantially reduce net returns, we find that large positive cross-platform returns were possible in 2017 and 2018. However, starting in 2019, the strategy does not provide consistent profits any longer. Gross returns of the 7-1 strategy continue to be positive, but ultimately net returns are negative due to trading costs. Note that the results do not indicate that it is no longer possible to exploit arbitrage opportunities in the crypto market; however, the frequency with which arbitrage opportunities occur and their magnitude have become significantly smaller over time.

As discussed above, a cross-platform strategy that executes trades simultaneously would be better to exploit arbitrage opportunities. We can interpret the discounts in Panel A of Figure 7 as the gross returns of such a strategy. However, as the discounts do not substantially deviate from the gross returns, the return on a simultaneous long–short strategy would be similar to the return of the strategy considered in this paper.

Part B of Table 4 summarizes the discounts and returns of ether. The cross-platform strategy can be executed in the same manner as for bitcoin; however, ether exploits a different blockchain, which enables faster transaction times. The confirmation time of ether is between seconds to several minutes during our sample period. In fact, the larger part of the transaction time is due to processing times of the exchanges rather than the Ethereum network. Consequently, we assume a transaction time of one hour, compared to two hours for bitcoin. As ether was not as frequently traded in the earlier part of our sample period, we only calculate the returns starting in October 2017. Thus, the results of Part B only allow for a limited comparison to Part A because (potentially) high discounts and returns in the first half of 2017 are missing.

A comparison between the gross returns for the cross-platform strategy using bitcoin (Part A) and ether (Part B) shows that the bid-ask spreads reduce the gross returns of the long–short strategy twice as much as for ether pairs compared to bitcoin pairs. This lower liquidity may explain the slightly higher price differences of ether compared to bitcoin in Figure 4. As for bitcoin, the currency pairs in the extreme have, on average, higher bid-ask spreads. This is consistent with the notion that higher price differences are associated with less liquid crypto pairs. As for the arbitrage indices, the patterns of the discounts and returns over time (Part B of Figure 7) are similar to those of bitcoin.

5.3 Restrictions of the cross-platform strategy

So far, the analysis is based on the assumption that the cross-platform strategy can be executed on all exchanges at all times. However, in reality, the cross-platform strategy is subject to some restrictions. In this section, we explain constraints of the cross-platform strategy and examine the potential effect on returns. We focus on bitcoin in this section because the bitcoin can be traded on all exchanges.

5.3.1 Location

Depending on the place of residence or the nationality, investors may not be allowed to trade on certain exchanges. South Korean exchanges pose a prominent example. Fiat-to-crypto exchanges do not offer their services in all countries due to (additional) regulatory hurdles and costs. Only larger exchanges (such as Bittrex) have created new entities that target international markets. Smaller exchanges tend to focus on regional markets.

We quantify to which extent geographical restrictions from the exchanges affect returns of the cross-platform strategy, using a U.S. and an European investor as an example. Since there can be differences within the European market depending on the country, we specifically refer to Germany. We obtain the information on whether an investor is allowed to trade on a given exchange or with a specific currency pair from the exchange websites. If the information on the website is ambiguous, we directly contacted the exchange. For exchanges that do not explicitly state on their website that certain restrictions apply and that did not reply to our request, we assume that no restrictions exist.

U.S. investors face stricter restrictions compared to European investors. Exchanges that want to operate in the U.S. must be registered as money service businesses, which implies a variety of regulations. International exchanges that are not licensed in the U.S. but still accept U.S. clients run the risk of being fined by U.S. authorities (Newbery, 2022). For example, BitMEX, which is not licensed in the U.S., was fined USD 100 million by the CFTC in August 2021 for "illegally operating a cryptocurrency trading platform and Anti-Money Laundering Violations" (CFTC, 2021b). Consequently, most non-U.S. licensed exchanges do not accept U.S. citizens.

Table A.3 in the Appendix provides an overview of the exchanges/currency pairs available for investors in the given regions. For some regions, certain currency pairs have not always been available for trading. For example, German citizens are only allowed to trade USD-denominated cryptocurrencies on Bittrex since October 2019. While Germans are allowed to trade on Quoine/Liquid in all currency pairs, only one base pair is allowed, which can be traded at normal conditions. Trading other fiat currencies comes at an additional cost of 25 basis points for each trade.

We summarize the returns considering the exchange-specific geographic restrictions in Table 5. Gross portfolio returns are significantly smaller for a U.S. investor compared to the strategy shown in Table 4. The gross returns of the upper portfolios and the gross returns of the long leg in "portfolio 7 and short in portfolio 1"-investments are affected. Returns are also lower for the European investor, albeit not as much as for the U.S. investor. Considering bid-ask spreads and transaction costs, we find that only the return of portfolio 7 is positive for an U.S. investor, albeit with the caveat of very high standard deviations. As a result, returns are statistically not significant. The return of the long–short portfolio is negative at -16 basis points. Analogous to the gross returns, an European investor is less affected.

Figure 5

Figure 8 shows the discounts and returns of the U.S. and European investors over time. Of particular interest are the returns in 2017 and 2018. Compared to the returns of investors not facing restrictions (Figure 7), the returns in 2017 are noticeably lower in general, albeit less so for the European investor. As of spring 2018, net returns and returns for the long–short portfolio are negative for both the U.S. and the European investor, while they are still positive without restrictions.

Figure 8

Overall, the analysis shows that geographic restrictions substantially reduce the returns of the cross-platform strategy, leading to negative returns from the beginning of 2018 onward. Returns are also lower in 2017. This evidence suggests that geographic restrictions may to some extent explain unexploited price differences. Market participants not being allowed to trade on all markets leads to market segmentation and fragmentation (Auer and Claessens, 2018). Even though certain cryptocurrency markets are accessible to investors offshore, they often require a bank account in foreign jurisdictions causing additional costs. While the geographical restrictions are most likely not insurmountable hurdles for—in this case, an U.S. or European investor—they nonetheless introduce additional risks. Violating regulations, investors risk being confronted with authorities and risk exchanges restricting the access to their funds.

5.3.2 Confirmation time

The analysis of arbitrage returns on bitcoin is based on the assumption that it takes two hours to send bitcoin from Kraken to another exchange. Two hours correspond to the average confirmation time between 2017 and 2021. However, Figure A.2 indicates that the confirmation time varies significantly over time. In particular, between 2017 and early 2018 and in the first half of 2021, confirmation times were rather high. Higher transaction times increase the risk of cross-exchange transactions because the exposure to potential bitcoin price changes is longer.

Alternatively, one may interpret longer confirmation times as leading to higher costs, making cross-exchange transactions also more costly. If investors do not offer miners adequate rewards, confirmation times of a particular transaction can be significantly longer than the average confirmation time. Consequently, arbitrageurs have incentives to pay higher fees to compete for faster execution of their orders.

Overall, higher miner fees and longer transfer times may discourage market participants from transferring bitcoins at all (Easley, O'Hara, and Basu, 2019). Thus, higher transaction times represent frictions that could lead to greater price distortions across exchanges.

We account for changes in confirmation times and re-calculate returns with daily varying confirmation times (see Figure A.2 in the Appendix). We show the results in Table 6. Varying confirmation times only have a limited impact on the gross returns. Interestingly, the returns of portfolios 1 to 4 are lower, while the return of portfolio 7 is larger. During periods with longer confirmation times, price changes of the underlying coin have a stronger impact on returns, but the direction does not necessarily decrease. Prices of portfolios with deep discounts are lower, and prices of portfolios that do not offer discounts are higher. The return of the long–short strategy is noticeably higher with varying confirmation times, as the price deviations are higher.

Table 6

One takeaway from this analysis is that longer confirmation times are associated with higher price distortions. In addition, however, the standard deviations of the returns are higher, which increases the risk of any arbitrage strategy. The analysis indicates that the impact of transaction costs on arbitrage returns is similar to the impact of longer transaction times, in line with the notion that a higher demand for confirmation leads to higher rewards paid to miners.

We plot the returns over time in Figure 9. They show a similar pattern compared to our main analysis, with a slightly different magnitude. While the returns in mid-2017 are slightly lower, the returns at the end of 2017 are higher. At the end of 2017, the bitcoin price rose sharply and the confirmation time was very long. Here, the fact that the confirmation time is longer has a positive impact on the returns. As noted above, longer transaction times influence price discovery and can lead to larger price deviations across exchanges. We shed more light on this observation in the following section.

Figure 9

6 Determinants of arbitrage evolution over time

The results of our analyses thus far indicate that arbitrage opportunities in the cryptocurrency market have decreased over time. In this section, we shed light on various factors that may explain why price deviations in the cryptocurrency market decrease over time.

6.1 Explanatory variables

Section 5.3 already discussed two potential factors that influence the profitability of arbitrage strategies when studying the impact of geographic restrictions for investors and of varying blockchain confirmation times. We now discuss and further study potential determinants that may explain changes in arbitrage opportunities over time. In particular, we study the effects of volatility, funding liquidity and market liquidity, market fragmentation, institutional engagement in the crypto market, informed retail investor engagement in the market, and—in line with Section 5.3—confirmation times. Finally, we also study the relationship between cryptocurrency-market related news and price deviations.

First, to account for volatility, we calculate the intraday volatility of the weighted-average return (*volatility*). We expect a positive correlation between volatility and price deviations, as high volatility complicates price discovery. Higher volatility may cause short-term price deviations between exchanges and create uncertainty in the duration of these.

Another key driver of price differentials across exchanges may be liquidity (Kroeger and Sarkar, 2017). Higher liquidity is associated with lower frictions and leads to more uniform prices. Wei (2018) discusses liquidity as an important factor of efficient cryptocurrency markets. Thus, one potential explanation for reduced arbitrage opportunities over time may be that markets have become more liquid over time. We use the bid-ask spread as our measure for liquidity. Specifically, we use the hourly pair-specific average bid-ask spread (*Bid-ask spread*) of the two currency pairs that had the highest price deviation. The pair-specific bid-ask spread defines the level of liquidity on those exchanges that are responsible for the maximum price deviations. We expect higher liquidity to be associated with lower arbitrage opportunities.

Next, we also study the impact of overall trading volume on price deviations (*log volume*). Based on the evidence in the literature, we expect price deviations to be negatively related to volume (Kroeger and Sarkar, 2017). At the same time, however, a high trading volume could also be related to noise trading. Uninformed investors trading on specific exchanges may influence prices on these exchanges and create price deviations with respect to other exchanges. Thus, a higher trading may also be related to increased arbitrage opportunities.

Arbitrage opportunities may also be related to investors' funding liquidity (Brunnermeier and Pedersen, 2008; Gârleanu and Pedersen, 2011; Macchiavelli and Zhou, 2022). Stricter or more expensive funding opportunities may make exploiting price deviations less attractive. We proxy funding liquidity using the *term spread* (Chen and Lu, 2018). *Term spread* denotes the yield spread between the 10-year Treasury bond (constant maturity) and the 3-month Treasury bills, the Treasury bond term spread. We collect the daily data from the Federal Reserve's FRED database.

A fourth important factor that may influence arbitrage opportunities is the market fragmentation of the crypto market—or, in other words, the competition between exchanges (O'Hara and Ye, 2011). The addition of new trading venues increases competition and—theoretically—forces exchanges to reduce trading costs and to improve latency for traders, which should reduce arbitrage opportunities across exchanges. In the same direction, the literature also provides arguments that competitive effects shift the balance in favor of fragmented markets due to reduced inventory risk of dealers (O'Hara and Ye, 2011). At the same time, fragmentation of trading may harm market quality by reducing the liquidity available in a particular market and potentially in the market overall (O'Hara and Ye, 2011). Madhavan (2015) argues that fragmentation induces market distortion, such as increases in price volatility. Reduced liquidity and increased volatility should increase arbitrage opportunities. In the case of the crypto market, market fragmentation is at least to some extent driven by regulatory restrictions and capital controls, thus yielding potentially fractured, not only fragmented, markets. In addition, the regulatory restrictions also hinder (retail) investors from benefiting from increased competition. Hence, one may argue that the adverse effects outweigh the positive effects. Overall, given the mixed evidence in the literature, we do not have clear expectations on the effect of fragmentation on price deviations. We measure competitiveness with the Herfindahl–Hirschman Index (HHI), following Chao, Yao, and Ye (2017) and Gresse (2017). In particular, we calculate

$$HHI_{i,j,t} = \sum_j \left(\frac{ExchVol_{i,j,t}}{TotalVol_{i,t}} \right)^2,$$

where $ExchVol$ denotes the trading volume of pair i on exchange j at time t, and $TotalVol$ denotes the total trading volume of the underlying cryptocurrency. A lower HHI implies more fragmented trading.

Another plausible explanation for changes in price deviations may be provided by increasing awareness of market participants. Today, a series of websites, such as bitsgap, tokenspread, or cryptohopper, collects and provides detailed information on mispricing in the crypto market, which can then be exploited (see also Borri and Shakhnov, 2022). Some platforms simply document price deviations, while others even provide automatic trading strategies to exploit such deviations. Today, even "established" data providers of crypto trade data, such as Kaiko, provide several measures for price deviations in real time. The increasing awareness of investors for opportunities to purchase a given cryptocurrency at a discount and the reduced barriers to obtain such information (i.e., reduced information costs) may also be an important driver toward more efficient market pricing. We collect the traffic to websites that provide information on discounts in the crypto market (bitsgap, tokenspread, cryptohopper) and use the total traffic (i.e., the sum) as a proxy for the awareness (*informed trading*) of the investor base for such price deviations. We expect that higher awareness is associated with lower price deviations.

In a similar vein, the increasing involvement of institutional investors in the crypto market may also explain the decrease in price deviations. In particular, institutional investors could evoke a reduction in price differentials due to their tendency to engage in arbitrage trading strategies. In fact, in 2021, 30% of hedge funds involved in the crypto market reported practicing arbitrage strategies (PwC, 2021). PwC (2021) also provides evidence in support of the notion that the number of institutional investors who engage in the crypto market has increased in recent years. We proxy institutional involvement in the crypto market using 13F filings. In the U.S., the Securities and Exchange Commission requires all institutions with at least USD 100 million in assets under management to disclose 13F institutional holdings every quarter. We realize that this proxy of institutional involvement in the market is restricted to sufficiently large U.S. investors and to investments in assets that are on the *Official List of Section 13(f) Securities*. Nonetheless, we believe that this provides a rough estimate that allows us to proxy overall institutional involvement in the crypto market. We download all 13F institutional holdings from EDGAR and search the filings for crypto-related investment. We then use the number of unique investments to quantify institutional involvement. We rely on the number of investments rather than the value, as the value is not only affected by the decision to invest in the crypto market but also by the evolution of market prices. The number on investments, on the other hand, provides a proxy that is not directly affected by market prices.

Next, as discussed in Section 5.3, higher confirmation times may influence the profitability of arbitrage opportunities. Higher confirmation times are the result of the network load with the specific cryptocurrency. A high network load leads to a higher confirmation time and thus affects the duration, and also the costs, of cross-exchange trades. This could—to some extent—explain price differentials as exploiting arbitrage opportunities may be riskier and/or more costly when the network load and average confirmation times are higher. *Confirmation time* captures the daily average confirmation time. We expect a positive correlation between confirmation times and price deviations.

Finally, we study the impact of news on price deviations over time. Similar to volatility, news may complicate price discovery and cause short-term price deviations between exchanges. Specifically, a higher news rate may create the need to quickly adjust prices, and in the short run, prices on one trading venue may react faster than prices on another trading venue, thus creating short-term arbitrage opportunities. We proxy for news in the crypto market using data from Ravenpack Global

Macro. Ravenpack has covered news from the crypto market since 2011, starting with news on Bitcoin. Today, Ravenpack covers news on about 800 different coins. We follow the Ravenpack suggestion to only consider news with a relevance score of at least 75%. We then count the number of cryptocurrency-related news reports on any given day to proxy for the effect of news. As the news data is published with a delay, our data set only covers news until December 31, 2020.

6.2 Descriptive statistics

We first shed some light on the correlations of the determinants of arbitrage with the arbitrage index (Table 7). Bivariate correlations provide the first evidence that arbitrage opportunities increase with bid-ask spreads (.35, $p < .05$), volatility (.54, $p < .05$), and funding liquidity (term spread, .23, $p < .05$). We observe significant negative correlations between arbitrage opportunities and trading volume (-.13, $p < .05$), institutional trading (-.23, $p < .05$), and informed trading (-.39, $p < .05$). Correlations between price deviations and confirmation times are also positive (.07, $p < .05$).

Next, we turn to correlations between explanatory variables. Most strikingly, we observe strong positive correlations between institutional engagement, informed (retail) trading, and overall trading volume. Correlations are between 48% and 90% for these measures, in line with the notion that all of these measures are somewhat related to crypto market attractiveness. Not surprisingly, we also observe a positive correlation between bid-ask spreads and volatility.

Table 7

6.3 Regression analysis

We analyze the impact of the potential determinants using an ordinary least squares (OLS) regression model with Newey–West standard errors (Newey and West, 1994). For the dependent variable, we calculate the hourly maximum price difference between exchanges, the arbitrage index of Makarov and Schoar (2020). Due to the previously discussed limitations, we exclude South Korean exchanges and Bitfinex in our analysis. We aggregate all variables at the daily level using simple averages.

Table 8

We summarize the results of our analysis in Table 8. We first study the relation of each explanatory variable separately before we estimate the full model, including all potential determinants. To streamline the discussion, we discuss the individual models and the full models together.

In Column (1), we first study the impact of time on price deviations and thereby provide a formal test in favor of the notion that price deviations decrease over time. In line with the previous discussion, we find a statistically significant coefficient (t-statistic 8.93), indicating decreasing price variations over time.

As expected, we observe a significant positive relation between volatility and price deviations (Column (2)). The results hold in the full model (Column (10), coefficient 1.35, t-statistic 9.50). This observation is consistent with prior studies (Kroeger and Sarkar, 2017).

Funding liquidity is also significantly correlated to price deviations. In particular, an increase in the term spread, indicating more expensive funding opportunities, is positively related to price deviations (Column (3), t-statistic 7.46). In a related vein, we observe a positive relationship between market liquidity, measured with the bid-ask spread (Column (4), t-statistic 5.67), which is again consistent with previous literature (Kroeger and Sarkar, 2017). The findings are in line with our expectations—higher liquidity is related to lower price deviations. Both results also hold in the full model (Column (10)).

We study the relation between market fragmentation and price deviations in Column (5). We observe a negative coefficient for HHI that is, however, not—or at best marginally—statistically significant (t-statistic 1.65) and that does not hold in the full model. In addition, the R^2 of Column (5) indicates that the model using the HHI as the lone explanatory variable has virtually no explanatory power.

The variables for institutional involvement, informed retail trading, and overall trading volume are in line with expectations and show statistically significant negative coefficients in the individual models (Columns (6)–(8)). t-statistics range between 5.93 and 8.58, well above conventional thresholds indicating statistical significance. The observation that trading volume is negatively correlated to price deviations is also consistent with prior literature (Kroeger and Sarkar, 2017). However, turning to the full model, we find that the coefficients on institutional and informed (retail) trading remain statistically significant and negative, while the coefficient on volume turns positive.

Additional analyses in Table 9 indicate that in particular informed trading seems to have an impact on the relationship between trading volume and price deviations. Specifically, Column (4) of Table 9 shows that a regression of volume on informed trading (including cryptocurrency-fixed effects) features a positive and statistically significant coefficient (.27, t-statistic of 23.69) with a high explanatory power of 69%. Thus, informed trading and trading volume is highly correlated (see also Table 7). In Column (5), we take the residual of the estimation in Column (4) and regress price deviations on the residual. The results indicate that trading volume beyond informed trading is positively related to price deviations (coefficient .0021, t-statistic 2.57). Overall, our findings point in the direction that—not accounting for informed trading—volume decreases price deviations; however, holding informed trading constant, volume increases arbitrage opportunities. Informed investors quickly correct arbitrage opportunities between exchanges, while trading beyond informed trading may be called noise trading that increases, on average, price deviations between exchanges.

Table 9

Last, Column (9) focuses on confirmation times and shows the expected positive coefficient. However, the coefficient is insignificant in the full model (Column (10)), and the explanatory power of Column (9) is negligible ($< 1\%$).

Next, we compare the explanatory power of the various explanatory variables. The R^2 in Column (2) indicates that volatility has the largest explanatory power of the covariates considered in our analysis. By comparison, institutional trading and informed (retail) trading have a much lower explanatory power with R^2 of 5% and 13%, respectively.

Finally, we study the relationship between news that relate to the crypto market and price deviations. We summarize the results in Table 10. Column (1) indicates that a model that focuses on news alone shows a positive coefficient on news (.0001, t-statistic of 2.01), pointing in the direction of a positive relation between news and price deviations. However, the coefficient does not remain significant in the full model. In addition, the explanatory power of news for price deviations is virtually nonexistent with a R^2 below 1%. The coefficients of our other explanatory variables in the full model (Column (2)) are very similar to the full model displayed in Table 8.

Table 10

7 Discussion and conclusion

Our paper analyzes market efficiency in terms of price deviations across exchanges and arbitrage opportunities in the cryptocurrency market and, thus, contributes to our understanding of the functioning of a rapidly growing market in the investment domain. Our analyses demonstrate that in the five-year time period between 2017 and 2021, there were continuous price discrepancies between cryptocurrencies that are traded on different exchanges. This is in line with anectodal evidence (e.g., the FTX bankruptcy) and previous research (Kroeger and Sarkar, 2017; Makarov and Schoar, 2020). However, having a much more extended time horizon under investigation, we are able to document that price deviations substantially decreased after the first quarter of 2018.

To explore the practical relevance of our findings, we implement and test a cross-platform strategy and a zero-cost long–short strategy, neither of which are completely risk-free, yet resemble an arbitrage strategy. Analogous to the price differences, from April 2018 onward, returns from a zero-cost strategy are substantially smaller, and negative, on average. Trading fees are a key factor of cross-platform returns. Fees depend on the amount of trading volume, which again is crucial for the returns. Ultimately, we find that arbitrage is practically hardly possible anymore after the end of the observation period of previous papers, i.e., since April 2018. Using different filter techniques we document that our conclusions are not driven by limiting the analysis to a subset of exchanges.

Given that we can document that price deviations have substantially decreased, it is important to explore why. Consequently, we aim to shed some first light on the mechanisms that explain this decrease in arbitrage. Consistent with previous literature, we show that price discrepancies between cryptocurrencies are positively related to price volatility above all. Furthermore, our proxies for institutional involvement and retail trader attention show explanatory power for market efficiency in the expected direction with higher informed activity leading to lower price discrepancies. Both institutional involvement and retail trader attention increase significantly over time, and thus may plausibly explain the decrease in arbitrage opportunities over time. We also find increased trading volume to have contributed to price deviations, giving some indication of noise trading. Furthermore, we find a positive relationship for investors' funding liquidity. Other influential factors are rather small in effect. We do not find market fragmentation (competition among exchanges) to have a meaningful influence on price deviations.

In addition, it is important to note that many restrictions exist that prevent the exploitation of seemingly available arbitrage opportunities in the market for cryptocurrencies. These include regulatory and geographical restrictions, and higher risks when trading on undeveloped exchanges. These risks are underlined by substantial media attention when exchanges do not function properly, or even cease to exist suddenly.

Summarizing these findings, we conclude that arbitrage in the market for cryptocurrencies is hardly possible anymore, as price differences across exchanges are relatively low given present frictions. Also, many of the observed price discrepancies exist only for a brief period of time, because of flash crashes or hacker activities at individual exchanges, or due to pump and dump activities. Furthermore, given the increasing professionalization and coverage of these markets, and the increased market capitalization, we do not expect that persistent arbitrage opportunities will be available in the future, at least not for more established cryptocurrencies and cryptocurrency exchanges.

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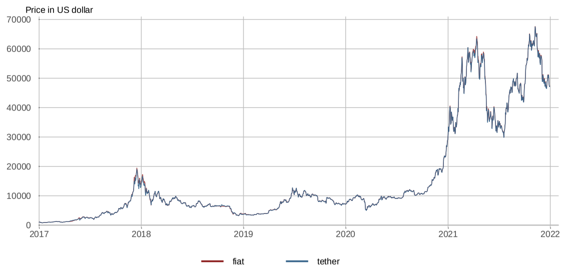
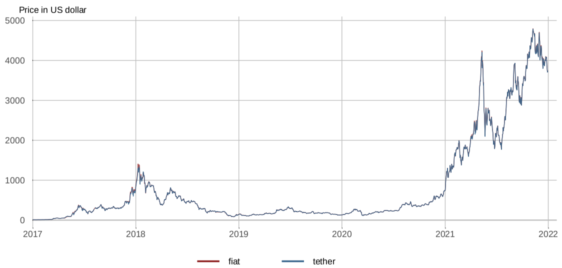
Figure 1 – Summary Statistics of Prices, Volume and Bid-Ask-Spreads

This figure plots the price, daily volume, and the bid-ask-spread of bitcoin, ether, and ripple, separately for fiat-to-crypto exchanges and for crypto-to-crypto exchanges. Additionally, we show bid-ask-spreads for the ten most liquid fiat pairs.

(a) Bitcoin: Price

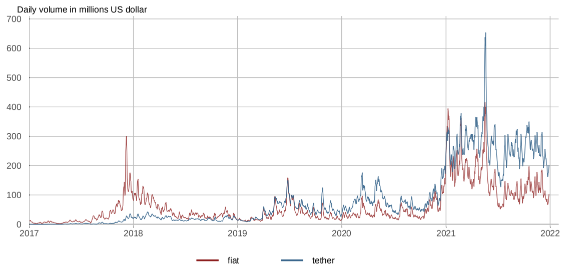


(b) Ether: Price

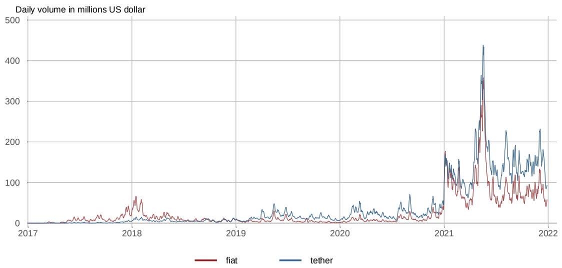


(c) Ripple: Price

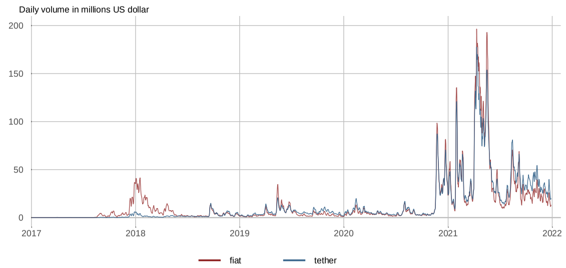
(d) Bitcoin: Volume



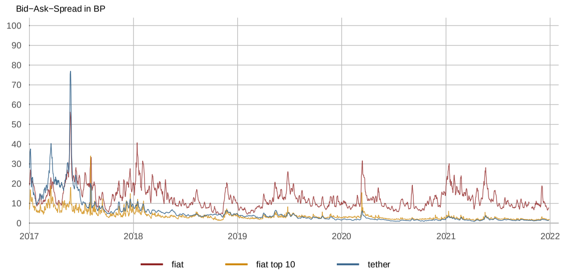
(e) Ether: Volume



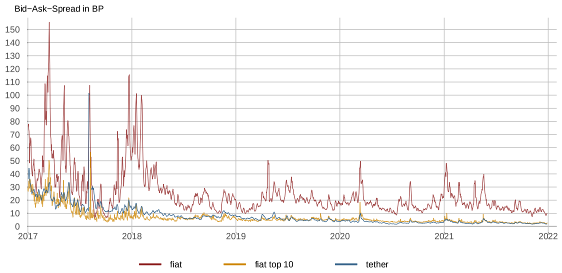
(f) Ripple: Volume



(g) Bitcoin: Bid-Ask-Spread



(h) Ether: Bid-Ask-Spread



(i) Ripple: Bid-Ask-Spread

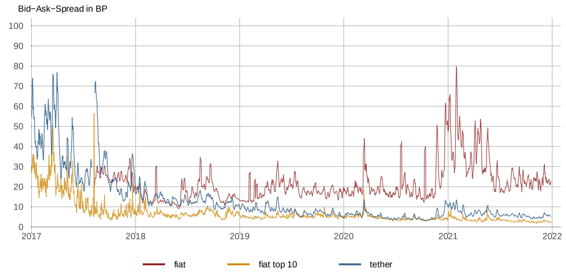


Figure 2 – Arbitrage opportunities across exchanges

The figure illustrates simple arbitrage opportunities across exchanges. The inside bid of venue X is larger than the inside ask of venue Y, allowing investors to exploit price differences across exchanges (adapted from Shkilko, Van Ness, and Van Ness (2008).

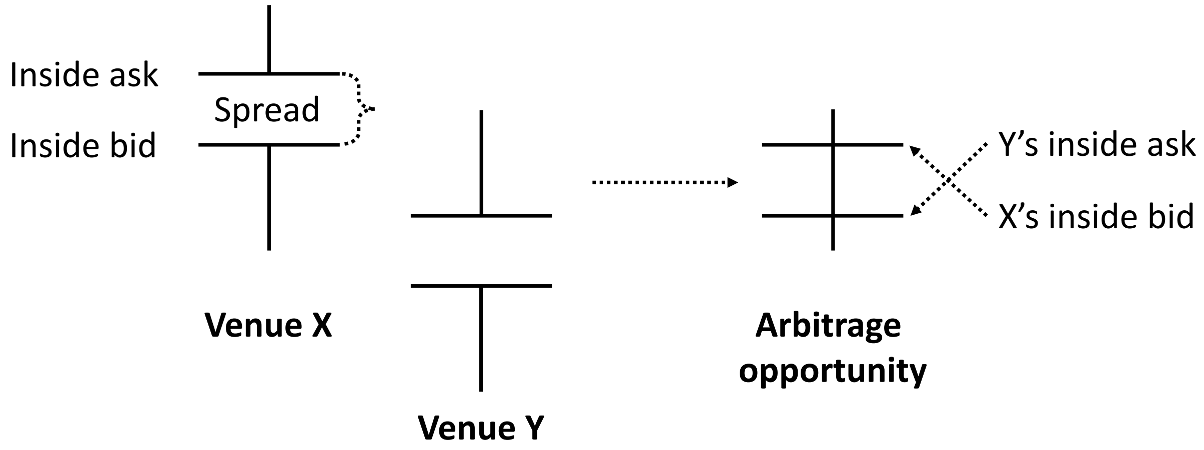


Figure 3 – Panel A: The evolution of simple arbitrage opportunities across exchanges

The figure shows the difference between the highest inside bid and the lowest inside ask for a cryptocurrency across exchanges over time. The highest bid and the lowest ask for a given cryptocurrency across all exchanges are collected for every five-second interval. The figure plots the largest of these differences for every day in the sample period. In Panel A, only quotes with a volume of at least 0.5 are considered. Panel B [C] considers only quotes with a volume of at least 0.05 [5].

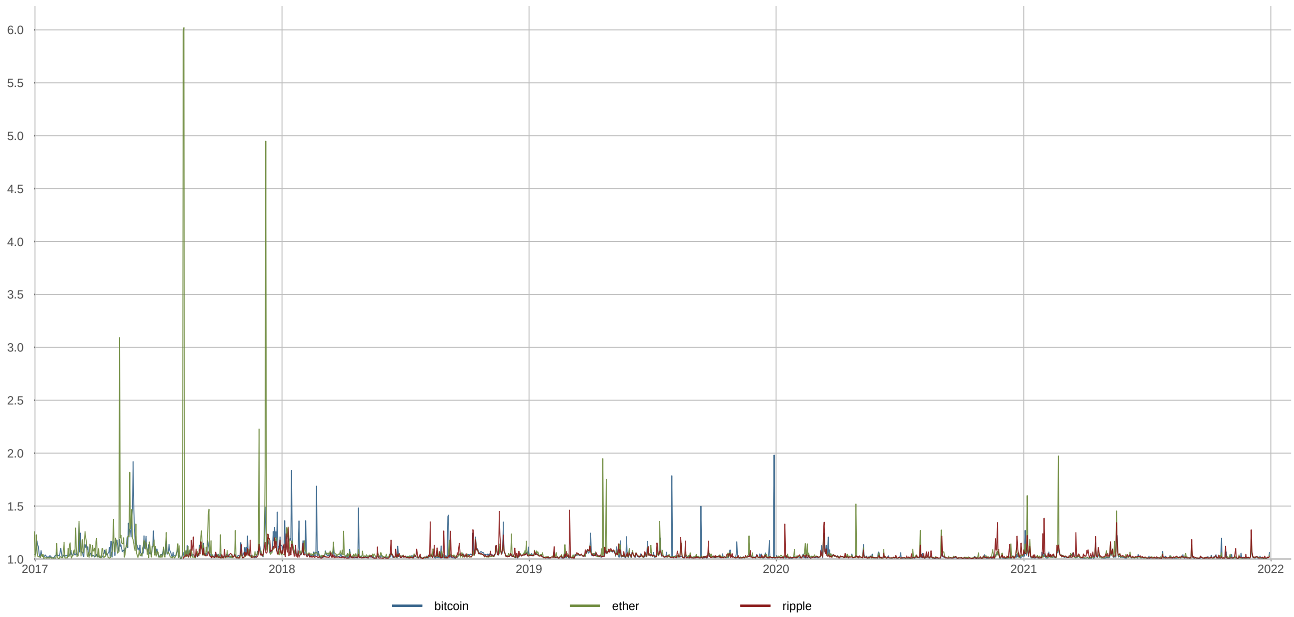


Figure 3 – Panel B: The evolution of simple arbitrage opportunities across exchanges

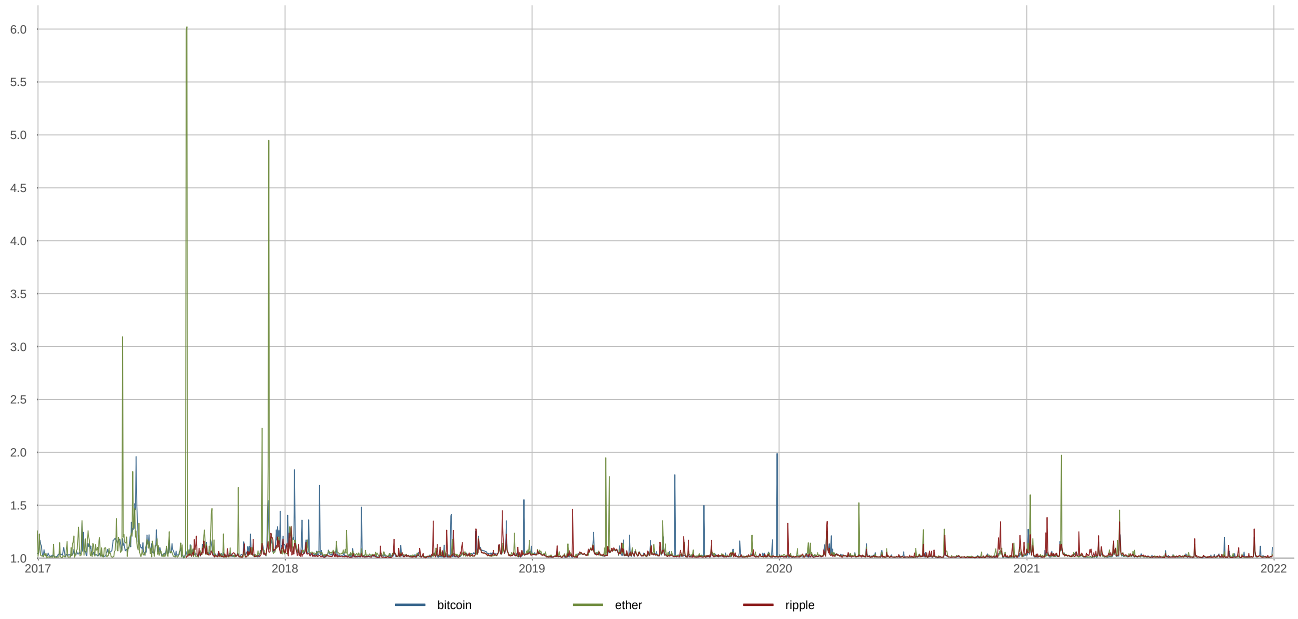


Figure 3 – Panel C: The evolution of simple arbitrage opportunities across exchanges

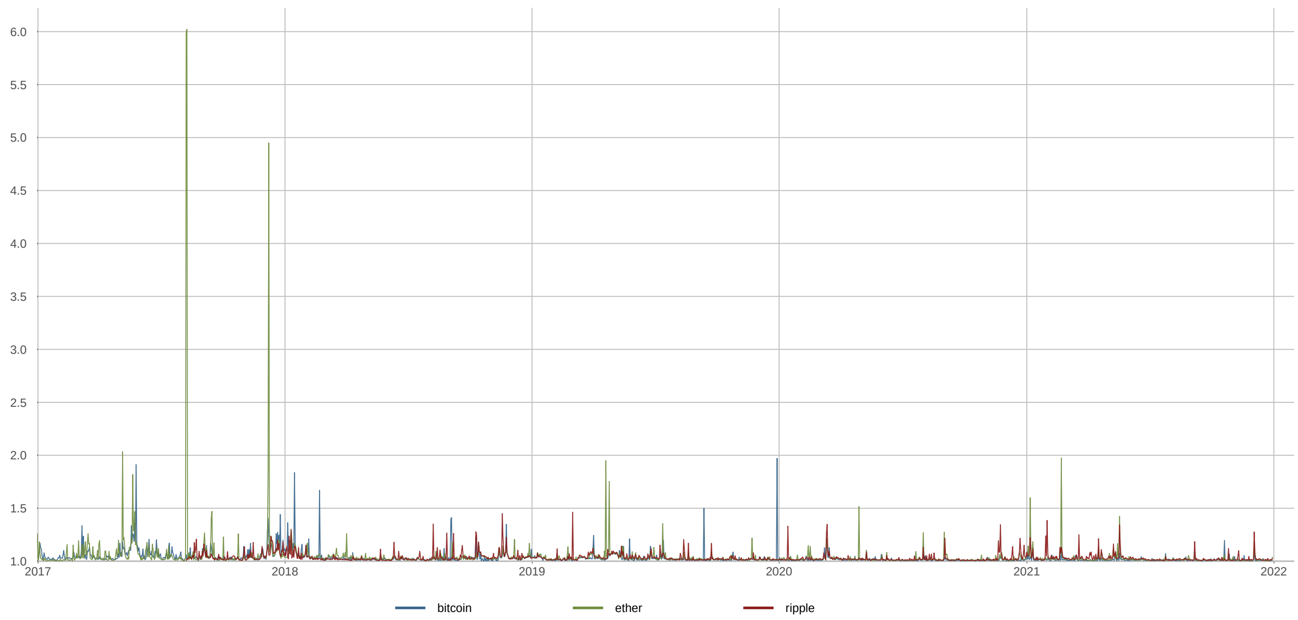
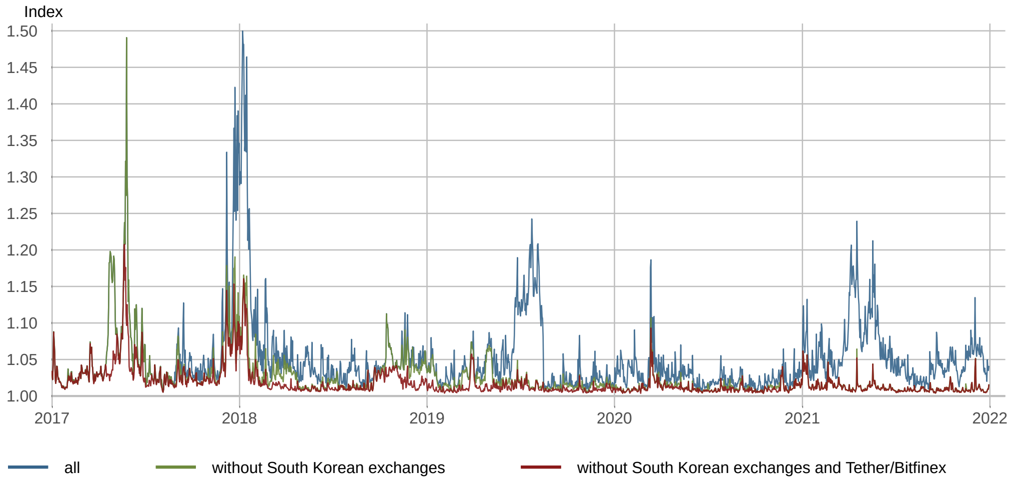


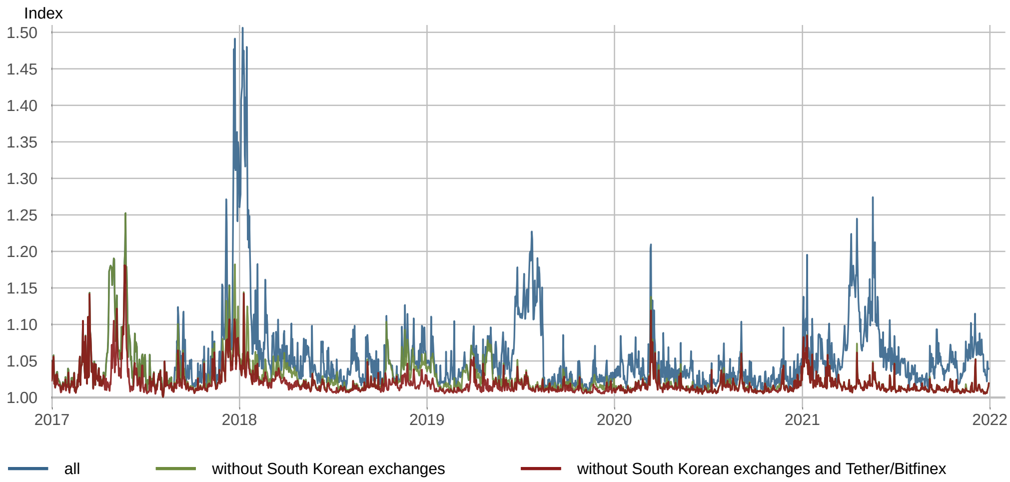
Figure 4 – Arbitrage indices

The arbitrage indices are formed by dividing the highest price of an hour by the lowest price. All price differences are aggregated on a daily basis.

(a) Bitcoin



(b) Ether



(c) Ripple

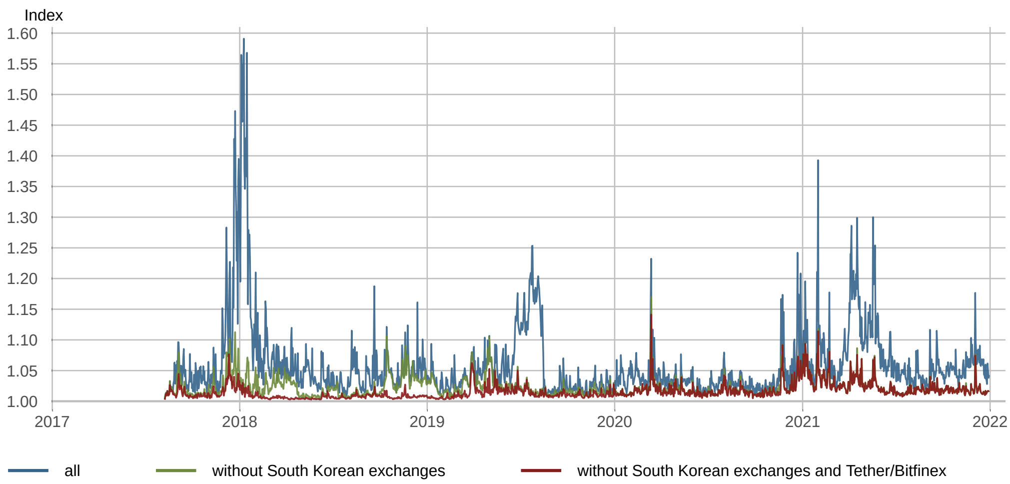
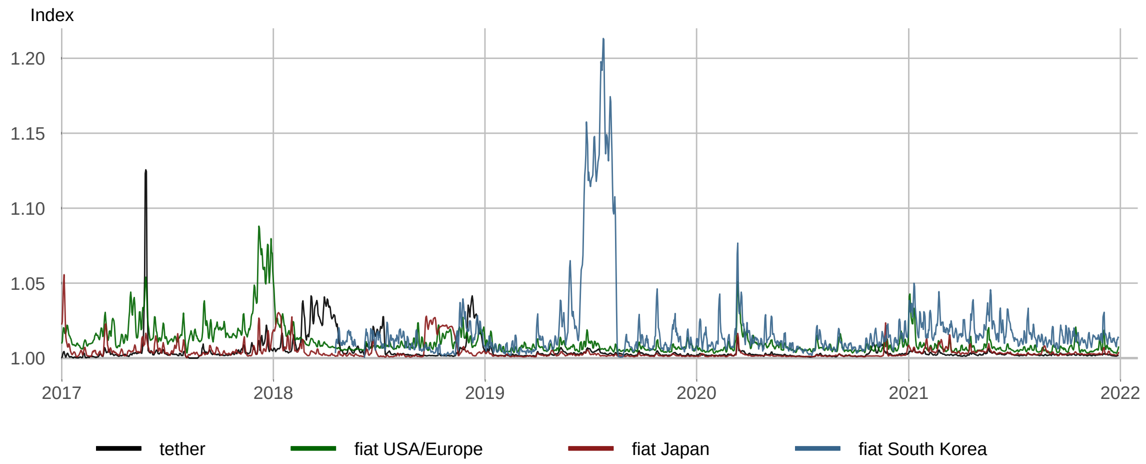


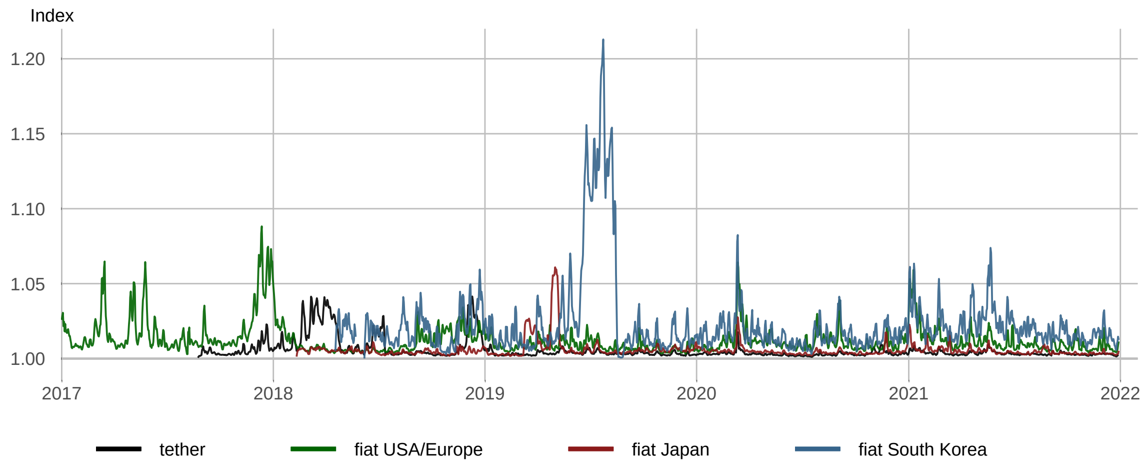
Figure 5 – Arbitrage indices within regions

The arbitrage indices are formed by dividing the highest price of an hour by the lowest price. All price differences are aggregated on a daily basis. Tether contains all crypto-only exchanges and the fiat exchanges are split by their main geographic focus.

(a) Bitcoin



(b) Ether



(c) Ripple

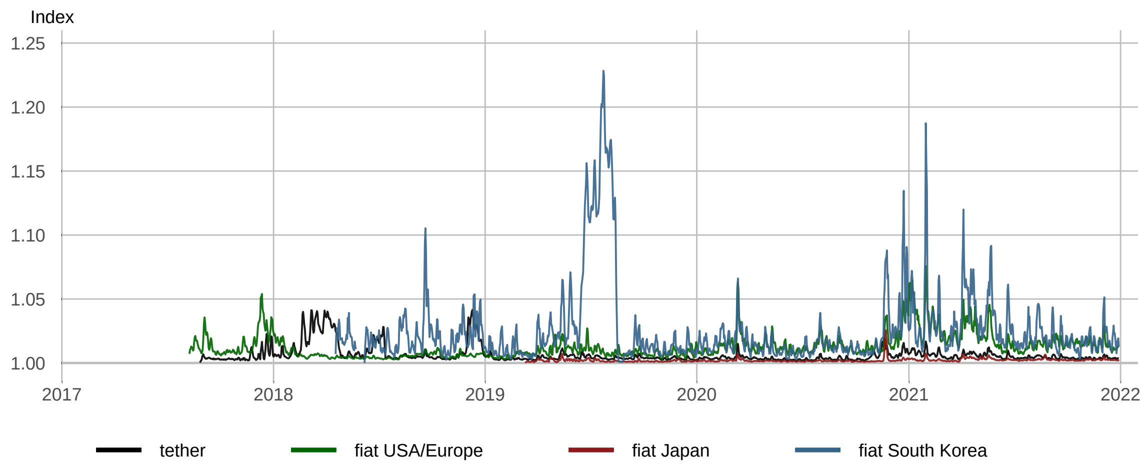


Figure 6 – Illustration of the long–short strategy

This figure shows the capital and transaction flows of the cross-platform strategy for a long and a short position. For the long position, bitcoin is purchased on Kraken using US dollars at time *t*. Then, funds are transferred to another exchange. On this exchange, bitcoin is sold at time *t+1*. If the cryptocurrency is not listed in US dollars it is exchanged into US dollars via the foreign exchange market. For the short position, bitcoin is sold on Kraken at time *t*. In case bitcoin is denominated in a non-USD currency, USD is first exchanged on the foreign exchange market and then bitcoin is bought at *t+1* on the other exchange. Then, the bitcoins are transferred to Kraken to close the position. Finally, USD is withdrawn from the Kraken exchange.

time t | **time $t + 1$**

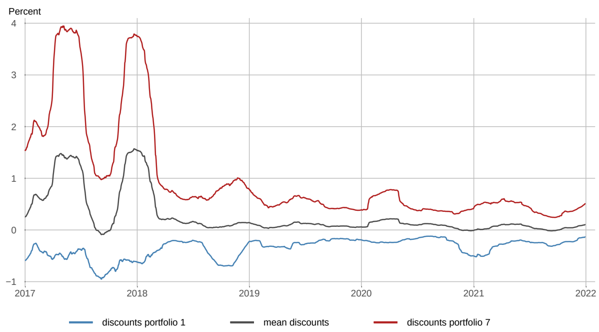
long $\text{USD} \xrightarrow[\text{Kraken}]{\text{buy}} \text{BTC} \dashrightarrow^{\text{transfer}} \text{BTC} \xrightarrow[\text{Exchange}]{\text{sell}} \text{Fiat} \xrightarrow[\text{Fx market}]{\text{exchange}} \text{USD}$

short $\text{BTC} \xrightarrow[\text{Kraken}]{\text{short sell}} \text{USD} \dashrightarrow^{\text{exchange}}_{\text{Fx market}} \text{Fiat} \xrightarrow[\text{Exchange}]{\text{buy}} \text{BTC} \xrightarrow[\text{to Kraken}]{\text{transfer}} \text{BTC} \xrightarrow{\text{withdrawal}} \text{USD}$

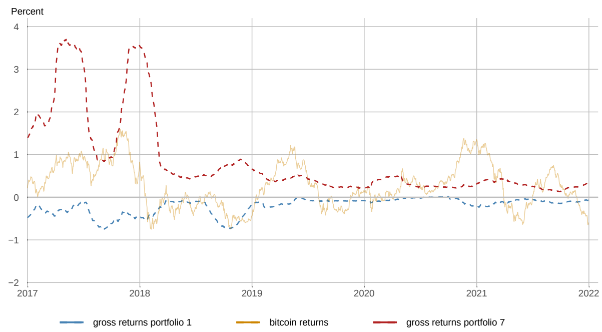
Figure 7 – Returns of the cross-platform strategy over time (Part A)

The figure shows the discounts (Panel a), gross and net returns of the portfolios (Panels b and c), and the returns of the zero-cost strategy (Panel d) over time using 100-day-rolling windows. Part A shows the cross-platform strategy for bitcoin; Part B shows the cross-platform strategy for ether.

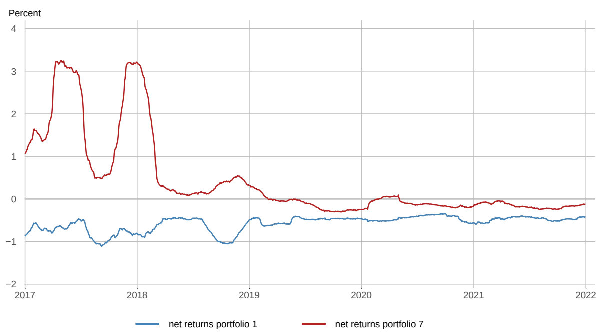
(a) Discounts



(b) Gross returns



(c) Net returns



(d) Long–short returns

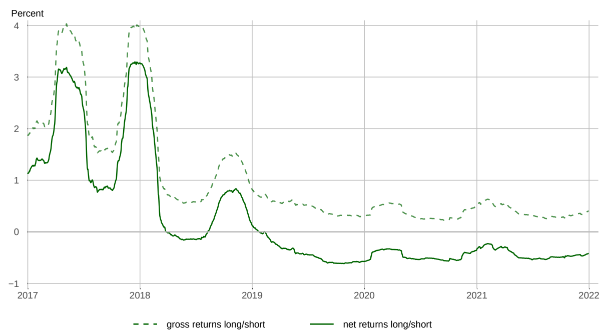


Figure 7 – Returns of the cross-platform strategy over time (Part B)

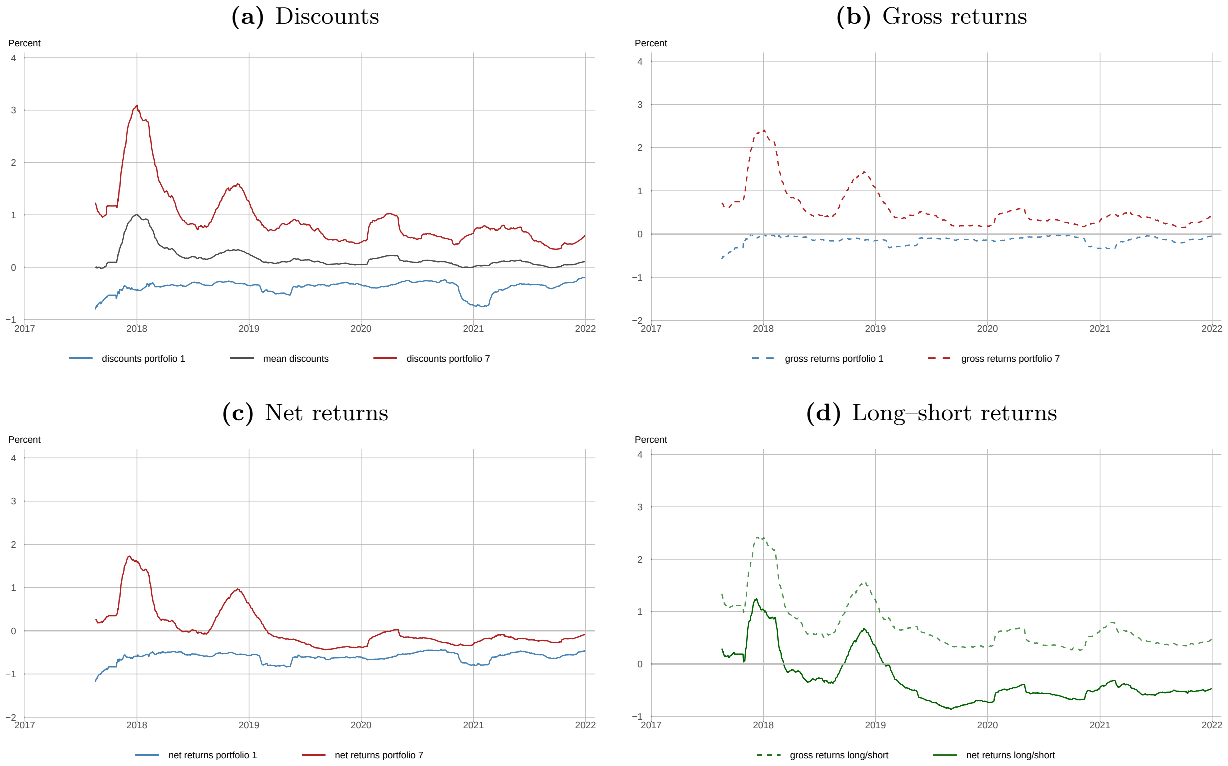


Figure 8 – Cross-platform strategy over time for bitcoin considering restrictions (Part A)]

This figure shows the discounts, portfolio returns, and returns of the zero-cost strategy for an U.S. investor (Part A) [European investor (Part B)] for bitcoin over time. All graphs are presented using 100-day rolling windows.

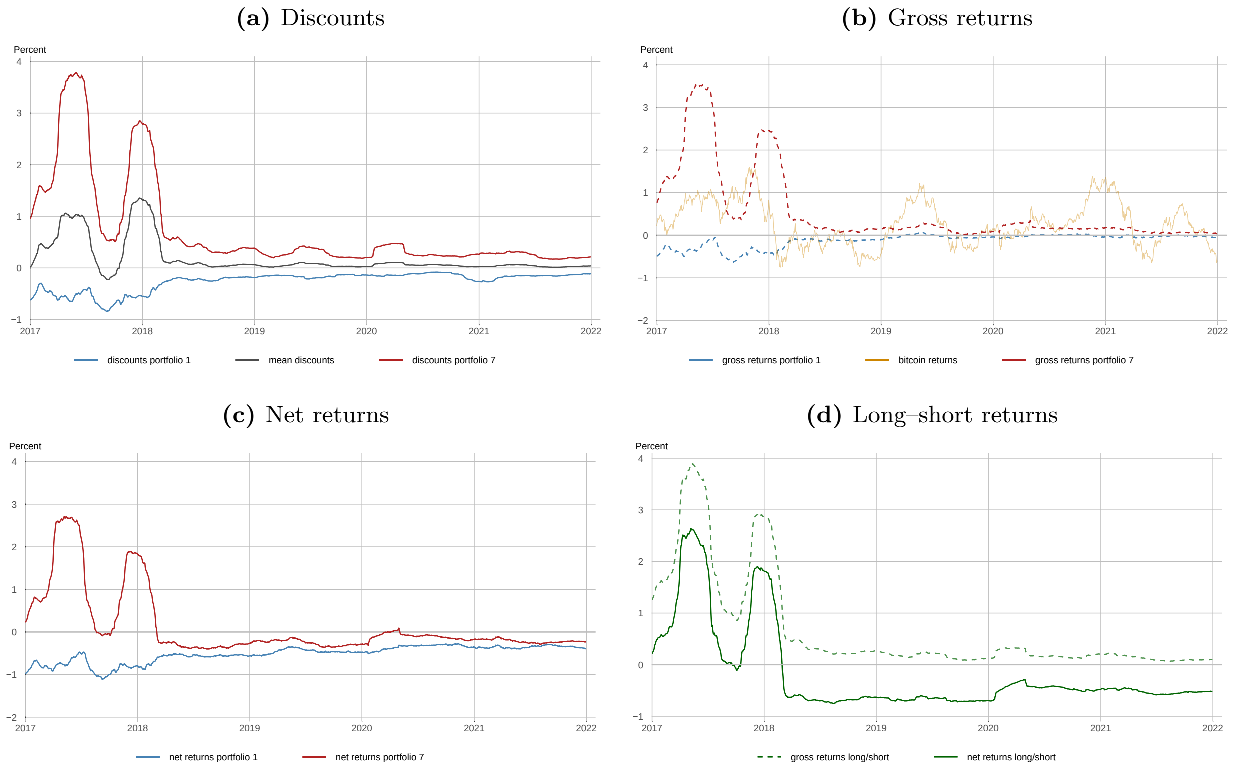
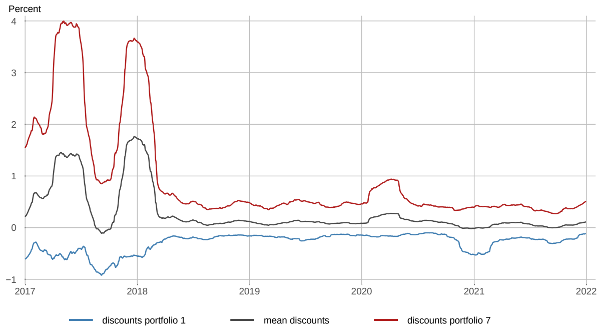
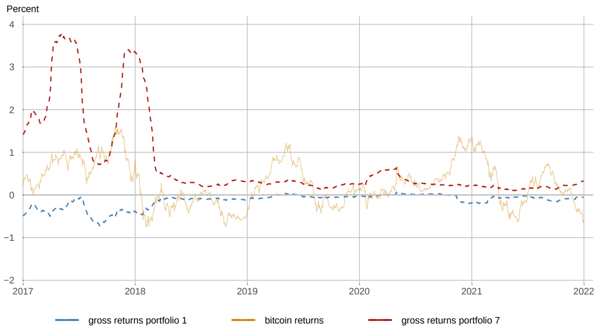


Figure 8 – Cross-platform strategy over time for bitcoin considering restrictions (Part B)]

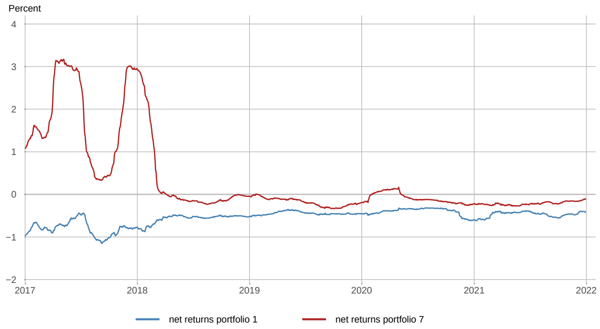
(a) Discounts



(b) Gross returns



(c) Net returns



(d) Long–short returns

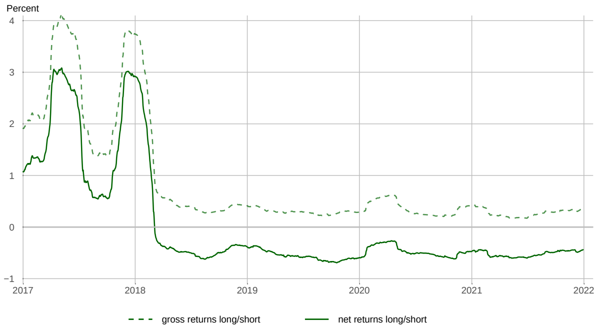
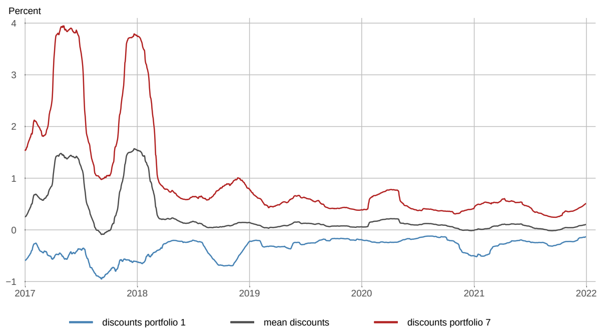


Figure 9 – Varying confirmation times and returns of the cross-platform strategy over time

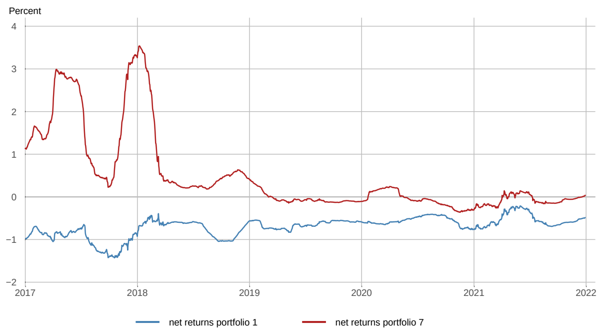
The figure shows the discounts, returns of the portfolios and the returns of the zero-cost strategy, considering exact daily confirmation times of bitcoin. All graphs are presented using 100 day rolling windows.

(a) Discounts



(b) Gross returns

(c) Net returns



(d) Long–short returns

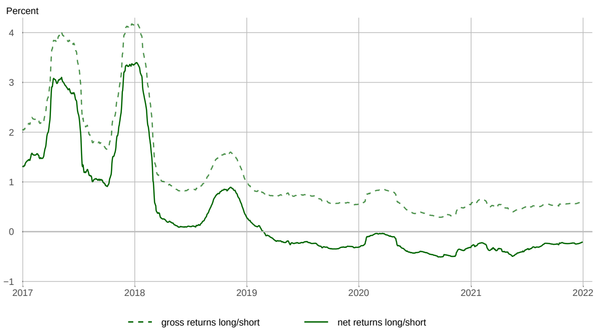


Table 1 – Summary Statistics

This table summarizes descriptive statistics of price premiums, daily trading volumes, and average bid-ask spreads of sample exchanges using the most used currency, sorted by geography. We consider the US and Europe together, as the main currencies (USD, EUR, and GBP) can be traded in both regions. The price premium shows the percentage-difference of prices to the average price of all exchanges. Price premiums are calculated separately for fiat-to-crypto and crypto-to-crypto exchanges. Bid-ask spreads denote the difference between successive bid and ask orders, aggregated hourly.

	Price Premium in %			Standard deviation of Price Premium			Daily volume in millions US dollar			Average Bid-Ask-Spread in BP		
Currency	BTC	ETH	XRP	BTC	ETH	XRP	BTC	ETH	XRP	BTC	ETH	XRP
Europe/USA												
BitBay (EUR)	0.144	0.213	0.456	0.97	1.49	3.22	0.59	0.10	0.00	37.89	72.17	419.58
Bitstamp (USD)	-0.447	-0.294	-0.609	1.08	0.82	1.89	102.90	32.17	22.36	5.34	6.97	9.93
Bittrex (USD)	-0.211	-0.194	-0.253	0.66	0.67	0.95	7.66	2.58	0.54	6.53	11.20	23.52
Coinbase (USD)	-0.339	-0.296	0.050	0.98	1.11	0.65	257.80	178.63	9.17	1.25	2.92	6.33
Coinfloor (GBP)	-0.008	-	-	0.78	-	-	1.10	-	-	19.68	-	-
Gemini (USD)	-0.378	-0.348	-	1.02	1.15	-	44.62	25.86	-	3.64	8.96	-
Itbit (USD)	-0.393	-0.196	-	1.02	0.70	-	15.33	3.74	-	4.62	10.98	-
Kraken (USD)	-0.403	-0.429	-0.528	1.06	1.21	1.80	83.26	52.42	9.20	4.12	7.89	10.39
Japan												
Bitbank (JPY)	-0.135	-	-0.171	0.63	-	0.82	13.93	-	19.31	1.60	-	2.31
BitFlyer (JPY)	0.070	-0.181	-0.852	1.04	0.59	0.84	113.92	16.94	1.20	3.58	5.04	10.90
Coincheck (JPY)	-0.146	-	-	0.62	-	-	18.40	-	-	2.42	-	-
Quoine (JPY)	-0.007	-0.142	-0.207	0.91	1.59	0.85	165.21	5.73	6.02	3.27	29.95	13.61
Zaif (JPY)	-0.012	-0.170	-	1.11	0.66	-	25.07	1.08	-	2.92	21.10	-
South Korea												
Bithumb (KRW)	1.559	1.557	1.427	4.78	5.02	4.91	86.75	49.13	56.46	4.81	8.21	14.65
Korbit (KRW)	0.419	-0.452	-0.779	3.34	3.76	3.83	4.53	0.64	0.94	6.72	6.67	6.74
Upbit (KRW)	1.030	1.057	1.021	2.68	2.79	2.63	126.96	83.18	147.15	3.17	4.80	29.08
Other												
Bitfinex (USD)	-0.020	0.024	-0.051	1.00	0.98	1.14	110.22	51.91	10.85	1.08	4.74	6.58
Bitso (MXN)	-0.066	-0.029	-0.190	0.80	0.79	0.90	2.18	0.70	2.12	23.77	47.61	35.59
Tether												
BigONE (USDT)	0.011	0.015	0.011	0.16	0.18	0.26	60.67	35.18	11.72	1.50	2.64	4.36
Binance (USDT)	-0.053	-0.045	-0.019	0.19	0.20	0.13	908.55	508.44	172.37	1.87	2.79	2.82
Bitfinex (UST)	0.001	-0.007	-0.018	0.15	0.18	0.33	18.58	6.52	0.33	4.19	8.51	16.77
Bittrex (USDT)	-0.061	-0.045	-0.042	0.38	0.23	0.33	13.76	3.56	1.93	11.27	13.01	22.84
CoinEx (USDT)	0.004	0.008	0.008	0.10	0.12	0.16	25.42	10.06	4.11	1.62	2.31	3.71
HitBTC (USDT)	0.181	0.176	0.172	0.58	0.59	0.60	348.59	163.98	44.46	2.33	2.92	5.35
KuCoin (USDT)	-0.001	0.001	0.006	0.07	0.09	0.21	61.44	47.57	14.71	0.70	1.34	2.84
OkEX (USDT)	-0.059	-0.054	-0.066	0.18	0.19	0.22	334.02	112.86	30.88	1.38	1.93	3.71
Poloniex (USDT)	-0.018	-0.042	-0.049	0.37	0.20	0.27	26.33	12.33	4.25	5.40	9.65	16.59
ZB (USDT)	-0.002	-0.004	-0.000	0.08	0.11	0.12	228.43	41.36	25.53	1.57	2.41	2.90

Table 2 – Summary statistics of arbitrage indices

This table summarizes descriptive statistics of all exchanges with their most used currency by geography. We consider the US and Europe together, as the main currencies (USD, EUR, and GBP) can be traded in both regions. The price premium shows the percentage-difference of prices to the average price of all exchanges. Price premiums are calculated separately for fiat-to-crypto and crypto-to-crypto exchanges.

	2017			2018			2019			2020			2021			Average		
Currency	BTC	ETH	XRP	BTC	ETH	XRP	BTC	ETH	XRP	BTC	ETH	XRP	BTC	ETH	XRP	BTC	ETH	XRP
All	1.064	1.061	-	1.065	1.069	1.071	1.048	1.052	1.053	1.027	1.034	1.038	1.058	1.064	1.074	1.053	1.056	1.059
All without South Korean	1.052	1.045	-	1.033	1.03	1.024	1.02	1.022	1.022	1.012	1.016	1.02	1.012	1.017	1.025	1.026	1.026	1.023
All wtithout South Korean and Tether/Bitfinex	1.036	1.031	-	1.021	1.02	-	1.011	1.014	1.013	1.011	1.015	1.018	1.012	1.017	1.025	1.018	1.019	1.019
Tether	-	-	-	1.011	1.012	1.012	1.003	1.004	1.004	1.002	1.003	1.004	1.002	1.004	1.005	1.005	1.006	1.006
Fiat western	1.021	1.019	-	1.011	1.011	-	1.007	1.009	1.008	1.008	1.011	1.014	1.007	1.012	1.02	1.011	1.012	1.014
Fiat Japan	1.006	-	-	1.007	1.004	-	1.002	1.008	-	1.002	1.005	1.002	1.004	1.005	1.003	1.004	1.004	-
Fiat Korea	-	-	-	1.008	1.013	1.014	1.032	1.035	1.036	1.012	1.016	1.018	1.017	1.021	1.028	1.014	1.017	1.024

Table 3 – Descriptive statistics of price discounts

The table summarizes descriptive statistics of price discounts for all exchanges against Kraken.

	Average Price Discount in %			Standard deviation in %			Number of observations		
Exchange	BTC	ETH	XRP	BTC	ETH	XRP	BTC	ETH	XRP
Bitbank (JPY)	0.097	-	0.093	0.41	-	0.55	24536	-	24538
BitBay (EUR)	0.416	0.488	1.017	0.94	1.72	3.49	10754	12964	6299
BitBay (GBP)	0.594	1.054	-	2.66	4.82	-	435	1098	-
BitBay (USD)	-0.186	-0.197	0.091	2.23	4.03	5.58	1358	3042	2435
BitFlyer (EUR)	0.043	-	-	0.46	-	-	15872	-	-
BitFlyer (JPY)	0.486	0.054	0.089	1.75	0.42	0.4	43440	19607	6580
BitFlyer (USD)	-0.007	-	-	0.33	-	-	20634	-	-
Bitso (MXN)	0.169	0.166	0.075	0.78	0.82	0.85	23478	23729	24511
Bitso (USD)	0.000	-0.003	0.026	0.33	0.45	0.72	8653	9803	10767
Bitstamp (EUR)	0.060	0.079	0.068	0.47	0.33	0.55	43381	34566	38252
Bitstamp (GBP)	0.081	0.072	0.07	0.25	0.34	0.45	12206	12194	12571
Bitstamp (USD)	-0.031	0.006	-0.059	0.41	0.23	0.51	43420	34598	38235
Bittrex (EUR)	0.066	0.085	0.083	0.57	0.61	0.98	10336	12001	7504
Bittrex (USD)	-0.003	0	0.009	0.20	0.26	0.38	30257	29525	28753
Coinbase (EUR)	0.301	0.27	0.118	0.80	0.8	0.46	43548	38379	16597
Coinbase (GBP)	0.468	0.297	0.192	0.78	0.62	0.38	43327	28977	4350
Coinbase (USD)	0.077	0.147	0.031	0.54	0.8	0.23	43531	43528	16576
Coincheck (JPY)	0.090	-	-	0.39	-	-	24243	-	-
Coinfloor (EUR)	0.080	-	-	0.52	-	-	2960	-	-
Coinfloor (GBP)	0.157	-	-	0.42	-	-	16766	-	-
Gemini (USD)	0.035	0.092	-	0.46	0.75	-	43323	43011	-
Itbit (EUR)	0.108	0.615	-	0.83	1.98	-	8041	582	-
Itbit (USD)	0.022	0.006	-	0.47	0.26	-	43144	23032	-
Quoine (AUD)	0.737	0.206	-	2.29	1.19	-	7470	4290	-
Quoine (EUR)	0.300	0.092	0.083	1.48	0.99	0.82	18767	14176	10423
Quoine (JPY)	0.411	0.328	0.077	1.51	1.93	0.52	43506	38175	30881
Quoine (SGD)	0.421	0.208	-	1.68	1.36	-	22395	14486	-
Quoine (USD)	0.188	0.115	0.058	1.06	1.15	0.57	40281	34212	20791
Zaif (JPY)	0.398	0.094	-	1.82	0.65	-	42882	32921	-

Table 4 – Returns of a cross-platform strategy (Part A)

This table reports the average price discounts of each portfolio together with the returns. *long–short* shows the returns when going long in portfolio 7 and short in portfolio 1. *Gross returns* are returns ignoring bid-ask spreads and any other trading costs. *Returns net of bid/ask* take into account the bid-ask spreads and the *returns net of bid/ask and transaction fees* include exchange fees and fees for the foreign exchange market. Part A shows returns for bitcoin; Part B shows returns for ether.

Portfolio	1	2	3	4	5	6	7	long/short
				Panel A: discounts				
Mean	-0.35	-0.07	0.06	0.21	0.38	0.61	1.00	
Std	0.58	0.43	0.50	0.75	1.04	1.42	1.67	
				Panel B: gross returns				
Mean	-0.20	-0.02	0.07	0.21	0.33	0.54	0.84	1.04
Std	1.30	1.26	1.28	1.39	1.55	1.83	1.98	1.71
SE	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
				Panel C: returns net of bid/ask				
Mean	-0.25	-0.06	0.04	0.17	0.29	0.50	0.77	0.93
Std	1.31	1.27	1.29	1.39	1.54	1.83	1.99	1.72
SE	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
				Panel D: returns net of bid/ask and minimal transaction fees				
Mean	-0.46	-0.26	-0.17	-0.05	0.07	0.28	0.53	0.46
Std	1.31	1.27	1.29	1.38	1.53	1.82	2.00	1.72
SE	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
				Panel E: returns net of bid/ask and transaction fees with USD 1 million monthly volume				
Mean	-0.57	-0.37	-0.27	-0.14	-0.02	0.19	0.43	0.25
Std	1.31	1.27	1.29	1.38	1.53	1.82	2.01	1.74
SE	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
				Panel F: returns net of bid/ask and maximal transaction fees				
Mean	-0.75	-0.55	-0.46	-0.33	-0.19	0.02	0.24	-0.12
Std	1.31	1.27	1.29	1.39	1.54	1.84	2.03	1.79
SE	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01

Table 4 – Returns of a cross-platform strategy (Part B)

Portfolio	1	2	3	4	5	6	7	long/short
				Panel A: discounts				
Mean	-0.37	-0.09	0.01	0.10	0.22	0.38	0.85	
Std	0.63	0.29	0.28	0.31	0.40	0.53	1.10	
				Panel B: gross returns				
Mean	-0.14	-0.04	0.01	0.07	0.14	0.23	0.52	0.66
Std	1.08	0.99	0.98	0.99	1.00	1.05	1.24	1.01
SE	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
				Panel C: returns net of bid/ask				
Mean	-0.25	-0.10	-0.05	0.00	0.06	0.14	0.35	0.38
Std	1.18	1.00	0.99	0.99	1.00	1.03	1.23	1.11
SE	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
				Panel D: returns net of bid/ask and minimal transaction fees				
Mean	-0.47	-0.32	-0.26	-0.21	-0.16	-0.10	0.09	-0.12
Std	1.18	1.00	0.99	0.99	1.00	1.03	1.23	1.11
SE	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
				Panel E: returns net of bid/ask and transaction fees with USD 1 million monthly volume				
Mean	-0.59	-0.43	-0.37	-0.32	-0.26	-0.19	-0.02	-0.36
Std	1.19	1.01	0.99	0.99	1.00	1.04	1.24	1.13
SE	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
				Panel F: returns net of bid/ask and maximal transaction fees				
Mean	-0.77	-0.65	-0.60	-0.55	-0.49	-0.40	-0.22	-0.74
Std	1.18	1.00	0.99	0.99	1.01	1.04	1.24	1.13
SE	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01

Table 5 – Returns of cross-platform strategy for bitcoin considering geographic restriction

This table shows the returns for each portfolio and for the 7-1 long–short strategy. The returns are grouped by geographic restrictions according to Table A.3.

Portfolio	1	2	3	4	5	6	7	long/short
gross returns without restrictions								
Mean	-0.20	-0.02	0.07	0.21	0.33	0.54	0.84	1.04
Std	1.30	1.26	1.28	1.39	1.55	1.83	1.98	1.71
SE	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
returns net of bid/ask and minimal transaction fees without restrictions								
Mean	-0.57	-0.37	-0.27	-0.14	-0.02	0.19	0.43	0.27
Std	1.31	1.27	1.29	1.38	1.53	1.82	2.01	1.74
SE	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
US investor								
gross returns								
Mean	-0.12	-0.03	0.02	0.14	0.23	0.31	0.52	0.65
Std	1.28	1.27	1.27	1.44	1.51	1.59	1.87	1.53
SE	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
returns net of bid/ask and transaction fees								
Mean	-0.51	-0.41	-0.36	-0.24	-0.18	-0.11	0.10	-0.16
Std	1.30	1.29	1.29	1.44	1.50	1.55	1.81	1.47
SE	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
European investor								
gross returns								
Mean	-0.14	-0.01	0.12	0.23	0.32	0.49	0.76	0.92
Std	1.30	1.27	1.37	1.51	1.58	1.80	2.06	1.78
SE	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
returns net of bid/ask and transaction fees								
Mean	-0.54	-0.41	-0.29	-0.19	-0.11	0.09	0.39	0.15
Std	1.33	1.29	1.39	1.50	1.55	1.78	2.13	1.86
SE	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01

Table 6 – Returns of cross-platform strategy with varying confirmation time of bitcoin

This table shows the returns for each portfolio and for the 7-1 long–short strategy with a fixed confirmation time of 2 hours and with a varying confirmation time according to Figure A.2.

Portfolio	1	2	3	4	5	6	7	long/short
				gross returns with 2 hours confirmation time				
Mean	-0.20	-0.02	0.07	0.21	0.33	0.54	0.84	1.04
Std	1.30	1.26	1.28	1.39	1.55	1.83	1.98	1.71
SE	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
				returns net of bid/ask and transaction fees with 2 hours confirmation time				
Mean	-0.57	-0.37	-0.27	-0.14	-0.02	0.19	0.43	0.25
Std	1.31	1.27	1.29	1.38	1.53	1.82	2.01	1.74
SE	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
				gross returns with varying confirmation time				
Mean	-0.32	-0.09	0.03	0.18	0.33	0.54	0.88	1.21
Std	1.62	1.59	1.61	1.74	1.90	2.09	2.24	1.68
SE	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
				returns net of bid/ask and transaction fees with varying confirmation time				
Mean	-0.69	-0.43	-0.31	-0.17	-0.02	0.20	0.47	0.39
Std	1.62	1.58	1.60	1.73	1.87	2.08	2.24	1.71
SE	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01

Table 7 – Pearson's correlation matrix

The table shows the pairwise Pearson correlation coefficients between the arbitrage index and explanatory variables. Variable definitions can be found in Section 6.1. * $p < 0.05$.

	Arbitrage index	Bid-ask spread	Volatility	Volume	Term spread	HHI	Institutional	Informed trading
Bid-ask spread	0.35*							
Volatility	0.54*	0.39*						
Volume	-0.13*	0.00	0.03					
Term spread	0.23*	-0.01	0.22*	0.06*				
HHI	0.00	0.00	0.00	-0.08*	0.15*			
Institutional	-0.23*	-0.13*	-0.06*	0.48*	0.35*	-0.09*		
Informed trading	-0.39*	-0.12	-0.14	0.57*	0.20*	-0.18*	0.90*	
Confirmation time	0.07*	0.06*	0.02	0.15*	0.12*	-0.01	0.05*	-0.04

Table 8 – The determinants of cryptocurrency arbitrage

The table shows the regression results of an OLS panel estimation. The dependent variable is price deviations. Variable definitions of explanatory variables can be found in Section 6.1. *t*-statistics based on Newey–West standard errors are in parentheses.

	Dependent variable:									
	Price deviations									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Time	−0.0047									
	(−8.9318)									
Volatility		1.9304								1.3462
		(11.7261)								(9.5018)
Term spread			0.0073							0.0088
			(7.4564)							(5.9938)
Bid-ask spread				0.0144						0.0058
				(5.6650)						(4.7213)
HHI					−0.0017					0.0008
					(−1.6495)					(0.7523)
Institutional						−0.0002				−0.0002
						(−8.5787)				(−6.2729)
Informed trading							−0.0013			−0.0007
							(−6.3485)			(−1.9924)
Volume								−0.0025		0.0028
								(−5.9309)		(3.3279)
Confirmation time									0.0098	0.0020
									(2.2712)	(0.7047)
Obs.	3,652	3,652	3,648	3,652	3,652	3,652	3,652	3,652	3,652	3,648
Adj. R^2	0.1378	0.3024	0.0513	0.1212	0.0004	0.0547	0.1300	0.0534	0.0072	0.4141

Table 9 – Trading volume, informed trading, and price deviations

The table shows the regression results of an OLS panel estimation. The dependent variable is price deviations. Variable definitions of explanatory variables can be found in Section 6.1. Residual volume is the residual of the regression of volume on informed trading in Column (4). t-statistics based on Newey–West standard errors are in parentheses.

	Dependent variable:				
	Price deviations			Volume	Price deviations
	(1)	(2)	(3)	(4)	(5)
Volume	−0.0025		0.0021		
	(−5.9309)		(2.7127)		
Informed trading		−0.0013	−0.0019	0.2700	
		(−6.3485)	(−5.0474)	(23.6904)	
Residual Volume					0.0021
					(2.5739)
Obs.	3,652	3,652	3,652	3,652	3,652
Adj. R^2	0.0534	0.1300	0.1418	0.6868	0.0123

Table 10 – Crypto news and price deviations

The table shows the regression results of an OLS panel estimation. The dependent variable is price deviations. Variable definitions of explanatory variables can be found in Section 6.1. t-statistics based on Newey–West standard errors are in parentheses.

	Dependent variable:	
	Price deviations	
	(1)	(2)
News	0.0001	0.0000
	(2.0111)	(0.3205)
Volatility		1.1823
		(7.8456)
Term spread		0.0111
		(5.7293)
Bid-ask spread		0.0054
		(3.9048)
HHI		−0.0709
		(−1.6442)
Institutional		−0.0009
		(−6.1641)
Informed trading		−0.0007
		(−1.9976)
Volume		0.0058
		(4.3010)
Confirmation time		0.0044
		(0.7645)
Obs.	2,922	2,918
Adj. R^2	0.0068	0.4290

8 Appendix

Figure A.1 – Exchange filter criteria and simple arbitrage opportunities across exchanges

The figure shows the difference between the highest inside bid and the lowest inside ask for a cryptocurrency across exchanges over time, applying various exchange filter criteria. The highest bid and the lowest ask for a given cryptocurrency across all exchanges are collected for every five-second interval. The figure plots the largest of these differences for every day in the sample period. Filter criteria are detailed in Section 2: We require exchanges to fulfill the minimum quality criteria of the leading crypto data providers, CoinMarketCap (2022c) and Cryptocompare (2021) (*Rating*); we require that each exchange has operated for at least two years (equal to 40%) of our sample period (*Age*); we omit Chinese exchanges (*Chinese*); additionally, we report the effects of a potential *liquidity* filter that is subsumed in the age filter.

(a) Bitcoin

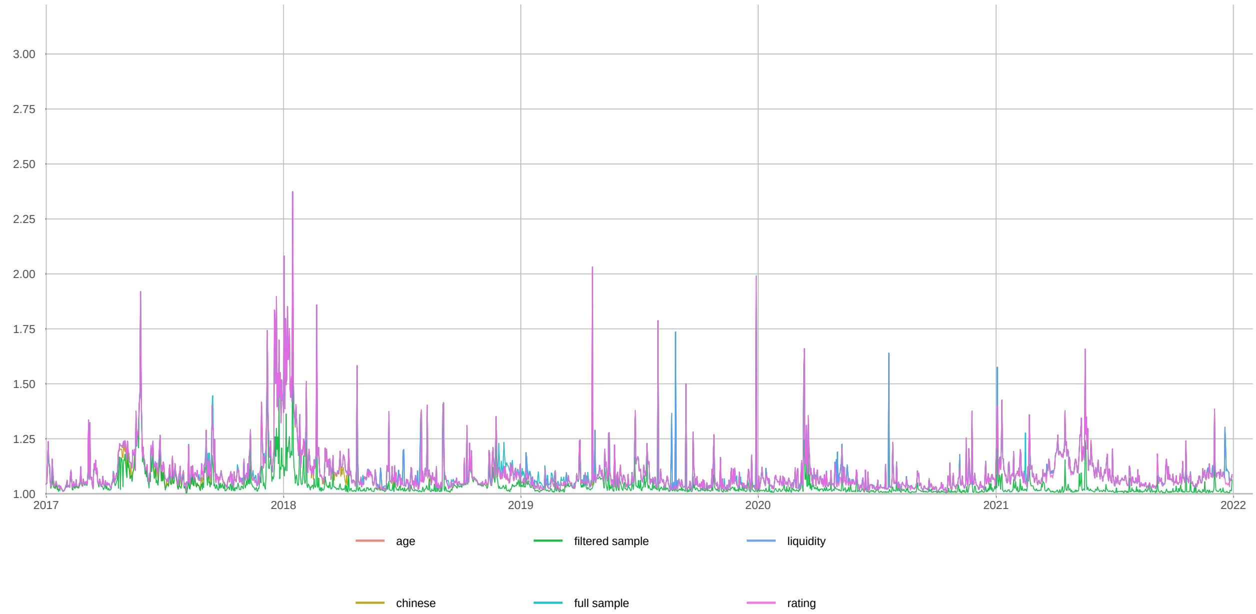


Figure A.1 – Filter criteria and simple arbitrage opportunities across exchanges (cont.)

(b) Ether

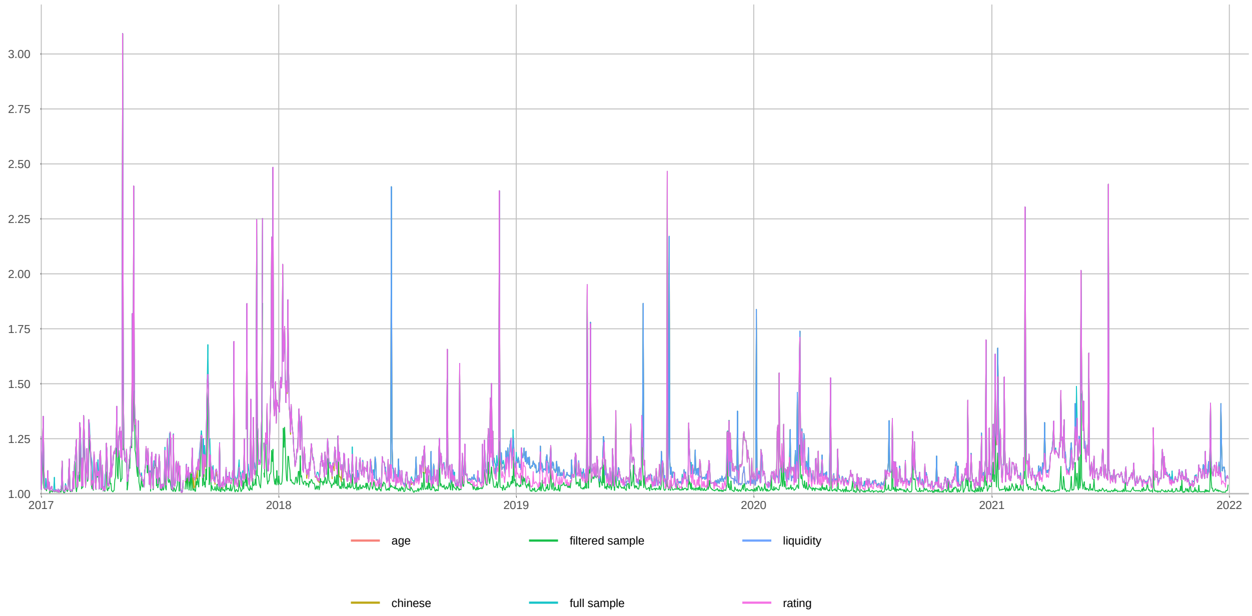


Figure A.1 – Filter criteria and simple arbitrage opportunities across exchanges (cont.)

(c) Ripple

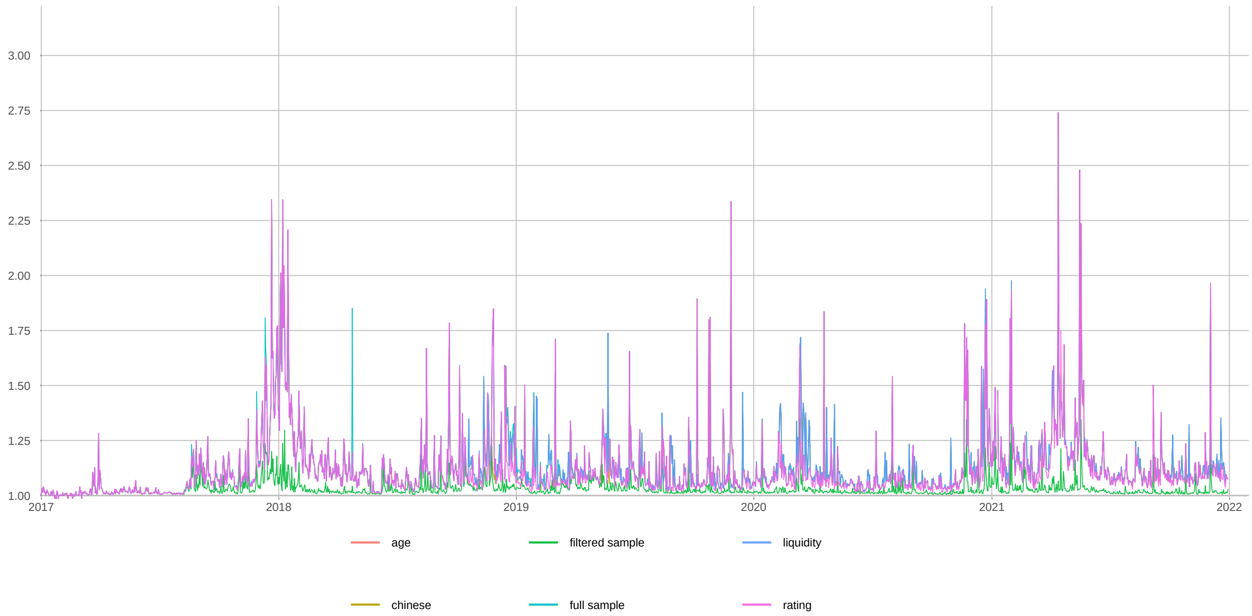
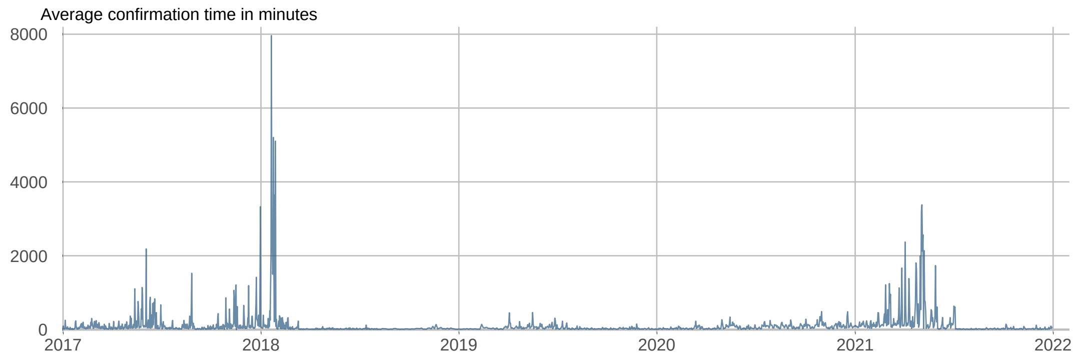


Figure A.2 – **Average confirmation time of bitcoin and ether transactions**

This figure shows the daily average confirmation time of bitcoin (Panel a) and ether (Panel b). The data is from Blockchain (2022).

(a) Bitcoin



(b) Ether

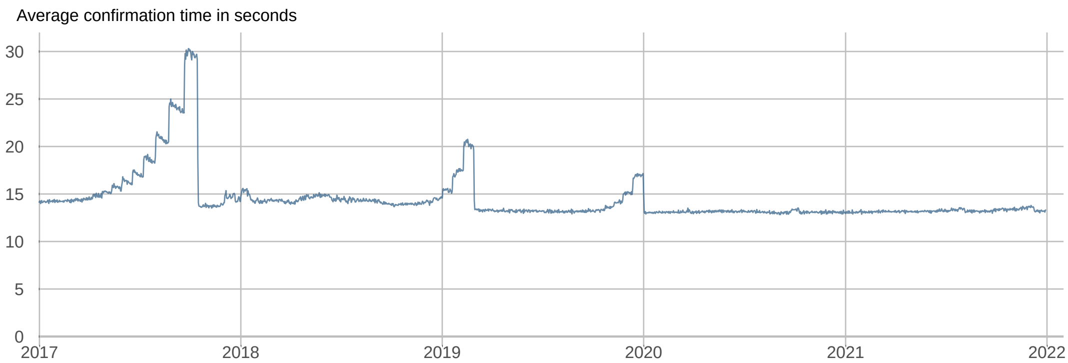


Figure A.3 – **Arbitrage indices with Kraken-USD as minimum**

The figure shows arbitrage indices that are consistent with the investment strategy, using the Kraken-USD pair as baseline. All price differences are relative to the Kraken-USD pair and are aggregated on a daily basis.

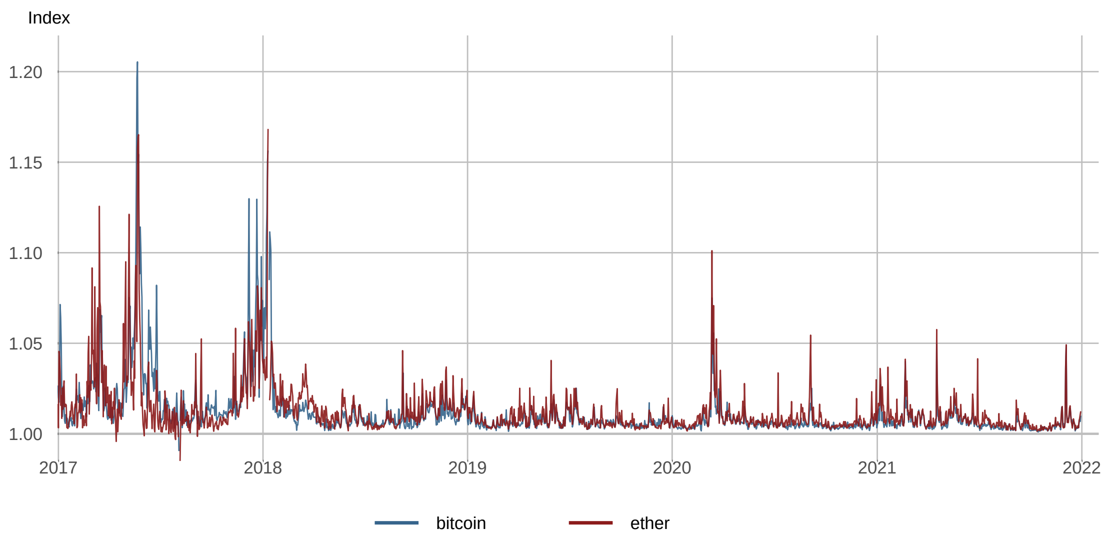


Table A.1 – Overview Exchanges

This table lists all exchanges used in the filtered dataset. *Country* refers to the base country of the exchange; however, many exchanges operate in multiple countries. *Data availability* always refers to the bitcoin pair with the most used fiat currency of an exchange.

		Currency			Data availability	
Exchange	Country	Bitcoin	Ether	Ripple	Start	End
Bitbank	Japan	JPY	-	JPY	01.03.19	31.12.21
Bitbay/Zonda	Estonia	USD, EUR, GBP	USD, EUR, GBP	USD, EUR	01.01.17	31.12.21
Bitfinex	Hong Kong	USD, EUR, GBP, JPY	USD, EUR, GBP, JPY	USD	11.03.19	31.12.21
Bitflyer	Japan	USD, EUR, JPY	JPY	JPY	01.01.17	31.12.21
Bithumb	South Korea	KRW	KRW	KRW	26.08.17	31.12.21
Bitso	Mexico	USD, MXN	USD, MXN	USD, MXN	13.03.19	31.12.21
Bitstamp	UK	USD, EUR, GBP	USD, EUR, GBP	USD, EUR, GBP	01.01.17	31.12.21
Bittrex	USA	USD, EUR	USD, EUR	USD, EUR	01.01.17	31.12.21
Coinbase	USA	USD, EUR, GBP	USD, EUR, GBP	USD, EUR, GBP	01.01.17	31.12.21
Coincheck	Japan	JPY	-	-	20.03.19	31.12.21
Coincorner	UK	EUR, GBP	-	-	05.03.19	04.10.21
Gemini	USA	USD	USD	-	01.01.17	31.12.21
Itbit	USA	USD, EUR	USD, EUR	-	01.01.17	31.12.21
Korbit	South Korea	KRW	KRW	KRW	20.04.18	31.12.21
Kraken	USA	USD, EUR, GBP, AUD	USD, EUR, GBP, AUD	USD, EUR, GBP, AUD	01.01.17	31.12.21
Quoine/Liquid	Japan	USD, EUR, JPY, AUD, SGD	USD, EUR, JPY, AUD, SGD	USD, EUR, JPY	01.01.17	31.12.21
Upbit	South Korea	KRW	KRW	KRW	05.03.19	31.12.21
Zaif	Japan	JPY	JPY	-	01.01.17	31.12.21
Tether						
BigONE	-	USDT	USDT	USDT	31.03.19	31.12.21
Binance	-	USDT	USDT	USDT	28.10.17	31.12.21
Bitfinex	Hong Kong	USDT	USDT	USDT	01.01.17	31.12.21
Bittrex	USA	USDT	USDT	USDT	01.01.17	31.12.21
CoinEx	-	USDT	USDT	USDT	09.04.19	31.12.21
HitBTC	-	USDT	USDT	USDT	26.08.17	31.12.21
KuCoin	-	USDT	USDT	USDT	09.04.19	31.12.21
OKEx	-	USDT	USDT	USDT	12.02.18	31.12.21
Poloniex	-	USDT	USDT	USDT	01.01.17	31.12.21
ZB	-	USDT	USDT	USDT	05.03.19	31.12.21

Table A.2 – Overview exchange fees

This table shows the transaction (taker) fees for each individual transaction in basis points. Withdrawal fees are nominal in the corresponding currency. "Network fee" means that the miners' confirmation fees are charged and "-" means that this currency is not offered on the corresponding exchange. All fees are collected from the websites of the exchanges as of January 2022.

		Transaction (taker) fees			Withdrawal fees		
Exchange	Country	Min	USD 1 Mio. Volume	Max	Bitcoin	Ether	Ripple
Bitbank	Japan	12	12	12	0.0006	0.005	0.15
Bitbay/Zonda	Estonia	25	25	43	0.0005	0.010	0.10
Bithumb	South Korea	4	25	25	0.0010	0.001	1.00
Bitso	Mexico	13	50	65	0.00002	0.002	0.00
Coincheck	Japan	0	0	0	0.0005	0.005	0.15
Coincorner	UK	100	100	100	Network fee	-	-
Korbit	South Korea	15	15	15	0.0010	0.010	1.00
Quoine/Liquid	Japan	3	16	29	0.0005	0.014	0.25
Zaif	Japan	10	10	10	0.0001	0.010	-
Itbit	USA	6	18	35	Network fee	Network fee	Network fee
Bitfinex	Hong Kong	6	20	20	0.0004	0.004	0.10
Bitflyer	Japan	1	15	15	0.0004	0.005	0.00
Bitstamp	UK	0	13	50	0.0005	0.005	0.02
Bittrex	USA	5	15	35	Network fee	Network fee	Network fee
Coinbase	USA	5	18	50	Network fee	Network fee	Network fee
Gemini	USA	3	25	35	0.0010	0.001	-
Kraken	USA	10	16	26	0.0002	0.004	0.02
Upbit	South Korea	20	20	20	0.0005	0.018	1.00
Tether							
Binance	-	4	10	10	0.0010	0.010	0.25
Bitfinex	Hong Kong	6	20	20	0.0004	0.004	0.10
Bittrex	USA	5	15	35	Network fee	Network fee	Network fee
Poloniex	-	4	12	16	Network fee	Network fee	Network fee
BigONE	-	8	18	20	0.0005	0.006	0.10
CoinEx	-	5	20	20	0.0001	0.005	0.01
HitBTC	-	10	20	20	Network fee	Network fee	Network fee
KuCoin	-	3	10	10	0.0005	0.010	0.50
OKEx	-	6	10	10	Network fee	Network fee	Network fee
ZB	-	6	20	20	0.0005	0.010	0.10

Table A.3 – Restrictions of exchanges/currencies by region

This table shows which exchanges and currencies are allowed for US and European investors. Data was retrieved individually for each exchange, either from the websites of the exchanges or from directly contacting them. For the Quoine/Liquid exchange, an investor has a base currency depending on her location; if she wants to trade in other currencies, she has to pay additional 25 basis points of fees.

Exchange	USA	Europe (Germany)
Bitbank (JPY)	No	No
BitBay (EUR)	No	Yes
BitBay (GBP)	No	Yes
BitBay (USD)	No	Yes
BitFlyer (EUR)	No	Yes
BitFlyer (JPY)	Since Sep. 2020, but withdrawal possible	Since Sep. 2020, but withdrawal possible
BitFlyer (USD)	Yes, since Dec. 2017	No
Bitso (MXN)	No	No
Bitso (USD)	Yes	No
Bitstamp (EUR)	Yes	Yes
Bitstamp (GBP)	Yes	Yes
Bitstamp (USD)	Yes	Yes
Bittrex (EUR)	No	Yes
Bittrex (USD)	Yes	Yes, since Oct. 2019
Coinbase (GBP)	No	No
Coinbase (USD)	Yes	No
Coinbase (EUR)	No	Yes
Coincheck (JPY)	Yes	Yes
Coinfloor (EUR)	No	Yes
Coinfloor (GBP)	No	Yes
Gemini (USD)	Yes	No
Itbit (EUR)	Yes	Yes
Itbit (USD)	Yes	Yes
Quoine (AUD)	No, but until Mar. 2020; one base pair	Yes, but one base pair
Quoine (EUR)	No, but until Mar. 2020; one base pair	Yes, but one base pair
Quoine (JPY)	No, but until Mar. 2020; one base pair	Yes, but one base pair
Quoine (SGD)	No, but until Mar. 2020; one base pair	Yes, but one base pair
Quoine (USD)	No, but until Mar. 2020; one base pair	Yes, but one base pair
Zaif (JPY)	No	No