The impact of derivatives on cash markets: Evidence from the introduction of bitcoin futures contracts[*]

Patrick Augustin,[†] Alexey Rubtsov,[‡] and Donghwa Shin[§]

This draft: May 17, 2021

Abstract

Cryptocurrencies provide a unique opportunity to identify how derivatives impact cash markets. They are fully fungible across multiple trading venues and futures contracts were selectively introduced on bitcoin (BTC) exchange rates against the USD in December 2017. Following the futures introduction, we find a significantly greater increase in cross-exchange price synchronicity for BTC–USD relative to other exchange rate pairs, as demonstrated by an increase in price correlations and a reduction in arbitrage opportunities. We also find support for an increase in price efficiency, market quality, and liquidity. Overall, our analysis supports the view that the introduction of BTC–USD futures was beneficial to the bitcoin cash market by making the underlying prices more informative.

JEL Classification Codes: G12, G13, G14, O33, Y80

Keywords: bitcoin, blockchain, cryptocurrencies, derivatives, fintech, regulation

[*]We thank Alex Ferko, Sean Foley, Louis Gagnon, Franz Hinzen, Esen Onur, Andreas Park, Michael A. Penick, Jiasun Li, Fahad Saleh, Amin Shams, Bruce Tuckman, Jordan Weide, Peter Zimmermann, Marius Zoican and participants in seminars and conferences sponsored by the Virtual Derivatives Workshop, Macquarie University and McGill University for comments and helpful suggestions. We thank Roy Zhang and Linlong Wu for excellent research assistance. The authors acknowledge financial support from the Global Risk Institute. Augustin acknowledges financial support from the Canadian Derivatives Institute.

[†]McGill University and Canadian Derivatives Institute; patrick.augustin@mcgill.ca.

[‡]Global Risk Institute; arubtsov@globalriskinstitute.org.

[§]University of North Carolina at Chapel Hill; Donghwa_Shin@kenan-flagler.unc.edu.

1 Introduction

Hailed as "one of the most powerful innovations in finance in 500 years" (Casey and Vigna, 2015), the cryptocurrency cash market has grown to a market capitalization of more than $2 trillion with more than 5,000 cryptocurrencies (CoinMarketCap, 2021). In parallel, there has been a proliferation of cryptocurrency derivatives and trading platforms. Trading volume in cryptocurrency derivatives, including futures, options, and swaps, surpassed $12 trillion in 2020 (CryptoCompare, 2021; TokenInsight, 2021). Despite the rapid expansion of cryptocurrency derivatives, we do not know whether their introduction is beneficial or detrimental to cryptocurrency cash markets. We take a first step to fill this gap.

The nature of the impact of the introduction of derivatives on their corresponding cash markets has been the subject of controversial debates and mixed empirical evidence.[1] In complete markets without frictions, derivatives are redundant, and their introduction should be irrelevant for spot assets. However, in the presence of frictions, the impact of derivatives on cash markets depends primarily on whether both assets are complements or substitutes.

We exploit the introduction of bitcoin futures by Cboe Global Markets, Inc. (CBOE) and the Chicago Mercantile Exchange (CME) Group in December 2017 to revisit the mixed evidence on the impact of derivatives on cash markets. That event is unique because of the particular bitcoin trading infrastructure and the selective introduction of bitcoin futures.

First, bitcoins trade on multiple exchanges and are fully fungible across trading venues. Across markets, bitcoins also trade at different prices with different degrees of liquidity, giving rise to inefficiencies and arbitrage opportunities (Makarov and Schoar, 2019, 2020). Thus, cryptocurrencies provide a near perfect setting to study the pricing of an identical asset traded on multiple exchanges in the spirit of Hasbrouck (1995). While price discrepancies of similar assets have been studied in other contexts, assets are typically not fully fungible, even in closely related securities such as ADRs (Gagnon and Karolyi, 2010).

Second, the CBOE and CME selectively introduced futures contracts on bitcoin-USD (BTC–USD) exchange rates, but not on any other bitcoin-fiat currency pairs (e.g., BTC–EUR). Third, the contract launch was largely unanticipated, as we describe in more detail below.

These features enable us to isolate the impact of the futures introduction on BTC–USD relative to other cryptocurrency exchange rates. In particular, we can exploit differential variation of the corresponding cryptocurrency attributes around the futures introduction within exchanges and account for their unobserved time-varying characteristics. We consider various market attributes related to cryptocurrency pricing efficiency and market quality.

Specifically, we first quantify four sets of characteristics of cryptocurrency exchange rates. We consider measures of price synchronicity such as pairwise cross-exchange price correlations and price integration following Kapadia and Pu (2012), market quality following

[1] We review the evidence in detail in the literature section.

Hasbrouck (1993), price efficiency following Hou and Moskowitz (2005), and several liquidity measures, including the Amihud (2002) price impact measure, the Roll (1984) illiquidity measure, the Abdi and Ranaldo (2017) bid-ask spread measure, and trading volume. In the appendix, we further consider measures of volatility and arbitrage opportunities based on price levels as in Makarov and Schoar (2020).

We next estimate whether the introduction of the BTC–USD futures contract in December 2017 improved the characteristics of BTC–USD exchange rates more than those of other bitcoin-fiat currency pairs, which we broadly refer to as BTC–CCY. Thus, we exploit both the unique features of cryptocurrency markets and the selective introduction of bitcoin futures on BTC–USD to capture the treatment effect through cross-sectional differences in the evolution of market attributes between BTC–USD and BTC–CCY.

Whether the listing of derivatives products linked to cryptocurrency assets affects the underlying's market attributes is relevant for current regulatory debates. For example, proposals for bitcoin (BTC) exchange-traded funds (ETFs) have consistently been denied approval by the SEC, due to concerns of manipulation in related spot markets.

The debate is further emphasized by opposing views expressed amid policymakers and industry participants. Former chairman of the U.S. Commodity Futures Trading Commission (CFTC), Christopher Giancarlo, argues that regulators allowed the launch of bitcoin futures contracts in December 2017 because it was widely believed that it would pop the bitcoin bubble and make prices better reflect fundamental values. Similarly, the company Bitwise Index Services proposes that, among other things, "the launch of futures ... dramatically improved the efficiency of the bitcoin market in 2018."

Other commentators suggest that "bitcoin's price dictates BTC derivatives market and not vice-versa" (Biraajmaan, 2019). Against the backdrop of these debates, we provide formal evidence on how the bitcoin futures introduction impacted the quality, efficiency, liquidity, and price informativeness of the bitcoin cash market.

For our analysis, we combine data from Kaiko and CryptoCompare, which provide cryptocurrency price and trade information for bitcoin exchange rates against the USD (BTC–USD) and a set of other fiat currencies (BTC–CCY). Trades are timestamped to the millisecond and executed on numerous trading platforms. Given our identification strategy of comparing the evolution of market characteristics for BTC–USD relative to other bitcoin exchange rate pairs around BTC–USD futures listing, we collect bitcoin-fiat exchange rate pairs on exchanges that are operational between July 1, 2016 and December 31, 2018.

Our working sample contains 10 bitcoin-fiat currency exchange rates traded on 22 different exchanges. In all tests, we compare the treated BTC–USD to the control group that includes BTC–EUR, BTC–GBP, BTC–HKD, BTC–SGD, BTC–JPY, BTC–AUD, BTC–IDR, BTC–CAD, and BTC–RUB. The 22 exchanges in our sample include Bitfinex, bitFlyer, Bitstamp, Bittrex, BTCbox, BTCC, BTC–e, Cex.io, Coinbase, Exmo, Gatecoin, Gemini, HitBTC, itBit, Kraken, LakeBTC, Liquid, OKCoin, Poloniex, QuadrigaCX, Quoine, and Zaif. In light of claims that cryptocurrency volumes are being manipulated (Gandal, Hamrick, Moore, and Oberman, 2018; Griffin and Shams, 2020; Aloosh and Li, 2020; Cong, Li, Tang, and Yang, 2021; Amiram, Lyandres, and Rabetti, 2021), we also focus on the subset of nine exchanges that are allegedly insulated from such manipulations, according to Bitwise Asset Management's exchange traded fund proposal filed with the SEC.

We compute daily log returns and trading volume by aggregating the daily quantity of traded bitcoins. These raw data are used to compute the metrics of price synchronicity, price efficiency, market quality, and liquidity, which we estimate at a monthly frequency.

We run difference-in-differences tests to examine how the imputed characteristics of BTC–USD exchange rates vary around the introduction of BTC–USD futures relative to those of other bitcoin-fiat exchange rates, i.e., BTC–CCY. Our main tests are based on regressions with exchange fixed effects, allowing us to exploit the within exchange variation of BTC–USD relative to other exchange rate pairs following futures listings. We also include currency fixed effects to account for time-invariant cross-sectional differences at the exchange rate level, and we include monthly time fixed effects to absorb common cross-exchange variation that could be associated with a maturing and growing market. In our most conservative specifications, we include currency fixed effects together with interactions of exchange and time fixed effects to absorb unobserved time-varying characteristics at the exchange level.

Overall, we find strong evidence in favor of an increase in cross-exchange price synchronicity and integration. Following the futures introduction, the Pearson correlation coefficient between cross-exchange returns increases on average by about 5 to 12 percentage points more for BTC–USD compared to other bitcoin-fiat exchange rates. This is economically meaningful as the average in-sample correlation coefficients of the treatment and control currencies are 0.87 and 0.85, respectively. Similarly, we find that the differential increase in price concordance ranges between 5 and 14 percentage points, depending on the specification, implying a significant reduction in arbitrage opportunities.

We also find supporting evidence that BTC–USD exchange rates become significantly more efficient than other exchange rate pairs regarding the speed at which information gets incorporated into prices. Furthermore, the market quality of BTC–USD exchange rates increases. In the appendix, we provide further evidence for a reduction in volatility and arbitrage opportunities as measured by an arbitrage index using price levels.

Finally, our evidence supports the view that there is a stronger increase in liquidity for BTC–USD following the futures introduction. We derive our baseline evidence using an aggregate liquidity factor following Dick-Nielsen, Feldhutter, and Lando (2012) and Schwert (2017). Results for individual liquidity metrics are noisier if measured for exchanges suspect of market manipulation. Excluding the allegedly fraudulent exchanges, we estimate a significantly greater reduction in price impact for BTC–USD exchange rate returns using the Amihud price impact measure, and a comparatively greater increase in trading volume.

As a refinement of our tests, we exploit the settlement mechanisms of bitcoin futures. Contracts on both the CME and the CBOE are settled in cash, but the reference cash price differs between the two exchanges. Specifically, the CME relies on the bitcoin reference rate, which is determined at 4:00 p.m. London time using price inputs from four exchanges (itBit, Kraken, BitStamp, and GDAX/Coinbase) sampled between 3:00 p.m. and 4:00 p.m. The CBOE relies on BTC–USD prices from the Gemini exchange determined at 4:00 p.m. Eastern time. We repeat our tests using daily returns computed from hourly prices sampled at 4:00 p.m. in the corresponding time zones and from the corresponding exchanges. Consistent with our expectation, our results are overall economically and statistically stronger if we rely on prices that are directly connected to the settlement of the futures contracts.

Furthermore, we examine channels that may explain the positive impact from the futures introduction on bitcoin cash. Asynchronous price movements and arbitrage opportunities may be due to a lack of arbitrage capital and liquidity frictions or to limited investor attention. We measure these attributes using variables that are likely to be correlated with liquidity frictions and investor attention. We rely on our liquidity metrics from previous tests and measure investor attention using the Google search intensity for cryptocurrency exchanges. We find significantly different results in terms of liquidity, price efficiency, and market quality for exchanges ranked as being above or below the median level of frictions, but not for attention, supporting a limits-to-arbitrage channel (Shleifer and Vishny, 1997).

Finally, we verify the role of triangular arbitrage in explaining cross-currency differences in market characteristics. Makarov and Schoar (2020) explain that "customers from different countries can usually only trade cryptocurrencies on their local exchange and in their local currency." Thus, triangular arbitrage is challenging if it involves one leg with a pure fiat exchange rate (e.g., USD–EUR), which is not listed on cryptocurrency exchanges.

In contrast, arbitrage is easier if it does not involve a fiat exchange rate pair (e.g., Dyhrberg, 2020). Consistent with that view, we find that the futures introduction is associated with a greater increase in price synchronicity for BTC–USD relative to ether-USD (ETH–USD) across exchanges, but not within exchanges. Notably, all exchanges that list BTC–USD and ETH–USD also reference BTC–ETH.

Relatedly, we find no significant effect for ETH–USD relative to ETH–CCY around the introduction of bitcoin futures in 2017, suggesting that we capture a bitcoin effect rather than a USD effect. On the other hand, we document (in the appendix) a significant effect of ETH–USD relative to ETH–CCY around the introduction of *ethereum* futures in 2021, further supporting the view that the derivatives introduction helps align prices in the underlying cash market.

The remainder of this paper is organized as follows. We discuss the literature in Section 2 and describe the institutional details of blockchains and cryptocurrencies in Section 3. We develop our hypotheses in Section 4. In Section 5, we describe the data, present summary statistics, and discuss the main results. In Section 6, we discuss potential channels, refinements, and robustness. We conclude in Section 7.

2 Related Literature

We exploit the unique design of the cryptocurrency market to provide new evidence on the mixed findings regarding the impact of derivatives on cash markets. Thus, we relate primarily to the emerging literature on cryptocurrencies and blockchains (Section 2.1), and to research on the impact of derivatives on cash markets (Section 2.2).[2]

2.1 Cryptocurrencies and blockchain

Bitcoin was officially introduced in 2009 as a peer-to-peer digital currency, following the publication of a white paper by pseudonymous Satoshi Nakamato in 2008 (Nakamoto, 2008). Böhme, Christin, Edelman, and Moore (2015) provide a review of bitcoin and its potential blockchain-based applications. Yermack (2015) evaluates bitcoin's status as a real currency, Harvey (2016) reviews applications in cryptofinance, and Howden (2015) discusses the regulatory aspects of cryptocurrencies.

As a decentralized payment system built on aggregate consensus and free of intervention by central authorities, bitcoin was initially idealized as immutable and secure. Yet, Griffin and Shams (2020) suggest that bitcoin (and other cryptocurrency) prices are subject to market manipulation. That could come in the form of pump-and-dump schemes (Li, Shin, and Wang, 2018) or wash trades (Cong, Li, Tang, and Yang, 2021; Aloosh and Li, 2020; Amiram, Lyandres, and Rabetti, 2021). Similarly, Gandal, Hamrick, Moore, and Oberman (2018) associate bitcoin volatility increases with suspicious trading activity. Anecdotally, multiple cryptocurrency exchanges have been hacked. Foley, Karlsen, and Putnins (2019) quantify that bitcoin facilitates about $76 billion in yearly illegal activity.

Our work is most closely related to studies on frictions and inefficiencies in bitcoin and other cryptocurrencies. Easley, O'Hara, and Basu (2019) examine the endogenous emergence of transaction costs on the blockchain, while we are concerned with bitcoin trading on cryptocurrency exchanges. Makarov and Schoar (2020) pinpoint significant cross-exchange arbitrage opportunities, which are larger across than within countries, and suggest that arbitrageurs counterbalance the price impact of noise traders (see also Krückeberg and Scholz (2020); Dyhrberg (2020)). Kroeger and Sarkar (2017) relate cross-exchange price differences to liquidity frictions (e.g., bid-ask spread, order book depth, volatility), Hautsch, Scheuch, and Voigt (2019) to stochastic settlement latency, and Borri and Shaknov (2021) to risk premiums. Yu and Zhang (2018) associate restrictions to cross-border capital flows with price discrepancies between spot exchange rates and their cryptocurrency implied synthetic counterparts (see also Choi, Lehar, and Stauffer (2018) for related work on the "Kimchi premium"). In contrast to these studies, we provide the first evidence on how

[2]By studying price discrepancies of fully fungible assets across exchanges, we relate more broadly to the literature on limits to arbitrage (Shleifer and Vishny, 1997; Gromb and Vayanos, 2010).

the introduction of the BTC–USD futures contract in December 2017 impacts the cross-exchange market quality, efficiency, and price synchronicity in the bitcoin cash market.

A growing literature provides descriptive evidence on the interaction between bitcoin cash and futures markets (Hale, Krishnamurthy, Kudlyak, and Shultz, 2018; Corbet, Lucey, Peat, and Vigne, 2018; Köchling, Müller, and Posch, 2019; Nan and Kaizoji, 2019; Kim, Lee, and Kang, 2020), focusing primarily on the relative price discovery process (Kapar and Olmo, 2019; Baur and Dimpfl, 2019; Karkkainen, 2019; Akyildirim, Corbet, Katsiampa, Kellard, and Sensoy, 2021; Alexander and Heck, 2020). Shi and Shi (2019) study how South Korea's ban on bitcoin futures impacts intraday spot volatility.

More tangentially, we relate to the literature that is focused on understanding the economics of blockchain technology (we describe the institutional aspects of the blockchain technology and cryptocurrencies in Appendix A). For example, Biais, Bisiére, Bouvard, and Casamatta (2019) study consensus for the Proof-of-Work (PoW) blockchain protocol and find that persistent disagreement may arise in equilibrium. Hinzen, John, and Saleh (2019) highlight that PoW's consensus structure may explain limited cryptocurrency adoption. Chiu and Koeppl (2019) examine the implications of the PoW blockchain technology for asset trading and settlement. Cong, He, and Li (2021) argue that PoW leads to excessive energy expenditure and an endogenous formation of mining pools, while Alsabah and Capponi (2020) show how PoW may lead to mining centralization.

Focusing on the Proof-of-Stake (PoS) blockchain protocol, Saleh (2021) studies conditions for consensus and Rosu and Saleh (2021) consider the evolution of wealth dynamics. More generally, Cong and He (2019) show how the blockchain technology can lead to greater competition and consumer surplus, as well as to welfare-destroying collusion. See also Gandal and Halaburda (2014) for an examination of competition in cryptocurrency markets. Additional work by Malinova and Park (2017) suggests that the blockchain may enhance welfare through increased transparency. Zimmerman (2019) demonstrates that the blockchain technology can lead to excessive price volatility and speculative activity.

Finally, Biais, Bisiere, Bouvard, Casamatta, and Menkveld (2018) and Pagnotta and Buraschi (2018) study the equilibrium pricing of bitcoin. Yermack (2017) discusses implications of blockchains for corporate governance. For further discussions, see also Dwyer (2015) and Gans and Halaburda (2015).

2.2 Introduction of derivatives and impact on cash markets

Our work also relates to the vast literature that studies how the introduction of derivatives affects market attributes of the underlying cash markets. Hodges (1992), Damodaran and Subrahmanyam (1992) and Mayhew (1999) provide early reviews that highlight the conflicting theoretical predictions. These often depend on the incentives of informed and uninformed investors to trade in either market venue. For example, Subrahmanyam (1991) predicts that stock bid-ask spreads should increase following the introduction of equity futures contracts, because of greater adverse selection costs. This is explained by a greater fraction of informed investors because of uninformed investors migrating towards the futures market. Alternatively, because futures represent a low-cost hedging instrument for specialists, bid-ask spreads could reduce in response to futures introduction, due to an increase in hedging activity (Silber, 1985). See also Gammill Jr and Perold (1989) and Gorton and Pennacchi (1991) for related work.

The evidence found in empirical studies is likewise mixed. For example, Jegadeesh and Subrahmanyam (1993) find that stocks' bid-ask spreads increase in response to S&P500 futures introduction. In contrast, Bessembinder and Seguin (1992) report that futures markets enhance the liquidity and depth of equity markets. Choi and Subrahamanyam (1994) argue that the reduction in bid-ask spreads is small, despite increases in volume that are possibly associated with increased price informativeness. Mayhew (1999) studies results from the introduction of futures on spot volatility for commodity, fixed income, and stock index futures, respectively. The large list of studies (e.g., Figlewski, 1981; Stoll and Whaley, 1990; Edwards, 1988a,b; Chan, Chan, and Karolyi, 1991; Brenner, Subrahmanyam, and Uno, 1994; Harris, 1989; Gulen and Mayhew, 2000; Gagnon, 2018) presents by and large results that are inconclusive with respect to the impact on spot volatility.

Another set of studies has examined the impact of option listing on the volatility and the beta of the spot market (Mayhew, 1999), trading volume, bid-ask spreads, and price informativeness. Initial tests are indicative of a reduction in spot volatility (e.g., Skinner, 1989; Conrad, 1989; Detemple and Jorion, 1990; Damodaran and Lim, 1991). However, similar findings for stocks without listed options suggest that these results may be spurious. Consequently, Mayhew and Mihov (2004) find little support for a reduction in spot volatility after controlling for the endogeneity of option listing. Kumar, Sarin, and Shastri (1998) argue that option listings improve the market quality of the underlying stocks.

With the growth of credit derivatives over the last two decades, researchers have examined the relation between credit default swaps (CDS) and bonds. Das, Kalimipalli, and Nayak (2014) find a reduction in price efficiency and no improvement in bond liquidity following the onset of CDS trading. In contrast, Ismailescu and Phillips (2015) suggest that prices of sovereign bonds became more efficient following the inception of sovereign CDS contracts.

3 Institutional Background

We first provide background information on cryptocurrency cash markets (Section 3.1), and then provide an overview of the current landscape of cryptocurrency derivatives (Section 3.2). Additional details about blockchains and cryptocurrencies are in Appendix A.

3.1 Cryptocurrency cash markets and exchanges

Blockchain constitutes an electronic ledger that records entries in discrete chunks referenced as blocks. Bitcoin was created as the first permissionless blockchain, and possesses a native currency known as bitcoin. Bitcoin's model has been imitated numerous times, leading to a profusion of cryptocurrencies and other decentralized applications that feature native tokens, which are typically classified as cryptocurrencies.

Bitcoin was launched as the first cryptocurrency in 2009. Many similar cryptocurrencies started trading in subsequent years. Irresberger, John, and Saleh (2019) document 907 cryptocurrencies that possess market capitals exceeding $1 million. According to CoinMarketCap (2021), there exist more than 5,000 listed cryptocurrencies as of May 2021, with a market capitalization north of $2 trillion. Bitcoin is especially dominant and consistently accounts for the largest market capitalization among all cryptocurrencies.

A unique feature of cryptocurrencies (e.g., BTC) is that they trade in multiple venues called cryptocurrency exchanges. On these platforms, investors buy and sell cryptocurrencies in exchange for fiat currencies (e.g., USD or EUR) or other cryptocurrencies. CoinMarketCap (2020) reports that, as of April 2020, there exist 297 (66) cryptocurrency exchanges with an aggregate daily trading volume over $2 million ($100 million). Investors may buy bitcoins on one exchange and sell them on another, implying that bitcoins are fully fungible across exchanges. Thus, cross-exchange prices of, say, BTC–USD, ought to be identical despite being exchanged in multiple trading venues. Nonetheless, cross-exchange prices of a given currency pair differ, likely due to exchange-specific risks and frictions.

The properties of cryptocurrencies – multi-listing and fungibility – make them an ideal laboratory for studying the effect of bitcoin futures introduction on bitcoin cash markets.

3.2 Cryptocurrency derivatives

With the proliferation of cryptocurrencies has come a proliferation of cryptocurrency derivatives. Bitcoin largely dominates as the underlying cash asset, but the menu of contracts tied to other cryptocurrencies is growing. The significant bitcoin price volatility naturally attracts speculative investors, but also other investors which hedge price movements.

A major distinction among existing derivatives is whether they are regulated or not. In 2015, the CFTC maintained that bitcoin is a commodity as defined under section 1a(9) of the Commodity Exchange Act (CEA), and declared the same for ether in 2019. Thus, bitcoin and ether derivatives are under the purview of the CFTC and regulated by the CEA.

The most prominent cryptocurrency derivatives are likely bitcoin futures, which were first offered as CFTC-regulated contracts by the CME and the CBOE in December 2017. While the CBOE stopped trading bitcoin futures in June 2019, trading volumes on the CME have been steadily rising, leading the CME to self-certify an increase of the spot month position limits for its investors in October 2019. According to Cointelegraph, an average of 4,929 daily contracts were traded in its first two years of existence, corresponding to $182 million in notional value (Avan-Nomayo, 2019). The CME started offering futures options in 2020, ethereum futures in February 2021, and micro bitcoin futures are scheduled for May 2021.

Prior to the introduction of bitcoin futures by the CME and the CBOE, TeraExchange was the first U.S. regulated swap execution facility to launch non-deliverable bitcoin forward contracts in 2014. The CFTC approval of Tassat as a regulated crypto derivatives exchange in 2019 adds to the growing number of swap execution facilities and designated contract markets that offer cryptocurrency derivatives trading. Since September 2019, Bakkt offers physically settled bitcoin futures and options, which are listed on the Intercontinental Exchange. Other regulated exchanges include, for example, LedgerX, which offers physically-settled European style bitcoin options with maturities ranging between 1 week to 1 quarter.

Besides U.S.-regulated crypto derivatives exchanges, there is a bigger and growing market of non-regulated cryptocurrency derivatives exchanges, with a proliferation of trading platforms and product offerings. Several unregulated exchanges (e.g., Phemex, BitMex, Bitfinex) offer up to 100 times leveraged perpetual futures contracts for various cryptocurrencies, including bitcoin, ethereum, ripple, litecoin, and EOS. These platforms are registered outside the U.S. and are, therefore, not accessible to U.S. customers. Countries take vastly different approaches to regulation, with some countries (e.g., Singapore) being more receptive to regulated platforms than others (e.g., United Kingdom).

TokenInsight (2021) estimates that more than $12 trillion in derivatives was traded in 2020. Trading in regulated bitcoin derivatives is dominated by the CME. While less than 3% of all trading happened on traditional exchanges in 2019, approximately 97% of it was taken up by token futures trading. Trading volumes are heavily concentrated, with approximately 80% tied to bitcoin and ethereum contracts. Concentration is visible at the exchange level, too. The top 3 (4) exchanges accounted for 85% (90%) of the annual trading volume in 2019, with BitMEX, OKEx, and Huobi DM (Bybit) recording $973 billion, $869 billion, and $661 billion ($149 billion), respectively (Song and Wu, 2020; CryptoCompare, 2020).

In December 2019, New York Digital Investment Group was the first company to receive SEC approval for a fund (Stone Ridge Trust) that invests in cash-settled bitcoin futures traded on CFTC-regulated exchanges (Song and Wu, 2020). The SEC has since persistently rejected proposals for bitcoin related ETFs by Winklevoss, VanEck, SolidX, and Bitwise.

4 Development of Hypotheses and Analysis

Several studies show that cryptocurrencies are prone to trading frictions (e.g., Makarov and Schoar, 2020; Hautsch, Scheuch, and Voigt, 2019; Yu and Zhang, 2018). We, therefore, first describe and quantify the characteristics of bitcoin exchange rates relative to fiat currencies.

We consider characteristics related to price synchronicity and integration, price efficiency, market quality, and liquidity, where $Characteristic_{i,j,t} \in \{Synchronicity,\ Efficiency,\ Quality,\ Liquidity\}$; i refers to cryptocurrency exchange rate pair (cross-exchange cryptocurrency exchange rate pairs) in the analyses on efficiency, quality, and liquidity (synchronicity); j denotes the exchange trading platform (exchange pair for synchronicity); t denotes the time of the observed characteristic. In the appendix, we also consider measures of price volatility and arbitrage opportunities. In our benchmark tests, we measure all characteristics at the monthly frequency using daily data.

In the presence of frictions, derivatives are non-redundant and may complete the market. We thus examine how the BTC–USD futures introduction by the CBOE and the CME in December 2017 impacts the efficiency, quality, price synchronicity, and liquidity of BTC–USD relative to other bitcoin-fiat exchange rate pairs. Whether the introduction of futures is beneficial or detrimental to the cash market is subject of a long-standing debate.

Several features of the bitcoin futures introduction are particularly useful for identifying the impact of futures on cash markets. First, the BTC–USD futures introduction was largely unanticipated until shortly before their inception. Figure 1.a shows that Google searches for the word "bitcoin futures" were inexistent before the CME officially announced their launch on October 31, 2017. Futures were also unlikely introduced in response to hedging needs of institutional investors. They face regulatory barriers to invest in bitcoin through unregulated exchanges, and major public institutions like JP Morgan officially denied their participation in the cryptocurrency market at the time (e.g., Son, Levitt, and Louis, 2017). In Figure D.1 of the appendix, we further show that that the number of "whale wallets" with holdings above 1,000 bitcoins, a proxy for large investors, was decreasing before the CME announcement.

Second, the futures contract was selectively introduced for BTC–USD, but not for other currency pairs (e.g., BTC–EUR). Third, bitcoin is a close to perfect example of an identical asset traded on multiple exchanges in the spirit of Hasbrouck (1995). As bitcoins are fully fungible across exchanges, they ought to trade at the same price. Accordingly, observed price differences of a currency pair across exchanges should be driven by exchange-specific frictions, while price differences between BTC–USD and BTC–CCY exchange rate pairs should be driven by market-specific frictions.[3]

Our identification strategy relies on comparing cross-sectional differences in the variation of characteristics between BTC–USD and other bitcoin-fiat exchange rate pairs (BTC–CCY) around the time of futures listing.[4] Thus, to test whether the introduction of the BTC–USD futures contracts is beneficial to USD-denominated bitcoin cash, we implement the

[3]We could include other control assets like bitcoin cash (BCH), which was created through a bitcoin hard fork and which shares common characteristics with bitcoin. We focus on comparing BTC–USD and BTC–CCY because they are *identical* assets and, therefore, fully fungible. Relying on fully fungible assets helps better identify the effect of the introduction of bitcoin futures on the various characteristics.

[4]In the absence of BTC–USD, we replace it with BTC–Tether because of the one-to-one convertibility between USD and the Tether stablecoin.

following benchmark regression:

$$Characteristic_{i,j,t} = \alpha_0 + \alpha_1 Treatment_{BTC-USD} \times Post_{futures} + \delta_i + \eta_j + \gamma_t + \varepsilon_{i,j,t}, \quad (1)$$

where $Treatment_{BTC-USD}$ is an indicator variable equal to one for the BTC–USD price series and zero otherwise, $Post_{futures}$ is an indicator variable equal to one after the introduction of the BTC–USD futures contracts in December 2017 and zero otherwise, and $\varepsilon_{i,j,t}$ are standard normal residuals. The parameters δ_i and η_j capture currency-pair and exchange (or exchange pair for price synchronicity) fixed effects to absorb unobserved time-invariant variation at the currency-pair and exchange (or exchange pair for price synchronicity) level, respectively. We account for unobserved common factors through the time fixed effects γ_t.

In our most saturated regression, we exploit the within exchange variation of BTC-USD relative to BTC-CCY and control for latent trends at the exchange level using the interaction term $\eta_j \times \gamma_t$. In our benchmark tests, we cluster the standard errors at the exchange-currency pair level (or exchange pair level for price synchronicity) to correct for serial correlation. In untabulated robustness tests, we verify that our results remain significant when we also cluster at the time dimension.

4.1 Price synchronicity and integration

We measure price synchronicity using the Pearson correlation coefficient between cross-exchange returns. Denote $r_{i,j,t+1} = \ln(p_{i,j,t+1}/p_{i,j,t})$ the log return of cryptocurrency pair i on exchange j from time t to $t+1$, and $p_{i,j,t}$ the corresponding exchange rate levels. The Pearson correlation coefficient of currency pair i between exchanges j and j' is given by:

$$\rho_{i,j/j',t} = cov\left(r_{i,j,t}, r_{i,j',t}\right) / \left(\sigma_{i,j,t}\sigma_{i,j',t}\right), \quad (2)$$

where $cov(\cdot,\cdot)$ denotes the covariance of pairwise log returns, and $\sigma_{i,\cdot,t}$ their standard deviations. We compute pairwise correlation coefficients at a monthly frequency using daily data up to 3 months. Our results are similar if we use one month of daily observations and non-overlapping data. This simple measure of price synchronicity is informative about the cross-exchange alignment of cryptocurrency returns, and reflects, therefore, the pricing efficiency of cryptocurrency exchange rates.

We also compute a non-parametric measure of cross-exchange price synchronicity. We adapt the Kapadia and Pu (2012) measure of market integration based on the concordance of price changes between stocks and bonds. Thus, we assume that cross-exchange prices are aligned if returns move in the same direction, i.e., $\mathcal{I}\left(r_{i,j,t} \cdot r_{i,j',t} > 0\right)$, and misaligned if they move in opposite directions, i.e., $\mathcal{I}\left(r_{i,j,t} \cdot r_{i,j',t} < 0\right)$, where $\mathcal{I}(\cdot)$ is an indicator function that is one if the condition inside the brackets is met and zero otherwise. The integration measure $\kappa_{i,j/j',t}$ captures the frequency of price synchronicity over a trading horizon τ:

$$\kappa_{i,j/j',t} = \sum_{k=1}^{M-\tau} \mathcal{I}\left(r^{\tau}_{i,j,k} r^{\tau}_{i,j',k} > 0\right), \quad (3)$$

where we have M observations of daily price changes on two exchanges. We compute $\kappa_{i,j/j',t}$ at the monthly frequency, using non-overlapping intervals over 90 days and a trading horizon of $\tau = 1$ day. We provide robustness tests using other frequencies and trading horizons in the Appendix. We map $\kappa_{i,j/j',t}$ into Kendall's Tau coefficient, $K_{i,j/j',t} = \left[2\kappa_{i,j/j',t}/\left(M-\tau\right)\right]-1$, which has well-known properties for statistical inference. Higher values are associated with more integration, with $K_{i,j/j',t} = 1$ for perfectly synchronous cross-exchange returns.

4.2 Price efficiency

We measure the price efficiency of cryptocurrency log returns using the $D1$ measure proposed by Hou and Moskowitz (2005). Thus, we first regress daily returns on their lags, and the contemporaneous and lagged market returns $r_{m,t}$ up to 4 days:

$$r_{i,j,t} = \alpha_{i,j} + \beta_{i,j} r_{m,t} + \sum_{n=1}^{4} \delta_{i,j}^{-n} r_{m,t-n} + \sum_{n=1}^{4} \phi_{i,j}^{-n} r_{i,j,t-n} + \varepsilon_{i,j,t}. \tag{4}$$

We follow Benedetti (2018) and use the MVIS CryptoCompare Digital Asset 10 Index (a modified market cap-weighted index that tracks the performance of the ten largest and most liquid digital assets) as the market return in the cryptocurrency space.

If returns incorporate new information instantaneously, then $\beta_{i,j}$ is significantly different from zero and the lagged coefficients $\delta_{i,j}^{-n}$ and $\phi_{i,j}^{-n}$ will be insignificant. If information is incorporated with lags, then the lagged coefficients $\delta_{i,j}^{-n}$ are significantly different from zero.

The $D1$ measure compares the fit of a constrained model ($Constrained\ R^2$), based only on contemporaneous variables on the right-hand side of the regression in Equation (4), with that of an unconstrained model ($Unconstrained\ R^2$), which incorporates both contemporaneous and lagged data. $D1 \in [0,1]$ is defined as:

$$D1 = 1 - \left(\frac{Constrained\ R^2}{Unconstrained\ R^2} \right). \tag{5}$$

We compute $D1$ at the monthly frequency using rolling windows of up to three months of daily data. $D1$ measures the extent to which cryptocurrency returns are explained by lagged information. Lower values are associated with greater cryptocurrency efficiency.

4.3 Market quality

We measure market quality/price accuracy using the q measure of Hasbrouck (1993). In that model, (log) returns r_t (we omit currency pair and exchange subscripts for simplicity) reflect changes in the efficient price m_t and changes in the pricing error s_t, such that

$r_t = m_t - m_{t-1} + s_t - s_{t-1}$. Given the variances of returns (σ_r^2) and pricing errors (σ_s^2), respectively, the market quality measure q is defined by the normalized pricing error σ_s^2/σ_r^2:

$$q = 1 - \sigma_s^2/\sigma_r^2, \tag{6}$$

where a higher q indicates a higher market quality because prices deviate less from their efficient level. We estimate market quality at a monthly frequency using the estimated parameters $\{a, \sigma_e^2\}$ of the MA(1) model $r_t = e_t - ae_{t-1}$ over a 3-month window and compute the resulting q measure defined as:

$$q = \frac{\sigma_e^2 - 2a \cdot cov(e_t, e_{t-1})}{\sigma_e^2 + a\sigma_e^2 - 2a \cdot cov(e_t, e_{t-1})} \in (0, 1)\,. \tag{7}$$

For details, see Hasbrouck (1993) and Das, Kalimipalli, and Nayak (2014).

4.4 Liquidity

We compute four liquidity measures that are likely to be correlated with liquidity frictions. First, we compute the Roll price impact measure (Roll, 1984), an estimate of illiquidity based on the autocorrelation of price changes. Denoting by $p_{i,j,t}$ the log price of cryptocurrency pair i (e.g., BTC–USD) on exchange j on day t, we estimate the covariance of log returns using a window of three months (one month for robustness), i.e., $\widehat{cov}_{i,j,t} = \mathbf{E}\left(\Delta p_{i,j,t}, \Delta p_{i,j,t-1}\right)$. We then compute, at a monthly frequency, the Roll measure defined as:

$$Roll_{i,j,t} = \left\{ \begin{array}{ll} = 2\sqrt{-\widehat{cov}_{i,j,t}} & if \quad \widehat{cov}_{i,j,t} < 0 \\ 0 \quad otherwise & \end{array} \right\}. \tag{8}$$

Second, we approximate bid-ask spreads through closing, low, and high (log) prices using the CHL measure of Abdi and Ranaldo (2017). Given daily closing ($c_{i,j,t}$), low ($l_{i,j,t}$), and high ($h_{i,j,t}$) prices of bitcoin currency i on exchange j at time t, we first compute $\eta_{i,j,t} = \left(l_{i,j,t} + h_{i,j,t}\right)/2$. We then compute, at a monthly frequency using windows of up to three months of daily data (one month for robustness), the CHL measure defined as:

$$CHL_{i,j,t} = \frac{1}{N}\sum_{n=0}^{N} \hat{s}_{i,j,t-n}, \quad \text{where} \quad \hat{s}_{i,j,t} = \sqrt{\max\{4(c_{i,j,t} - \eta_{i,j,t})(c_{i,j,t} - \eta_{i,j,t+1}), 0\}}. \tag{9}$$

Third, we consider trading volume in units of 1,000 bitcoins for each exchange and cryptocurrency pair. We measure volume at the monthly frequency using the average daily volume over three months. We examine windows of one month for robustness.

Fourth, we compute the Amihud illiquidity measure (Amihud, 2002). Given the volume of currency i, say BTC–USD, at exchange j on day t ($Volume_{i,j,t}$) and N daily observations, the Amihud price impact is computed as the average absolute return scaled by the corresponding period's volume:

$$Amihud_{i,j,t} = \frac{1}{N}\sum_{n=0}^{N} \frac{|r_{i,j,t-n}|}{Volume_{i,j,t-n}}. \tag{10}$$

We compute the Amihud measure at the monthly frequency using three months of daily data in our benchmark tests, and using one month in robustness tests.

We follow Dick-Nielsen, Feldhutter, and Lando (2012) and Schwert (2017) and construct a liquidity factor λ to reduce the dimensionality of our data. For each currency pair i traded on exchange j at time t, we construct $\lambda_{i,j,t}$ as an equal-weighted average of all k ($k = 1, 2, 3, 4$) liquidity metrics $L^k_{i,j,t}$:

$$\lambda_{i,j,t} = \frac{1}{4}\sum_{k=1}^{4} \frac{L^k_{i,j,t} - \mu^k}{\sigma^k}, \tag{11}$$

wher μ^k and σ^k are the mean and standard deviation, respectively, of liquidity metric k computed over the entire sample period.[5] We sign all variables so that a higher λ is associated with greater illiquidity.

5 Evidence

We discuss the data in Section 5.1 and summary statistics in Section 5.2. Preliminary evidence is illustrated in Section 5.3. We present the main results in Section 5.4.

5.1 Data

Our primary data source for digital currencies is Kaiko, a commercial vendor used in earlier academic studies (e.g., Makarov and Schoar, 2020; Li, Shin, and Wang, 2018). Kaiko provides price and trade information for transactions, timestamped to the millisecond, for more than 80 different exchanges on which bitcoin trades against other fiat currencies. For each transaction, the data include ticker symbol (e.g., BTC–USD), execution price, trade quantity, time stamp, and an indicator that flags trades as buyer- or seller-initiated.

We augment the Kaiko data with price and trade information for additional exchanges and currency pairs from CryptoCompare, a global cryptocurrency market data provider. These data are sourced manually from CryptoCompare's public data feeds.

We consider all cryptocurrency-exchange pairs with regular data availability between July 1, 2016 and December 31, 2018. Thus, we examine the evolution of all characteristics from 12 months before to 12 months after the introduction of the futures contracts in December 2017, excluding a 6-month anticipation period from July 2017 to December 2017 in the run-up to the futures introduction. Our pre-event period runs from July 1, 2016 to June

[5] We use the logarithms of volume and Amihud due to the significant heterogeneity across exchanges.

30, 2017, and the post-event period runs from January 1, 2018 to December 31, 2018.[6] We require a minimum amount of trading activity for an exchange to be included in our analysis and, thus, drop exchanges with aggregate daily trading volumes below 1,000 bitcoin units. Appendix B provides details regarding the data collection and cleaning process.

Our benchmark sample contains 10 bitcoin-fiat currency exchange rate pairs traded on 22 exchanges, with a total of 46 bitcoin-fiat currency-exchange pairs. In addition to the treatment currency BTC–USD, our control group includes 9 exchange rate pairs: BTC–EUR, BTC–GBP, BTC–HKD, BTC–SGD, BTC–JPY, BTC–AUD, BTC–IDR, BTC–CAD, and BTC–RUB, traded on the following 22 exchanges: Bitfinex, bitFlyer, Bitstamp, Bittrex, BTCbox, BTCC, BTC–e, Cex.io, Coinbase, Exmo, Gatecoin, Gemini, HitBTC, itBit, Kraken, LakeBTC, Liquid, OKCoin, Poloniex, QuadrigaCX, Quoine, and Zaif.

While BTC–USD trades on 19 exchanges, the BTC–EUR and BTC–JPY pairs trade on 9 and 6 exchanges, respectively; BTC–CAD, BTC–GBP, BTC–HKD, BTC–RUB, and BTC–SGD trade on 2 exchanges, and BTC–AUD and BTC–IDR trade on only 1 exchange. Our most restrictive tests that exploit the within exchange variation of BTC-USD relative to BTC-CCY are based on the subsample of exchanges that have a minimum of one additional bitcoin-fiat currency pair besides BTC–USD.

All cryptocurrency exchange rates are quoted in terms of number of fiat currency units per bitcoin. Since our measures of market characteristics are based on returns and trading volumes, we compute daily log returns using the last trade of each day. We aggregate intraday quantities of traded bitcoins to obtain a measure of daily trading volume.

There exists evidence that cryptocurrencies are subject to price manipulation (Gandal, Hamrick, Moore, and Oberman, 2018; Griffin and Shams, 2020), pump-and-dump schemes (Li, Shin, and Wang, 2018), and wash trading (Cong, Li, Tang, and Yang, 2021; Aloosh and Li, 2020; Amiram, Lyandres, and Rabetti, 2021). To alleviate concerns that our results may be driven by exchanges exposed to manipulation, we exclude suspect trading platforms in subsample analysis. In its ETF proposal filed with the SEC in April 2018, Bitwise Asset Management Inc. highlights the incentives of cryptocurrency exchanges for inflating trading volumes and identifies 11 exchanges with legitimate volumes: Binance, Bitfinex, Kraken, Bitstamp, Coinbase, bitFlyer, Gemini, itBit, Bittrex, Poloniex, and Cex.io. In our analysis, we assume that the exchanges that are not among these 11 exchanges are prone to trading volume manipulation.

5.2 Descriptive statistics

We first describe the trading activity across currencies and exchanges. Panel A of Table 1 shows that the aggregate trading volume across our exchanges increases from 11.383 million

[6] In our benchmark regressions with metrics computed using 3 months of daily data, we exclude observations in January and February 2018 because they contain information from before the futures introduction.

BTC in Q3 2016 to a peak of 22.977 million BTC in Q4 2017, the month of the futures introduction, and then decreases again to 14.739 million BTC in Q4 2018.

Trading activity is dominated by BTC–USD, which accounts on average for about 53% of all volume, with a market share ranging between 32.36% in Q4 2016 to 69.37% in Q3 2017. Trading in BTC–JPY (BTC–EUR) ranks second (third), with market shares that fluctuate between 18.04% and 58.55% (5.08% and 12.64%). There is less trading activity in other cryptocurrencies, which account for about 3.11% of aggregate trading activity, on average.

In Panel B of Table 1, we illustrate the dispersion of trading activity across the five largest exchanges in terms of BTC–USD trading activity between July 1, 2016 and December 31, 2018: Bitfinex, Coinbase, Bitstamp, Gemini, and HitBTC. The largest exchange, Bitfinex, captures up to 40.9% of all BTC–USD volume in Q1 2018, followed by Coinbase (up to 16.56%, Q2 2017) and Bitstamp (up to 15.27%, Q2 2017). The residual category "All others" accounts for up to 54.22% of all BTC–USD trading, suggesting a non-trivial amount of trading across multiple exchanges.

While trading volumes in BTC-EUR are lower than those for BTC–JPY, BTC–EUR trading is spread out across more exchanges. In our benchmark tests, we, therefore, independently compare BTC–USD to BTC–EUR. Panel C in Table 1 shows the cross-exchange distribution of BTC-EUR trading volume between July 1, 2016 and December 31, 2018. Kraken dominates BTC–EUR trading and accounts, on average, for about 62.21% of all BTC–EUR volume. Next, Bitstamp, Coinbase, Quoine, and Cex.io, record market shares of 13.43%, 12.18%, 5.06% and 2.31%, respectively. The remaining 4.81% of trading for the residual category is spread across 4 exchanges. Note that the largest exchanges are not the same across currency pairs, suggesting a fair amount of heterogeneity across exchanges. Our (untabulated) statistics also indicate that BTC–USD volumes are on average about 7 times larger than those of BTC–EUR, which range from about 578 thousand BTC in Q3 2016 to 1.978 million BTC in Q1 2018.

Bitcoin prices went through a period of boom and bust. Figure 1.b shows that bitcoin first peaked at approximately $20,000 around the introduction of the futures contracts in December 2017. Bitcoin prices then lost about 75% in value over the subsequent year. As of February 2021, bitcoin has surged back up north of $40,000.

In Table 2, we provide summary statistics for daily bitcoin exchange rate returns by currency pair and exchange. In Panel A, we focus on BTC–USD. The return distributions are similar across exchanges, with average returns around zero, ranging between 0.13% and 0.39%, and standard deviations ranging between 3.74% and 5.02%. All distributions exhibit mild negative skewness (except for HitBTC, Liquid, and Quoine) and kurtosis that ranges between 5.88 and 9.93. The return distributions of BTC–EUR and all other bitcoin-fiat currency exchange rates, reported in Panels B and C, respectively, are similar, although the return distributions reported in Panel C exhibit more leptokurtic distributions and more often positive skewness.

In Table 3, we report summary statistics for our measures of price synchronicity, market efficiency, market quality, and liquidity. For each metric, we compare the statistics between BTC–USD and the 9 other cryptocurrency exchange rate pairs. Their unconditional means are comparable for measures of price synchronicity, efficiency, quality, the Roll price impact measure, and bid-ask spreads (CHL). For example, the average efficiency measure $D1$ is 0.3069 for BTC–USD and 0.3305 for other exchange rate pairs. Similarly, the corresponding market quality is on average 0.9449 and 0.9370, while the average bid-ask spread is 1.45% and 1.55% for BTC–USD and BTC–CCY, respectively. The distributions for these metrics look broadly similar across groups.

In contrast, BTC–USD exhibit significantly greater trading volume, and less price impact based on Amihud's price impact metric. For instance, the average daily trading volume for BTC–USD is 4,622, while it is only 2,735 BTC for other currency pairs. Average Amihud values, which capture the price impact per unit of trading volume, are large because daily trading volume is often low. The median values suggest that the average daily price impact is 1.98% per 1,000 BTC, while it is 14.90% for other currency pairs.

5.3 Preliminary evidence

We provide preliminary evidence using changes in BTC–USD price synchronicity around the introduction of bitcoin futures. We report in Table 4 Pearson correlation coefficients for daily cross-exchange BTC–USD returns in the pre- and post-event periods. For brevity, we focus on the five biggest exchanges by volume between July 1 and December 31, 2016.

The correlation coefficients in the pre-event period range between 0.8751 and 0.9812. That heterogeneity in price synchronicity suggests that cross-exchange prices of fully fungible BTC–USD exchange rates were not aligned before the futures introduction. The correlation coefficients significantly increase in the post-event period, indicating an increase in cross-exchange price synchronicity. For example, the correlation between returns on Bitfinex and Quoine increases from 0.8751 to 0.9856 after the futures listing. Similarly, the correlation coefficient between returns for trades registered on itBit and Bitfinex increases from 0.9437 to 0.9929. The notable heterogeneity in terms of levels and dynamics of return correlations is useful for identifying the impact of futures introduction on cash markets.

Our identification strategy relies on comparing the evolution of, for example, price synchronicity between BTC–USD and BTC–CCY, i.e., all other bitcoin-fiat currency exchange rate returns. Thus, we compute the average pairwise return correlation across all exchanges for BTC–USD and BTC–CCY in both the pre- and post-event periods. Figure 2 shows the average difference between both categories before and after the futures announcement (first vertical line) and introduction (second vertical line), in addition to the difference in correlations computed in rolling windows of 90 days. The figure highlights a pronounced shift in October 2017 when the futures launch was announced. Before the introduction, the average return correlation for BTC–USD returns is about five percentage points lower than that of all other pairs (dotted horizontal line). In the period following the futures introduction, it is about five percentage points higher. This suggests that the increase in correlations following the introduction of the futures contract is much more pronounced for BTC–USD than for other exchange rate pairs. We now proceed to a more formal analysis of the changes in integration, quality, efficiency, and liquidity of cryptocurrencies around the futures introduction.

5.4 Main results

We successively discuss the results for price synchronicity and integration, price efficiency, market quality, and liquidity. For each characteristic, we estimate the model in Equation (1) to test whether the futures introduction in December 2017 made cryptocurrency cash markets more integrated, efficient, liquid, and informative. The null hypothesis is that there is no differential impact for BTC–USD (the treatment group) and other bitcoin-fiat currency pairs (i.e., BTC–CCY, the control group) following the BTC–USD futures introduction.

Price synchronicity and integration

In Panel A of Table 5, we report the results for price synchronicity, as measured by the cross-exchange Pearson correlation coefficients between cryptocurrency returns. The result in column (1) suggests that, unconditionally, pairwise correlations are on average 5.3 percentage points lower for BTC–USD returns. Further, the level of correlations drops by about 7.3 percentage points after the futures listing. This is largely the result of exchanges that are suspected to be exposed to market manipulations, which we have formally validated in unreported results.

The main coefficient of interest is the one associated with the interaction term $Treatment \times Post$. This coefficient is highly statistically significant with a point estimate of 0.121, which is economically meaningful. The magnitude of the coefficient hardly changes if we add a battery of fixed effects in columns (2) to (5). In column (2), we add exchange-pair fixed effects to absorb unobserved and time-invariant heterogeneity at the exchange-pair level, thereby accounting for cross-exchange differences in the level of price synchronicity. In column (3), we control for monthly time fixed effects to absorb common temporal variation in price synchronicity across exchanges. In column (4), we add currency-pair fixed effects to capture time-invariant differences across bitcoin currency pairs. Adding all fixed effects together in column (5) has little impact on the coefficient's magnitude.

In the most conservative specification in column (6), we compare variation between BTC–USD and BTC–CCY at the exchange-pair level by controlling for unobserved time-varying characteristics of exchange pairs. That specification indicates a statistically significant increase in BTC–USD price synchronicity of 5.0 percentage points relative to BTC–CCY.

In columns (7) to (9) of Table 5, we report subsample results when the treatment group is restricted to BTC–EUR (EUR), BTC–CCY excluding BTC–EUR (CCY*), or when we exclude the exchanges that are suspected of manipulation (X-M). In all specifications, the coefficient of interest remains significant and ranges between 0.050 and 0.144.

In Figure 3, we report a model-implied plot from an extended difference-in-differences regression in which we interact a treatment indicator for BTC–USD correlations with quarterly fixed effects around the futures introduction. We use the third quarter in 2017 as the base for comparison. Each point estimate in Figure 3 thus represents the relative difference in price correlations between BTC–USD and other bitcoin exchange rate pairs at a particular point in time.

In the pre-event period, none of the coefficients is statistically significant, suggesting that the parallel trend assumption needed for the valid inference of the difference-in-differences test is respected. In the fourth quarter of 2017, when BTC–USD futures start trading, the difference-in-differences estimator jumps up to about 3.15%, and all following estimates are significantly different from zero. The coefficient increases to about 15.48% in the fourth quarter in 2018, indicating that the differential increase in BTC–USD price correlations relative to other bitcoin-fiat currency pairs between Q3 2017 and Q4 2018 is about 15.48 percentage points. This evidence supports the view that the introduction of BTC–USD futures contracts is associated with an increase in BTC–USD cross-exchange price synchronicity that is not similarly experienced by other exchange rate pairs.

In Panel B of Table 5, we examine the impact of futures listing on the Kapadia and Pu (2012) non-parametric measure of price synchronicity κ. Higher values of κ reflect a higher degree of cross-exchange price integration. The results in columns (1) to (5) suggest again that there is a positive and statistically significant increase in price integration for the treatment group relative to the control group. The average differential increase in the frequency of price concordance ranges between 11.8 and 13.5 percentage points. Given the average BTC–USD value for κ of 0.7003, this change is economically meaningful.

Based on the most conservative estimate reported in column (6), where we compare the change in price synchronicity around futures listing for BTC–USD relative to BTC–CCY at the exchange-pair level, the differential increase in the frequency of price concordance is 4.7 percentage points. The results in columns (7) and (8) suggest that the increase in integration of BTC–USD returns is stronger relative to BTC–EUR than relative to other currency pairs. In the subsample results for exchanges that are not accused of market manipulation, the coefficient estimate is 0.114.

Market quality

We next discuss the implications of the futures introduction for market quality, as measured by the q metric of Hasbrouck (1993). Specifically, we report in Panel A of Table 6 the results from the projection of the market quality metric on the BTC–USD treatment indicator, the post-futures introduction event dummy, and their interaction. Unconditionally, we find no significant difference in market quality between BTC–USD and other cryptocurrency exchange rates. In columns (1) to (6), we do, however, find that the market quality of BTC–USD increases relative to all other cryptocurrency exchange rates, with a statistically significant coefficient estimate of around 3.0% to 3.8%. That coefficient remains significant in our most conservative specification in column (6), where we examine the within exchange variation of BTC–USD relative to other cryptocurrency exchange rates. The coefficients are of roughly similar magnitudes for the subsample results with different treatment groups in columns (7) and (8). The coefficient is insignificant for the subsample of exchanges that are free from alleged manipulation, as shown in column (9), but this insignificance could be driven by a lack of power as we lose a non-trivial number of observations.

Price efficiency

In Panel B of Table 6, we report the results for the $D1$ price efficiency measure suggested by Hou and Moskowitz (2005). In unreported results, we find that the results are insignificant for the aggregate sample, which is primarily due to noisy measurements of the $D1$ metric for cryptocurrency exchange rate returns other than BTC–USD and BTC–EUR. For that reason, we only report the results where BTC–EUR is the comparison group.

A lower $D1$ metric indicates that prices are more efficient, in the sense that new information gets more quickly incorporated into prices. The negative and statistically significant coefficient estimate in all specifications suggests that the increase in price efficiency is more pronounced for BTC–USD following the BTC–USD futures introduction. The differential increase in price efficiency ranges from 2.7% to 7.8%. This is economically meaningful, as the average efficiency measure for BTC–USD (BTC–CCY) is 30.69% (33.05%), as reported in Table 3. Importantly, we note a differential increase in price efficiency both across exchanges (columns (1) to (5)) and within exchange (columns (6) to (7)). Overall, we find support for the hypothesis that the derivatives introduction improves the price efficiency of the underlying cash market.

Liquidity

In Table 7, using the aggregate liquidity factor λ, we evaluate whether the introduction of BTC–USD futures is associated with an improvement of BTC–USD liquidity relative to other exchange rate pairs. We find a statistically significant improvement in liquidity across the specifications reported in columns (1) to (8). That impact is also economically significant. For example, the magnitude of the estimated coefficient of 0.351 in column (4) corresponds to about 55% of the standard deviation of λ for BTC-USD. Importantly, the coefficient's magnitude is stable across specifications with different fixed effects.

The liquidity factor is computed as an equal-weighted average of standardized liquidity metrics, whereby the mean and standard deviation are computed across the entire sample. To account for significant differences across exchanges and currencies, especially for volume and Amihud, we include in our most conservative specifications in columns (5) to (9) interactions of exchange and currency fixed effects. This effectively absorbs such level differences across currency-exchange pairs and also accounts for related selection effects. We find that these specifications do not significantly impact the magnitude of our results.

The coefficient is reduced by half to -0.170 for the specification reported in column (6), where we add interaction terms of exchange and month fixed effects. Thus, we compare the evolution of BTC–USD and BTC–CCY around the futures introduction at the exchange level, while controlling for unobserved time-invariant differences across exchange and currency pairs. Even in this conservative specification, the coefficient estimate still corresponds to about 27% of the sample standard deviation of λ for BTC-USD.

Only the estimate in column (9) for the subsample of non-manipulated exchanges is insignificant. This is likely the result of a loss in power in combination with the use of many fixed effects, as the coefficient's magnitude does not change, standard errors increase, while the number of observations drops.

We also discuss and report results for the individual liquidity metrics in Section 6.4. These results are qualitatively similar to those based on the aggregate liquidity factor λ.

6 Refinements, Channels, and Robustness

We strengthen the evidence about the impact of BTC–USD futures on the bitcoin cash market by exploiting the futures settlement mechanism. In addition, we shed light on the potential channels for our results, and we provide evidence that the results are associated with improvements in BTC rather than USD. We end the section with robustness tests.

6.1 Evidence around the fixing of the settlement index

We exploit the institutional details of the futures settlement index to provide additional supportive evidence for our hypothesis. The respective contracts on the CME and the CBOE rely on different indices, which are fixed at different times of the day.

The CME bitcoin futures are cash settled based on the CME CF bitcoin reference rate (BRR) determined at 4:00 p.m. *London time* on the expiration day of the futures contract. The BRR is computed daily and represents the USD value of one bitcoin at its fixing time. Designed jointly by the CME and CF Benchmarks, it is constructed to ensure its "resilience and replicability" and represents a weighted average of prices registered for trades executed on the four constituent exchanges between 3:00 p.m. and 4:00 p.m. London time each day. The four constituent exchanges are itBit, Kraken, BitStamp, and GDAX.

Futures contracts on the CBOE are also cash settled but rely on a different bitcoin cash price. Specifically, contract values are based on the official USD auction price for bitcoin, which is determined at 4:00 p.m. *Eastern time* by the Gemini exchange.

Given that cash indices for futures settlement are computed at 4:00 p.m. Eastern and London times, respectively, we expect greater trading activity around these fixing times, with more reliable and less noisy prices (see Aleti and Mizrach (2021) for supporting evidence). Hence, our results should be sharper if we focus our analysis on prices obtained during the fixing times from those exchanges used in the computation of settlement indices. Thus, we repeat our analysis using daily returns with prices sampled from the Gemini Exchange at 4:00 p.m. *Eastern time*, and prices sampled from itBit, Kraken, and BitStamp at 4:00 p.m. *London time*. The GDAX exchange is not covered by our data.

In Table 8, we report the results from the difference-in-differences regressions after we sample prices at 4:00 p.m. on the corresponding exchanges. For a fair comparison, we also report identical regressions based on the same sample composition when prices are sampled end-of-day. We emphasize that the observations drop significantly in Table 8, as the analysis is restricted to four exchanges. This has implications for the statistical power of our tests. Despite this caveat, there is some support for stronger results when prices are sampled around times when the futures settlement indices are computed.

In Panel A, we find supportive evidence for an increase in market quality using prices sampled at 4:00 p.m. in the specification without fixed effects in column (4) and with exchange, month and currency fixed effects in column (5), while results based on prices sampled at the end-of-day are statistically insignificant (columns (1) and (2)). The estimated coefficients in columns (2) and (5) are statistically different from each other at the 10% significance level.

In Panel B, we focus on the aggregate liquidity metric λ. The coefficient estimates in columns (1) to (6) are all significant at the 1% to 5% significance level. However, the economic magnitudes of the coefficients in columns (4) to (6) are significantly larger than those in columns (1) to (3), indicating that the effects are stronger when we sample the prices around 4:00 pm. In the appendix, we provide qualitatively similar results using the individual liquidity metrics Roll, Amihud, and bid-ask spreads.

As we do not find any differential effects for the analysis of price synchronicity, we do not report the results. We cannot conduct the same tests for price efficiency because the market return is observed only end-of-day. Overall, our findings are supportive of stronger results when we focus on prices at times that are more relevant for the futures markets and during which prices could potentially be less noisy.

6.2 Channels

Our evidence suggests that, following the introduction of BTC–USD futures contracts, BTC–USD cash prices become more aligned, allow for fewer arbitrage opportunities, and exhibit a higher degree of market quality and price efficiency. We next explore the channels through which this effect may arise. We focus on two plausible explanations related to a reduction in trading frictions and a reduction in informational frictions.

Shleifer and Vishny (1997) suggest that arbitrage opportunities may arise if there is a lack of arbitrage capital. This could be reflected in large transaction costs such as bid-ask spreads or price impact measures. In the specific context of integration between credit and equity markets, Kapadia and Pu (2012) relate the discordance in prices to idiosyncratic volatility and other measures typically associated with illiquidity.

An imperfect alignment of prices could also be due to a lack of investor attention (Duffie, 2010). Inattention may be driven by distraction (Hirshleifer, Lim, and Teoh, 2009), limited cognitive resources (Peng and Xiong, 2006), or costly information acquisition (Nieuwerburgh and Veldkamp, 2010).

While we cannot directly measure limitations to free movement of arbitrage capital or investor attention, we examine whether there are cross-exchange differences in the treatment effect according to exchange-specific measures that are correlated with trading frictions and investor attention. We examine cross-sectional differences for the results of price synchronicity. For trading frictions, we use the average value of the liquidity factor λ for each exchange in the pre-event period. For attention, we collect the average Google search intensity for each exchange name in the pre-event period. To ensure comparability across exchanges, we download each exchange's search intensity together with that of the word "bitcoin". Using these measures of attention and illiquidity, we run triple difference-in-differences regressions:

$$\begin{aligned}
&Price\ Synchronicity_{i,j,t} = \alpha_0 + \alpha_1 Treatment_{BTC-USD} \times Post_{futures} \\
&+ \alpha_2 Treatment_{BTC-USD} \times High\ Attention\ (or\ High\ Liquidity) \\
&+ \alpha_3 High\ Attention\ (or\ High\ Liquidity) \times Post_{futures} \\
&+ \alpha_4 Treatment_{BTC-USD} \times Post_{futures} \times High\ Attention\ (or\ High\ Liquidity) \\
&+ \delta_i + \eta_j + \gamma_t + \varepsilon_{i,j,t},
\end{aligned} \tag{12}$$

where *High Attention* (*High Liquidity*) is one if the average search intensity (average liquidity λ) of the pair of exchanges used to compute the price synchronicity measure in the pre-event period is above (below) the sample median and zero otherwise. All other variables are defined in Equation (1). Thus, we test whether, following the futures introduction, any improvement in BTC–USD asset characteristics relative to those of other bitcoin-fiat currency pairs is greater on exchanges that have lower transaction costs or more attention.

The results in Table 9 are supportive of the liquidity but not the attention channel. The triple interaction coefficient is statistically significant across all specifications in Panels

B and D, and insignificant in Panels A and C. This suggests different impacts from the introduction of bitcoin futures on bitcoin cash markets for exchanges with high and low liquidity. Surprisingly, however, we find that the results are weaker for exchanges with higher liquidity. We speculate that exchanges where liquidity was already high in the pre-event period had higher price synchronicity before the futures introduction. The potential improvement in price synchronicity is, therefore, smaller relative to the other exchanges. In the appendix, we report similar findings when we use the individual liquidity metrics instead of the aggregate liquidity factor.

In unreported tables, we conduct triple difference-in-differences analyses for price efficiency, market quality, and liquidity measures with the same specifications as in columns (1) to (6) of Tables 6 and 7. We observe that the results for Roll's measure and the q measure are weaker and statistically significant at the 5%-10% level with higher liquidity. Moreover, the results for the Amihud price impact measure are weaker and statistically significant at 10% level in the most conservative specification with greater liquidity. The results for CHL, $D1$, and volume are statistically insignificant. Overall, the results are largely consistent with those for price synchronicity.

6.3 Triangular arbitrage

We find that the introduction of bitcoin futures is associated with a greater price alignment of BTC–USD than of, for example, BTC–EUR. This result may seem surprising given the possibility of triangular arbitrage through a liquid EUR–USD exchange rate. However, Makarov and Schoar (2020) explain that "customers from different countries can usually only trade cryptocurrencies on their local exchange and in their local currency." Thus, arbitrage across cryptocurrency-fiat exchange rates within exchange is challenging (Dyhrberg, 2020). That argument is reinforced by the inability to trade a pure fiat exchange rate (e.g., EUR–USD) on the cryptocurrency exchanges in our sample.

In contrast, triangular arbitrage may be easier if it involves two cryptocurrency assets in the triangular relation, without a pure fiat exchange rate. We examine this conjecture using the second most popular cryptocurrency ether (ETH) as another test asset. This also allows us to keep the characteristics of the fiat currency leg constant. Notably, every exchange that lists both BTC–USD and ETH–USD also lists BTC–ETH. Consistent with that view, our results in columns (1) to (4) of Table 10 indicate that the futures introduction is associated with a greater increase in price synchronicity for BTC–USD relative to ETH–USD across exchanges, but not within exchanges.

Finally, to emphasize that we capture a bitcoin rather than a USD effect, we report our benchmark tests when we compare the impact from the futures introduction on ETH–USD relative to ETH–CCY. Based on the results in columns (5) to (8) of Table 10, we find no significant difference between both exchange rates.

6.4 Robustness and Additional Tests

Besides the robustness analysis that we explain in our main text, we conduct a battery of additional robustness tests to further ensure the validity of our main findings. Here, we limit ourselves to a discussion of these results, which are provided in the Internet Appendix.

We first revisit our benchmark results when we compute all market characteristics at different frequencies. In Table C.2, we report our benchmark results when we compute our measures of price synchronicity, market quality, efficiency, and liquidity at a monthly frequency using a rolling window of one month of daily returns. In contrast to a rolling window of three months of daily returns, this eliminates any data overlap in the construction of our metrics of market characteristics.

In Panels A and B of Table C.2, we report the coefficient estimates under the specification that corresponds to columns (5) and (6), respectively, in Tables 5, 6, and 7. The statistical significance and economic magnitudes of the coefficient estimates are comparable to those that we observe in our benchmark results, suggesting that our baseline results are robust to the specific choice of the length of rolling windows used to compute market characteristics.

In Appendix Table C.3, we repeat the same analysis when we compute all metrics at the daily (as opposed to monthly) frequency using rolling windows of 30 and 90 days. Neither the data frequency nor the choice of rolling windows is material for our findings. We observe that, using longer windows for measures of market quality and price efficiency, results are either statistically and economically stronger or remain unchanged. In untabulated results, we observe similar patterns when we change the length of the window to 180 days.

In Appendix Table C.4, we show that our results for price integration are robust to an alternative trading horizon of five days. The analysis yields similar statistical significance with a lower economic magnitude. This suggests that asynchronous price movements are more pronounced at shorter horizons, and that arbitrageurs are partially disciplining prices over longer trading horizons (Makarov and Schoar, 2020).

In our baseline regressions, we exclude the observations in the anticipation period. In Table C.5, we show that our results are robust to different definitions of the pre-event and post-event periods. Columns (1) to (4) in each Panel correspond to the baseline results from column (5) in Tables 5, 6, and 7, while those in columns (5) to (8) correspond to the baseline results from column (6) in the same tables.

In columns (1) and (5) of Table C.5, we exclude observations from the anticipation period and from January and February 2018. This is because our metrics computed at the monthly frequency with a rolling window of three months of daily returns partially contain information from the anticipation period; in columns (2) and (6), we only exclude observations from the anticipation period; in columns (3) and (7), we exclude the observations from January and February 2018. in columns (4) and (8), we do not exclude any observations.

The magnitudes and statistical significance of the coefficients are largely consistent with those of our baseline results.

In untabulated results, we find that our results for several measures (including Roll, CHL, and D1) become stronger if we shorten the length of the post-event period by 6 months to June 2018. This suggests that the effect of the introduction of futures on the cash market's liquidity and efficiency is more pronounced in the early part of the post-event period.

We also conduct two placebo tests by considering hypothetical announcement dates on January 1, 2017 and July 1, 2018. Panels A and B in Table C.6 report the results for each of our metrics using three months before and after these hypothetical event days. None of the treatment effects is statistically significant.

In Appendix Table C.7, we show that our results are robust to different ways of clustering and standard error correction. We again provide specifications for the baseline results corresponding to the specifications in columns (5) and (6) from Tables 5, 6, and 7. These results are again consistent with our benchmark findings.

In our baseline results, we provide evidence for subsamples that compare BTC–USD to BTC–EUR, because BTC–EUR trades on more exchanges than BTC–JPY, which is a dominant trading currency in the BTC space. For robustness, we provide in Table C.8 results for the comparison with BTC–JPY. These findings largely confirm our earlier evidence.

In Appendix Table C.9, we provide the difference-in-differences results for the individual liquidity metrics. For Roll's measure of liquidity in Panel A, we find a statistically significant effect across all specifications reported in columns (1) to (6). The reduction in price impact ranges between 0.005 to 0.007. The differential change in price impact corresponds to about 31% of the average price impact of 0.0163 measured for BTC–USD returns, as reported in Table 3. If we focus on the subsample of BTC–EUR exchange rates in the treatment group in column (7), the magnitude of the regression coefficient doubles. For the subsample results in columns (8) and (9), the coefficient is insignificant.

In Panel B of Table C.9, we report the results for bid-ask spreads. We find a negative and significant coefficient on the interaction term in columns (1) to (5) when we compare the evolution of cross-exchange bid-ask spreads between BTC–USD and other cryptocurrency exchange rates. However, the coefficient is insignificant for the within exchange comparison reported in column (6). The results in columns (7) to (9) suggest that the reduction in bid-ask spreads is primarily driven by an improvement of BTC–USD relative to BTC–EUR. The average bid-ask spread for BTC–USD is 0.0145, with a standard deviation of 0.0064 (see Table 3.) Thus, the estimate represents a reduction in bid-ask spreads of about 14%, and corresponds to approximately one third of the sample variation in bid-ask spreads.

The results for (log) volume are reported in Panel C of Table C.9. The results for volume are only weakly significant at the 5%-10% level across selective specifications. We suspect that these results are noisy and less reliable because of the evidence about volume manipulation and wash trading reported by Gandal, Hamrick, Moore, and Oberman (2018); Cong, Li, Tang, and Yang (2021); Aloosh and Li (2020); Li, Shin, and Wang (2018); Amiram, Lyandres, and Rabetti (2021). Indeed, when we focus on the subset of exchanges that are not allegedly involved in market manipulation, as pointed out by Bitwise, we find a statistically significant coefficient estimate of 1.941 in column (9). Specifically, the results suggest that the differential increase in trading volume for BTC–USD is about 194%.

Finally, in Panel D of Table C.9, we report the estimated coefficients for the Amihud price impact measure. As for the other measures, we find a reduction in price impact following the futures listing which is significantly greater for BTC–USD than for other exchange rate pairs. In the fully saturated specification in column (5), the estimated coefficient for the interaction between the futures listing indicator and the BTC–USD treatment group is –1.60, indicating a differential reduction in price impact of approximately 160%. This effect is primarily driven by currency pairs other than BTC–EUR, as we see a greater statistical significance and a greater magnitude of the coefficient in column (8). We observe a statistically and economically significant coefficient estimate of -2.059 in column (9), indicating that the effect is larger for the exchanges that are less prone to trading volume manipulation. This is possibly because the Amihud measure, which is based on trading volume, is more reliably estimated for those exchanges.

In Appendix Table C.10, we revisit the evidence using prices sampled from futures settlement times for the individual liquidity metrics. In Panel A, we study the effect on Roll's price impact measure. While the coefficient estimate for the interaction term is close to zero and statistically insignificant using end-of-day prices in columns (1) to (3), it becomes negative and statistically significant at the 5% or 10% level in specifications using 4:00 p.m. prices in columns (4) to (5). While the coefficient estimate in column (6) is insignificant, it is negative, whereas the coefficient estimate is positive in column (3).

In Panel B of Table C.10, the results for bid-ask spreads based on end-of-day prices are insignificant. Using prices that are more relevant for the futures market, we find a negative and weakly significant effect in the specification without fixed effects in column (4) and with exchange $\times$ currency and month fixed effects in column (5). In column (6), the coefficient magnitude is more negative than the one reported in column (3), although the coefficient is insignificantly estimated. In Panel C, we find that the results for the Amihud price impact measure have similar statistical significance in both samples, but the economic significance becomes stronger if we use 4:00 p.m. prices.

In Appendix Table C.11, we further support the evidence of a liquidity channel discussed in Section 6.2 based on the aggregate liquidity factor λ. We repeat the analysis using the individual liquidity metrics Roll, Amihud, volume, and bid-ask spreads. Our findings support the view that the differential impact of the futures introduction on BTC–USD relative to BTC–CCY is amplified for currency-exchange pairs that are above/below the median level of liquidity.

In Appendix Table C.12, we strengthen our evidence by showing results for additional cryptocurrency attributes. In Panel A, we consider an annualized measure of volatility computed as the standard deviation of daily log returns. In Panel B, we report results for an arbitrage index measured using the absolute price deviation between prices measured across a pair of exchanges. These results are largely in line with our earlier evidence and suggest that there is a drop in volatility and a reduction in arbitrage opportunities following the futures introduction.

Finally, we consider additional evidence from the introduction of ethereum futures by the CME in February 2021. As for the introduction of bitcoin futures, the CME selectively launched contracts on ETH against the USD, but not against other fiat exchange rates. Thus, we consider the impact of the futures introduction on ETH–USD relative to ETH–CCY from three months before the announcement of ethereum futures on December 15, 2020 to three months after the contract launch on February 8, 2021. We describe the data for this extension in Appendix B.2 and report results for our measures of price synchronicity in Table C.13.

Panel A in Table C.13 presents the results for cross-exchange price correlations. This table highlights that, regardless of the specification, the increase in cross-exchange price synchronicity is larger for ETH–USD than for other ETH exchange rates. The most conservative specifications in columns (5) and (6) suggest an increase in correlations of 1.9 and 1.6 percentage points. This economic magnitude is smaller than that reported in Table 5 for the introduction of bitcoin futures, which is intuitive, given that the cryptocurrency market may have matured over the three years since the introduction of the first regulated cryptocurrency futures in 2017. The results for market integration in Panel B of Table C.13 provide a qualitatively similar picture.

7 Conclusion

The U.S. CFTC approved the launch of bitcoin futures contracts in December 2017 because it was widely believed that it would make bitcoin prices better reflect fundamental values. Currently, numerous proposals for bitcoin ETFs are being denied by the SEC due to concerns of manipulation in related spot markets. Despite the ongoing regulatory debates, there exists no evidence on how the listing of derivatives products linked to cryptocurrency assets affects the underlying cash market's characteristics such as price efficiency and market quality. We take a first step to fill this gap.

Specifically, we examine how the introduction of bitcoin futures contracts in December 2017 affects the price synchronicity, efficiency, market quality, and liquidity of the underlying cash market. We exploit a unique feature of the cryptocurrency market, where fully fungible assets with identical cash flows trade on different exchanges. As futures contracts were selectively introduced for BTC–USD, and not for other bitcoin-fiat currency pairs, we can isolate cross-sectional variation at the exchange level and examine whether the bitcoin futures introduction was beneficial to the underlying cash market.

Our results suggest that the BTC–USD futures introduction significantly enhanced the price synchronicity of BTC–USD relative to other cryptocurrency exchange rates, and that this was accompanied with an increase in cross-exchange integration of BTC–USD prices. Moreover, we find supporting evidence for an increase in pricing efficiency, market quality, and liquidity.

References

Abdi, Farshid, and Angelo Ranaldo, 2017, A Simple Estimation of Bid-Ask Spreads from Daily Close, High, and Low Prices, *The Review of Financial Studies* 30, 4437–4480.

Akyildirim, Erdinc, Shaen Corbet, Paraskevi Katsiampa, Neil Kellard, and Ahmet Sensoy, 2021, The development of Bitcoin futures: Exploring the interactions between cryptocurrency derivatives, *Finance Research Letters* 34, 1–9.

Aleti, Saketh, and Bruce Mizrach, 2021, Bitcoin Spot and Futures Market Microstructure, *Journal of Futures Markets* 41, 194–225.

Alexander, Carol, and Daniel F. Heck, 2020, Price discovery in Bitcoin: The impact of unregulated markets, *Journal of Financial Stability* 50, 1–18.

Aloosh, Arash, and Jiasun Li, 2020, Direct Evidence of Bitcoin Wash Trading, *Working Paper George Mason University.*

Alsabah, Humoud, and Agostino Capponi, 2020, Pitfalls of Bitcoin's Proof-of-Work: R&D Arms Race and Mining Centralization, *SSRN Working Paper 3273982.*

Amihud, Yakov, 2002, Illiquidity and stock returns: cross-section and time-series effects, *Journal of Financial Markets* 5, 31–56.

Amiram, Dan, Evgeny Lyandres, and Daniel Rabetti, 2021, Competition and Product Quality: Fake Trading on Crypto Exchanges, *SSRN Working Paper 3745617.*

Avan-Nomayo, Osato, 2019, US Bitcoin Derivatives Market, Highlights of 2019, *Cointelegraph* 27 December 2019.

Baur, Dirk G., and Thomas Dimpfl, 2019, Price discovery in bitcoin spot or futures?, *Journal of Futures Markets* 39, 803–817.

Benedetti, Hugo, 2018, The economics of digital token cross-listings, *ESE Business School Working Paper.*

Bessembinder, Hendrik, and Paul J. Seguin, 1992, Futures-Trading Activity and Stock Price Volatility, *Journal of Finance* 47, 2015–2034.

Biais, Bruno, Christophe Bisiére, Matthieu Bouvard, and Catherine Casamatta, 2019, The Blockchain Folk Theorem, *Review of Financial Studies* 32, 1662–1715.

Biais, Bruno, Christophe Bisiere, Matthieu Bouvard, Catherine Casamatta, and Albert J. Menkveld, 2018, Equilibrium Bitcoin Pricing, *SSRN Working Paper 3261063.*

Biraajmaan, Tamuly, 2019, Bitcoin's price dictates BTC derivatives market and not vice-versa, *AMB Crypto.*

Böhme, Rainer, Nicolas Christin, Benjamin Edelman, and Tyler Moore, 2015, Bitcoin: Economics, Technology, and Governance, *Journal of Economic Perspectives* 29, 213–38.

Borri, Nicola, and Kirill Shaknov, 2021, The Cross-Section of Cryptocurrency Returns, .

Brenner, Menachem, Marti G. Subrahmanyam, and Jun Uno, 1994, *The Volatility of the Japanese Stock Indices: Evidence from the Cash and Futures Markets, in Japan, Europe and International Financial Markets.* (Cambridge University Press).

Casey, Michael J., and Paul Vigna, 2015, Bitcoin and the Digital-Currency Revolution, *The Wall Street Journal* Jan. 23, 2015.

Chan, Kalok, K.C. Chan, and Andrew G. Karolyi, 1991, Intraday Volatility in the Stock Index and Stock Index Futures Markets, *Review of Financial Studies* 4, 657–684.

Chiu, Jonathan, and Thorsten V Koeppl, 2019, Blockchain-Based Settlement for Asset Trading, *The Review of Financial Studies* 32, 1716–1753.

Choi, Hong, and Avanidhar Subrahamanyam, 1994, Using intraday data to test for effects of index futures on the underlying stock market, *Journal of Futures Markets* 14, 293–322.

Choi, Kyoung Jin, Alfred Lehar, and Ryan Stauffer, 2018, Bitcoin Microstructure and the Kimchi premium, *Working Paper.*

CoinMarketCap, 2020, Top 100 Cryptocurrencies by Market Capitalization, *https://coinmarketcap.com/.*

CoinMarketCap, 2021, Today's Cryptocurrency Prices by Market Cap, retrieved on 14 May 2021.

Cong, Lin William, and Zhiguo He, 2019, Blockchain Disruption and Smart Contracts, *The Review of Financial Studies* 32, 1754–1797.

Cong, Lin William, Zhiguo He, and Jiasun Li, 2021, Decentralized Mining in Centralized Pools, *Review of Financial Studies* 34, 1191–1235.

Cong, Lin William, Xi Li, Ke Tang, and Yang Yang, 2021, Crypto Wash Trading, *SSRN Working Paper 3530220.*

Conrad, Jennifer C., 1989, The Price Effect of Option Introduction, *Journal of Finance* 44, 487–498.

Corbet, Shaen, Brian Lucey, Maurice Peat, and Samuel Vigne, 2018, Bitcoin Futures–What use are they?, *Economics Letters* 172, 23–27.

CryptoCompare, 2020, 2019 Exchange Review, *Industry Report.*

CryptoCompare, 2021, Exchange Review January 2021, .

Damodaran, Aswath, and Joseph Lim, 1991, The Effects of Option Listing on the Underlying Stocks' Return Processes, *Journal of Banking & Finance* 15, 647–664.

Damodaran, Aswath, and Marti G. Subrahmanyam, 1992, The Effects of Derivative Securities on the Markets for the Underlying Assets in the United States: A Survey, *Financial Markets, Institutions & Instruments*.

Das, Sanjiv, Madhu Kalimipalli, and Subhankar Nayak, 2014, Did CDS trading improve the market for corporate bonds?, *Journal of Financial Economics* 111, 495–525.

Detemple, Jerome, and Philippe Jorion, 1990, Option Listing and Stock Returns, *Journal of Banking & Finance* 14, 781–801.

Dick-Nielsen, Jens, Peter Feldhutter, and David Lando, 2012, Corporate bond liquidity before and after the onset of the subprime crisis, *Journal of Financial Economics* 103, 471–492.

Duffie, Darrell, 2010, Presidential Address: Asset Price Dynamics with Slow-Moving Capital, *The Journal of Finance* 65, 1237–1267.

Dwyer, Gerald P., 2015, The economics of Bitcoin and similar private digital currencies, *Journal of Financial Stability* 17, 81–91 Special Issue: Instead of the Fed: Past and Present Alternatives to the Federal Reserve System.

Dyhrberg, Anna Haubo, 2020, One Coin, Many Markets - How Market Frictions A ect Arbitrageurs, .

Easley, David, Maureen O'Hara, and Soumya Basu, 2019, From mining to markets: The evolution of bitcoin transaction fees, *Journal of Financial Economics* 134, 91–109.

Edwards, Franklin R., 1988a, Does Futures Trading Increase Stock Market Volatility?, *Financial Analysts Journal* 44, 63–69.

Edwards, Franklin R., 1988b, Futures Trading and Cash Market Volatility: Stock Index and Interest Rate Futures, *Journal of Futures Markets* 8, 421–439.

Figlewski, Stephen, 1981, Futures Trading and Volatility in the GNMA Market, *Journal of Finance* 36, 445–456.

Foley, Sean, Jonathan R Karlsen, and Talis J Putnins, 2019, Sex, Drugs, and Bitcoin: How Much Illegal Activity Is Financed through Cryptocurrencies?, *The Review of Financial Studies* 32, 1798–1853.

Gagnon, Louis, 2018, Short Sale Constraints and Single Stock Futures Introductions, *Financial Review* 53, 5–50.

Gagnon, Louis, and G. Andrew Karolyi, 2010, Multi-market trading and arbitrage, *Journal of Financial Economics* 97, 53–80.

Gammill Jr, James F, and Andre F Perold, 1989, The changing character of stock market liquidity, *Journal of Portfolio Management* 15, 13.

Gandal, Neil, and Hanna Halaburda, 2014, Competition in the Cryptocurrency Market, *Bank of Canada Working Paper 2014-33*.

Gandal, Neil, JT Hamrick, Tyler Moore, and Tali Oberman, 2018, Price manipulation in the Bitcoin ecosystem, *Journal of Monetary Economics* 95, 86 – 96.

Gans, Joshua S., and Hanna Halaburda, 2015, *Some Economics of Private Digital Currency*University of Chicago Press pp. 257–276.

Gorton, Gary, and George Pennacchi, 1991, Security baskets and index-linked securities, Working paper, National Bureau of Economic Research.

Griffin, John M., and Amin Shams, 2020, Is Bitcoin Really Un-Tethered?, *Journal of Finance* 75, 1913–1964.

Gromb, Denis, and Dimitri Vayanos, 2010, Limits of Arbitrage: The State of the Theory, *Annual Review of Financial Economics* 2, 251–275.

Gulen, Huseyin, and Stewart Mayhew, 2000, Stock Index Futures Trading and Volatility in International Equity Markets, *Working Paper Purdue University*.

Hale, Galina, Arvind Krishnamurthy, Marianna Kudlyak, and Patrick Shultz, 2018, How Futures Trading Changed Bitcoin Prices, *FRBSF Economic Letter* May 7, 2018.

Harris, Lawrence, 1989, S&P 500 Cash Stock Price Volatilities, *Journal of Finance* 46, 1155–1175.

Harvey, Campbell R., 2016, Cryptofinance, *SSRN Working Paper 2438299*.

Hasbrouck, Joel, 1993, Assessing the Quality of a Security Market: A New Approach to Transaction-Cost Measurement, *Review of Financial Studies* 6, 191–212.

Hasbrouck, Joel, 1995, One Security, Many Markets: Determining the Contributions to Price Discovery, *The Journal of Finance* 50, 1175–1199.

Hautsch, Nikolaus, Christoph Scheuch, and Stefan Voigt, 2019, Limits to Arbitrage in Markets with Stochastic Settlement Latency, *SSRN Working Paper 3302159*.

Hinzen, Franz J., Kose John, and Fahad Saleh, 2019, Bitcoin's Fatal Flaw: The Limited Adoption, *SSRN Working Paper 3334262*.

Hirshleifer, David, Sonya Seongyeon Lim, and Siew Hong Teoh, 2009, Underreaction to Earnings News, *Journal of Finance* 64, 2289–2325.

Hodges, Stewart, 1992, *Do Derivative Instruments Increase Market Volatility?* (Manchester University Press) stewart hodges, ed. edn.

Hou, Kewei, and Tobias J. Moskowitz, 2005, Market Frictions, Price Delay, and the Cross-Section of Expected Returns, *Review of Financial Studies* 18, 981–1020.

Howden, Ed, 2015, The Crypto-currency Conundrum: Regulating an uncertain future, *Emory International Law Review* 29, 741–798.

Irresberger, Felix, Kose John, and Fahad Saleh, 2019, The Public Blockchain Ecosystem: An Empirical Analysis, *NYU Stern Working Paper*.

Ismailescu, Iuliana, and Blake Phillips, 2015, Savior or Sinner? Credit Default Swaps and the Market for Sovereign Debt, *Journal of Banking and Finance* 52, 43–61.

Jegadeesh, Narasimhan, and Avanidhar Subrahmanyam, 1993, Liquidity Effects of the Introduction of the S&P 500 Index Futures Contract on the Underlying Stocks, *Journal of Business* 66, 171–187.

Kapadia, Nikunj, and Xiaoling Pu, 2012, Limited arbitrage between equity and credit markets, *Journal of Financial Economics* 105, 542–564.

Kapar, Burcu, and Jose Olmo, 2019, An analysis of price discovery between Bitcoin futures and spot markets, *Economics Letters* 174, 62–64.

Karkkainen, Tatja, 2019, Price Discovery in the Bitcoin Futures and Cash Markets, *Working Papepr University of Glasgow*.

Kim, Wonse, Junseok Lee, and Kyungwon Kang, 2020, The effects of the introduction of Bitcoin futures on the volatility of Bitcoin returns, *Finance Research Letters* 33, 1–8.

Köchling, Gerrit, Janis Müller, and Peter N. Posch, 2019, Does the introduction of futures improve the efficiency of Bitcoin?, *Finance Research Letters* 30, 367–370.

Kroeger, Alexander, and Asani Sarkar, 2017, The Law of One Bitcoin Price?, *New York Fed Working Paper*.

Krückeberg, Sinan, and Peter Scholz, 2020, Decentralized Efficiency? Arbitrage in Bitcoin Markets, *Financial Analysts Journal* 76, 135–152.

Kumar, Raman, Atulya Sarin, and Kuldeep Shastri, 1998, The Impact of Options Trading on the Market Quality of the Underlying Security: An Empirical Analysis, *Journal of Finance* 53, 717–732.

Li, Tao, Donghwa Shin, and Baolian Wang, 2018, Cryptocurrency Pump-and-Dump Schemes, *SSRN Working Paper*.

Makarov, Igor, and Antoinette Schoar, 2019, Price Discovery in Crypto Currency Markets, *AEA Papers & Proceedings*.

Makarov, Igor, and Antoinette Schoar, 2020, Trading and Arbitrage in Cryptocurrency Markets, *Journal of Financial Economics* 135, 293–319.

Malinova, Katya, and Andreas Park, 2017, Market Design with Blockchain Technology, *SSRNWorking Paper 2785626*.

Mayhew, Stewart, 1999, The Impact of Derivatives on Cash Markets: What Have We Learnt?, *Working Paper, Department of Banking & Finance, University of Georgia, Athens*.

Mayhew, Stewart, and Vassil Mihov, 2004, How Do Exchanges Select Stocks for Option Listing?, *The Journal of Finance* 59, 447–471.

Nakamoto, Satoshi, 2008, Bitcoin: A Peer-to-Peer Electronic Cash System, *White Paper*.

Nan, Zheng, and Taisei Kaizoji, 2019, Market efficiency of the bitcoin exchange rate: Weak and semi-strong form tests with the spot, futures and forward foreign exchange rates, *International Review of Financial Analysis* 64, 273–281.

Nieuwerburgh, Stijn Van, and Laura Veldkamp, 2010, Information Acquisition and Under-Diversification, *Review of Economic Studies* 77, 779–805.

Pagnotta, Emiliano, and Andrea Buraschi, 2018, An Equilibrium Valuation of Bitcoin and Decentralized Network Assets, *SSRN Working Paper 3142022*.

Peng, Lin, and Wei Xiong, 2006, Investor attention, overconfidence and category learning, *Journal of Financial Economics* 80, 563–602.

Roll, R., 1984, A simple implicit measure of the effective bid-ask spread in an efficient market, *The Journal of Finance* 39, 1127–1139.

Rosu, Ioanid, and Fahad Saleh, 2021, Evolution of Shares in a Proof-of-Stake Cryptocurrency, *Management Science* Forthcoming.

Saleh, Fahad, 2021, Blockchain Without Waste: Proof-of-Stake, *Review of Financial Studies* 34, 1156–1190.

Schwert, Michael, 2017, Municipal Bond Liquidity and Default Risk, *Journal of Finance* 72, 1683–1722.

Shi, Shimeng, and Yukun Shi, 2019, Bitcoin futures: trade it or ban it?, *The European Journal of Finance* Forthcoming.

Shleifer, Andrei, and Robert W. Vishny, 1997, The limits of arbitrage, *The Journal of Finance* 52, 35–55.

Silber, William L, 1985, *The economic role of financial futures.* (Salomon Brothers Center for the Study of Financial Institutes, Graduate).

Skinner, Douglas J., 1989, Options Markets, and Stock Return Volatility, *Journal of Financial Economics* 23, 61–78.

Son, Hugh, Hannah Levitt, and Brian Louis, 2017, Jamie Dimon Slams Bitcoin as a 'Fraud', *Bloomberg* 12 September 2017.

Song, Amber, and Julio Wu, 2020, 2019 Cryptocurrency Derivatives Exchange Industry Annual Report, *TokenInsight.*

Stoll, Hans R., and Robert E. Whaley, 1990, The Dynamics of Stock Index and Stock Index Futures Returns, *Journal of Financial and Quantitative Analysis* 25, 441–468.

Subrahmanyam, Avanidhar, 1991, A Theory of Trading in Stock Index Futures, *Review of Financial Studies* 4, 17–51.

TokenInsight, 2021, 2020 Cryptocurrency Futures Exchange Industry Report, .

Yermack, David, 2015, Chapter 2 - Is Bitcoin a Real Currency? An Economic Appraisal, in David Lee Kuo Chuen, eds.: *Handbook of Digital Currency* (Academic Press, San Diego).

Yermack, David, 2017, Corporate Governance and Blockchains, *Review of Finance* 21, 7–31.

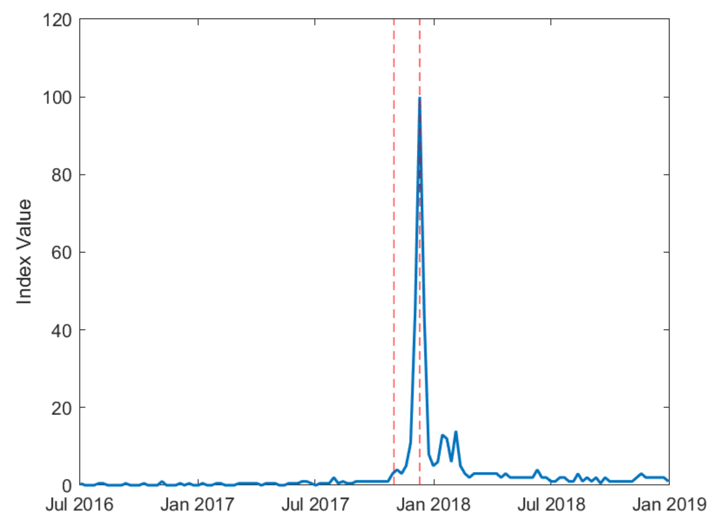
Yu, Yang Gloria, and Jinyuan Zhang, 2018, A Revisit to Capital Controls Policies When Bitcoin Is in, *SSRN Working Paper 3053474.*

Zimmerman, Peter, 2019, Blockchain structure and cryptocurrency prices, *Working Paper.*

Figure 1: Bitcoin Futures Google Search Intensity and Bitcoin Price History

In Figure 1.a, we plot the Google search intensity for the word "bitcoin futures" between July 1, 2016 and December 31, 2018. Google search data is available at https://trends.google.com/trends/explore?date=today%205-y&q=bitcoin%20futures. In Figure 1.b, we report the daily time series of BTC–USD prices for the sample period July 1, 2016 to December 31, 2018. In both figures, the first dashed vertical line represents the CME's first announcement of the bitcoin futures launch on October 31, 2017. The second dashed line represents the introduction of the first bitcoin futures contract by the CBOE on December 10, 2017.

(a)



(b)

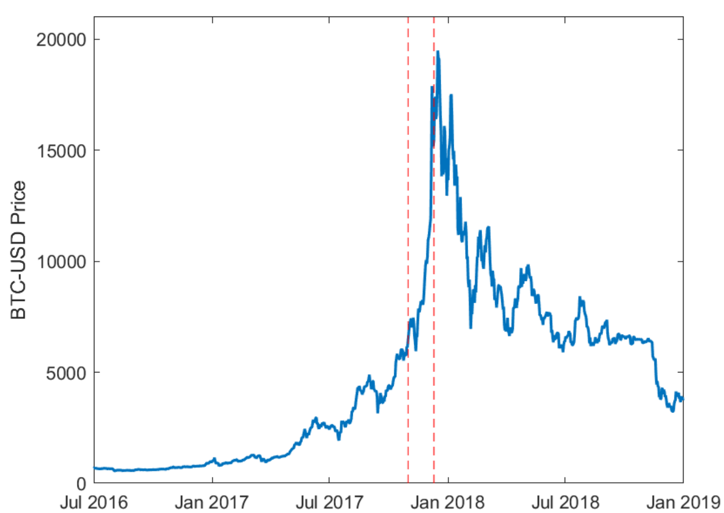


Figure 2: Bitcoin Cross-Exchange Return Correlations

In this figure, we illustrate the difference in the average pairwise cross-exchange Pearson correlation coefficients between BTC–USD and all other bitcoin-fiat exchange rate returns. Pairwise correlations are computed in rolling windows using 90 days of data, averaged across exchanges for BTC–USD and BTC–CCY, respectively, where CCY refers to EUR, HKD, GBP, CAD, JPY, SGD, AUD, RUB, IDR. The figure starts with a lag of 90 days on September 28, 2016 and also ends on December 31, 2018. The first dashed vertical line represents the CME's first announcement of the bitcoin futures launch on October 31, 2017. The second dashed line represents the introduction of the first bitcoin futures contract by the CBOE on December 10, 2017. Horizontal lines indicate the equally-weighted average difference between pairwise return correlations in the pre-event and post-event periods shown in this figure.

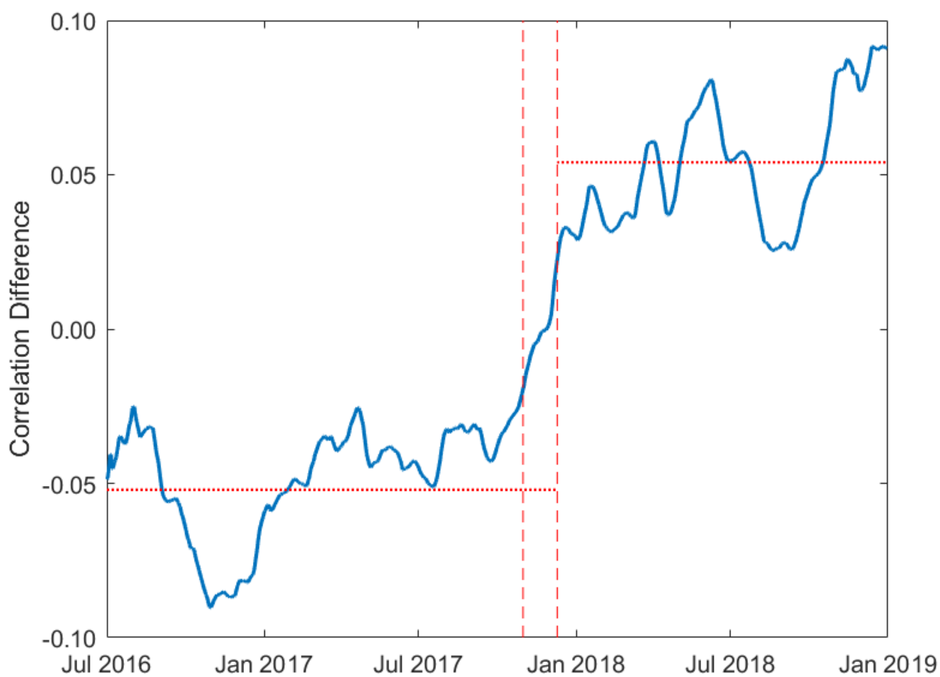


Figure 3: Impact of Bitcoin Futures Introduction on Price Synchronicity

In this figure, we report the results from a difference-in-differences regression for the pairwise cross-exchange return correlations $\rho_{i,j,t}$ between USD–BTC and other bitcoin-fiat exchange rate pairs. Specifically, we run the regression

$$\rho_{i,j,t} = \alpha_0 + \sum_{t=-5}^{+5} \alpha_t Treatment_{BTC-USD} \times Quarter_t + \delta_i + \eta_j + \gamma_t + \varepsilon_t,$$

where $Treatment_{BTC-USD}$ is one for BTC–USD cross-exchange return correlations and zero otherwise (i.e., the treatment group), $Quarter_t$ captures the timing of the futures introduction (we use 2017Q3 as the benchmark), γ_t are quarterly time fixed effects, δ_i are cryptocurrency exchange rate pair fixed effects (e.g., BTC–USD, BTC–EUR), and η_j are exchange fixed effects. Pairwise correlations are computed at a monthly frequency using three months of daily data. We compare correlations of BTC–USD to those of BTC–CCY, where CCY refers to EUR, HKD, GBP, CAD, JPY, SGD, AUD, RUB, IDR. Standard errors are clustered at the exchange pair level. In the figure, we report 95% confidence bounds. The sample period is July 1, 2016 to December 31, 2018. The vertical line indicates the day of the first BTC–USD futures introduction on December 10, 2017.

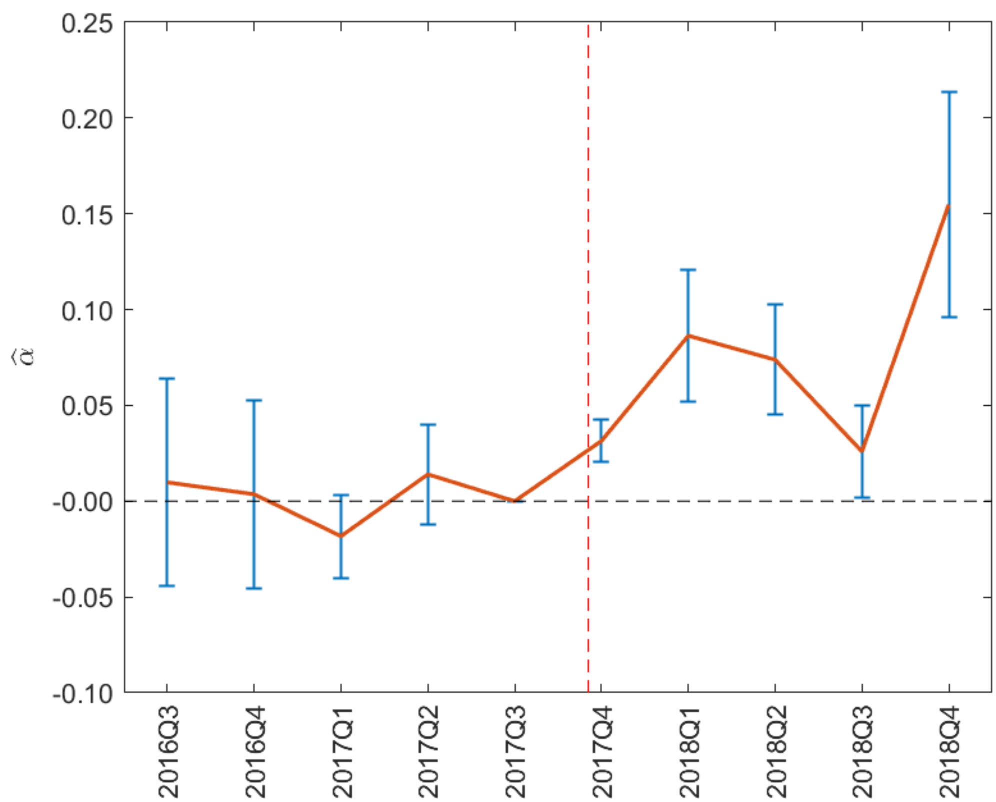


Table 1: Bitcoin Trading Volumes

In this table, we report the quarterly time series of bitcoin trading activity. The sample period is July 1, 2016 to December 31, 2018. In Panel A, we illustrate the relative market shares (in %) of BTC trading volume in terms of currencies (BTC–CCY), together with the aggregate BTC–CCY trading volume in units of 1,000,000 BTC. In Panel B, we represent the market shares (in %) of BTC–USD trading volumes for the 5 largest exchanges in terms of aggregate BTC–USD trading volume during our sample period. The sixth category "All Others" groups all remaining exchanges together. In Panel C, we represent the market shares (in %) of BTC–EUR trading volumes for the 5 largest exchanges in terms of aggregate BTC–EUR trading volume during our sample period.

Currency	**'16Q3**	**'16Q4**	**'17Q1**	**'17Q2**	**'17Q3**	**'17Q4**	**'18Q1**	**'18Q2**	**'18Q3**	**'18Q4**
Panel A. BTC–CCY trading volume (market shares, %)										
BTC-USD	37.16	32.36	41.45	63.15	69.37	59.22	59.36	55.04	52.89	56.78
BTC-JPY	53.57	58.55	44.55	21.94	18.04	24.61	29.55	36.82	39.83	35.61
BTC-EUR	5.08	6.04	8.19	12.64	10.35	7.75	9.17	7.05	6.23	6.59
BTC-IDR	2.74	1.16	1.75	0.08	0.07	2.09	0.09	0.00	0.00	0.00
BTC-SGD	0.99	0.94	2.03	0.37	0.31	1.47	0.53	0.16	0.08	0.11
BTC-HKD	0.00	0.05	0.41	0.63	0.65	2.35	0.08	0.01	0.01	0.02
BTC-AUD	0.01	0.15	0.94	0.04	0.36	1.76	0.41	0.04	0.04	0.01
BTC-RUB	0.21	0.36	0.27	0.32	0.18	0.23	0.27	0.49	0.43	0.30
BTC-CAD	0.15	0.27	0.30	0.54	0.43	0.27	0.30	0.21	0.24	0.19
BTC-GBP	0.10	0.11	0.12	0.29	0.23	0.24	0.24	0.18	0.25	0.40
BTC–CCY trading volume (1,000,000 BTC)										
Volume	11.383	11.253	17.511	11.125	14.078	22.977	21.566	12.751	11.097	14.739
Exchanges	**'16Q3**	**'16Q4**	**'17Q1**	**'17Q2**	**'17Q3**	**'17Q4**	**'18Q1**	**'18Q2**	**'18Q3**	**'18Q4**
Panel B. BTC–USD trading volume (market shares, %)										
Bitfinex	23.31	20.53	30.52	14.54	28.85	37.89	40.9	38.84	38.73	27.86
Coinbase	11.22	12.01	10.27	16.56	12.41	14.7	14.75	12.58	12.91	13.52
Bitstamp	8.46	11.76	11.95	15.27	13.33	10.41	11.9	13.43	10.99	9.82
Gemini	2.74	5.49	4.52	10.29	10.35	6.09	5.88	4.49	4.25	4.85
HitBTC	0.05	0.06	0.01	0.11	1.52	4.04	4.12	9.3	15.77	23.06
All Others	54.22	50.15	42.73	43.23	33.54	26.87	22.45	21.36	17.35	20.89
Panel C. BTC–EUR trading volume (market shares, %)										
Kraken	68.72	67.43	68.6	76.26	65.48	38.63	57.92	60.99	58.36	59.72
Bitstamp	5.88	7.48	6.21	11.68	13.37	18.34	18.89	16.03	18.41	17.98
Coinbase	5.34	6.19	5.49	8.44	10.37	19.74	18.66	16.49	16.05	15
Quoine	1.12	8.29	13.89	0.74	2.58	20.56	2.05	0.36	0.45	0.56
Cex.io	7.00	4.41	0.67	0.96	0.88	1.13	0.83	0.79	2.11	4.28
All Others	11.94	6.2	5.14	1.92	7.32	1.6	1.65	5.34	4.62	2.46

Table 2: Summary Statistics for Cryptocurrency Returns

We provide summary statistics for daily bitcoin-fiat currency exchange rate log returns by currency pair and exchange for BTC–USD (Panel A), BTC–EUR (Panel B), BTC–CCY excluding BTC–EUR, where CCY refers to EUR, HKD, GBP, CAD, JPY, SGD, AUD, RUB, IDR (Panel C). In each panel, we report the exchange's name, the start and end dates of the data, the number of observations (N), and the average (Mean), standard deviation (SD), skewness (Skew), kurtosis (Kurt), and the 5th and 95th percentiles (p5, p95) of the return distributions. The sample period is July 1, 2016 to December 31, 2018.

Currency	**Exchange**	**Start**	**End**	**N**	**Mean**	**SD**	**Skew**	**Kurt**	**p5**	**p95**
Panel A. BTC–USD (Daily)										
BTC–USD	Bitfinex	07/01/2016	12/31/2018	905	0.0018	0.0433	-0.1983	6.3730	-0.0713	0.0693
BTC–USD	Bitstamp	07/01/2016	12/31/2018	913	0.0017	0.0426	-0.1508	6.4964	-0.0722	0.0650
BTC–USD	Bittrex	07/01/2016	12/31/2018	899	0.0018	0.0460	-0.2577	5.8873	-0.0766	0.0727
BTC–USD	BTCC	11/02/2016	09/05/2018	609	0.0039	0.0498	-0.3102	6.5016	-0.0836	0.0777
BTC–USD	BTCe	07/01/2016	11/28/2018	793	0.0021	0.0374	-0.3427	7.0350	-0.0628	0.0563
BTC–USD	Cex.io	07/01/2016	12/31/2018	914	0.0019	0.0412	-0.3334	7.5609	-0.0678	0.0671
BTC–USD	Coinbase	07/01/2016	12/31/2018	914	0.0019	0.0425	-0.0427	6.4581	-0.0721	0.0665
BTC–USD	Exmo	07/01/2016	12/31/2018	909	0.0021	0.0389	-0.3075	7.3961	-0.0640	0.0601
BTC–USD	Gatecoin	08/22/2016	12/31/2018	789	0.0023	0.0471	-0.2080	5.8837	-0.0812	0.0739
BTC–USD	Gemini	07/01/2016	12/31/2018	913	0.0019	0.0431	-0.0977	6.6002	-0.0711	0.0675
BTC–USD	HitBTC	07/01/2016	12/31/2018	914	0.0019	0.0441	0.0557	7.2958	-0.0741	0.0675
BTC–USD	itBit	07/01/2016	12/31/2018	914	0.0019	0.0425	-0.1277	6.4742	-0.0702	0.0653
BTC–USD	Kraken	07/01/2016	12/31/2018	911	0.0018	0.0426	-0.1665	6.0843	-0.0711	0.0664
BTC–USD	LakeBTC	07/01/2016	12/31/2018	786	0.0017	0.0423	-0.0142	7.0901	-0.0682	0.0666
BTC–USD	Liquid	07/01/2016	12/31/2018	681	0.0017	0.0502	0.2502	8.8083	-0.0768	0.0800
BTC–USD	OKCoin	07/01/2016	12/31/2018	790	0.0013	0.0391	-0.5371	6.9466	-0.0663	0.0609
BTC–USD	Poloniex	07/01/2016	12/31/2018	894	0.0016	0.0436	-0.1580	6.4362	-0.0735	0.0701
BTC–USD	QuadrigaCX	08/16/2016	12/31/2018	860	0.0022	0.0476	-0.0528	6.1302	-0.0785	0.0763
BTC–USD	Quoine	07/01/2016	12/31/2018	914	0.0019	0.0456	0.1224	9.9324	-0.0743	0.0703
Panel B. BTC–EUR (Daily)										
BTC–EUR	Bitstamp	07/01/2016	12/31/2018	913	0.0017	0.0421	-0.2898	6.1981	-0.0728	0.0673
BTC–EUR	BTCe	07/01/2016	11/26/2018	791	0.0021	0.0380	-0.1554	7.0665	-0.0660	0.0583
BTC–EUR	Cex.io	07/01/2016	12/31/2018	914	0.0018	0.0405	-0.3008	6.6004	-0.0685	0.0629
BTC–EUR	Coinbase	07/01/2016	12/31/2018	913	0.0018	0.0423	-0.2200	6.7720	-0.0713	0.0652
BTC–EUR	Exmo	07/01/2016	12/31/2018	910	0.0020	0.0422	-0.5165	9.1056	-0.0675	0.0663
BTC–EUR	Gatecoin	08/23/2016	12/31/2018	703	0.0026	0.0574	0.1394	7.2037	-0.0912	0.0885
BTC–EUR	itBit	07/01/2016	12/31/2018	883	0.0020	0.0429	-0.3712	6.2388	-0.0752	0.0648
BTC–EUR	Kraken	07/01/2016	12/31/2018	911	0.0016	0.0426	-0.2537	6.1465	-0.0726	0.069
BTC–EUR	Quoine	07/01/2016	12/31/2018	805	0.0006	0.0510	-1.3671	21.8378	-0.0793	0.0733
Panel C. BTC–CCY excluding BTC–USD and BTC–EUR (Daily)										
BTC–AUD	Quoine	07/01/2016	12/31/2018	760	0.0017	0.0532	-0.1735	10.4065	-0.0861	0.0813
BTC–CAD	Kraken	07/01/2016	12/31/2018	913	0.0018	0.0446	-0.5871	8.0918	-0.0733	0.0688
BTC–CAD	QuadrigaCX	08/16/2016	12/31/2018	868	0.0023	0.0411	-0.2412	6.3111	-0.0673	0.0682
BTC–GBP	Coinbase	07/01/2016	12/31/2018	913	0.0019	0.0423	-0.1112	6.4211	-0.0703	0.0669
BTC–GBP	Kraken	07/01/2016	12/31/2018	849	0.0015	0.0655	-0.0323	11.2428	-0.0957	0.0886
BTC–HKD	Gatecoin	08/22/2016	12/28/2018	776	0.0036	0.0651	1.4335	26.6648	-0.0896	0.0890
BTC–HKD	Quoine	11/16/2016	12/31/2018	578	-0.0001	0.0563	-0.3501	8.5622	-0.1008	0.0804
BTC–IDR	Quoine	07/01/2016	12/30/2018	688	0.0035	0.0541	0.3921	10.6577	-0.0928	0.0788
BTC–JPY	bitFlyer	07/01/2016	12/31/2018	912	0.0021	0.0459	-0.0124	12.6350	-0.0719	0.0657
BTC–JPY	BTCbox	07/01/2016	12/31/2018	912	0.0017	0.0462	-0.1386	14.0268	-0.0726	0.0626
BTC–JPY	Kraken	07/01/2016	12/31/2018	911	0.0019	0.0469	0.0270	7.9342	-0.0781	0.0695
BTC–JPY	Liquid	07/01/2016	12/31/2018	914	0.0019	0.0462	0.0462	12.3595	-0.0738	0.0677
BTC–JPY	Quoine	07/01/2016	12/31/2018	914	0.0019	0.0462	0.0362	12.3907	-0.0738	0.0677
BTC–JPY	Zaif	07/01/2016	12/31/2018	914	0.0019	0.0465	-0.0163	12.5598	-0.0704	0.0688
BTC–RUB	Exmo	07/01/2016	12/31/2018	909	0.0022	0.0369	0.0129	8.0244	-0.0584	0.0566
BTC–RUB	BTCe	09/16/2016	11/28/2018	716	0.0023	0.0363	-0.2006	6.5161	-0.0626	0.0584
BTC–SGD	itBit	09/06/2016	12/31/2018	592	0.0024	0.0490	-0.4494	7.0476	-0.0875	0.0753
BTC–SGD	Quoine	07/01/2016	12/31/2018	913	0.0019	0.0445	0.0362	10.2756	-0.0694	0.0675

Table 3: Summary Statistics for Market Characteristics.

We provide summary statistics (Mean, standard deviation, median, 5th and 95th percentiles), number of observations, start and end dates for all market characteristics. For each metric, we provide statistics independently for BTC–USD and for the 9 other BTC–fiat currency pairs (EUR, HKD, GBP, CAD, JPY, SGD, AUD, RUB, IDR) across all exchanges. Our metrics, computed at a monthly frequency using daily data over 3 months, relate to (1) price synchronicity: pairwise correlations ρ and integration κ; (2) market efficiency $D1$; (3) market quality q; (4) liquidity: Roll, CHL, Amihud, and Volume (in units of 1,000 BTC). Volume is measured at a daily frequency in this table whereas we use trading volume measured at a monthly frequency in our regression analysis. The sample period is July 1, 2016 to December 31, 2018.

Measure	**Currency**	**Start**	**End**	**N**	**Mean**	**SD**	**Median**	**p5**	**p95**
ρ	BTC-USD	07/31/2016	12/31/2018	4,890	0.8704	0.1686	0.9384	0.5200	0.9969
	Other	07/31/2016	12/31/2018	1,658	0.8475	0.2401	0.9362	0.3424	0.9976
κ	BTC-USD	07/31/2016	12/31/2018	4,890	0.7003	0.2206	0.7528	0.2500	0.9560
	Other	07/31/2016	12/31/2018	1,670	0.6906	0.2455	0.7363	0.2771	0.9778
D1	BTC-USD	07/31/2016	12/31/2018	555	0.3069	0.2189	0.2808	0.0477	0.7426
	Other	07/31/2016	12/31/2018	777	0.3305	0.2318	0.2984	0.0399	0.8146
q	BTC-USD	07/31/2016	12/31/2018	557	0.9449	0.0760	0.9772	0.8081	1.0000
	Other	07/31/2016	12/31/2018	795	0.9370	0.0811	0.9635	0.7805	1.0000
Roll	BTC-USD	07/31/2016	12/31/2018	558	0.0163	0.0153	0.0139	0.0000	0.0437
	Other	07/31/2016	12/31/2018	794	0.0197	0.0217	0.0165	0.0000	0.0570
CHL	BTC-USD	07/31/2016	12/31/2018	558	0.0145	0.0064	0.0134	0.0057	0.0266
	Other	07/31/2016	12/31/2018	802	0.0155	0.0089	0.0138	0.0057	0.0298
Amihud	BTC-USD	07/31/2016	12/31/2018	558	691.07	8422.94	0.0198	0.0017	23.0785
	Other	07/31/2016	12/31/2018	802	1410.07	22795.13	0.1490	0.0017	439.264
Volume	BTC-USD	07/31/2016	12/31/2018	16,796	4.6215	9.7154	1.2211	0.0000	19.1523
	Other	07/31/2016	12/31/2018	23,868	2.7346	6.6164	0.2062	0.0000	15.1631

Table 4: Cryptocurrency Exchange Rate Return Correlations.

In this table, we provide pairwise cross-exchange Pearson correlation coefficients of BTC–USD daily log returns for the five biggest exchanges in terms of aggregate BTC–USD trading volume between July 1, 2016 and December 31, 2016, the first 6 months of our sample period, which stretches from July 1, 2016 to December 31, 2018. In Panel A (Panel B), we show pairwise correlation coefficients for the 12 months before (after) the futures introduction from July 1, 2016 to June 30, 2017 (January 1, 2018 to December 31, 2018), excluding an anticipation period of 6 months between July 1, 2017 and December 31, 2017.

Panel A: Exchange Rate Return Correlations, Jul 1, 2016 - Jun 30, 2017					
	Bitfinex	Coinbase	itBit	Bitstamp	Quoine
Bitfinex	1				
Coinbase	0.9421	1			
itBit	0.9437	0.9812	1		
Bitstamp	0.9518	0.9736	0.9801	1	
Quoine	0.8751	0.9009	0.9047	0.9079	1
Panel B: Exchange Rate Return Correlations, Jan 1, 2018 - Dec 31, 2018					
	Bitfinex	Coinbase	itBit	Bitstamp	Quoine
Bitfinex	1				
Coinbase	0.9925	1			
itBit	0.9929	0.9975	1		
Bitstamp	0.9942	0.9984	0.9975	1	
Quoine	0.9856	0.9875	0.9881	0.9885	1

Table 5: Difference-in-Differences Results - Price Synchronicity/Correlations

In Panel A (Panel B) of this table, we report regression results from the projection of monthly pairwise cross-exchange Pearson correlation coefficients (Kapadia and Pu (2012) price synchronicity measures) on the treatment indicator ($Treatment$) that takes the value one for BTC–USD return pairs and zero otherwise; an event indicator ($Post$) that takes the value one in the months following the introduction of bitcoin futures on December 10, 2017; and their interaction ($Treatment \times Post$). Pearson correlation coefficients and the integration measures are computed at a monthly frequency in rolling windows using three months of daily returns. We indicate whether the control group contains all bitcoin-fiat currency pairs (ALL), only BTC–EUR (EUR), all currency pairs except BTC–EUR (CCY^*), or the subset of exchanges that are not exposed to volume manipulation (X-M). The sample period is July 1, 2016 to December 31, 2018, but we exclude the anticipation period between July 1, 2017 and December 31, 2017. Standard errors are clustered at the exchange pair level.

Panel A: Synchronicity ρ	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Treatment	-0.053***	-0.001	-0.054***						
	(0.012)	(0.011)	(0.012)						
Post	-0.073***	-0.054***		-0.070***					
	(0.020)	(0.019)		(0.019)					
Treatment×Post	0.121***	0.110***	0.121***	0.119***	0.109***	0.050***	0.144***	0.050***	0.073***
	(0.019)	(0.017)	(0.019)	(0.018)	(0.017)	(0.010)	(0.022)	(0.017)	(0.018)
N	4310	4310	4310	4310	4310	1586	3906	3606	1056
adj. R^2	0.030	0.370	0.081	0.054	0.437	0.812	0.440	0.456	0.510
Panel B: Integration κ	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**
Treatment	-0.065***	0.001	-0.065***						
	(0.020)	(0.016)	(0.020)						
Post	0.020	0.045**		0.023					
	(0.020)	(0.018)		(0.019)					
Treatment×Post	0.135***	0.121***	0.133***	0.132***	0.118***	0.047***	0.139***	0.080***	0.114***
	(0.019)	(0.017)	(0.019)	(0.018)	(0.016)	(0.009)	(0.020)	(0.024)	(0.026)
N	4310	4310	4310	4310	4310	1586	3906	3606	1056
adj. R^2	0.104	0.549	0.173	0.135	0.662	0.863	0.657	0.683	0.709
Control	ALL	ALL	ALL	ALL	ALL	ALL	EUR	CCY*	X-M
Xchange-Pair FE		✓			✓		✓	✓	✓
Month FE			✓		✓		✓	✓	✓
Ccy FE				✓	✓	✓	✓	✓	✓
Xchange-Pair×Month FE						✓			

Table 6: Difference-in-Differences Results - Market Quality and Price Efficiency

In Panel A (Panel B) of this table, we report regression results from the projection of monthly Hasbrouck (1993) q market quality measures (Hou and Moskowitz (2005) $D1$ price efficiency measures) on the treatment indicator ($Treatment$) that takes the value one for BTC–USD return pairs and zero otherwise; an event indicator ($Post$) that takes the value one in the months following the introduction of bitcoin futures on December 10, 2017; and their interaction ($Treatment \times Post$). Market quality and price efficiency measures are computed at a monthly frequency in rolling windows using three months of daily returns. We indicate whether the control group contains all bitcoin-fiat currency pairs (ALL), only BTC–EUR (EUR), all currency pairs except BTC–EUR (CCY^*), or the subset of exchanges that are not prone to trading volume manipulation (X-M). The sample period is July 1, 2016 to December 31, 2018, but we exclude the anticipation period between July 1, 2017 and December 31, 2017. Standard errors are clustered at the exchange×currency level.

Panel A: Market quality q	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Treatment	-0.011	-0.009	-0.011						
	(0.013)	(0.012)	(0.013)						
Post	-0.017**	-0.013**		-0.015**					
	(0.007)	(0.006)		(0.007)					
Treatment×Post	0.038***	0.037***	0.038***	0.036***	0.036***	0.030**	0.052***	0.027**	0.015
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.015)	(0.012)	(0.015)
N	920	920	920	920	920	683	573	733	430
adj. R^2	0.015	0.095	0.395	0.049	0.539	0.589	0.650	0.545	0.711
Control	ALL	ALL	ALL	ALL	ALL	ALL	EUR	CCY*	X-M
Xchange FE		✓			✓		✓	✓	✓
Month FE			✓		✓		✓	✓	✓
Ccy FE				✓	✓	✓	✓	✓	✓
Xchange×Month FE						✓			
Panel B: Price efficiency $D1$	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**
Treatment	0.036	-0.003	0.046						
	(0.044)	(0.025)	(0.041)						
Post	0.059**	0.048*		0.059**					
	(0.022)	(0.025)		(0.022)					
Treatment×Post	-0.068**	-0.061*	-0.078**	-0.068**	-0.072**	-0.035**	-0.027***		
	(0.033)	(0.035)	(0.030)	(0.033)	(0.031)	(0.013)	(0.004)		
N	573	573	573	573	573	374	220		
adj. R^2	0.003	0.142	0.523	0.003	0.663	0.792	0.968		
Control	EUR	EUR	EUR	EUR	EUR	EUR	X-M		
Xchange FE		✓			✓				
Month FE			✓		✓				
Ccy FE				✓	✓	✓	✓		
Xchange×Month FE						✓	✓		

Table 7: Difference-in-Differences Results - Liquidity

In this table, we report regression results from the projection of the monthly liquidity factor λ on the treatment indicator ($Treatment$) that takes the value one for BTC–USD return pairs and zero otherwise; an event indicator ($Post$) that takes the value one in the months following the introduction of bitcoin futures on December 10, 2017; and their interaction ($Treatment \times Post$). We measure the liquidity factor λ as described in Equation (11). We indicate whether the control group contains all bitcoin-fiat currency pairs (ALL), only BTC–EUR (EUR), all currency pairs except BTC–EUR (CCY^*), or the subset of exchanges that are not prone to trading volume manipulation (X-M). The sample period is July 1, 2016 to December 31, 2018, but we exclude the anticipation period between July 1, 2017 and December 31, 2017. Standard errors are clustered at the exchange×currency level.

Panel A: Liquidity λ	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Treatment	-0.059	-0.180	-0.051						
	(0.185)	(0.147)	(0.184)						
Post	0.497***	0.427***		0.469***					
	(0.079)	(0.054)		(0.070)					
Treatment×Post	-0.379**	-0.327**	-0.382**	-0.351**	-0.347**	-0.170**	-0.322*	-0.362**	-0.378
	(0.166)	(0.154)	(0.170)	(0.163)	(0.153)	(0.080)	(0.166)	(0.159)	(0.221)
N	920	920	920	920	920	683	573	733	430
adj. R^2	0.093	0.482	0.133	0.258	0.749	0.847	0.701	0.738	0.753
Control	ALL	ALL	ALL	ALL	ALL	ALL	EUR	CCY*	X-M
Xchange FE		✓							
Month FE			✓		✓		✓	✓	✓
Ccy FE				✓					
Xchange×Ccy FE					✓	✓	✓	✓	✓
Xchange×Month FE						✓			

Table 8: Difference-in-Differences Results - 4:00 p.m. Settlement Prices

In this table, we report difference-in-differences regression results when we measure prices at the futures settlement times on the corresponding cash markets. Thus, prices are sampled daily at 4:00 p.m. London time from itBit, Kraken, and Bitstamp, and at 4:00 p.m. Eastern time from Gemini. We regress different measures on the treatment indicator (*Treatment*) that takes the value one for BTC–USD return pairs and zero otherwise; an event indicator (*Post*) that takes the value one following the introduction of bitcoin futures on December 10, 2017; and their interaction ($Treatment \times Post$). In Panel A, we present results for the Hasbrouck (1993) q market quality measure using rolling windows of three months. In Panel B, we present results for the aggregate liquidity factor λ, described in Equation (11). In each panel, we present the results using end-of-day prices, and 4:00 p.m. settlement prices. We present only the coefficient estimates for the interaction term $Treatment \times Post$. In Panels A and B, we present results for the comparison between BTC–USD and BTC–CCY. The sample period is July 1, 2016 to December 31, 2018, but we exclude the anticipation period between July 1, 2017 and December 31, 2017. We use heteroskedasticity robust errors to estimate the standard errors.

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Market quality q, BTC–USD vs. BTC–CCY						
	End-of-day prices			*Settlement prices*		
Treatment×Post	-0.001	-0.003	-0.003	0.028*	0.023*	0.012
	(0.016)	(0.007)	(0.007)	(0.016)	(0.012)	(0.011)
N	232	232	210	232	232	210
adj. R^2	0.037	0.788	0.739	0.045	0.423	0.440
Control	ALL	ALL	ALL	ALL	ALL	ALL
Xchange FE		✓			✓	
Month FE		✓			✓	
Ccy FE		✓	✓		✓	✓
Xchange×Month FE			✓			✓
Panel B: Liquidity λ, BTC–USD vs. BTC–CCY						
	End-of-day prices			*Settlement prices*		
Treatment×Post	-0.288**	-0.275***	-0.216***	-0.556***	-0.519***	-0.369***
	(0.139)	(0.063)	(0.064)	(0.181)	(0.108)	(0.103)
N	232	232	210	232	232	210
adj. R^2	0.363	0.857	0.844	0.296	0.723	0.691
Control	ALL	ALL	ALL	ALL	ALL	ALL
Month FE		✓			✓	
Ccy FE						
Xchange×Ccy FE		✓	✓		✓	✓
Xchange×Month FE			✓			✓

Table 9: Difference-in-Differences Results - Liquidity and Attention Channels

In this table, we estimate Equation (12) to identify the effect of attention and liquidity on daily pairwise cross-exchange Pearson correlation coefficients (Kapadia and Pu (2012) price synchronicity measures) in Panels A and B (Panels C and D) after the introduction of bitcoin futures by using the same data as in Table 5. *High Attention* is equal to 1 if the average Google search intensities for both exchanges are above the median sample value in the pre-event period and 0 otherwise. *High Liquidity* is equal to 1 if the average liquidity factors λ of both exchanges in the pre-event period are below the sample median and 0 otherwise. Daily pairwise Pearson correlation coefficients and Kapadia and Pu (2012) price synchronicity measures are computed in rolling windows with lags of three months. We only report results using all bitcoin-fiat currency pairs. We report coefficient estimates for *Treatment×Post* and *Treatment×Post×High Attention* (*Treatment×Post×High Liquidity*) in Panels A and C (Panels B and D). The sample period is July 1, 2016 to December 31, 2018, but we exclude the anticipation period between July 1, 2017 and December 31, 2017. Standard errors are clustered at the exchange pair level.

Panel A: Synchronicity ρ	(1)	(2)	(3)	(4)	(5)	(6)
Treatment×Post	0.109***	0.093***	0.110***	0.105***	0.093***	0.045***
	(0.020)	(0.017)	(0.021)	(0.019)	(0.017)	(0.013)
Treatment×Post×High Attention	0.059	0.069*	0.055	0.060	0.066	0.012
	(0.044)	(0.042)	(0.044)	(0.043)	(0.041)	(0.017)
N	4310	4310	4310	4310	4310	1586
adj. R^2	0.039	0.376	0.089	0.061	0.444	0.813
Panel B: Synchronicity ρ	(1)	(2)	(3)	(4)	(5)	(6)
Treatment×Post	0.136***	0.127***	0.135***	0.135***	0.126***	0.051***
	(0.021)	(0.020)	(0.021)	(0.020)	(0.019)	(0.010)
Treatment×Post×High Liquidity	-0.130***	-0.118***	-0.127***	-0.129***	-0.120***	-0.053***
	(0.022)	(0.021)	(0.022)	(0.022)	(0.021)	(0.010)
N	4310	4310	4310	4310	4310	1586
adj. R^2	0.086	0.373	0.136	0.099	0.441	0.813
Panel C: Integration κ	(1)	(2)	(3)	(4)	(5)	(6)
Treatment×Post	0.129***	0.107***	0.128***	0.123***	0.104***	0.044***
	(0.022)	(0.018)	(0.022)	(0.021)	(0.017)	(0.011)
Treatment×Post×High Attention	0.038	0.052	0.037	0.040	0.051	0.001
	(0.048)	(0.045)	(0.047)	(0.046)	(0.044)	(0.017)
N	4310	4310	4310	4310	4310	1586
adj. R^2	0.115	0.549	0.184	0.145	0.662	0.866
Panel D: Integration κ	(1)	(2)	(3)	(4)	(5)	(6)
Treatment×Post	0.149***	0.138***	0.146***	0.148***	0.135***	0.048***
	(0.021)	(0.018)	(0.020)	(0.020)	(0.018)	(0.009)
Treatment×Post×High Liquidity	-0.137***	-0.119***	-0.132***	-0.135***	-0.118***	-0.041***
	(0.045)	(0.044)	(0.044)	(0.044)	(0.043)	(0.009)
N	4310	4310	4310	4310	4310	1586
adj. R^2	0.188	0.551	0.260	0.205	0.664	0.864
Control	ALL	ALL	ALL	ALL	ALL	ALL
Xchange-Pair FE		✓			✓	
Month FE			✓		✓	
Ccy FE				✓	✓	✓
Xchange-Pair×Month FE						✓

Table 10: Difference-in-Differences Results - ETH pairs

In this table, we repeat the analysis of Table 5 with a different definition for the treatment and the control groups. In columns (1)-(4), the treatment group is BTC–USD and the control group is ETH–USD. In columns (5)-(8), the treatment group is ETH–USD and the control group consists of all ether-fiat currency pairs except ETH–USD, i.e., ETH–CCY. Synchronicity and the integration measures are computed at a monthly frequency in rolling windows using three months of daily returns. The sample period is July 1, 2016 to December 31, 2018, but we exclude the anticipation period between July 1, 2017 and December 31, 2017. Standard errors are clustered at the exchange pair level.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	BTC–USD vs ETH–USD				ETH–USD vs ETH–CCY			
	Synchronicity ρ		Integration κ		Synchronicity ρ		Integration κ	
Treatment×Post	0.068***	-0.006	0.062***	-0.006	-0.088	0.003	-0.213	-0.107
	(0.016)	(0.007)	(0.022)	(0.014)	(0.113)	(0.035)	(0.153)	(0.036)
N	3778	1376	3778	1376	777	60	777	60
adj. R^2	0.471	0.867	0.672	0.730	0.399	0.838	0.574	0.961
Xchange-Pair FE	✓		✓		✓		✓	
Month FE	✓		✓		✓		✓	
Ccy FE	✓	✓	✓	✓	✓	✓	✓	✓
Xchange-Pair×Month FE		✓		✓		✓		✓

Internet Appendix

Contents

A Institutional Background

The Wall Street Journal refers to cryptocurrencies as "one of the most powerful innovations in finance in 500 years" (Casey and Vigna, 2015). Regulators have struggled to adapt existing laws in the areas of banking and securities regulation, and central banks around the world (e.g., Bank of England, Bank of Canada, U.S. Federal Reserve, Bank of China) are exploring issuance of their own cryptocurrencies. The distributed ledger technology underlying cryptocurrencies has many other potential applications in diverse areas such as property registration, accounting and auditing, and financial derivatives. On January 9, 2017, the Wall Street Journal announced joint efforts by IBM and the Depository Trust & Clearing Corp., the New York-based utility that settles and clears all stock and bond trades in the U.S., to clear all credit derivatives clearing through blockchain technology (Demos, Jan. 9, 2017). These developments underscore the rapid transformation of the market for financial derivatives. In this section, we first provide some background information on blockchains, and second about cryptocurrencies.

A.1 Blockchains

Blockchain constitutes an electronic ledger that records entries in discrete chunks referenced as blocks. The blocks possess a specific order such that they form a chain, which in turn motivates the "blockchain" name.

Blockchain dates back to Haber and Stornetta (1991), but rose to mainstream prominence only after Nakamoto (2008) employed the data structure as the underlying technology behind Bitcoin. In his seminal white paper, Nakamoto (2008) argues that Bitcoin provides "a system for electronic transactions without relying on trust." The associated argument relies not only upon the blockchain data structure but also upon the usage of several other extant computer science concepts.*

Bitcoin was created as the first permissionless blockchain. The term "permissionless" arises from the fact that agents do not need special permission to update Bitcoin's ledger; rather, Bitcoin employs a protocol, known as Proof-of-Work (PoW), that theoretically allows any agent to update the ledger. PoW, introduced by Dwork and Naor (1992) and named by Jakobsson and Juels (1999), requires that agents solve a difficult but easily verifiable puzzle to earn the authority to update the ledger. Nakamoto (2008) argues that PoW enables Bitcoin to overcome the need for a trusted intermediary.

The Bitcoin blockchain possesses a native currency known as bitcoin. This native currency facilitates payments among users. Moreover, newly issued bitcoins accrue exclusively to those updating the ledger and thereby provide an economic incentive for an agent to update the ledger.

*For a more detailed historical context, the interested reader may consult Narayanan and Clark (2017).

Bitcoin's model has been imitated numerous times, leading to a profusion of cryptocurrencies (Irresberger, John, and Saleh, 2019). In recent years, though, prominent blockchain platforms have opted for a different structure than Bitcoin. Ethereum, for example, features a rich scripting language that facilitates operations beyond payments. EOS.IO, akin to Ethereum, facilitates operations beyond payments, but deviates from both Bitcoin and Ethereum by replacing PoW with PoS (Saleh, 2021).

The rich functionality of platforms such as Ethereum and EOS.IO allows for decentralized applications that themselves feature native tokens, which are typically classified as cryptocurrencies. Currently, there exist more than 5,000 cryptocurrencies (CoinMarketCap, 2021), with the majority not operating on an independent blockchain. Among cryptocurrencies operating on their own blockchains, almost all operate with either PoW or PoS protocols.

For completeness, we note that blockchain does not require a cryptocurrency. Such blockchains exist in industry settings and extend beyond the scope of this study.

A.2 Cryptocurrencies

We define a cryptocurrency as any digital asset that settles on a distributed ledger. Our definition is standard, but involves an abuse of language, as we explain below.

Digital currency dates back to Chaum (1982), but bitcoin, a currency operating on a blockchain, was launched as the first cryptocurrency in 2009. Many cryptocurrencies, with only slight differences from bitcoin, started trading in subsequent years. For example, litecoin, released in 2011, operates on a blockchain that allows for blocks to be created more quickly than for Bitcoin. As another example, PPCoin, released in 2012, operates on a blockchain that employs both PoS and PoW as part of the ledger updating process. Like bitcoin, the cryptocurrencies that emerged after bitcoin's introduction serve as mediums for payment processing and operate on a blockchain.

The term cryptocurrency took on a broader meaning with the birth of Ethereum in 2015. Ethereum, a blockchain with the ability to initiate and execute smart contracts, possesses a native asset known as ether. Ether, like bitcoin, constitutes a digital asset that settles on a blockchain. However, ether is not a currency in the sense that its primary usage is not intended for payments. Accordingly, the inclusion of ether (and related assets) as a cryptocurrency constitutes a standard abuse of language. Since Ethereum's birth, several other smart contract blockchains have arisen with native assets that, like ether, are cryptocurrencies by our definition.

A smart contract blockchain enables the execution of an Initial Coin Offering (ICO) which involves the sale of a newly created asset, typically referenced as a token, that also constitutes a cryptocurrency. Prominent examples of tokens include the basic attention token and binance coin. A token typically settles on the smart contract blockchain on which the associated ICO was conducted, but some tokens migrate away. Currently, tokens constitute the majority of cryptocurrencies. For more detail regarding ICOs, the interested reader may consult Lee, Li, and Shin (2018).

Due to the ease of launching a blockchain, and, thus, a cryptocurrency, a precise account of the number of cryptocurrencies in circulation is difficult to obtain. Nonetheless, Irresberger, John, and Saleh (2019) document 907 cryptocurrencies that possess market capitals exceeding 1 million USD. Collectively, those cryptocurrencies possess a market capital of approximately 200 billion USD. Nonetheless, few cryptocurrencies account for the bulk of that market capitalization. Bitcoin is especially dominant and consistently accounts for the largest market capitalization among all cryptocurrencies.

Cryptocurrencies trade frequently and on a variety of exchanges. The total number of exchanges varies over time, largely because of exchange failures and hacks that lead to a suspension of trading (e.g., Mt. Gox in 2014). A given currency pair (e.g., BTC–USD) may thus trade on several different exchanges. As the BTC–USD is the same asset in spite of being exchanged in multiple trading venues (i.e., it is fully fungible), prices ought to be the same. Nonetheless, prices of a given currency pair may differ across exchanges due to exchange-specific risks and frictions.

B Data Appendix

B.1 Main Sample

In our analysis we combine data from two sources: Kaiko and CryptoCompare. Kaiko is a commercial data vendor used in several recent academic studies (e.g., Makarov and Schoar, 2020; Li, Shin, and Wang, 2018). Kaiko provides price and trade information for transactions, timestamped to the millisecond, for more than 80 different exchanges on which bitcoin trades against other fiat currencies. For each transaction, the data include ticker symbol (e.g., BTC–USD), execution price, trade quantity, time stamp, and an indicator that flags trades as buyer- or seller-initiated. CryptoCompare provides similar data and is publicly available. The data can be sourced manually from CryptoCompare's public data feeds.

Data availability does not always overlap between the two data sources. For those periods when they do overlap, we check the consistency in prices across Kaiko and CryptoCompare, and find that prices are identical. When data for a particular exchange are available in both Kaiko and CryptoCompare, we choose the time series that has more observations, except for Bittrex (USD). The reason is that data for Bittrex (USD) provided by Kaiko starts only after August 24, 2016 and CrytpoCompare has observations before that date. Thus, we combine the data from two databases for Bittrex (USD).

In our analysis of BTC, we exclude exchanges that have observations starting after January 1, 2017 and that do not have observations for more than three months in the post-event period. In addition, we exclude exchanges with average monthly volume below 1,000 BTCs in the anticipation period. In a similar vein, we exclude currency-exchange pairs that have observations on fewer than 50% of all days in our sample, corresponding to a cut-off level of 457 daily observations. For the computation of cryptocurrency characteristics, we require a minimum of 45 observations within a 3-month period to ensure sufficient statistical precision of the estimates. This criterion does not apply for the measurement of volume, which is not subject to estimation error. Similarly, in the robustness tests where we use other estimation windows, we require more than 50% of available data points in the estimation window.

These data cleaning procedures lead to a benchmark sample with 10 bitcoin-fiat currency exchange rate pairs traded on 22 exchanges, with a total of 46 bitcoin-fiat currency-exchange pairs. In addition to the treatment currency BTC–USD, our control group includes 9 exchange rate pairs: BTC–EUR, BTC–GBP, BTC–HKD, BTC–SGD, BTC–JPY, BTC–AUD, BTC–IDR, BTC–CAD, and BTC–RUB, traded on the following 22 exchanges: Bitfinex, bitFlyer, Bitstamp, Bittrex, BTCbox, BTCC, BTC–e, Cex.io, Coinbase, Exmo, Gatecoin, Gemini, HitBTC, itBit, Kraken, LakeBTC, Liquid, OKCoin, Poloniex, QuadrigaCX, Quoine, and Zaif.

Among the 46 currency-exchange pairs, the following are from the Kaiko database: Bitstamp (EUR, USD), Coinbase (EUR, GBP, USD), itBit (EUR, SGD, USD), Kraken (CAD, EUR, GBP, JPY, USD), Quoine (AUD, EUR, HKD, IDR, JPY, SGD, USD), BTCe (EUR, USD, RUB), Bitfinex (USD), Gemini (USD), OKCoin (USD), Poloniex (USD), bitFlyer (JPY), BTCBox (JPY), and Zaif (JPY).

Among the 46 currency-exchange pairs, the following are from the CryptoCompare database: Gatecoin (EUR, HKD, USD) Cex.io (EUR, USD), Exmo (EUR, RUB, USD), QuadrigaCX (CAD, USD), HitBTC (USD), BTCC (USD), LakeBTC (USD), and Liquid (USD,JPY).

In our analysis of ETH, we apply the same data cleaning procedure to construct the sample for ETH currency-exchange pairs. We identify 6 bitcoin-fiat currency exchange rate pairs traded on 11 centralized exchanges, with a total of 18 bitcoin-fiat currency-exchange pairs. Exchange rates are BTC–USD, BTC–JPY, BTC–EUR, BTC–GBP, BTC–CAD, and BTC–RUB. The following exchanges are from the Kaiko database: BTCe (USD, RUB), Bitfinex (USD), Coinbase (USD), Gemini (USD), Poloniex (USD), and Quoine (USD, JPY). The following exchanges are from the CryptoCompare database: Kraken (USD, EUR, GBP, JPY, CAD), Cex.io (USD), Exmo (USD, RUB), Gatecoin (EUR), and QuadrigaCX(CAD).

We clean all price observations based on the magnitude of log returns. In particular, we delete daily returns if it is greater than 200% (in absolute value) based on either the daily low, high, or closing price. As a result, 20 daily returns were excluded from BTC and 4 daily observations are eliminated from the ETH price series. In addition, we identify one negative price entry in CryptoCompare (Quoine, BTC–USD), which we also exclude from the data. Unusual volume data (more than 5,000,000 BTC traded within one hour) are eliminated in the CryptoCompare data. There were 3 such observations.

We provide a tabular overview of the data cleaning process in Table C.1.

B.2 Sample for Ethereum Futures Introduction

The CME filed an announcement on December 15, 2020 that it plans to introduce trading of ethereum (ETH) futures on February 8, 2021. As for the introduction of bitcoin futures, the CME selectively launched contracts on ETH against the USD, but not against other fiat exchange rates. We extend our analysis to consider the impact of the introduction of ETH futures on the ETH cash market.

Our starting point is the 55 exchanges on which ETH traded between February 1, 2020 and April 30, 2021. We exclude 18 exchanges for which the market share (ETH trading volume relative to aggregate ETH trading volume during the period between February 1, 2020 and January 31, 2021) is below 0.01%. This reduces the sample to 36 exchanges. Our sample includes 6 bitcoin-fiat currency pairs: BTC–AUD, BTC–EUR, BTC–HKD, BTC–JPY, BTC–RUB, and BTC–USD.

CoinMarketCap, a leading firm for cryptocurrency price and market data, ranks and scores exchanges based on their web traffic, their average liquidity, and on their confidence that the volume reported by an exchange is legitimate. Weights are assigned to the above-mentioned factors and a score from 0.0 to 10.0 is given to each exchange.[†] We flag 12 exchanges as being potentially subject to market manipulation. That includes 3 exchanges that are not covered by CoinMarketCap; 4 exchanges that are covered by CoinMarketCap but that do not have an exchange score; 5 exchanges that are covered by CoinMarketCap with an exchange score below 4.0/10. We use the cutoff score of 4.0 as it coincides with the cutoff level for the lowest category imposed by CoinMarketCap.

We estimate our measures of price synchronicity (ρ) and price integration following Kapadia and Pu (2012) using a rolling window of one month of daily data. To ensure sufficient statistical precision in the estimation of our measures, we require a minimum of 15 daily return observations within each month.

[†]Details are provided at the web address https://support.coinmarketcap.com/hc/en-us/articles/360052030111-Exchange-Ranking.

C Additional Tables

Table C.1: Data Cleaning Process

In this table, we describe the data sampling and cleaning process. We source all data from Kaiko and CryptoCompare. In Panel A, we focus on BTC against fiat exchange rate pairs. In Panel B, we focus on ETH against fiat exchange rate pairs. At each decision step, we indicate the number of exchanges ($Exch$), the number of cryptocurrency pairs ($Curr$), the number of exchange-currency pairs ($Exch - Curr$), and the number of daily price observations (Obs). A detailed description of the data cleaning process is provided in Appendix B. Note that data for the Bittrex exchange come from both data sources. For this exchange the number of observations taken from CryptoCompare is 50 and the number of observations taken from Kaiko is 849.

Panel A: BTC

	Kaiko				**CryptoCompare**			
	Exch	**Curr**	**Exch-Curr**	**Obs**	**Exch**	**Curr**	**Exch-Curr**	**Obs**
Original sample	17	10	36	28,741	36	10	123	54,592
Start before January 1, 2017	16	10	35	28,310	20	10	74	38,596
Mean volume in anticip. period >1,000BTC	16	10	33	26,835	18	10	39	31,946
Returns <200% (in absolute terms)	16	10	33	26,824	18	10	39	31,943
Positive prices	16	10	33	26,823	18	10	39	31,943
Volume <5,000,000BTC	16	10	33	26,823	18	10	39	31,940
Longest time series between 2 sources	13	10	30	25,362	8	6	15	12,456

Panel B: ETH

	Kaiko				**CryptoCompare**			
	Exch	**Curr**	**Exch-Curr**	**Obs**	**Exch**	**Curr**	**Exch-Curr**	**Obs**
Original sample	11	10	26	16,197	26	10	81	27,554
Start before January 1, 2017	8	7	15	9,865	8	7	15	10,021
More than 450 observations	6	6	12	8,534	6	6	12	8,832
Returns <200% (in absolute terms)	6	6	12	8,533	6	6	12	8,831
Longest time series between 2 sources	6	4	8	6,282	5	6	10	7,592

Table C.2: Monthly Frequency – Alternative Rolling Windows.

In this table, we report regression results from the projection of market characteristics on the treatment indicator ($Treatment$) that takes the value one for BTC–USD return pairs and zero otherwise; an event indicator ($Post$) that takes the value one in the months following the introduction of bitcoin futures on December 10, 2017; and their interaction ($Treatment \times Post$). Panel A is based on the specification in column (5) of Tables 5, 6, and 7 in the paper. Panel B is based on the specification in column (6) of Tables 5, 6, and 7. All metrics are computed at a monthly frequency using rolling windows of one month of daily returns. We indicate whether the control group contains all bitcoin-fiat currency pairs (ALL), or only BTC–EUR (EUR). The sample period is July 1, 2016 to December 31, 2018, but we exclude the anticipation period between July 1, 2017 and December 31, 2017. Standard errors are clustered at the exchange pair level for price synchronicity and price integration, and at the exchange×currency level for all other measures.

Panel A	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	ρ	κ	q	D1	λ	Roll	CHL	Volume	Amihud
Treatment×Post	0.083***	0.108***	0.028***	-0.050**	-0.293**	-0.005***	-0.002*	1.152*	-1.479*
	(0.014)	(0.015)	(0.009)	(0.023)	(0.132)	(0.002)	(0.001)	(0.635)	(0.756)
N	4745	4745	1011	630	1011	1011	1011	1061	1011
adj. R^2	0.379	0.558	0.626	0.705	0.687	0.527	0.672	0.704	0.713
Control	ALL	ALL	ALL	EUR	ALL	ALL	ALL	ALL	ALL
Ccy FE	✓	✓	✓	✓					
Month FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Xchange (or-Pair) FE	✓	✓	✓	✓					
Xchange (or-Pair)×Ccy FE					✓	✓	✓	✓	✓
Panel B	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	ρ	κ	q	D1	λ	Roll	CHL	Volume	Amihud
Treatment×Post	0.016**	0.039***	0.022***	-0.025***	-0.133*	-0.004**	-0.001	0.614	-0.598*
	(0.007)	(0.009)	(0.008)	(0.008)	(0.068)	(0.002)	(0.001)	(0.412)	(0.343)
N	1741	1741	753	408	753	753	753	801	753
adj. R^2	0.692	0.727	0.650	0.834	0.780	0.553	0.712	0.819	0.840
Control	ALL	ALL	ALL	EUR	ALL	ALL	ALL	ALL	ALL
Ccy FE	✓	✓	✓	✓					
Xchange (or-Pair)×Ccy FE					✓	✓	✓	✓	✓
Xchange (or-Pair)×Month FE	✓	✓	✓	✓	✓	✓	✓	✓	✓

Table C.3: Daily Frequency – 30 and 90 Day Rolling Windows

In this table, we report regression results from the projection of market characteristics on the treatment indicator ($Treatment$) that takes the value one for BTC–USD return pairs and zero otherwise; an event indicator ($Post$) that takes the value one in the months following the introduction of bitcoin futures on December 10, 2017; and their interaction ($Treatment \times Post$). All metrics are computed at a daily frequency using rolling windows of 30 days (90 days) in Panels A and C (B and D). Panels A and B (C and D) are based on the specification in column (5) (column (6)) of Tables 5, 6, and 7 in the paper. We indicate whether the control group contains all bitcoin-fiat currency pairs (ALL), or only BTC–EUR (EUR). The sample period is July 1, 2016 to December 31, 2018, but we exclude the anticipation period between July 1, 2017 and December 31, 2017. Standard errors are clustered at the exchange pair level for price synchronicity and price integration, and at the exchange×currency level for all other measures.

Panel A. 30 day horizon	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	ρ	κ	q	D1	λ	Roll	CHL	Volume	Amihud
Treatment×Post	0.092***	0.115***	0.031***	-0.048**	-0.305**	-0.006***	-0.002*	1.175*	-1.499*
	(0.013)	(0.015)	(0.009)	(0.019)	(0.134)	(0.002)	(0.001)	(0.659)	(0.772)
N	141347	141347	30023	18680	30023	30023	30023	31495	30023
adj. R^2	0.449	0.572	0.494	0.775	0.721	0.582	0.692	0.721	0.735
Panel B. 90 day horizon	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	ρ	κ	q	D1	λ	Roll	CHL	Volume	Amihud
Treatment×Post	0.102***	0.120***	0.038***	-0.073**	-0.360**	-0.007***	-0.002*	1.239*	-1.624*
	(0.015)	(0.015)	(0.012)	(0.026)	(0.156)	(0.002)	(0.001)	(0.693)	(0.876)
N	127286	127286	27209	17010	27209	27209	27209	29422	27209
adj. R^2	0.477	0.686	0.498	0.764	0.767	0.580	0.768	0.727	0.754
Control	ALL	ALL	ALL	EUR	ALL	ALL	ALL	ALL	ALL
Day FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Ccy FE	✓	✓	✓	✓					
Xchange (or-Pair) FE	✓	✓	✓	✓					
Xchange (or-Pair)×Ccy FE					✓	✓	✓	✓	✓
Panel C. 30 day horizon	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	ρ	κ	q	D1	λ	Roll	CHL	Volume	Amihud
Treatment×Post	0.025***	0.045***	0.022***	-0.029***	-0.141**	-0.005***	-0.001	0.573	-0.589*
	(0.007)	(0.009)	(0.006)	(0.006)	(0.059)	(0.002)	(0.000)	(0.354)	(0.298)
N	51494	51494	30022	18679	30022	30022	30022	31495	30022
adj. R^2	0.708	0.716	0.370	0.742	0.855	0.504	0.749	0.903	0.918
Panel D. 90 day horizon	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	ρ	κ	q	D1	λ	Roll	CHL	Volume	Amihud
Treatment×Post	0.042***	0.047***	0.031***	-0.041***	-0.170**	-0.006**	-0.001	0.627	-0.637*
	(0.010)	(0.009)	(0.010)	(0.009)	(0.069)	(0.002)	(0.000)	(0.408)	(0.337)
N	46726	46726	27209	17010	27209	27209	27209	29422	27209
adj. R^2	0.814	0.847	0.607	0.849	0.914	0.710	0.877	0.900	0.925
Control	ALL	ALL	ALL	EUR	ALL	ALL	ALL	ALL	ALL
Ccy FE	✓	✓	✓	✓					
Xchange (or-Pair)×Ccy FE					✓	✓	✓	✓	✓
Xchange (or-Pair)×Day FE	✓	✓	✓	✓	✓	✓	✓	✓	✓

Table C.4: Alternative Trading Horizon for Price Integration

In Panel A of this table, we report regression results from the projection of monthly pairwise cross-exchange Kapadia and Pu (2012) price synchronicity measures, with a trading horizon of τ =5 days, on the treatment indicator (*Treatment*) that takes the value one for BTC–USD return pairs and zero otherwise; an event indicator (*Post*) that takes the value one in the months following the introduction of bitcoin futures on December 10, 2017; and their interaction (*Treatment* $\times$ *Post*). Pearson correlation coefficients and the integration measures are computed at a monthly frequency in rolling windows using three months of daily returns. We indicate whether the control group contains all bitcoin-fiat currency pairs (*ALL*), only BTC–EUR (*EUR*), all currency pairs except BTC–EUR (*CCY*), or the subset of exchanges that are not prone to trading volume manipulation (*X-M*). The sample period is July 1, 2016 to December 31, 2018, but we exclude the anticipation period between July 1, 2017 and December 31, 2017. Standard errors are clustered at the exchange pair level.

Panel A: Integration κ	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Treatment	-0.063***	-0.040***	-0.061***						
	(0.010)	(0.010)	(0.010)						
Post	-0.037***	-0.026**		-0.035***					
	(0.013)	(0.012)		(0.013)					
Treatment×Post	0.083***	0.079***	0.080***	0.081***	0.075***	0.043***	0.076***	0.074***	0.068***
	(0.013)	(0.012)	(0.012)	(0.012)	(0.011)	(0.010)	(0.014)	(0.013)	(0.019)
N	4310	4310	4310	4310	4310	1586	3906	3606	1056
adj. R^2	0.031	0.282	0.181	0.056	0.477	0.826	0.462	0.482	0.666
Control	ALL	ALL	ALL	ALL	ALL	ALL	EUR	CCY*	X-M
Xchange-Pair FE		✓			✓		✓	✓	✓
Month FE			✓		✓		✓	✓	✓
Ccy FE				✓	✓	✓	✓	✓	✓
Xchange-Pair×Month FE						✓			

Table C.5: Alternative Sample Periods

In this table, we verify the robustness of our results to alternative sample periods. In columns (1) and (5), we exclude the observations in the anticipation period, as well as in January and February in 2018 because the 3-month horizon to compute our measures of market characteristics for these months includes data from the anticipation period. In columns (2) and (6), we only exclude the observations in the anticipation period. In columns (3) and (7), we exclude the observations from January and February 2018. Finally, in columns (4) and (8), we do not exclude any observations. In each panel of this table, we report regression results from the projection of various measures on the treatment indicator ($Treatment$) that takes the value one for BTC–USD return pairs and zero otherwise; an event indicator ($Post$) that takes the value one in the months following the introduction of bitcoin futures on December 10, 2017; and their interaction ($Treatment \times Post$). All measures are computed at a monthly frequency in rolling windows using three months of daily returns. We use all bitcoin-fiat currency pairs as the control group except for $D1$. For $D1$, we define the control group that contains only BTC-EUR. Standard errors are clustered at the exchange pair level for price synchronicity (ρ) and price integration following Kapadia and Pu (2012) whereas the standard errors are clustered at the exchange $\times$ currency level for the other measures.

Pre-Event	07/16-06/17	07/16-06/17	07/16-12/17	07/16-12/17	07/16-06/17	07/16-06/17	07/16-12/17	07/16-12/17
Post-Event	03/18-12/18	01/18-12/18	03/18-12/18	01/18-12/18	03/18-12/18	01/18-12/18	03/18-12/18	01/18-12/18
Panel A: Synchronicity ρ	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treatment×Post	0.109***	0.103***	0.098***	0.092***	0.050***	0.045***	0.047***	0.043***
	(0.017)	(0.015)	(0.015)	(0.013)	(0.010)	(0.008)	(0.008)	(0.007)
N	4310	4728	5535	5953	1586	1752	2000	2166
adj. R^2	0.437	0.428	0.439	0.432	0.812	0.799	0.808	0.796
Panel B: Integration κ	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treatment×Post	0.118***	0.107***	0.104***	0.094***	0.047***	0.040***	0.045***	0.039***
	(0.016)	(0.015)	(0.014)	(0.013)	(0.009)	(0.009)	(0.008)	(0.008)
N	4310	4728	5535	5953	1586	1752	2000	2166
adj. R^2	0.662	0.658	0.647	0.645	0.863	0.857	0.846	0.840
Panel C: Market quality q	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treatment×Post	0.036***	0.034***	0.032***	0.030***	0.030**	0.028**	0.028***	0.026***
	(0.012)	(0.011)	(0.009)	(0.009)	(0.012)	(0.011)	(0.009)	(0.009)
N	920	1010	1177	1267	683	753	876	946
adj. R^2	0.539	0.538	0.476	0.481	0.589	0.590	0.567	0.567
Panel D: Market efficiency $D1$	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treatment×Post	-0.072**	-0.068**	-0.055**	-0.053**	-0.035**	-0.029**	-0.026*	-0.021*
	(0.031)	(0.029)	(0.024)	(0.022)	(0.013)	(0.012)	(0.013)	(0.012)
N	573	627	731	785	374	410	472	508
adj. R^2	0.663	0.669	0.734	0.730	0.792	0.797	0.830	0.829
Control	ALL	ALL	ALL	ALL	ALL	ALL	ALL	ALL
Xchange (or-Pair) FE	✓	✓	✓	✓				
Month FE	✓	✓	✓	✓				
Ccy FE	✓	✓	✓	✓	✓	✓	✓	✓
Xchange (or-Pair)×Month FE					✓	✓	✓	✓

Pre-Event	07/16-06/17	07/16-06/17	07/16-12/17	07/16-12/17	07/16-06/17	07/16-06/17	07/16-12/17	07/16-12/17
Post-Event	03/18-12/18	01/18-12/18	03/18-12/18	01/18-12/18	03/18-12/18	01/18-12/18	03/18-12/18	01/18-12/18
Panel E: Liquidity λ	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treatment×Post	-0.347**	-0.364**	-0.299**	-0.306**	-0.170**	-0.176**	-0.177**	-0.179**
	(0.153)	(0.156)	(0.132)	(0.135)	(0.080)	(0.086)	(0.080)	(0.084)
N	920	1010	1177	1267	683	753	876	946
adj. R^2	0.749	0.728	0.667	0.663	0.847	0.808	0.787	0.764
Panel F: Roll	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treatment×Post	-0.006**	-0.007**	-0.006**	-0.006**	-0.005*	-0.005*	-0.005**	-0.005**
	(0.002)	(0.003)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.002)
N	920	1010	1177	1267	683	753	876	946
adj. R^2	0.525	0.506	0.477	0.475	0.602	0.580	0.573	0.562
Panel G: CHL	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treatment×Post	-0.002**	-0.002**	-0.002**	-0.002**	-0.001	-0.001*	-0.001**	-0.001**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
N	920	1010	1177	1267	683	753	876	946
adj. R^2	0.757	0.800	0.731	0.770	0.807	0.840	0.783	0.813
Panel H: log(Volume)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treatment×Post	1.270*	1.199*	0.884	0.823	0.722	0.693	0.599	0.575
	(0.687)	(0.663)	(0.533)	(0.511)	(0.495)	(0.474)	(0.403)	(0.381)
N	992	1083	1268	1359	750	820	960	1030
adj. R^2	0.705	0.705	0.669	0.675	0.808	0.809	0.811	0.814
Panel I: log(Amihud)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treatment×Post	-1.597*	-1.568*	-1.166*	-1.111	-0.680*	-0.565	-0.602*	-0.487*
	(0.853)	(0.850)	(0.686)	(0.676)	(0.374)	(0.349)	(0.307)	(0.260)
N	920	1010	1177	1267	683	753	876	946
adj. R^2	0.741	0.732	0.688	0.689	0.850	0.838	0.839	0.833
Control	ALL	ALL	ALL	ALL	ALL	ALL	ALL	ALL
Month FE	✓	✓	✓	✓				
Xchange (or-Pair)×Ccy FE	✓	✓	✓	✓	✓	✓	✓	✓
Xchange (or-Pair)×Month FE					✓	✓	✓	✓

Table C.6: Placebo tests

In this table, we verify the robustness of our results to placebo event studies. We consider hypothetical announcement dates on January 1, 2017 in Panel A and July 1, 2018 in Panel B. Results in both panels yse three months of data before and after the hypothetical announcement dates. In each panel of this table, we report regression results from the projection of various measures on the treatment indicator ($Treatment$) that takes the value one for BTC–USD return pairs and zero otherwise; an event indicator ($Post$) that takes the value one in the months following the introduction of bitcoin futures on December 10, 2017; and their interaction ($Treatment \times Post$). All measures are computed at a monthly frequency in rolling windows using three months of daily returns. We use all bitcoin-fiat currency pairs as the control group except for $D1$. For $D1$, we define the control group that contains only BTC-EUR. Standard errors are clustered at the exchange pair level for price synchronicity (ρ) and price integration following Kapadia and Pu (2012) whereas the standard errors are clustered at the exchange $\times$ currency level for the other measures.

Panel A – January 2017	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	ρ	κ	q	D1	Volatility	λ	Roll	CHL	Volume	Amihud
Treatment×Post	0.011	0.011	0.011	0.044	-0.009	0.027	0.001	0.001	-0.159	0.375
	(0.012)	(0.016)	(0.017)	(0.052)	(0.019)	(0.119)	(0.003)	(0.001)	(0.244)	(0.334)
N	1100	1100	249	249	249	249	249	249	269	249
adj. R^2	0.798	0.821	0.642	0.678	0.839	0.793	0.502	0.713	0.858	0.823
Control	ALL	ALL	ALL	EUR	ALL	ALL	ALL	ALL	ALL	ALL
Ccy FE	✓	✓	✓	✓	✓					
Month FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Xchange (or-Pair) FE	✓	✓	✓	✓	✓					
Xchange (or-Pair)×Ccy FE						✓	✓	✓	✓	✓

Panel B – July 2018	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	ρ	κ	q	D1	Volatility	λ	Roll	CHL	Volume	Amihud
Treatment×Post	-0.027	-0.026	0.010	-0.008	0.015	0.006	-0.004	0.001	0.031	-0.045
	(0.021)	(0.017)	(0.013)	(0.028)	(0.029)	(0.131)	(0.004)	(0.001)	(0.207)	(0.365)
N	1301	1301	260	260	260	260	260	260	275	260
adj. R^2	0.585	0.799	0.613	0.479	0.847	0.711	0.611	0.638	0.746	0.846
Control	ALL	ALL	ALL	EUR	ALL	ALL	ALL	ALL	ALL	ALL
Ccy FE	✓	✓	✓	✓	✓					
Month FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Xchange (or-Pair) FE	✓	✓	✓	✓	✓					
Xchange (or-Pair)×Ccy FE						✓	✓	✓	✓	✓

Table C.7: Alternative Standard Error Corrections

In each table of this table, we show that our results are robust to different methods of clustering. In columns (1) and (6), we report OLS standard errors; in columns (2) and (7), we report heteroskedasticity-robust standard errors; in columns (3) and (8), standard errors are clustered at exchange pair level for price synchronicity and price integration, and clustered at the exchange × currency level for the other measures; in columns (4) and (9), standard errors are clustered at the month level for all measures; in columns (5) and (10), standard errors are two-way clustered at exchange pair and month level for price synchronicity and price integration, and two-way clustered at exchange × currency and month level for all other measures. In all panels, we report regression results from the projection of various measures on the treatment indicator ($Treatment$) that takes the value one for BTC–USD return pairs and zero otherwise; an event indicator ($Post$) that takes the value one in the months following the introduction of bitcoin futures on December 10, 2017; and their interaction ($Treatment \times Post$). All measures are computed at a monthly frequency in rolling windows using three months of daily returns. We use all bitcoin-fiat currency pairs as the control group except for $D1$. For $D1$, we define the control group that constains only BTC-EUR.

Panel A: Synchronicity ρ	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Treatment×Post	0.109***	0.109***	0.109***	0.109***	0.109***	0.050***	0.050***	0.050***	0.050**	0.050**
	(0.008)	(0.009)	(0.017)	(0.018)	(0.023)	(0.008)	(0.007)	(0.010)	(0.021)	(0.022)
N	4310	4310	4310	4310	4310	1586	1586	1586	1586	1586
adj. R^2	0.437	0.437	0.437	0.437	0.437	0.813	0.813	0.812	0.812	0.812
Panel B: Integration κ	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Treatment×Post	0.118***	0.118***	0.118***	0.118***	0.118***	0.047***	0.047***	0.047***	0.047***	0.047***
	(0.008)	(0.009)	(0.016)	(0.008)	(0.017)	(0.007)	(0.007)	(0.009)	(0.011)	(0.012)
N	4310	4310	4310	4310	4310	1586	1586	1586	1586	1586
adj. R^2	0.662	0.662	0.662	0.662	0.662	0.863	0.863	0.863	0.863	0.863
Panel C: Market quality q	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Treatment×Post	0.036***	0.036***	0.036***	0.036***	0.036***	0.030***	0.030***	0.030**	0.030***	0.030***
	(0.007)	(0.006)	(0.012)	(0.005)	(0.011)	(0.008)	(0.008)	(0.012)	(0.004)	(0.009)
N	920	920	920	920	920	683	683	683	683	683
adj. R^2	0.539	0.539	0.539	0.538	0.538	0.589	0.589	0.589	0.588	0.588
Panel D: Market efficieny $D1$	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Treatment×Post	-0.072***	-0.072***	-0.072**	-0.072***	-0.072**	-0.035**	-0.035**	-0.035**	-0.035	-0.035
	(0.021)	(0.021)	(0.031)	(0.023)	(0.032)	(0.017)	(0.017)	(0.013)	(0.023)	(0.021)
N	573	573	573	573	573	374	374	374	374	374
adj. R^2	0.663	0.663	0.663	0.662	0.662	0.792	0.792	0.792	0.791	0.791
Control	ALL	ALL	ALL	ALL	ALL	ALL	ALL	ALL	ALL	ALL
Xchange (or-Pair) FE	✓	✓	✓	✓	✓					
Month FE	✓	✓	✓	✓	✓					
Ccy FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Xchange (or-Pair)×Month FE						✓	✓	✓	✓	✓
S.E. Correction										
OLS	✓					✓				
Robust		✓					✓			
Cluster Xchange (or-Pair)×Ccy			✓		✓			✓		✓
Cluster Month				✓	✓				✓	✓

Panel E: Liquidity λ	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Treatment_Post	-0.347***	-0.347***	-0.347**	-0.347***	-0.347**	-0.170***	-0.170***	-0.170**	-0.170***	-0.170**
	(0.049)	(0.050)	(0.153)	(0.033)	(0.149)	(0.049)	(0.040)	(0.080)	(0.034)	(0.066)
N	920	920	920	920	920	683	683	683	683	683
adj. R^2	0.749	0.749	0.749	0.749	0.749	0.851	0.851	0.847	0.847	0.847
Panel F: Roll	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Treatment×Post	-0.006***	-0.006***	-0.006**	-0.006***	-0.006**	-0.005***	-0.005***	-0.005*	-0.005***	-0.005**
	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)	(0.003)	(0.001)	(0.002)
N	920	920	920	920	920	683	683	683	683	683
adj. R^2	0.525	0.525	0.525	0.525	0.525	0.612	0.612	0.602	0.602	0.602
Panel G: CHL	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Treatment×Post	-0.002***	-0.002***	-0.002**	-0.002***	-0.002*	-0.001	-0.001*	-0.001	-0.001*	-0.001
	(0.000)	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
N	920	920	920	920	920	683	683	683	683	683
adj. R^2	0.757	0.757	0.757	0.757	0.757	0.812	0.812	0.807	0.807	0.807
Panel H: log(Volume)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Treatment×Post	1.270***	1.270***	1.270*	1.270***	1.270*	0.722***	0.722***	0.722	0.722***	0.722*
	(0.196)	(0.199)	(0.687)	(0.141)	(0.675)	(0.193)	(0.157)	(0.495)	(0.104)	(0.407)
N	992	992	992	992	992	750	750	750	750	750
adj. R^2	0.705	0.705	0.705	0.705	0.705	0.813	0.813	0.808	0.808	0.808
Panel I: log(Amihud)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Treatment×Post	-1.597***	-1.597***	-1.597*	-1.597***	-1.597*	-0.680***	-0.680***	-0.680*	-0.680***	-0.680**
	(0.244)	(0.257)	(0.853)	(0.202)	(0.841)	(0.226)	(0.194)	(0.374)	(0.159)	(0.310)
N	920	920	920	920	920	683	683	683	683	683
adj. R^2	0.742	0.742	0.741	0.741	0.741	0.854	0.854	0.850	0.850	0.850
Control	ALL	ALL	ALL	ALL	ALL	ALL	ALL	ALL	ALL	ALL
Month FE	✓	✓	✓	✓	✓					
Xchange (or-Pair)×Ccy FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Xchange (or-Pair)×Month FE						✓	✓	✓	✓	✓
S.E. Correction										
OLS	✓					✓				
Robust		✓					✓			
Cluster Xchange (or-Pair)×Ccy			✓		✓			✓		✓
Cluster Month				✓	✓				✓	✓

Table C.8: BTC–USD vs. BTC–JPY

In this table, we report regression results from the projection of all market characteristics on the treatment indicator (*Treatment*) that takes the value one for BTC–USD return pairs and zero otherwise; an event indicator (*Post*) that takes the value one in the months following the introduction of bitcoin futures on December 10, 2017; and their interaction ($Treatment \times Post$) by using BTC–USD pairs as a treatment group and BTC–JPY pairs as a control group. All metrics are computed at a monthly frequency in rolling windows using three months of daily returns. The sample period is July 1, 2016 to December 31, 2018, but we exclude the anticipation period between July 1, 2017 and December 31, 2017. Standard errors are clustered at the exchange pair level for price synchronicity and price integration, and at the exchange×month level for all other measures.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	ρ	κ	q	D1	λ	Roll	CHL	Volume	Amihud
Treatment×Post	0.029**	0.058**	0.031**	-0.027	-0.365*	-0.007**	-0.003***	0.957	-1.163
	(0.013)	(0.026)	(0.012)	(0.028)	(0.188)	(0.003)	(0.001)	(0.765)	(0.914)
N	3527	3527	517	517	517	517	517	539	517
adj. R^2	0.461	0.681	0.637	0.708	0.713	0.572	0.765	0.684	0.696
Month FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Xchange (or-Pair)×Ccy FE	✓	✓	✓	✓	✓	✓	✓	✓	✓

Table C.9: Results for Individual Liquidity Metrics

In this table, we report regression results from the projection of four monthly individual liquidity measures on the treatment indicator ($Treatment$) that takes the value one for BTC–USD return pairs and zero otherwise; an event indicator ($Post$) that takes the value one in the months following the introduction of bitcoin futures on December 10, 2017; and their interaction ($Treatment \times Post$). In Panel A (B, C, D), we consider the Roll (1984) price impact measure (Abdi and Ranaldo (2017) CHL bid-ask spreads; log of trading volume; log of Amihud (2002) price impact measure). All measures are computed at a monthly frequency in rolling windows using three months of daily returns/volume. We indicate whether the control group contains all bitcoin-fiat currency pairs (ALL), only BTC–EUR (EUR), all currency pairs except BTC–EUR (CCY^*), or the subset of exchanges that are not prone to trading volume manipulation (X-M). The sample period is July 1, 2016 to December 31, 2018, but we exclude the anticipation period between July 1, 2017 and December 31, 2017. Standard errors are clustered at the exchange×currency level.

Panel A: Roll	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Treatment×Post	-0.007***	-0.007**	-0.007***	-0.006**	-0.006**	-0.005*	-0.010***	-0.004	-0.002
	(0.003)	(0.002)	(0.003)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)
N	920	920	920	920	920	683	573	733	430
adj. R^2	0.080	0.212	0.275	0.149	0.525	0.602	0.601	0.489	0.643
Panel B: CHL	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Treatment×Post	-0.002*	-0.002**	-0.002*	-0.002**	-0.002**	-0.001	-0.002**	-0.002	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)
N	920	920	920	920	920	683	573	733	430
adj. R^2	0.114	0.373	0.370	0.227	0.757	0.807	0.754	0.746	0.789
Panel C: log(Volume)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Treatment×Post	1.261*	1.238*	1.264*	1.227*	1.270*	0.722	0.521	1.652**	1.941**
	(0.695)	(0.694)	(0.701)	(0.696)	(0.687)	(0.495)	(0.693)	(0.770)	(0.849)
N	992	992	992	992	992	750	605	794	438
adj. R^2	0.058	0.453	0.056	0.253	0.705	0.808	0.666	0.699	0.803
Panel D: log(Amihud)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Treatment×Post	-1.702*	-1.422	-1.732*	-1.555*	-1.597*	-0.680*	-1.010	-1.927**	-2.059*
	(0.905)	(0.861)	(0.922)	(0.890)	(0.853)	(0.374)	(0.881)	(0.907)	(1.175)
N	920	920	920	920	920	683	573	733	430
adj. R^2	0.055	0.500	0.051	0.252	0.741	0.850	0.684	0.731	0.724
Control	ALL	ALL	ALL	ALL	ALL	ALL	EUR	CCY*	X-M
Xchange FE		✓							
Month FE			✓		✓		✓	✓	✓
Ccy FE				✓					
Xchange×Ccy FE					✓	✓	✓	✓	✓
Xchange×Month FE						✓			

Table C.10: 4:00 p.m. Settlement Prices – Alternative Characteristics

In this table, we report differences-in-differences regression results when we measure prices at the futures settlement times on the corresponding cash markets. Thus, prices are sampled daily at 4:00 p.m. London time from itBit, Kraken, and Bitstamp, and at 4:00 p.m. Eastern time from Gemini. We regress different measures on the treatment indicator (*Treatment*) that takes the value one for BTC–USD return pairs and zero otherwise; an event indicator (*Post*) that takes the value one following the introduction of bitcoin futures on December 10, 2017; and their interaction (*Treatment* × *Post*). In Panel A (B, C), we consider the Roll (1984) price impact measure (Abdi and Ranaldo (2017) *CHL* bid-ask spreads; log of trading volume; log of Amihud (2002) price impact measure). All measures are computed at a monthly frequency in rolling windows using three months of daily returns/volume. In each panel, we present the results using end-of-day prices, and 4:00 p.m. settlement prices. We present only the coefficient estimates for the interaction term *Treatment* × *Post*. In Panel A and B, we present results for the comparison between BTC–USD and BTC–CCY. The sample period is July 1, 2016 to December 31, 2018, but we exclude the anticipation period between July 1, 2017 and December 31, 2017. We use heteroskedasticity robust errors to estimate the standard errors.

	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A: Roll, BTC–USD vs. BTC–CCY					
	End-of-day prices			*Settlement prices*		
Treatment×Post	0.001	0.002	0.002	-0.013**	-0.011**	-0.005
	(0.003)	(0.002)	(0.002)	(0.006)	(0.004)	(0.004)
N	232	232	210	232	232	210
adj. R^2	0.164	0.674	0.627	0.068	0.404	0.372
	Panel B: CHL, BTC–USD vs. BTC–CCY					
	End-of-day prices			*Settlement prices*		
Treatment×Post	-0.002	-0.001	-0.001	-0.004*	-0.003**	-0.002
	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)
N	232	232	210	232	232	210
adj. R^2	0.191	0.727	0.680	0.189	0.651	0.577
	Panel C: log(Amihud), BTC–USD vs. BTC–CCY					
	End-of-day prices			*Settlement prices*		
Treatment×Post	-1.441**	-1.562***	-1.187**	-1.706***	-1.815***	-1.535***
	(0.604)	(0.338)	(0.456)	(0.607)	(0.332)	(0.443)
N	232	232	210	232	232	210
adj. R^2	0.383	0.826	0.859	0.399	0.837	0.865
Control	ALL	ALL	ALL	ALL	ALL	ALL
Month FE		✓			✓	
Xchange×Ccy FE		✓	✓		✓	✓
Xchange×Month FE			✓			✓

Table C.11: Liquidity Channel – Alternative Definitions of High Liquidity

In this table, we estimate Equation (12) from the manuscript to identify the effect of liquidity on daily pairwise cross-exchange Pearson correlation coefficients (Kapadia and Pu (2012) price synchronicity measures) in Panel A (Panel B) after the introduction of bitcoin futures by using the same data as in Table 5 with various liquidity measures. *High Liquidity* is equal to 1 if the average liquidity measures of both exchanges in the pre-event period are above the sample median and 0 otherwise. For liquidity measures, we use Roll in columns (1) and (5), CHL in columns (2) and (6), trading volume in columns (3) and (7), and Amihud in columns (4) and (8). Daily pairwise Pearson correlation coefficients and Kapadia and Pu (2012) price synchronicity measures are computed in rolling windows with lags of three months. We only report results using all bitcoin-fiat currency pairs. We report coefficient estimates for *Treatment*×*Post*×*High Liquidity* in each panel. The sample period is July 1, 2016 to December 31, 2018, but we exclude the anticipation period between July 1, 2017 and December 31, 2017. Standard errors are clustered at the exchange pair level.

Panel A: Synchronicity ρ	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treatment×Post	0.126***	0.105***	0.160***	0.125***	0.058***	0.051***	0.063***	0.053***
	(0.018)	(0.018)	(0.024)	(0.019)	(0.013)	(0.015)	(0.012)	(0.010)
Treatment×Post×High Liquidity	-0.062	-0.040	-0.168***	-0.118***	-0.036**	-0.007	-0.043**	-0.050***
	(0.042)	(0.031)	(0.031)	(0.021)	(0.014)	(0.018)	(0.017)	(0.011)
N	4310	4310	4310	4310	1586	1586	1586	1586
adj. R^2	0.458	0.452	0.451	0.441	0.816	0.814	0.814	0.815
Panel B: Integration κ	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treatment×Post	0.134***	0.123***	0.153***	0.135***	0.051***	0.048***	0.051***	0.049***
	(0.017)	(0.018)	(0.021)	(0.018)	(0.011)	(0.013)	(0.011)	(0.009)
Treatment×Post×High Liquidity	-0.048	-0.060**	-0.138***	-0.119***	-0.006	-0.003	-0.009	-0.026*
	(0.038)	(0.030)	(0.030)	(0.038)	(0.015)	(0.016)	(0.017)	(0.014)
N	4310	4310	4310	4310	1586	1586	1586	1586
adj. R^2	0.679	0.668	0.670	0.664	0.867	0.863	0.868	0.863
Liquidity measure	Roll	CHL	Volume	Amihud	Roll	CHL	Volume	Amihud
Control	ALL	ALL	ALL	ALL	ALL	ALL	ALL	ALL
Xchange-Pair FE	✓	✓	✓	✓				
Month FE	✓	✓	✓	✓				
Ccy FE	✓	✓	✓	✓	✓	✓	✓	✓
Xchange-Pair×Month FE					✓	✓	✓	✓

Table C.12: Volatility and Arbitrage Index

In Panel A (Panel B) of this table, we report regression results from the projection of monthly volatility (arbitrage price index) on the treatment indicator ($Treatment$) that takes the value one for BTC–USD return pairs and zero otherwise; an event indicator ($Post$) that takes the value one in the months following the introduction of bitcoin futures on December 10, 2017; and their interaction ($Treatment \times Post$). Volatility is annualized and measured using the standard deviation of daily log returns. The arbitrage price index is measured as the absolute price deviation (in units of USD $1,000) between each pair of exchanges. All measures are computed at a monthly frequency in rolling windows using three months of daily returns (prices for the arbitrage index). We indicate whether the control group contains all bitcoin-fiat currency pairs (ALL), only BTC–EUR (EUR), all currency pairs except BTC–EUR (CCY^*), or the subset of exchanges that are not prone to trading volume manipulation (X-M). The sample period is July 1, 2016 to December 31, 2018, but we exclude the anticipation period between July 1, 2017 and December 31, 2017. Standard errors are clustered at the exchange×currency level for volatility and at the exchange pair level for the arbitrage index.

Panel A: Volatility σ	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Treatment	-0.002	-0.003	0.002						
	(0.021)	(0.018)	(0.018)						
Post	0.140***	0.131***		0.137***					
	(0.012)	(0.011)		(0.013)					
Treatment×Post	-0.044**	-0.039**	-0.043**	-0.041**	-0.039**	-0.026*	-0.056***	-0.030	-0.023
	(0.017)	(0.019)	(0.018)	(0.019)	(0.017)	(0.015)	(0.019)	(0.019)	(0.024)
N	920	920	920	920	920	683	573	733	430
adj. R^2	0.094	0.172	0.735	0.172	0.827	0.839	0.888	0.817	0.896
Control	ALL	ALL	ALL	ALL	ALL	ALL	EUR	CCY*	X-M
Xchange FE		✓			✓		✓	✓	✓
Month FE			✓		✓		✓	✓	✓
Ccy FE				✓	✓	✓	✓	✓	✓
Xchange×Month FE						✓			
Panel B: Arbitrage index	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**
Treatment	-0.275***	0.359***	-0.275***						
	(0.066)	(0.130)	(0.066)						
Post	1.409***	1.492***		1.484***					
	(0.298)	(0.313)		(0.310)					
Treatment×Post	-1.164***	-1.257***	-1.164***	-1.239***	-1.257***	-0.325	-0.030	-3.395***	-0.586
	(0.297)	(0.314)	(0.297)	(0.309)	(0.313)	(0.202)	(0.051)	(0.635)	(0.566)
N	4310	4310	4310	4310	4310	1586	3906	3606	1056
adj. R^2	0.178	0.446	0.184	0.462	0.568	0.556	0.359	0.684	0.617
Control	ALL	ALL	ALL	ALL	ALL	ALL	EUR	CCY*	X-M
Xchange-Pair FE		✓			✓		✓	✓	✓
Month FE			✓		✓		✓	✓	✓
Ccy FE				✓	✓	✓	✓	✓	✓
Xchange-Pair×Month FE						✓			

Table C.13: Evidence from Introduction of Ethereum Futures

In Panel A (Panel B) of this table, we report regression results from the projection of monthly pairwise cross-exchange Pearson correlation coefficients (Kapadia and Pu (2012) price synchronicity measures) on the treatment indicator ($Treatment$) that takes the value one for ETH–USD return pairs and zero otherwise; an event indicator ($Post$) that takes the value one in the three months (February, March, April) following the introduction of ethereum futures on February 8, 2021 and zero in three months before (September, October, November) the announcement of ethereum futures on December 15, 2020; and their interaction ($Treatment \times Post$). Pearson correlation coefficients and the integration measures are computed at a monthly frequency in rolling windows using one month of daily returns. We indicate that the control group contains all ethereum-fiat currency pairs (ALL). The sample period is September 1, 2020 to April 30, 2021, but we exclude the period between the anncouncement and the launch of the ethereum futures contract between December 15, 2020 and February 8, 2021. Standard errors are clustered at the exchange pair level.

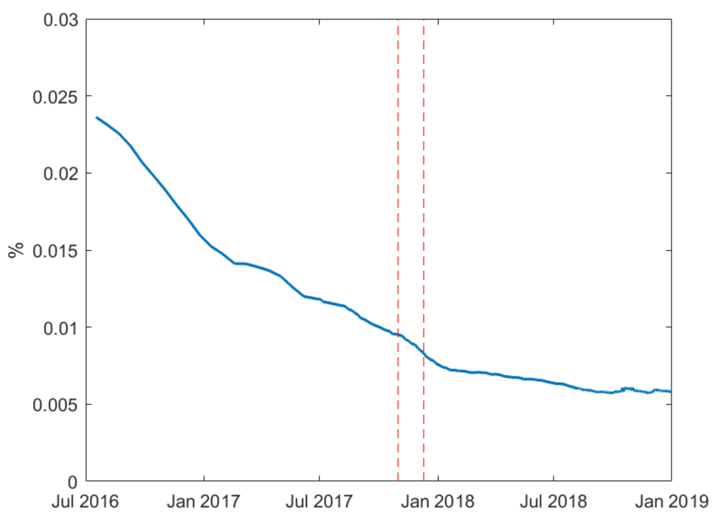
Panel A: Synchronicity (ρ)	(1)	(2)	(3)	(4)	(5)	(6)
Treatment	-0.044***	-0.004	-0.044***			
	(0.009)	(0.005)	(0.009)			
Post	0.004	0.003		0.003		
	(0.002)	(0.002)		(0.002)		
Treatment×Post	0.055***	0.019***	0.055***	0.055***	0.019***	0.016**
	(0.008)	(0.004)	(0.008)	(0.008)	(0.004)	(0.006)
N	3172	3172	3172	3172	3172	1491
adj. R^2	0.059	0.678	0.073	0.065	0.700	0.233
Panel B: Integration (κ)	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Treatment	-0.012	0.057***	-0.011			
	(0.015)	(0.008)	(0.015)			
Post	0.021***	0.018***		0.021***		
	(0.005)	(0.005)		(0.005)		
Treatment×Post	0.086***	0.031***	0.086***	0.086***	0.031***	0.026***
	(0.014)	(0.008)	(0.014)	(0.014)	(0.007)	(0.010)
N	3172	3172	3172	3172	3172	1491
adj. R^2	0.064	0.630	0.098	0.070	0.673	0.302
Control	ALL	ALL	ALL	ALL	ALL	ALL
Xchange-Pair FE		✓			✓	
Month FE			✓		✓	
Ccy FE				✓	✓	✓
Xchange-Pair×Month FE						✓

D Additional Figures

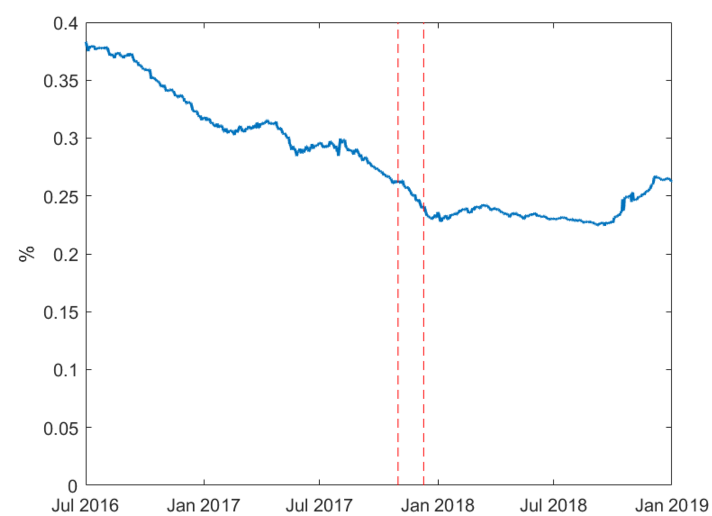
Figure D.1: Whale wallets

In Figures D.1.a and D.1.b, we plot ratios of "whale wallets". A whale wallet is defined as a wallet that holds more than 1,000 bitcoins. In Figure D.1.a, we report the ratio of whale wallets to the total number of existing wallets. In Figure D.1.b, we plot the ratio of whale walltets to the number of wallets that hold more than 1 bitcoin. All values are expressed in percentage terms. The sample period is July 1, 2016 to December 31, 2018. In both figures, the first dashed vertical line represents the CME's first announcement of the bitcoin futures launch on October 31, 2017. The second dashed line represents the introduction of the first bitcoin futures contract by the CBOE on December 10, 2017.

(a)



(b)



References

Abdi, Farshid, and Angelo Ranaldo, 2017, A Simple Estimation of Bid-Ask Spreads from Daily Close, High, and Low Prices, *The Review of Financial Studies* 30, 4437–4480.

Amihud, Yakov, 2002, Illiquidity and stock returns: cross-section and time-series effects, *Journal of Financial Markets* 5, 31–56.

Casey, Michael J., and Paul Vigna, 2015, Bitcoin and the Digital-Currency Revolution, *The Wall Street Journal* Jan. 23, 2015.

Chaum, David, 1982, Blind Signatures for Untraceable Payments, *Advances in Cryptology* pp. 199–203.

CoinMarketCap, 2021, Today's Cryptocurrency Prices by Market Cap, retrieved on 14 May 2021.

Demos, Telis, Jan. 9, 2017, Wall Street Backs Blockchain for Savings on Derivatives, *The Wall Street Journal*.

Dwork, Cynthia, and Moni Naor, 1992, Pricing via Processing or Combatting Junk Mail, in *Advances in Cryptology - CRYPTO '92, 12th Annual International Cryptology Conference, Santa Barbara, California, USA, August 16-20, 1992, Proceedings* pp. 139–147.

Haber, Stuart, and W. Scott Stornetta, 1991, How to Time-stamp a Digital Document, *Journal of Cryptology* 3, 99–111.

Irresberger, Felix, Kose John, and Fahad Saleh, 2019, The Public Blockchain Ecosystem: An Empirical Analysis, *NYU Stern Working Paper*.

Jakobsson, Markus, and Ari Juels, 1999, Proofs of Work and Bread Pudding Protocols, in *Proceedings of the IFIP TC6/TC11 Joint Working Conference on Secure Information Networks: Communications and Multimedia Security* CMS '99 pp. 258–272 Deventer, The Netherlands, The Netherlands. Kluwer, B.V.

Kapadia, Nikunj, and Xiaoling Pu, 2012, Limited arbitrage between equity and credit markets, *Journal of Financial Economics* 105, 542–564.

Lee, Jongsub, Tao Li, and Donghwa Shin, 2018, The Wisdom of Crowds in FinTech: Evidence from Initial Coin Offerings, *Working Paper*.

Li, Tao, Donghwa Shin, and Baolian Wang, 2018, Cryptocurrency Pump-and-Dump Schemes, *SSRN Working Paper*.

Makarov, Igor, and Antoinette Schoar, 2020, Trading and Arbitrage in Cryptocurrency Markets, *Journal of Financial Economics* 135, 293–319.

Nakamoto, Satoshi, 2008, Bitcoin: A Peer-to-Peer Electronic Cash System, *White Paper*.

Narayanan, Arvind, and Jeremy Clark, 2017, Bitcoin's Academic Pedigree, *Commun. ACM* 60, 36–45.

Roll, R., 1984, A simple implicit measure of the effective bid-ask spread in an efficient market, *The Journal of Finance* 39, 1127–1139.

Saleh, Fahad, 2021, Blockchain Without Waste: Proof-of-Stake, *Review of Financial Studies* 34, 1156–1190.