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The Impact of Derivatives on Spot Markets: Evidence From the Introduction of Bitcoin Futures Contracts

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

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Abstract

Cryptocurrencies provide a unique opportunity to identify how derivatives impact spot markets. They are fully fungible, trade across multiple spot exchanges at different prices, 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 and volatility. We also find support for an increase in price efficiency, market quality, and liquidity. The evidence suggests that futures contracts allowed investors to circumvent trading frictions associated with short sale constraints, arbitrage risk associated with block confirmation time, and market segmentation. Overall, our analysis supports the view that the introduction of BTC–USD futures was beneficial to the bitcoin spot market by making the underlying prices more informative.

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

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1 Introduction

One of the most fundamental questions for financial derivatives is whether their introduction is beneficial or detrimental to their underlying spot markets. A definite answer to this question has thus far remained elusive due to opposite predictions made by extant theories and important identification challenges in the empirical literature.[1]

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 spot markets. That event is unique because the particular bitcoin trading infrastructure and the selective introduction of bitcoin futures allow us to overcome many of the identification challenges faced by the earlier literature.

First, bitcoins trade on multiple exchanges at different prices with varying liquidity, giving rise to inefficiencies and arbitrage opportunities (Makarov and Schoar, 2019, 2020). Importantly, bitcoins are fully fungible across trading venues, so they provide an optimal setting to study price discrepancies of identical assets traded on multiple exchanges (Hasbrouck, 1995). Even closely related securities like American Depository Receipts that share identical firm fundamentals are typically not fully fungible (Gagnon and Karolyi, 2010).

Second, the CBOE and CME selectively introduced futures contracts on the bitcoin-USD (BTC–USD) exchange rate and not on other bitcoin-fiat currency pairs (e.g., BTC–EUR). Thus, we can examine differential treatment effects across exchanges, and, most crucially, within exchanges or exchange pairs while controlling for latent time-varying trends specific to an exchange (or exchange-pair). This rules out concerns that effects are due to changing technology or popularity of a particular exchange. It also rules out that our results are driven by confounding common events around the time of futures introduction.

Third, the contract launch was largely unanticipated, as we further describe below, supporting a causal interpretation of the effect of futures introduction. To support that interpretation, we can invoke novel theories on endogenous bitcoin adoption and mining concentration, which help differentiate the effect of futures introduction from that of anticipated adoption (Cong, He, and Li, 2021; Alsabah and Capponi, 2020; Datta and Hodor, 2021). Since bitcoin's supply is limited by design and new investors were legally allowed to acquire bitcoin exposure only following the bitcoin futures introduction, we can also invoke theories of derivatives introduction that depend on the scarcity of the underlying asset (Banerjee and Graveline, 2014) or entry of outside investors (Sambalaibat, 2022).

[1] We review the evidence and corresponding identification challenges in detail in the literature section.

Fourth, trading frictions are directly measurable across exchanges, eliminating the need to rely on indirect proxies that are likely to correlate with trading frictions. Thus, we can exploit cross-exchange heterogeneity in terms of short selling constraints, arbitrage risk associated with block confirmation time as well as legal and geographical market segmentation to examine the economic channels of the impact of futures introduction.

Unique variation across and within exchanges or exchange pairs permits a difference-in-differences framework that helps isolate the impact of futures introduction on characteristics of BTC–USD exchange rates (the treatment group) relative to those of other bitcoin-fiat currency pairs (the control groups). In our most conservative tests, we use exchange-time or exchange-pair-time fixed effects to absorb unobserved time-varying characteristics of exchanges/exchange-pairs. This mitigates concerns that our results are driven by time-varying popularity or technology of any exchange (Howell, Niessner, and Yermack, 2020), or by time-varying selection effects across exchange-pairs.

Our results strongly suggest that the futures introduction was beneficial to the bitcoin spot market. We find that the cross-exchange price synchronicity increases on average by about 5 to 12 percentage points more for BTC–USD compared to other bitcoin-fiat exchange rates. This is sizeable since the average in-sample return correlations across the treatment and control currencies are 0.87 and 0.85, respectively. In support of a direct link between the futures market and bitcoin spot prices, we show that our results are stronger when there is greater futures trading volume and weaker when the futures market is closed for trading.

While our analysis focuses on cross-exchange price synchronicity and integration, the evidence also supports the conclusion that BTC–USD experiences a greater increase in price informativeness and market quality, and a greater reduction in illiquidity and volatility. The latter finding helps differentiate the impact of futures introduction from confounding factors since theory predicts an increase in volatility if anticipation of BTC–USD bitcoin futures would induce greater BTC–USD adoption and mining concentration (Cong, He, and Li, 2021; Alsabah and Capponi, 2020; Datta and Hodor, 2021).

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 other fiat currencies (BTC–CCY). Since we focus on the unique event of the bitcoin futures listing, we collect information for 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, giving rise to 46 exchange pairs.

We explore the trading mechanism to support the interpretation that futures help circumvent arbitrage frictions, and, therefore, facilitate better price alignment. This is because arbitrage trading before the futures introduction requires cross-exchange transfers, which can be avoided by investors who trade the futures together with the spot in one centralized exchange. In support of that mechanism, we show that cross-exchange flows drop more after the futures introduction between exchanges where BTC–USD accounted for more than 50% of all transactions before the futures introduction.

We further show that our results are driven by currency pairs for which triangular arbitrage can only be executed through cross-exchange transfers. In contrast, we find no evidence of a differential improvement in price synchronicity if triangular arbitrage is feasible within exchange, e.g., a strategy that involves ethereum (ETH) using BTC–USD, ETH–USD, and BTC–ETH. This evidence aligns with Makarov and Schoar (2020) who explain that legal investment restrictions complicate cross-exchange arbitrage, and Dyhrberg (2020), who shows that arbitrage without pure fiat exchange rate pair is less challenging.

To understand the economic channels that impede efficient pricing, we sort exchanges based on measurable trading frictions. We collect exchange-specific information on short sale restrictions, mining confirmation time, legal and geographical market segmentation. Alternatively, asynchronous price movements and arbitrage opportunities may be due to limited investor attention, which we measure using the Google search intensity for exchange names. Overall, we find strong evidence that our effects are more pronounced in the presence of short sale constraints, when arbitrage risk associated with block confirmation time is high, and when markets are segmented. We find no evidence that investor attention matters.

In a final step, we examine whether the ETH–USD futures introduction in 2021 improved the cross-exchange price synchronicity of ETH–USD relative to that of ETH–CCY. Since arbitrage frictions are lower on the Ethereum blockchain, we identify effects with smaller magnitudes and at lower trading horizons compared to BTC–USD in 2017. In contrast, we find no significant effect for ETH–USD relative to ETH–CCY around the 2017 futures introduction, suggesting that we capture a bitcoin rather than a USD effect.

Our findings have broader implications for the introduction of derivatives, regardless of the asset class. This is because bitcoin futures share with other assets generic features that are central to theories on derivatives introduction. The payoff of bitcoin futures correlates with that of spot bitcoin, allowing investors to gain exposure to the risk of the underlying. Thus, derivatives transactions may replace or complement transactions in the underlying, depending on whether they are used for speculative, hedging or arbitrage purposes.

Cryptocurrencies also bear institutional similarities with other assets. Liu and Tsyvinski (2021); Liu, Tsyvinski, and Wu (2022) use traditional asset pricing theory to study the cross-section of cryptocurrency returns, and Shams (2020); Schwenkler and Zheng (2021) show that shock propagation and information spillovers are similar in cryptocurrency and other markets. Moreover, just like commodity markets are geographically segmented due to costly transportation of steel and import/export tariffs (Martin, 2021), cryptocurrency trading is impacted by costly processing and block validation time (Irresberger, John, Mueller, and Saleh, 2021) in addition to geographical trading restrictions (Makarov and Schoar, 2020).

2 Related Literature and Conceptual Framework

Our work relates first and foremost to the vast literature that studies how the introduction of derivatives affects spot markets. The benchmark view is that in complete markets without frictions, derivatives are redundant because they can be replicated by dynamic trading.

Depending on assumptions about market incompleteness, model parameterization, and the focus (price levels, volatility, microstructure), arguments can be constructed in favor or against derivatives being beneficial for spot assets (see Hodges, 1992; Damodaran and Subrahmanyam, 1992; Mayhew, 1999, for early reviews). Sources of incompleteness often relate to investment opportunity or information sets, regulatory and institutional constraints, or trading frictions including search and transaction costs or short-sale constraints.

Banerjee and Graveline (2014) show how derivatives relax aggregate capacity constraints by allowing more short and long positions of scarce assets, even in otherwise frictionless markets.[2] That framework is a useful benchmark in our context since bitcoin supply is limited by design and the introduction of regulated futures by designated contract markets enable a fundamental change in investor composition (Ferko, Moin, Onur, and Penick, 2021).

Ross (1976) shows how options improve the efficiency of the underlying by expanding the payoff space. Relatedly, Turnovsky (1983) and Danthine (1978) emphasize the stabilizing effects of derivatives, while Stein (1987) underscores their potentially destabilizing effects.

Focusing on asymmetric information, Subrahmanyam (1991) predicts that uninformed investors migrate towards futures markets. This can enhance price informativeness of spot

[2]While Banerjee and Graveline (2014) focus on linear derivatives, the payoff structure is not relevant for all theories and results can generalize regardless of the type of derivative (e.g., Bhamra and Uppal, 2009).

markets and increase bid-ask spreads due to greater adverse selection costs. Alternatively, bid-ask spreads may reduce if specialists increase their hedging activity with low-cost futures (Silber, 1985). Biais and Hillion (1994) predict ambiguous effects for price efficiency while Cao (1999) suggests that volatility increases in response to greater incentives for information acquisition following derivatives introduction. See also Gorton and Pennacchi (1991); Detemple and Selden (1991); Back (1993); Brennan and Cao (1996); Zapatero (1998).

Whether derivatives are used for hedging or speculative activity, and, therefore, increase or decrease trading activity in the spot market, may also depend on differential transaction and search costs and the possibility of market entry (e.g., Oehmke and Zawadowski, 2015; Sambalaibat, 2022). The introduction of centralized derivatives may reduce search costs in over-the-counter markets (Duffie, Dworczak, and Zhu, 2017) and reduce price dispersion and informational inefficiencies (Martin, 2021). Price informativeness may also be driven by how hedgers and speculators learn from price dynamics (Goldstein, Li, and Yang, 2014).

Evidence in empirical studies is likewise mixed, which reflects important identification challenges. A spurious relation between option listing and volatility or liquidity may arise if exchanges select liquid or volatile stocks (Mayhew and Mihov, 2004). Studies thus debate whether option listing increases or decreases volatility (Skinner, 1989; Conrad, 1989; Detemple and Jorion, 1990; Damodaran and Lim, 1991; Kumar, Sarin, and Shastri, 1998; Mayhew, 1999). Relatedly, credit derivatives may be introduced on bonds with higher credit risk, nurturing a debate regarding their impact on the price and liquidity of the underlying assets (Das, Kalimipalli, and Nayak, 2014; Ismailescu and Phillips, 2015; Che and Sethi, 2014).

Another large list of studies presents, by and large, results that are inconclusive with respect to the impact on spot volatility, bid-ask spreads and liquidity (e.g., Figlewski, 1981; Stoll and Whaley, 1990; Edwards, 1988a,b; Chan, Chan, and Karolyi, 1991; Bessembinder and Seguin, 1992; Jegadeesh and Subrahmanyam, 1993; Figlewski and Webb, 1993; Brenner, Subrahmanyam, and Uno, 1994; Choi and Subrahamanyam, 1994; Harris, 1989; Mayhew, 1999; Gulen and Mayhew, 2000; Danielsen and Sorescu, 2001; Gagnon, 2018; Martin, 2021). Against the backdrop of these identification challenges, our key contribution is to propose a novel and unique setting for us to isolate the impact of futures introduction on spot markets.

Our work is also closely related to studies on frictions and inefficiencies of cryptocurrencies, including Easley, O'Hara, and Basu (2019); Makarov and Schoar (2020, 2019); Krückeberg and Scholz (2020); Dyhrberg (2020); Kroeger and Sarkar (2017); Hautsch, Scheuch, and Voigt (2019); Borri and Shaknov (2021); Choi, Lehar, and Stauffer (2018). 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 and liquidity.

3 Institutional Background and Development of Hypotheses

We first discuss cryptocurrency spot markets and exchanges (Section 3.1), and the BTC–USD futures introduction (Section 3.2). We then develop our hypotheses (Section 3.3) and describe the measurement of all outcome variables (Section 3.4).

3.1 Cryptocurrency spot markets and exchanges

Launched as the first cryptocurrency in 2009, bitcoin is now one among close to 20,000 listed cryptocurrencies, exceeding a market capitalization of $1.25 trillion (CoinMarketCap, 2022). We focus on bitcoin, since it is the most dominant cryptocurrency and consistently accounts for the largest market share (Irresberger, John, Mueller, and Saleh, 2021). Importantly, it is the underlying for the first regulated and centrally cleared cryptocurrency derivative.

Cryptocurrencies (e.g., BTC) 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 (2022) lists more than 500 crypto spot exchanges as of May 2022, with aggregate daily trading volume of $250 billion.

Investors may buy bitcoins on one exchange and sell them on another, implying that bitcoins are fully fungible across exchanges with equal fundamentals by design. Thus, cross-exchange prices of, say, BTC–USD, ought to be identical despite being exchanged in multiple trading venues. This makes them close to a perfect example of an identical asset traded on multiple exchanges in the spirit of Hasbrouck (1995). Moreover, bitcoin exchange rates all share the same underlying fundamentals up to being measured in different numeraires.

Nonetheless, bitcoins trade at vastly different prices across exchanges (Makarov and Schoar, 2020; Hautsch, Scheuch, and Voigt, 2019; Yu and Zhang, 2018). While price differences of currency pairs across exchanges could be driven by exchange-specific frictions, dynamics of price differences across currency pairs within exchanges (e.g., BTC–USD vs. BTC–EUR) are most likely driven by market-specific frictions. We exploit the rich price heterogeneity within and across exchanges and currency pairs for identification purposes.

Importantly, cryptocurrencies are also subject to trading frictions that are explicit and measurable. These frictions relate, for example, to institutional and legal market segmentation (Makarov and Schoar, 2020; Dyhrberg, 2020), block confirmation time (Irresberger, John, Mueller, and Saleh, 2021), and short-sale constraints (Borri and Shaknov, 2021).

3.2 Cryptocurrency derivatives and the BTC–USD futures introduction

A major distinction among cryptocurrency 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 and centrally cleared contracts by the CME and the CBOE (i.e., designated contract markets, henceforth DCM) in December 2017. Self-certification of bitcoin futures by the world's largest derivatives exchanges was likely impactful for future market growth. The listing by a US regulated DCM and derivatives clearing organization also increased market access to a large class of investors, who are otherwise legally prevented from trading bitcoin risk through unregulated securities or exchanges.

The CBOE stopped trading bitcoin futures in June 2019, but 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 ($\approx$ \$182 million in notional value) were traded in its first two years (Avan-Nomayo, 2019). The proliferation and growth of cryptocurrency derivatives resembles that in other markets. The CME started offering bitcoin futures options in 2020, ethereum and micro crypto futures in 2021, and options on micro crypto futures in 2022.

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 hardly inexistent before the CME officially announced their launch on October 31, 2017.[3]

[3] Anecdotally, the CME's chief economist denied intentions of bitcoin futures listing at a Q&A session of the SoFiE Financial Econometrics Summer School luncheon at Northwestern University in July 2017.

Futures were also unlikely introduced in response to hedging needs of institutional investors. Institutions 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 C.1 of the appendix, we further show that the number of "whale wallets" with holdings above 1,000 bitcoins, a proxy for large investors, was decreasing before the CME announcement.

Another important aspect of the event is that the futures contract was selectively introduced for BTC–USD, but not for other currency pairs (e.g., BTC–EUR). This allows us to examine the impact of the futures introduction on spot bitcoin in a difference-in-differences setting.

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. Since these contracts were bilaterally cleared, they imply much greater concern for counterparty risk, especially in times of exchange failures and hacks that lead to a suspension of trading (e.g., Mt. Gox in 2014). Importantly, TeraExchange was sued by the CFTC for alleged wash trading in 2015 (CFTC, September 24, 2015).

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.

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 rejected proposals for bitcoin related ETFs by Winklevoss, VanEck, SolidX, and Bitwise until October 2021, when it approved BITO, the first bitcoin ETF.

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).

3.3 Development of hypotheses and identification strategy

The various features of the BTC-USD futures introduction (multi-listing and fungibility of spot assets, measurable cross-exchange trading frictions, selective BTC–USD futures introduction) make them uniquely suited for identifying the impact of derivatives on spot markets. The combination of these properties is challenging to find in other markets, since either related assets are not fully fungible (Gagnon and Karolyi, 2010; Martin, 2021), frictions are low enough to have price discrepancies arbitraged away in milliseconds due to high frequency trading (Shkilko and Sokolov, 2020), or derivatives were not selectively introduced as to allow for a difference-in-differences setting.

We thus examine how the BTC–USD futures introduction impacts price, trade and microstructure characteristics of BTC–USD (treatment group) relative to those of other bitcoin-fiat exchange rate pairs (control groups). Our identification strategy relies on comparing cross-sectional differences in the variation of characteristics between BTC–USD and other bitcoin-fiat exchange rate pairs (henceforth BTC–CCY) around the time of futures listing.[4] Our null hypothesis is that the futures introduction has no differential impact on BTC–USD, since derivatives are redundant in the frictionless benchmark.

Specifically, we consider characteristics related to price synchronicity and integration, price efficiency, market quality, liquidity, and volatility, i.e., $Characteristic_{i,j,t} \in \{Synchronicity, Efficiency, Quality, Liquidity, Volatility\}$. We measure these characteristics for each cryptocurrency exchange rate i on exchange trading platform j at time t. For price synchronicity, j refers to a pair of exchanges since this metric is measured across two trading venues. We implement the 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.

[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.

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 $\eta_j \times \gamma_t$. This specification is conservative in that it mitigates concerns that our results may be driven by time-varying popularity or technology of any exchange associated with the boom in initial coin offereings (Howell, Niessner, and Yermack, 2020). It also accounts for time-varying selection of trading between exchange-pairs.

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 tests, we verify that our results remain significant when we also cluster by time.

3.4 Measurement of market characteristics

Price synchronicity and integration: Denote $r_{i,j,t+1} = \ln\left(p_{i,j,t+1}/p_{i,j,t}\right)$ 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. We measure price synchronicity of currency pair i between returns on exchanges j and j' using their Pearson correlation coefficient $\rho_{i,jj',t}$ given by:

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

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 cross-exchange price alignment and, therefore, reflective of pricing efficiency.

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. We assume that cross-exchange prices are aligned if returns over a trading horizon $t-\tau$ to t move in the same direction, $\mathcal{I}\left(r^{\tau}_{i,j,t} \cdot r^{\tau}_{i,j',t} > 0\right)$, and misaligned if they move in opposite directions, $\mathcal{I}\left(r^{\tau}_{i,j,t} \cdot r^{\tau}_{i,j',t} < 0\right)$, where $\mathcal{I}(\cdot)$ is an indicator function that is one if the condition inside the brackets is met and zero otherwise. Thus, $\kappa_{i,j/j',t}$ captures the frequency of price synchronicity over a trading horizon τ:

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

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.

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 and Nikbakht (2021) 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 $D1_{i,j}$ measure for exchange rate i at exchange j compares the fit of a constrained model ($Constrained\ R_{i,j}^2$), based only on contemporaneous variables on the right-hand side of the regression in Equation (4), with that of an unconstrained model ($Unconstrained\ R_{i,j}^2$), which incorporates both contemporaneous and lagged data. $D1_{i,j} \in [0,1]$ is defined as:

$$D1_{i,j} = 1 - \left(Constrained\ R_{i,j}^2 / Unconstrained\ R_{i,j}^2\right). \tag{5}$$

We compute $D1_{i,j}$ at the monthly frequency using rolling windows of up to three months of daily data. $D1_{i,j}$ measures the extent to which cryptocurrency returns are explained by lagged information. Lower values are associated with greater cryptocurrency efficiency.

Market quality: We measure market quality/price accuracy using the q measure of Hasbrouck (1993). In that model, (log) returns $r_{i,j,t}$ reflect changes in the efficient price $m_{i,j,t}$ and changes in the pricing error $s_{i,j,t}$, such that $r_{i,j,t} = m_{i,j,t} - m_{i,j,t-1} + s_{i,j,t} - s_{i,j,t-1}$. Given the variances of returns ($\sigma_{r_{i,j}}^2$) and pricing errors ($\sigma_{s_{i,j}}^2$), respectively, the market quality measure $q_{i,j}$ is defined by the normalized pricing error $\sigma^2_{s_{i,j}}/\sigma^2_{r_{i,j}}$:

$$q_{i,j} = 1 - \sigma^2_{s_{i,j}}/\sigma^2_{r_{i,j}}, \tag{6}$$

where a higher $q_{i,j}$ indicates a higher market quality because prices deviate less from their efficient level. We compute market quality at a monthly frequency using the parameter estimates $\{a_{i,j}, \sigma^2_{e_{i,j}}\}$ of the MA(1) model $r_{i,j,t} = e_{i,j,t} - a_{i,j}e_{i,j,t-1}$ over a 3-month window. The $q_{i,j}$ measure is then defined as (Hasbrouck, 1993; Das, Kalimipalli, and Nayak, 2014):

$$q_{i,j} = \frac{\sigma^2_{e_{i,j}} - 2a_{i,j} \cdot cov(e_{i,j,t}, e_{i,j,t-1})}{\sigma^2_{e_{i,j}} + a_{i,j}\sigma^2_{e_{i,j}} - 2a_{i,j} \cdot cov(e_{i,j,t}, e_{i,j,t-1})} \in (0,1)\,. \tag{7}$$

Liquidity: We first compute the Roll (1984) price impact measure, 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 three-month window (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:

$$Roll_{i,j,t} = 2\sqrt{\max\{-\widehat{cov}_{i,j,t}, 0\}}. \tag{8}$$

Second, we approximate bid-ask spreads 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, we compute $\eta_{i,j,t} = \left(l_{i,j,t} + h_{i,j,t}\right)/2$. We then compute, at a monthly frequency using a three-month window 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 sum of daily volume over three months. We examine windows of one month for robustness.

Fourth, given the volume of cryptocurrency i at exchange j on day t, $Volume_{i,j,t}$, and N daily observations, we compute the (Amihud, 2002) price impact measure defined 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 an aggregate illiquidity variable λ to reduce the dimensionality of our data. We construct $\lambda_{i,j,t}$ as an equal-weighted average of all $k = 1, 2, 3, 4$ illiquidity 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 sample mean and standard deviation, respectively, of illiquidity metric k.[5] We sign all variables so that a higher λ is associated with greater illiquidity.

Volatility: We measure volatility using the standard deviation of daily log returns over a three-month horizon (one month for robustness) and annualize it using 252 trading days.

4 Evidence

We discuss the data in Section 4.1 and summary statistics in Section 4.2. Preliminary evidence is illustrated in Section 4.3. We present the main results in Sections 4.4 to 4.6.

4.1 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.

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

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 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 A provides details regarding the data collection and cleaning process.

Our benchmark sample contains 10 bitcoin-fiat exchange rates and 46 bitcoin-fiat currency-exchange pairs. Besides the treatment currency BTC–USD, there are 9 control currency pairs: BTC–EUR, BTC–GBP, BTC–HKD, BTC–SGD, BTC–JPY, BTC–AUD, BTC–IDR, BTC–CAD, and BTC–RUB, traded on 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, BTC–EUR and BTC–JPY trade on 9 and 6 exchanges, respectively; BTC–CAD, BTC–GBP, BTC–HKD, BTC–RUB, and BTC–SGD on 2 exchanges, and BTC–AUD and BTC–IDR on only 1 exchange. Our most restrictive tests that exploit within-exchange variation of BTC-USD relative to BTC-CCY are based on the exchanges that have a minimum of one bitcoin-fiat currency pair besides BTC–USD.[7]

All cryptocurrency exchange rates are quoted in terms of number of fiat currency units per bitcoin. To measure market characteristics, we compute daily log returns using the last available trading price each day based on coordinated universal time. We aggregate intraday quantities of traded bitcoins to obtain a measure of daily trading volume.

4.2 Descriptive statistics

Panel A of Table 1 shows that the aggregate trading volume across exchanges increases from 11.383 million BTC in Q3 2016 to a peak of 22.977 million BTC in Q4 2017, when futures were introduced. It then decreases again to 14.739 million BTC in Q4 2018.

[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.

[7] We compare BTC–USD and BTC–CCY because they are *identical* assets and fully fungible. We do not include different control assets like bitcoin cash (BCH), created through a bitcoin hard fork.

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 for BTC–USD volumes between July 2016 and December 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 non-trivial trading activity across exchanges.

Trading volumes for BTC-EUR are lower than those for BTC–JPY, but its trading is spread out across more exchanges. Panel C in Table 1 shows the cross-exchange distribution of BTC-EUR trading volume between July 2016 and December 2018. Kraken dominates BTC–EUR trading and accounts, on average, for about 62.21% of all BTC–EUR volume. 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. The largest exchanges are not the same across currency pairs, suggesting a fair amount of heterogeneity across exchanges. 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.

In Table 2, we provide summary statistics for daily 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 other bitcoin-fiat currency exchange rates, reported in Panels B and C, respectively, are similar, although the return distributions in Panel C exhibit more leptokurtic distributions and more often positive skewness.

In Table 3, we report summary statistics for measures of price synchronicity, market efficiency, market quality, liquidity, and volatility. We compare statistics between BTC–USD and the 9 other exchange rate pairs. Their unconditional means are comparable for measures of price synchronicity, efficiency, quality, Roll price impact, bid-ask spreads (CHL), and volatility. For example, the average efficiency measure $D1$ is 0.3069 for BTC–USD and 0.3305 for other exchange rate pairs. Similarly, 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.

4.3 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. 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 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 spot 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.

4.4 Main results: price synchronicity and integration

In Panel A of Table 5, we focus on price synchronicity. The result in column (1) suggests that pairwise correlations are unconditionally 5.3 percentage points lower for BTC–USD returns and that pairwise correlations drop, on average, by about 7.3 percentage points after the futures listing. Both results are driven by exchanges suspected of market manipulation, as demonstrated by the insignificant coefficient of -0.001 after the inclusion of exchange-pair fixed effects in column (2), and additional (unreported) subsample results.

The main coefficient of interest is the one associated with the interaction term $Treatment \times Post$. The point estimate of 0.121 is highly statistically significant, economically meaningful, and its magnitude hardly changes after adding a battery of fixed effects. In column (2), we absorb unobserved and time-invariant heterogeneity at the exchange-pair level using exchange-pair fixed effects, 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. Combining all fixed effects 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) and (8) of Table 5, we report subsample results when the treatment group is restricted to BTC–EUR (EUR) or BTC–CCY excluding BTC–EUR (CCY*). The coefficient of interest remains significant and ranges between 0.050 and 0.144. In light of concerns 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), we also exclude in column (9) the exchanges that are suspected of manipulation (X-M).[8] The coefficient remains statistically significant.

In Figure 3, we report a model-implied plot from an extended difference-in-differences regression in which we interact the treatment indicator for BTC–USD with quarter 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 currency 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 control for time-varying selection and heterogeneity at the exchange-pair level, the differential increase in the frequency of price concordance of BTC–USD vs. BTC–CCY 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 to other currency pairs. The coefficient estimate is 0.114 in the subsample of exchanges not accused of market manipulation.

[8]We identify exchanges not subject to volume manipulation using a report presented by Bitwise Asset Management Inc. to the U.S. SEC in March 2019. In our sample, we identify 10 exchanges with legitimate volumes: Bitfinex, Kraken, Bitstamp, Coinbase, bitFlyer, Gemini, itBit, Bittrex, Poloniex, and Cex.io.

4.5 A direct link between futures and spot markets

To establish a more direct and potentially causal link between the bitcoin futures and spot markets, we explore time variation in the treatment effect based on futures trading activity. We find that the improvement in synchronicity and price integration is stronger on days when trading volume is larger and concentrated in times when the futures market is open.

We collect aggregate trading volume across all contract maturities offered by the CME and CBOE from Bloomberg. Since we only have 12 months in the post-introduction period, we examine variation at the daily frequency. We compute an indicator variable that is one if volume over a two-week period is in the top quartile of the volume distribution and zero otherwise. We then interact that indicator variable with our treatment effect.[9]

The results in Panel A of Table 6 suggest that our effects are stronger in periods when futures volume is larger. Comparing the coefficient from the most conservative specification in columns (6) and (12) to those in column (6) of Panels A and B in Table 5 suggests that most of our effect is driven by periods in which there is more futures trading.

Bitcoin futures are open for trading between Sunday 6:00 p.m. and Friday 5:00 p.m. Eastern time (Aleti and Mizrach, 2021). Thus, we compute price synchronicity based on returns that are sampled separately for periods when bitcoin futures market are open and closed, using the first and last recorded price in each period, respectively. The most conservative specifications in columns (2) and (4), and (8) and (10) of Panel B in Table 6 suggest that our effect is determined in times when futures markets are open for trading.

4.6 Other results: market quality, price efficiency, liquidity, volatility

We report in Table 7 the results for price efficiency, market quality, liquidity, and volatility based on the two most conservative specifications of the model in Equation (1).

The result for the Hasbrouck (1993) market quality metric q in column (1) indicates that the market quality of BTC–USD increases relative to all other cryptocurrency exchange rates after the futures introduction, with a statistically significant coefficient estimate of 3.6%. That coefficient remains significant in our most conservative specification in column (2),

[9]Pre-introduction futures volume is mechanically zero, implying perfect collinearity between $Post \times High\ Volume$ and $High\ Volume$, and $Treatment \times High\ Volume$ and $Treatment \times Post \times High\ Volume$.

where we examine the within exchange variation of BTC–USD relative to other cryptocurrency exchange rates. The coefficient is of slightly higher magnitude for the (unreported) subsample results where BTC–EUR is the only control currency.

In columns (3) to (4) Panel B of Table 7, we report the results for the Hou and Moskowitz (2005) $D1$ price efficiency measure. 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 prices more quickly incorporate new information. 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 3.5% to 7.2%. 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 (column 3) and within exchange (column 4). Overall, we find support for the hypothesis that the derivatives introduction improves the price efficiency of the underlying cash market.

In columns (5) and (6) of Table 7, we evaluate whether the introduction of BTC–USD futures is associated with an improvement of BTC–USD liquidity relative to other exchange rate pairs, using the illiquidity variable λ. We find a statistically significant improvement in liquidity that is also economically significant. For example, the magnitude of the estimated coefficient of 0.347 in column (5) corresponds to about 54% of the standard deviation of λ for BTC-USD. Importantly, the coefficient's magnitude is stable across specifications with different fixed effects. We discuss results for the individual illiquidity metrics in Section 5.5. These results are qualitatively similar to those based on the aggregate variable λ.

In columns (7) and (8) of Table 7, we report our findings for volatility. Both coefficients point towards a reduction in volatility that is between 2.6 and 3.9 percentage points greater for BTC–USD than for BTC–CCY. The economic magnitude thus corresponds to about 12% to 17% of the sample standard deviation of BTC–USD return volatility. This result is intriguing, because increased adoption and mining concentration of BTC–USD in response to BTC–USD futures introduction is suggested to increase the volatility of the BTC–USD spot more (Cong, He, and Li, 2021; Alsabah and Capponi, 2020; Datta and Hodor, 2021).

5 Mechanism, Economic Channels and Robustness

We strengthen our evidence using cross-exchange bitcoin flows (5.1). In addition, we discuss triangular arbitrage (5.2), shed light on economic channels (5.3), and examine the ethereum futures introduction (5.4). We end with robustness tests (5.5).

5.1 Evidence on cross-exchange flows

Without the futures contracts, investors may exploit price discrepancies across spot exchanges by buying bitcoin on an exchange where the price is low, sending it to another exchange and selling it there at a higher price. With futures, investors can circumvent the trading frictions associated with fund transfers across exchanges.

Figure 4 illustrates how the introduction of the futures is anticipated to shift arbitrage activity from bilateral trading between spot exchanges to trading with the centralized futures counterparty. We test that mechanism by verifying whether flows between exchanges dropped after the futures introduction. For that purpose, we purchase flow data from Crystal Blockchain, a commercial data provider specialized in cryptocurrency transaction analysis and blockchain monitoring. See Appendix A.2 for details.

While we benefit from detailed information on the direction of the flows, we only obtain aggregate flows by exchange, not broken down by currency. We, therefore, examine whether cross-exchange flows drop more after the futures introduction on exchanges where BTC–USD trading accounts for more than 50% of all transactions before the futures introduction.

This sample split leads to a clear distinction. The high BTC–USD share group contains 13 exchanges, the average share of BTC–USD in the pre-event period is 95.12%, and the lowest share is 76.70%. The low BTC–USD share group contains 9 exchanges, the average share of BTC–USD in the pre-event period is 12.92%, and the highest share is 36.60%.

The findings in Table 8 support that cross-exchange flows drop more after the futures introduction on exchanges where BTC–USD accounts for most trading activity before the futures introduction. In columns (1) and (2), we examine flows at the monthly frequency and account for seasonality using month fixed effects in column (2). In all specifications, we control for selection effects between two exchanges using directional flow fixed effects. Thus, we include interaction effects between indicator variables that are one for flows from one exchange to or from another exchange and zero otherwise.

In column (3), we show that our results are robust if we aggregate all flows in the pre- and post-event period. The negative and statistically significant coefficient of -0.883 suggests that following the futures introduction, cross-exchange flows drop, on average, by approximately 60% more for exchanges dominated by BTC–USD trading.

5.2 Triangular arbitrage

Our results may seem surprising given the possibility of triangular arbitrage through liquid fiat exchange rates (e.g., EUR–USD). 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).

These arguments are supported by the difficulty of trading pure fiat exchange rates in our sample of cryptocurrency exchanges. Specifically, we find that only Bitstamp and BTC-e had trades with pure fiat exchange rates. In unreported results, we find that excluding these exchanges increases the economic magnitude of the coefficients in column (6) of Panels A and B in Table 5 from 0.050 to 0.061 and from 0.047 to 0.064, respectively.

Triangular arbitrage may be easier among cryptocurrencies when fiat exchange rates are not involved. We examine this conjecture using the second most popular cryptocurrency ether (ETH).[10] Notably, every exchange that lists both BTC–USD and ETH–USD also lists BTC–ETH. Our results in Table 9 indicate, indeed, that the futures introduction is associated with a greater increase in price synchronicity for BTC–USD relative to ETH–USD across exchanges (columns 1 and 3), but not within exchanges (columns 2 and 4).

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 9, we find no significant difference between both exchange rates.

5.3 Economic channels

We next examine the economic channels of the impact of futures introduction to understand how it mitigates frictions to allow for more arbitrage trading and better price alignment.

[10]One added benefit of this test is that we can keep the characteristics of the fiat currency leg constant.

First, we consider short sale constraints, which may bias prices and prevent them from quickly incorporating new information (e.g., Miller, 1977; Jarrow, 1980; Diamond and E.Verrecchia, 1987; Hong and Stein, 2003). Derivatives can complete the market by allowing investors to invest in securities that profit when the underlying security has negative returns. In addition, it may lower the cost of establishing short positions if short-selling is allowed (e.g., Figlewski and Webb, 1993; Danielsen and Sorescu, 2001; Gagnon, 2018).

Some cryptocurrency exchanges (e.g., Kraken) allowed short selling before the BTC–USD futures introduction (Borri and Shaknov, 2021). Thus we can exploit cross-exchange differences in short sale constraints to test whether the introduction of a synthetic shorting technology was instrumental in relaxing such short sale constraints for trading spot assets.

Second, we test whether trading frictions prevent the free flow of arbitrage capital to eliminate price discrepancies in real time (e.g., Shleifer and Vishny, 1997). Impediments to arbitrage trading are driven both by the time it takes to transfer bitcoins across exchanges and by their corresponding price volatilities (i.e., without price uncertainty, transfer time is irrelevant). Thus, we combine bitcoin transfer time with price volatility to construct a measure of arbitrage risk. Since the futures enables arbitrageurs to implement long-short strategies without trading across exchanges, we expect weaker results for exchanges that featured low arbitrage risk before the futures introduction.

Specifically, we use the number of block confirmations required by exchange to deposit or withdraw bitcoins (Irresberger, John, Mueller, and Saleh, 2021). For each exchange pair, we sum their confirmation times and multiply the square root of aggregate confirmation time with their average price volatility in the pre-event period. For exchanges with multiple control currencies, we compute the volume-weighted price volatility across currency pairs.

Third, cryptocurrency markets face legal and geographical restrictions that prevent investors from freely trading bitcoin across different fiat denominations (Makarov and Schoar, 2020), giving rise to mild market segmentation (Errunza and Losq, 1985). In addition, arbitrage activity that requires the repatriation of arbitrage capital may be hampered by capital controls. Thus, we test whether heterogeneity in market segmentation based on the intensity of capital controls can explain variation in the strength of price alignment.

A fourth channel relates to information. The introduction of a centralized derivatives contract creates a benchmark price that may reduce informational asymmetries, reduce search costs, encourage entry, and increase competition among market participants (e.g., Duffie, Dworczak, and Zhu, 2017; Martin, 2021). Relatedly, imperfect alignment of prices could also be due to a lack of investor attention (Duffie, 2010), which 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 investor attention, we consider whether there are cross-exchange differences in the treatment effect according to exchange-specific measures that are correlated with investor attention. Thus, we collect the average Google search intensity for each exchange name in the pre-event period. To ensure comparability, we download each exchange's search intensity together with that of the word "bitcoin".

We extend Eq. (1) and examine channels using triple difference-in-differences regressions:

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

where $Channel$ is a zero-one indicator variable that captures cross-exchange heterogeneity in terms of trading frictions or attention. See Appendix A.3 for details.

Table 10 reports our findings. Broadly speaking, we find strong evidence in favor of futures enabling investors to circumvent trading frictions. Following the introduction, improvements in BTC–USD price synchronicity relative to those of other bitcoin-fiat pairs are greater on exchanges that do not allow for short-selling, that have higher arbitrage risk, and that are more segmented. There is little change in the magnitude of the coefficients in specifications with and without fixed effects, underscoring the stability of the estimates.

We find no support that the informational channel matters for cross-sectional differences in the impact of futures introduction. This may be due to electronic markets with transactions registered on public blockchains, where asymmetric information arguably matters less.

We cannot rule out the importance of alternative channels that affect all exchanges equally and are not identifiable through cross-exchange heterogeneity. For example, futures may relax capacity constraints by allowing for more short and long positions (Banerjee and Graveline, 2014), especially since bitcoin supply is limited by design and institutional investors are by and large prohibited from investing in unregulated cryptocurency markets. Thus, the introduction of centralized and regulated futures may change the investor composition by improving market access, which can increase spot liquidity (Sambalaibat, 2022).

5.4 The introduction of ethereum futures

To strengthen the external validity of our results, we consider additional evidence from the introduction of ethereum futures by the CME in February 2021. The CME also 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 six months before the announcement on December 16, 2020 to six months after the contract launch on February 8, 2021. We describe the data for this extension in Appendix A.4.

Since the blockchain confirmation time is lower on the Ethereum than on the Bitcoin blockchain, cross-exchange trading frictions are weaker for ethereum (Irresberger, John, Mueller, and Saleh, 2021). Thus, we expect to find an effect with a smaller economic magnitude that is identified at higher trading frequencies.

Indeed, our results in Table 11 show that the introduction of ethereum futures improves the price synchronicity of ETH–USD pairs more than that of ETH–CCY pairs. The coefficient 0.109 from our benchmark BTC result (column 5, Table 5) reported for comparability in column (1), is significantly larger than the value of 0.007 estimated in column (2).

In column (3), we separate those exchanges that do and do not permit triangular arbitrage based on supported currency pairs in CryptoCompare. The coefficient estimate for the triple difference estimator - 0.014 - is, similarly, an order of magnitude smaller than that found for the introduction of bitcoin futures reported in column (1).

In column (4) we report similar results when we sample prices at the hourly frequency. Consistent with the intuition that trading frictions should be stronger at higher trading frequencies, the coefficient is larger than that estimated in column (3).

Overall, our findings are largely similar for price integration (Panel B) and when we account for time varying unobserved differences across exchanges in columns (6) to (8).

5.5 Robustness, Additional Tests, and Discussion

We discuss a battery of additional robustness tests to support the validity of our main findings. We report these results in the Internet Appendix.

In Appendix Table B.3, we show that our benchmark results are robust to computing all market characteristics using a rolling window of one month of daily returns, which eliminates any data overlap in the construction of these metrics. In Table B.4, 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. Table B.5 also shows that our results are robust to different ways of clustering and standard error correction.

In Table B.6, 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 Table B.7, we show that our results are robust to different definitions of the pre-event and post-event periods. In columns (1) and (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 Table B.8, we find that shortening the sample period to plus and minus 9 or 6 months around the announcement has little impact on our results.

Placebo tests in Table B.9 with three months of data before and after hypothetical announcement dates on January 1, 2017 and July 1, 2018, yield insignificant results.

In our baseline results, we compare BTC–USD to the subsample BTC–EUR. Comparing BTC–USD to BTC–JPY in Table B.10 largely confirms our earlier evidence.

In Appendix Table B.11, we provide results for the individual liquidity metrics, including Roll's measure (Panel A), bid-ask spreads (Panel B), log volume (Panel C), and Amihud price impact (Panel D). Overall, these results largely confirm an improvement in liquidity following the futures introduction that we find based on the results for the aggregate illiquidity metric. The results for volume and the Amihud price impact measure 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 (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).

When we focus on the subset of exchanges that are not accused of market manipulation, as pointed out by Bitwise, we find a statistically significant and economically larger coefficient estimate in column (9) of Panels C and D.

We further report results using returns sampled at different frequencies (hourly, daily, weekly) in Table B.12. Many of the frictions that prevent perfect price alignment should be less binding for longer trading horizons. Indeed, we find that the magnitude of the main coefficients of interest and the explanatory power become smaller as we increase the sampling frequency from hourly to weekly trading horizons.

Finally, we report in Panel A of Table B.13 our benchmark regression specifications for all outcome variables when we exclude those exchanges where we substituted USDT for USD. In Panel B, we compute the BTC–USD exchange rates using cross-rates, that is, we compute BTC/USD = BTC/USDT × USDT/USD. Our conclusions remain largely unchanged across these robustness tests.

6 Conclusion

Are derivatives beneficial to spot markets? In this paper, we provide robust evidence in favor using the introduction of bitcoin futures contracts in December 2017. That event provides a distinctive opportunity to revisit a widely debated question because of its unique attributes compared to other derivatives listings.

Cryptocurrencies are perfectly fungible assets that trade on multiple exchanges at different prices. Futures contracts were selectively introduced for BTC–USD, and not for other bitcoin-fiat currency pairs, and trading frictions are directly measurable across exchanges. These features allow us to isolate cross-sectional variation at the exchange level to identify whether the bitcoin futures introduction was beneficial to its spot market.

Our results suggest that the BTC–USD futures introduction significantly enhanced cross-exchange price synchronicity and integration of BTC–USD relative to other cryptocurrency exchange rates. Moreover, we find supporting evidence for an increase in pricing efficiency, market quality, and liquidity, and a reduction in volatility. These improvements arise because futures enable investors to circumvent trading frictions in spot markets associated with short sale constraints, arbitrage risk, and market segmentation.

Activity in cryptocurrency derivative markets is growing exponentially, both in regulated and unregulatd markets. Our findings thus contribute to important ongoing regulatory debates about the benefits of cryptocurrency derivatives and related exchange traded funds.

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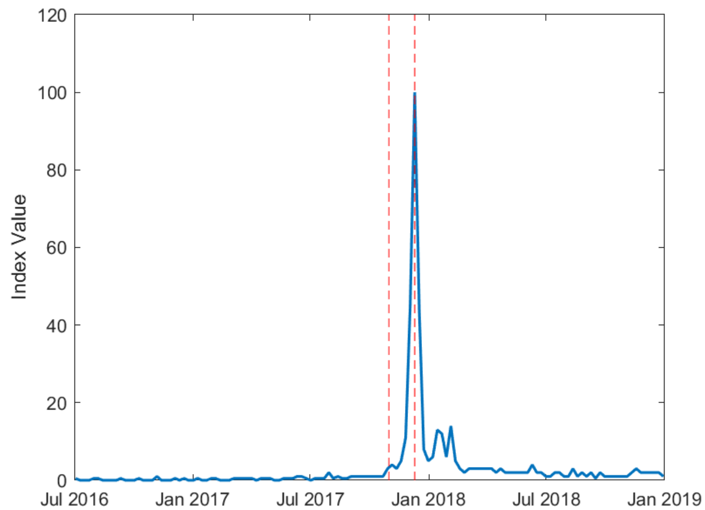
Figure 1: Bitcoin Futures Google Search Intensity and Bitcoin Price History

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)

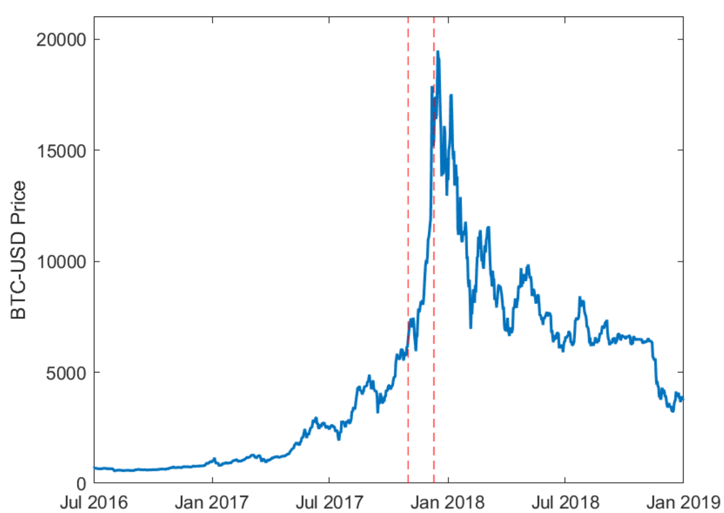


Figure 2: Bitcoin Cross-Exchange Return Correlations

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, averaged across exchanges for BTC–USD and BTC–CCY, respectively, where CCY refers to EUR, HKD, GBP, CAD, JPY, SGD, AUD, RUB, IDR. For better visualization, we smooth each time series using a moving average of correlation coefficients. The figure starts on July 1, 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.

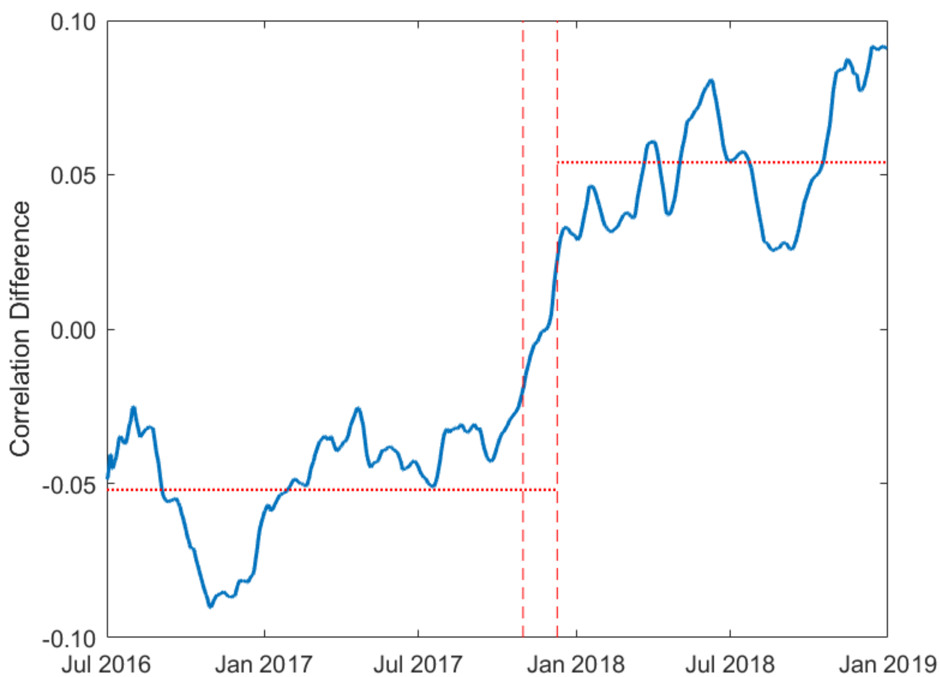


Figure 3: Impact of Bitcoin Futures Introduction on Price Synchronicity

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.

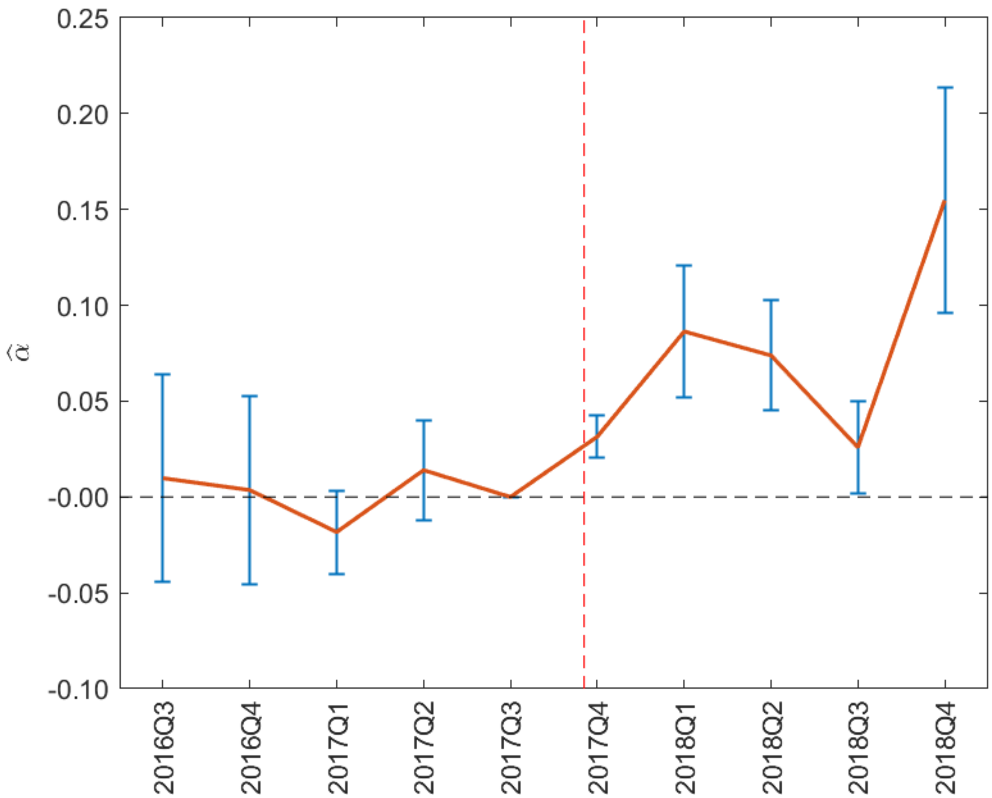


Figure 4: Supporting Evidence from Flows

In this figure, we provide a stylized illustration of anticipated changes in cross-exchange bitcoin flows after the bitcoin futures introduction. Before the futures introduction, arbitrage trading is characterized by bilateral flows across exchanges. After the futures introduction, investors can avoid sending funds across exchanges by initiating trades on one spot exchange and on the centralized futures exchange. We thank Nicola Fusari for suggesting this illustration.

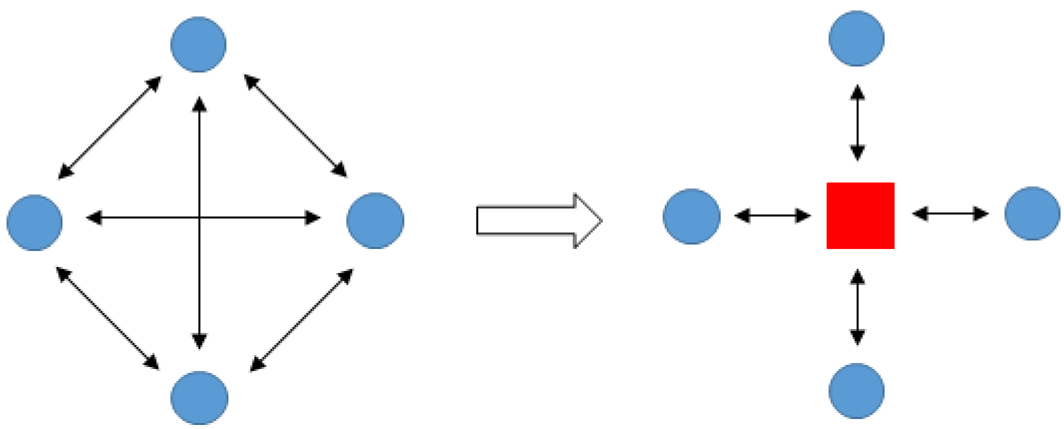


Table 1: Bitcoin Trading Volumes

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) illiquidity: Roll, CHL, Amihud, and Volume (in units of 1,000 BTC); (5) volatility σ. 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
Volatility	BTC-USD	07/31/2016	12/31/2018	557	0.6455	0.2257	0.6162	0.2855	1.0312
	Other	07/31/2016	12/31/2018	795	0.6901	0.3031	0.6302	0.2770	1.1787

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 (reported in parentheses) are clustered at the exchange pair level. ***, **, * indicate statistical significance at the one, five, or ten percent level, respectively.

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: The Importance of Bitcoin Futures Volume and Week-day/Week-end effects

In Panel A of this table, we report regression results from the projection of daily pairwise cross-exchange Pearson correlation coefficients (columns 1 to 6) and of Kapadia and Pu (2012) price synchronicity measures (columns 7 to 12) 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 days 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 daily frequency in rolling windows using fourteen days of daily returns. We aggregate the trading volume across all bitcoin futures contracts and measure the average trading volume in rolling windows of fourteen days. We add an indicator variable ($High\ Volume$) that is one if the trading volume is in the top 25% of the post-introduction volume distribution (it is mechanically zero in the pre-introduction period). In Panel B, we separately identify week-day and week-end effects. Bitcoin futures are open for trading between Sunday 6:00 p.m. and Friday 5:00 p.m. Eastern time. We compute returns separately for periods when the Bitcoin futures market is open and closed for trading, using the first and last recorded prices in each period, respectively. The control group contains all bitcoin-fiat currency pairs (ALL). 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 (reported in parentheses) are clustered at the exchange pair level. ***, **, * indicate statistical significance at the one, five, or ten percent level, respectively.

Panel A	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	ρ						κ					
Treatment×Post	0.085***	0.074***	0.081***	0.084***	0.071***	-0.000	0.122***	0.107***	0.118***	0.119***	0.104***	0.024**
	(0.012)	(0.011)	(0.012)	(0.012)	(0.010)	(0.008)	(0.016)	(0.013)	(0.015)	(0.015)	(0.013)	(0.011)
Treatment×Post×High Volume	0.042**	0.038**	0.043**	0.042**	0.039**	0.054***	0.034**	0.030*	0.036**	0.035**	0.030*	0.051***
	(0.017)	(0.016)	(0.017)	(0.017)	(0.017)	(0.020)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.014)
N	144711	144711	144711	144711	144711	52470	144711	144711	144711	144711	144711	52470
adj. R^2	0.030	0.273	0.161	0.046	0.419	0.674	0.055	0.305	0.191	0.072	0.463	0.570
Control	ALL	ALL	ALL	ALL	ALL	ALL	ALL	ALL	ALL	ALL	ALL	ALL
Xchange-Pair FE		✓			✓			✓			✓	
Day FE			✓		✓				✓		✓	
Ccy FE				✓	✓	✓				✓	✓	✓
Xchange-Pair×Day FE						✓						✓

Panel B	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	ρ						κ					
	ρ (benchmark)		ρ (week-day)		ρ (week-end)		κ (benchmark)		κ (week-day)		κ (week-end)	
Treatment×Post	0.109***	0.050***	0.119***	0.049***	0.087***	0.008	0.118***	0.047***	0.110***	0.077***	0.035	0.011
	(0.017)	(0.010)	(0.014)	(0.009)	(0.021)	(0.016)	(0.016)	(0.009)	(0.014)	(0.013)	(0.023)	(0.023)
N	4310	1586	4310	1586	4310	1586	4310	1586	4310	1586	4310	1586
adj. R^2	0.437	0.812	0.431	0.750	0.432	0.813	0.662	0.863	0.661	0.825	0.527	0.686
Control	ALL	ALL	ALL	ALL	ALL	ALL	ALL	ALL	ALL	ALL	ALL	ALL
Xchange-Pair FE	✓		✓		✓		✓		✓		✓	
Month FE	✓		✓		✓		✓		✓		✓	
Ccy FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Xchange-Pair×Month FE		✓		✓		✓		✓		✓		✓

Table 7: Main Results for Market Quality, Price Efficiency, Liquidity, Volatility

In 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, illiquidity variables λ, and volatility σ, 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 variables 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) or only BTC–EUR (EUR) currency pairs. 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 (reported in parentheses) are clustered at the exchange×currency level. ***, **, * indicate statistical significance at the one, five, or ten percent level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	q		D1		λ		σ	
Treatment×Post	0.036***	0.030**	-0.072**	-0.035**	-0.347**	-0.170**	-0.039**	-0.026*
	(0.012)	(0.012)	(0.031)	(0.013)	(0.154)	(0.080)	(0.017)	(0.015)
N	920	683	573	374	920	683	920	683
adj. R^2	0.539	0.589	0.663	0.792	0.743	0.847	0.827	0.839
Control	ALL	ALL	EUR	EUR	ALL	ALL	ALL	ALL
Xchange FE	✓		✓				✓	
Month FE	✓		✓		✓		✓	
Ccy FE	✓	✓	✓	✓			✓	✓
Xchange×Month FE		✓		✓		✓		✓
Xchange×Ccy FE					✓	✓		

Table 8: Flow Patterns Around Futures Introduction

In this table, we report the estimation from a regression of cross-exchange flows on the treatment indicator ($Treatment$) that takes the value one for an exchange pair where BTC–USD trading volume accounts for more than 50% of all trading volume on both exchanges in the pair 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 flows as $Flows = \ln(1 + flows)$, where $flows$ is the aggregate BTC volume transferred between two exchanges. We account for the direction of flows using interaction effects between indicator variables that are one for flows from one exchange to or from another exchange and zero otherwise. As a result, the treatment indicator ($Treatment$) drops out from the specification. Flows are measured at the monthly frequency. For the specification in column (3), we collapse monthly flows to the aggregate amounts before and after introduction. 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. ***, **, * indicate statistical significance at the one, five, or ten percent level, respectively based on standard errors (reported in parentheses) clustered at the interaction of the exchange where bitcoins are sent to and the exchange from which bitcoins are received.

	(1) Monthly Flows	(2) Monthly Flows	(3) Aggregate Flows
Post	-0.577***		-0.810***
	(0.155)		(0.263)
Treatment×Post	-0.994***	-1.000***	-0.883**
	(0.273)	(0.273)	(0.429)
N	10628	10628	916
adj. R^2	0.673	0.684	0.528
Exchange from FE×Exchange to FE	✓	✓	✓
Month FE		✓	

Table 9: 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 (reported in parentheses) are clustered at the exchange pair level. ***, **, * indicate statistical significance at the one, five, or ten percent level, respectively.

	(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		✓		✓		✓		✓

Table 10: Economic Channels

In this table, we estimate Equation (12) to identify the effect of channels on 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. *Short Selling* is equal to 1 if an exchange pair allows short selling in the pre-event period on both exchanges and 0 otherwise. *High Arbitrage Risk* is equal to 1 if the arbitrage risk measure is above its sample median and 0 otherwise. *Strict Capital Control* is equal to 1 if an exchange is head-quartered in a country with capital controls and 0 otherwise. *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. Monthly 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*×*Short Selling* (*Treatment*×*Post*×*High Arbitrage Risk*; *Treatment*×*Post*×*Strict Capital Control*; *Treatment*×*Post*×*High Attention*) in Panels A and B. 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 (reported in parentheses) are clustered at the exchange pair level. ***, **, * indicate statistical significance at the one, five, or ten percent level, respectively.

Panel A: Synchronicity ρ	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treatment×Post	0.128***	0.107***	0.006	0.002	0.103***	0.097***	0.109***	0.093***
	(0.023)	(0.017)	(0.011)	(0.011)	(0.017)	(0.013)	(0.020)	(0.017)
Treatment×Post×Short Selling	-0.115***	-0.101***						
	(0.027)	(0.022)						
Treatment×Post×High Arbitrage Risk			0.091***	0.095***				
			(0.022)	(0.022)				
Treatment×Post×Strict Capital Control					0.169***	0.142***		
					(0.033)	(0.030)		
Treatment×Post×High Attention							0.059	0.066
							(0.044)	(0.041)
N	2933	2933	2309	2309	4310	4310	4310	4310
adj. R^2	0.082	0.501	0.134	0.435	0.120	0.494	0.039	0.444
Panel B: Integration κ	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treatment×Post	0.170***	0.134***	0.030	0.025	0.117***	0.109***	0.129***	0.104***
	(0.026)	(0.017)	(0.026)	(0.025)	(0.020)	(0.015)	(0.022)	(0.017)
Treatment×Post×Short Selling	-0.131***	-0.108***						
	(0.033)	(0.027)						
Treatment×Post×High Arbitrage Risk			0.097***	0.101***				
			(0.035)	(0.034)				
Treatment×Post×Strict Capital Control					0.154***	0.118***		
					(0.037)	(0.035)		
Treatment×Post×High Attention							0.038	0.051
							(0.048)	(0.044)
N	2933	2933	2309	2309	4310	4310	4310	4310
adj. R^2	0.244	0.716	0.346	0.682	0.168	0.688	0.115	0.663
Control	ALL	ALL	ALL	ALL	ALL	ALL	ALL	ALL
Xchange (or-Pair) FE		✓		✓		✓		✓
Month FE		✓		✓		✓		✓
Ccy FE		✓		✓		✓		✓

Table 11: Ethereum Futures Introduction

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 months following the introduction of ethereum futures on February 8, 2021; and their interaction ($Treatment \times Post$). The indicator NTA is one if triangular arbitrage is not feasible within an exchange and zero otherwise. Pearson correlation coefficients and the integration measures are computed at a monthly frequency in rolling windows using three months of daily returns. Because of data sparsity, we require a minimum of 40% of observations with each estimation interval to insure stability of the parameter estimates. The control group contains all bitcoin-fiat currency pairs (ALL). We examine 6 months before and after the futures introduction but exclude the anticipation period. Thus, the sample period is March 1, 2020 to August 31, 2021, but we exclude the anticipation period between September 1, 2020 and February 28, 2021 (ethereum futures introduction was announced on December 16, 2020 and launched on February 8, 2021). Standard errors (reported in parentheses) are clustered at the exchange pair level. ***, **, * indicate statistical significance at the one, five, or ten percent level, respectively.

Panel A: Synchronicity ρ	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	BTC	ETH	ETH	ETH	BTC	ETH	ETH	ETH
	Daily	Daily	Daily	Hourly	Daily	Daily	Daily	Hourly
Treatment×Post	0.109***	0.007***	0.003	-0.009	0.050***	-0.000	-0.002	0.002
	(0.017)	(0.003)	(0.003)	(0.014)	(0.010)	(0.004)	(0.004)	(0.019)
Treatment×Post×NTA			0.014**	0.082***			0.016*	0.110**
			(0.005)	(0.026)			(0.008)	(0.042)
N	4310	1693	1693	1693	1586	836	836	836
adj. R^2	0.437	0.246	0.277	0.538	0.812	0.302	0.314	0.484
Panel B: Integration κ	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	BTC	ETH	ETH	ETH	BTC	ETH	ETH	ETH
	Daily	Daily	Daily	Hourly	Daily	Daily	Daily	Hourly
Treatment×Post	0.118***	0.012*	0.000	-0.026	0.047***	0.005	-0.000	-0.001
	(0.016)	(0.007)	(0.008)	(0.020)	(0.009)	(0.009)	(0.009)	(0.023)
Treatment×Post×NTA			0.040***	0.071*			0.046**	0.155***
			(0.013)	(0.039)			(0.022)	(0.056)
N	4310	1693	1693	1693	1586	836	836	836
adj. R^2	0.662	0.539	0.562	0.734	0.863	0.620	0.625	0.689
Control	ALL	ALL	ALL	ALL	ALL	ALL	ALL	ALL
Xchange-Pair FE	✓	✓	✓	✓				
Month FE	✓	✓	✓	✓				
Ccy FE	✓	✓	✓	✓	✓	✓	✓	✓
Xchange-Pair FE× Month FE					✓	✓	✓	✓