THE IMPACT OF DERIVATIVES ON CASH MARKETS:

Evidence from the Introduction of Bitcoin Futures Contracts

FINAL REPORT

Authors

Patrick Augustin
McGill University & Canadian Derivatives Institute

Alexey Rubtsov
Global Risk Institute

Donghwa Shin
University of North Carolina at Chapel Hill

GRI GLOBAL RISK INSTITUTE

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ABOUT THIS REPORT:

Hailed as "one of the most powerful innovations in Finance in 500 years", there now exist more than 2,000 cryptocurrencies with total market capitalization of more than $200 billion USD. Furthermore, according to industry research, total cryptocurrency derivatives trading volume in futures, options, and swaps surpassed $3 trillion USD. The central question that we study in this research is whether the introduction of cryptocurrency derivatives is beneficial or detrimental to the underlying cryptocurrency spot markets.

The answer to that question is not obvious. On the one hand, derivatives could be used as a substitute for spot markets and, therefore, lower their informational efficiency due to a reduction of spot trading activity. On the other hand, derivatives could complement spot markets and make them more efficient and informative, because they can provide the ability to hedge spot price fluctuations. In this respect, empirical evidence from other asset classes (e.g., equities or commodities) is far from conclusive. More importantly, however, this question is critical in the context of ongoing discussion among regulators, who actively debate whether to allow new cryptocurrency investment products. For example, in the United States, the Securities and Exchange Commission has persistently rejected applications for the listing of bitcoin exchange traded funds.

To shed light on our question, we exploit the introduction of bitcoin futures on the Chicago Mercantile Exchange and the Chicago Board of Options Exchange in December 2017. This event is particularly well suited for our analysis, because the futures contract was only introduced on bitcoin against the U.S. dollar (BTC-USD), and not on any other bitcoin-fiat currency pair. Moreover, fully fungible (i.e., mutually interchangeable) BTC-USD assets trade on multiple exchanges. By comparing the dynamics of BTC-USD relative to other bitcoin-fiat pairs (e.g., BTC-CAD) traded on the same exchange, these features allow us to identify whether the introduction of the bitcoin futures was beneficial or detrimental to the bitcoin spot market.

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

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

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Abstract

We exploit a unique feature of cryptocurrency markets to provide new evidence on how derivatives impact cash markets. In December 2017, the CME and the CBOE both introduced futures contracts on bitcoin (BTC) against USD, but not on any other cryptocurrency exchange rate pairs. Because identical cryptocurrencies trade on multiple exchanges, we can examine how the introduction of bitcoin futures changed various attributes of BTC-USD relative to other cryptocurrency pairs, keeping exchange characteristics constant. Following the futures introduction, we find a significant increase in cross-exchange BTC-USD price synchronicity relative to other exchange rate pairs, as demonstrated by an increase in price correlations and a reduction in arbitrage opportunities. We also find evidence in support of an increase in market efficiency and market quality. There is suggestive evidence of increasing market liquidity, although these results are weaker. Overall, our analysis supports the view that the introduction of BTC-USD futures was beneficial to the bitcoin cash market by making the underlying prices more informative.

JEL Classification Codes: C1, C2, G12, G13, G14, O33, Y80

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

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

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

1 Introduction

Hailed as "one of the most powerful innovations in finance in 500 years" (Casey and Vigna, Jan. 23, 2015), there now exist more than 2,000 listed cryptocurrencies with a market capitalization of more than $200 billion (CoinMarketCap, 2020). A parallel development to the growth in the cryptocurrency cash markets is an explosive growth of cryptocurrency derivatives contracts and trading platforms. According to industry research, total cryptocurrency derivatives trading volume in futures, options, and swaps surpassed $3 trillion in 2019, with 19 swap execution facilities approved and regulated by the U.S. Commodity Futures and Trading Commission (CFTC) (Song and Wu, 2020; CryptoCompare, 2020). The U.S. Securities and Exchange Commission (SEC) approved the first cryptocurrency derivatives fund, but has repeatedly rejected applications for the listing of exchange traded funds. Despite the rapid expansion of the cryptocurrency derivatives space, little is known about whether the introduction of such derivatives is beneficial or detrimental to cryptocurrency cash markets.

The nature of the impact of the introduction of derivatives on their corresponding cash markets has been the subject of controversial debates and mixed empirical evidence.[1] In frictionless markets, derivatives are redundant, and their introduction should be irrelevant for spot assets. However, a role for derivatives emerges if markets are incomplete, investors face leverage, funding, or short selling constraints, or if spot prices are not perfectly revealing underlying fundamentals. In the presence of such frictions, the impact of derivatives on cash markets depends primarily on whether related assets are complements or substitutes.

The introduction of bitcoin futures contracts by the Chicago Board of Options Exchange (CBOE) and the Chicago Mercantile Exchange (CME) Group in December 2017 provides a unique opportunity to revisit the mixed evidence on the impact of derivatives on cash markets. First, futures contracts were introduced only for bitcoin-USD (BTC-USD), but not for any other bitcoin-fiat currency pairs (e.g., BTC-EUR), allowing us to examine cross-sectional differences in changes of bitcoin attributes in response to the introduction of the futures contract.

Second, identical BTC-USD assets trade on multiple exchanges at different prices with different degrees of liquidity, giving rise to seeming market inefficiencies and arbitrage opportunities (Makarov and Schoar, 2019). Thus, the market for digital assets is a near perfect setting to study the pricing of an identical asset traded on multiple exchanges in the spirit of Hasbrouck (1995). While price discrepancies of similar assets have been studied in other contexts, assets are typically not fully fungible, even in closely related securities such as ADRs (Gagnon and Karolyi, 2010). In contrast, bitcoin is fully fungible across exchanges. Thus, we can examine the within-exchange variation of BTC-USD relative to other cryptocurrency pairs in response to the introduction of bitcoin futures, keeping exchange characteristics constant.

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

Specifically, we first quantify the pricing efficiency and market quality of cryptocurrency exchange rates. We compute four sets of characteristics: measures of price synchronicity such as pairwise cross-exchange price correlations and price integration following Kapadia and Pu (2012); market quality following Hasbrouck (1993), price efficiency following Hou and Moskowitz (2005), and several liquidity measures, including the Amihud (2002) price impact measure, the Roll (1984) illiquidity measure, the Abdi and Ranaldo (2017) bid-ask spread measure, and trading volume. Following the quantification of these market characteristics, we estimate whether the introduction of the BTC-USD futures contract in December 2017 improved the characteristics of BTC-USD exchange rate pairs more than those of other bitcoin-fiat currency pairs, which we broadly refer to as BTC-CCY. Given cross-sectional differences in treatment (BTC-USD vs. BTC-CCY), we can examine the impact on BTC-USD relative to other cryptocurrency exchange rates, and isolate the impact of the futures introduction.

Despite the large literature on the introduction of derivatives markets on cash markets, new evidence is needed. First, the existing empirical evidence is mixed at best, and divided at worst. Thus, providing novel evidence from new asset markets that permit better identification improves our understanding of a longstanding and unresolved question in asset pricing. We exploit the unique setup of cryptocurrency markets, where fully fungible assets trade on different exchanges at differential prices, to better identify the impact of futures listing on the market quality and efficiency of cryptocurrency cash markets.

More importantly, there exists no evidence on how the listing of derivatives products linked to cryptocurrency assets affects the underlying's market attributes, despite the importance of that matter for current regulatory debates. Several proposals for bitcoin (BTC) exchange-traded funds (ETF) have been denied approval by the SEC, due to concerns of manipulation in related spot markets. The debate is further emphasized by opposing views expressed amid policymakers and industry participants. For example, former chairman of the CFTC, Christopher Giancarlo, argues that regulators allowed the launch of bitcoin futures contracts in December 2017 because it was widely believed by the CFTC, the Treasury, the SEC and former National Economic Council director Gary Cohn, that it would pop the bitcoin bubble and make prices better reflect fundamental values. Similarly, the company Bitwise proposes that "the launch of futures ... dramatically improved the efficiency of the bitcoin market in 2018." Other commentators suggest that "bitcoin's price dictates BTC derivatives market and not vice-versa" (Biraajmaan, 2019). Against the backdrop of these debates, we provide formal evidence on how the bitcoin futures introduction impacted the quality, efficiency, liquidity, and price informativeness of the bitcoin cash market.

For our analysis, we use data from Kaiko, which provides cryptocurrency price and trading volume information for bitcoin exchange rates against the USD (BTC-USD) and a set of other fiat currencies (BTC-CCY). Trades are timestamped to the millisecond and executed on numerous trading platforms. Given our identification strategy of comparing the evolution of market characteristics for BTC-USD relative to other bitcoin exchange rate pairs around BTC-USD futures listing, we require, at any given point in time, a minimum of two currency pairs on each exchange. Our working sample contains 10 bitcoin-fiat currency exchange rates traded on 14 different exchanges between July 1, 2016 and December 31, 2018. In all tests, the treatment exchange rate BTC-USD is compared to the control group made up of BTC-EUR, BTC-GBP, BTC-HKD, BTC-SGD, BTC-JPY, BTC-AUD, BTC-IDR, BTC-CAD, and BTC-RUB. The 14 exchanges that are included in our sample are Binance, Bitfinex, Bitstamp, Bittrex, BTC-e, Coinbase, Gemini, GateCoin, HitBTC, Itbit, Kraken, OkCoin, Poloniex, and Quoine. In light of claims that cryptocurrency trading platforms are subject to market manipulations, we also focus on the subset of nine exchanges that are considered to be insulated from such manipulations, and that are, therefore, included in Bitwise's exchange traded fund proposal filed with the SEC. We compute daily and hourly log returns, and aggregate the quantity of traded bitcoins within each hour/day to obtain a measure of trading volume. These raw data are used to compute the metrics of price synchronicity, price efficiency, market quality, and liquidity.

We run differences-in-differences tests whereby we examine how the different characteristics for BTC-USD exchange rates change around the introduction of BTC-USD futures contracts relative to the characteristics of other bitcoin-fiat exchange rates, i.e., BTC-CCY. Our main tests are based on regressions with trading exchange platform fixed effects, which allows us to exploit the within exchange variation of BTC-USD relative to other exchange rate pairs following futures listings. We also include currency fixed effects to account for time-invariant cross-sectional differences at the exchange rate level, and we include daily time fixed effects to absorb common variation across exchanges that could be associated with a maturing and growing market.

Overall, we find strong evidence in favor of an increase in cross-exchange price synchronicity and integration. On average, the Pearson correlation coefficient between cross-exchange returns significantly increases by about 9 percentage points more for BTC-USD returns following the futures introduction than for returns of other bitcoin-fiat exchange rates. This is economically also meaningful given that their average in-sample correlation coefficients are 0.91 and 0.83 for the treatment and control currencies, respectively. Similarly, we find that the differential increase in price synchronicity is about 12.8 percentage points, implying a statistically significant reduction in arbitrage opportunities.

We also find supporting evidence that BTC-USD exchange rates become significantly more informationally efficient than other exchange rate pairs, and that the market quality of BTC-USD exchange rates increases. Finally, our evidence supports the view that there is a differential increase in liquidity following the futures introduction, which is stronger for BTC-USD, but the evidence for liquidity is overall weaker than for the other characteristics. The liquidity metrics are noisier if measured for exchanges that are suspect of market manipulation. Excluding the allegedly fraudulent exchanges, we estimate a statistically significant greater reduction in price impact for BTC-USD exchange rate returns, as measured by the Roll and Amihud price impact measures, and a comparatively greater increase in trading volume. However, we find no supporting evidence for a reduction in bid-ask spreads.

As a refinement of our tests, we exploit the settlement mechanisms of bitcoin futures.

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

Furthermore, we exploit the channels that may explain the positive impact from the introduction of futures contracts on bitcoin cash prices. According to theory, asynchronous price movements and arbitrage opportunities may arise because of either a lack of arbitrage capital and liquidity frictions, or limited investor attention. While it is challenging to measure these attributes perfectly, we use proxies that are likely correlated with liquidity frictions and investor attention. We rely on the liquidity metrics computed in our previous tests, and measure investor attention using the Google search intensity for cryptocurrency exchanges in our sample. Indeed, we do find significantly different results in terms of price synchronicity, liquidity, and price efficiency for exchanges ranked as being above or below the median level of frictions or attention. However, to our surprise, we find that the results are weaker for exchanges with higher liquidity and greater attention.

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

2 Related Literature

We relate primarily to two strands of literature: the emerging literature on cryptocurrencies and blockchains, and research on the impact of derivatives on cash markets.

2.1 Cryptocurrencies and Blockchain

Following the publication of a white paper by pseudonymous Satoshi Nakamato in 2008 (Nakamoto, 2008), bitcoin was officially introduced in 2009 as a peer-to-peer digital currency. While at inception, one bitcoin was not even traded, its price has since soared close to \$20,000 in December 2017, only to free fall back to about \$5,000 in December 2018. Together with the boom and bust of bitcoin and other cryptocurrencies, the financial economics literature on blockchains and cryptocurrencies has grown exponentially. Böhme, Christin, Edelman, and Moore (2015) provide a review of bitcoin and its potential blockchain-based applications. Yermack (2015) evaluates bitcoin's status as a real currency, Harvey (2016) reviews applications in cryptofinance, and Howden (2015) discusses the regulatory aspects of cryptocurrencies.

As a decentralized payment system built on aggregate consensus and free of intervention by central authorities, bitcoin was initially idealized as immutable and secure. Yet, Griffin and Shams (2019) suggest that bitcoin (and other cryptocurrency) prices are subject to market manipulation. Similarly, Gandal, Hamrick, Moore, and Oberman (2018) associate bitcoin volatility increases with suspicious trading activity. Li, Shin, and Wang (2018) suggest that pump-and-dump schemes in cryptocurrency markets are detrimental to the liquidity and price level of cryptocurrencies. Historical evidence also suggests that multiple cryptocurrency exchanges have been vulnerable to hacks, and Foley, Karlsen, and Putnins (2019) argue that bitcoin facilitates about $76 billion in yearly illegal activity.

We study market quality, efficiency, and price discovery in cryptocurrencies. Thus, our work is most closely related to studies on frictions and inefficiencies in bitcoin and other cryptocurrencies. Easley, O'Hara, and Basu (2019) examine the endogenous emergence of transaction costs. Makarov and Schoar (2019) pinpoint significant cross-exchange arbitrage opportunities in the prices of bitcoin, which are larger across than within countries. The authors provide suggestive evidence that arbitrageurs counterbalance the price impact of noise traders. Kroeger and Sarkar (2017) relate similar price differences to liquidity frictions, such as the bid-ask spread, order book depth and volatility, while Hautsch, Scheuch, and Voigt (2019) relate them to stochastic settlement latency. Yu and Zhang (2018) study price differences between spot exchange rates and matched synthetic exchange rates implied by cryptocurrencies, and relate price discrepancies to cross-border capital flow frictions (see also Choi, Lehar, and Stauffer (2018) for related work on the "Kimchi premium"). We differ from these studies by focusing on the quantification of price discovery and market quality in cryptocurrencies, and how these characteristics change with the introduction of the BTC-USD futures contract in December 2017, which ought to improve the efficiency of bitcoin by completing the market.

By studying price discrepancies of fully fungible assets across exchanges, we also relate more broadly to the literature on limits to arbitrage (Shleifer and Vishny, 1997; Gromb and Vayanos, 2010). Studies on the violations of the law of one price include, but are not limited to, examinations of "Siamese twin stocks" (Rosenthal and Young, 1990; Froot and Dabora, 1999; De Jong, Rosenthal, and Van Dijk, 2009), parent and subsidiary company stocks (Mitchell, Pulvino, and Stafford, 2002; Lamont and Thaler, 2003), differences between off-the-run and on-the-run Treasury spreads (Amihud and Mendelson, 1991; Krishnamurthy, 2002), and cross-listed stocks (Gagnon and Karolyi, 2010).

More tangentially, we relate to the literature that is focused on understanding the economics of blockchain technology (the institutional aspects of the blockhain technology and cryptocurrencies are described in Appendix A). For example, Biais, Bisiére, Bouvard, and Casamatta (2019) study consensus for the Proof-of-Work (PoW) blockchain protocol and find that persistent disagreement may arise in equilibrium. Hinzen, John, and Saleh (2019) highlight that PoW's structure generates limited adoption of cryptocurrencies that function solely as mediums of payment. Chiu and Koeppl (2019) examine the implications of the PoW blockchain technology for asset trading and settlement. Saleh (2019) studies conditions under which the Proof-of-Stake (PoS) blockchain protocol generates consensus. Rosu and Saleh (2019) also study PoS, focuing on the evolution of wealth dynamics. Cong and He (2019) show how the blockhain technology can lead to greater competition and consumer surplus, as well as to welfare-destroying collusion. See also Gandal and Halaburda (2014) for an examination of competition in cryptocurrency markets.

Additional work by Malinova and Park (2017) suggests that the blockhain may enhance welfare through increased transparency, and Cong, He, and Li (2019) argue that PoW leads to excessive energy expenditure and an endogenous formation of mining pools. Zimmerman (2019) demonstrates that the blockchain technology can lead to excessive price volatility and speculative activity. Finally, Yermack (2017) discusses implications of blockchains for corporate governance. For further discussions, see also Dwyer (2015) and Gans and Halaburda (2015).

2.2 Introduction of Derivatives and Impact on Cash Markets

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

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

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

With the growth of credit derivatives over the last two decades, researchers have also examined the relation between credit default swaps (CDS) and bonds. Das, Kalimipalli, and Nayak (2014) find a reduction in price efficiency and no improvement in bond liquidity following the onset of CDS trading. In contrast, Ismailescu and Phillips (2011) suggest that prices of sovereign bonds became more efficient following the inception of sovereign CDS contracts.

We provide the first evidence on how the introduction of bitcoin futures impacts the market quality, efficiency, and price synchronicity in the bitcoin cash market. In addition, we exploit the special design of the cryptocurrency market to provide new evidence on the longstanding question regarding the impact of derivatives on cash markets.

3 Institutional Background

The Wall Street Journal refers to cryptocurrencies as "one of the most powerful innovations in finance in 500 years" (Casey and Vigna, Jan. 23, 2015). Regulators have struggled to adapt existing laws in the areas of banking and securities regulation, and central banks around the world are exploring issuance of their own cryptocurrencies. There is a parallel proliferation of cryptocurrency derivatives. This raises the importance of understanding the implications of cryptocurrency derivatives listings on their corresponding cash markets. In this section, we first provide some background information on cryptocurrency cash markets, and then provide an overview of the current landscape of cryptocurrency derivatives.

3.1 Cryptocurrency Cash markets and Exchanges

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

Bitcoin was launched as the first cryptocurrency in 2009. Many cryptocurrencies, with only slight differences from bitcoin, started trading in subsequent years. A precise account of the number of cryptocurrencies in circulation is difficult to obtain. Nonetheless, Irresberger, John, and Saleh (2019) document 907 cryptocurrencies that possess market capitals exceeding 1 million USD. According to CoinMarketCap (2020), there exist more than 2,000 listed cryptocurrencies as of April 2020, with a market capitalization of more than $200 billion. Nonetheless, few cryptocurrencies account for the bulk of that market capitalization. Bitcoin is especially dominant and consistently accounts for the largest market capitalization among all cryptocurrencies.

One of the unique features of the cryptocurrency market is that cryptocurrencies (e.g., bitcoin) trade on many different trading venues, called cryptocurrency exchanges. On these platforms, investors can easily buy and sell cryptocurrencies in exchange for either fiat currencies, such as USD or EUR, or other cryptocurrencies. CoinMarketCap (2020) reports that, as of April 2020, there exist 297 (66) cryptocurrency exchanges where the aggregate daily trading volume is over $2 million ($100 million). Investors may easily buy a bitcoin on one exchange and sell it on another exchange. In other words, a given bitcoin-fiat currency is fully fungible across exchanges, and so the prices of, say, BTC-USD, ought to be the same across exchanges in spite of being exchanged in multiple trading venues. Nonetheless, cross-exchange prices of a given currency pair differ, likely due to exchange-specific risks and frictions.

The two aforementioned properties of cryptocurrencies, multi-listing and fungibility, provide us with an ideal laboratory to study the effect of bitcoin futures introduction on bitcoin cash markets. We provide additional details regarding blockchains and cryptocurrencies in Appendix A.

3.2 Cryptocurrency Derivatives

With the proliferation of cryptocurrencies has come a proliferation of cryptocurrency derivatives. Bitcoin largely dominates the market as the underlying cash asset, although the menu of contracts tied to other cryptocurrencies is growing. The significant price swings of bitcoin naturally attract speculative investors to benefit from the high price volatility and others to hedge price movements.

One major distinction between the existing derivatives products is whether they are regulated or not. In 2015, the CFTC maintained that bitcoin is a commodity, and declared the same for ether in 2019. Thus, the regulation of bitcoin and ether derivatives is governed by the 1936 Commodity Exchange Act, and under the purview of the CFTC.

The most prominent cryptocurrency derivatives are likely bitcoin futures contracts, which started being offered as regulated and CFTC approved products by the CME and the CBOE in December 2017. While CBOE stopped trading bitcoin futures in June 2019, trading volumes on the CME have been steadily increasing, leading the CME to request CFTC-approval for higher position limits for its investors in late 2019. According to an article in Cointelegraph, there was an average of 4,929 daily contracts traded in its first two years of existence, corresponding to $182 million in notional value (Avan-Nomayo, 27 December 2019). The CME also started to offer options on futures contracts in 2020.

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. Following the CFTC's approval for Tassat to become a regulated crypto derivatives exchange in 2019, it is estimated that there are 19 CFTC-licensed platforms in total. 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. Several exchanges, like Phemex, BitMex and Bitfinex offer up to 100 times leveraged perpetual futures contracts for various cryptocurrencies, including bitcoin, ethereum, ripple, litecoin, and EOS, among others. A full review of all contracts is outside the scope of this paper.

Besides the market of U.S. regulated crypto derivatives exchanges, there is an even bigger and growing market of non-regulated cryptocurrency derivatives exchanges, with a proliferation of trading platforms and product offerings. Countries take vastly different approaches to regulation, with some countries, such as Singapore, being more receptive to allowing regulated platforms than others, e.g., the United Kingdom. Market data suggest that a total of $3 trillion in derivatives was traded in 2019 (Song and Wu, 2020). While less than 3% of the overall trading happened on traditional exchanges, approximately 97% was taken up by token futures trading in 2019. Overall trading volume is also heavily concentrated, with contracts tied to bitcoin and ethereum accounting for approximately 80% of total trading volume. Concentration is furthermore visible at the exchange level. The top 3 (4) exchanges accounted for 85% (90%) of total annual trading volume, with BitMEX, OKEx, and Huobi DM (Bybit) recording $973 billion, $869 billion, and $661 billion ($149 billion), respectively (Song and Wu, 2020; CryptoCompare, 2020).

In early December 2019, the New York Digital Investment Group was the first company to receive approval from the SEC to launch a fund called Stone Ridge Trust, set to invest in cash-settled bitcoin futures contracts traded on CFTC-regulated exchanges (Song and Wu, 2020). However, at the time of writing, the SEC has rejected various proposals for bitcoin related ETFs by Winklevoss, VanEck, SolidX, and Bitwise.

4 Development of Hypotheses and Analysis

Our goal is to describe and quantify the characteristics of the cryptocurrency market, focusing on bitcoin. We consider several characteristics relating to price synchronicity and integration, price efficiency, market quality, and liquidity. We describe below how we estimate and compute these characteristics, which we generally refer to as $Characteristic_{i,j,t}$, where $Characteristic \in \{Synchronicity,\ Efficiency,\ Quality,\ Liquidity\}$, i refers to cryptocurrency exchange rate pair (cross-exchange cryptocurrency exchange rate pairs) in the analyses on efficiency, quality, and liquidity (synchronicity); j denotes the exchange trading platform (exchange pair for synchronicity) on which the currency pair is being traded, and t refers to the time of the observed characteristic. For most of our analysis, we consider either a daily or an hourly frequency.

We are interested in describing the state, as well as the evolution of the quality and efficiency of cryptocurrencies. Accordingly, we examine how these characteristics evolved with the introduction of the BTC-USD futures contracts by the CBOE and the CME in December 2017. Several developments of the market at the time are particularly useful for our purpose. First, the introduction of the BTC-USD futures contract was largely unanticipated until shortly before the date of introduction. In support of this, we highlight in Figure 1 that Google searches of the word "bitcoin futures" were largely non-existent before the CME officially announced their launch on October 31, 2017. Second, the futures contract was only introduced for the BTC-USD currency pair, but not for other currency pairs (e.g., BTC-EUR). Third, bitcoin is a close to perfect example of one asset traded on multiple exchanges in the spirit of Hasbrouck (1995). As bitcoins traded on different exchanges are fully fungible, they ought to trade at the same price. Accordingly, observed price differences of a currency pair across exchanges should be driven by exchange-specific frictions, while price differences between BTC-USD and BTC-CCY exchange rate pairs should be driven by market-specific frictions.[2]

Thus, with some abuse of language, we apply a differences-in-differences test to understand how the introduction of the BTC-USD futures contract improved the efficiency and market quality of USD-denominated bitcoin cash relative to other fiat denominations. Absent frictions, derivatives are redundant assets. In the presence of frictions, derivatives may complete the market. Several studies have shown that cryptocurrencies are prone to trading frictions (e.g., Makarov and Schoar, 2019; Hautsch, Scheuch, and Voigt, 2019; Yu and Zhang, 2018). Thus, it is plausible to expect that the futures introduction could reduce these frictions in the cryptocurrency market, and improve the efficiency, quality, price synchronicity, and liquidity of BTC-USD relative to other bitcoin-fiat exchange rate pairs. More specifically, we test the following benchmark regression:

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

[2] While it is possible to include other control assets such as bitcoin cash (BCH), which was created through a bitcoin hard fork and which shares common characteristics with bitcoin, we focus on comparing BTC-USD and BTC-CCY because they are *identical* assets and, therefore, fully fungible. Relying on fully fungible assets helps better identify the effect of the introduction of bitcoin futures on the various characteristics.

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 contract in December 2017, 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. We account for unobserved common factors through the time fixed effects γ_t. In our benchmark tests, we cluster the standard errors at the exchange and currency level to correct for serial correlation. In robustness tests, we verify that our results remain significant when we also cluster at the time dimension. In the following paragraphs, we describe how we compute the characteristics.

4.1 Price Synchronicity and Integration

Our first characteristic for cryptocurrency returns relates to their price synchronicity, which we measure as the simple Pearson correlation coefficient between log returns across exchanges. For example, 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 at time t, where $p_{i,j,t}$ denotes the exchange rate level. Then we compute the Pearson correlation coefficient of currency pair i between exchanges j and j' as

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

where $cov\left(\cdot,\cdot\right)$ denotes the covariance of pairwise log returns, and $\sigma_{i,\cdot,t}$ their standard deviations. We compute these pairwise correlation coefficients both at an hourly and at a daily level, using rolling windows of 14 days. This simple measure of price synchronicity directly indicates the alignment of cryptocurrency returns across exchanges, and therefore reflects the pricing efficiency of cyptocurrency exchange rate pairs.

Kapadia and Pu (2012) compute a non-parametric measure of price synchronicity between stocks and bonds that can be interpreted as a measure of market integration. As an alternative to correlation coefficients, we adopt a similar approach and measure price synchronicity between prices of BTC-USD and BTC-CCY across different exchanges. We compute these both at an hourly and at a daily frequency, using rolling windows of 14 days. We assume that prices across exchanges are aligned if returns move in the same direction, i.e., $\mathcal{I}\left(r_{i,j,t}r_{i,j',t} > 0\right)$, and misaligned if they move in opposite directions, i.e., $\mathcal{I}\left(r_{i,j,t}r_{i,j',t} < 0\right)$. The integration measure $\kappa_{i,j/j',t}$ captures the frequency of price synchronicity over a given horizon τ:

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

where we have M observations of BTC-USD price changes across two exchanges. As the price discrepancy measure relies exclusively on the concordance of BTC-USD or BTC-CCY prices, $\kappa_{i,j/j',t}$ can be mapped into the Kendall's tau coefficient, $K_{i,j/j',t}$, defined as $K_{i,j/j',t} = 4\kappa_{i,j/j',t}/\left(M\left(M-1\right)\right) - 1$, which has well-known statistical properties to test for inference. For perfectly synchronous cross-exchange returns, $K_{i,j/j',t} = 1$. The higher its value, the more integrated are cryptocurrency prices across exchanges. We exploit the cross-sectional differences and time series variation in the Kapadia and Pu (2012) integration measure. Specifically, we examine whether there is an increase in price integration following futures listing that is significantly greater for BTC-USD than for other bitcoin-fiat currency pairs.

4.2 Price Efficiency

We measure the price efficiency of cryptocurrency log returns, computed as $r_{i,j,t+1} = \ln(p_{i,j,t+1}/p_{i,j,t})$, where $p_{i,j,t}$ denotes the price of the exchange rate pair i on exchange j at day t. To that end, we use the $D1$ measure proposed by Hou and Moskowitz (2005). As in their work, we employ the return on the market $r_{m,t}$ as the relevant news to which cryptocurrencies respond. Ex-ante, it is less clear what we should use as the market return in the cryptocurrency space. We follow Benedetti (2018) and use the MVIS CryptoCompare Digital Asset 10 Index (a modified market cap-weighted index that tracks the performance of the ten largest and most liquid digital assets). At the end of each day, we regress returns on the contemporaneous and lagged market returns up to 4 days:

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

If new information is instantaneously incorporated into returns, then $\beta_{i,j}$ is significantly different from zero, and the lagged coefficients $\delta_{i,j}^{-n}$ will not be significant. If information gets incorporated with a lag, then some of the lagged coefficients $\delta_{i,j}^{-n}$ will be significantly different from zero.

Based on these regression estimates, we compute the $D1$ measure, which compares the fit of a constrained model, based only on contemporaneous variables on the right-hand side of the regression in Equation (4), and an unconstrained regression model, which has both contemporaneous and lagged data on the right-hand side of the regression. The measure is given by:

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

where $Constrained\ R^2$ ($Unconstrained\ R^2$) is obtained from a constrained (unconstrained) version of the regression in Equation (4). We use rolling windows of 90 days to evaluate the measure. $D1$ is bounded between 0 and 1. The higher the $D1$ measure, the greater the extent to which cryptocurrency returns are explained by lagged information. Thus, $D1$ is a measure of cryptocurrency inefficiency. We can compute this measure separately for different cryptocurrency exchange rate returns, and compare cross-sectional differences between BTC-USD relative to other bitcoin-fiat exchange rate pairs around the time of futures listing.

4.3 Market Quality

We measure market quality using the q measure proposed by Hasbrouck (1993). Price quality reflects the accuracy of prices. According to Hasbrouck (1993), returns r_t (we omit the currency pair and exchange subscripts for simplicity), i.e., (log) changes in a security's price, reflect changes in the efficient price m_t, and changes in the pricing error s_t, such that $r_t = m_t - m_{t-1} + s_t - s_{t-1}$. Both returns and pricing errors have a variance, denoted by σ_r^2 and σ_s^2, respectively, and σ_s^2/σ_r^2 is a normalized pricing error. The measure of market quality q is then given by:

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

where a higher q suggests that prices deviate less from their efficient level, and so market quality is higher. To estimate the market quality, in a first step, we estimate the parameters $\{a, \sigma_e^2\}$ from an MA(1) model for returns over a 90-day window:

$$r_t = e_t - ae_{t-1}, \tag{7}$$

and use them in rolling windows of 90 days to compute the resulting q measure defined as:

$$q = \frac{\sigma_e^2 - 2aCov(e_t, e_{t-1})}{\sigma_e^2 + a\sigma_e^2 - 2aCov(e_t, e_{t-1})} \in (0, 1)\,. \tag{8}$$

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

4.4 Liquidity

To examine liquidity across exchanges, we compute four measures that are likely correlated with liquidity frictions.

First, we compute the Roll impact illiquidity measure based on Roll (1984). The Roll measure is a simple estimate of illiquidity based on the correlation of subsequent price changes. Denoting by $p_{i,t}$ the log price of cryptocurrency pair, such as BTC-USD, on exchange i on day t, we estimate $Cov\{\Delta p_{i,t}, \Delta p_{i,t-1}\}$ using all observations within the past 14 days for daily data (we use 7 and 30 days for robustness). If $Cov\{\Delta p_{i,t}, \Delta p_{i,t-1}\} < 0$, the Roll measure is not defined, hence $Roll_{i,t} = 0$. Thus, the Roll measure is defined as:

$$Roll_{i,t} = \left\{ \begin{array}{ll} = 2\sqrt{-Cov\{\Delta p_{i,t}, \Delta p_{i,t-1}\}} & if \;\; Cov\{\Delta p_{i,t}, \Delta p_{i,t-1}\} < 0 \\ 0 \;\;\; otherwise & \end{array} \right\}. \tag{9}$$

Second, we compute a daily bid-ask spread using closing, low, and high prices following the method suggested by Abdi and Ranaldo (2017). Define the natural logarithm of the close, low, and high of bitcoin prices on exchange i at time t as $c_{i,t}$, $l_{i,t}$, and $h_{i,t}$, respectively. In a first step, we compute

$$\eta_{i,t} = \frac{l_{i,t} + h_{i,t}}{2}, \tag{10}$$

which we then use to compute the CHL measure using all observations within the past 14 days for daily data (we use 7 and 30 days for robustness) as follows:

$$CHL_{i,t} = \frac{1}{N}\sum_{t=1}^{N} \hat{s}_{i,t}, \quad \text{where} \quad \hat{s}_{i,t} = \sqrt{\max\{4(c_{i,t} - \eta_{i,t})(c_{i,t} - \eta_{i,t+1}), 0\}} \tag{11}$$

Third, we compute the trading volume in 1,000 bitcoin units at the daily level as the aggregate volume for each exchange and cryptocurrency pair.

Fourth, we compute the Amihud illiquidity measure following Amihud (2002). Denote by $r_{i,t}$ and $Volume_{i,t}$ the log return and volume, respectively, of BTC-USD or BTC-CCY at exchange i on day t. The Amihud price impact is computed as the average absolute return divided by the volume during the corresponding time period.

$$Amihud_{i,t} = \frac{1}{N}\sum_{t=1}^{N} \frac{|r_{i,t}|}{Volume_{i,t}}, \tag{12}$$

where N denotes the number of hours within a day, or, alternatively, the number of days within a week. We compute this measure daily using rolling windows of 14 days in our benchmark tests, and both 7 and 30 days for the robustness tests.

5 Evidence

We first discuss the data in Section 5.1, then summary statistics in Section 5.2. Preliminary evidence is illustrated in Section 5.3. We discuss the main results in Section 5.4.

5.1 Data

Our primary data source for digital currencies is Kaiko, a data provider that has collected cryptocurrency trading data since 2014. Kaiko provides price and quantity information, timestamped to the millisecond, for more than 80 different exchanges on which bitcoin trades against other fiat currencies. The data has been used in several academic studies in cryptocurrency (e.g. Makarov and Schoar (2019), and Li, Shin, and Wang (2018)) and contains detailed information on transactions, which is essential in our study. For each transaction, we have the ticker symbol (e.g. BTC/USD, where USD is a base fiat currency), execution price, trade quantity, time stamp, and a dummy variable that indicates whether the trade is initiated by buyers or by sellers.

Our identification strategy relies on the within-exchange variation in characteristics between BTC-USD and other bitcoin-fiat exchange rate pairs (BTC-CCY) around futures listing. Thus, to be included in our sample, we require a minimum of one additional bitcoin-fiat currency pair besides BTC-USD. The CBOE and the CME introduced bitcoin futures on December 10 and 17, 2017, respectively. We compare all characteristics 12 months before and 12 months after the introduction of the futures contracts in December 2017. However, in order to account for a potential anticipation period in the run-up to the futures introduction on December 2017, we exclude information from July 2017 to December 2017. Thus, our overall sample period is between July 1, 2016 and December 31, 2018, with the pre-event period running from July 1, 2016 to June 30, 2017, and the post-event period running from January 1, 2018 to December 31, 2018.

These restrictions lead to a control group made up of 10 bitcoin-fiat currency exchange rate pairs traded on 14 different exchanges. In addition to the treatment currency BTC-USD, our sample includes the 9 following exchange rate pairs: BTC-EUR, BTC-GBP, BTC-HKD, BTC-SGD, BTC-JPY, BTC-AUD, BTC-IDR, BTC-CAD, and BTC-RUB, traded on the following 14 exchanges: Binance, Bitfinex, Bitstamp, Bittrex, BTC-e, Coinbase, Gemini, GateCoin, HitBTC, Itbit, Kraken, OkCoin, Poloniex, Quoine. The BTC-EUR pair is traded on seven exchanges, BTC-GBP, BTC-HKD, BTC-SGD, and BTC-JPY pairs are traded on two exchanges, and BTC-AUD, BTC-CAD, BTC-IDR, and BTC-RUB pairs are traded on only one exchange. In total, our sample contains 33 bitcoin-fiat currency pairs.

One of the concerns in studying the cryptocurrency market is that market manipulation activities are prevalent. Gandal, Hamrick, Moore, and Oberman (2018) provide evidence for bitcoin price manipulation in the Mt. Gox exchange and Griffin and Shams (2019) document suspicious bitcoin transactions, attributing the rise of bitcoin prices to market manipulation. Li, Shin, and Wang (2018) highlight prevalent market manipulation practices, such as cryptocurrency pump-and-dump schemes. Therefore, it is important to provide sufficient evidence that empirical results offered in our study are not driven by a few cryptocurrency exchanges that are subject to manipulation.

In order to alleviate the concern, we identify, among the 14 exchanges in our sample, those exchanges that are prone to manipulation based on Bitwise's proposal for an exchange traded fund filed with the SEC in April 2018. In this proposal, Bitwise Asset Management, Inc. highlights that cryptocurrency exchanges have clear incentives to manipulate (or inflate) trading volumes, and presents an extensive analysis to detect the suspicious exchanges that are prone to manipulation. We find that five of them are in our sample: OkCoin, GateCoin, HitBTC, BTC-e, and Quoine. This analysis does not provide direct evidence that the identified exchanges are involved in manipulative activities. However, we exclude those exchanges in additional subsample analysis to provide more convincing evidence that our results are not driven by the suspicious exchanges.

All cryptocurrency exchange rates are quoted in terms of number of fiat currency units per bitcoin. We compute hourly and daily log returns, using the last trade within each hour/day. We aggregate the quantity of traded bitcoins within each hour/day to obtain a measure of trading volume. Our main tests report results for daily returns. Results based on hourly results are qualitatively similar and reported in the Appendix. For all tests, we report results for all exchanges and for the subset of 9 exchanges that are less likely to be subject to market manipulations.

5.2 Descriptive Statistics

In Figure 2.a, we plot the price evolution of bitcoin, which went through a period of boom and bust. Peaking at approximately $20,000 around the introduction of the futures contracts in December 2017, prices of bitcoin lost about 75% in value over the subsequent year. In Figure 3, we illustrate the time series evolution of bitcoin trading volumes across exchanges and currency pairs at a quarterly frequency between July 1, 2016 and December 31, 2018. Panel A illustrates the trading volumes for the five largest exchanges in terms of quantity of BTC-USD traded during our sample period. The five largest exchanges are Quoine, Bitfinex, Coinbase, Gemini, and Bitstamp. Bitfinex absorbs the largest fraction of trading volume, with a market share of 33.12% on average, followed by Coinbase (13.55%) and Bitstamp (12.08%). The residual category "all others" takes up a significant market share of 30.89%, on average, suggesting a non-trivial amount of trading across the different exchanges. In levels, the trading volume ranges from a low of 86,962 bitcoin units in Q4 2016 to a high of 377,190 bitcoin units in Q1 2018, the first quarter after the futures introduction.

Panel B in Figure 3 illustrates a similar distribution of bitcoin trading volumes across exchanges for the third largest bitcoin-fiat currency pair, i.e., BTC-EUR. Trading of BTC-EUR ranges between a low of 21,031 units in Q3 2016 to a high of 59,533 in Q1 2018. On average, the trading volume of BTC-USD is about 7 times as large as that of BTC-EUR. Panel B in Figure 3 also suggests that it is not the same exchanges that capture all the market share across currency pairs, even though there exists some overlap. For BTC-EUR, Kraken absorbs the most significant market share of 64.95%, followed by Bitstamp, Coinbase, Quoine, and Itbit, with 12.77%, 11.79%, 4.97% and 2.82%, respectively. The residual category absorbs a market share of 2.70%, on average, shared by 9 exchanges. In Panel C of Figure 3, we further report the distribution of trading volume across exchanges for BTC-JPY, the second most traded cryptocurrency exchange rate. Because BTC-JPY trading is largely dominated by transactions on Quoine, we use BTC-EUR with a more diversified trading landscape as our main comparison group relative to BTC-USD.

In terms of cryptocurrency pairs, BTC-USD by and large dominates trading with a market share that is on average 69.67% during our sample period (Panel D). The second and third most traded cryptocurrencies are BTC-JPY and BTC-EUR, with market shares that are on average 14.92% and 10.94%, respectively. BTC-IDR (1.82%), BTC-SGD (1.11%), BTC-HKD (0.55%), BTC-AUD (0.50%), BTC-GBP (0.29%), BTC-RUB (0.13%), and BTC-CAD (0.08%) represent the next most traded cryptocurrencies, but they represent insignificant market shares compared with BTC-USD, BTC-EUR, and BTC-JPY. While BTC-JPY has slightly greater trading volume during our sample period than BTC-EUR, trading activity is concentrated on only two exchanges.

In Table 1, we provide summary statistics for daily bitcoin exchange rate returns by currency pair and exchange. In Panel A, we focus on BTC-USD. The return distributions are similar across exchanges, with average returns around zero, ranging between -0.103% and 0.205%, and standard deviations ranging between 3.74% and 4.79%. All return distributions exhibit mild negative skewness and kurtosis that ranges between 5.27 and 9.89. In Panels B and C, we provide similar statistics for the return distributions of BTC-EUR and all other bitcoin-fiat currency exchange rates, respectively. While these distributions appear largely similar, the exchange rate returns reported in Panel C exhibit more leptokurtic distributions, and occasionally positive skewness. Table A.1 provides similar return distributions at the hourly frequency. Hourly returns are smaller on average, display larger volatility, and more frequently large movements, as evidenced by significantly higher kurtosis.

In Table 2, we furthermore report summary statistics for our measures of price synchronicity, market efficieny, market quality, and liquidity. For each metric, we compare the statistics for the BTC-USD currency pair relative to all other 9 cryptocurrency exchange rate pairs. The unconditional means are comparable across the two groups for measures of price synchronicity, efficiency, quality, and some of the liquidity metrics such as price impact (Roll) and bid-ask spreads (CHL). For example, the average efficiency measure $D1$ is 0.1789 for BTC-USD and 0.2431 for all other exchange rate pairs. Similarly, the average market quality is 0.9641 and 0.9481 respectively, while the average bid-ask spread is 1.38% and 1.62%, respectively. Moreover, the distributions for these metrics look broadly similar across groups.

On the other hand, BTC-USD returns exhibit significantly greater trading volume, and less price impact based on Amihud's metric of price impact. For instance, the average daily trading volume for BTC-USD is 7,474 units, while it is only 1,836 units for other currency pairs. Average values for the Amihud measure are inflated, because there are many instances on which the daily trading volume is tiny. As the Amihud measure captures the price impact per unit of trading volume, this puts significant upward pressure on this statistic. The median values suggest that the average daily price impact is 0.62% per 1,000 bitcoin units, while it is 21.92% for the other pairs.

5.3 Preliminary Evidence

To provide some preliminary evidence on changes in BTC-USD price synchronicity around the introduction of bitcoin futures, we report in Table 3 the average pairwise Pearson correlation coefficients for daily BTC-USD log returns in the pre-event and post-event periods. These periods stretch from July 2016 to June 2017, and from January 2018 to December 2018, respectively. We report the statistics only for the five biggest exchanges in terms of aggregate trading volume between July 1, 2016 and December 31, 2016.

The correlation coefficients for the pre-event period highlight differences in price movements across exchanges. These values indicate that the market may not have been efficient prior to futures introduction. Values ranging between 0.8751 and 0.9813 suggest that there is cross-exchange heterogeneity in the levels of price synchronicity, which is useful for the identification of the impact of futures introduction on cash markets. The correlation coefficients reported for the post-event period indicate a significant increase in cross-exchange price synchronicity. For example, the average pairwise correlations for BTC-USD returns traded on Bitfinex and Quoine increase from 0.8751 to 0.9856 after the futures listing. Similarly, the average pairwise correlation coefficient for BTC-USD returns traded on Itbit and Bitfinex increase from 0.9436 to 0.9929. The results in Table A.2, reported in the Appendix, suggest that the increase in price synchronicity is much more pronounced if returns are measured at the hourly frequency.

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 returns relative to that of all other currency pairs. We illustrate the difference between both categories in Figure 2.b. This figure emphasizes the relative change in cross-exchange return correlations around the introduction of bitcoin futures. Before the introduction, the average return correlation for BTC-USD returns is about one percentage point higher relative to all other pairs (dotted horizontal line). It is evident that there is marked shift in December 2017, with the difference being on average 8.5 percentage points higher for BTC-USD returns. This suggests that the increase in correlations following the introduction of the futures contract is much more pronounced for BTC-USD than for other exchange rate pairs. We now proceed to a more formal analysis of the changes in integration, quality, efficiency, and liquidity of cryptocurrencies around the futures listing in December 2017.

5.4 Main Results

We successively discuss the results along the four sets of characteristics of interest: price synchronicity and integration, price efficiency, market quality, liquidity. For each characteristic, we estimate the main regression model described in Equation (1), which allows us to examine the null hypothesis that the treatment cryptocurrency exchange rate BTC-USD is not differentially affected following the BTC-USD futures introduction compared to other bitcoin-fiat currency pairs. Our tests allow us to examine whether the introduction of the futures contract in 2017 has made cryptocurrency markets more integrated, efficient, liquid, and informative.

Price Synchronicity and Integration

In Table 4, we report the results for pairwise cross-exchange Pearson correlation coefficients, which, for a given currency, capture the degree of price return synchronicity across exchanges. In Panel A, we focus on all currency pairs. The result in column (1) suggests that, unconditionally, the level of correlations is on average about 3.53 percentage points higher for BTC-USD returns. In addition, it appears that, on average, the level of correlations drops by about 7.46 percentage points following the futures listing. However, this is largely the result of exchanges that are suspected to be subject to market manipulations. When we exclude these exchanges in Panel B, the coefficient on $Post$ is positive and statistically significant, indicating that the average level of price correlations increases by 3 percentage points.

The main coefficient of interest is the one associated with the interaction term $Treatment \times Post$. In Panel A, this coefficient is highly statistically significant with a point estimate of 0.0920, which is economically meaningful. Some of the variation is absorbed if we add exchange-pair fixed effects, but the estimate remains statistically significant at the 5% level. Exchange-pair fixed effects control for unobserved and time-invariant heterogeneity at the exchange-pair level, accounting for cross-exchange differences in the level of price synchronicity. Again, this effect is driven by the subset of exchanges that are suspected to be prone to market manipulations, as the same coefficient in column (2) of Panel B in Table 4 hardly changes in magnitude relative to the estimate reported in column (1) of Panel B.

In column (3), we control for daily 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. In both instances, the coefficient estimate hardly changes in magnitude and remains highly statistically significant. In Panel C, we report the results for a subset of the data, in which we only compare BTC-USD with BTC-EUR cross-exchange pairwise return correlations. The results are again statistically significant for all specifications. Furthermore, the coefficient estimate reported for the most conservative specification in column (5) suggests that the differential increase in correlations for BTC-USD relative to BTC-EUR returns is of similar magnitude than the differential increase relative to all other exchange rate pairs. Table A.3 in the Appendix contains qualitatively similar results when we compute the cryptocurrency returns at an hourly frequency.

In Figure 4, we report a plot for an extended differences-in-differences regression in which we interact a treatment indicator for BTC-USD correlations with quarterly fixed effects around the futures introduction. We use the third quarter in 2017 as the base for comparison. Each point estimate in Figure 4 thus represents the relative difference in price correlations between BTC-USD and other bitcoin exchange rate pairs at a particular point in time. In the pre-event period, none of the coefficients is statistically significant, suggesting that the parallel trend assumption needed for the valid inference of the differences-in-differences test is respected. In the fourth quarter of 2017, when BTC-USD futures start trading, the differences-in-differences estimator jumps up to about 9%, and all individual estimates are significantly different from zero. The coefficient increases to about 16% 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 16 percentage points.

This evidence supports the view that the introduction of BTC-USD futures contracts is associated with an increase in in BTC-USD cross-exchange price synchronicity that is not experienced similarly by other exchange rate pairs.

In Table 5, we also examine the impact of futures listing with respect to the Kapadia and Pu (2012) non-parametric measure of price synchronicity κ. Higher values of κ reflect a higher degree of price integration across exchanges. Here, we only focus on the subset exchanges that are not suspected of market manipulation, as price movements on other exchanges are quite noisy. The results for all bitcoin currency pairs in Panel A suggest again that there is a positive and statistically significant increase in price integration for the treatment group relative to the control group. Based on the most conservative estimate reported in column (5), the average differential increase in the frequency of price concordance is 12.8 percentage points. Given the average BTC-USD value for κ of 0.8224, this change is economically meaningful. Panel A suggests that the increase in price integration for BTC-USD relative to BTC-EUR is of similar magnitude than compared with the overall sample. Table A.4 in the Appendix provides similar findings using returns computed at the hourly frequency.

Price Efficiency

The results for the $D1$ price efficiency measure suggested by Hou and Moskowitz (2005) are reported in Table 6. In Panel A, we report the estimated coefficients for the total sample. The insignificance of the differences-in-differences estimator is due to noisy measurements of the $D1$ metric for cryptocurrency exchange rate returns other than BTC-USD and BTC-EUR. This is supported by the results in Panel B, where the coefficients for the treatment following the futures listing are statistically significant at either the 5% or the 10% level. Specifically, a more negative $D1$ metric indicates that the prices are more efficient, in the sense that new information gets more quickly incorporated into prices. The differential increase in price efficiency ranges from 4.88% to 5.81%. This is economically meaningful, as the average efficiency measure for BTC-USD (BTC-CCY) is 17.89% (24.31%), as reported in Table 2. Focusing on the subset of exchanges that are less likely subject of market manipulation in Panel C, we find that the statistical significance and the economic magnitude become stronger. Overall, we find support for the hypothesis that the derivatives introduction improves the price efficiency of the underlying cash market.

Market Quality

We next discuss the implications of the futures introduction for market quality q, in the sense of Hasbrouck (1993). Specifically, we report in Table 7 the results from the projection of the market quality metric on the BTC-USD treatment indicator, the post-futures introduction event dummy, and their interaction. Unconditionally, we find no significant difference in market quality between BTC-USD and other cryptocurrency exchange rates throughout both panels A and B. In Panel A, where we examine the change in market quality of BTC-USD relative to all other cryptocurrency pairs, we find a weakly significant effect of around 2.25% to 2.68%. Importantly, the magnitude of the coefficient does not meaningfully change across the different specification. A slightly stronger increase in market quality of approximately 3.21% to 3.73% is found in Panel B, where we compare BTC-USD to BTC-EUR only. In that case, the coefficients are also consistently statistically significant at the 5% level.

Liquidity

Finally, we evaluate changes in liquidity characteristics around the introduction of the BTC-USD futures in December 2017. In Table 8, we consecutively report results based on daily measures of Roll's liquidity (Roll, 1984), the CHL metric of bid-ask spreads computed using open, closing, high, and low trading prices (Abdi and Ranaldo, 2017), trading volume, and Amihud's measure of price impact (Amihud, 2002). We focus our analysis for liquidity on the more reliable estimates using only data for those exchanges that are allegedly not subject to manipulation.

For Roll's measure of liquidity, we find a weakly statistically significant effect for the comparison of BTC-USD and BTC-EUR exchange rates. The reduction in price impact ranges between 0.0032 to 0.0033. The differential change in price impact corresponds to about 12% of the average price impact of 0.0268 measured for BTC-USD returns, as reported in Table 2.

In Panel B of Table 8 we report the results for bid-ask spreads. While the coefficient on the interaction term is negative, it is insignificant. In unreported results, we find marginally statistically significant results when we compare the change in bid-ask spreads for BTC-USD and BTC-EUR in the aggregate sample. In that case, the estimated coefficient is 0.00154 in the most conservative specification (corresponding to column (5) in all tables). The average bid-ask spread for BTC-USD is 0.0138, with a standard deviation of 0.0096. Thus, the estimate represents a reduction in bid-ask spreads of about 11%.

The results for volume are reported in Panel C of Table 8. We report the somewhat weaker results for BTC-USD vs. other bitcoin-fiat currency exchange rates. The significantly estimated coefficient for the treatment indicator ranges between 3.378 and 3.435, implying that, unconditionally, the trading volume of BTC-USD is greater by about 340%. We find a statistically insignificant coefficient for the post-event period indicator. However, the trading volume increases significantly more for BTC-USD than for other bitcoin-fiat currency pairs following the futures introduction. Specifically, the results suggest that the differential increase in trading volume for BTC-USD ranges between 260% and 279%, depending on the specification.

Finally, we report in Panel D of Table 8 the estimated coefficients for the Amihud price impact measure, focusing again on the control sample that excludes BTC-EUR. As for the other measures, we find a reduction in price impact following the futures listing which is significantly greater for BTC-USD than for other exchange rate pairs. The estimated coefficient for the interaction between the futures listing indicator and the BTC-USD treatment group is around negative 3.5, indicating a differential reduction in price impact of approximately 350%.

6 Refinements, Channels, and Robustness

In this section, we strengthen the evidence about the impact of BTC-USD futures on the bitcoin cash market by exploiting the settlement mechanism of the futures contract. In addition, we shed some light on the potential channels for our results. We end with a series of robustness tests.

6.1 Evidence around the Fixing of the Settlement Index

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

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

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

Given that cash indices for futures settlement are computed at 4:00 p.m. Eastern and London times respectively, we expect greater trading activity around these fixing times, with more reliable and less noisy prices. Hence, our results should be sharper if we focus our analysis on prices obtained during the fixing times from those exchanges used in the computation of settlement indices. Thus, we repeat our analysis using daily returns with prices sampled from the Gemini Exchange at 4:00 p.m. *Eastern time*, and prices sampled from itBit, Kraken, and BitStamp at 4:00 p.m. *London time*. The GDAX exchange is not covered by our study because it has no trading other than BTC-USD during our sample period. Therefore, we focus on the four exchanges (itBit, Kraken, BitStamp, and Gemini) in the following analysis.

In Table 9, we report the results from the differences-in-differences regressions after we sample prices at 4:00 p.m. on the corresponding exchanges. For a fair comparison, we also report identical regressions based on the same sample composition when prices are sampled end-of-day. We emphasize that the number of observations drops significantly in Table 9, as the analysis is restricted to four exchanges. This has implications for the statistical power of our tests. Despite this caveat, there is some support for stronger results when prices are sampled around times when the futures settlement indices are computed.

In Panel A, we study the effect on Roll's illiquidity measure. While the coefficient estimate for the interaction term is close to 0 and statistically insignificant using end-of-day prices, it becomes negative and statistically significant at the 5% level in most specifications using 4:00 p.m. prices. In Panel B, the results based on end-of-day prices are only weakly statistically significant, but positive. Using prices that are more relevant for the futures market, we find negative but statistically insignificant results. In Panel C, we find that the results for the Amihud price impact measure have similar statistical significance in both tests, but the economic significance becomes slightly stronger if we use 4:00 p.m. prices. Finally, in Panel D, we find supportive evidence for an increase in market quality using prices sampled at 4:00 p.m., while results based on prices sampled at the end-of-day are statistically insignificant. As we do not find any differential effects for the analysis of price synchronicity and price efficiency, we don't report the results. Overall, our findings are supportive of stronger results when we focus on prices at times that are more relevant for the futures markets and during which prices could potentially be less noisy.

6.2 Channels

Our evidence suggests that, following the introduction of BTC-USD futures contracts, BTC-USD cash prices become more aligned, allow for fewer arbitrage opportunities, and exhibit a higher degree of market quality and price efficiency. We next explore the channels through which this effect may arise. We focus on two plausible explanations related to a reduction in trading frictions and a reduction in informational frictions, which may not necessarily be mutually exclusive.

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

On the other hand, perfect alignment of prices could also arise because of a lack of investor attention (Duffie, 2010). Inattention can possibly be driven by distraction (Hirshleifer, Lim, and Teoh, 2009), limited cognitive resources (Peng and Xiong, 2006), or by costly acquisition of information (Nieuwerburgh and Veldkamp, 2010).

While we cannot directly measure limitations to free movement of arbitrage capital or investor attention, we examine if we can associate cross-exchange differences in the differential change of BTC-USD characteristics with exchange-specific measures that are correlated with transaction costs and investor attention. We examine cross-sectional differences for the results of price synchronicity. For transaction costs, we use the average trading volume on each exchange in the pre-event period. For attention, we collect the average Google search intensity for each exchange name in the pre-event period. To ensure comparability across exchanges, we download the search intensities relative to that of the word "bitcoin". Using these measures of attention and illiquidity, we run triple differences-in-differences regressions as follows:

$$\begin{aligned}
&Price\ Syncronicity_{i,j,t} \\
&= \alpha_0 + \alpha_1 Treatment_{BTC-USD} \times Post_{futures} \\
&+ \alpha_2 Treatment_{BTC-USD} \times High\ Attention\ (or\ High\ Liquidity) \\
&+ \alpha_3 High\ Attention\ (or\ High\ Liquidity) \times Post_{futures} \\
&+ \alpha_4 Treatment_{BTC-USD} \times Post_{futures} \times High\ Attention\ (or\ High\ Liquidity) \\
&+ \delta_i + \eta_j + \gamma_t + \varepsilon_{i,j,t},
\end{aligned} \tag{13}$$

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

The results, which we report in Table 10, are supportive of both a liquidity and an attention channel. The triple interaction coefficient is statistically significant across almost all specifications. This suggests different impacts from the introduction of bitcoin futures on bitcoin cash markets for exchanges with high and low attention or liquidity. Surprisingly, however, we find that the results are weaker for exchanges with higher liquidity and greater attention. We speculate that exchanges where liquidity and attention were already high in the pre-event period had higher price synchronicity before the futures introduction. The potential improvement in price synchronicity is, therefore, marginal relative to the other exchanges.

In unreported tables, we conduct triple differences-in-differences analyses for price efficiency, market quality, and liquidity measures with the same specifications of Table 6, 7, and 8. We observe that the results for trading volume and Amihud price impact measure are weaker and statistically significant at 1% level with higher liquidity and greater attention. Moreover, the results for D1 are weaker and statistically significant at 5% level with greater attention. The results for Roll's measure, CHL, and market quality are statistically insignificant. Overall, the results are largely consistent with those for price synchronicity.

6.3 Robustness

We conduct a battery of robustness tests to ensure the validity of our main findings. In this section, we limit ourselves to a discussion of the results of these tests, which are available upon request.

With respect to the price synchronicity measures, we evaluate different time windows. In the main analysis, we compute the Pearson correlation coefficients using a 14-day window. Our results remain economically and statistically significant when we use different window lengths of 7 or 30 days. For the Kapadia and Pu (2012) price synchronicity measure, the results become economically and statistically stronger if we focus exclusively on the shorter time (τ) horizon rather than using the average effect across all τ as defined in Equation (3). This suggests that short-term and asynchronous bitcoin price movements are more pronounced at shorter horizons, and that arbitrageurs are partially disciplining prices over longer trading horizons (Makarov and Schoar, 2019). This argument is also supported by our results with returns measured at the hourly frequency. In that case, we show in Table A.4 that the differences-in-differences estimator becomes significantly larger, while remaining highly statistically significant. Specifically, for the most conservative specification reported in column (5), the coefficient estimates range between 0.181 and 0.486, compared to the values ranging between 0.128 and 0.131 at the daily frequency. Furthermore, we find that our results regarding price synchronicity are robust to different specifications of clustering. Whether we cluster along one dimension at the exchange-currency pair level, or along two dimenions at the exchange-currency pair level and by time, has only a marginal impact on the standard errors of the estimated coefficients, and leaves the estimates statistically significant.

We observe that, using longer windows for measures of market quality and price efficiency, results are either statistically stronger or remain unchanged. For example, if we extend the window length for market quality from 90 to 180 days, the statistical significance of the differences-in-differences estimator increases, while the magnitudes of the estimates remain largely unchanged. This finding is likely the result of a more precise estimate of the market quality measure q due to the inclusion of additional price information. We also increase the length of the window for the price efficiency measure $D1$ from 90 days to 180 days and observe that the results are largely unchanged.

For the liquidity metrics, we use as an alternative rolling windows of 7 and 30 days, in addition to our benchmark window of 14 days. The estimates for the differences-in-differences coefficients remain largely unchanged and statistically significant at similar levels. Moreover, if we shorten the length of the post-event period by 6 months to the time frame January to June 2018, the magnitudes of the coefficient estimates become larger and the estimates become more statistically significant. This suggests that the effect of the introduction of futures on the cash market's liquidity is more pronounced in the early part of the post-event period.

7 Conclusion

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

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

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

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Figure 1: Google Search Intensity – Bitcoin Futures

In this figure, we plot the Google search intensity for the word "bitcoin futures" between July 1, 2016 and 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. Google search data is available at https://trends.google.com/trends/explore?date=today%205-y&q=bitcoin%20futures.

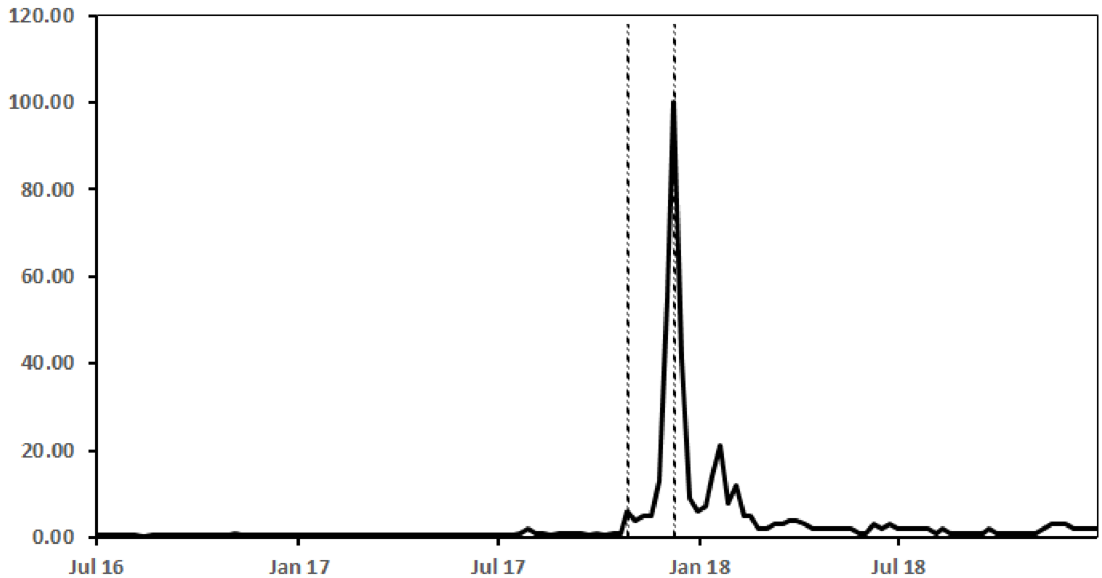
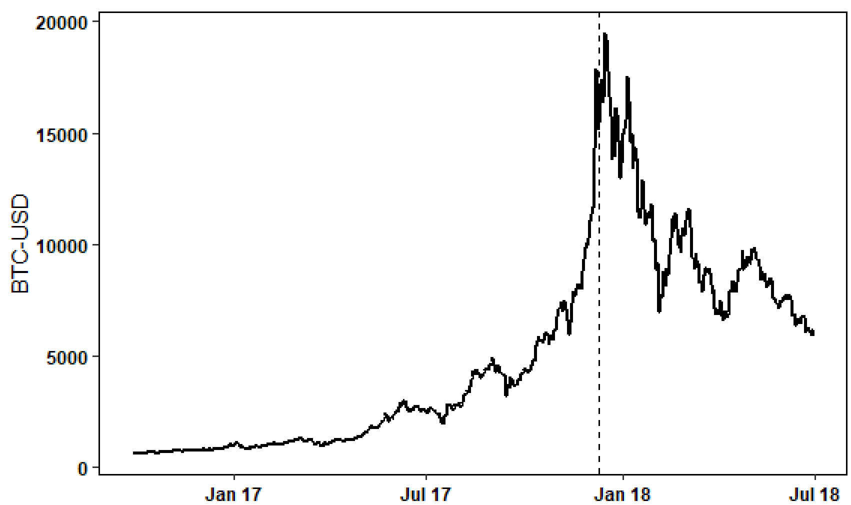


Figure 2: Bitcoin Price History

In Figure 2.a, we report the daily time series of BTC-USD prices for the sample period July 1, 2016 to June 29, 2018. In Figure 2.b, we illustrate the difference in the average pairwise cross-exchange Pearson correlation coefficients between BTC-USD and all other bitcoin-fiat exchange rate returns. Pairwise correlations are computed in rolling windows using 90 days of data, averaged across exchanges for BTC-USD and BTC-CCY, respectively, where CCY refers to EUR, HKD, GBP, CAD, JPY, SGD, AUD, RUB, IDR. Figure 2.b starts with a lag of 90 days on September 28, 2016 and also ends on June 29, 2018. The vertical line indicates the day of the first BTC-USD futures introduction on December 10, 2017. Horizontal lines indicate the equally-weighted average difference between pairwise return correlations in the pre-event and post-event periods.

(a)



(b)

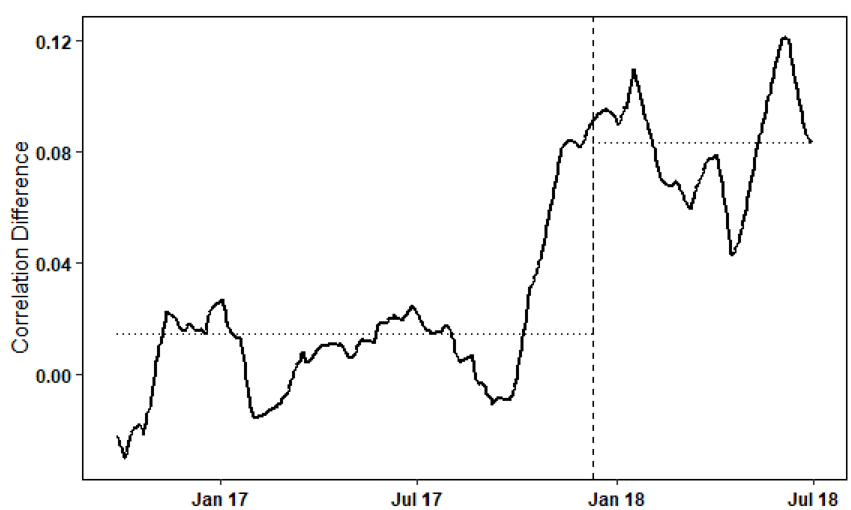
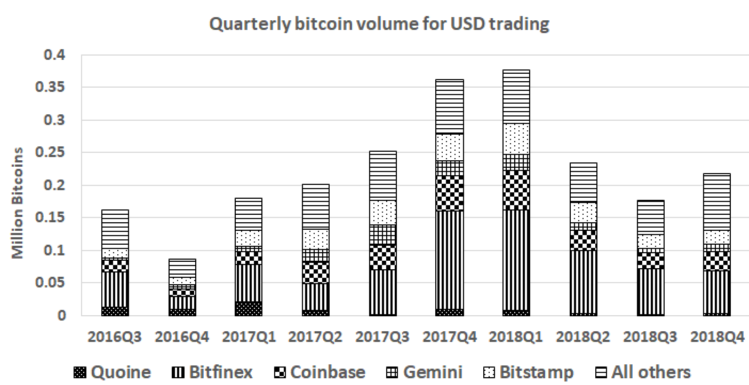


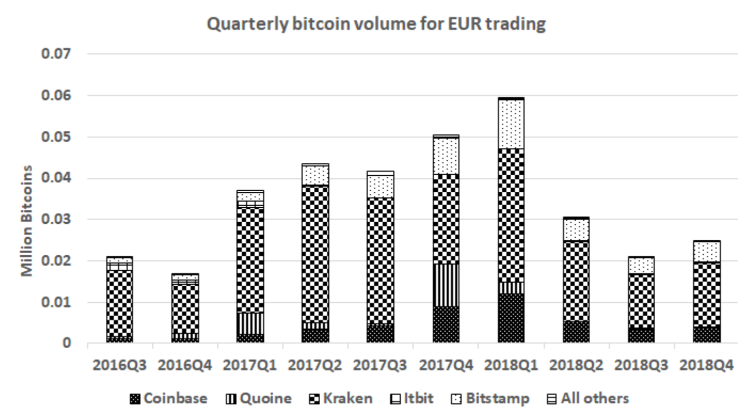
Figure 3: Bitcoin Trading Volumes

In this figure, we report the quarterly time series of bitcoin trading volumes. The sample period is July 1, 2016 to December 31, 2018. In Figure 3.a, we represent the market shares of BTC-USD trading volumes for the 5 largest exchanges in terms of aggregate trading volumes during our sample period. The sixth category "All Others" groups all remaining exchanges together. In Figure 3.b, we represent the market shares of BTC-EUR trading volumes for the 5 largest exchanges in terms of aggregate trading volumes during our sample period. In Figure 3.c, we represent the market shares of BTC-JPY trading volumes for the 2 exchanges with BTC-JPY trading volumes during our sample period. In Figure 3.d, we illustrate the relative market shares of BTC trading volume in terms of currencies.

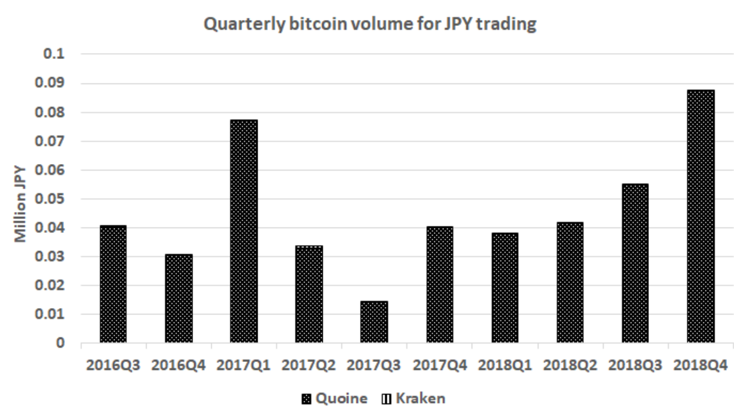
(a)



(b)



(c)



(d)

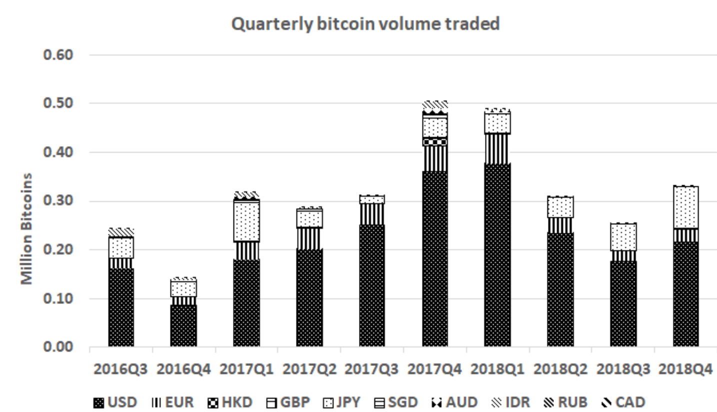


Figure 4: Bitcoin Pairwise Correlation History

In this figure, we report the results from a differences-in-differences regression for the pairwise cross-exchange return correlations $\rho_{i,j,t}$ for USD-BTC relative to other bitcoin-fiat exchange rate pairs based on daily data. Specifically, we run the regression

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

where $Treatment_{BTC\_USD}$ is one for cross-exchange BTC-USD return correlations and zero otherwise (i.e., the treatment group), $Post\_Futures_t$ captures the timing of the futures introduction (we use 2017Q3 as the benchmark), γ_t are quarterly time fixed effects, δ_i are cryptocurrency fixed effects (e.g., BTC-USD, BTC-EUR), and η_j are exchange fixed effects. Pairwise correlations are computed in rolling windows using 14 days of data, averaged across exchanges for BTC-USD and BTC-CCY, respectively, where CCY refers to EUR, HKD, GBP, CAD, JPY, SGD, AUD, RUB, IDR. Standard errors are clustered at the exchange pair level. The sample period is July 1, 2016 to December 31, 2018. The vertical line indicates the day of the first BTC-USD futures introduction on December 10, 2017.

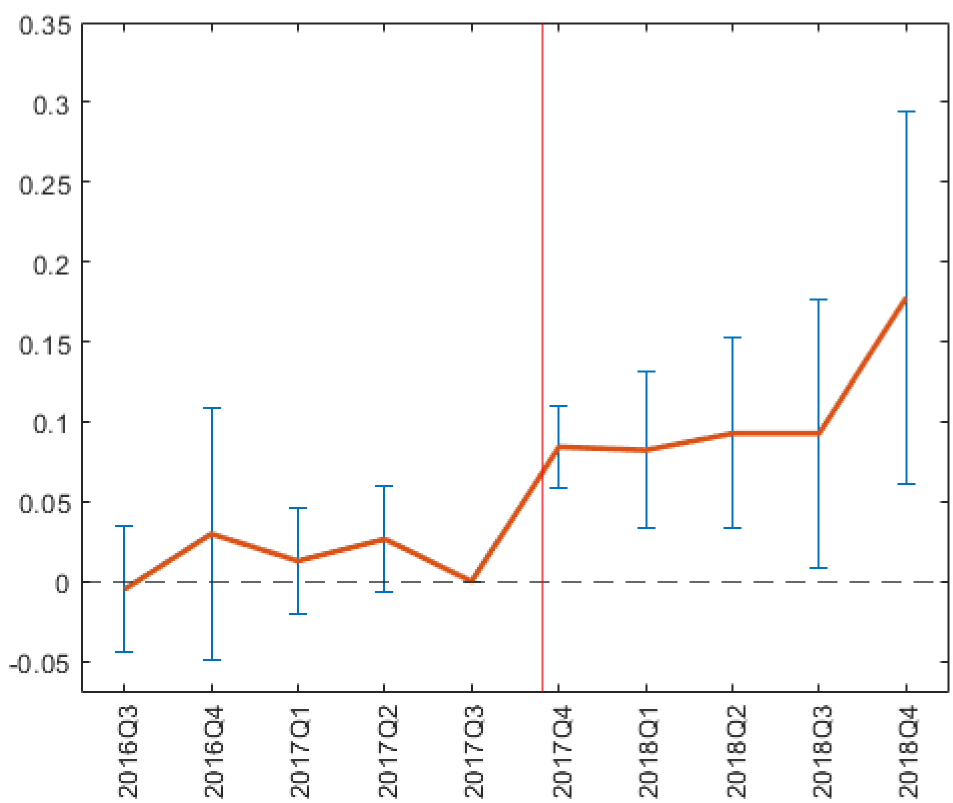


Table 1: Summary Statistics for Cryptocurrency Returns

In this table, we provide summary statistics for daily bitcoin-fiat currency exchange rate returns by currency pair and exchange. In Panel A, we focus on BTC-USD, in Panel B, we focus on BTC-EUR, and in Panel C, we focus on the remaining bitcoin currency pairs. In each panel, we report the exchange's name, the start and end dates of the data, the number of observations, 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.

Panel A. BTC-USD (Daily)

Currency	**Exchange**	**Start**	**End**	**N**	**Mean**	**SD**	**Skew**	**Kurt**	**p5**	**p95**
BTC-USD	Binance	10/28/2017	12/31/2018	430	-0.00103	0.0479	-0.1584	5.3016	-0.0812	0.0833
BTC-USD	Bitfinex	07/01/2016	12/31/2018	903	0.00175	0.0433	-0.1979	6.3547	-0.0713	0.0692
BTC-USD	Bitstamp	07/01/2016	12/31/2018	912	0.00173	0.0426	-0.1513	6.4773	-0.0722	0.0650
BTC-USD	Bittrex	01/01/2017	12/31/2018	728	0.00172	0.0480	-0.2009	5.5320	-0.0825	0.0789
BTC-USD	BTC-e	07/01/2016	11/28/2018	792	0.00205	0.0374	-0.3421	7.0107	-0.0628	0.0563
BTC-USD	Coinbase	07/01/2016	12/31/2018	914	0.00186	0.0425	-0.0430	6.4400	-0.0721	0.0665
BTC-USD	Gatecoin	08/25/2017	12/26/2018	475	0.00001	0.0475	-0.1194	4.9226	-0.0849	0.0743
BTC-USD	Gemini	07/01/2016	12/31/2018	912	0.00187	0.0431	-0.0979	6.5810	-0.0711	0.0675
BTC-USD	HitBTC	08/27/2017	12/31/2018	492	-0.00031	0.0467	-0.0876	5.2678	-0.0783	0.0847
BTC-USD	Itbit	07/01/2016	12/31/2018	914	0.00186	0.0425	-0.1280	6.4555	-0.0702	0.0652
BTC-USD	Kraken	07/01/2016	12/31/2018	909	0.00181	0.0425	-0.1664	6.0674	-0.0710	0.0664
BTC-USD	OkCoin	07/01/2016	12/31/2018	789	0.00129	0.0391	-0.5369	6.9228	-0.0663	0.0609
BTC-USD	Poloniex	07/01/2016	12/31/2018	893	0.00155	0.0435	-0.1579	6.4175	-0.0735	0.0700
BTC-USD	Quoine	07/01/2016	12/31/2018	914	0.00186	0.0456	0.1225	9.8987	-0.0742	0.0702

Panel B. BTC-EUR (Daily)

Currency	**Exchange**	**Start**	**End**	**N**	**Mean**	**SD**	**Skew**	**Kurt**	**p5**	**p95**
BTC-EUR	Bitstamp	07/01/2016	12/31/2018	912	0.00170	0.0421	-0.2901	6.1805	-0.0728	0.0673
BTC-EUR	BTC-e	07/01/2016	11/26/2018	790	0.00204	0.0379	-0.1538	7.0395	-0.0659	0.0583
BTC-EUR	Coinbase	07/01/2016	12/31/2018	912	0.00179	0.0423	-0.2199	6.7522	-0.0712	0.0651
BTC-EUR	Gatecoin	08/25/2017	12/27/2018	434	-0.00026	0.0592	-0.1866	5.9802	-0.1044	0.0937
BTC-EUR	Itbit	07/01/2016	12/31/2018	867	0.00198	0.0429	-0.3718	6.2152	-0.0752	0.0648
BTC-EUR	Kraken	07/01/2016	12/31/2018	909	0.00162	0.0426	-0.2535	6.1294	-0.0725	0.0690
BTC-EUR	Quoine	07/02/2016	12/31/2018	774	0.00062	0.0510	-1.3645	21.7086	-0.0793	0.0733

Panel C. BTC-CCY excluding BTC-EUR (Daily)

Currency	**Exchange**	**Start**	**End**	**N**	**Mean**	**SD**	**Skew**	**Kurt**	**p5**	**p95**
BTC-GBP	Coinbase	07/01/2016	12/31/2018	912	0.0019	0.0423	-0.1116	6.4025	-0.0703	0.0669
BTC-GBP	Kraken	07/01/2016	12/31/2018	844	0.0015	0.0655	-0.0329	11.1995	-0.0956	0.0886
BTC-HKD	Gatecoin	08/25/2017	12/20/2018	433	0.0008	0.0605	0.4025	6.5115	-0.1054	0.0953
BTC-HKD	Quoine	11/17/2016	12/24/2018	487	-0.0001	0.0563	-0.3490	8.4929	-0.1008	0.0804
BTC-SGD	Itbit	09/07/2016	12/31/2018	546	0.0024	0.0490	-0.4482	6.9997	-0.0875	0.0753
BTC-SGD	Quoine	07/01/2016	12/31/2018	912	0.0019	0.0444	0.0362	10.2404	-0.0694	0.0674
BTC-JPY	Kraken	07/01/2016	12/31/2018	908	0.0019	0.0468	0.0260	7.9076	-0.0781	0.0695
BTC-JPY	Quoine	07/01/2016	12/31/2018	914	0.0019	0.0461	0.0366	12.3458	-0.0738	0.0674
BTC-AUD	Quoine	07/10/2016	12/31/2018	720	0.0017	0.0532	-0.1732	10.3469	-0.0861	0.0813
BTC-IDR	Quoine	07/01/2016	12/27/2018	633	0.0035	0.0541	0.3921	10.6042	-0.0927	0.0788
BTC-RUB	BTC_e	09/17/2016	11/28/2018	714	0.0023	0.0363	-0.2002	6.4832	-0.0626	0.0584
BTC-CAD	Kraken	07/01/2016	12/31/2018	912	0.0019	0.0446	-0.5867	8.0663	-0.0732	0.0687

Table 2: Summary Statistics for Market Characteristics.

In this table, we provide summary statistics (Mean, standard deviation, median, 5th and 95th percentiles), number of observations, start and end dates for all characteristic measures. The data frequency is daily. For each measure, 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. The reported characteristics relate to (1) price synchronicity: pairwise correlations ρ and integration κ; (2) market efficieny: $D1$; (3) market quality q; (4) liquidity: Roll, CHL, Amihud, and Volume (1,000 BTC). The overall sample period is July 1, 2016 to December 31, 2018.

Measure	**Currency**	**Start**	**End**	**N**	**Mean**	**SD**	**Median**	**p5**	**p95**
ρ	BTC-USD	07/01/2016	12/31/2018	63,850	0.9111	0.1720	0.9789	0.5439	0.9993
	Other	07/01/2016	12/31/2018	18,645	0.8255	0.2628	0.9374	0.2309	0.9969
κ	BTC-USD	07/01/2016	12/31/2018	64,057	0.8224	0.2867	0.9121	0.3187	1.0000
	Other	07/01/2016	12/31/2018	19,103	0.6200	0.4824	0.8242	−0.6703	0.9780
D1	BTC-USD	07/01/2016	12/31/2018	11,419	0.1789	0.2107	0.1002	0.0193	0.6266
	Other	07/01/2016	12/31/2018	16,377	0.2431	0.2798	0.1128	0.0196	0.9369
q	BTC-USD	07/01/2016	12/31/2018	11,122	0.9641	0.0506	0.9920	0.8611	1.0000
	Other	07/01/2016	12/31/2018	16,119	0.9481	0.0650	0.9749	0.8090	1.0000
Roll	BTC-USD	07/01/2016	12/31/2018	11,760	0.0211	0.0268	0.0108	0.0000	0.0702
	Other	07/01/2016	12/31/2018	17,124	0.0245	0.0328	0.0132	0.0000	0.0824
CHL	BTC-USD	07/01/2016	12/31/2018	11,209	0.0138	0.0096	0.0120	0.0028	0.0314
	Other	07/01/2016	12/31/2018	15,750	0.0162	0.0150	0.0127	0.0024	0.0394
Amihud	BTC-USD	07/01/2016	12/31/2018	11,203	929.42	21,940.0	0.0062	0.0008	4.1682
	Other	07/01/2016	12/31/2018	15,818	1,170.9	19,376.7	0.2192	0.0023	571.38
Volume	BTC-USD	07/01/2016	12/31/2018	11,805	7.4736	12.586	3.1889	0.0000	31.637
(1,000 BTC)	Other	07/01/2016	12/31/2018	17,154	1.8357	6.1069	0.0908	0.0000	10.155

Table 3: Cryptocurrency Exchange Rate Return Correlations.

In this table, we provide pairwise BTC-USD daily log return correlations (Pearson correlations) across the five biggest exchanges in terms of aggregate trading volume between July 1, 2016 and December 31, 2016. BTC-e is excluded because it shut down its business in 2018. The sample period is July 2016 to December 2018. In Panel A (Panel B), we show pairwise correlation coefficients for the 12 months before (after) the futures introduction from July 2016 to June 2017 (January 2018 to December 2018).

Panel A: Average daily correlation, Jul 2016 - Jun 2017					
	Bitfinex	Bitstamp	Coinbase	Itbit	Quoine
Bitfinex	1	0.9517	0.9424	0.9436	0.8751
Bitstamp	0.9517	1	0.9736	0.9801	0.9078
Coinbase	0.9424	0.9736	1	0.9813	0.9009
Itbit	0.9436	0.9801	0.9813	1	0.9046
Quoine	0.8751	0.9078	0.9009	0.9046	1
Panel B: Average daily correlation, Jan 2018 - Dec 2018					
	Bitfinex	Bitstamp	Coinbase	Itbit	Quoine
Bitfinex	1	0.9942	0.9925	0.9929	0.9856
Bitstamp	0.9942	1	0.9984	0.9975	0.9885
Coinbase	0.9925	0.9984	1	0.9975	0.9875
Itbit	0.9929	0.9975	0.9975	1	0.9881
Quoine	0.9856	0.9885	0.9875	0.9881	1

Table 4: Differences-in-Differences Results - Price Synchronicity/Correlations

In this table, we report regression results from the projection of daily pairwise cross-exchange Pearson correlation coefficients on the treatment indicator ($Treatment$) that takes the value one for BTC-USD return pairs and zero otherwise; an event indicator ($Post$) that takes the value one following the introduction of bitcoin futures on December 10, 2017; and their interaction ($Treatment \times Post$). Daily pairwise Pearson correlation coefficients are computed in rolling windows with lags of 14 days. Panel A contains all cryptocurrency pairs, Panel B focuses on the subset of exchanges that are not prone to trading volume manipulation, Panel C focuses on the difference between BTC-USD and BTC-EUR. The sample period is July 1, 2016 to December 31, 2018, but we exclude the anticipation period between July 1, 2017 and December 31, 2017. Standard errors are clustered at the exchange pair level.

Panel A: All BTC currency pairs	(1)	(2)	(3)	(4)	(5)
Treatment	0.0353*	0.0385*	0.0360*		
	(0.0192)	(0.0209)	(0.0193)		
Post	-0.0746**	-0.00804		-0.0710**	
	(0.0353)	(0.0276)		(0.0318)	
Treatment×Post	0.0920***	0.0507**	0.0923***	0.0884***	0.0568**
	(0.0338)	(0.0242)	(0.0340)	(0.0304)	(0.0236)
N	66891	66891	66891	66891	66891
adj. R^2	0.038	0.244	0.144	0.058	0.373
Panel B: Excluding suspicious exchanges	(1)	(2)	(3)	(4)	(5)
Treatment	-0.00320	0.0169	-0.00268		
	(0.0386)	(0.0283)	(0.0388)		
Post	0.0300***	0.0300***		0.0300***	
	(0.00666)	(0.00666)		(0.00666)	
Treatment×Post	0.0665***	0.0702***	0.0659***	0.0665***	0.0704***
	(0.0185)	(0.0192)	(0.0182)	(0.0185)	(0.0193)
N	28078	28078	28078	28078	28078
adj. R^2	0.116	0.239	0.238	0.260	0.474
Panel C: BTC-USD vs. BTC-EUR	(1)	(2)	(3)	(4)	(5)
Treatment	0.00829	0.0124	0.00902		
	(0.0171)	(0.0163)	(0.0171)		
Post	-0.0845**	-0.0176		-0.0845**	
	(0.0330)	(0.0291)		(0.0330)	
Treatment×Post	0.102***	0.0605**	0.101***	0.102***	0.0608**
	(0.0314)	(0.0250)	(0.0315)	(0.0314)	(0.0254)
N	64642	64642	64642	64642	64642
adj. R^2	0.027	0.257	0.141	0.027	0.372
Exchange Pair FE		✓			✓
Daily FE			✓		✓
Currency FE				✓	✓

Table 5: Differences-in-Differences Results - Price Synchronicity/Integration

In this table, we report regression results from the projection of daily pairwise cross-exchange Kapadia and Pu (2012) price synchronicity measures on the treatment indicator (*Treatment*) that takes the value one for BTC-USD cryptocurrency pairs and zero otherwise; an event indicator (*Post*) that takes the value one following the introduction of bitcoin futures on December 10, 2017; and their interaction ($Treatment \times Post$). Daily pairwise price synchronicity measures are computed in rolling windows of 14 days. We only report results using data from the subset of exchanges that are not prone to trading volume manipulation. Panel A contains all cryptocurrency pairs, Panel B focuses on the difference between BTC-USD and BTC-EUR. The sample period is July 1, 2016 to December 31, 2018, but we exclude the anticipation period between July 1, 2017 and December 31, 2017. Standard errors are clustered at the exchange pair level.

Panel A: All BTC currency pairs	(1)	(2)	(3)	(4)	(5)
Treatment	-0.00447	0.0389	-0.00607		
	(0.0349)	(0.0255)	(0.0354)		
Post	0.0127	0.0127		0.0127	
	(0.0205)	(0.0205)		(0.0205)	
Treatment×Post	0.120***	0.125***	0.122***	0.120***	0.128***
	(0.0294)	(0.0299)	(0.0299)	(0.0294)	(0.0308)
N	28092	28092	28092	28092	28092
adj. R^2	0.093	0.171	0.288	0.128	0.404
Panel B: BTC-USD vs. BTC-EUR	(1)	(2)	(3)	(4)	(5)
Treatment	-0.0441	0.00659	-0.0455		
	(0.0275)	(0.0210)	(0.0280)		
Post	0.00948	0.00948		0.00948	
	(0.0227)	(0.0227)		(0.0227)	
Treatment×Post	0.124***	0.128***	0.125***	0.124***	0.131***
	(0.0310)	(0.0314)	(0.0315)	(0.0310)	(0.0323)
N	27362	27362	27362	27362	27362
adj. R^2	0.090	0.171	0.291	0.090	0.379
Exchange Pair FE		✓			✓
Daily FE			✓		✓
Currency FE				✓	✓

Table 6: Differences-in-Differences Results - Price Efficiency

In this table, we report regression results from the projection of daily Hou and Moskowitz (2005) $D1$ price efficieny measures on the treatment indicator (*Treatment*) that takes the value one for BTC-USD cryptocurrency pairs and zero otherwise; an event indicator (*Post*) that takes the value one following the introduction of bitcoin futures on December 10, 2017; and their interaction (*Treatment* $\times$ *Post*). Panel A contains all cryptocurrency pairs, Panel B focuses on the difference between BTC-USD and BTC-EUR, Panel C reports results for BTC-USD vs. BTC-EUR using data from the subset of exchanges that are not prone to trading volume manipulation. The sample period is July 1, 2016 to December 31, 2018, but we exclude the anticipation period between July 1, 2017 and December 31, 2017. Standard errors are clustered at the exchange and currency level.

Panel A: All BTC currency pairs	(1)	(2)	(3)	(4)	(5)
Treatment	-0.0412	-0.0492	-0.0394		
	(0.0321)	(0.0283)	(0.0333)		
Post	-0.158***	-0.167***		-0.163***	
	(0.0456)	(0.0436)		(0.0421)	
Treatment×Post	-0.0296	-0.0264	-0.0291	-0.0248	-0.0219
	(0.0470)	(0.0443)	(0.0498)	(0.0437)	(0.0451)
N	21542	21542	21542	21542	21542
adj. R^2	0.101	0.126	0.609	0.135	0.657
Panel B: BTC-USD vs. BTC-EUR	(1)	(2)	(3)	(4)	(5)
Treatment	0.0282	0.0121	0.0250		
	(0.0232)	(0.0154)	(0.0235)		
Post	-0.166***	-0.176***		-0.166***	
	(0.0292)	(0.0263)		(0.0292)	
Treatment×Post	-0.0581**	-0.0527*	-0.0547*	-0.0581**	-0.0488*
	(0.0277)	(0.0253)	(0.0276)	(0.0277)	(0.0257)
N	13813	13813	13813	13813	13813
adj. R^2	0.175	0.191	0.778	0.175	0.795
Panel C: Panel B excl. susp. exchanges	(1)	(2)	(3)	(4)	(5)
Treatment	0.0508***	0.0365***	0.0468***		
	(0.0151)	(0.00764)	(0.0143)		
Post	-0.172***	-0.172***		-0.172***	
	(0.0238)	(0.0238)	(7.51e-18)	(0.0238)	
Treatment×Post	-0.0567**	-0.0585**	-0.0527**	-0.0567**	-0.0543**
	(0.0239)	(0.0246)	(0.0237)	(0.0239)	(0.0241)
N	9069	9069	9069	9069	9069
adj. R^2	0.197	0.205	0.867	0.197	0.873
Exchange FE		✓			✓
Daily FE			✓		✓
Currency FE				✓	✓

Table 7: Differences-in-Differences Results - Market Quality

In this table, we report regression results from the projection of daily Hasbrouck (1993) q market quality measures on the treatment indicator ($Treatment$) that takes the value one for BTC-USD cryptocurrency pairs and zero otherwise; an event indicator ($Post$) that takes the value one following the introduction of bitcoin futures on December 10, 2017; and their interaction ($Treatment \times Post$). Panel A contains all cryptocurrency pairs, Panel B focuses on the difference between BTC-USD and BTC-EUR. The sample period is July 1, 2016 to December 31, 2018, but we exclude the anticipation period between July 1, 2017 and December 31, 2017. Standard errors are double clustered by day and at the exchange × currency level.

Panel A: All BTC currency pairs	(1)	(2)	(3)	(4)	(5)
Treatment	0.00342	0.00490	0.00448		
	(0.00856)	(0.00757)	(0.00890)		
Post	-0.0266***	-0.0190***		-0.0256***	
	(0.00961)	(0.00645)		(0.00773)	
Treatment×Post	0.0268**	0.0241**	0.0258**	0.0258**	0.0225*
	(0.0111)	(0.0115)	(0.0112)	(0.00957)	(0.0115)
N	19398	19398	19398	19398	19398
adj. R^2	0.045	0.163	0.382	0.072	0.528
Panel B: BTC-USD vs. BTC-EUR	(1)	(2)	(3)	(4)	(5)
Treatment	-0.00551	-0.00286	-0.00592		
	(0.00693)	(0.00513)	(0.00740)		
Post	-0.0369***	-0.0286***		-0.0369***	
	(0.0127)	(0.00861)		(0.0127)	
Treatment×Post	0.0371**	0.0321**	0.0373**	0.0371**	0.0322**
	(0.0138)	(0.0120)	(0.0137)	(0.0138)	(0.0123)
N	12232	12232	12232	12232	12232
adj. R^2	0.047	0.131	0.568	0.047	0.666
Exchange FE		✓			✓
Daily FE			✓		✓
Currency FE				✓	✓

Table 8: Differences-in-Differences Results - Liquidity

In this table, we report regression results from the projection of daily liquidity measures projected on the treatment indicator ($Treatment$) that takes the value one for BTC-USD cryptocurrency pairs and zero otherwise; an event indicator ($Post$) that takes the value one following the introduction of bitcoin futures on December 10, 2017; and their interaction ($Treatment\_Post$). All results are based on the subset of exchanges that are not prone to trading volume manipulation. In Panels A and B (C and D), we present results for the comparison between BTC-USD and BTC-EUR (BTC-CCY^x), where CCY^x refers to HKD, GBP, CAD, JPY, SGD, AUD, RUB, IDR (excluding EUR). In Panel A, we present results for the Roll (1984) price impact measure using rolling windows of 14 days. In Panel B, present results for Abdi and Ranaldo (2017) CHL bid-ask spreads at the daily frequency. In Panel C, we present results for log of daily trading volume. In Panel D, we present results for the log of Amihud (2002) price impact measure using rolling windows of 14 days. The sample period is July 1, 2016 to December 31, 2018, but we exclude the anticipation period between July 1, 2017 and December 31, 2017. Standard errors are double clustered by day and at the exchange × currency level.

Panel A: Roll, BTC-USD vs. BTC-EUR	(1)	(2)	(3)	(4)	(5)
Treatment	0.0008	0.0001	0.0009		
	(0.00096)	(0.00069)	(0.00115)		
Post	0.0124***	0.0124***		0.0124***	
	(0.00194)	(0.00194)		(0.00194)	
Treatment×Post	-0.0033**	-0.0032**	-0.0033*	-0.0033**	-0.0033*
	(0.00140)	(0.00145)	(0.00175)	(0.00140)	(0.00180)
N	9056	9056	9056	9056	9056
adj. R^2	0.042	0.044	0.776	0.042	0.779
Panel B: CHL, BTC-USD vs. BTC-EUR	(1)	(2)	(3)	(4)	(5)
Treatment	0.00058	0.00022	0.00058		
	(0.00080)	(0.00048)	(0.00082)		
Post	0.00507***	0.00507***		0.00507***	
	(0.00051)	(0.00051)		(0.00051)	
Treatment×Post	-0.00073	-0.00071	-0.00073	-0.00073	-0.00071
	(0.00078)	(0.00084)	(0.00084)	(0.00078)	(0.00090)
N	9071	9071	9071	9071	9071
adj. R^2	0.073	0.086	0.781	0.073	0.796
Panel C: Volume, BTC-USD vs. BTC-CCY^x	(1)	(2)	(3)	(4)	(5)
Treatment	3.378***	3.435***	3.382***		
	(0.759)	(0.395)	(0.758)		
Post	-1.509	-1.545		-1.585*	
	(0.894)	(0.881)		(0.878)	
Treatment×Post	2.713**	2.604**	2.728**	2.790**	2.666**
	(1.066)	(1.062)	(1.071)	(1.053)	(1.070)
N	9464	9464	9464	9464	9464
adj. R^2	0.575	0.746	0.591	0.586	0.792
Panel D: Amihud, BTC-USD vs. BTC-CCY^x	(1)	(2)	(3)	(4)	(5)
Treatment	-3.648***	-3.907***	-3.646***		
	(1.001)	(0.591)	(0.995)		
Post	2.562*	2.559*		2.556*	
	(1.209)	(1.209)		(1.207)	
Treatment×Post	-3.543**	-3.411**	-3.529**	-3.537**	-3.394**
	(1.447)	(1.462)	(1.438)	(1.446)	(1.451)
N	9667	9667	9667	9667	9667
adj. R^2	0.550	0.729	0.523	0.592	0.747
Exchange FE		✓			✓
Daily FE			✓		✓
Currency FE				✓	✓

Table 9: Differences-in-Differences Results - 4:00 p.m. Settlement Prices

In this table, we report differences-in-differences regression results when we measure prices at the futures settlement times on the corresponding cash markets. Thus, prices are sampled daily at 4:00 p.m. London time from Itbit, Kraken, and Bitstamp, and at 4:00 p.m. Eastern time from Gemini. We regress different measures on the treatment indicator ($Treatment$) that takes the value one for BTC-USD return pairs and zero otherwise; an event indicator ($Post$) that takes the value one following the introduction of bitcoin futures in December 10, 2017; and their interaction ($Treatment\_Post$). In Panel A, we present results for the Roll (1984) price impact measure using rolling windows of 14 days. In Panel B, we present results for Abdi and Ranaldo (2017) CHL bid-ask spreads at the daily frequency. In Panel C, we present results for the log of the Amihud (2002) price impact measure using rolling windows of 14 days. In Panel D, we present results for the Hasbrouck (1993) q market quality measure using rolling windows of 90 days. In each panel, we present the results using end-of-day prices, and 4:00 p.m. settlement prices. We present only the coefficient estimates for the interaction term $Treatment\_Post$. In Panels A and B (C), we present results for the comparison between BTC-USD and BTC-EUR (BTC-CCY^x), where CCY^x refers to HKD, GBP, CAD, JPY, SGD, AUD, RUB, IDR (excluding EUR). In Panel D, we present results for the comparison with all other bitcoin-fiat exchange rate 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 are double clustered by day and at the exchange × currency level.

Panel A: Roll, BTC-USD vs. BTC-EUR	(1)	(2)	(3)	(4)	(5)
End-of-day prices					
Treatment×Post	-0.00008	-0.00008	-0.00008	-0.00008	-0.00008
	(0.00027)	(0.00028)	(0.00102)	(0.00028)	(0.00102)
N	5110	5110	5110	5110	5110
adj. R^2	0.055	0.055	0.893	0.055	0.893
Settlement prices					
Treatment_Post	-0.00520**	-0.00520**	-0.00520*	-0.00520**	-0.00520*
	(0.00208)	(0.00203)	(0.00247)	(0.00199)	(0.00248)
N	5110	5110	5110	5110	5110
adj. R^2	0.034	0.035	0.810	0.034	0.812
Panel B: CHL, BTC-USD vs. BTC-EUR	(1)	(2)	(3)	(4)	(5)
End-of-day prices					
Treatment×Post	0.00063*	0.00063**	0.00063	0.00063**	0.00063
	(0.00030)	(0.00024)	(0.00043)	(0.00024)	(0.00043)
N	5110	5110	5110	5110	5110
adj. R^2	0.094	0.097	0.754	0.094	0.759
Settlement prices					
Treatment×Post	-0.00075	-0.00075	-0.00075	-0.00075	-0.00075
	(0.00137)	(0.00125)	(0.00148)	(0.00124)	(0.00148)
N	5110	5110	5110	5110	5110
adj. R^2	0.080	0.098	0.710	0.080	0.732
Exchange FE		✓			✓
Daily FE			✓		✓
Currency FE				✓	✓

Panel C: Amihud, BTC-USD vs. BTC-CCY^x	(1)	(2)	(3)	(4)	(5)
End-of-day prices					
Treatment×Post	-3.334**	-3.332**	-3.299**	-3.330**	-3.294**
	(1.226)	(1.225)	(1.187)	(1.226)	(1.187)
N	5708	5708	5708	5708	5708
adj. R^2	0.778	0.797	0.763	0.835	0.835
Settlement prices					
Treatment×Post	-3.368*	-3.365*	-3.344**	-3.362*	-3.338**
	(1.449)	(1.448)	(1.412)	(1.449)	(1.411)
N	5705	5705	5705	5705	5705
adj. R^2	0.668	0.693	0.644	0.741	0.733
Panel D: q, All BTC currency pairs	(1)	(2)	(3)	(4)	(5)
End-of-day prices					
Treatment×Post	-0.00167	-0.00068	-0.00239	-0.00004	-0.00093
	(0.00882)	(0.00812)	(0.00970)	(0.00792)	(0.00874)
N	7100	7100	7100	7100	7100
adj. R^2	0.044	0.075	0.572	0.187	0.728
Settlement prices					
Treatment×Post	0.0266*	0.0279*	0.0242	0.0291*	0.0263*
	(0.0131)	(0.0134)	(0.0138)	(0.0136)	(0.0140)
N	7098	7098	7098	7098	7098
adj. R^2	0.057	0.097	0.311	0.191	0.448
Exchange FE		✓			✓
Daily FE			✓		✓
Currency FE				✓	✓

Table 10: Differences-in-Differences Results - Liquidity and Attention Channels

In this table, we estimate Equation (13) to identify the effect of attention and liquidity on daily pairwise cross-exchange Pearson correlation coefficients (Kapadia and Pu (2012) price synchronicity measures) in Panels A and B (Panels C and D) after the introduction of bitcoin futures. *High Attention* is equal to 1 if the average Google search intensity for an exchange is above the median sample value in the pre-event period and 0 otherwise. *High Liquidity* is equal to 1 if the average trading volumes (in BTCs) in the pre-event period is above the sample median and 0 otherwise. Daily pairwise Pearson correlation coefficients and Kapadia and Pu (2012) price synchronicity measures are computed in rolling windows with lags of 14 days. We only report results using data from the subset of exchanges that are not prone to trading volume manipulation. We report coefficient estimates for *Treatment×Post* and *Treatment×Post×High Attention* (*Treatment×Post×High Liquidity*) in Panels A and C (Panels B and D). The sample period is July 1, 2016 to December 31, 2018, but we exclude the anticipation period between July 1, 2017 and December 31, 2017. Standard errors are clustered at the exchange pair level.

Panel A: Pearson correlation coefficient	(1)	(2)	(3)	(4)	(5)
Treatment×Post	0.0747***	0.0791***	0.0742***	0.0747***	0.0794***
	(0.0224)	(0.0230)	(0.0218)	(0.0224)	(0.0229)
Treatment×Post×High Attention	-0.0429*	-0.0473**	-0.0424*	-0.0429*	-0.0476**
	(0.0224)	(0.0230)	(0.0221)	(0.0224)	(0.0231)
N	28078	28078	28078	28078	28078
adj. R^2	0.186	0.266	0.309	0.276	0.483
Panel B: Pearson correlation coefficient	(1)	(2)	(3)	(4)	(5)
Treatment×Post	0.0813***	0.0857***	0.0807***	0.0813***	0.0861***
	(0.0226)	(0.0234)	(0.0221)	(0.0228)	(0.0234)
Treatment×Post×High Liquidity	-0.0772***	-0.0817***	-0.0767***	-0.0772***	-0.0820***
	(0.0232)	(0.0239)	(0.0228)	(0.0234)	(0.0241)
N	28078	28078	28078	28078	28078
adj. R^2	0.128	0.245	0.250	0.268	0.479
Panel C: Kapadia and Pu (2012) measure	(1)	(2)	(3)	(4)	(5)
Treatment×Post	0.154***	0.159***	0.156***	0.154***	0.163***
	(0.0381)	(0.0384)	(0.0385)	(0.0381)	(0.0392)
Treatment×Post×High Attention	-0.138***	-0.144***	-0.141***	-0.138***	-0.148***
	(0.0380)	(0.0382)	(0.0389)	(0.0380)	(0.0396)
N	28092	28092	28092	28092	28092
adj. R^2	0.112	0.181	0.308	0.143	0.415
Panel D: Kapadia and Pu (2012) measure	(1)	(2)	(3)	(4)	(5)
Treatment×Post	0.142***	0.147***	0.144***	0.142***	0.150***
	(0.0362)	(0.0368)	(0.0366)	(0.0362)	(0.0377)
Treatment×Post×High Liquidity	-0.120***	-0.125***	-0.122***	-0.120***	-0.129***
	(0.0379)	(0.0383)	(0.0381)	(0.0379)	(0.0390)
N	28092	28092	28092	28092	28092
adj. R^2	0.103	0.176	0.298	0.135	0.407
Exchange FE		✓			✓
Daily FE			✓		✓
Currency FE				✓	✓

APPENDIX
The impact of derivatives on cash markets: Evidence from the introduction of bitcoin futures contracts

Patrick Augustin, Alexey Rubtsov and Donghwa Shin

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Abstract

We exploit a unique feature of cryptocurrency markets to provide new evidence on how derivatives impact cash markets. In December 2017, the CME and the CBOE both introduced futures contracts on bitcoin (BTC) against USD, but not on any other cryptocurrency exchange rate pairs. Because identical cryptocurrencies trade on multiple exchanges, we can examine how the introduction of bitcoin futures changed various attributes of BTC-USD relative to other cryptocurrency pairs, keeping exchange characteristics constant. Following the futures introduction, we find a significant increase in cross-exchange BTC-USD price synchronicity relative to other exchange rate pairs, as demonstrated by an increase in price correlations and a reduction in arbitrage opportunities. We also find evidence in support of an increase in market efficiency and market quality. There is suggestive evidence of increasing market liquidity, although these results are weaker. Overall, our analysis supports the view that the introduction of BTC-USD futures was beneficial to the bitcoin cash market by making the underlying prices more informative.

JEL Classification Codes: C70, G18, O31, O32, O33

Keywords: Bitcoin, Blockchain, Cryptocurrencies, Derivatives, FinTech, Futures

A Institutional Background

The Wall Street Journal refers to cryptocurrencies as "one of the most powerful innovations in finance in 500 years" (Casey and Vigna, Jan. 23, 2015). Regulators have struggled to adapt existing laws in the areas of banking and securities regulation, and central banks around the world (e.g., Bank of England, Bank of Canada, U.S. Federal Reserve, Bank of China) are exploring issuance of their own cryptocurrencies. The distributed ledger technology underlying cryptocurrencies has many other potential applications in diverse areas such as property registration, accounting and auditing, and financial derivatives. On January 9, 2017, the Wall Street Journal announced joint efforts by IBM and the Depository Trust & Clearing Corp., the New York-based utility that settles and clears all stock and bond trades in the U.S., to clear all credit derivatives clearing through blockchain technology (Demos, Jan. 9, 2017). These developments underscore the rapid transformation of the market for financial derivatives. In this section, we first provide some background information on blockchains, and second about cryptocurrencies.

A.1 Blockchains

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

Blockchain dates back to Haber and Stornetta (1991), but rose to mainstream prominence only after Nakamoto (2008) employed the data structure as the underlying technology behind Bitcoin. In his seminal white paper, Nakamoto (2008) argues that Bitcoin provides "a system for electronic transactions without relying upon trust." The associated argument relies not only upon the blockchain data structure but also upon the usage of several other extant computer science concepts.[3]

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

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

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

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

The rich functionality of platforms such as Ethereum and EOS.IO allows for decentralized applications that themselves feature native tokens, which are typically classified as cryptocurrencies. Currently, there exist over 2000 cryptocurrencies, with the majority not operating on an independent blockchain. Among cryptocurrencies operating on their own blockchains, almost all operate with either PoW or PoS protocols.

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

A.2 Cryptocurrencies

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

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

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

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

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

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

Table A.1: Summary statistics for Cryptocurrency Returns

In this table, we provide summary statistics for hourly cryptoccurency returns by currency pair and exchange. In Panel A, we focus on BTC-USD, in Panel B, we focus on BTC-EUR, and in Panel C, we focus on the remaining bitcoin currency pairs. In each panel, we report the exchange's name, the start and end dates of the data, the number of observations, 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.

Panel A. BTC-USD (Hourly)

Currency	**Exchange**	**Start**	**End**	**N**	**Mean**	**SD**	**Skew**	**Kurt**	**p5**	**p95**
BTC-USD	Binance	10/27/2017	12/31/2018	10253	-0.00005	0.0118	-0.1584	14.9947	-0.0176	0.0163
BTC-USD	Bitfinex	07/01/2016	12/31/2018	21482	0.00007	0.0098	-0.3209	19.6452	-0.0142	0.0137
BTC-USD	Bitstamp	07/01/2016	12/31/2018	21862	0.00007	0.0096	-0.4107	20.6412	-0.0141	0.0134
BTC-USD	Bittrex	01/01/2017	12/31/2018	15964	0.00006	0.0134	-0.1358	30.6430	-0.0193	0.0180
BTC-USD	BTC-e	07/01/2016	11/28/2018	18850	0.00009	0.0089	-0.2620	21.5147	-0.0123	0.0123
BTC-USD	Coinbase	07/01/2016	12/31/2018	21812	0.00007	0.0096	-0.3790	22.9719	-0.0138	0.0131
BTC-USD	Gatecoin	08/24/2017	12/28/2018	4598	0.00013	0.0196	0.6891	24.1965	-0.0247	0.0245
BTC-USD	Gemini	07/01/2016	12/31/2018	21399	0.00007	0.0096	-0.4314	22.4428	-0.0140	0.0132
BTC-USD	HitBTC	08/26/2017	12/31/2018	11770	-0.00001	0.0107	0.1272	15.1063	-0.0163	0.0156
BTC-USD	Itbit	07/01/2016	12/31/2018	21676	0.00008	0.0096	-0.3825	22.2319	-0.0139	0.0133
BTC-USD	Kraken	07/01/2016	12/31/2018	21695	0.00008	0.0097	-0.3228	21.8182	-0.0141	0.0136
BTC-USD	OkCoin	07/01/2016	12/31/2018	17834	0.00005	0.0093	-0.6796	25.2996	-0.0133	0.0131
BTC-USD	Poloniex	07/01/2016	12/31/2018	21325	0.00006	0.0102	-0.4562	20.2860	-0.0146	0.0140
BTC-USD	Quoine	07/01/2016	12/31/2018	18398	0.00006	0.0109	-0.1986	29.5571	-0.0149	0.0141

Panel B. BTC-EUR (Hourly)

Currency	**Exchange**	**Start**	**End**	**N**	**Mean**	**SD**	**Skew**	**Kurt**	**p5**	**p95**
BTC-EUR	Bitstamp	07/01/2016	12/31/2018	21558	0.00008	0.0098	-0.2707	19.2586	-0.0142	0.0135
BTC-EUR	BTC-e	07/01/2016	11/25/2018	18437	0.00011	0.0087	-0.2077	33.1492	-0.0115	0.0115
BTC-EUR	Coinbase	07/01/2016	12/31/2018	21806	0.00007	0.0098	-0.1261	27.5685	-0.0136	0.0127
BTC-EUR	Gatecoin	08/24/2017	12/21/2018	2780	0.00052	0.0239	0.3128	26.9457	-0.0302	0.0304
BTC-EUR	Itbit	07/01/2016	12/31/2018	10438	-0.00006	0.0108	-0.4355	24.6929	-0.0160	0.0142
BTC-EUR	Kraken	07/01/2016	12/31/2018	21784	0.00007	0.0096	-0.1933	22.9485	-0.0138	0.0133
BTC-EUR	Quoine	07/09/2016	12/31/2018	9002	-0.00003	0.0135	-0.1837	20.4974	-0.0199	0.0173

Panel C. BTC-CCY excluding BTC-EUR (Hourly)

Currency	**Exchange**	**Start**	**End**	**N**	**Mean**	**SD**	**Skew**	**Kurt**	**p5**	**p95**
BTC-GBP	Coinbase	07/01/2016	12/31/2018	21779	0.00007	0.0100	-0.3918	21.5796	-0.0146	0.0134
BTC-GBP	Kraken	07/01/2016	12/31/2018	7160	0.00047	0.0335	-0.4702	68.8689	-0.0402	0.0411
BTC-HKD	Gatecoin	08/24/2017	12/20/2018	3574	0.00018	0.0239	-0.0840	27.0225	-0.0339	0.0330
BTC-HKD	Quoine	11/20/2016	12/19/2018	3923	-0.00006	0.0189	0.3398	58.4692	-0.0252	0.0223
BTC-SGD	Itbit	09/06/2016	12/31/2018	5573	-0.00005	0.0122	-0.5546	21.5976	-0.0187	0.0170
BTC-SGD	Quoine	07/01/2016	12/31/2018	15537	0.00004	0.0123	-0.7087	42.6459	-0.0173	0.0161
BTC-JPY	Kraken	07/01/2016	12/31/2018	10581	-0.00012	0.0184	0.3115	29.4217	-0.0254	0.0249
BTC-JPY	Quoine	07/01/2016	12/31/2018	21786	0.00009	0.0102	1.3436	88.1706	-0.0134	0.0130
BTC-AUD	Quoine	07/01/2016	12/31/2018	6682	0.00016	0.0165	0.3105	65.5203	-0.0211	0.0192
BTC-AIDR	Quoine	07/01/2016	12/20/2018	7737	-0.00003	0.0129	-0.2646	78.2127	-0.0166	0.0152
BTC-RUB	BTC-e	09/16/2016	11/27/2018	16798	0.00012	0.0091	0.6333	37.3787	-0.0120	0.0122
BTC-CAD	Kraken	07/01/2016	12/31/2018	17005	0.00004	0.0156	0.1384	20.8442	-0.0228	0.0228

Table A.2: Cryptocurrency Return Correlations.

In this table, we provide pairwise BTC-USD hourly log return correlations (Pearson correlatoins) across the five biggest exchanges in terms of aggregate trading volume between July 1, 2016 and December 31, 2016. BTC-e is excluded because it shut down its business in 2018. The sample period is July 2016 to December 2018. In Panel A (Panel B), we show pairwise correlation coefficients for the 12 months before (after) the futures introduction from July 2016 to June 2017 (January 2018 to December 2018).

Panel A: Average hourly correlation, July 2016 - Jun 2017					
	Bitfinex	Bitstamp	Coinbase	Itbit	Quoine
Bitfinex	1	0.8166	0.8082	0.8192	0.5678
Bitstamp	0.8166	1	0.8821	0.8879	0.6058
Coinbase	0.8082	0.8821	1	0.8971	0.6274
Itbit	0.8192	0.8879	0.8971	1	0.6153
Quoine	0.5678	0.6058	0.6274	0.6153	1
Panel B: Average hourly correlation, Jan 2018 - Dec 2018					
	Bitfinex	Bitstamp	Coinbase	Itbit	Quoine
Bitfinex	1	0.9767	0.9737	0.9733	0.9014
Bitstamp	0.9767	1	0.9865	0.9858	0.9133
Coinbase	0.9737	0.9865	1	0.9885	0.9191
Itbit	0.9733	0.9858	0.9885	1	0.9172
Quoine	0.9014	0.9133	0.9191	0.9172	1

Table A.3: Differences-in-Differences Results - Price Synchronicity/Correlations - Hourly

In this table, we report regression results from the projection of hourly pairwise cross-exchange Pearson correlation coefficients on the treatment indicator (*Treatment*) that takes the value one for BTC-USD return pairs and zero otherwise; an event indicator (*Post*) that takes the value one following the introduction of bitcoin futures on December 10, 2017; and their interaction ($Treatment \times Post$). Daily pairwise Pearson correlation coefficients are computed in rolling windows with lags of 14 days. We only report results using data from the subset of exchanges that are not prone to trading volume manipulation. Panel A contains all cryptocurrency pairs, Panel B focus on the difference between BTC-USD and BTC-EUR. The sample period is July 1, 2016 to December 31, 2018, but we exclude the anticipation period between July 1, 2017 and December 31, 2017. Standard errors are clustered at the exchange pair level.

Panel A: All BTC currency pairs	(1)	(2)	(3)	(4)	(5)
Treatment	0.0554	0.0990**	0.0531		
	(0.0615)	(0.0451)	(0.0619)		
Post	0.204***	0.204***		0.204***	
	(0.0334)	(0.0334)		(0.0334)	
Treatment×Post	0.0929**	0.0970**	0.0951**	0.0929**	0.0998**
	(0.0433)	(0.0433)	(0.0437)	(0.0433)	(0.0440)
N	27678	27678	27678	27678	27678
adj. R^2	0.369	0.501	0.437	0.494	0.672
Panel B: BTC-USD vs. BTC-EUR	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
Treatment	-0.0194	0.0435	-0.0217		
	(0.0412)	(0.0328)	(0.0419)		
Post	0.219***	0.219***		0.219***	
	(0.0362)	(0.0362)		(0.0362)	
Treatment×Post	0.0782*	0.0824*	0.0805*	0.0782*	0.0852*
	(0.0451)	(0.0452)	(0.0455)	(0.0451)	(0.0458)
N	26962	26962	26962	26962	26962
adj. R^2	0.407	0.536	0.487	0.407	0.622
Exchange Pair FE		✓			✓
Daily FE			✓		✓
Currency FE				✓	✓

Table A.4: Differences-in-Differences Results - Price Synchronicity/Integration - Hourly

In this table, we report regression results from the projection of hourly pairwise cross-exchange Kapadia and Pu (2012) price synchronicity measures on the treatment indicator (*Treatment*) that takes the value one for BTC-USD cryptocurrency pairs and zero otherwise; an event indicator (*Post*) that takes the value one following the introduction of bitcoin futures on December 10, 2017; and their interaction ($Treatment \times Post$). Daily pairwise price synchronicity measures are computed in rolling windows of 14 days. Panel A contains all cryptocurrency pairs, Panel B focuses on the difference between BTC-USD and BTC-EUR, Panel C reports results using data from the subset of exchanges that are not prone to trading volume manipulation. The sample period is July 1, 2016 to December 31, 2018, but we exclude the anticipation period between July 1, 2017 and December 31, 2017. Standard errors are clustered at the exchange pair level.

Panel A: All BTC currency pairs	(1)	(2)	(3)	(4)	(5)
Treatment	0.472***	0.464***	0.473***		
	(0.131)	(0.103)	(0.132)		
Post	-0.318***	0.0239		-0.309***	
	(0.108)	(0.0559)		(0.102)	
Treatment×Post	0.379***	0.218***	0.380***	0.370***	0.236***
	(0.106)	(0.0764)	(0.106)	(0.101)	(0.0764)
N	66398	66398	66398	66398	66398
adj. R^2	0.192	0.642	0.211	0.211	0.684
Panel B: BTC-USD vs. BTC-EUR	(1)	(2)	(3)	(4)	(5)
Treatment	0.396***	0.433***	0.396***		
	(0.142)	(0.115)	(0.143)		
Post	-0.309***	0.0674		-0.309***	
	(0.115)	(0.0596)		(0.115)	
Treatment×Post	0.371***	0.179**	0.372***	0.371***	0.181**
	(0.110)	(0.0752)	(0.111)	(0.110)	(0.0759)
N	64004	64004	64004	64004	64004
adj. R^2	0.146	0.645	0.165	0.146	0.665
Panel C: Excluding suspicious exchanges	(1)	(2)	(3)	(4)	(5)
Treatment	0.249	0.395**	0.248		
	(0.155)	(0.149)	(0.155)		
Post	-0.0988	-0.0988		-0.0988	
	(0.0637)	(0.0637)		(0.0637)	
Treatment×Post	0.467***	0.483***	0.469***	0.467***	0.486***
	(0.110)	(0.112)	(0.110)	(0.110)	(0.113)
N	27685	27685	27685	27685	27685
adj. R^2	0.238	0.435	0.270	0.303	0.547
Exchange Pair FE		✓			✓
Daily FE			✓		✓
Currency FE				✓	✓