Slowed-Down Capital: Using Bitcoin to Avoid Capital Controls*

Jiakai Chen† Asani Sarkar‡

August 15, 2022

Abstract

We provide evidence consistent with residents buying bitcoin in China and selling them for US dollars on foreign (i.e. non-Chinese) exchanges, thereby using bitcoin to evade capital controls. Specifically, on Chinese bitcoin exchanges, the Bitcoin price premium and the buy imbalance increases with our measure of capital control. Conversely, on foreign exchanges, the Bitcoin price discount and the sell imbalance increases with our measure of capital control. Our paper highlights the prominent role of Bitcoin in evading capital controls, which was strict in China during our sample period of 2014-2016, when most bitcoin trading also occurred in China.

Keywords: bitcoin exchanges, limits to arbitrage, cryptocurrencies, capital flights

JEL classification: G12, G14

*This paper supercedes an earlier version titled "The Law of One Bitcoin Price?" The views expressed in this article are those of the authors and do not necessarily reflect the views of the Federal Reserve Bank of New York or of the Federal Reserve System. The authors thank participants at the Inaugural Conference on the International Roles of the U.S. Dollar, the Fintech conferences at Fordham University, FRB Philadelphia, the IWFSA conference, and Cass Business School for comments on previous drafts of the paper. Any errors or omissions are the responsibility of the authors.

†University of Hawaii; e-mail: jiakai@hawaii.edu

‡Federal Reserve Bank of New York; e-mail: asani.sarkar@ny.frb.org

1 Introduction

Bitcoins trading on different exchanges are by design the same, fully fungible, asset with identical payoffs. In theory – and unlike traditional asset pairs – they constitute ideal, textbook examples where the law of one price should be satisfied. However, since bitcoin exchanges are independent and there are no explicit regulations to ensure best execution for investors, only arbitrageurs and speculators can maintain the Law of One Price. Consistent with limits to arbitrage, there is evidence of large and recurring deviations in cryptocurrency prices across exchanges ((Kroeger and Sarkar, 2016, 2017) and Makarov and Schoar (2020)), pointing to significant market segmentation. While trading and bitcoin network frictions limit arbitrage, the literature suggests that capital controls may also slow down arbitrage capital (Makarov and Schoar (2020) and Choi et al. (2022)).

In this paper, we provide additional, unique evidence that capital controls drive wedges between the prices of bitcoin trading in different exchanges. During our sample (June 2014 to December 2016), China had strict capital controls and Chinese investors accounted for more than 90% of bitcoin trade (Liu et al. (2021)). Thus, Chinese residents both had the incentive and the opportunity to use bitcoin to take Renminbi (RMB) out of China.[1] A Chinese investor could buy bitcoin using RMB in China – either in an exchange (the "home" exchange; see Figure 8) or from a miner – transfer it to the digital wallet of a foreign exchange outside China (the "target" exchange) and sell it for US dollars (USD) or another fiat currency of choice. This capital evasion trade implies that days with substantial bitcoin-related capital *outflows* from China results in a higher bitcoin price and higher bitcoin buy imbalances at the home exchange, relative to foreign exchanges. Moreover, in the target foreign exchanges, bitcoin is expected to trade at a discount and experience higher sell imbalances, relative to non-target foreign exchanges, on days with large capital evasion trades by Chinese residents. We provide evidence in support of these hypotheses using several measures of capital controls in China.

To implement our tests, we use bitcoin trading data for the dominant Chinese exchanges BTCC and OKCoin (with a combined 90% share of bitcoin-RMB trades during our sample). To find potential target foreign exchanges, we initially assume that Chinese residents move RMB for USD and select six exchanges that account for 90% of bitcoin-USD trades during our sample. While Chinese residents can sell bitcoin for, say, euro and then exchange euro for USD, such transactions

[1] Chinese exchanges accounted for more than 90% of global bitcoin trading in 2016 (see Bitcoin Trading in China). The article states that "The bitcoin network, composed of traders around the globe accessing virtual platforms via their computers and the Internet, also allows a discreet way for a Chinese to move money beyond the country's tightly-controlled borders."

introduce foreign exchange risk. By focusing only on bitcoin-USD trades, we are able to examine the bitcoin price differences separately from the failure of parity conditions in fiat exchange markets (Frenkel and Levich (1975) and Du et al. (2018)).[2] However, for robustness, we also consider bitcoin trades on foreign bitcoin exchanges that are denominated in the euro.

We first show that bitcoin on average trades at a premium on Chinese exchanges relative to the foreign exchanges, consistent with Makarov and Schoar (2020) who find for a later sample (2017-2018) that bitcoin typically trades at premium on non-US relative to US exchanges. Further, when we consider price differences between the six foreign exchanges, we find that the mean price difference is statistically different from zero for 13 of 15 exchange pairs. More interesting, some non-US exchanges trade at a *discount* relative to US exchanges, different from Makarov and Schoar (2020). These exchanges offered enhanced anonymity, and less restrictions in converting bitcoin to USD, relative to US exchanges – features that made them attractive as "target" exchanges for capital evasion trades. For example, the US Justice Department filed a complaint against one non-US exchange (BTC-e) stating that "it made no effort to maintain any elements of an Anti-Money Laundering (AML) program, as its business model obscured and anonymized transactions and sources of funds."[3]

We hypothesize that capital controls prevent the closing of bitcoin price gaps. To test this hypothesis, we construct three measures of the effectiveness of China's capital control. Two are market-based daily measures that indicate the presence of arbitrage opportunities: the spread between the onshore and offshore exchange rates of RMB and the deviation between the RMB deposit rate and the interest rate implied by the covered interest parity (CIP) condition between RMB and USD. While capital control policies do not change frequently, their effectiveness varies (depending, for example, on the demand for USD by Chinese residents), resulting in time-varying arbitrage opportunities (Ma and McCauley (2008), Craig et al. (2013a) and Funke et al. (2015a)). To account for factors unrelated to capital controls, we regress the measures on variables related to macroeconomic conditions, market liquidity and risk premia, and use the residuals as our proxy measures of capital control. The third measure is a *de jure* capital outflow control index based on monthly Chinese balance of payments data, following Chen and Qian (2016).

Our first set of results show that the *magnitude* of price differences between Chinese and foreign exchanges is significantly correlated with all three of our capital control measures, especially rela-

[2] The composition of intrinsic bitcoin price and exchange rate differences, when bitcoins denominated in different fiat currencies are commingled, is further explained in section A of the internet appendix.

[3] See #18 on page 4 and #24 on page 5 of USA versus BTC-e complaint, June 2016 reddit post and May 2015 review).

tive to foreign exchanges with poor governance. Further, the price premium on Chinese exchanges, relative to foreign exchanges, increases with the capital control measures. Conversely, on foreign exchanges with poor governance (and so more apt to be used for capital flight trades), bitcoin typically trades at a *discount* to other exchanges, and the bitcoin price discount widens during periods when capital controls are more binding.

Our second set of results relate to the relationship of the bitcoin order imbalance and capital controls. On days when capital controls are more binding, we find that bitcoin buy imbalance increases on Chinese exchanges while the bitcoin sell imbalance increases on foreign exchanges. These results are consistent with using bitcoins for capital evasion: there is buying (selling) pressure on bitcoin prices trading, resulting in price premium (discounts) in Chinese (foreign) exchanges. These effects are especially manifest in the target exchanges that are more heavily utilized for capital evasion trades. Consistent with this interpretation, on US-registered exchanges (where governance standards such as adherence to KYC/AML standards are superior), both the bitcoin price differences and order imbalances are generally unrelated to our capital outflow measures.

In addition to capital controls, trading illiquidity, network congestion and trading clienteles also explain failures to arbitrage the bitcoin price differences. Regression analysis shows that the price difference is positively related to network trading fees, suggesting that network congestion impedes arbitrage. Increased trading frictions – such as higher bid-ask spread, and higher price volatility — widens the price differences. However, evan after accounting for these frictions, we continue to find statistically significant relationships between capital controls, price differences and bitcoin order imbalances.

Our study contributes to the literature that examines the role of capital controls behind persistent bitcoin price differences. For example, Makarov and Schoar (2020) show persistent price differences in bitcoin prices during 2017-2018 that are smaller within than across a given country or region, suggesting market segmentation. As evidence of capital controls, Makarov and Schoar (2020) find that country pairs with relatively closed capital flows also have correlated arbitrage spreads. Hu et al. (2021) use Bitcoin blockchain data to infer cross-border fiat currency flows via cryptocurrencies. They identify capital avoidance transactions under the assumption that such trades incur losses ex-post due to the price pressure induced by capital flight. Yu and Zhang (2020) document profits from triangular arbitrage between bitcoin, USD and another fiat currency and show that it increases in the intensity of capital controls between the relevant countries. Pieters (2016) finds that countries engage in short-term capital controls by comparing the exchange rate implied by bitcoin prices in different currencies and the official exchange rate.

Different from these papers, we provide evidence consistent with Chinese residents selling bitcoins in a target non-Chinese exchange to evade capital controls (see Figure 8) during a sample period when Chinese capital controls were strict *and* most bitcoin trading occurred in China. We show that bitcoin trades at a *discount* and there is selling pressure in the target exchange relative to other exchanges, thus providing evidence on both price and quantity effects on bitcoin from capital flights. Our results are complementary to Makarov and Schoar (2020) and Choi et al. (2022) who show that the marginal non-US investor is willing to pay *more* for bitcoin than a US investor, suggesting a non-pecuniary value to holding bitcoin in the home country. Regarding quantities, while Makarov and Schoar (2020) show a positive relation between net order flows and crypto prices, we find a positive association between cross-exchange price differences and the bitcoin sell imbalance.

Our second contribution is that we develop measures of capital controls at daily and monthly frequencies that allow us to separate capital inflow from *outflow* controls, which is useful since bitcoin is typically used to avoid outflow controls. By comparison, Makarov and Schoar (2020) do not separate capital inflows from outflow controls and use an annual measure.

The literature has extended the phenomenon of slow-moving capital (Duffie (2010) and Duffie and Strulovici (2012)) to cryptocurrency markets. We contribute to this literature by showing that block size and trading clienteles impede arbitrage between bitcoin exchanges, in addition to the microstructure variables and network fees previously documented by Kroeger and Sarkar (2017) and Choi et al. (2022). Similar to CITE, our results extend the phenomenon of slow-moving capital to cryptocurrency markets and to the role of capital controls which induces selling pressure that tend to widen a price discount in the target exchange.

Finally, our paper contributes to the debate on the value of bitcoins, and cryptocurrencies more generally. Proponents have pointed to its potential as a payment mechanism and digital money (Luckner et al. (2021)). Opponents argue that bitcoins have few legitimate uses and derives its value from illicit and speculative activities (Foley et al. (2019), Amiram et al. (2020) and Sokolov (2021)), although Makarov and Schoar (2021) report that illegal transactions, scams and gambling take up less than 3% of bitcoin volume. Our paper provides evidence consistent with a specific type of illicit activity – evading capital controls – that circumvents legitimate government policy and has significant implications for the real economy.[4]

The article is organized as follows. Section 2 reviews the literature. Section 3 provides more information on the sources of data and provides descriptive evidence on the bitcoin price differences.

[4]Whether capital controls are beneficial or not remains a matter of debate and is outside the scope of this paper.

Section 4 develops our hypotheses and describes our empirical methodology. Section 5 presents the results. Section 6 concludes.

2 Literature Review

In this section, we describe the relevant literature on using cryptocurrency to evade capital and limits to arbitraging cryptocurrency prices across exchanges. We further discuss the various measures of capital controls in the literature.

Makarov and Schoar (2020) argue that capital controls are one reason for bitcoin price differences across countries based on the observation that bitcoin trades at a premium in non-US relative to US countries (indicating an additional benefit to non-US investors in holding bitcoin). A particular case is the "Kimchi premium" whereby bitcoin traded at an average premium of 2% in 2016-2018 in South Korea relative to other crypto exchanges, in part due to Korean capital export restrictions (Choi et al. (2022)). In contrast, we provide evidence for the capital evasion mechanism illustrated in Figure 8 which imply persistent price discounts and excess selling pressure on bitcoins from capital flight trades in the target exchange outside the host country. These different mechanisms drive the differences in our analyses. Thus, for country pairs, Makarov and Schoar (2020) show a positive correlation between the arbitrage spread and the product of their capital control indexes (due to Fernandez et al. (2016)).[5] By comparison, we analyze exchange pairs and separate out capital inflow from outflow control measures. Moreover, unlike these papers, the arbitrage trades we examine do not require the exchange of fiat currencies (e.g., of Korean won for USD in Choi et al. (2022)), as previously discussed. Finally, during our sample – which precedes that in Makarov and Schoar (2020) – bitcoin exchange liquidity was worse and capital controls in China was more stringent, likely contributing to more persistent price differences.

Another branch of the literature seeks to identify cross-border transactions under specific assumptions. Luckner et al. (2021) develop a matching algorithm and apply it to exchange data to provide a lower bound on "crypto vehicle transactions" (that use crypto as a vehicle between fiat currencies) with unique trade size and occurring in short time windows. They show, for the period 2017-2021, that a large fraction of these transactions is used to move capital across borders, particularly in countries with significant restrictions on international capital flows. The exchange

[5] In addition, Makarov and Schoar (2020) show that arbitrage spreads between cryptocurrencies (which are relatively unaffected by capital controls) are smaller compared to spreads between a fiat currency and a cryptocurrency for the same exchange pairs.

of bitcoin for fiat currency involved delays of several business days during our sample (see section 4.2), as compared to five hours allowed for in the matching algorithm. Hu et al. (2021) use bitcoin blockchain data to reconstruct fund flows from one fiat currency to another, across borders, via cryptocurrencies. They identify those flows related to capital flight under the assumption that, unlike other transactions, they incur a loss. The authors identify about 5% of trades as "capital flight" trades between 2011 and 2018. Since illicit, speculative trades or triangular arbitrage may also incur losses ex-post, the identification is likely to overstate the capital flight trades. Consistently, about half of "capital flight" trades are also identified as illicit trades.

Pieters (2016) proposes a method to use bitcoin-transaction prices in various currencies to construct a currency's unofficial exchange rate, based on the idea that buying bitcoin in one currency and selling it in a different currency implies an unofficial exchange rate. For 2014-2015, they find China's official and bitcoin-implied exchange rates deviated from each other, suggesting that its exchange rate regime was increasingly managed during this period.

A large literature examines the failure of arbitrage in cryptocurrency markets. Bitcoin provides an ideal laboratory for examining the law of one price as they are identical assets trading on different venues. In contrast, payoffs from traditional asset pairs are close but not identical.[6] Nevertheless, the literature has repeatedly found significant violations of the law of one bitcoin price. Kroeger and Sarkar (2016, 2017) document substantial and persistent price differences on 6 exchanges for bitcoin trades denominated in USD for 2012-2016. Makarov and Schoar (2020) use data for 34 exchanges and 19 countries during 2017-2018 to document cross-exchange price differences in cryptocurrencies. Cross-exchange execution risk limits arbitrage – for example, settlement latency inherent in proof-of-work consensus mechanisms (Hautsch et al. (2021)) or exchange confirmation requirements (Borri and Shakhnov (2021)) limit how quickly arbitrageurs can exploit cross-exchange price differences.

Arbitrage spreads appear to have declined over time. While Krueckeberg and Scholz (2020) find that average arbitrage spreads increased from 2013 to 2018, Crépellière and Zeisberger (2020) uses more recent data from October 2018 to June 2019 to test arbitrage strategies for specific cryp-

[6] For example, cross-listed stocks, such as American Depository Receipts (ADRs), of the same company in geographically-dispersed exchanges trade at different prices but ADRs and the foreign shares they represent are not fully fungible (Gagnon and Karolyi, 2010). Other examples of violations of the law of one price in traditional asset pairs are "Siamese-twin" stocks with almost-identical dividend streams that trade at different prices (Jong et al., 2009; Rosenthal and Young, 1990; Debora and Froot, 1999), parent and subsidiary company stocks trading at prices such that the parent company value is negative (Mitchell et al., 2002; Lamont and Thaler, 2003) and the off-the-run minus on-the-run Treasury bond spread (Amihud and Mendelson, 1991; Warga, 1992; Krishnamurthy, 2009). Nevertheless, this evidence exists for only a limited set of asset pairs since those with closely related payoffs are hard to come by (Gromb and Vayanos, 2010).

tocurrency and fiat currency pairs and find that arbitrage opportunities are minimal. Trimborn et al. (2022) come to a similar conclusion: using network analysis, they argue that efficiency has improved since 2018 as no individual bitcoin exchange influences other exchanges.

Our paper relates to the literature that examine the relation of cryptocurrencies and illicit activities. For instance, Foley et al. (2019) present evidence of bitcoin usage by drug dealers and human traffickers. Amiram et al. (2020) show that bitcoin has been used in financing terrorist attacks. Griffin and Shams (2020) argue that Bitcoin prices are subject to gaming by a small number of actors. Bitcoin was widely used on the online marketplace for Silk Road, nicknamed the "eBay of drugs," which was shut down by the FBI in 2013 (Caffyn, 2015). It has also been used by hackers to collect ransoms from their targets (see the LA Times). Sokolov (2021) demonstrate that, after massive ransonware attacks, the bitcoin blockchain congestion worsened due to increased amount of transactions.

A number of papers examine restrictions on cross-border flows by constructing measures of capital control (see the survey by Magud and Reinhart (2007)). Our preferred measure is the index constructed by Chen and Qian (2016) after extracting detailed information from the text of the IMF's Annual Report on Exchange Arrangements and Exchange Restrictions (AREAER). The index is successful in capturing both the trend and time-series variations in China's capital controls from 1999 to 2012. The index has several advantages over other capital control indices. Its construction tracks the gradual implementation of policy that is typical of China by extracting the information about these changes from each line of the source text. The index separates out capital inflow and outflow controls, as recommended by Magud and Reinhart (2007), and also different types of capital flows that are affected deferentially by capital controls (Ma and McCauley (2008)). It is at a monthly-frequency and so can be used to study short-term capital flows whereas other *de jure* indices are at annual or quarterly frequencies. Finally, the coding procedure departs from the traditional binary yes-or-no style of capital control indices and instead numerically measures changes in the intensity of capital account restrictions over time.[7]

[7] Among alternative measures, Chinn and Ito (2008) use the number of legal restrictions a government has in place on the flow of capital, according to the AREAER. Ilzetzki et al. (2019) constructs a measure (the IRR19 index) that draws on the AREAER and assigns a value of 1 to a country in each year where any one of three criteria is met. The IRR19 index reflects a lower bound on the actual incidence of capital controls, given the myriad of other controls a government could impose on the flow of capital.

3 Data and Bitcoin Price Differences

We discuss the bitcoin trading data (section 3.1) and provide descriptive statistics on the price differences between bitcoin exchanges in sections 3.2 and 3.3. In section 3.4, we discuss our capital control measures.

3.1 Bitcoin Trading Data

As, unlike major fiat currencies, bitcoin does not serve as a widely quoted unit of account in and of itself (Ali et al. (2014)), bitcoin prices are quoted in terms of a conversion of the fiat price at current exchange rates.[8] Price discovery in the bitcoin market occurs via online exchanges that allow customers to exchange bitcoins for fiat currency (or in some cases, other digital currencies). Makarov and Schoar (2021) report that 75% of real bitcoin volume since 2015 is linked to exchanges or exchange-like entities. Thus, these exchanges provide the main ways to obtain bitcoins. They act either as brokers that host a platform where buyers and sellers meet for a fee, or as dealers that profit from bid-ask spreads.

Our sample period is June 2014 to December 2016. As discussed before, most bitcoin trades occurred in China during our sample, which is important for our analysis since we hypothesize that Chinese capital controls were a significant factor in explaining price differences between bitcoin exchanges. For example, Hu et al. (2021) argue that capital flight trades out of China occurred mainly between 2013 and early 2017. Although we have data from 2012, activity was tiny in 2012 (Panel (a) of Figure 1) and in 2013, bitcoin prices spiked from about $200 to about $1000 during the year (Panel (b) of Figure 1). Then, in February 2014, Mt. Gox – the dominant bitcoin exchange at the time – became bankrupt and caused bitcoin activity to plunge globally before normalizing in June (Figure 1). We end the sample in 2016 because China banned trading on its bitcoin exchanges in 2017.[9] Notably, bitcoin price differences between exchanges have essentially disappeared since 2018 (Crépellière and Zeisberger (2020)).

[8] For instance, during our sample period, Overstock.com, an early adopter of bitcoin, provided an option at checkout to allow the customer to pay the USD equivalent in bitcoin. Refunds were also made in the USD value of the item, not the amount of bitcoin paid. Relatedly, many companies that initially accepted bitcoin, such as Dell and Microsoft, never actually received bitcoin. Rather, they used third parties such as BitPay and Coinbase to process bitcoin payments from their customers and then forward dollars (or another fiat currency) to the merchant.

[9] China banned mainland residents from trading in cryptocurrencies on its exchanges in September 2017. The two largest Chinese exchanges, BTCC and OkCoin, shut down their operations completely. On other Chinese exchanges, the purchase of cryptocurrencies with fiat currencies was no longer allowed. See China Ban1 and China Ban2.

Our primary source of exchange data is bitcoincharts.com which aggregates the entire trade histories of exchanges that conform to its formatting standards and makes them available for download. While many exchanges participate, it is not comprehensive. According to bitcoinity.org, the bitcoincharts.com data covered about 70% of the BTC-USD market from the beginning of 2015 to August 2016. From bitcoinity.org, we pull summarized order book information—namely bid-ask spreads as well as the sum of orders at a daily frequency for major exchanges.

We select exchanges with large market share and active trading during our sample. Associated with traders' accounts on an exchange is a virtual wallet in which traders can store their bitcoins and currencies accepted by the exchange. In China, we include BTC China (BTCN) which accounted for 81% of trading volume (in bitcoin units) of the bitcoin-RMB market during our sample. For foreign exchanges, the currency of trade is salient as typically, an exchange will accept multiple currencies for trading. As previously discussed, we provide separate analyses for a specific fiat currency that bitcoin is traded for. Initially, we only consider exchanges that accepted USD during our sample period to remove the foreign exchange risk from converting between fiat currencies. For this paper, six exchanges are considered—Bitfinex, Bitstamp, BTC-e, Coinbase, itBit, and Kraken—yielding 15 unique exchange pairs. These six exchanges that accounted for 90% of trading volume (in bitcoin units) of Bitcoin-USD market during our sample.

Historically, the bitcoin exchange market has been dominated by a few large players, such as Mt.Gox prior to its demise in February 2014. Figure 1 shows the volume of bitcoin-USD exchange trades during our sample, broken out by exchanges. After the collapse of Mt. Gox, three exchanges largely filled the void in the USD–bitcoin market: Bitfinex, Bitstamp, and BTC-e. By the end of our sample, itBit and Coinbase had also emerged as significant exchanges. Section 2 and Table 1 in the internet appendix provide more details about the exchanges, including their location and governance. To note, Coinbase, Itbit and Kraken are registered in the US, while the others are registered in Europe or off-shore locations. Further, BTC-e closed on July 28, 2017 after an investigation by the Justice Department.

Data is available for all exchanges for the full sample except Coinbase, for which the data with good quality starts on January 12, 2015. Most exchanges operate continuously except for operational outages, and so business hours are not observed in the data. Instead, an observation consists of a trade with a UTC (coordinated universal time) timestamp, the amount of bitcoin traded (in units of BTC), and the USD price at which the trade occurred. Table 1 provides a list the variable definitions.

We calculate the volume-weighted average price for exchange i and date t as $P_t^i = \frac{\sum_{\tau \in t} v_\tau p_\tau}{\sum_{\tau \in t} v_\tau}$, where p_τ and v_τ are the price and volume, respectively, at time τ on day t. Then, for each exchange pair i and $j \neq i$, we obtain the price difference as:

$$PriceDiff_{i,j,t} = \frac{P_t^i - P_t^j}{(P_t^i + P_t^j)/2} \times 100\%, \tag{1}$$

To filter outliers, we winsorize $PriceDiff$ at the one and 99 percentiles.[10]

Similar to price differences, we also compute the difference in order imbalance per exchange pair. For exchange pair i and $j \neq i$, we obtain the order imbalance OIMB as:

$$OIMB_{i,t} = \frac{Buy_{i,t} - Sell_{i,t}}{Buy_{i,t} + Sell_{i,t}} \times 100\% \tag{2}$$

where the bid and ask orders are within 1% of the trading prices. OIMB is winsorized at the 1 and 99 percentiles. Then, the difference in order imbalance between exchange pair i and $j \neq i$:

$$OimbDiff_{i,j,t} = OIMB_t^i - OIMB_t^j \tag{3}$$

3.2 Bitcoin Price Differences between Chinese and Foreign Exchanges

We begin by considering the daily bitcoin price differences between BTC China and the six foreign exchanges in our sample. In theory, bitcoin prices should be identical across exchanges. Bitcoin is a truly homogeneous asset, highly transferable and perfectly fungible and, further, bitcoin ownership can be transferred in a short amount of time at low cost.[11] Therefore, absent frictions and capital controls, an arbitrageur could in theory obtain riskless profits by buying bitcoin on an exchange where it is less expensive and then selling it or establishing a short position on an exchange where it is more expensive.

The daily time series of price differences $PriceDiff$ between Chinese and foreign exchanges indicates they are significantly different from zero. Figure 3 reports the bitcoin price on BTC China minus that on the six foreign exchanges, shown as a blue area plot. On average, bitcoin trades at a significant premium on BTC China relative to all foreign exchanges. The premium appears to be

[10] It is less desirable to calculate the price difference at higher frequency due to the high level of intraday volatility of bitcoin prices.

[11] While transaction fees related to transferring bitcoin had started to rise towards the end of our sample due to block size constraints, they remained negligible – especially for large bitcoin transactions.

more persistent since August 2015 when the People's Bank of China (PBOC) reformed the Chinese exchange rate system resulting in increased expectation of an exchange rate depreciation and hence of capital flight from China.

Panel A of Table 2 shows that the BTC China price premium ranges from 0.22% versus Kraken to 1.50% versus BTC-e. The China premium is at least as large relative to non-US exchanges (the first three rows of the panel) where it ranges between 0.32% and 1.50%, as it is to US exchanges (the last three rows) where it ranges between 0.22% and 0.52%. Panel B of Table 2 shows that qualitatively similar price premium exists in OKCoin over foreign exchanges, from −0.666% versus Kraken to 1.174% versus BTC-e. Moreover, OKCoin also presents a China premium that is at least as large relative to non-US exchanges as it is to US exchanges.

3.3 Bitcoin price differences between foreign exchange pairs

We next focus on the daily bitcoin price differences *between* the 15 foreign exchange pairs in our sample. We find that the Law of One Price is violated frequently and sometimes substantively. To illustrate, Figure 4 shows the pair-wise price differences between BTC-e and the remaining exchanges, shown as a blue area plot. The orange line indicates the average unsigned price difference, while the red line shows the average absolute price difference between the two exchanges. Bitcoin on BTC-e generally trades at a *discount* relative to the other exchanges. The mean absolute price differences are around 1.1% to 1.5%, and the mean signed price differences are from 0.9% to 1.2%.

Figure 5 shows the pair-wise price differences between Bitfinex and other exchanges except BTC-e (i.e., Bitstamp, Coinbase, itBit, and Kraken). The mean absolute price differences are less than 1%, and the mean signed price differences are 0.25% or less. The mean signed price differences are statistically different from zero for two exchange pairs out of four. The mean absolute price differences are larger than the mean unsigned price differences, suggesting that the price differences revert and switch signs quickly. Overall, compared to the BTC-e related exchange pairs, the price deviations for Bitfinex are more two-sided and appear to dissipate quicker.

Panel C of Table 2 shows the distribution of price differences between the foreign exchanges. The null hypothesis that the mean signed price difference equals zero is rejected for 13 of 15 exchange pairs. Price differences relative to BTC-e are notably larger compared to exchange pairs not including BTC-e. Moreover, bitcoin on BTC-e trades at a discount relative to every exchange – even relative to the US exchanges, different from Makarov and Schoar (2020) who find that bitcoin typically trades at a premium on non-US exchanges relative to US exchanges in their sample.[12] Bitcoin also on average traded at a discount on Bitstamp relative to other exchanges except BTC-e, although the magnitude is much smaller than that for BTC-e. The mean price difference between the remaining exchanges does not follow a specific pattern. Exchanges operating across multiple countries (Bitstamp, Coinbase and Kraken in our sample) may facilitate the circumvention of capital controls but price differences for these exchanges are not smaller, as also noted by Makarov and Schoar (2020). One reason for the cross-exchange variations in price differences may be the desire of Chinese residents to evade capital controls in China. The next section describes the measures of capital control that we use to examine this hypothesis.

The descriptive evidence shows two kinds of violations to the law of one bitcoin price. The first type consists of short-term, two-sided price deviations among bitcoin exchanges, implying limits to arbitrage.

3.4 Measures of Capital Control in China

Capital controls refer to interventions in the capital account that records financial transactions between domestic and foreign actors. Our sample period coincides with a reduction in capital flows to emerging market countries, including China, following the announcement of the tapering of Federal Reserve asset purchases in May 2013. With the end of the ‘super-cycle’ of commodity prices in 2014, there were capital outflows from China and, in response, new regulations on capital outflows by Chinese authorities in 2016 (Ocampo (2017)). Section A.1 of the appendix provides further background on Chinese capital control measures before 2017.

Measures of capital controls can be *de facto* (i.e, inferred from the financial outcomes in the presence of capital controls) or *de jure* (i.e., based on the formal rules regulating capital flows for different asset classes).[13] We construct both types of measures of capital controls in China – the *de facto* measure based on daily market variables and the monthly *de jure* index using Chinese capital accounts data. The market-based measure is useful for indicating high frequency time-variation in the effectiveness of capital controls, whereas the *de jure* index captures policy changes in a more exogenous manner but are less useful in capturing time-series variations at high frequencies. Further, the *de jure* index may overstate the incidence of capital controls given that the private sector may in many cases be able to circumvent legal restrictions to capital mobility.

[12] Although users have noticed the persistent discount of BTC-e prices, the discount remained through the end of 2016. See this Reddit post or this Stack Exchange post for examples of users discussing the arbitrage.

[13] Quinn et al. (2011) and Erten et al. (2019) survey the available indices.

Our *de facto* market-based measure is the Chinese onshore-offshore spot exchange rate differential, which has been interpreted as an indicator of China's capital account liberalization (Craig et al., 2013b; Funke et al., 2015b). Unlike the onshore CNY market, the offshore CNH market is not subject to restricted access, foreign exchange interventions by the PBOC or the Hong Kong Monetary Authority (HKMA), or stipulation of a daily trading band around exchange rate movements (Funke et al., 2015b). Persistent deviations exist between the CNH and CNY rates, suggesting limits to arbitraging the differential (Craig et al., 2013b). We define the CNH spread in percent as follows:

$$CNHSpread_t = \frac{S_t^{CNH} - S_t^{CNY}}{S_t^{CNY}} \times 100\% \tag{4}$$

S^{CNH} is the offshore spot exchange rate (in CNH per USD) and S^{CNY} is the onshore spot exchange rate (in CNY per USD). Section A.2 contains more details about the measure construction.

A positive CNH spread indicates the presence of capital outflow controls which impedes the flow of capital from the mainland to the offshore market. Panel (a) of Figure 9 displays the daily time series of CNH spread. Following the announcement of the PBOC's exchange rate reform in August 2015 – which increased expectations of a depreciation in the CNY (Krugman (2015)) – the CNH spread jumped, suggesting a capital flight may have occurred.

The particular *de jure* index we construct tracks China's capital *outflow* control policy regarding portfolio investments (equity, bond, and money market instruments) as well as trade and financial credit. A higher value of the index indicates stricter capital outflow controls in China. The index, based on the methodology proposed by Chen and Qian (2016), is constructed by extracting detailed capital control information from the text of the IMF's Annual Report on Exchange Arrangements and Exchange Restrictions (AREAER). Further details of constructing the index are discussed in section A.3 of the appendix.

4 Hypotheses Development and Empirical Methodology

Our main hypothesis is that price differences between exchanges are in part driven by persistent order flows arising from regulatory arbitrage trades – specifically, Chinese residents using bitcoin to move capital out of China. In section 4.1, we discuss the mechanics of such trades and the implications for bitcoin prices and orders in Chinese and foreign exchanges. In addition, the price differences may be explained by frictions that limit arbitrage. – perhaps relating to "search frictions" that delay trades because of the need to find a trading counter-party (Duffie, 2010). In section 4.2, we discuss (and describe empirical measures of) some candidate search frictions, including the microstructure of bitcoin trading, network frictions in the bitcoin blockchain, and trading clientele effects. The second type of arbitrage violations is observed particularly in trading between BTC-e and other exchanges in the form of persistent price discounts that In both sections, we discuss our hypotheses and the regression methodology to test them.

4.1 Capital Controls in China

The anonymity and lack of central regulation create incentives for bitcoin to be used for illicit activities. In particular, bitcoin is a widely used medium of capital evasion in countries with strict capital controls (Luckner et al. (2021)) or experiences of inflationary spirals.[14] Of particular relevance to our study is the use of bitcoin to evade capital controls in China, given the dominance of Chinese investors in bitcoin trading during our sample. Among the largest economies, China is the only nation that still maintains both a pegged currency and rigorous capital controls, as further discussed in section A.1 of the appendix.

Anecdotal evidence shows that bitcoin was a popular way to circumvent capital controls during our sample period.[15] While alternative means of avoiding Chinese capital controls – such as mis-invoicing of imports and exports – also existed (Gunter (1996)), bitcoin-based strategies appear to have also played an important part.[16] China banned cryptocurrency exchanges in September 2017, although Chinese residents could still trade in decentralized exchanges.[17] And, in Sept 2021, China declared all financial transactions involving cryptocurrencies illegal and banned cryptocurrency mining.[18]

[14]For instance, bitcoin adoption surged in Argentina in 2013 when inflation was 25% annually and Argentinian residents were banned from exchanging Peso for gold or USD (Wells, 2013; Russo, 2013; Matonis, 2013). Again, in 2019, when the Argentine government imposed capital controls, peso to bitcoin trades spiked (Luckner et al. (2021)).

[15]See South China Morning Post.

[16]Hu et al. (2021) argue that a quarter of trading volume in Chinese bitcoin exchanges between 2011 and 2018 were related to capital flight. Between 2019Q3 and 2020Q2, about $45 billions of cryptocurrency is estimated to have moved from China-based bitcoin addresses to addresses in other regions – although it is unclear how much was related to capital flight – whereas the total amount of personal transfer out of China through the traditional, regulated payment system was $3.7 billions during the same period, according to Chinese Balance of Payment data ((Chainalysis, 2020)).

[17]See China crypto ban.

[18]See China mining ban. While the use of cryptocurrency to avoid capital controls likely continues to this day, stablecoins may have superseded bitcoins for this purpose (Zhao (2020)).

One way that Chinese residents could use bitcoin to circumvent their nation's strict capital controls is illustrated in Figure 8. The Chinese resident buys bitcoin in the local market with Yuan, either from a Chinese miner (where 60% to 80% of global mining capacity was located between 2015 and 2020 (Makarov and Schoar (2021)) or from a China-registered exchange. They then transfer the bitcoin to the digital wallet of an overseas exchange and finally sells the bitcoin for USD or another fiat currency of choice.[19] This capital evasion strategy is expected to create persistent price gaps between Chinese and foreign exchanges, especially with respect to those foreign exchanges that are heavily utilized for capital evasion trades.

Hypothesis 1: Effect of capital controls on absolute price differences: Chinese relative to foreign exchanges. When capital flows out of China increase, the absolute bitcoin price differences between Chinese and foreign exchanges (a) increase on average and (b) increase more relative to those foreign exchanges heavily utilized for capital flight trades.

To investigate Hypothesis 1a, we estimate the following regression for exchange pair i and j, where i is a Chinese exchange and j is a foreign exchange, in period t:

$$Y_{i,j,t} = \alpha_0 + \alpha_{i,j} + \beta_1 \times CapCon_t + \varepsilon_{i,j,t} \tag{5}$$

The outcome variable Y is $\left|PriceDiff_{i,j,t}\right|$, the absolute price difference. Hypothesis 1(a) implies that $\beta_1 > 0$. All regressions include the exchange-pair fixed effect $\alpha_{i,j}$ to account for factors specific to each exchange pair, such as differences in governance, transaction fees charged and different levels of compliance with AML and KYC regulations. In some specifications, we also include a period fixed effect α_t. The regressions are estimated with OLS and standard errors are clustered by exchange-pairs.

To test Hypothesis 1(b), we modify regression (5) as follows:

$$\begin{aligned} Y_{i,j,t} = {} & \alpha + \alpha_{i,j} + \beta_1 \times CapCon_t \\ & + \sum_{j=1}^{3} \gamma_j \times CapCon_t \times ExchangeDummies_{i,j} + \varepsilon_{i,j,t} \end{aligned} \tag{6}$$

ExchangeDummies are three dummy variables that equal 1 when one of the non-US exchanges (BTC-e, Bitfinex and Bitstamp) are included as the $j-th$ foreign exchange. Since US-registered bitcoin exchanges are expected to have stricter governance and compliance, capital evasion traders

[19]While we focus on selling bitcoin for USD, other currencies may also be involved. For example, a recent legal prosecution involved using bitcoin to exchange Yuan for the Korean won (Helms (2017)).

are more likely to avoid these exchanges for fear of detection. Thus, Hypothesis 1(b) implies that $\gamma_j > 0$.

Which non-US exchanges are likely be favored for capital evasion trades? Foreign exchanges with lower levels of compliance with AML and KYC regulations may provide a gateway to gray activities (Makarov and Schoar (2021)).[20] For example, BTC-e lacked KYC compliance as the exchange required very little personal information to transact over its platform. By contrast, the US-registered exchanges have high levels of KYC/AML compliance. Factors such as jurisdiction of the exchange's operations are likely to be relevant. Section B in the appendix provides more details on governance and KYC/AML compliance levels for exchanges in our sample. In particular, we expect that $\gamma_j > 0$ for BTC-e since its governance standards were loose, as alleged in the complaint by the US Justice Department.

A countervailing argument is that the poor compliance record of some exchanges could also hinder their use for capital evasion strategies for some investors by delaying the transfer of USD from the exchange wallet to banks. For example, due to BTC-e's poor KYC/AML compliance, U.S. banks delayed or blocked transactions deemed to be high risk, such as fund transfers from a U.S. bank to BTC-e. Further, there may be considerable delays in transferring USD into an exchange account. For example, during our sample period, deposits of USD via wire took five to ten days to complete on BTC-e. By comparison, transferring bitcoin from one exchange to another is typically quick. A bitcoin transfer on the blockchain took roughly 10 minutes to settle (i.e., to be added to a block) during our sample. These considerations suggest that there were offsetting costs to engaging in the capital evasion trade. Nevertheless, workarounds existed to ensure the viability of the capital evasion strategies. For example, investors could transfer USD to a third-party account first, and then to BTC-e.

In addition to the *magnitude* of price differences, the capital evasion strategy has implications for its *direction*. In particular, due to buying pressure on Chinese exchanges, the bitcoin price premium relative to foreign exchanges is expected to widen on days with greater capital evasion trades. On foreign exchanges with poor governance, bitcoin is hypothesized to trade at a greater discount with respect to all other exchanges, with the discount widening on days with more capital evasion trades.

[20] KYC compliance refers to the requirement for financial institutions to be able identify their customers, should the need arise to examine financial transactions to track illicit activity. Pieters and Vivanco (2016) explore how varying levels of compliance (and therefore varying levels of anonymity) affect prices across exchanges. Makarov and Schoar (2021) argue that effective KYC regulations may not be possible for individual exchanges given the ability of users to trade freely across regulated and unregulated venues.

Hypothesis 2: Effect of capital controls on signed price differences: Chinese minus foreign exchanges, and poor-governed minus better-governed foreign exchanges. When capital flows out of China increase, (a) the price premium on Chinese exchanges widens relative to foreign exchanges and more so relative to poorly-governed foreign exchanges and, (b) the price discount widens more on poorly-governed foreign exchanges, relative to better-governed foreign exchanges.

To test hypothesis 2(a), we repeat regressions (5) and (6) except that the outcome variable Y is the positive component of the signed price difference: $PriceDiff^{+}_{i,j,t} = max(PriceDiff_{i,j,t}, 0)$. For specification (5), the prediction is that $\beta_1 > 0$. For specification (6), the prediction is that $\gamma_j > 0$. In other words, on days when bitcoin trades at a premium on Chinese exchanges, the price premium is correlated with the capital control measure and more so relative to non-US exchanges.

We also consider the negative component $PriceDiff^{-}_{i,j,t} = min(PriceDiff_{i,j,t}, 0)$. These are days when bitcoin trades at a discount, on average, on Chinese exchanges and, as such, capital flight trades are likely less prevalent. Nevertheless, when capital controls become more binding, we expect that the discount shrinks. Thus, we predict that $\beta_1 > 0$ and $\gamma_j > 0$.

To test hypothesis 2(b), we estimate regression (5) using $PriceDiff^{+}_{i,j,t}$ and $PriceDiff^{-}_{i,j,t}$ as the outcome variables, separately for each pair i and j of *foreign* exchanges. The prediction is that $\beta_1 < 0$: the price discount widens and the price premium shrinks with the capital control measure.

To move capital out of China, residents need to buy bitcoin on Chinese exchanges and sell them on foreign exchanges. Thus, when capital controls are more binding, we expect greater buy (sell) order imbalances on the Chinese (foreign) exchange.

Hypothesis 3: Effect of capital controls on bitcoin absolute and signed order imbalances. When capital outflows are higher, (a) the absolute value of order imbalances increases on all exchanges, (b) the buy imbalance increases on Chinese exchanges and (c) the sell imbalance increases on foreign exchanges, especially on foreign exchanges with poor governance.

To test Hypothesis 3(a), we estimate the following regression for each exchange i in period t:

$$\begin{aligned} Y_{i,t} &= \alpha + \alpha_i + \beta_1 \times CapCon_t \\ &\quad + \sum_{j=1}^{4} \gamma_j \times CapCon_t \times ExchangeDummies_i + \varepsilon_{i,t} \end{aligned} \tag{7}$$

Y is the absolute value of the *buy* order imbalance *Oimb*. *ExchangeDummies* are four dummy variables that equal 1 for each of the non-US exchanges (China, BTC-e, Bitfinex and Bitstamp), where *China*=1 for either BTCC or OKCoin. Hypothesis 3(a) implies that $\beta_1 > 0$ and $\gamma_j > 0$.

To test Hypothesis 3(b), we use the positive and negative components of the buy order imbalance as the outcome variables in (7). When we use the positive component $OimbP_{i,t} = max(Oimb_{i,t}, 0)$, Hypothesis 3(b) implies that $\gamma_j > 0$ for $j = China$. When we use the negative component $OimbN_{i,t} = min(Oimb_{i,t}, 0)$, Hypothesis 3(b) implies that $\gamma_j < 0$ for j=BTC-e, Bitfinex or Bitstamp.

4.2 Trading and Network Frictions, and Trading Clientele Effects

In addition to capital controls, trading and network frictions may impede arbitrage. We describe in detail the trading strategy required to arbitrage price differences between bitcoin exchanges and then discuss our measures of the various frictions.

Short-term price deviations between bitcoin exchange prices suggest frictions to acting on the potential arbitrage opportunity (Shleifer and Vishny, 1997). In order to exploit bitcoin price differences across exchanges, an arbitrageur could execute a simple trade: buy bitcoin on the exchange where it is relatively cheap and sell it where it is relatively expensive. The mechanics of this trade is shown in Figure 6 using as an example the case where bitcoin is priced relatively lower on BTC-e and relatively higher on Bitfinex, as is typically the case in the data. The sequence of steps and associated frictions in the arbitrage trade is as follows. The arbitrageur

- transfers USD into an account with BTC-e to fund the trade, which entails a fee and a delay of several business days,
- purchases bitcoin on BTC-e at the "ask" price, paying a trading fee,
- either shorts bitcoin at the "bid" price on Bitfinex and transfers the bitcoin purchased on BTC-e to cover the short position, paying a margin funding fee, or transfers the bitcoin from BTC-e to an account on Bitfinex and sells it at the "bid" price after the transfer, paying a trading fee, and finally
- transfers USD out of the Bitfinex account to realize profits on the trade, incurring fees and experiencing time delays in the wire transfer.

Each step of the arbitrage trade involves trading frictions and bitcoin network frictions due to transaction fees and delays. Suppose that the bitcoin price is lower in exchage i than in exchange j.

To execute an arbitrage strategy, arbitrageurs pay a trading fee to buy bitcoin in exchange i, a miner's fee to validate the transfer of the bitcoin to exchange j, another trading fee to sell bitcoin in exchange j and, finally, a withdrawal fee to convert the bitcoin to the local fiat currency (**?**). In particular, the exchange of bitcoin for fiat currency involves high fees as well as delays of several business days. While some of these frictions may be avoided by short selling bitcoin on the more expensive exchange, only Bitfinex and Kraken offered shorting as a service during our sample period, and it entailed additional fees.[21]

In addition to fees and delays, retail investor sentiments may also create limits to arbitrage. Accordingly, we hypothesize the following relation between the absolute value of price differences between exchange pairs and our explanatory variables.

To account for these frictions in our regressions, we include measures of trading frictions $TFrictions_{i,j,t}$, network frictions $NFrictions_t$ and the relative incidence of retail trading $OneRetail_{i,j,t}$ for the exchange pair i, j in period t. We expect the absolute value of price differences between bitcoin exchange pairs to be positively related to measures of trading and network frictions, and to the relative incidence of retail trading in the exchanges.

$TFrictions_{i,j}$ is a set of three regressors that represent trading frictions, defined as an average of the values for the two exchanges in the pair i, j. One regressor is the proportional bid-ask spread. Since the arbitrageur must buy bitcoin in one exchange at the higher "ask" price and sell it at the other exchange at the lower "bid" price, we expect the price difference to be higher when the average bid-ask spread on the two exchanges is higher. Second is the depth of the order book close to the inside quotes. If the inside depth is of insufficient quantity, then the arbitrageur may incur a large and adverse price impact, and thus we expect the price difference to decrease when the order book is deeper. Finally, we include the standard deviation of intraday prices since increased price volatility creates uncertainty as to the duration of the arbitration opportunity and thus is expected to increase price differences. In our sample, the intraday standard deviation of the Bitcoin price index often exceeds the average Bitcoin price difference between BTC-e and Bitfinex and the two series appear correlated (Figure 2).

$NFrictions_t$ include $AvgNetworkFee$ and represent network frictions in the bitcoin blockchain. Network transaction fees are used to incentivize miners to include the transaction in their blocks, thus leading to faster confirmation by addition to the blockchain. An arbitrageur would incur the

[21] As an alternative to shorting, arbitrageurs may trade bitcoin on margin and profit if prices converge, as noted by Makarov and Schoar (2020). In addition to convergence risk (which is considerable for exchange pairs involving BTC-e), this strategy faces the risk of delayed transfer of capital across exchanges, as further discussed below.

transaction fee when depositing bitcoin in the higher priced exchange in order to sell it or to cover a short trade. Since network frictions are expected to increase price differences, the coefficient on *AvgNetworkFee* is expected to be positive.[22]

Trading clientele effects may impede arbitrage. Bitcoin exchanges serve different types of traders. For example, the regulatory position of one exchange in our sample (BTC-e) makes it less likely that U.S. traders participate, potentially reducing arbitrage activity. Bitfinex and itBit facilitated larger trades than other bitcoin-USD exchanges during our sample, suggesting that they may serve larger, institutional clients who are more likely to engage in arbitrage activities ((Shleifer and Vishny, 1997)), thus making the prices on exchanges that cater to these clients more integrated. Conversely, exchanges where transaction sizes are typically smaller may primarily serve sentiment-driven retail users of bitcoin. Makarov and Schoar (2020) argue that arbitrage capital may be overwhelmed by noise traders who push up prices or withdraw when negative information about bitcoin is released. Since it may take longer to arbitrage price differences between exchanges dominated by retail clients, we expect the coefficient on $OneRetail_{i,j}$ to be estimated as positive.

The indicator variable $OneRetail_{i,j}$ reflects the degree to which trading on one exchange in the i, j pair is dominated by retail clients, relative to the other exchange. The variable is defined as follows. First, each exchange on day t is classified as "retail" if its trade size is below its 75$^{\text{th}}$ percentile of trade size of the past 30 days relative to the other exchanges; otherwise it is "institutional." Then *OneRetail* indicates that *at least* one of the exchanges in the pair was classified as a retail exchange on day t. The omitted group is the case where both exchanges were classified as institutional.

5 Capital Controls, Bitcoin Price Differences and Order Imbalances

In this section, we empirically test our hypotheses regarding the effects of capital controls on Bitcoin price differences and order imbalances. We provide descriptive statistics of liquidity and volatility in section 5.1. Then, we examine in section 5.2 how price differences between exchange pairs relate to capital controls, after accounting for trading frictions, congestion in the Bitcoin blockchain, and trading clientele effects. Following hypotheses 1 and 2, we consider the correlation between

[22] In addition to network fees, delays in network confirmations also cause frictions to arbitrage (Hautsch et al. (2021) and Choi et al. (2022)). For instance, during our sample period, Bitfinex and Bitstamp each required three network confirmations, which took roughly 30 minutes. This delay is potentially avoidable by short selling bitcoin on the more expensive exchange but, as noted before, a shorting service was not widely available and required additional fees.

capital control measures and Bitcoin price differences between Chinese and foreign exchanges, and betweeen foreign exchanges. Following hypothesis 3, we then examine the effect of capital controls on Bitcoin order imbalances (section 5.3).

5.1 Trading and Network Frictions: Descriptive Statistics

Table 3 reports descriptive statistics on exchange liquidity and volatility. The US exchanges Coinbase and Itbit have the lowest daily standard deviation of prices of between 0.82% and 0.88% while Coinbase – along with BTCChina and Bitfinex– also has the lowest bid-ask spread of between 0.03% and 0.13%. Liquidity in the remaining exchanges, except for Kraken, is similar, varying between 0.13% and 0.16%. The order book size (i.e., the inside depth or accumulated orders within 1% of the current price) is relatively high for itBit and Kraken, and relatively low for BTCN whereas the opposite is true for volume (in bitcoin units). Given the divergence between inside depth and volume, we only use inside depth as a regressor in the regressions. In spite of being a US-registered exchange, Kraken has the highest volatility and the worst liquidity of all exchanges, due to its poor liquidity and volatility in 2014-2015. The main conclusion from the table, however, is that variations in liquidity and volatility are unlikely to explain the price differences. For example, BTC-e has the largest price differences but does not poor liquidity and volatility, relative to the other exchanges.

5.2 Bitcoin Price Differences and Capital Flight: Results

Following Hypothesis 2, we expect the absolute value of Bitcoin price differences between Chinese and foreign exchanges to be correlated with our measures of capital control from China. Further, the correlation is expected to be stronger with respect to foreign exchanges, such as BTC-e, with weaker governance, compared to pairs of exchanges both of which are US-registered. Following hypothesis 3, the Bitcoin price premium (discount) on Chinese (foreign) exchanges is expected to widen with capital control flows.

5.2.1 Absolute Bitcoin Price Differences

Table 4 reports the coefficients from estimating regression (5) using the CNH spread as the measure of capital control. The outcome variable is the absolute value of the Bitcoin price difference between Chinese exchanges BTC China and OKCoin relative to foreign exchanges. Column 1 shows that the CNH spread is positively and significantly associated with the absolute price difference beween Chinese and foreign exchanges, as hypothesized. Column 2 reports that the price difference with respect to BTC-e is higher by about 36 basis points, relative to other exchange pairs, on days when the CNH spread is higher by one percent. Moreover, the correlation is smaller (by 17 basis points) but still significant relative to BitFinex. In contrast, the interaction of the CNH spread with BitStamp is not significant. The results are robust to adding exchange controls (column 3 of the table). Finally, after adding period fixed effects in column 4, the results are similar. These results are consistent with the exchange characteristics described in Table 1 of the Appendix. In particular, BTC-e had the worst governance record, and most likely to be used for capital evastion trades. Bitfinex is based in Hongkong and thus also a convenient location for such trades. Bitstamp is London-based and, like the US exchanges, less convenient for taking Bitcoin out of China.

It is notable that adding exchange controls improve the adjusted R-squared from 0.06 in column 2 to 0.25 in column 3. We find that the estimated coefficients on the measures of trading frictions have the expected signs and are significant. Higher bid-ask spread and volatility of Bitcoin prices, averaged over each exchange pair, are associated with greater absolute price differences, and both effects are statistically significant. The inside depth is not significantly associated with absolute price differences. The absolute price difference widens with the average network transaction fee.[23] When we add *OneRetail* as an indicator of trading clienteles, we find that its coefficient is not significant. Overall, the Bitcoin exchange market microstructure and blockchain network congestions significantly impede the arbitrage of Bitcoin price differences between exchanges.

As an addition test, we report in the appendix the results for the absolute value of the Bitcoin price difference textitonly between the foreign exchange pairs. The results in Table 4 imply that price differences on BTC-e widen relative to the other foreign exchanges when the CNH spread increases. Table 5 reports the coefficients from estimating regression (5) for the foreign exchange panel. Column 1 shows that, across all foreign exchange pairs, the measure is insignificantly associated with the absolute price difference. This is intuitive since we do not expect that price differences between foreign exchanges in the aggregate are mostly related to capital controls. Column 2 reports that the average price difference on BTC-e related exchange pairs increases by about 14 basis points, relative to other exchange pairs, on days when the CNH spread is higher by one percent, consistent with the results in Table 4. In contrast, there is no effect of the CNH spread on the price differences for BitStamp- and BitFinex-related exchange pairs. These results remain robust When we add exchange controls and period fixed effects (column 4 of the table).

[23] As the network fee is a time-series variable, it is absorbed by the period fixed effects in column 4.

Overall, the robust result is that price differences between Chinese and foreign exchanges are correlated with our measure of capital controls. The correlation is even higher with respect to BTC-e which, in turn, implies that BTC-e price differences relative to other foreign exchanges widen when capital controls are more binding. Since these results take into account the effects of microstructure and network frictions, they highlight the effect of non-arbitrage flows from capital flights on the Bitcoin price differences.

5.2.2 Signed Bitcoin Price Differences

Following Hypothesis 3, we focus on the *signed* price difference between exchange pairs as the outcome variable. These regressions establish whether on average the price premium on Chinese exchanges and price discounts on foreign exchanges widen when capital controls are more binding.

To understand which exchange pairs show a consistent *direction* in price differences over our sample, the final column of Table C.2 in the appendix shows exchange-pair fixed effects when the signed price difference (see equation (1)) is used, instead of the absolute price difference, as the dependent variable. These results confirm that on average Bitcoin consistently trades at a discount on BTC-e relative to all other exchanges. Bitcoin also trades at a discount on BitStamp relative to BitFinex and Coinbase. By comparison, on BitFinex, Bitcoin generally trades at a premium relative to other exchanges, with the exception of Coinbase, in which case the price difference is not statistically different from zero. Signed price differences between US-registered exchange pairs are insignificantly different from zero, except that Bitcoin trades at a premium on Kraken relative to Itbit.

We estimate equations (5) and (6), using as outcome variables the positive and negative components $PriceDiff^{+}$ and $PriceDiff^{-}$, respectively, of the signed price differences. Results for price differences between Chinese and foreign exchanges are reported in Tables 6. Panel A of the table reports results for $PriceDiff^{+}$. Column 1 establishes that the "China price premium" is positively correlated with the CNH spread. Columns 2 and 3 indicate the correlation is higher for BTC-e and lower for Bitstamp, consistent with results in Table 4. Panel B shows results using $PriceDiff^{-}$ as the outcome variable. On days when Bitcoin trades at a discount in China, the discount shrinks when the CNH spread is higher. In contrast to Panel A, however, the correlation is similar with respect to all foreign exchanges (column 2), suggesting that, on price discount days, there may be a reduced prevalence of capital flight trades.

We now turn to the signed price differences among BTC/USD exchanges and report the empirical estimates in Tables 7. Panel A of the table shows results when the outcome variable is $PriceDiff^{+}$. Column 1 of the table reports results for all BTC-e related exchange pairs. We find that on average when Bitcoin trades at a premium on BTC-e, the premium shrinks significantly by 8 basis points when the CNH spread increases by 1%. Column 2 reports that the Bitcoin price difference for BitStamp, relative to all other exchanges except BTC-e, is unaffected by changes in the CNH spread. Similarly, the Bitcoin price difference for BitFinex, relative to all other exchanges except BTC-e and BitFinex, is insignificantly related to changes in the CNH spread (column 3). Columns 4-5 show results for Bitcoin price differences between US-registered exchange pairs and find that the price differences are unaffected by variations in the CNH spread.

Panel C of the table reports results when the outcome variable is $PriceDiff^{-}$. Price discounts on BTC-e related exchange pairs widen significantly by 17 basis points when the CNH spread increses by 1%. Results for other exchange pairs are insignificant or weakly significant.

Overall, there is consistent evidence that investors used Bitcoins to evade capital controls in China during our sample, creating upward (downward) pressure on Bitcoin prices when investors purchased (sold) Bitcoin on Chinese (foreign) exchanges. This evidence exists strongly for price differences with respect to BTC-e, where Bitcoin typically trades at a discount not only with respect to Chinese exchanges but also relative to other foreign exchanges. It also exists for Hongkong-based BitStamp, another exchange where Bitcoin often trades at a discount. Conversely, there is weaker association between price differences and capital control measures for London-based BitFinex, where Bitcoin trades at a premium, and for US-registered exchanges.

5.3 Bitcoin Exchange Order Imbalance and Capital Controls

The capital evasion strategy implies a buy (sell) imbalance on the exchange where the Bitcoin is (bought) sold (Hypothesis 3). To examine this hypothesis, we estimate (7) using the Bitcoin order imbalance as the outcome variable.

Columns (1) and (2) of Table 8 reports the results when using the absolute value of the order imbalance as the outcome variable. On average across all exchanges, the size of order imbalances is unrelated to the CNH spread (column 1). However, the correlation is positive and significant for the Chinese exchanges and for BTC-e (column 2). Columns (5) and (6) show results when using the positive component of signed order imbalance *OIMBP* as the outcome variable. As hypothesized, the correlation is positive and significant for Chinese exchanges (column 6) but not for other exchanges. In other words, the buy imbalance on Chinese exchanges increases when the CNH spread is higher. Columns (7) and (8) show results using the negative component of signed order imbalance *OIMBN* as the outcome variable. We find that the correlation with the CNH spread is negative for BTC-e but not for any other exchange.

In summary, we show that when the capital control measure is more binding, the buy imbalance increases on Chinese exchanges whereas the sell imbalance increases on foreign exchanges, and significantly so for BTC-e. Thus, we find evidence for both the price and quantity implications of the capital evasion trade.

6 Conclusion

In this paper, we provide evidence consistent with Chinese residents using bitcoin to evade capital controls, which was strict in China during our sample period of 2014-2016. Moreover, 90% of bitcoin trading also occurred in China during this period. Hence, both motive and opportunity were present to use bitcoin to avoid capital controls. We consider the price and quantity implications of the following capital flight trade: buy Bitcoin on a Chinese exchange and sell it for USD on a foreign, non-Chinese exchange.

Our first set of results show that the *magnitude* of price differences between Chinese and foreign exchanges is significantly correlated with all three of our capital control measures, especially relative to foreign exchanges with poor governance. Further, the price premium on Chinese exchanges, relative to foreign exchanges, increases with the capital control measures. Conversely, on foreign exchanges with poor governance (and so more apt to be used for capital flight trades), bitcoin typically trades at a *discount* to other exchanges, and the bitcoin price discount widens during periods when capital controls are more binding.

Our second set of results relate to the relationship of the bitcoin order imbalance and capital controls. On days when capital controls are more binding, we find that bitcoin buy imbalance increases on Chinese exchanges while the bitcoin sell imbalance increases on foreign exchanges. These results are consistent with using bitcoins for capital evasion: there is buying (selling) pressure on bitcoin prices trading, resulting in price premium (discounts) in Chinese (foreign) exchanges. These effects are especially manifest in the target exchanges that are more heavily utilized for capital evasion trades. Consistent with this interpretation, on US-registered exchanges (where governance standards such as adherence to KYC/AML standards are superior), both the bitcoin price differences and order imbalances are generally unrelated to our capital outflow measures.

In addition to capital controls, trading illiquidity, network congestion and trading clienteles also explain failures to arbitrage the bitcoin price differences. Regression analysis shows that the price difference is positively related to network trading fees, suggesting that network congestion impedes arbitrage. Increased trading frictions – such as higher bid-ask spread, and higher price volatility — widens the price differences. However, evan after accounting for these frictions, we continue to find statistically significant relationships between capital controls, price differences and bitcoin order imbalances.

References

Agarwal, Isha, Grace Weishi Gu, and Eswar S. Prasad (2019) "China's Impact on Global Financial Markets," *NBER Working Paper 26311*.

Ali, Robleh, John Barrdear, Roger Clews, and James Southgate (2014) "The economics of digital currencies," *Bank of England Quarterly Bulletin*.

Amihud, Y. and H. Mendelson (1991) "Liquidity, Maturity, and the Yield on U.S. Treasury Securities," *Journal of Finance*, Vol. 46, pp. 479–486.

Amiram, Dan, Bjorn Jorgensen, and Daniel Rabetti (2020) "Coins for Bombs-Does Bitcoin Finance Terrorist Attacks?" *Working Paper*, Available at SSRN 3616207.

Andrews, Donald W. K. (1993) "Tests for Parameter Instability and Structural Change With Unknown Change Point," *Econometrica*, Vol. 61, p. 821–856.

Borri, Nicola and Kirill Shakhnov (2021) "The Cross-Section of Cryptocurrency Returns," *Working Paper*, Available at SSRN: https://ssrn.com/abstract=3241485.

Caffyn, Grace (2015) "Bitcoin on the Dark Web: The Facts," *CoinDesk*.

Chainalysis (2020) "The Chainalysis 2020 Geography of Cryptocurrency Report,"Technical report, Chainalysis.

Chen, Jinzhao and Xingwang Qian (2016) "Measuring on-going changes in China's capital controls: A de jure and a hybrid index data set," *China Economic Review*, Vol. 38, pp. 167–182.

Chinn, Menzie D and Hiro Ito (2008) "A new measure of financial openness," *Journal of comparative policy analysis*, Vol. 10, pp. 309–322.

Choi, Kyoung Jin, Alfred Lehar, and Ryan Stauffer (2022) "Bitcoin Microstructure and the Kimchi Premium," *Working Paper*.

Craig, R, Changchun Hua, Philip Ng, and Raymond Yuen (2013a) "Chinese capital account liberalization and the internationalization of the renminbi," *IMF Working Paper*.

——— (2013b) "Development of the Renminbi market in Hong Kong SAR: Assessing Onshore-Offshore Market Integration," *IMF Working Paper*.

Crépellière, Tommy and Stefan Zeisberger (2020) "Arbitrage in the Market for Cryptocurrencies," *Working Paper*.

Debora, E. and K. Froot (1999) "How are Stock Prices Affected by the Location of Trade?" *Journal of Financial Economics*, Vol. 53, pp. 189–216.

Du, Wenxin, Alexander Tepper, and Adrien Verdelhan (2018) "Deviations from covered interest rate parity," *The Journal of Finance*, Vol. 73, pp. 915–957.

Duffie, Darrell (2010) "Presidential address: Asset price dynamics with slow-moving capital," *The Journal of finance*, Vol. 65, pp. 1237–1267.

Duffie, Darrell and Bruno Strulovici (2012) "Capital Mobility and Asset Pricing," *Econometrica*, Vol. 80, pp. 2469–2509, URL: https://onlinelibrary.wiley.com/doi/abs/10.3982/ECTA8822, DOI: http://dx.doi.org/10.3982/ECTA8822.

Eraslan, Sercan (2017) "Asymmetric arbitrage trading on offshore and onshore renminbi markets," *Deutsche Bundesbank Discussion Paper No 13/2017*.

Erten, Anton, Bilge Korinek, and José Antonio Ocampo (2019) "Capital Controls: Theory and Evidence," *NBER Working Paper 26447*.

Fernandez, Andres, Michael Klein, Alessandro Rebucci, Martin Schindler, and Martin Uribe (2016) "Capital Control Measures: A New Dataset," *IMF Economic Review*, Vol. 64, pp. 548–574.

Foley, Sean, Jonathan R Karlsen, and Tālis J Putniņš (2019) "Sex, drugs, and bitcoin: How much illegal activity is financed through cryptocurrencies?" *The Review of Financial Studies*, Vol. 32, pp. 1798–1853.

Frenkel, Jacob A and Richard M Levich (1975) "Covered interest arbitrage: Unexploited profits?" *Journal of Political Economy*, Vol. 83, pp. 325–338.

Funke, Michael, Chang Shu, Xiaoqiang Cheng, and Sercan Eraslan (2015a) "Assessing the CNH–CNY pricing differential: Role of fundamentals, contagion and policy," *Journal of International Money and Finance*, Vol. 59, pp. 245–262.

——— (2015b) "Assessing the CNH–CNY pricing differential: Role of fundamentals, contagion and policy," *Journal of International Money and Finance*, Vol. 59, pp. 245–262.

Gagnon, Louis and George Andrew Karolyi (2010) "Multi-Market Trading and Arbitrage," *Journal of Financial Economics*, Vol. 97, pp. 53–80.

Griffin, John M and Amin Shams (2020) "Is Bitcoin really untethered?" *The Journal of Finance*, Vol. 75, pp. 1913–1964.

Gromb, Denis and Dimitri Vayanos (2010) "Limits of Arbitrage," *Annual Reviews of Financial Economics*, Vol. 2, pp. 251–275.

Gunter, Frank R. (1996) "Capital flight from the People's Republic of China: 1984–1994," *China Economic Review*, Vol. 7, pp. 77–96.

Hautsch, Nikolaus, Christoph Scheuch, and Stefan Voigt (2021) "Building Trust Takes Time: Limits to Arbitrage in Blockchain-Based Markets," *Working Paper*, Available at SSRN https://ssrn.com/abstract=3302159 publisher=.

Helms, Kevin (2017) "Operation to Bypass China's Capital Controls Using Bitcoin Ends up in South Korean Court," *Bitcoin.com*, https://news.bitcoin.com/operation-bypass-chinas-capital-controls-bitcoin-south-korean-court/.

Hu, Maggie, Adrian D. Lee, and Talis J. Putnins (2021) "Evading Capital Controls via Cryptocurrencies: Evidence from the Blockchain," *Working Paper*, Available at SSRN: https://ssrn.com/abstract=3956933orhttp://dx.doi.org/10.2139/ssrn.3956933.

Ilzetzki, Ethan, Carmen M. Reinhart, and Kenneth Rogoff (2019) "Exchange Arrangements Entering the 21st Century: Which Anchor Will Hold?" *Quarterly Journal of Economics*, Vol. 134, pp. 599–646.

Jong, Abe De, Leonard Rosenthal, and Mathijs A. Van Dijk (2009) "The Risk and Return of Arbitrage in Dual-Listed Companies," *Review of Finance*, Vol. 13, pp. 495–520.

Krishnamurthy, A. (2009) "The bond/old-bond spread," *Journal of Financial Economics*, Vol. 66, pp. 463–506.

Kroeger, Alexander and Asani Sarkar (2016) "Is Bitcoin Really Frictionless?" *Liberty Street Economics*, Available at: https://libertystreeteconomics.newyorkfed.org/2016/03/is-bitcoin-really-frictionless/.

——— (2017) “The Law of One Bitcoin Price,” *Working Paper*, Available at: https://www.philadelphiafed.org/-/media/frbp/assets/events/2017/consumer-finance/fintech-2017/day-1/law-of-one-bitcoin-price.pdf.

Krueckeberg, Sinan and Peter Scholz (2020) “Decentralized Efficiency? Arbitrage in Bitcoin Markets,” *Financial Analysts Journal*, Vol. 76, pp. 135–152.

Krugman, Paul (2015) “China Bites the Cherry,” August, URL: https://krugman.blogs.nytimes.com/2015/08/12/china-bites-the-cherry/.

Lamont, Owen and Richard Thaler (2003) “Can the Market Add and Subtract? Mispricing in Tech Stock Carve-outs,” *Journal of Political Economy*, Vol. 111(2), pp. 227–268.

Liu, Zheng, Mark M Spiegel, and Jingyi Zhang (2021) “Optimal capital account liberalization in China,” *Journal of Monetary Economics*, Vol. 117, pp. 1041–1061.

Luckner, Clemens Graf von, Carmen M. Reinhart, and Kenneth Rogoff (2021) “Decrypting New Age International Capital Flows,” *NBER Working Paper No. 29337*.

Ma, Guonan and Robert N McCauley (2008) “Efficacy of China’s Capital Controls: Evidence From Price and Flow Data: efficacy of china’s capital controls,” *Pacific Economic Review*, Vol. 13, pp. 104–123.

Magud, Nicolas and Carmen M. Reinhart (2007) “Capital Controls: An Evaluation,” in *Capital Controls and Capital Flows in Emerging Economies: Policies, Practices and Consequences*, ed. Sebastian Edwards, University of Chicago Press.

Makarov, Igor and Antoinette Schoar (2020) “Trading and arbitrage in cryptocurrency markets,” *Journal of Financial Economics*, Vol. 135, pp. 293–319.

——— (2021) “Blockchain analysis of the bitcoin market,” *NBER Working Paper 29396*.

Matonis, Jon (2013) “Bitcoin’s Promise In Argentina,” Apr, URL: https://www.forbes.com/sites/jonmatonis/2013/04/27/bitcoins-promise-in-argentina/?sh=5115039133d5.

Mitchell, M., T. Pulvino, and E. Stafford (2002) “Limited Arbitrage in Equity Markets,” *Journal of Finance*, Vol. 57, pp. 551–584.

Ocampo, J.A. (2017) “Resetting the International Monetary (Non)System,” WIDER Studies in Development Economics, Oxford: Oxford University Press.

Pieters, Gina C. (2016) "Does Bitcoin Reveal New Information About Exchange Rates and Financial Integration?" *FRB Dallas Working Paper No. 292*.

Pieters, Gina and Sofia Vivanco (2016) "Bitcoin: A Hub of Criminal Activity?" *Working Paper*.

Quinn, Dennis P, Martin Schindler, and A. Maria Toyoda (2011) "Assessing Measures of Financial Openness and Integration," *IMF Economic Review*, Vol. 59, pp. 771–813.

Rosenthal, L. and C Young (1990) "The Seemingly Anomalous Price Behavior of Royal Dutch/Shell and Unilever," *Journal of Financial Economics*, Vol. 26, pp. 123–141.

Russo, Camila (2013) "Bitcoin Dreams Endure to Savers Crushed by CPI: Argentina Credit," Apr, URL: https://www.bloomberg.com/news/articles/2013-04-16/bitcoin-dreams-endure-to-savers-crushed-by-cpi-argentina-credit.

Shleifer, Andrei and Robert Vishny (1997) "The Limits of Arbitrage," *The Journal of Finance*, Vol. 52(1), pp. 35–55.

Sokolov, Konstantin (2021) "Ransomware activity and blockchain congestion," *Journal of Financial Economics*.

Trimborn, Simon, Ying Chen, and Ray-Bing Chen (2022) "Influencers, Inefficiency and Fraud – The Bitcoin Price Discovery Network Under the Microscope," *Working Paper*.

Warga, A. (1992) "Bond Returns, Liquidity and Missing Data," *Journal of Financial and Quantitative Analysis*, Vol. 27, pp. 605–617.

Wells, Georgia (2013) "Bitcoin Downloads Surge in Argentina," June, URL: https://www.wsj.com/articles/BL-MBB-4753.

Yu, Gloria and Jinyuan Zhang (2020) "A Revisit to Capital Control Policies When Bitcoin Is in Town," *Working Paper*.

Zhao, Wolfie (2020) "Chinese Police Freezing OTC Traders' Bank Accounts Over 'Tainted' Crypto Transactions," *Coindesk.com*, https://www.coindesk.com/china-police-freeze-otc-traders-bank-accounts-tainted-crypto.

Table 1: **Definition of variables**

Variable	Definition	Data Source
Price Difference $PriceDiff$	Difference in the volume-weighted average daily Bitcoin prices between two exchanges, over the average of the two prices (see equation (1)), winsorized at 1 and 99 percentiles. Frequency: daily.	http://bitcoinity.com
Order Imbalance Difference	Difference in the order imbalance OIMB between two exchanges (see equation (3)). OIMB equals buy minus sell orders, both within 1% of trade prices, over the average of the buy and sell orders, winsorized at 1 and 99 percentiles (see equation (2)). Frequency: daily.	http://bitcoinity.com
Avg. Bid-Ask Spread	Bid-ask spread over the mid-quote, averaged by exchange-pair. Frequency: daily.	http://bitcoinity.com
Avg. Inside Depth	Total orders (in $1,000$ BTC) within 1% of the trading prices, averaged by exchange-pair. Frequency: daily.	http://bitcoinity.com
Avg. BTC volume	Trading volume (in $1,000$ BTC), averaged by exchange-pair. Frequency: daily.	http://bitcoinity.com
Avg. SD of Price	Standard deviation of BTC transaction prices over the average price, averaged by exchange-pair. Frequency: daily.	http://bitcoinity.com
Avg. Network Transaction Fee	The average fee per transaction (in USD) added to the Bitcoin blockchain, over the Bitcoin price. Frequency: daily.	http://blockchain.com
Block Size	The average block size in Bitcoin blockchain (in Megabytes). Frequency: daily.	http://blockchain.com
One Retail	Dummy variable equal to one when at least one of the exchanges in the exchange pair is classified as "retail" (i.e., the trade size is below 75^{th} percentile of trade size of the past 30 days relative to the other exchange in an exchange pair), and zero otherwise. Frequency: daily.	Calculated by authors.
CNH spread	The offshore Renminbi exchange rate (in CNH per USD) minus the onshore Renminbi exchange rate (in CNY per USD), divided by the CNY rate. Frequency: daily.	Haver
Outflow Ctrl.	The change in the *de jure* index of capital outflow control, constructed following Chen and Qian (2016). Frequency: daily.	Balance of payment data from China's State Administration of Foreign Exchange

Table 2: **Bitcoin Price Differences: Summary Statistics**

This table reports the mean and (in parenthesis) the standard error of bitcoin price differences between pairs of exchanges in our sample. Panels A and B show the difference in bitcoin prices for foreign (i.e. non-Chinese) exchanges relative to BTCChina and OKCoin, respectively. Panel C shows the price differences between foreign exchanges. The sample period is from June 1, 2014 to December 31, 2016.

(a) **Price differences: Foreign exchanges minus BTCChina**

	Mean	Median	Std Dev.	Min.	Max.	N
btcchina vs. bitfinex	0.321	0.185	1.202	-2.799	4.731	554
btcchina vs. bitstamp	0.595	0.406	1.303	-5.208	6.770	547
btcchina vs. btce	1.496	1.257	1.610	-3.585	9.985	547
btcchina vs. coinbase	0.519	0.285	1.310	-3.561	7.547	404
btcchina vs. itbit	0.453	0.314	1.446	-5.644	5.526	551
btcchina vs. kraken	0.220	0.209	1.924	-10.861	7.956	528

(b) **Price differences: Foreign exchanges minus OKCoin**

	Mean	Median	Std Dev.	Min.	Max.	N
okcoin vs. bitfinex	-0.203	-0.169	0.885	-3.277	2.408	187
okcoin vs. bitstamp	-0.028	-0.157	1.034	-2.544	4.487	182
okcoin vs. btce	1.174	0.993	1.090	-1.457	5.139	184
okcoin vs. coinbase	-0.485	-0.516	0.498	-1.235	1.213	36
okcoin vs. itbit	-0.120	-0.059	1.747	-5.638	8.098	187
okcoin vs. kraken	-0.666	-0.499	2.267	-10.120	5.849	176

(c) **Price differences among foreign exchanges**

	Mean	Median	Std Dev.	Min.	Max.	N
bitfinex vs. bitstamp	0.245	0.220	0.547	-1.086	2.315	626
bitfinex vs. coinbase	-0.012	-0.034	0.461	-1.647	1.462	479
bitfinex vs. itbit	0.148	0.146	0.875	-2.725	3.671	608
bitfinex vs. kraken	-0.008	0.078	1.241	-4.550	3.638	603
bitstamp vs. coinbase	-0.315	-0.296	0.412	-3.052	0.907	480
bitstamp vs. itbit	-0.121	-0.099	0.743	-3.175	2.061	601
bitstamp vs. kraken	-0.274	-0.246	1.056	-3.623	2.759	597
btce vs. bitfinex	-1.132	-1.123	1.158	-5.067	1.666	625
btce vs. bitstamp	-0.901	-0.892	1.132	-5.370	1.348	619
btce vs. coinbase	-1.117	-1.111	1.275	-6.995	1.555	474
btce vs. itbit	-1.027	-0.937	1.400	-6.816	2.207	600
btce vs. kraken	-1.222	-1.018	1.463	-6.464	1.874	595
itbit vs. coinbase	-0.192	-0.170	0.533	-2.842	1.686	454
kraken vs. coinbase	-0.172	-0.117	0.755	-3.624	1.644	462
kraken vs. itbit	0.160	0.138	1.304	-3.998	4.131	578

Table 3: **Summary Statistics by Exchange**

This table reports the exchange level mean and (in parenthesis) standard deviation of prices, BTC and USD volumes, price-normalized intraday price standard deviation, price-normalized spreads, volume normalized orderbook size within 1% of the price, and orderbook imbalance. Sample period is from June 1, 2014 to December 31, 2016.

	BTC/USD Exchanges						BTC/CNY Exchanges	
	BTC-e (1)	Bitstamp (2)	Bitfinex (3)	itBit (4)	Coinbase (5)	Kraken (6)	BTCChina (7)	OKcoin (8)
Price	429.247	429.277	425.625	429.746	426.611	432.963	433.934	402.304
	(167.719)	(170.414)	(164.034)	(174.664)	(181.926)	(175.278)	(173.487)	(135.465)
BTC Volume (thousands)	7.104	10.752	22.836	3.824	7.388	0.527	226.095	107.589
	(5.620)	(10.811)	(26.579)	(4.334)	(7.420)	(0.954)	(579.888)	(78.716)
USD Volume (millions)	2.781	4.008	8.813	1.636	3.011	0.311	146.283	38.309
	(2.057)	(3.671)	(10.841)	(2.349)	(3.414)	(0.622)	(455.673)	(27.315)
Intraday Price SD / Price (%)	0.941	0.971	0.984	0.880	0.822	1.068	0.955	1.255
	(0.952)	(0.885)	(0.911)	(2.035)	(0.869)	(1.196)	(1.037)	(1.065)
Spread / Price (%)	0.135	0.160	0.063	0.126	0.030	1.718	0.031	0.039
	(0.056)	(0.238)	(0.074)	(0.109)	(0.028)	(2.262)	(0.021)	(0.204)
Normalized Orderbook Size	0.194	0.170	0.172	0.646	0.114	4.009	0.024	0.016
	(1.693)	(0.151)	(0.171)	(2.116)	(0.077)	(31.925)	(0.040)	(0.015)
Orderbook Imbalance	-0.087	-0.147	-0.026	-0.025	-0.155	0.040	-0.064	0.077
	(0.262)	(0.246)	(0.210)	(0.265)	(0.188)	(0.318)	(0.243)	(0.150)
Obs.	921	917	929	895	706	886	575	192

Table 4: **Absolute Price Differences between Chinese (BTC/CNY) and Non-Chinese (BTC/USD) Exchanges**
This table reports the OLS estimate of the effect of CNH spread on $|PriceDiff_{i,t}|$, which is the date t Bitcoin price absolute value of difference between exchange pair i normalized by the average of the Bitcoin prices on the two exchanges. The sample BTC/CNY exchanges include BTCChina and OKCoin, and the sample BTC/USD exchanges include Bitfinex, Bitstamp, BTC-e, Coinbase, Kraken, and ItBit. The dummy variable BTC-e equals 1 for exchange pairs that include BTC-e, and equals 0 otherwise. The dummy variable BitFinex equals 1 for exchange pairs that include BitFinex, and equals 0 otherwise. Finally, the dummy variable BitStamp equals 1 for exchange pairs that include Bitstamp, and equals 0 otherwise. We control for the following groups of dependent variables on microstructure, blockchain information, market segmentation, and risk factors. The group of three microstructure control variables of Bitcoin exchange pair i on date t include the average bid-ask spread divided by the mid-quote, intraday price standard deviation normalized by the daily price, and the daily sum of orders in the order book within 1% of the average daily price divided by the daily volume. The blockchain information contains the daily average transaction fee (in BTC) for each transaction added to the blockchain. $Segmentation_{i,t}$ is the indicator for one the exchanges in pair i was classified as a retail exchange on the day t; Sample period is from June 1, 2014 to December 31, 2016. Exchange-pair clustered standard errors are reported in parentheses. *** indicates statistical significance at the 1% level, ** at the 5% level, and * at the 10% level.

	| Price Diff. |			
	(1)	(2)	(3)	(4)
CNH spread	0.184***	0.092***	0.107***	
	(0.052)	(0.025)	(0.028)	
CNH spread × BTC-e		0.358***	0.353***	0.335***
		(0.049)	(0.068)	(0.092)
CNH spread × BitFinex		0.167***	0.110***	0.107*
		(0.031)	(0.031)	(0.054)
CNH spread × BitStamp		0.016	-0.020	-0.018
		(0.026)	(0.030)	(0.052)
Avg. Spread / Price			0.422***	0.414***
			(0.044)	(0.029)
Avg. Intraday Price SD			0.363***	0.307***
			(0.052)	(0.055)
Avg. $\log_{10}$ Normalized Orderbook Size			-0.077	0.042
			(0.086)	(0.102)
Avg. Network Transaction Fee			15.778**	
			(6.117)	
One Retail			-0.272	-0.025
			(0.181)	(0.130)
Constant	1.098***	1.097***	0.271	0.743***
	(0.010)	(0.003)	(0.188)	(0.117)
Observations	4,083	4,083	4,083	4,083
Exchange-pair FE	Yes	Yes	Yes	Yes
Date FE	No	No	No	Yes
Exchange Ctrl.	No	No	Yes	Yes
Adj. R^2	0.055	0.056	0.248	0.607

Table 5: **Absolute Price Differences among Non-Chinese (BTC/USD) Exchanges**

This table reports the OLS estimate of the effect of CNH spread on $|PriceDiff_{i,t}|$, which is the date t Bitcoin price absolute value of difference between exchange pair i normalized by the average of the Bitcoin prices on the two exchanges. The sample exchanges are Bitfinex, Bitstamp, BTC-e, Coinbase, Kraken, and ItBit. The dummy variable BTC-e equals 1 for exchange pairs that include BTC-e, and equals 0 otherwise. The dummy variable BitFinex equals 1 for exchange pairs that include BitFinex, and equals 0 otherwise. Finally, the dummy variable BitStamp equals 1 for exchange pairs that include Bitstamp, and equals 0 otherwise. We control for the following groups of dependent variables on microstructure, blockchain information, market segmentation, and risk factors. The group of three microstructure control variables of Bitcoin exchange pair i on date t include the average bid-ask spread divided by the mid-quote, intraday price standard deviation normalized by the daily price, and the daily sum of orders in the order book within 1% of the average daily price divided by the daily volume. The blockchain information contains the daily average transaction fee (in BTC) for each transaction added to the blockchain. $Segmentation_{i,t}$ is the indicator for one the exchanges in pair i was classified as a retail exchange on the day t; Sample period is from June 1, 2014 to December 31, 2016. Exchange-pair clustered standard errors are reported in parentheses. *** indicates statistical significance at the 1% level, ** at the 5% level, and * at the 10% level.

	| Price Diff. |			
	(1)	(2)	(3)	(4)
CNH spread	-0.024	-0.084	-0.021	
	(0.037)	(0.070)	(0.058)	
CNH spread × BTC-e		0.142*	0.107	0.150*
		(0.077)	(0.070)	(0.070)
CNH spread × BitFinex		0.045	-0.007	0.043
		(0.067)	(0.067)	(0.073)
CNH spread × BitStamp		-0.008	-0.039	0.016
		(0.068)	(0.070)	(0.074)
Avg. Spread / Price			0.277***	0.232***
			(0.015)	(0.025)
Avg. Intraday Price SD			0.160***	0.115***
			(0.024)	(0.021)
Avg. $\log_{10}$ Normalized Orderbook Size			-0.406***	0.016
			(0.107)	(0.067)
Avg. Network Transaction Fee			3.338	
			(2.115)	
One Retail			0.191***	0.133**
			(0.046)	(0.055)
Constant	0.831***	0.831***	0.054	0.543***
	(0.008)	(0.007)	(0.105)	(0.056)
Observations	8,401	8,401	8,401	8,401
Exchange-pair FE	Yes	Yes	Yes	Yes
Date FE	No	No	No	Yes
Adj. R^2	0.177	0.178	0.377	0.490

Table 6: **Price premium on Chinese (BTC/CNY) over Non-Chinese (BTC/USD) Exchanges**

This table reports the OLS estimate of the effect of CNH spread on $PriceDiff_{i,t}$, which is the date t Bitcoin price difference between exchange pair i normalized by the average of the Bitcoin prices on the two exchanges. The sample BTC/CNY exchanges include BTCChina and OKCoin, and the sample BTC/USD exchanges include Bitfinex, Bitstamp, BTC-e, Coinbase, Kraken, and ItBit. The dummy variable BTC-e equals 1 for exchange pairs that include BTC-e, and equals 0 otherwise. The dummy variable BitFinex equals 1 for exchange pairs that include BitFinex, and equals 0 otherwise. Finally, the dummy variable BitStamp equals 1 for exchange pairs that include Bitstamp, and equals 0 otherwise. Exchange controls include the groups of dependent variables on microstructure, blockchain information, and market segmentation as in Table 5. Sample period is from June 1, 2014 to December 31, 2016. Exchange-pair clustered standard errors are reported in parentheses. *** indicates statistical significance at the 1% level, ** at the 5% level, and * at the 10% level.

(a)

	Price Diff. +		
	(1)	(2)	(3)
CNH spread	0.295***	0.227***	
	(0.050)	(0.033)	
CNH spread × BTC-e		0.299***	0.220**
		(0.068)	(0.085)
CNH spread × BitFinex		0.018	-0.042
		(0.045)	(0.045)
CNH spread × BitStamp		-0.122**	-0.160***
		(0.044)	(0.041)
Constant	0.745***	0.223	0.412***
	(0.009)	(0.205)	(0.085)
Observations	4,083	4,083	4,083
Exchange-pair FE	Yes	Yes	Yes
Date FE	No	No	Yes
Exchange Ctrl.	No	Yes	Yes
Adj. R^2	0.103	0.211	0.733

(b)

	Price Diff. -		
	(1)	(2)	(3)
CNH spread	0.111**	0.120**	
	(0.037)	(0.043)	
CNH spread × BTC-e		-0.054	-0.115**
		(0.043)	(0.044)
CNH spread × BitFinex		-0.092*	-0.148**
		(0.048)	(0.049)
CNH spread × BitStamp		-0.102*	-0.142**
		(0.052)	(0.050)
Constant	-0.352***	-0.048	-0.331***
	(0.007)	(0.061)	(0.062)
Observations	4,083	4,083	4,083
Exchange-pair FE	Yes	Yes	Yes
Date FE	No	No	Yes
Exchange Ctrl.	No	Yes	Yes
Adj. R^2	0.084	0.205	0.446

Table 7: **Price Differences Among Non-Chinese (BTC/USD) Exchanges**

The table reports the OLS estimates for each exchange *i*, when the outcome variable is the *signed* Bitcoin price difference generated by a step-wise comparison. For instance, Column (1) is for the price differences between BTC-e and all other BTC/USD exchanges, whereas Column (6) is for the price difference between Coinbase and Kraken. Exchange controls include the groups of dependent variables on microstructure, blockchain information, and market segmentation as in Table 5. Sample period is from June 1, 2014 to December 31, 2016. Exchange-pair clustered standard errors are reported in parentheses. *** indicates statistical significance at the 1% level, ** at the 5% level, and * at the 10% level.

(a)

	Price Diff. +				
	(1)	(2)	(3)	(4)	(5)
CNH spread	-0.081**	0.026	-0.006	-0.004	0.032
	(0.024)	(0.047)	(0.058)	(0.045)	(0.065)
Constant	0.203***	0.076**	0.133*	0.157	0.240
	(0.018)	(0.015)	(0.032)	(0.166)	(0.165)
Observations	2,913	2,304	1,690	1,032	462
Exchange	BTC-e	Bitstamp	Bitfinex	itBit	Coinbase
Compare to	All others	Bitfinex; itBit; Coinbase; Kraken	itBit; Coinbase; Kraken	Coinbase; Kraken	Kraken
Exchange-pair FE	Yes	Yes	Yes	Yes	No
Exchange Ctrl.	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.038	0.168	0.127	0.171	0.249

(b)

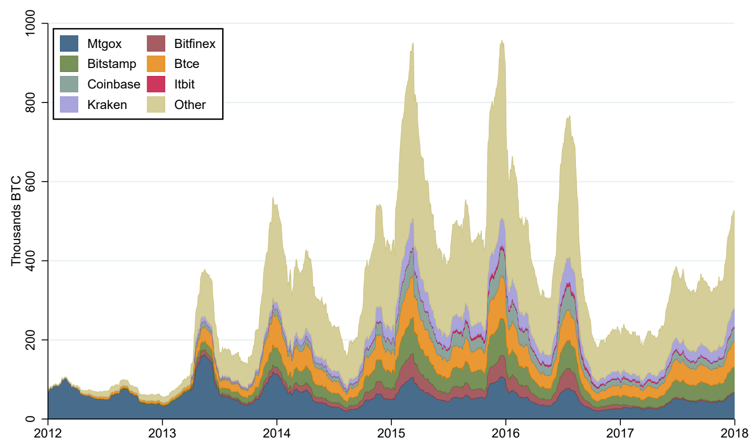
	Price Diff. -				
	(1)	(2)	(3)	(4)	(5)
CNH spread	-0.167**	0.113*	0.052	0.029	-0.087*
	(0.037)	(0.041)	(0.038)	(0.054)	(0.045)
Constant	0.193	-0.001	-0.004	-0.120	0.008
	(0.107)	(0.031)	(0.049)	(0.237)	(0.090)
Observations	2,913	2,304	1,690	1,032	462
Exchange	BTC-e	Bitstamp	Bitfinex	itBit	Coinbase
Compare to	All others	Bitfinex; itBit; Coinbase; Kraken	itBit; Coinbase; Kraken	Coinbase; Kraken	Kraken
Exchange-pair FE	Yes	Yes	Yes	Yes	No
Exchange Ctrl.	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.184	0.126	0.182	0.181	0.057

Table 8: **BTC exchange price difference and order imbalance**
The table reports the OLS estimates from estimating order imbalance for each exchange *i*. The sample exchanges are BTC/CNY exchanges including BTCChina and OKCoin, and BTC/USD exchanges including Bitfinex, Bitstamp, BTC-e, Coinbase, Kraken, and ItBit. Columns (1) and (2) are for the absolute order imbalances, Columns (3) and (4) are for the signed order imbalances. Columns (5) and (6) are for the positive component of the signed order imbalances, whereas Columns (7) and (8) are for the negative component. Sample period is from June 1, 2014 to December 31, 2016. Exchange clustered standard errors are reported in parentheses. *** indicates statistical significance at the 1% level, ** at the 5% level, and * at the 10% level.

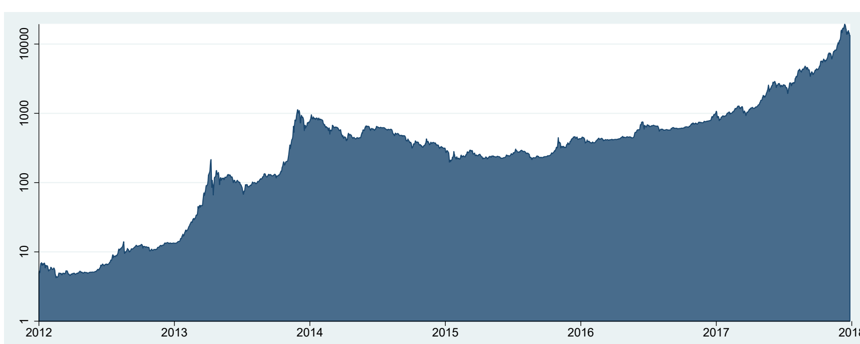
	| Order Imbal. |		Order Imbal.		Order Imbal.+		Order Imbal.-	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
CNH spread	0.012		-0.064*		-0.026**		-0.038	
	(0.016)		(0.028)		(0.010)		(0.020)	
CNH spread × BTC/CNY Exch.		0.074**		-0.000		0.037*		-0.037
		(0.022)		(0.039)		(0.018)		(0.026)
CNH spread × BTC-e		0.089***		-0.128**		-0.019		-0.108***
		(0.025)		(0.041)		(0.016)		(0.030)
CNH spread × BitFinex		0.038		-0.059		-0.011		-0.049
		(0.024)		(0.040)		(0.016)		(0.029)
CNH spread × BitStamp		0.007		-0.007		0.000		-0.007
		(0.023)		(0.038)		(0.016)		(0.027)
Constant	0.204***	0.200***	-0.050***	-0.057***	0.077***	0.071***	-0.127***	-0.128***
	(0.003)	(0.002)	(0.006)	(0.004)	(0.002)	(0.002)	(0.004)	(0.003)
Observations	4,383	4,383	4,383	4,383	4,383	4,383	4,383	4,383
Exchange FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Date FE	No	Yes	No	Yes	No	Yes	No	Yes
Adj. R^2	0.023	0.046	0.084	0.175	0.055	0.126	0.075	0.147

Figure 1: Total volume in the Bitcoin–USD exchange market: January 2012 to December 2017

Panel (a) shows the 60-day moving average of the daily volume in Bitcoin exchanges, in units of Bitcoin. The Bitcoin exchanges are Bitfinex, Bitstamp BTC-e, Coinbase, itBit, MtGox, Kraken and other USD-BTC exchanges. The data source is bitcoincharts.com. Panel (b) shows the time series of the Bitcoin index price. The average price is calculated as the trading volume weighted average across several currency markets, converted to USD at fiat exchange rates. The sample period in both panels is January 2012 to December 2017.



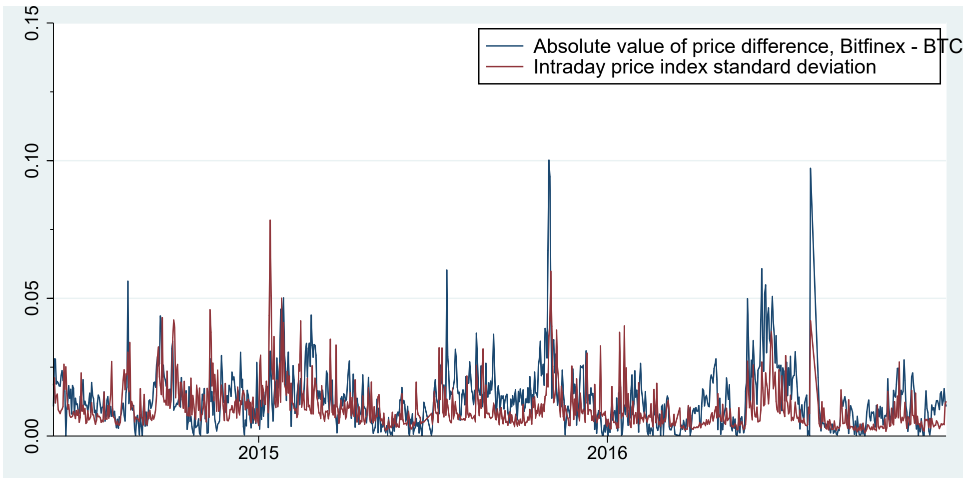
Daily BTC Volume (Thousands BTC)



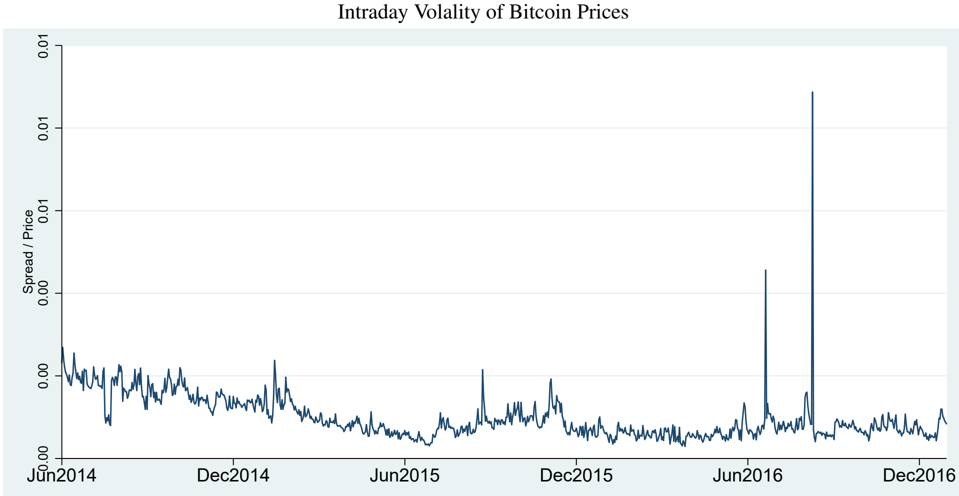
Average Price of Bitcoin in USD

Figure 2: Descriptive statistics of Bitcoin volatility and liquidity

Panel (a) shows the intraday volatility of the Bitcoin price index and the absolute value of the difference in prices of Bitcoin trading on Bitfinex and BTC-e. Panel (b) presents the volume-weighted average bid-ask spread normalized by price.



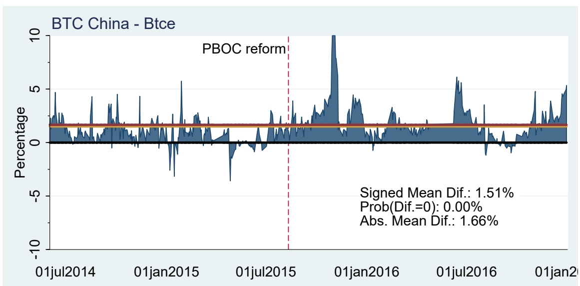
Intraday Volality of Bitcoin Prices



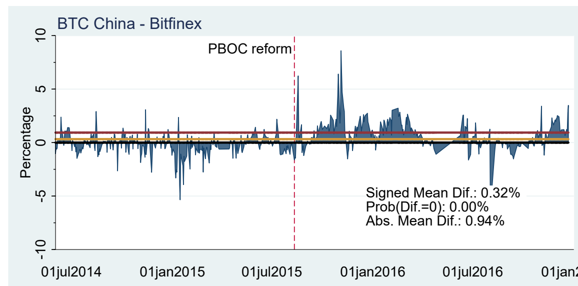
Bid-ask spread normalized by price

Figure 3: Bitcoin Price Differences: BTC China Relative to Non-Chinese Exchanges

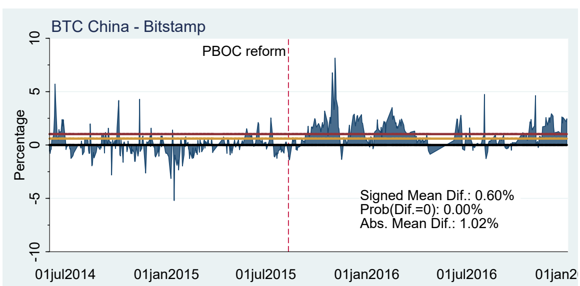
The figure plots the daily time series of differences between the price of Bitcoin on the Chinese exchange BTC China minus its price on a foreign, non-Chinese exchange X, normalized by the average of the prices on the two exchanges, where X=(Bitfinex, Bitstamp, Coinbase, itBit, Kraken). The price is the volume-weighted average price of the day. The price difference is capped in the range -10% to $+10\%$ but the maximum absolute difference is indicated below each chart. The magnitude of the normalized price difference is shown as a blue area plot. The orange line shows the average signed price differences for the respective exchange pair. The dark red line shows the average absolute price difference between the exchanges.



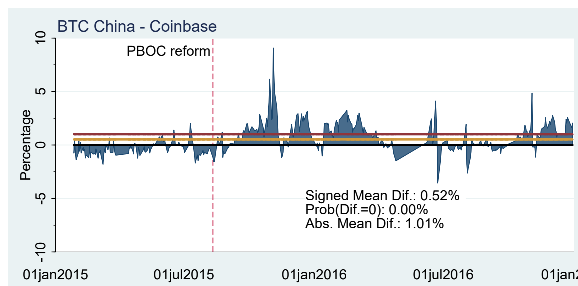
BTCN vs. BTC-e



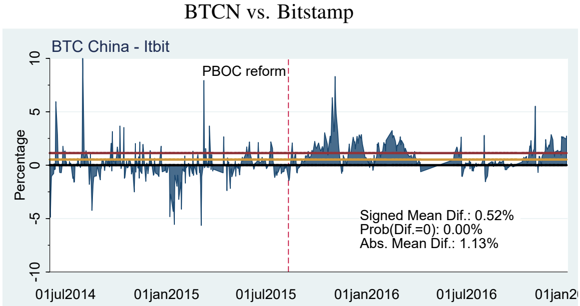
BTCN vs. Bitfinex



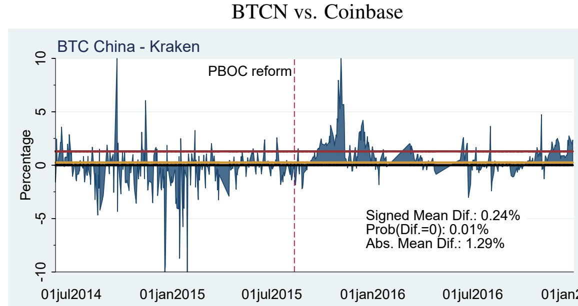
BTCN vs. Bitstamp



BTCN vs. Coinbase



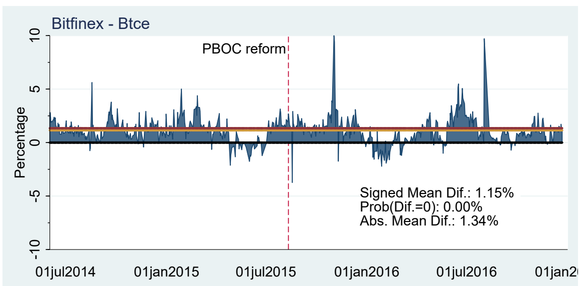
BTCN vs. Itbit



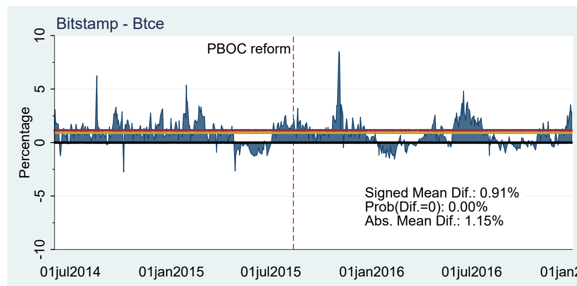
BTCN vs. Kraken

Figure 4: Deviations in Bitcoin Prices Relative to BTC-e

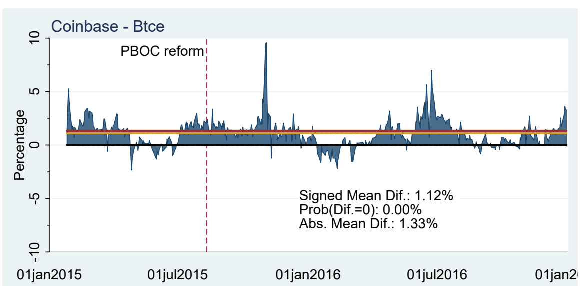
The figure plots the daily time series of differences between the price of Bitcoin on an exchange X minus its price on BTC-e, normalized by the average of the prices on the two exchanges, where X=(Bitfinex, Bitstamp, Coinbase, itBit, Kraken). The price is the volume-weighted average price of the day. The price difference is capped in the range -10% to $+10\%$ but the maximum absolute difference is indicated below each chart. The magnitude of the normalized price difference is shown as a blue area plot. The orange line shows the average signed price differences for the respective exchange pair. The dark red line shows the average absolute price difference between the exchanges. The data source is bitcoincharts.com.



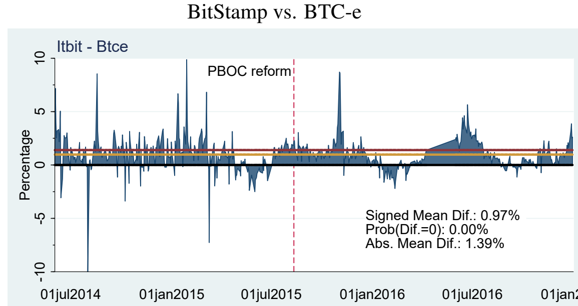
Bitfinex vs. BTC-e



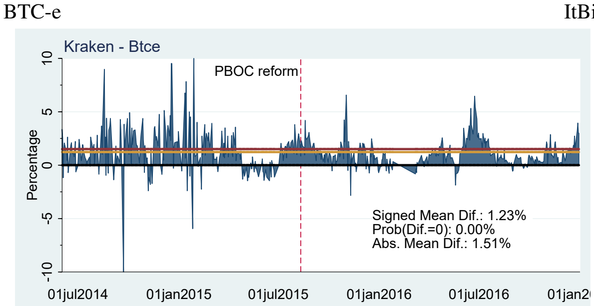
BitStamp vs. BTC-e



Coinbase vs. BTC-e



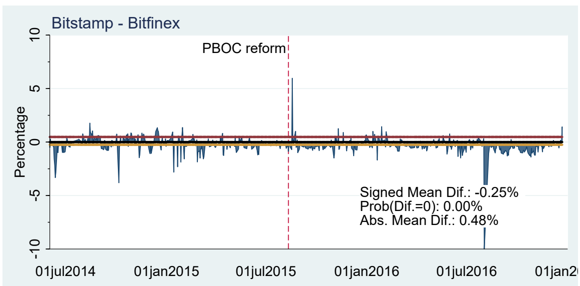
ItBit vs. BTC-e



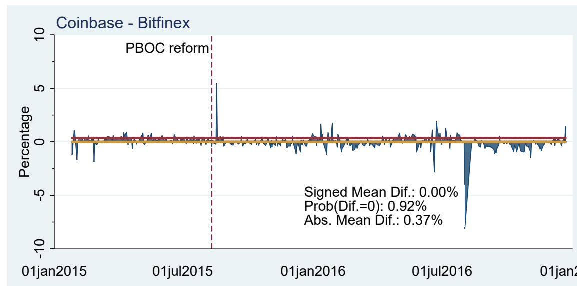
Kraken vs. BTC-e

Figure 5: Deviations in Bitcoin Prices Relative to Bitfinex

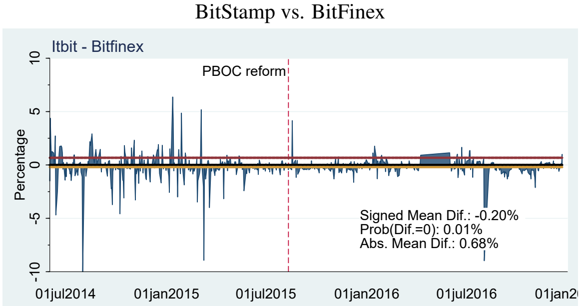
The figure plots the daily time series of differences between the price of Bitcoin on an exchange X minus its price on Bitfinex, normalized by the average of the prices on the two exchanges, where X=(Bitstamp, Coinbase, itBit, Kraken). The price is the volume-weighted average price of the day. The price difference is capped in the range -10% to $+10\%$ but the maximum absolute difference is indicated below each chart. The magnitude of the normalized price difference is shown as a blue area plot. The orange line shows the average signed price differences for the respective exchange pair. The dark red line shows the average absolute price difference between the exchanges. The data source is bitcoincharts.com.



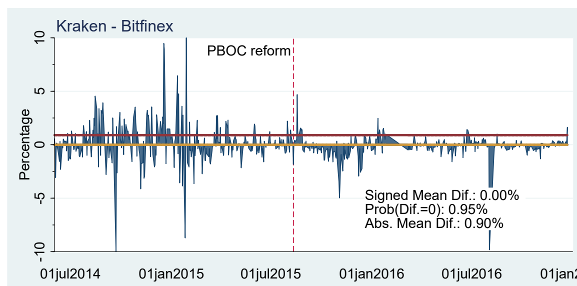
BitStamp vs. BitFinex



Coinbase vs. BitFinex



ItBit vs. BitFinex



Kraken vs. BitFinex

Figure 6: Mechanics of a Bitcoin Arbitrage Strategy

The diagram shows the execution of a possible arbitrage strategy involving buying Bitcoin on BTC-e and selling it on Bitfinex. The data on fees are from the exchange websites, as of September 2016.

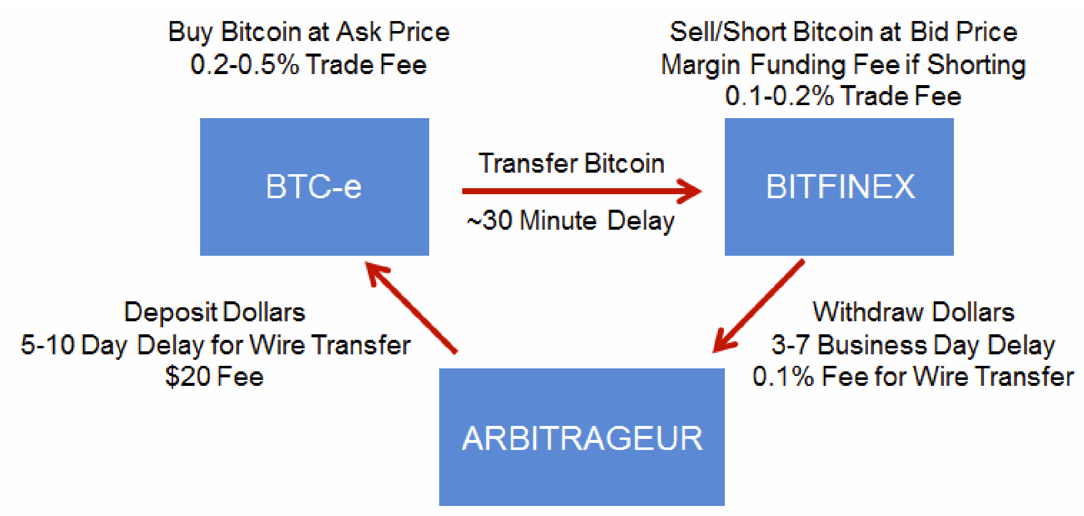
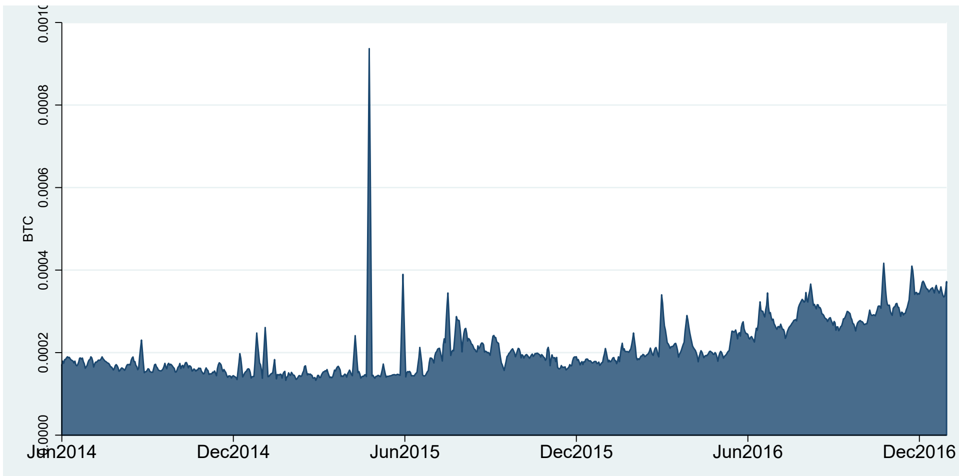
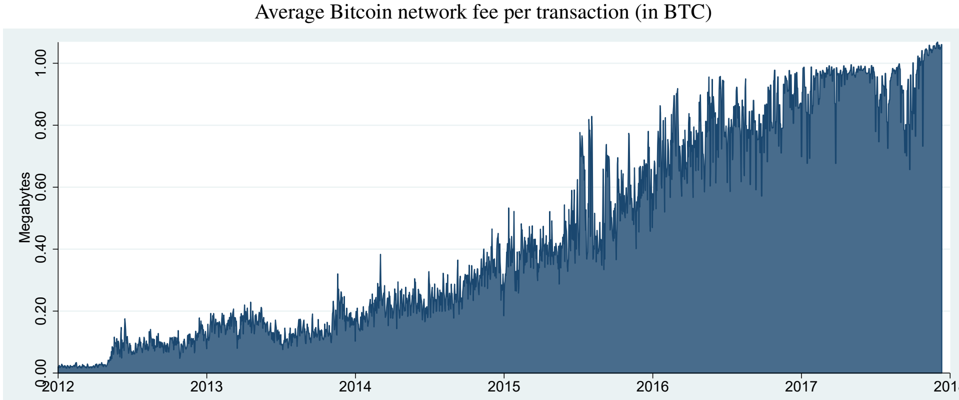


Figure 7: Descriptive statistics of Bitcoin blockchain

Panel (a) shows the average per transaction of Bitcoin network transaction fees that are used to incentivize miners to include the transaction in their blocks. The high average fee in April 2015 was likely due to an error when a user specified a transaction fee of 316 BTC, or roughly $147,000 at the time (Coindesk). The data is obtained from Blockchain.info. Panel (b) shows the Bitcoin blockchain block size over the sample period.



Average Bitcoin network fee per transaction (in BTC)



Blocksize

Figure 8: Mechanics of Evading Capital Controls Using Bitcoin

The diagram shows one way that Bitcoin may be used to evade capital controls.

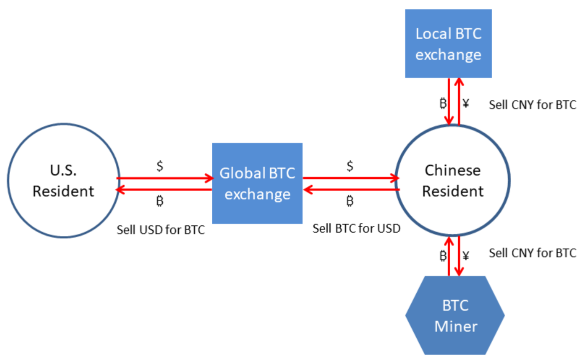
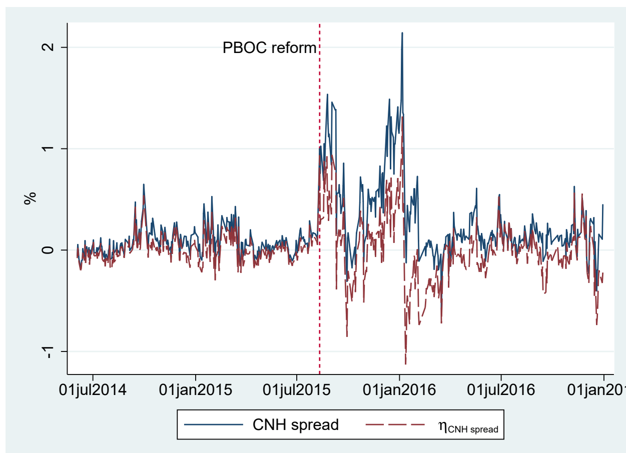


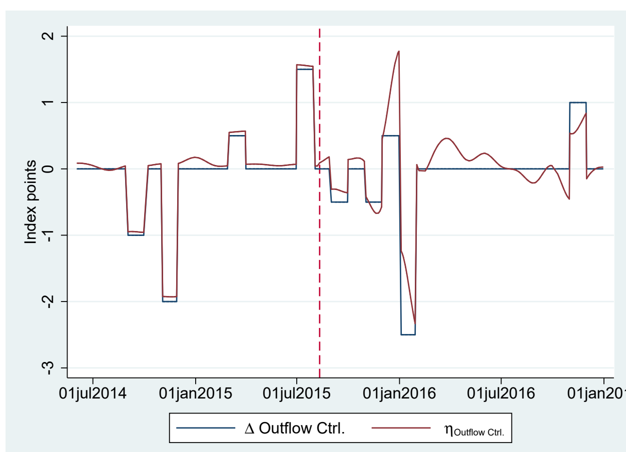
Figure 9: **CNH spreads and *de jure* capital control index**

This figure presents the daily time series of CNH spread and *de jure* capital control index. The sample period is from June 1, 2014to December 31, 2016. The vertical line represents the August 11th, 2015 PBOC reform in exchange rate policy.

CNH spread



de jure capital control index



A Capital control measures

We provide background on China's capital control policy during our sample in section A.1 and then discuss the construction of the three capital control measures: the *de jure* index (A.3) and the market-based measure (section A.2).

A.1 Chinese capital controls before 2017: Background

Various indices of Chinese capital control show it has among the strictest capital controls of all countries – although, by 2017, they had eased considerably (Fernandez et al. (2016)). Most formal restrictions on capital outflow in China are quantity-based. For example, since 2007, individuals face an annual foreign exchange purchases and sales quota of USD 50,000, exceeding which requires a permit from the State Administration of Foreign Exchange (SAFE).[24] Since 2006, select domestic financial institutions can trade in overseas-listed equities and debt securities subject to a quota that has remained small.

Even though these *de jure* restrictions do not change much, the *de facto* capital control regime does. China has tightened capital accounts through administrative and other restrictions rather than directly changing capital regulations (Agarwal et al. (2019)). When faced with depreciation pressures on the CNY, China has tightened administrative controls – for example, by having individuals provide details of why they need to purchase foreign currency. The possibility of increased outflow restrictions when the foreign exchange market is stressed, provides incentives for Chinese residents to move capital out, perhaps by using Bitcoin. For example, when the CNY faced depreciation pressures in late 2014, unaccounted capital outflows increased between 2015-2017 (Agarwal et al. (2019)). And China's exchange rate inferred from bitcoin prices and its official exchange rate deviated from each other in 2014-2015, suggestive of increasing capital controls (Pieters (2016)).

A.2 Market-based measures of capital outflows

Our market-based measure is based on the wedge between its onshore (CNY) and offshore (CNH) exchange rates. The CNH market refers to the offshore renminbi market in Hong Kong with spot and deliverable forwards, a crucial aspect of the CNY internationalization. It is closely tied to the demand and supply conditions for the currency as it requires the actual renminbi liquidity (Eraslan

[24] See https://www.elibrary-areaer.imf.org/Pages/Reports.aspx

(2017)). The daily turnover of spot transactions traded offshore had grown to about 70% of the CNY spot turnover in the onshore market by 2013. We calculate the CNH spread as follows:

$$CNHSpread_t = 100 \times \frac{S_t^{CNH} - S_t^{CNY}}{S_t^{CNY}} \tag{A.1}$$

S^{CNH} is the offshore spot exchange rate and S^{CNY} is the onshore spot exchange rate. The spread is divided by the onshore exchange rate and multiplied by 100 to convert to percent, facilitating comparison with the CIP spread (which is also in percent). However, the results are robust to using just the numerator in (A.1), without the normalization. We obtain the daily CNH and CNY spot exchange rates, in currency units per USD, from Bloomberg using ticker CNH and CNY, respectively.

A.3 *De jure* capital outflow control index

We build our *de jure* capital outflow control index following Chen and Qian (2016), who extract detailed capital control information from the text of IMF's Annual Report on Exchange Arrangements and Exchange Restrictions (AREAER) and supplementary materials from other sources. Chen and Qian (2016) construct monthly *de jure* indices from 1999 to 2012.

To compile the *de jure* index data, Chen and Qian (2016) set January 1999 as the benchmark and assign it a score of 0, then adding (subtracting) 1 to the previous score if capital control tightens (relaxes) in the next month. The score remains the same if there is no policy change. Hence, a high index score indicates tighter Chinese capital controls in the particular category of financial transactions.

In this paper, we focus on constructing an index from controls on *outflows* of funds and transactions made by Chinese residents and nonresidents. We include five subcategories from China's capital accounts: equity investment, bond investment, money market, commercial credits, and financial credits. We construct the *de jure* capital outflow control index as the unweighted sum of the five subcategory monthly scores listed above. The data is obtained from AREAER.

We depart from Chen and Qian (2016) in excluding the scores on the constraints on China's foreign direct investments (FDI). China's regulatory system discriminates among different cross-border flows and, within the capital account, encouraging foreign direct investment (FDI) has been a long-held polic. Further, our interest is in shorter-term capital flight, whereas FDI movements tend to be long-term.

Tests of structural break points confirm evidence of significant structural breaks in the CNH and CIP spreads. Specifically, the Quandt-Andrews (Andrews (1993)) unknown breakpoint test rejects the null hypothesis of no breakpoint on August 11 2015 at a significance level of 1% or less.[25] By comparison, there is no evidence of a structural break in the *de jure* index on August 11 2015.

B Bitcoin exchanges

Table B.1 provides detail information about the non-Chinese exchanges, in particular, their *KYC and AML compliance*. The US Justice Department, in its complaint against BTC-e, stated that BTC-e made no effort to maintain any elements of an AML program, as its business model obscured and anonymized transactions and sources of funds (see #18 on page 4 and #24 on page 5 of USA versus BTC-e complaint, June 2016 reddit post and May 2015 review).

Due to BTC-e's poor KYC/AML compliance, U.S. banks delayed or blocked transactions deemed to be high risk, such as fund transfers from a U.S. bank to BTC-e. During our sample period, deposits of USD via wire took five to ten days to complete on BTC-e.[26] Workarounds existed to ensure the viability of the capital evasion strategies. For example, investors could transfer USD to a third-party account first, and then to BTC-e.[27]

[25] Relatedly, Pieters (2016) argues that CNY and USD were better aligned following August 15, 2015, based on a comparison of the official and bitcoin-implied exchange rates.

[26] See BTC-e USD wire. By comparison, transferring bitcoin from one exchange to another is typically quick. A bitcoin transfer on the blockchain took roughly 10 minutes to settle (i.e., to be added to a block) during our sample.

[27] See #19 on page 4 of USA versus BTC-e complaint.

Table B.1: **BTC Exchanges Information**

	BTC-e	BitFinex	BitStamp	Coinbase	itBit	Kraken
Headquarter Location	Russia	Hongkong, PRC	London, UK	No HQ	New York, NY	San Francisco, CA
Founded	July 2011	December 2012	August 2011	June 2012	2012	July 28, 2011
Closed?	Yes, on July 28, 2017	No	No	No	No	No
Owned/Operated by	Always Efficient LLP	iFinex Inc.	NXMH	Publicly Listed	Paxos Trust Co.	Payward, Inc.
Registered Location	London, UK	British Virgin Islands	Luxembourg	U.S.	U.S.	U.S.
Listed Exchange	N/A	N/A	N/A	Nasdaq	N/A	N/A
AML Compliant?	No	Unclear	High (Self-regulated)	High	High	High
KYC Compliant?	No	Partially	Yes	Yes	Yes	Partially
Withdrawal Limits Without KYC	None	2 BTC	N/A	N/A	N/A	$5,000 USD
Fees: USD Deposit*	Blocked	$20	$7.5	$10	$10	$20
Fees: USD Withdraw*	Blocked	$20	$15	$25	$20	$20
Website	N/A	bitfinex.com	bitstamp.net	coinbase.com	paxos.com	kraken.com

Notes: For BTC-e, information is from justice department indictment. For other exchanges, KYC information is from Non-KYC compliant exchanges. The fees for deposit or withdraw refer to the cost of deposit or withdraw $1,000 via wire transfer from or to a U.S. bank. Since late 2013, BTC-e has stopped accepting dollar transfers or transfers from U.S. banks, see https://www.coindesk.com/markets/2013/12/03/is-europes-second-largest-bitcoin-exchange-btc-e-having-banking-issues/.

C Additional Results for USD Panel Exchanges

Table C.1: **Determinants of Bitcoin Price Deviations Among BTC/USD Exchanges**
This table reports the OLS estimate of $|PriceDiff_{i,t}|$, which is the date t Bitcoin price absolute value of difference between exchange pair i normalized by the average of the Bitcoin prices on the two exchanges. The sample exchanges are Bitfinex, Bitstamp, BTC-e, Coinbase, Kraken, and ItBit from June 1, 2014 to December 31, 2016. We control for the following groups of dependent variables on microstructure, blockchain information, market segmentation, and risk factors. The group of three microstructure control variables of Bitcoin exchange pair i on date t include the average bid-ask spread divided by the mid-quote, intraday price standard deviation normalized by the daily price, and the daily sum of orders in the order book within 1% of the average daily price divided by the daily volume. The blockchain information contains the daily average transaction fee (in BTC) for each transaction added to the blockchain. $Segmentation_{i,t}$ is the indicator for one the exchanges in pair i was classified as a retail exchange on the day t; Exchange-pair clustered standard errors are reported in parentheses. *** indicates statistical significance at the 1% level, ** at the 5% level, and * at the 10% level.

	| Price Diff. |		
	(1)	(2)	(3)
Avg. Spread / Price	0.309***	0.276***	0.233***
	(0.014)	(0.015)	(0.025)
Avg. Intraday Price SD	0.161***	0.160***	0.115***
	(0.025)	(0.024)	(0.021)
Avg. $\log_{10}$ Normalized Orderbook Size	-0.395***	-0.406***	0.008
	(0.111)	(0.107)	(0.069)
Avg. Network Transaction Fee	1.535	3.406	
	(2.559)	(2.121)	
One Retail		0.198***	0.145**
		(0.043)	(0.056)
Constant	0.210*	0.049	0.544***
	(0.115)	(0.107)	(0.058)
Observations	8,401	8,401	8,401
Exchange-pair FE	Yes	Yes	Yes
Date FE	No	No	Yes
Adj. R^2	0.374	0.377	0.490

Table C.2: **Panel fixed effect estimates**

Column (1) reports estimates of the exchange-pair fixed effects from regression, where the outcome variable is the absolute value of Bitcoin price differences between exchange pairs. Column (2) reports estimates of the exchange-pair fixed effects when the dependent variable is the signed price difference. The omitted exchange pair is Coinbase-Itbit. The sample period is from June 1, 2014 to December 31, 2016. Exchange-pair and date two-way clustered standard errors are reported in parentheses. *** indicates statistical significance at the 1% level, ** at the 5% level, and * at the 10% level.

	| Price Diff. | (1)	Price Diff. (2)
bitfinex_bitstamp	0.114*	0.411***
	(0.065)	(0.067)
bitfinex_coinbase	-0.025	0.128***
	(0.021)	(0.027)
bitfinex_itbit	0.258***	0.343***
	(0.061)	(0.059)
bitfinex_kraken	0.236***	0.250***
	(0.039)	(0.074)
bitstamp_coinbase	0.014	-0.163***
	(0.021)	(0.027)
bitstamp_itbit	0.137**	0.090
	(0.057)	(0.057)
bitstamp_kraken	0.148***	-0.003
	(0.037)	(0.079)
btce_bitfinex	0.859***	-0.922***
	(0.029)	(0.023)
btce_bitstamp	0.658***	-0.678***
	(0.027)	(0.024)
btce_coinbase	0.921***	-0.966***
	(0.023)	(0.029)
btce_itbit	0.836***	-0.772***
	(0.017)	(0.016)
btce_kraken	0.760***	-0.930***
	(0.021)	(0.070)
kraken_coinbase	0.051***	0.057*
	(0.010)	(0.031)
kraken_itbit	0.263***	0.466***
	(0.042)	(0.082)
Constant	0.182**	-0.349***
	(0.064)	(0.068)
Observations	8,401	8,401
Exchange Char.	Yes	Yes
Date FE	Yes	Yes