Capital Flight: Evidence from the Bitcoin Blockchain

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Abstract

Using Bitcoin blockchain data and known Bitcoin exchange addresses, we identify traders that buy Bitcoin at Chinese exchanges and sell it at foreign exchanges as circumventing capital control. We find the aggregate volume of capital control trades is almost one third of Chinese Bitcoin exchange volume and is positively associated with Chinese economic policy uncertainty and the Bitcoin premium in Chinese Yuan, inconsistent with triangular arbitrage. Capital flight trade users are less likely to be illicit users and so have different trading motives and patterns. Our findings suggest that Bitcoin indeed allows for the circumventing of Chinese capital controls.

Key words: *bitcoin, blockchain, capital flight, cryptocurrency*

JEL Classification Code: *G15, G18*

1. Introduction

Our paper uses Bitcoin blockchain trade data to investigate the extent of capital control circumvention using Bitcoin trading cross exchanges. We can measure when circumvention is most extreme and the factors that contribute to circumvention. Prosecuted cases suggest that such schemes are large and wide scale.

An example is of a South Korean police officer who was indicted for moving $11 million USD of Chinese Yuan (CNY) out of China to South Korea using Bitcoin (Helms, 2017). In this scheme (similar to Appendix 1 Panel B), Bitcoin is bought in CNY and then transferred to a wallet that trades on a Korean Bitcoin exchange. The Bitcoin received by the Korean Bitcoin exchange is then sold on the Korean exchange in Korean Won. In this way, the capital control restrictions imposed by Chinese government domestically are circumvented as no CNY has left the country but the recipient receives foreign currency. In another anecdotal case, a Chinese beef salesman is quoted as saying that it was 'very normal to sell Bitcoin in the U.S. After selling Bitcoin, you can just buy anything you want.' (Cuen and Zhao, 2018).

Bitcoin and other cryptocurrencies therefore may act as conduits to circumvent capital control. Their open and decentralised nature means that anyone can open a cryptocurrency wallet and transfer cryptocurrency without government intervention. The ability to transfer securely due to cryptography and inability for the cryptocurrency network to be shut down1 further enhances its usefulness for capital control circumvention. While the total market capitalisation of cryptocurrencies is small at almost $300 billion as of August 2019, regulators fear upcoming cryptocurrencies like Facebook's Libra may increase the scale for users to engage in illegal activities such as money laundering (Michaels and Clozel, 2019).

While several papers show that triangular arbitrage opportunities exist for long periods between cryptocurrency and foreign exchange pairs and relate it to capital control rules (e.g. Choi et al, 2018; Yu and Zhang, 2018, Makarov and Schoar, 2019), our paper is the first to document direct evidence from blockchain data to the extent of such capital control circumvention.

Utilising Blockchain and known exchange wallets we find capital control trade volume is a third of Chinese Bitcoin exchange net volume and is positively correlated to Chinese economic policy uncertainty and the Bitcoin premium in Chinese Yuan. The results are robust to an alternative classification where we assume an intermediary is used to access non-Chinese Bitcoin exchanges. Our findings suggest that Bitcoin indeed allows for the circumventing of Chinese capital control.

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[1] As Bitcoin and other cryptocurrencies are peer-to-peer networks where every computer (node) on the network holds the entire ledger of past transactions, every node would need to have their ledgers erased for the cryptocurrency to be destroyed.

2. Background and Literature

2.1. Circumventing Capital Controls in China

China has strict outflow capital controls, particular on foreign exchange purchases. China's foreign exchange regulatory authority the State Administration of Foreign Exchange (SAFE) oversees capital control regulation. During our sample period, individuals were not allowed to make more than $50,000 USD per year on foreign exchange purchases.[2] For companies, there are no restrictions on cross-border flows of its currency for trade-related purposes but there are significant controls on cross-border flows for investment purposes (Walsh and Weir (2015)).

Capital flight from China has (or allegedly) is able to occur in the following ways, despite outflow capital controls:

Misinvoicing of imports/exports: According to Gunter (1996), if reported exports are much less than actual exports then the difference may be a form of capital flight. This is achieved by underinvoicing exports and transferring the difference to some financial haven. For example a company may receive USD$1,000,000 in exports but officially declare only USD$200,000 as export sales, thereby allowing USD$800,000 to be offshored in a financial haven. Alternatively a capital flight importer may overinvoice his imports to achieve the same effect. The estimate of capital flight in this fashion is by comparing the balance of trade amounts constructed using Chinese data versus International Monetary Fund data. Gunter (1996) finds misinvoicing increasing from USD$2.5B in 1984 to USD$44B in 1994. In an update, Gunter (2017) finds the figure to be $201B in 2014.

Incomplete foreign debt data: Debt owed to foreign banks may be underreported and as such be an avenue of capital flight. Misreported debt is estimated as the difference in the debt owed to foreign banks as reported by Chinese companies less the debt of Chinese companies to foreign banks as reported by foreign banks. Gunter (1996) estimates the underreported debt amount to be USD$16B from 1994 to 1996. Gunter (2017) estimates the figure in 2014 to be USD$72B.

Misreported travel expenses: Although Chinese nationals have individual restrictions in foreign exchange withdrawals as mentioned above, there are ways to circumvent it by masking it as travel or education expenses. Wong (2017) cites several anecdotal examples including pooling limits, fake invoices for purchases and using Unionpay cards for overseas purchases. One example is withdrawing a large amount of money from a Unionpay machine in Macau then passing it off as a jewelry purchase by signing a credit card receipt. Wong (2017) estimates that such misreported travel expenses are about 1% of Chinese GDP in 2015 and 2016 or $USD100B and $USD123B, respectively.

[2] Annual reports on China's foreign exchange regulation are available at IMF's website: https://www.elibrary-areaer.imf.org/Pages/Reports.aspx

Other methods: Gunter (2017) cites the purchase of gambling chips from Macau casinos from brokers then depositing the foreign currency as a means of circumventing controls. Wong (2017) cites the purchase of Hong Kong investment-related insurance policies in foreign currency. These have since been banned (e.g. Yu (2017)).

2.2. Circumventing Capital Controls with Bitcoin

A strategy to circumvent capital controls in China, is as follows:

1. Buy Bitcoin at a domestic Bitcoin exchange in CNY.
2. Sell the Bitcoin at a foreign exchange in USD.

This strategy would circumvent the CNY foreign transfer restrictions of $50,000 USD per annum for individuals as there is no way to stop the transfer of Bitcoin. Appendix 1 Panel A shows a diagram of the flows involving one Bitcoin user (direct capital flight). An individual first opens a wallet freely on the Bitcoin blockchain. She then purchases Bitcoin at a Chinese Bitcoin exchange using CNY or equivalents.[3] One intermediary step that may be necessary is that some non-Chinese exchanges require users to be registered due to anti-money laundering (AML) or know your client (KYC) rules. As such a Chinese user may not be able to access a non-Chinese exchange and so needs to find another user (indirect capital flight). In this case as depicted in Appendix 1 Panel B, Bitcoin is transferred between the wallets of the Chinese user to the second user. The transfer of Bitcoin from one wallet to another requires a network fee. Once the Bitcoin is transferred, the intermediary sells the Bitcoin on the Bitcoin exchange and transfers the fiat currency to the Chinese user's foreign account. In separate analysis, we account for this extra step in classifying capital flight trades.

2.3. Related Cryptocurrency Literature

Our paper is related to the growing literature on the Bitcoin premiums in fiat currency when converted into USD. Choi, Lehar and Stauffer (2018) find Bitcoin premium of 4.73% on Korean exchanges while Yu and Zhang (2018) study 14 currencies and find premiums for the majority. Both argue that these violations of the law of one price are exasperated by capital controls and limits to arbitrage such as the volatility of Bitcoin.

Ju, Lu and Tu (2016) suggest that the Chinese government's Dec 2013 announcement banning of financial institutions from using Bitcoin caused a reduction in Chinese Bitcoin transactions. They proxy this using the Chinese Bitcoin premium to the USD Bitcoin price which fell after the announcement. Thus they suggest this is a successful regulation to reduce the use of Bitcoin for capital

[3] Kaiser, Jurado and Ledger (2018) states that while the Chinese government cut off the ability to trade fiat currency for Bitcoin in China; other methods were employed to circumvent it such as by buying voucher codes offline to redeem on the exchange, using physical ATMs.

flight. One reason for using the Chinese Bitcoin premium as a measure of Chinese Bitcoin activity is that 'It is difficult to detect directly capital flight via Bitcoin because none of the bitcoin transactions is traceable.'

3. Data and Sample

Appendix 2 provides a list of our data sources. The sample is from 2nd September 2011 (when Chinese Yuan Bitcoin prices begin in Cryptocompare.com) to 8th February 2018 (end of the Bitcon blockchain sample). We obtain Bitcoin blockchain transaction data as extracted by Kondor, Pósfai, Csabai and Vattay (2014) and extended to 8th February 2018.[4] We obtain Bitcoin exchange wallets from walletexplorer.com. Daily CNY/USD rates are from the Federal Reserve Economic Data (FRED). We obtain intraday Bitcoin prices in CNY and USD from Bitconcharts.com and end of day prices from Cryptocompare.com as Yu and Zhang (2018) use to calculate CNY premium for Bitcoin. We obtain the monthly Chinese economic policy uncertainty index as Baker, Bloom and Davis (2016) use from policyuncertainty.com. We directly derive Bitcoin average network fee and number of transactions statistics from the Bitcoin blockchain data.

4. Empirical Methodology and Results

4.1. Classifying Capital Flight Trades

To identify capital control trades, we use transactions from the Bitcoin blockchain. Wallets are consolidated to the user level as one user may control many wallets. Kondor, Pósfai, Csabai and Vattay (2014) identify a user controlling multiple wallets when in one transaction multiple wallets are used to send Bitcoin to others. This method is also known as the Union-Find algorithm (e.g. Meiklejohn, Pomarole, Jordan, Levchenko, McCoy, Voelker and Savage (2013)).

We further augment this data with Bitcoin wallet addresses of Bitcoin exchanges from www.walletexplorer.com. Wallet-explorer.com collects Bitcoin exchange wallets either from public sites or when transacting with those exchanges. The Bitcoin exchange addresses are not a complete list of all wallets of an exchange nor does wallet-explorer contain all Bitcoin exchanges.[5] Appendix 4 shows a complete list of Bitcoin exchanges, ranked by blockchain turnover in USD. Our sample contains major non-Chinese exchanges such at Bitrex, bitfinex, etc and also major Chinese Bitcoin exchange such as Huobi.com and BTCC.com.

[4] The data can be obtained here: https://senseable2015-6.mit.edu/bitcoin/

[5] Appendix 3 compares the self-reported Bitcoin exchange volume to the actual blockchain transaction volume using Bitcoin exchange wallet addresses from www.wallet-explorer.com . We find overall the address volume represents 12 percent of self-reported transaction volume across 31 exchanges in the database. Coverage across years varies from 4.34 percent in 2011 to 20.12 percent in 2018.

Figure 1 reports the monthly exchange turnover in the identified exchange trades for Chinese and non-Chinese (other exchanges) and the Bitcoin to USD price. Figure 1 Panel A reports the turnover in Bitcoin and Panel B converted into USD. There is clearly more turnover in non-Chinese exchanges than Chinese exchanges and the turnover is positively correlated. Chinese exchange volume is peaks in 2015. In Panel B where volume is measured in USD, volume peaks in 2017 for both Chinese and non-Chinese exchanges due to the Bitcoin reaching over $10,000 USD.

[--- INSERT FIGURE 1 ABOUT HERE ---]

Linking the address data to blockchain transactions data, we can identify users who trade on one or more Bitcoin exchanges and also whether they are buying from the exchange (receiving Bitcoin) or selling to the exchange (sending Bitcoin). We are thus able to capture capital flight trades that occur as we depict in Appendix 1 Panel A.

We create a daily measure of Bitcoin trade types using the following method based on the direct capital flight definition in Appendix 1 Panel A. We define a day as being 24 hours in the Chinese time zone (UTC+8):

*Every day for each user we calculate the amount of net trading (buys less sells) to Bitcoin exchanges (Chinese vs. non-Chinese). The trading groups are:

*Net Sellers: Users with net selling in both Chinese and non-Chinese exchanges.

*Net Buyers: Users with net buying in both Chinese and non-Chinese exchanges.

*Chinese Only: Users that trade with Chinese exchanges and do not trade with non-Chinese exchanges

*Capital Flight: Users that net buy from Chinese exchanges and net sell at non-Chinese exchanges.

*Reverse Capital Flight: Users that net sell from Chinese exchanges and net buy at non-Chinese exchanges.

*Other: traders which only trade with non-Chinese exchanges or do not trade with an exchange.

Figure 2 Panel A shows the monthly Chinese exchange net trading volume in Bitcoin for each trader group with the aggregate figures in Table 1 Panel A. Chinese only traders are the most dominant group making up about 58.69% of Bitcoin trades (Table 1 Panel A row 2) followed by capital flight trades making up almost a third of trades. In USD in Figure 2 Panel B, Chinese only trades and capital flight trades each make up 41.61 percent and 28.27 percent, respectively (Table 1 Panel A, last row). Chinese only trades are most dominant pre-2013 while capital flight trades feature most prominently in 2016 and 2017. Overall, we estimate 8.78 million Bitcoin or 4.6 billion US were used for Chinese capital flight. Given there are just over 18 million Bitcoin in circulation as of January 2019, this means almost half of the Bitcoin supply has been used for capital control circumvention.

[--- INSERT FIGURE 2 ABOUT HERE ---]

[--- INSERT TABLE 1 ABOUT HERE ---]

To delve deeper into capital flight trades, Figure 2 Panel C and Figure 2 Panel D show monthly Chinese exchange Bitcoin net volume of capital flight trades in Bitcoin and in USD, respectively against the average Bitcoin network transaction fee and the BTC/CNY premium (Bitcoin price in Chinese yuan, converted into USD divided by the Bitcoin price in USD, less one). We find most capital flight trades occur during 2013 to early 2017 with a small positive BTC/CNY premium over this time period. The network fee is also low during this period. Post March 2017, capital flight trades are almost non-existent with the BTC/CNY premium being volatile and network fees peaking. Part of the reason for the low volume is the anticipated shut down of Chinese Bitcoin exchanges.

4.2. Determinants of Capital Flight Trades

In order to find out what affects the trader types, the table estimates the following regression:

$$\text{Chin\_net}_{jt} = \text{Intercept}_0 + \text{b}_1 * \Delta\text{Chinepu}_t + \text{b}_2 * \text{Chinprem}_t + \text{b}_3 * \text{Ntrans}_t + \text{b}_4 * \text{USDfeespertran}_t + \text{b}_5 * \text{Sqvol}_t + \text{b}_6 * \text{Dayid}_t + \text{e}_{it} \quad (1)$$

Where *Chin_net* is the unsigned net turnover on Chinese Bitcoin exchanges for trader type j on day *t*. *ΔChinepu* is the lagged monthly change in the Baker, Bloom and Davis (2016) Chinese economic policy uncertainty index (standardized), *Chinprem* is the CNY Bitcoin price converted into USD over the USD Bitcoin price. Bitcoin prices in CNY and USD are end of day prices from Cryptocompare.com. *Sqvol* is the daily sum of 1 minute squared USD Bitcoin returns. *Ntrans* is the daily number of trades. *USDfeespertran* is the daily average fee per trade in USD. *Dayid* is the number of days since the start of the sample period.

Table 1 Panel B reports summary statistics for the variables in the regression and Table 1 Panel C reports the correlation matrix of variables. From Table 1 Panel A, the average daily Bitcoin return in USD is 0.54 percent and in CNY 0.49 percent. The average Chinese premium on Bitcoin relative to USD is 0.64 percent. The average daily net trading by Chinese Only group is highest of 8,028.58 Bitcoin followed by Capital Flight group of 4,409.80 Bitcoin. However in USD, the highest group is Net Buyers of $8.7M USD. From Table 1 Panel C, we find that Capital Flight trades are positively correlated to the Chinese policy uncertainty (0.094), CNY Bitcoin premium (0.13), and to net trading of Chinese Only (0.365). This is consistent with capital flight trades not being arbitrage trades as more capital flight trades occur when it is expensive to buy Bitcoin in CNY (when *Chinprem* is positive) and also when there is greater policy uncertainty. All net trades groups are negatively correlated with volatility and with fees (with the exception of Net Buyers).

The regression results in Table 2 Panel A (in Bitcoin) and Panel B (in USD) shows that Capital Flight net volume in Chinese exchanges increases when Chinese policy uncertainty (Δ*Chinepu*) increases, a high Chinese Bitcoin premium (Δ*Chinprem*) and more trading on the Bitcoin network. Capital Flight is lower with higher network fees (*USDfeespertran*). Specifically, a one standard deviation increase in Δ*Chinepu* increases the daily Capital Flight by \$661,147. A one percent premium for *Chin*prem increases Capital Flight daily trades by \$77,563. Chinese Only net trades are also positively related to Δ*Chinepu* (but statistically insignificant when measured in Bitcoin) and is much less sensitive. For example for USD, the coefficient for ΔChinepu is about 55% of that of Capital Flight, despite Chinese Only trading volume being much larger. Overall, the evidence suggests that Capital Flight group are most sensitive to uncertainty in China's political climate and occur when Chinese Bitcoin premium is high which is inconsistent with the trades being for arbitrage purposes.

[--- INSERT TABLE 2 ABOUT HERE ---]

4.3. Classifying Indirect Capital Flight Trades

As a robustness check and a way to capture Capital Flight trades that involve another user facilitating the trade, we attempt to capture trade patterns as we depict in Appendix 1 Panel B. We classify indirect capital flight/reverse capital flight trades using the following algorithm:

1. Every day, for each user ID (as defined in Kondor, Pósfai, Csabai and Vattay (2014)), calculate each user's net trading in Chinese and non-Chinese Bitcoin exchanges. Record whether they are net buying or net selling at the exchanges.
2. For Chinese exchange or non-Chinese exchange net traders, collect their non-exchange blockchain trades that are the reverse direction. That is for net buyers, only collect trades where they are sending Bitcoin to other (non-exchange) users. For net sellers, only collect trades where they are receiving Bitcoin from other users.
3. For these collected trades from these users, match trades together where one identified Chinese exchange net trader is sending/receiving Bitcoin to/from another in the same transaction (i.e. they are trading pairs).
4. Indirect Capital Flight volume is identified as a Chinese exchange net buyer sending Bitcoin to a non-Chinese exchange net seller. Indirect Reverse Capital Flight volume is identified as a Chinese exchange net seller receiving Bitcoin from a non-Chinese exchange net buyer.
5. Reduce the volume of net buying/selling by Chinese/non-Chinese exchange traders involved in indirect trades to avoid double counting.

Appendix 5 provides a table that summarizes the indirect trade classifications between trader A (Chinese exchange trader) and B (non-Chinese exchange trader). Through this classification algorithm, net trades from Net Buyer, Net Seller and Chinese Only groups are recategorized as indirect trades. This is because this trader groups may be connected together by our algorithm due to

Blockchain trades with other users off-exchange. This is clear in Table 3 Panel A where we report the aggregate Chinese exchange net volume of trader groups including indirect trades in Bitcoin and USD. Total net trading volume of 32.18 million Bitcoin and 16.292 million USD is the same as not including indirect trades as in Table 1 Panel A. Instead, Net Buyer, Net Seller and Chinese Only have lower net volume that is reallocated to the Capital Flight and Indirect Capital Flight groups. With indirect trades, Capital Flight volume increases by 1.5 billion US dollars or about 35% compared with not including indirect Capital Flight Trades. Reverse Capital Flight net volume substantially increases by $277 million or 117% more than when excluding indirect trades. This implies that indirect trades make up a substantial part of Capital Flight and Reverse Capital Flight trades, particularly for the later.

[--- INSERT TABLE 3 ABOUT HERE ---]

We also apply the indirect trade adjusted volumes to the determinants of net trades regression from the previous section and report results in Table 3 Panel B (in Bitcoin) and Panel C (in USD). We find evidence of a similar effect as the baseline regression, namely capital flight trades in Bitcoin are positively correlated to the CNY premium in Bitcoin and capital flight trades in USD are positively correlated with Chinese economic policy uncertainty.

4.4. Split Sample Period Regression

As we see in Figure 2, the bulk of net trading in Chinese Bitcoin exchanges occurs from September 2015. As such, we test the sensitivity of our determinants of net trades regression by splitting the sample into before 1st September 2015 and from 1st September 2015 onwards. Table 4 reports results for before 1st September 2015 (Panel A) and from 1st September 2015 onwards (Panel B), in USD.

[--- INSERT TABLE 4 ABOUT HERE ---]

We find the results to persist in the sample from 1st September 2015 with larger coefficients for the Capital Flight group for the baseline regression for Δ*Chinepu* (741.67) and *Chinprem* (160.66), both statistically significant at the one percent level. The Reverse Capital Flight group also has a weekly significant *Chinprem* coefficient of 6.37 which implies more trading when the Chinese Bitcoin premium is high. However the magnitude is small as a one percent premium means just $6,370 more in trading. For before 1st September 2015, only *Chinprem* remains statistically significant for Capital Flight group but not the Chinese Only group. Δ*Chinepu* is positive but not statistically significant for both groups.

4.5. Profitability of Capital Flight Trades

As it is shown that capital control trades are occurring during times of a high CNY Bitcoin premium, it would be of interest to know the magnitude of profits or losses in engaging in capital flight/reverse capital flight trading. This is because our regression implies that capital control trades are buying high priced Bitcoin in CNY and selling at the lower price foreign exchanges. Knowing the potential losses involved in trade also allows us to estimate the costs of engaging in capital flight trades in comparison to other methods of capital control circumvention such as misquoting invoices or travel expenses.

We estimate trading profits by estimating two components of intraday profits. *Intra-exchange* profit is the profit from buying and selling within exchanges (Chinese or non-Chinese exchanges) within the same day. *Inter-exchange* profit is the profit from net buying or selling between exchanges (Chinese or non-Chinese). We calculate the traded price on exchanges every day based on the nearest 1 minute Bitcoin price (in CNY or USD) using trade level data from Bitcoin exchanges from bitcoincharts.com. The intraday dollar profits for trader *I* on day *t* for capital flight or reverse capital flight traders is calculated as:

$$\begin{aligned} Intra\text{-}exchange_{it} &= min(Chinbuy_{it}, Chinsell_{it}) * \left(Chinsell_{vwap,it} - Chinbuy_{vwap,it}\right)/USDCNY_t \\ &+ min(Nonchinbuy_{it}, Nonchinsell_{it}) * \left(Nonchinsell_{vwap,it} - Nonchinbuy_{vwap,it}\right) \end{aligned} \quad (2)$$

$$Inter\text{-}exchange_{it} = Chin\_net_{it} * \left(Nonchinsell_{vwap,it} - \frac{Chinbuy_{vwap,it}}{USDCNY_t}\right) \text{ for Capital Flight users} \quad (3)$$

$$Inter\text{-}exchange_{it} = Chin\_net_{it} * \left(\frac{Chinsell_{vwap,it}}{USDCNY_t} - Nonchinbuy_{vwap,it}\right) \text{ for Reverse Capital Flight Users} \quad (4)$$

Where *i* subscripts for user and *t* for day (in Chinese time UTC+8). *Chinbuy* and *Chinsell* is the number of Bitcoin bought or sold at Chinese Bitcoin exchanges, respectively. $Chinbuy_{vwap}$ and $Chinsell_{vwap}$ is the volume weighted average price of bitcoin bought or sold at Chines Bitcoin exchanges, respectively. Prices traded are the nearest one minute BTC/CNY prices of the volume weighed average price at Chinese Bitcoin exchanges. *Nonchin* relates to Bitcoin bought or sold at non-Chinese Bitcoin exchanges. *USDCNY* is the closing day price of USD/CNY. *Chin_net* is *Chinbuy* minus *Chinsell*. Dollar profits are all implicitly in US dollars. To calculate percentage gains or losses we divide the profits by the absolute net volume traded by the user in Chinese Bitcoin exchanges, converted into USD. Note that Net Buy, Chinese Only and Net Sell trader group do not have inter-exchange profits as they do not net buy in one exchange and net sell in the other.

Table 5 reports the aggregated profit results. We estimate that all trader types make small intra-exchange profits the only exception is the Capital Flight group which loses $475,000 USD or -0.01% of their Chinese exchange net volume. For interexchange profits/losses, the Capital Flight group overall lost \$31.6 million or -0.69% of their net volume traded. This partly reflects on Capital Flight trades being made when the Chinese Bitcoin premium is high. In comparison, the Reverse Capital Flight group made a profit of 0.04% of their net volume.

Overall, the 0.7% loss brought on to Capital Flight traders is small. During our sample period, there were no fees for Chinese Bitcoin exchanges while non-Chinese Bitcoin exchange fees ranged from 0.1% to 1% (see Bhaskar and Lee (2015) for a Bitcoin exchange fee schedule). Also during this period, Bitcoin network fees was about \$1.12 US per transaction. As such Capital Flight trades including intra/inter exchange losses, exchange fees and Bitcoin networks fees would cost at most 2% of the amount sent for capital loss. Such a cost is inconsequential in comparison to utilizing import/export companies. Also, provided there is sufficient liquidity on Bitcoin exchanges, the amount able to circumvent capital controls is scalable unlike utilizing casinos or misreported travel expenses.

[--- INSERT TABLE 5 ABOUT HERE ---]

4.6. Capital Flight Traders and Illegal Users of Bitcoin

In prior sections we find that both reverse capital flight and capital flight trades are not related to arbitrage opportunities. In this section we test for alternative motivations and if users of capital flight trades tend to be illicit users. For example, capital flight or reverse flight trades may be for the purpose of sending money abroad or repatriating money back to China for illegal means. To do this we use the illicit user database of Foley et al. (2019). Foley et al. (2019) estimate the probability of whether a Bitcoin user is an illegal user based on characteristics of users with actual illicit use (e.g. trades on silk road). We then estimate the following logit regression at the user level:

$$Logit(illegal_i=1) = b_0 + b_1*ExchangeUser + b_2*ChinExchangeUser + b_3*Netseller\_pct_i + b_4*Reverse\_pct_i + b_5*Chineseonly\_pct_i + b_6*Capflight\_pct_i + b_7*Netbuyer\_pct_i + b_8*Logn_i + b_9*Logtradesize_i + b_{10}*Concentration_i + e_i \quad (5)$$

where illegal is a dummy of 1 if user i is classified as an illegal user in Foley et al. (2019), 0 otherwise. *ExchangeUser* is a dummy of 1 if the trader ever traded with a Bitcoin exchange, 0 otherwise. *ChinExchangeUser* is a dummy of 1 if the trader ever traded with a Chinese Bitcoin exchange, 0 otherwise. Every day for each user, we calculate net turnover to each counterparty (Chinese Bitcoin exchanges, non-Chinese Bitcoin exchanges and other counterparties). Net turnover in each Chinese/non-Chinese venue is the absolute of buy less sell trades in USD. *Netseller_pct* is the dollar percentage of all net trading in USD by user i for days that they are net selling in both non-Chinese and Chinese Bitcoin exchanges. *Reverse_pct* is the percentage of net trades that is buying in non-Chinese Bitcoin exchanges and selling in Chinese exchanges. *Chineseonly_pct* is the percentages that are Chinese only trading. *Capflight_pct* is the percentage of net trades buying in Chinese exchanges and selling in non-Chinese exchanges. *Netbuyer_pct* is the percentage of net trades that is buying in both Chinese and non-Chinese exchanges. *Logn* is the natural log of number of trades by user. *Logtradesize* is the average USD trade size of a user's transactions. *Concentration* is a measure of the tendency for a user to transact with one or many counterparties. It ranges from 1 for a highly concentrated user who transacts with only one counterparty, to 0 for a user that has many transactions, each with a different counterparty. We obtain *Logn, logtradesize* and *concentration* user level variables from Foley et al. (2019).

We first check the extent of illegal trading by trading group in Table 6 Panel A. We find Net Seller and Reverse Capital Flight trades are most likely groups to be illegal (92.67 and 89.58 percent of net trading, respectively). In particular, the percentage of Reverse Capital Flight trades being illegal over the years is between 81.52% to 99.27%. The lowest groups are Chinese only trades and Other trades (users that trade on non-Chinese exchanges only and/or unclassified trades) of 41.03% and 37.03% of trades. 51.80% of Capital Flight trades are classified as illegal which is the third lowest of all groups.

[--- INSERT TABLE 6 ABOUT HERE ---]

Table 6 Panel B reports the logistic regression results and confirms the simple statistics in Table 6 Panel A. On our control variables, trading at a Chinese Bitcoin exchange increases the probability of being an illegal user (unconditional on trade type), while having less trades, less turnover and less concentrated trades (trades with few other users), increases the probability of being an illegal user.

On the trading group coefficients, users that do more Net Sell and Reverse Capital Flight trades are more likely to be illegal users. In contrast, users that do more Chinese Bitcoin exchange only or Capital Flight trades are less likely to be illegal users. For example, the coefficient of *Reverse_pct* is 0.014 and statistically significant suggesting that an increase of reverse trading by 1% increases the probability of being an illegal user by 1.4%.[6] In contrast, the coefficient for *Capflight_pct* is -0.011 and statistically significant which means an increase in capital flight trades by 1% leads to a reduction in probability the user is illegal by 0.11%. Overall, our results suggest that capital flight trades are not for illegal purposes nor are they for arbitrage.

4.7. Capital Flight Traders Classification by Week, Fortnight and Month

In this section we check for the robustness of our daily classification of trade types by netting user trades at weekly, fortnightly and monthly intervals. This is due to the fact that traders may take longer than a day to complete capital flight trades. We run the following regression:

$$\mathrm{Chin\_net}_{jt} = \mathrm{Intercept}_0 + b_1 * \Delta\mathrm{Chinepu}_t + b_2 * \mathrm{Chinprem}_t + b_3 * \mathrm{Ntrans}_t + b_4 * \mathrm{usdfeespertran}_t + b_5 * \mathrm{Sqvol}_t + b_6 * \mathrm{Periods}_t + e_{it} \quad (6)$$

[6] Exp(0.017)-1= 0.014098.

Which is similar to equation (1 except the dependent variables are the daily average over weekly, fortnightly or monthly intervals and we use *Periods* as the number of weeks, fortnights or months passed since the start of the sample, instead of *Dayid*.

Table 7 Panel A reports total net trading across groups for different frequencies while Panel B, C and D reports coefficient results of equation where the dependent variable is net trading over a week, fortnight or month in USD, respectively.[7] We find that total net trading is between $14.2 to $14.3 billion which is lower than at the daily frequency of $16.3 billion (Table 1 Panel A). This implies that over longer periods, users net out their trading at Bitcoin exchanges which reduces net volume. At these lower frequencies, Capital Flight trades are the largest group of between 35.81% (weekly) to 37.73% (monthly) of net trading. This is higher than at the daily interval of 28.27% of trading. In contrast, Chinese Only now only has between 24.77% (monthly) to 28.61% (weekly), down from 41.61% at the daily interval.

The regression results are similar to our baseline results when using a weekly regression in the fact that Capital Flight trades are positively associated with changes in economic policy uncertainty and the Chinese premium in Bitcoin. For fortnightly and monthly intervals, only the Bitcoin Chinese premium remains statistically significant and *ΔChinepu* is positive but not statistically significant. The results are consistent to capital flight strategies being completed in a short time frame and not being captured when using longer intervals.

[--- INSERT TABLE 7 ABOUT HERE ---]

5. Conclusion

Bitcoin's original intention was to act as a peer to peer transaction system free from the intervention of any intermediary. In this paper we investigate whether these good intentions allow Bitcoin to circumvent Chinese capital control restrictions. Using Bitcoin blockchain data matched to the address of Chinese and non-Chinese Bitcoin exchanges we find almost a third of Chinese Bitcoin buys are on sold on the same day at non-Chinese Bitcoin exchanges, effectively bypassing Chinese capital control restrictions. Such trades do not appear to be for arbitrage as more trades occur when Bitcoin is pricey in CNY relative to USD and when Chinese economic policy uncertainty is high. We therefore find direct evidence that Bitcoin can and is being used to bypass Chinese capital control restrictions.

[7] We find qualitatively similar results in Bitcoin.

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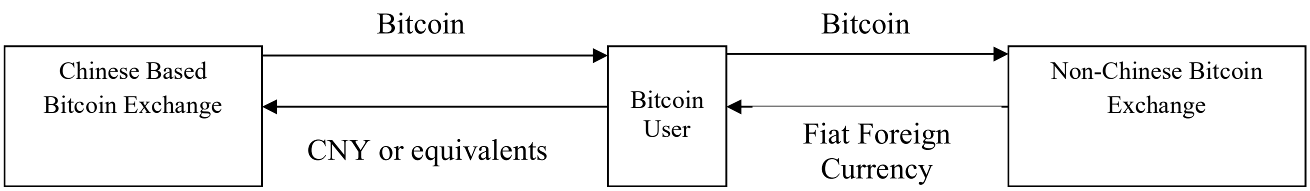
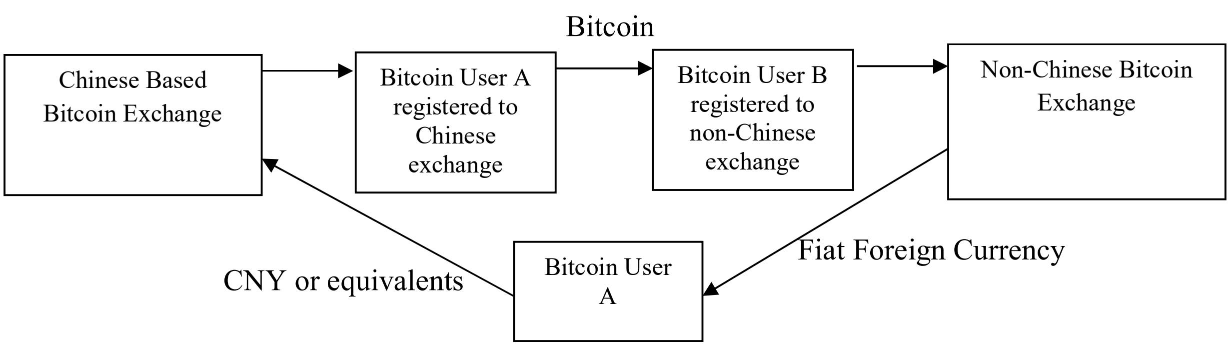
Appendix 1: Bitcoin Capital Control Circumvention

The diagrams below depict the flows of Bitcoin and fiat currency from a Bitcoin user wishing to exchange CNY to a foreign currency through Bitcoin, effectively bypassing regulatory checks. Panel A shows an example of a Chinese Bitcoin user that can register in both Chinese and non-Chinese Bitcoin exchanges (direct capital flight). Panel B depicts an example of a Chinese Bitcoin user being only able to register in a Chinese Bitcoin exchange and transferring Bitcoin to another user registered to a non-Chinese exchange (indirect capital flight).

Panel A: Direct Capital Flight



Panel B: Indirect Capital Flight through another User



Appendix 2: Data Sources

Data Description	Source
Bitcoin blockchain transactions with consolidated wallets	Bitcoin blockchain transactions as extracted by Kondor et al. (2014) and extended to February 2018.
Bitcoin exchange Bitcoin wallet addresses	walletexplorer.com
Daily CNY/USD	Federal Reserve Economic Data (FRED)
End of Day BTC/CNY and BTC/USD	Cryptocompare.com
Intraday Bitcoin prices in CNY and USD.	Bitcoincharts.com
Exchange reported trades with timestamps	Bitcoincharts.com
Economic Policy Uncertainty Index (China)	http://www.policyuncertainty.com/
Average Bitcoin fees per transaction and number of transaction per day	Calculated directly from blockchain data

Appendix 3: Matched Volume of Bitcoin Exchange Blockchain Trades to Self-Reported Trades

The table reports the percentage matched volume of Bitcoin exchange volume on the Bitcoin blockchain to the volume self-reported by the exchanges. We calculate percentage matched volume as the Bitcoin exchange Bitcoin trading volume on the blockchain as a percentage of self-reported Bitcoin volume from the exchanges. For every month, we sum the blockchain trades and self-reported volume for 31 Bitcoin exchanges that have both blockchain and self-reported volume. We only keep exchanges/months where both blockchain and self-reported volume for that exchange in the month and the percentage of matched trading in the month is greater than 1% and below 200%. A matched percentage above 100% may be due to Bitcoin exchanges underreporting trades. We identify Bitcoin exchange trades on the blockchain from known Bitcoin exchange wallet addresses obtained from Walletexplorer.com. Wallet Explorer collects publicly known addresses of Bitcoin exchanges (e.g. advertised addresses) or from identifying wallets after trading with the Bitcoin exchanges. We obtain self-reported trades from blockchain charts. Blockchain charts collects historical self-reported Bitcoin trades from the exchange's application programming interface (API) feeds. The sample period is from 2nd September 2011 to 8th February 2018.

% Matched Volume	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**	**All Years**
Mean	58.37	82.95	30.72	48.28	45.22	36.57	21.59	16.58	32.66
Median	17.66	81.37	15.83	25.80	23.97	25.10	5.99	2.07	18.66
Std Dev	64.39	61.95	44.78	54.00	52.78	38.82	27.26	24.91	38.17
Min	2.34	9.59	1.32	1.37	1.24	1.35	1.39	1.47	1.70
Max	167.56	171.61	148.74	179.93	150.98	148.20	92.75	56.06	140.04
Number of Exchanges	9	12	17	23	20	21	14	7	31
All Exchanges	**4.34**	**19.63**	**6.46**	**10.24**	**14.59**	**16.59**	**6.69**	**20.12**	**12.00**

Appendix 4: Bitcoin Exchanges Ranked by Matched Blockchain Trade Turnover (in USD)

The table ranks Bitcoin exchanges by their Bitcoin blockchain transaction turnover (buy and sell trades, divided by two) from our sample period from 2nd September 2011 to 8th February 2018. We identify exchanges by their Bitcoin wallets from walletexporer.com. We convert Bitcoin trades into US dollars using end of day BTC/USD prices from Cryptocompare.com. Bitcoin exchange country headquarters is based on physical headquarter location of the exchanges from exchange website information.

Rank	Exchange Name	Country HQ	Turnover (BTC thousands)	Turnover ($USD millions)
1	Bittrex.com	US	3,711.60	9,784.63
2	Poloniex.com	US	4,193.13	6,805.52
3	Bitstamp.net	Luxembourg	7,720.86	6,682.23
4	Huobi.com	China	6,540.51	4,549.28
5	MtGox	Japan	27,256.33	3,234.06
6	LocalBitcoins.com	Finland	9,750.24	2,929.61
7	BitX.co	UK	1,018.16	2,633.61
8	BTC-e.com	Russia	8,593.70	2,333.37
9	OKCoin.com	China	2,997.80	1,600.40
10	Kraken.com	US	2,138.70	1,232.30
11	Cryptsy.com	US	3,684.55	888.24
12	BTCC.com	China	2,842.60	868.81
13	Bitcoin.de	Germany	2,194.91	741.95
14	Bitfinex.com	HK	2,292.96	621.29
15	AnxPro.com	HK	525.43	603.23
16	Cex.io	UK	2,511.93	541.60
17	HitBtc.com	UK	302.70	450.31
18	BtcTrade.com	China	1,124.08	427.82
19	C-Cex.com	Germany	681.09	265.11
20	BitVC.com	China	724.70	242.7
21	Bter.com	China	1,354.44	241.3
22	YoBit.net	Russia	325.53	200.9
23	Paxful.com	US	544.98	185.94
24	MercadoBitcoin.com.br	Brazil	370.33	144.22
25	MaiCoin.com	Taiwan	497.11	135.33
26	BX.in.th	Thailand	300.61	131.97
27	McxNOW.com	Unknown	348.45	131.01
28	CoinSpot.com.au	Australia	70.18	126.55
29	BitBay.net	Poland	93.90	120.49
30	Cavirtex.com	Canada	689.31	118.22
31	VirWoX.com	Austria	393.37	104.77
32	ChBtc.com	China	172.52	94.91
33	Matbea.com	Russia	227.99	93.90
34	Vircurex.com	China	338.39	93.84
35	SpectroCoin.com	Lithuania	50.61	88.6
36	Bit-x.com	UK	60.67	86.88
37	Bleutrade.com	Brazil	300.21	79.40
38	BitBargain.co.uk	UK	335.85	75.70
39	CoinHako.com	Singapore	36.50	72.49
40	TheRockTrading.com	Malta	174.67	65.72
41	796.com	China	173.00	47.28
42	CampBX.com	US	339.81	42.03
43	Btc38.com	China	137.05	39.80
44	FYBSG.com	Singapore	152.92	38.50
45	Coinmate.io	UK	42.74	36.49
46	BtcMarkets.net	Australia	103.97	33.89
47	FoxBit.com	Brazil	62.01	32.36
48	Korbit.co.kr	Korea	92.81	27.60
49	CoinMotion.com	Finland	33.22	27.00

50	Exmo.com	UK	105.18	24.63
51	Coins-e.com	Canada	94.11	23.97
52	Igot.com	Australia	120.74	22.88
53	Bitcurex.com	Poland	81.65	17.62
54	Bitcoin-24.com	Unknown	186.92	17.41
55	HappyCoins.com	Netherlands	54.21	16.12
56	Coin.mx	US	73.81	16.03
57	Vaultoro.com	UK	33.36	15.78
58	Cryptorush.in	India	99.02	15.07
59	Crypto-Trade.com	Netherlands	71.59	14.8
60	AllCoin.com	Unknown	67.65	14.62
61	LiteBit.eu	Netherlands	66.63	14.01
62	VaultOfSatoshi.com	Canada	60.25	13.32
63	Gatecoin.com	HK	32.68	12.81
64	BlockTrades.us	Unknown	22.42	12.44
65	LakeBTC.com	China	37.92	9.31
66	SimpleCoin.cz	Czech	4.29	8.52
67	Bitcoinica.com	NZ	238.47	6.21
68	BitNZ.com	Unknown	16.52	5.93
69	CoinTrader.net	Canada	16.7	4.90
70	Exchanging.ir	Iran	4.27	1.49
71	UrduBit.com	Pakistan	0.54	0.28

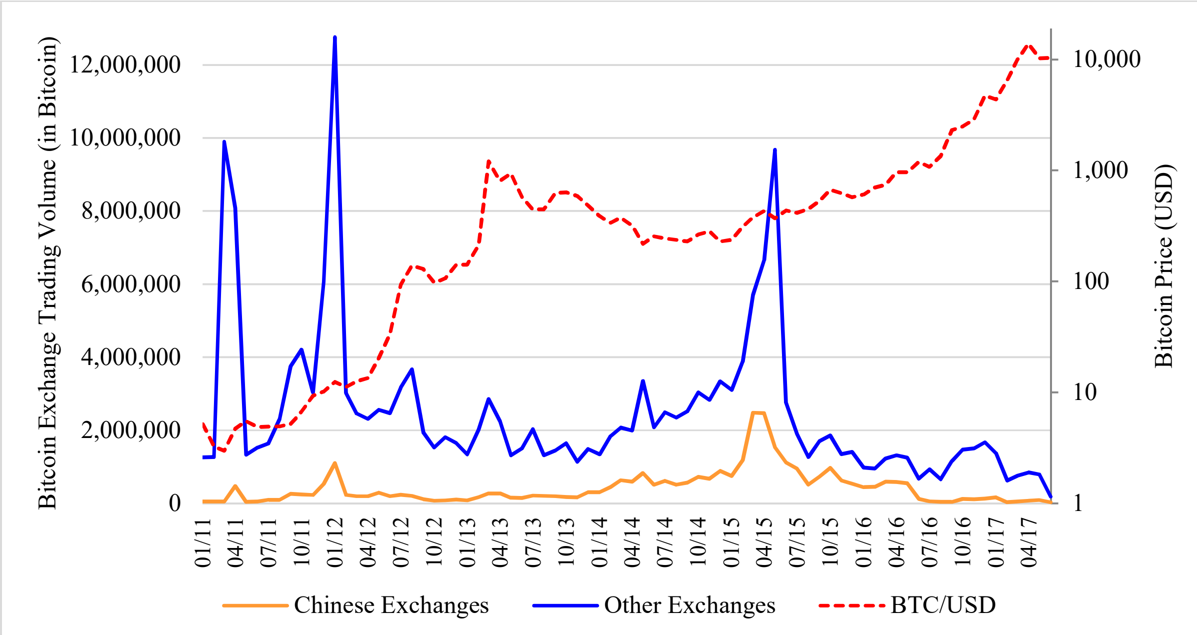
Appendix 5: Indirect Trades Classifications

The table below shows the pattern of trades involving two users, A and B, to identify indirect capital flight and reverse capital flight trades. User A trades on Chinese Bitcoin exchanges and user B trades on non-Chinese Bitcoin exchanges. Indirect trades involve two users as we depict in Appendix 1 Panel B.

Classification of Trade	User A (Chinese Exchange Trader)	Trade observed between User A and User B on Bitcoin Blockchain	User B (Non-Chinese Exchange Trader)
Indirect capital flight	Net buys at Chinese exchanges	A sends Bitcoin to B	Net sells on non-Chinese exchanges
Indirect reverse capital flight	Net sells at Chinese exchanges	A receives Bitcoin from B	Net buys on non-Chinese exchanges

Figure 1: Monthly Bitcoin Exchange Turnover by Region vs. Bitcoin Price

Panel A: Volume Measured in Bitcoin



Panel B: Volume Measured In USD

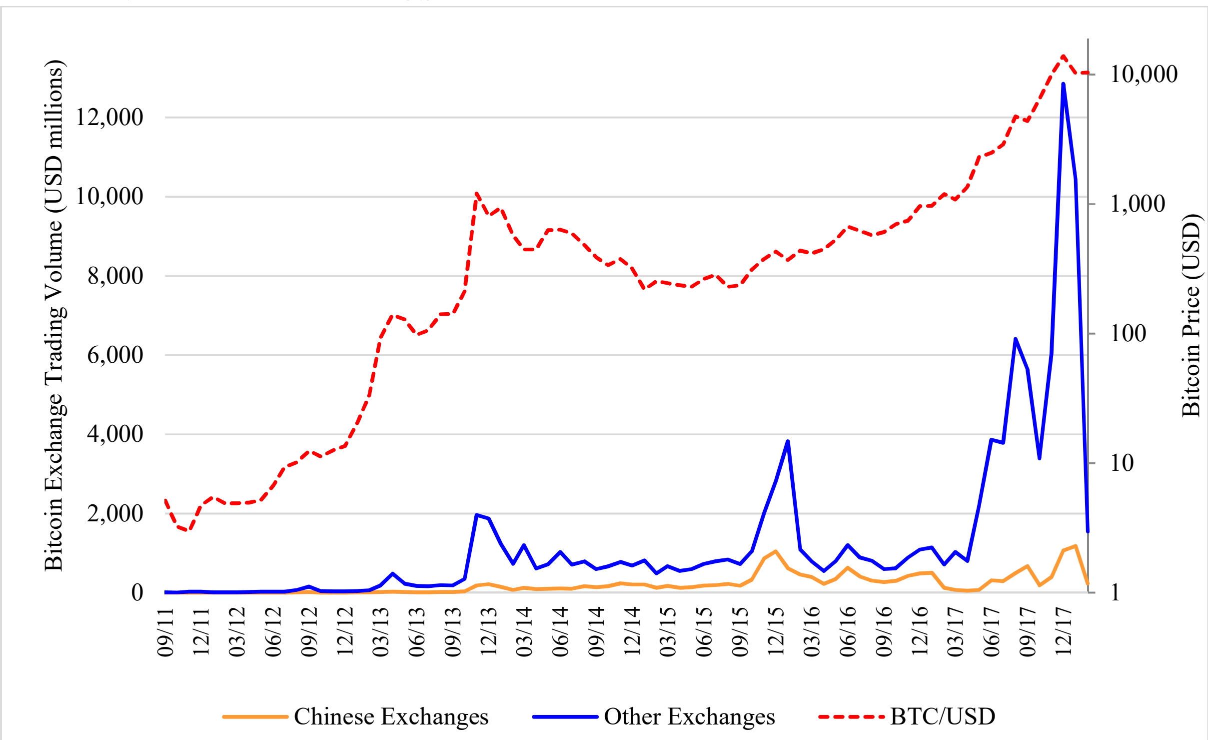
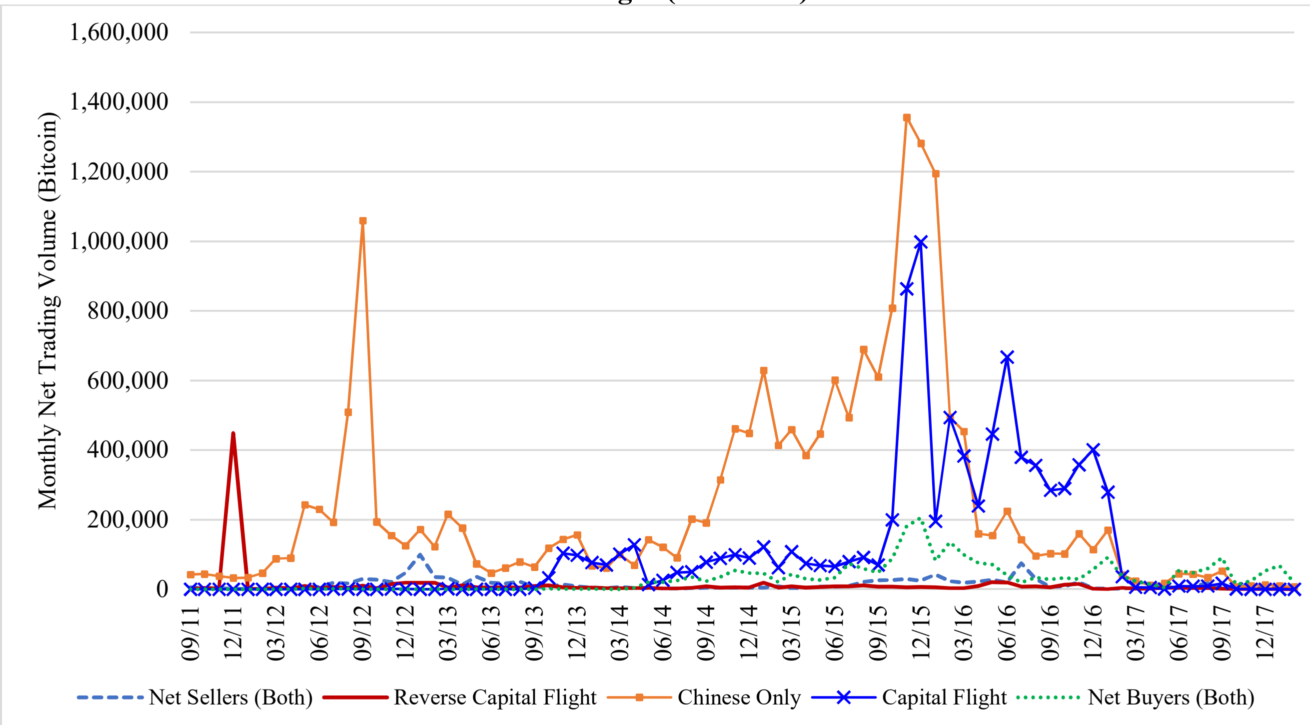
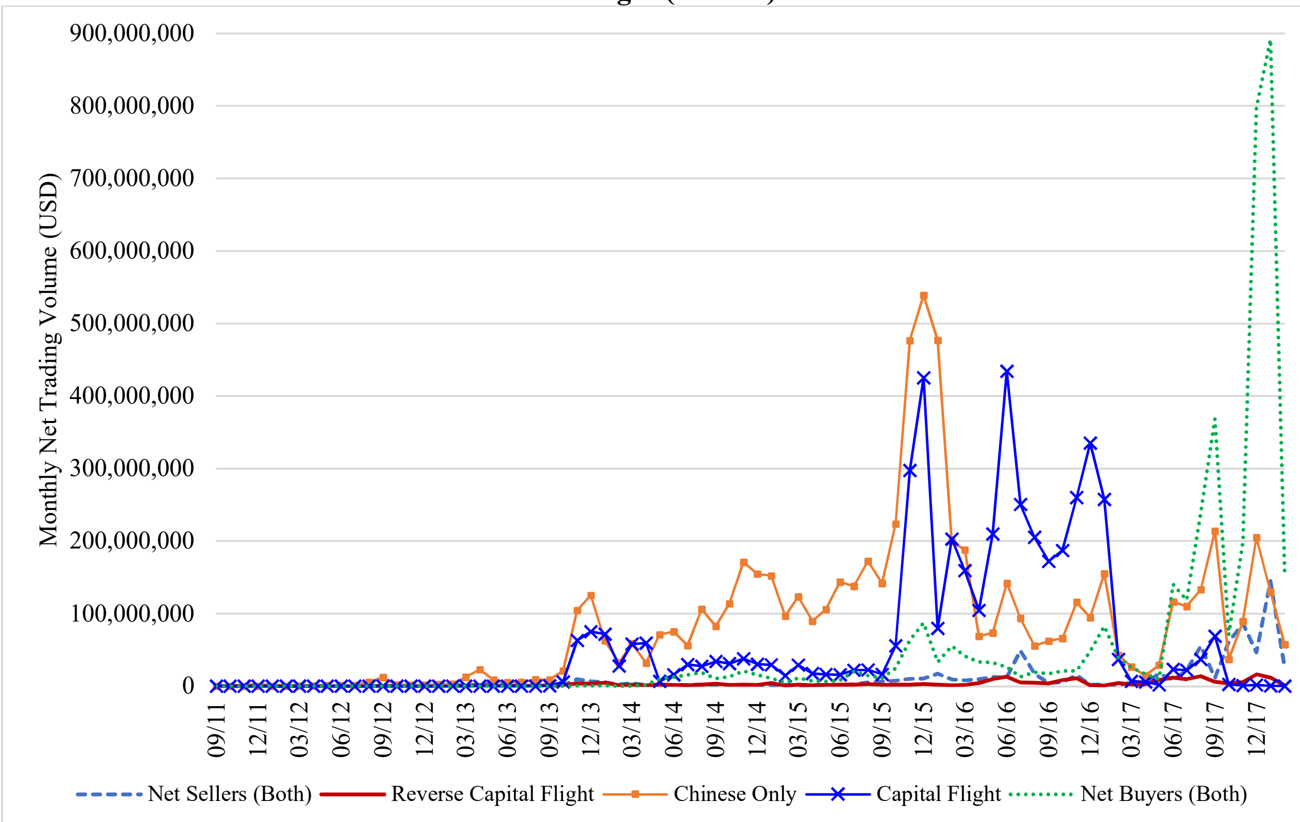


Figure 2: Monthly Absolute Bitcoin Net Volume from Chinese Bitcoin Exchanges by Trader Types

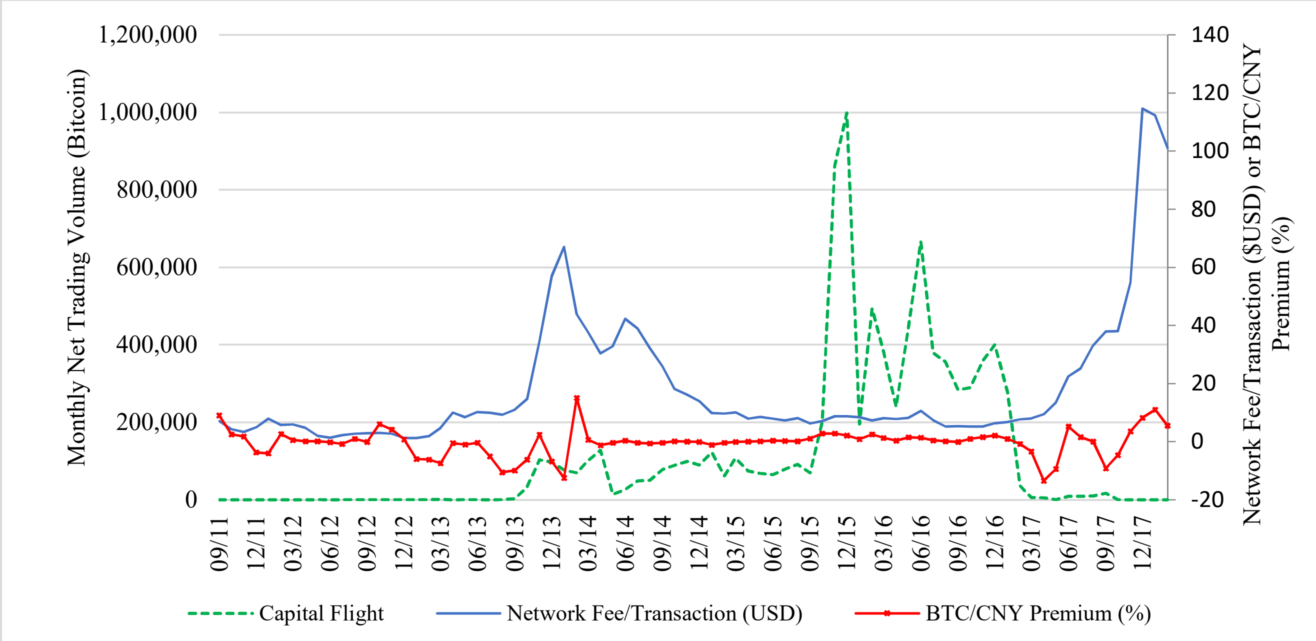
Panel A: Net Volume in Chinese Bitcoin Exchanges (in Bitcoin)



Panel B: Net Volume in Chinese Bitcoin Exchanges (in USD)



Panel C: Capital Flight Trades (in Bitcoin)



Panel D: Capital Flight Trades (in USD)

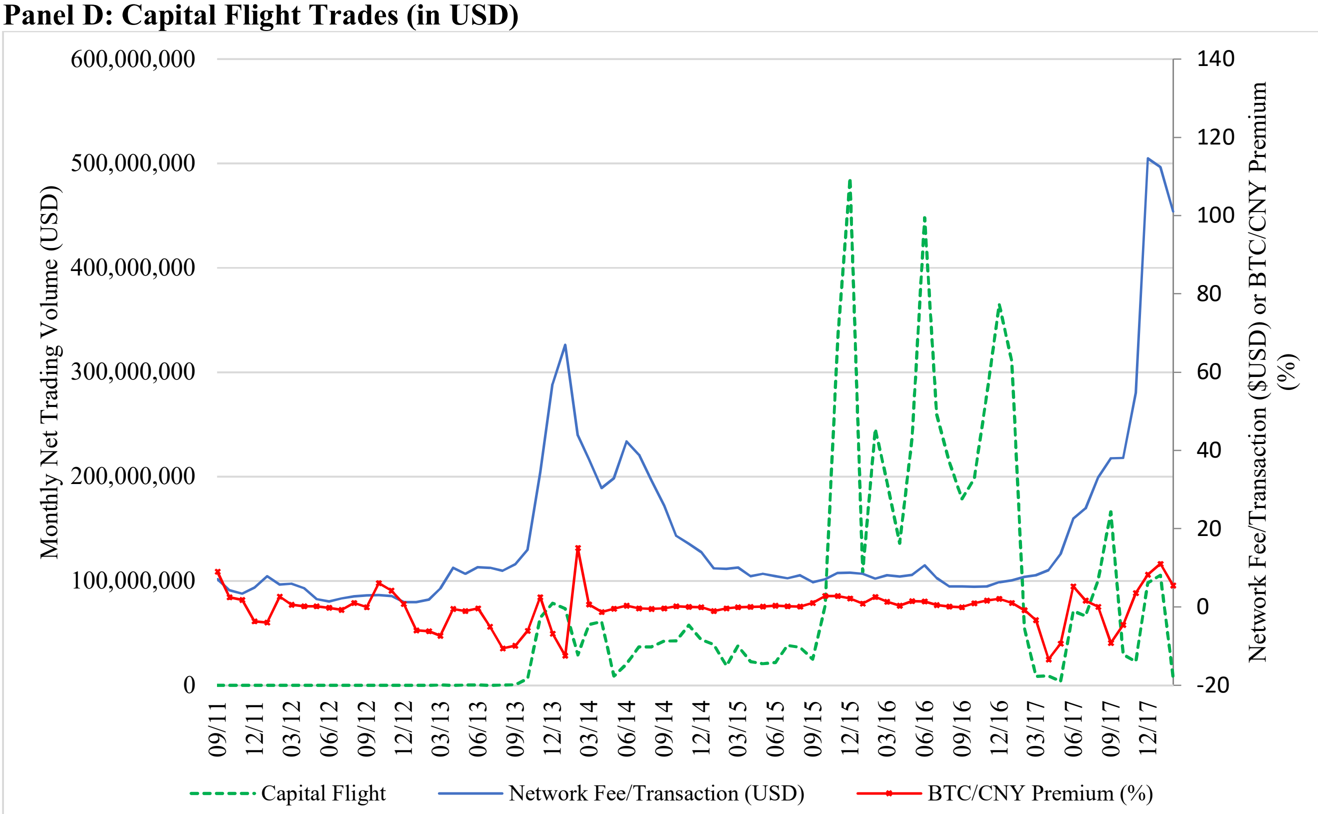


Table 1: Descriptive Statistics

The table reports daily descriptive statistics for our sample of Bitcoin transactions. *Bitcoin Return(USD)* and *Bitcoin_return(CNY)* are the daily percentage bitcoin returns in USD and CNY, respectively. *Chin_net* is the unsigned net turnover on Chinese Bitcoin exchanges for trader type *j* on day *t*. *ΔChinepu* is the monthly change in the Baker, Bloom and Davis (2016) Chinese economic policy uncertainty index (standardized), *Chinprem* is the Bitcoin/CNY price converted into USD over the Bitcoin/USD price -1 as a percentage. Bitcoin prices in CNY and USD are end of day prices from Cryptocompare.com. *Sqvol* is the daily sum of 1 minute squared USD Bitcoin returns. *Ntrans* is the daily number of Bitcoin blockchain transactions (in thousands). *USDfeespertran* is the daily average fee per trade in USD. The sample is from 2nd September 2011 to 8th February 2018. Panel A reports the total net trading volume (in Bitcoin and US$) at Chinese Bitcoin exchanges for different trade groups. Panel B. reports various summary statistics. Panel C reports the correlation matrix of variables.

Panel A: Net Trading by User Types at Chinese Bitcoin Exchanges (in millions)

	Trader Type							
Measure	**Net Sellers**	**Reverse Capital Flight**	**Chinese Only**	**Capital Flight**	**Net Buyers**	**Total Net Trades**	**Indirect Reverse Cap Flight**	**Indirect Cap Flight**
Bitcoin	1.13	0.94	18.88	8.78	2.45	32.18	0.00	0.00
% of Total	3.50	2.93	58.69	27.28	7.60	100.00	0.00	0.00
US$	767.62	235.42	6,779.07	4,605.43	3,904.48	16,292.02	0.00	0.00
% of Total	4.71	1.44	41.61	28.27	23.97	100.00	0.00	0.00

Panel B: Summary Statistics of Daily Variables

Variable	Mean	Median	Std Dev	P25	P75
Bitcoin Return(USD)	0.54	0.21	9.11	-1.17	2.10
Bitcoin Return(CNY)	0.49	0.00	6.24	-0.82	1.59
ΔChinEPU	0.00	0.01	0.72	-0.38	0.48
Chinprem	-0.32	0.07	6.87	-1.96	1.55
Ntrans	126.08	83.36	102.11	47.85	217.51
Sqvol	0.64	0.26	1.09	0.11	0.68
USDfeespertran	1.13	0.08	4.53	0.03	0.19
Chin Net (Net Sellers) Btc	2,416.12	893.93	5,455.71	319.53	2,357.99
Chin Net (Rev. Cap Flight) Btc	2,368.40	1,290.79	18,529.94	617.82	2,402.60
Chin Net (Chinese Only) Btc	8,028.58	3,400.02	13,291.16	1,282.33	10,111.41
Chin Net (Capital Flight) Btc	4,409.80	622.57	8,284.48	0.00	4,580.78
Chin Net (Net Buyers) Btc	2,555.43	1,095.78	3,866.42	64.02	3,173.56
Chin Net (Net Sellers) US$	2,938,861.48	218,384.68	11,098,705.95	51,798.07	951,789.81
Chin Net (Rev. Cap Flight)	1,827,098.85	388,157.43	5,635,905.03	49,522.67	1,105,594.81
Chin Net (Chinese Only) US$	2,882,259.66	1,607,251.79	4,558,881.22	177,066.09	3,798,537.60
Chin Net (Capital Flight) US$	2,417,420.95	383,446.33	4,785,955.53	0.12	2,374,355.52
Chin Net (Net Buyers) US$	8,739,903.77	425,100.17	33,715,884.88	2,988.05	1,534,637.15

Panel C: Correlation Matrix

No.	Variable	1	2	3	4	5	6	7	8	9	10	11	12
1	Bitcoin Return (USD)	1.000											
2	Bitcoin Return (CNY)	0.311	1.000										
3	ΔChinEPU	-0.020	-0.020	1.000									
4	Chinprem	-0.140	0.092	0.004	1.000								
5	Ntrans	0.003	0.028	-0.010	0.061	1.000							
6	Sqvol	-0.010	0.007	-0.020	-0.110	-0.090	1.000						
7	USDfeespertran	-0.010	0.030	-0.100	0.201	0.416	-0.100	1.000					
8	Chin Net (Net Sellers) Btc	0.000	0.004	-0.020	0.016	0.147	-0.080	0.002	1.000				
9	Chin Net (Rev. Cap Flight) Btc	0.017	0.000	-0.010	-0.030	-0.010	-0.010	-0.010	0.000	1.000			
10	Chin Net (Chinese Only) Btc	-0.010	-0.010	0.017	0.080	-0.010	-0.090	-0.130	0.099	-0.010	1.000		
11	Chin Net (Capital Flight) Btc	-0.010	-0.010	0.094	0.130	0.346	-0.040	-0.110	0.086	0.000	0.365	1.000	
12	Chin Net (Net Buyers) Btc	-0.020	-0.020	-0.090	0.192	0.603	-0.190	0.537	0.220	-0.010	0.126	0.272	1.000

Table 2: Determinants of Capital Flight Trade Volume

In order to find out what affects the trader types, the table estimates the following regression:

$$\text{Chin\_net}_{jt} = \text{Intercept}_0 + \text{b}_1 * \Delta\text{Chinepu}_t + \text{b}_2 * \text{Chinprem}_t + \text{b}_3 * \text{Ntrans}_t + \text{b}_4 * \text{USDfeespertran}_t + \text{b}_5 * \text{Sqvol}_t + \text{b}_6 * \text{dayid}_t + \text{e}_{it}$$

Where Chin_net is the unsigned net turnover for trader type j on day *t* at Chinese headquartered Bitcoin Exchanges. We identify trades to Chinese Bitcoin Exchanges from their Bitcoin wallet addresses from walletexplorer.com. Δchinepu is the lagged monthly change in the Baker, Bloom and Davis (2016) Chinese economic policy uncertainty index, *Chinprem* is the Bitcoin/CNY price converted into USD over the Bitcoin/USD price -1 as a percentage. Bitcoin prices in CNY and USD are end of day prices from Cryptocompare.com. *Sqvol* is the daily sum of 1 minute squared USD Bitcoin returns. Ntrans is the daily number of trades. USDfeespertran is the daily average fee per trade in USD. *Dayid* is the number of days since the start of the sample period. The sample is from 2nd September 2011 to 8th February 2018. Panel A reports results using Bitcoin net turnover volume (in '000s Bitcoin). Panel B reports results using Bitcoin net turnover volume converted into USD (in '000s). Standard errors in parentheses. ***, **, * signifies statistical significance at the 1, 5 and 10 percent level, respectively.

Panel A: Bitcoin Net Turnover Regression (in Bitcoin thousands)

Dependant Variable: Bitcoin Net Turnover Volume (in Bitcoin thousands)

	Trader Type				
	Net Sellers Both	Reverse Capital Flight	Chinese Only	Capital Flight	Net Buyers Both
ΔChinepu	0.032	-0.106	0.069	0.519***	-0.043
	(0.069)	(0.115)	(0.38)	(0.2)	(0.042)
Chinprem	-0.006	-0.039	0.198***	0.174***	0.029***
	(0.004)	(0.041)	(0.029)	(0.018)	(0.004)
Ntrans	0.002***	0.004	-0.037***	0.028***	0.001
	(0.001)	(0.004)	(0.006)	(0.004)	(0.001)
USDfeespertran	-0.013***	0.011	-0.52***	-0.523***	-0.046***
	(0.004)	(0.02)	(0.06)	(0.052)	(0.007)
Sqvol	-0.033**	-0.065	-1.249***	-0.064	-0.152***
	(0.014)	(0.067)	(0.134)	(0.067)	(0.015)
Dayid	0.000**	-0.001	0.007***	0.001	0.001***
	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)
Intercept	0.57***	1.122	6.152***	0.117	-0.137***
	(0.058)	(0.891)	(0.579)	(0.138)	(0.029)
Adj Rsq	0.002941	-0.00011	0.05457	0.2080	0.2598
N	2,352	2,352	2,352	2,352	2,352

Panel B: Bitcoin Net Turnover (in USD thousands) Regression

Dependant Variable: Bitcoin Net Turnover Volume (in USD thousands)

	Trader Type				
	Net Sellers Both	Reverse Capital Flight	Chinese Only	Capital Flight	Net Buyers Both
ΔChinepu	6.63	5.958	377.305***	661.147***	-119.699
	(47.649)	(8.495)	(127.856)	(107.371)	(77.854)
Chinprem	1.378	1.227	66.762***	77.563***	27.931**
	(4.022)	(0.91)	(10.88)	(9.637)	(13.442)
Ntrans	2.198***	0.596***	-8.689***	22.803***	3.071
	(0.824)	(0.159)	(2.166)	(2.486)	(2.824)
USDfeespertran	91.626***	7.84**	-53.087***	-278.407***	839.404***
	(21.223)	(3.11)	(20.523)	(26.626)	(70.915)
Sqvol	-26.666**	1.749	-261.713***	49.967	-176.385***
	(10.438)	(3.309)	(42.943)	(36.926)	(27.463)
Dayid	0.026	0.02	3.75***	-0.485*	0.82**
	(0.122)	(0.022)	(0.268)	(0.272)	(0.39)
Intercept	-66.971*	-7.512	-93.502	-52.036	-493.982***
	(36.912)	(7.281)	(82.667)	(70.844)	(112.591)
Adj Rsq	0.2024	0.1224	0.1559	0.2687	0.6863
N	2,352	2,352	2,352	2,352	2,352

Table 3: Determinants of Capital Flight Trade Volume (including indirect trades)

In order to find out what affects the trader types, the table estimates the following regression:

$$\mathrm{Chin\_net}_{jt} = \mathrm{Intercept}_0 + \mathrm{b}_1 * \Delta\mathrm{Chinepu}_t + \mathrm{b}_2 * \mathrm{Chinprem}_t + \mathrm{b}_3 * \mathrm{Ntrans}_t + \mathrm{b}_4 * \mathrm{USDfeespertran}_t + \mathrm{b}_5 * \mathrm{Sqvol}_t + \mathrm{b}_6 * \mathrm{dayid}_t + \mathrm{e}_{it}$$

Where Chin_net is the unsigned net trading volume for trader type j on day *t* at Chinese headquartered Bitcoin Exchanges. Indirect Capital Flight and Reverse Capital Flight trades are classified using the algorithm in Section 4.3. Indirect trades involve two users facilitating the trade. We identify trades to Chinese Bitcoin exchanges from exchange Bitcoin wallet addresses from walletexplorer.com. *ΔChinepu* is the lagged monthly change in the Baker, Bloom and Davis (2016) Chinese economic policy uncertainty index (standardized), *Chinprem* is the Bitcoin/CNY price converted into USD over the Bitcoin/USD price -1 as a percentage. Bitcoin prices in CNY and USD are end of day prices from Cryptocompare.com. *Sqvol* is the daily sum of 1 minute squared USD Bitcoin returns. *Ntrans* is the daily number of trades. *USDfeespertran* is the daily average fee per trade in USD. *Dayid* is the number of days since the start of the sample period. The sample is from 2nd September 2011 to 8th February 2018. Panel B reports results using Bitcoin net turnover volume including indirect volume (in '000s Bitcoin). Panel A reports aggregate net turnover of each trader group and separate statistics for indirect trades. Panel B reports regressions results using Bitcoin net turnover volume including indirect volume, converted into USD (in '000s). Panel C reports regressions results using Bitcoin net turnover volume including indirect volume, converted into USD (in '000s). Standard errors in parentheses. ***, **, * signifies statistical significance at the 1, 5 and 10 percent level, respectively.

Panel A: Net Trading by Users at Chinese Bitcoin Exchanges with indirect trades (in millions)

	Trader Group							
Measure	**Net Sellers**	**Reverse Capital Flight**	**Chinese Only**	**Capital Flight**	**Net Buyers**	**Total Net Trades**	**Indirect Reverse Cap Flight**	**Indirect Cap Flight**
₿ +Indirect	0.90	1.29	18.35	10.31	1.33	32.18	0.53	2.30
% of Total	2.78	4.02	57.02	32.04	4.14	100.00	1.64	7.15
US$+Indirect	638.47	411.72	6,506.42	5,730.19	3,005.21	16,292.02	277.31	1,523.7
% of Total	3.92	2.53	39.94	35.17	18.45	100.00	1.70	9.35

Panel B: Bitcoin Net Turnover with Indirect Trades Regression (in Bitcoin thousands)

Dependant Variable: Bitcoin Net Turnover Volume (in Bitcoin thousands)

	Trader Type				
	Net Sellers Both	Reverse Capital Flight	Chinese Only	Capital Flight	Net Buyers Both
ΔChinepu	0.032	-0.106	0.069	0.519***	-0.043
	(0.069)	(0.115)	(0.38)	(0.2)	(0.042)
Chinprem	-0.006	-0.039	0.198***	0.174***	0.029***
	(0.004)	(0.041)	(0.029)	(0.018)	(0.004)
Ntrans	0.002***	0.004	-0.037***	0.028***	0.001
	(0.001)	(0.004)	(0.006)	(0.004)	(0.001)
USDfeespertran	-0.013***	0.011	-0.52***	-0.523***	-0.046***
	(0.004)	(0.02)	(0.06)	(0.052)	(0.007)
Sqvol	-0.033**	-0.065	-1.249***	-0.064	-0.152***
	(0.014)	(0.067)	(0.134)	(0.067)	(0.015)
Dayid	0.000**	-0.001	0.007***	0.001	0.001***
	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)
Intercept	0.570***	1.122	6.152***	0.117	-0.137***
	(0.058)	(0.891)	(0.579)	(0.138)	(0.029)
Adj Rsq	0.002941	-0.00011	0.05457	0.2080	0.2598
N	2,352	2,352	2,352	2,352	2,352

Panel C: Bitcoin Net Turnover with Indirect Trades Regression (in USD thousands)

Dependant Variable: Bitcoin Net Turnover Volume (in USD thousands)

	Trader Type				
	Net Sellers Both	Reverse Capital Flight	Chinese Only	Capital Flight	Net Buyers Both
ΔChinepu	6.63	5.958	377.305***	661.147***	-119.699
	(47.649)	(8.495)	(127.856)	(107.371)	(77.854)
Chinprem	1.378	1.227	66.762***	77.563***	27.931**
	(4.022)	(0.91)	(10.88)	(9.637)	(13.442)
Ntrans	2.198***	0.596***	-8.689***	22.803***	3.071
	(0.824)	(0.159)	(2.166)	(2.486)	(2.824)
USDfeespertran	91.626***	7.84**	-53.087***	-278.407***	839.404***
	(21.223)	(3.11)	(20.523)	(26.626)	(70.915)
Sqvol	-26.666**	1.749	-261.713***	49.967	-176.385***
	(10.438)	(3.309)	(42.943)	(36.926)	(27.463)
Dayid	0.026	0.02	3.75***	-0.485*	0.82**
	(0.122)	(0.022)	(0.268)	(0.272)	(0.39)
Intercept	-66.971*	-7.512	-93.502	-52.036	-493.982***
	(36.912)	(7.281)	(82.667)	(70.844)	(112.591)
Adj Rsq	0.2024	0.1224	0.1559	0.2687	0.6863
N	2,352	2,352	2,352	2,352	2,352

Table 4: Split Sample Regression

The table estimates the following regression separately for two subsamples before and after 1st September 2015:

$$\mathrm{Chin\_net}_{jt} = \mathrm{Intercept}_0 + \mathrm{b}_1 * \Delta\mathrm{Chinepu}_t + \mathrm{b}_2 * \mathrm{Chinprem}_t + \mathrm{b}_3 * \mathrm{Ntrans}_t + \mathrm{b}_4 * \mathrm{USDfeespertran}_t + \mathrm{b}_5 * \mathrm{Sqvol}_t + \mathrm{b}_6 * \mathrm{dayid}_t + \mathrm{e}_{it}$$

Where *Chin_net* is the unsigned net turnover for trader type j on day *t* at Chinese Bitcoin exchanges. *ΔChinepu* is the lagged monthly change in the Baker, Bloom and Davis (2016) Chinese economic policy uncertainty index (standardized), *Chinprem* is the Bitcoin/CNY price converted into USD over the Bitcoin/USD price -1 as a percentage. Bitcoin prices in CNY and USD are end of day prices from Cryptocompare.com. *Sqvol* is the daily sum of 1 minute squared USD Bitcoin returns. *Ntrans* is the daily number of trades. *USDfeespertran* is the daily average fee per trade in USD. *Dayid* is the number of days since the start of the sample period. The sample is from 2nd September 2011 to 8th February 2018. Panel B reports results for the sample before 1st September 2015 using Bitcoin net turnover volume converted into USD (in '000s). Panel C reports results for the sample after 1st September 2015 using Bitcoin net turnover volume converted into USD (in '000s). Standard errors in parentheses. ***, **, * signifies statistical significance at the 1, 5 and 10 percent level, respectively.

Panel A: Before 1st September 2015 (in USD thousands)

Depend Variable: Bitcoin Net Turnover Volume (in USD thousands)

	Trader Type				
	Net Sellers Both	Reverse Capital Flight	Chinese Only	Capital Flight	Net Buyers Both
ΔChinepu	-7.930	7.775	36.344	25.551	21.436
	(5.808)	(6.193)	(91.851)	(38.399)	(15.901)
Chinprem	-0.257	-0.087	6.637	7.095**	1.469***
	(0.452)	(0.395)	(5.985)	(3.579)	(0.333)
Ntrans	1.574***	0.48**	22.479***	1.152	-0.105
	(0.429)	(0.191)	(4.234)	(1.871)	(0.693)
Usdfeespertran	679.836***	223.59***	2313.197**	5502.609***	-316.428***
	(165.973)	(64.906)	(1140.602)	(781.408)	(61.212)
Sqvol	-0.703	3.151	-239.46***	-63.947***	-35.823***
	(2.851)	(2.319)	(25.916)	(18.463)	(3.057)
Dayid	-0.088**	0.018	2.038***	0.53***	0.406***
	(0.04)	(0.015)	(0.355)	(0.161)	(0.051)
Intercept	-9.609**	-12.893***	-997.737***	-217.266***	-94.202***
	(3.943)	(3.952)	(49.125)	(17.36)	(5.901)
Adj Rsq	0.1508	0.1029	0.5130	0.2991	0.3610
N	1,460	1,460	1,460	1,460	1,460

Panel B: From 1st September 2015 (in USD thousands)

Dependant Variable: Bitcoin Net Turnover Volume (in USD thousands)

	Trader Type				
	Net Sellers Both	Reverse Capital Flight	Chinese Only	Capital Flight	Net Buyers Both
ΔChinepu	27.910	5.276	169.596	741.668***	-70.73
	(70.996)	(11.562)	(154.481)	(137.005)	(101.98)
Chinprem	14.576	6.369*	89.232***	160.662***	127.61***
	(15.892)	(3.267)	(25.182)	(26.504)	(49.001)
Ntrans	0.745	0.705**	-0.541	24.39***	-4.603
	(1.723)	(0.307)	(3.448)	(3.627)	(5.36)
Usdfeespertran	68.59***	3.568	137.31***	-148.674***	715.191***
	(26.171)	(3.61)	(24.658)	(29.716)	(79.383)
Sqvol	-365.983***	-64.607***	-2754.694***	-1162.032***	-1157.813***
	(101.959)	(20.485)	(343.537)	(269.88)	(172.666)
Dayid	0.89*	0.075	-11.291***	-11.157***	5.886***
	(0.484)	(0.09)	(1.337)	(0.89)	(1.45)
Intercept	-1103.186*	-96.561	27254.477***	20359.362***	-7333.448***
	(615.761)	(112.15)	(2236.271)	(1575.37)	(1755.142)
Adj Rsq	0.1519	0.05826	0.1840	0.2868	0.6592
N	892	892	892	892	892

Table 5: Profits from Trade

The table reports the total USD profit statistics for traders from 2nd September 2011 to 8th February 2018. Profits are in USD. We split intraday trading profits into two components: intra-exchange trading profits from buying and selling within Chinese or non-Chinese exchanges and inter-exchange profits from trading between Chinese and non-Chinese exchanges. These measures are calculated as:

$$
\begin{aligned}
&Intra\text{-}exchange_{it} \\
&\qquad = min(Chinbuy_{it}, Chinsell_{it}) * \left(Chinsell_{vwap,it} - Chinbuy_{vwap,it}\right)/USDCNY_t \\
&\qquad + min(Nonchinbuy_{it}, Nonchinsell_{it}) * \left(Nonchinsell_{vwap,it} - Nonchinbuy_{vwap,it}\right)
\end{aligned}
$$

$Inter\text{-}exchange_{it} = Chin\_net_{it} * \left(Nonchinsell_{vwap,it} - \frac{Chinb\quad_{vwap,it}}{USDCNY_t}\right)$ for capital flight users or

$Inter\text{-}exchange_{it} = Chin\_net_{it} * \left(\frac{Chinsell_{vwap,it}}{USDCNY_t} - Nonchinbuy_{vwap,it}\right)$ for reverse capital flight users

Where *i* subscripts for user and *t* for day (in Chinese time UTC+8). *Chinbuy* and *Chinsell* is the number of Bitcoin bought or sold at Chinese Bitcoin exchanges, respectively. $Chinbuy_{vwap}$ and $Chinsell_{vwap}$ is the volume weighted average price of bitcoin bought or sold at Chines Bitcoin exchanges, respectively. Prices traded are the nearest one minute BTC/CNY prices of the volume weighed average price at Chinese Bitcoin exchanges. *Nonchin* relates to Bitcoin bought or sold at non-Chinese Bitcoin exchanges. *USDCNY* is the closing day price of USD/CNY. *Chin_net* is *Chinbuy* minus *Chinsell*. We calculate percentage profits as the profit divided by the net Bitcoin volume traded in Chinese exchanges converted into USD.

Trader Type	Intra-Exchange ($'000)	Intra-Exchange (%)	Inter-Exchange ($'000)	Inter-Exchange (%)
Net Seller	544.47	0.1344	-	-
Reverse Cap Flight	56.06	0.0284	74.93	0.0380
Chinese Only	182.47	0.0029	-	-
Capital Flight	-475.95	-0.0103	-31,589.96	-0.6868
Net Buyer	198.77	0.0111	-	-

Table 6: Probability of Illegal Trading by Users

The table reports descriptive statistics and coefficient estimates for the following logit regression at the user level:

$$Logit(illegal_i=1) = b_0 + b_1{*}ExchangeUser + b_2{*}ChinExchangeUser + b_3{*}Netseller\_pct_i + b_4{*}Reverse\_pct_i + b_5{*}Chineseonly\_pct_i + b_6{*}Capflight\_pct_i + b_7{*}Netbuyer\_pct_i + b_8{*}Logn_i + b_9{*}Logtradesize_i + b_{10}{*}Concentration_i + e_i$$

where illegal is a dummy of 1 if user *i* is classified as an illegal user in Foley et al. (2019), 0 otherwise. *ExchangeUser* is a dummy of 1 if the trader ever traded with a Bitcoin exchange, 0 otherwise. *ChinExchangeUser* is a dummy of 1 if the trader ever traded with a Chinese Bitcoin exchange, 0 otherwise. Every day for each user, we calculate net turnover to each counterparty (Chinese Bitcoin exchanges, non-Chinese Bitcoin exchanges and other counterparties). Net turnover in each venue is the absolute of buy less sell trades in USD. *Netseller_pct* is the dollar percentage of all net trading in USD by user *i* for days that they are net selling in both non-Chinese and Chinese Bitcoin exchanges. *Reverse_pct* is the percentage of net trades that is buying in non-Chinese Bitcoin exchanges and selling in Chinese exchanges. *Chineseonly_pct* is the percentages that are Chinese only trading. *Capflight_pct* is the percentage of net trades buying in Chinese exchanges and selling in non-Chinese exchanges. *Netbuyer_pct* is the percentage of net trades that is buying in both Chinese and non-Chinese exchanges. *Logn* is the natural log of number of trades by user. *Logtradesize* is the average USD trade size of a user's transactions. *Concentration* is a measure of the tendency for a user to transact with one or many counterparties. It ranges from 1 for a highly concentrated user who transacts with only one counterparty, to 0 for a user that has many transactions, each with a different counterparty. Panel A reports descriptive statistics of the amount of legal and illegal trading by user classification and by year. Panel B reports coefficient estimates for the logistic regression.

Panel A: Illegal Trading by User Type by Year (USD Millions)

		Trade Type Classification					
Year	Legal/Illegal User	Net Seller	Reverse Flight	Chinese Only	Capital Flight	Net Buyer	Other Trades
2011	Legal	0.29	0.02	6.55	0.00	0.00	61.13
	Illegal	0.25	3.22	0.49	0.00	0.00	49.81
	Illegal (%)	47.15	99.27	6.93	100.00	99.26	44.90
2012	Legal	1.86	0.06	12.98	0.02	0.00	110.36
	Illegal	6.30	5.76	14.74	0.14	0.60	109.17
	Illegal (%)	77.18	99.04	53.17	86.46	99.79	49.73
2013	Legal	25.28	5.53	148.93	6.59	2.14	1,142.80
	Illegal	48.95	113.55	90.17	147.29	16.43	1,068.24
	Illegal (%)	65.94	95.36	37.71	95.72	88.46	48.31
2014	Legal	23.98	22.95	497.72	9.72	19.81	1,155.50
	Illegal	72.43	342.81	190.99	462.43	221.76	1,660.72
	Illegal (%)	75.13	93.73	27.73	97.94	91.80	58.97
2015	Legal	158.09	41.68	486.48	644.16	101.48	2,030.81
	Illegal	175.11	183.89	1,140.98	437.47	281.51	1,079.90
	Illegal (%)	52.55	81.52	70.11	40.45	73.50	34.72
2016	Legal	83.86	26.80	989.52	1,811.42	131.34	3,012.60
	Illegal	549.27	363.97	460.62	1,388.07	528.20	769.54
	Illegal (%)	86.75	93.14	31.76	43.38	80.09	20.35
2017	Legal	175.40	314.63	730.00	267.89	3,284.56	8,730.44
	Illegal	5,082.03	2,549.78	193.15	508.63	9,344.43	5,191.87
	Illegal (%)	96.66	89.02	20.92	65.50	73.99	37.29
2018	Legal	37.62	35.98	151.02	0.86	3,083.06	2,616.58
	Illegal	471.91	286.80	12.73	1.07	3,540.92	1,159.63
	Illegal (%)	92.62	88.85	7.77	55.42	53.46	30.71
All	Legal	506.38	447.65	3,023.20	2,740.67	6,622.39	18,860.22
	Illegal	6,406.25	3,849.77	2,103.87	2,945.11	13,933.87	11,088.88
	Illegal (%)	92.67	89.58	41.03	51.80	67.78	37.03

Panel B: Logit Regression

Dependent Variable:	**Logit(illegal$_i$=1)**
Variable	**Coefficient**
ExchangeUser	3.066***
	(0.5124)
ChinExchangeUser	0.552***
	(0.0089)
Netseller_pct	0.014***
	(0.0001)
Reverse_pct	0.014***
	(0.0002)
Chineseonly_pct	-0.006***
	(0.0001)
Capflight_pct	-0.011***
	(0.0002)
Netbuyer_pct	-0.002***
	(0.0004)
Logn	-0.049***
	(0.0002)
Logturnover	-0.087***
	(0.0001)
Concentration	0.411***
	(0.0011)
Intercept	0.056***
	(0.0008)
Adj Rsq	0.0266
N Users	54,469,162

Table 7: Capital Flight Traders Classification by Weekly, Fortnightly and Monthly

The table estimates the following regression:

$$\text{Chin\_net}_{jt} = \text{Intercept}_0 + b_1 * \Delta\text{Chinepu}_t + b_2 * \text{Chinprem}_t + b_3 * \text{Ntrans}_t + b_4 * \text{USDfeespertran}_t + b_5 * \text{Sqvol}_t + b_6 * \text{Periods}_t + e_{it}$$

Where Chin_net is the unsigned net turnover for trader type j during period t (week, fortnight or month). Traders are classified by their net trading in Chinese and non-Chinese exchanges during each period. *ΔChinepu* is the lagged monthly change in the Baker, Bloom and Davis (2016) Chinese economic policy uncertainty index, *Chinprem* is the Bitcoin/CNY price converted into USD over the Bitcoin/USD price -1 as a percentage. Bitcoin in CNY or USD are end of day prices from Cryptocompare.com. Sqvol is the average daily sum of 1 minute squared USD Bitcoin returns over period *t*. *Ntrans* is the average daily number of blockchain trades (in thousands) over period *t*. *USDfeespertran* is the daily average fee per trade in USD over period *t*. *Periods* is the number of periods (weeks, fortnights or months) since the start of the sample period. The sample is from 2nd September 2011 to 8th February 2018. Panel A reports the total Bitcoin net turnover at Chinese Bitcoin exchanges over weekly, fortnightly and monthly frequencies across trader types. Panel B reports results using weekly Bitcoin net turnover volume converted into USD. Panel C and D calculate net turnover volume on a fortnightly and monthly basis, respectively. Standard errors in parentheses. ***, **, * signifies statistical significance at the 1, 5 and 10 percent level, respectively.

Panel A: Distribution of Total Bitcoin Net Turnover across Frequencies (in USD millions)

Bitcoin Net Turnover in USD (millions)	Net Sellers Both	Reverse Capital Flight	Chinese Only	Capital Flight	Net Buyers Both	Total
Weekly	788.83	251.74	4,093.84	5,125.15	4,051.26	14,310.81
%	5.51	1.76	28.61	35.81	28.31	100.00
Fortnightly	765.03	288.01	3,862.91	5,221.13	4,165.42	14,302.51
%	5.35	2.01	27.01	36.51	29.12	100.00
Monthly	771.23	300.91	3,518.91	5,360.55	4,256.45	14,208.05
%	5.43	2.12	24.77	37.73	29.96	100.00

Panel B: Bitcoin Net Turnover (in USD) Weekly Regression

Dependant Variable:	Bitcoin Net Turnover Volume (in USD thousands)				
			Trader Type		
	Net Sellers Both	Reverse Capital Flight	Chinese Only	Capital Flight	Net Buyers Both
ΔChinepu	-348.258	-174.918*	1404.692	4088.838**	-523.973
	(557.716)	(98.527)	(1360.149)	(1867.782)	(1203.419)
Chinprem	59.281	11.718	507.649***	851.374***	290.435
	(42.075)	(8.338)	(168.318)	(227.691)	(234.583)
Ntrans	15.668	2.242	-55.192**	166.551***	-12.364
	(12.004)	(1.726)	(23.617)	(43.853)	(51.889)
Usdfeespertran	651.725**	43.591	-421.28**	-2269.894***	6246.567***
	(329.724)	(28.896)	(210.614)	(497.111)	(986.426)
Sqvol	-158.358	4.355	-509.057	798.224	-1404.885**
	(122.885)	(47.34)	(652.623)	(890.072)	(568.264)
Weeks	0.603	3.188*	132.063***	-14.022	72.762
	(10.252)	(1.809)	(19.826)	(32.787)	(49.729)
Intercept	-346.881	-120.733	-2130.933**	-1009.862	-4690.996**
	(409.548)	(87.984)	(863.324)	(1340.009)	(2118.112)
Adj Rsq	0.3938	0.2981	0.1954	0.3233	0.7730
N	336	336	336	336	336

Panel C: Bitcoin Net Turnover (in USD) Fortnightly Regression

Dependant Variable:	Bitcoin Net Turnover Volume (in USD thousands)				
	Trader Type				
	Net Sellers Both	Reverse Capital Flight	Chinese Only	Capital Flight	Net Buyers Both
Δchinepu	-780.878	-251.926	1232.784	7190.661	1099.254
	(1180.725)	(285.173)	(3583.962)	(5145.27)	(2864.207)
chinprem	171.154	7.33	1156.439**	2008.931***	623.13
	(112.056)	(26.398)	(481.356)	(722.936)	(755.13)
ntrans	21.141	3.322	-129.329**	340.059***	-83.073
	(23.267)	(5.589)	(54.999)	(120.047)	(126.616)
usdfeespertran	1098.563	342.093***	-1133.67**	-4911.561***	13462.535***
	(839.819)	(109.073)	(562.908)	(1294.59)	(2060.667)
sqvol	-318.667	67.206	-859.07	2108.568	-2809.327*
	(369.441)	(109.717)	(1910.544)	(2683.092)	(1639.386)
Fortnights	24.734	11.69	542.239***	-56.476	390.525
	(40.645)	(10.387)	(102.082)	(184.616)	(264.917)
Intercept	-1165.347	-112.838	-4345.837*	-2316.496	-10909.646*
	(927.266)	(227.222)	(2265.4)	(3747.588)	(5991.35)
Adj Rsq	0.3961	0.5241	0.2170	0.3375	0.8101
N	168	168	168	168	168

Panel D: Bitcoin Net Turnover (in USD) Monthly Regression

Dependant Variable:	Bitcoin Net Turnover Volume (in USD millions)				
	Trader Type				
	Net Sellers Both	Reverse Capital Flight	Chinese Only	Capital Flight	Net Buyers Both
Δchinepu	0.686	-0.441	1.756	19.824	-3.561
	(2.2)	(0.727)	(8.825)	(15.818)	(6.243)
chinprem	0.228	-0.007	2.567*	6.309**	-0.04
	(0.248)	(0.082)	(1.306)	(2.73)	(2.201)
ntrans	-0.012	0.021	-0.313*	0.947***	-0.162
	(0.048)	(0.017)	(0.16)	(0.348)	(0.22)
usdfeespertran	3.458**	0.336**	-2.88*	-14.139***	34.456***
	(1.634)	(0.14)	(1.662)	(2.999)	(3.431)
sqvol	-0.405	0.036	-0.572	9.193	-4.299
	(0.799)	(0.267)	(5.346)	(11.093)	(4.186)
Months	0.271	0.022	2.489***	-0.871	1.296
	(0.204)	(0.066)	(0.678)	(1.141)	(1.042)
Intercept	-366.743	-29.051	-3344.235***	1162.51	-1749.73
	(275.925)	(88.566)	(913.319)	(1537.212)	(1407.174)
Adj Rsq	0.5990	0.4081	0.2310	0.4014	0.9026
N	78	78	78	78	78