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 one third of Chinese cryptocurrency exchange volume and is positively associated with Chinese economic policy uncertainty and the Bitcoin premium in Chinese Yuan, consistent the notion of safe haven effect and the pursuit of higher investment return. Capital flight trade users are less likely to be illicit users and so have different trade motives. After the crackdown of cryptocurrency exchanges by Chinese government in Sep 2017, Chinese users reduce their Bitcoin balances more than users from other regions of the world. 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 cryptocurrency exchange. The Bitcoin received by the Korean crypto 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 down[1] 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,

[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 computer in the node would need to have their ledgers to be erased for the cryptocurrency to be destroyed.

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 cryptocurrency 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 cryptocurrency exchanges. Our findings suggest that Bitcoin indeed allows for the circumventing of Chinese capital control.

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

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

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.

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 Cryptocurrency

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

1. Buy Bitcoin at a domestic cryptocurrency 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 involved. An individual first opens a wallet freely on the Bitcoin blockchain. She then purchases Bitcoin at a Chinese cryptocurrency 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 an intermediary. In this case as depicted in Appendix 1 Panel B, Bitcoin must be transferred between the wallets of the Chinese user to the intermediary. The transfer of Bitcoin from one wallet to another requires a miner fee. Once the Bitcoin is transferred, the intermediary sells the Bitcoin on the crypto exchange and transfers the fiat currency to the Chinese user's foreign account. In robustness tests we attempt to account for this extra step in classifying capital flight trades. We call this classification 'with intermediary'.

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

[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.

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 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 1 September 2011 (when Chinese Yuan Bitcoin prices begin) to 8th February 2018 (end of the blockchain sample data). We obtain Bitcoin blockchain transaction data as extracted by Kondor, Pósfai, Csabai and Vattay (2014) extended to 8th February 2018.[4] We obtain cryptocurrency 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)).

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

We further augment this data with Bitcoin wallet addresses of crypto exchanges from www.walletexplorer.com. Wallet-explorer.com collects crypto exchange wallets either from public sites or when transacting with those exchanges. The crypto exchange addresses are not a complete list of all wallets of an exchange nor does wallet-explorer not contain all cryptocurrency exchanges.[5] It does however contain major exchanges such at btcchina, bitfinex etc. We classify these exchanges by their physical location.

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 greatest post 2014. In Panel B, the volume in USD is largest 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 are able to identify users who trade on one or more crypto 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. 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 crypto exchanges (Chinese vs. non-Chinese). The categories are:

*Net sellers (both): Users with net selling in both Chinese and non-Chinese exchanges.

*Net buyers (both): Users with net buying in both Chinese and non-Chinese exchanges.

[5] Appendix 3 compares the self-reported crypto exchange volume to the actual blockchain transaction volume using crypto 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.

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

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

*Reverse capital control trades: 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 amount of net trading volume in Bitcoin for each trader group every day that trades with Chinese exchanges. Chinese only traders are the most dominant group making up about 52% of trades followed by capital flight trades making almost a third of trades. In USD in Figure 2 Panel B, Chinese only trades and capital flight trades each make up a third of sales. Chinese only trades are most dominant pre-2013 while capital flight trades feature most prominently in 2016 and 2017.

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

To delve deeper into capital flight trades, Figure 2 Panel C and Figure 2 Panel D show monthly net volume of capital flight trades in Bitcoin and converted to USD, respectively against the average Bitcoin network transaction fee and the BTC/CNY premium. 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 crypto exchanges.

4.2 Determinants of Capital Flight Trades

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

$$\text{Chin\_net}_{jt} = \text{Intercept}_0 + b_1 * \Delta\text{chinepu}_t + b_2 * \text{chinprem}_t + b_3 * \text{ntrans}_t + b_4 * \text{usdfeespertran}_t + b_5 * \text{sqvol}_t + b_6 * \text{dayid}_t + e_{it} \quad (1)$$

Where *Chin_net* is the unsigned net turnover on Chinese crypto 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, *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 A reports summary statistics Panel B the correlation matrix of variables and Panel C reports our coefficient estimates for the determinants of trading regression. 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 net trading by Chinese only trades is highest of 6,125.39 Bitcoin followed by capital flight trades of 4,380.87 Bitcoin. From Table 1 Panel B we find that capital flight trades are positively correlated to the CNY Bitcoin premium, Chinese policy uncertainty and to Chinese only trades. 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 and also when there is greater uncertainty. All trades groups are negatively correlated with volatility and with fees (with the exception of Both Buyers).

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

The regression results in Table 2 Panel A (in Bitcoin) and Panel B (in USD) shows that capital flight trader volume increase when Chinese policy uncertainty increases, a high Chinese Bitcoin premium, more trading on the Bitcoin network. Capital flight is lower with higher network fees and higher volatility of the Bitcoin price. This evidence suggests that capital flight trades are 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 Trades where an Intermediary is used

As a robustness check, in order to capture trading where an intermediary is possibly used as in Appendix 1 Panel B. We group users to include a potential intermediary using the following algorithm:

1. Every day, for each user ID (as defined in Kondor, Pósfai, Csabai and Vattay (2014)), count the number of trades it is involved in, excluding exchange trades.
2. For each transaction, assign all users within that transaction[6] a new cluster ID which is based on the user ID with the highest number of trades on the day.
3. For each user on the day, assign all trades by user based on the cluster ID with the highest trades.

Using this algorithm, users that trade with each other are clustered together. This means that if user A buys at a Chinese crypto exchange, User B sells at a non-Chinese crypto exchange and User A and B made a trade with each other on the same day, then we consider the trade to be a capital flight trade as User A and B are clustered together.

We apply this algorithm to classify trades for the determinants of capital flight trades regression using net trades of clustered users instead of single users. The results are in Table 2 Panel C (for Bitcoin) and Panel D (in USD). We find a similar some evidence of a similar effect, 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 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 losses. 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. We do this by estimating two components of profits: the intraday profit and the overnight profit from Bitcoin held. We calculate this every day based on the nearest 1 minute

[6] Note a single Bitcoin transaction can have multiple users in it, particularly on the receiving side.

Bitcoin price (in CNY or USD) using trade level data from Bitcoin exchanges from bitcoincharts.com.

Intraday profit calculates the realized US dollar profit from buying and selling Bitcoin between foreign and Chinese exchanges. The intraday profit for trader *i* on day *t* for capital flight or reverse capital flight traders is calculated as:

$$\begin{aligned} \mathrm{Intraday}_{it} &= \min\left(\mathrm{abs}(\mathrm{chinvolume}_{it}), \mathrm{abs}(\mathrm{nonchinvolume}_{it})\right) * \mathrm{dflight}_{i} \\ &\quad * \left(\mathrm{nonchinvwap}_{it} - \frac{\mathrm{chinvwap}_{it}}{\mathrm{usdcny}_{t}}\right) \end{aligned} \tag{2}$$

Where *chinvolume* is the signed net trading of Bitcoin on Chinese exchanges for trader i on day t, *nonchinvolume* is the signed net trading of Bitcoin on non-Chinese exchanges, *dflight* has a value of 1 if the trader is classified as a capital flight trader, -1 if a reverse capital flight trader and 0 for other trade types. *Chinvwap* is the volume weighted average Bitcoin price in CNY traded. *Nonchinvwap* is the volume weighted average price of bitcoin in USD traded. *usdncy* is the closing USD/CNY price on the day. Note that other trader types do not have intraday profit as they do not net buy in one exchange and net sell in the other.

Table 3 reports the results using the single user algorithm in column one and including the intermediary in column 2. The total intraday losses are between $1.67m to $1.89m USD for capital flight trades. This suggests that although the turnover is large, the net loss due to the CNY premium on Bitcoin is small. Reverse trades earn modest profits of between $0.42m to $0.524m USD consistent with collecting some of the gain from the CNY premium on Bitcoin.

4.5 Capital Flight Traders after the Chinese Crypto Ban

In September 2017, Chinese crypto exchanges closed due to orders from the Chinese government.[7] Reasons for the closures include curbing speculation on cryptocurrencies and the prevalence of using cryptocurrencies to circumvent capital controls. We use this shutdown to derive simple statistics for how it affected trading by trader types.

[7] https://www.coindesk.com/document-lists-closure-steps-for-chinas-bitcoin-exchanges/

Table 4 Panel A reports the total turnover (buying plus selling volume) of Bitcoin for each user type by the exchange they traded at (Chinese, non-Chinese or other trading. Panel B reports the average total turnover at the individual user level. We find that Chinese crypto exchange users traded 271,606 Bitcoin in the pre-shutdown period and only 1,671 Bitcoin in the post-shutdown period. These users traded even less on non-Chinese exchanges post shutdown of 924 Bitcoin which suggests that they are restricted in going to overseas exchanges. Non-Chinese crypto users continue to trade in non-Chinese exchanges post shutdown as do users that trade in both Chinese and non-Chinese exchanges. This suggest that those users that traded only on Chinese crypto exchanges are able to trade on non-Chinese crypto exchanges to some extent.

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

Turnover does not show the direction of trading by user groups. As such we also calculate the net trading (buy volume minus sell volume) during the pre/post shutdown periods. We expect there to be net buying during pre-shutdown and negative net selling post-shutdown for Chinese crypto users. Table 4 Panel C and Panel D report net trading at the aggregate and individual user level, respectively. We find some evidence of net selling during the post-shutdown period by Chinese crypto users using non-Chinese exchanges. Chinese crypto users net sold 275 bitcoin or 0.01 bitcoin per user on average. This is in stark contrast to non-Chinese crypto users who *bought* 45,739 Bitcoin from non-Chinese Exchanges during the post-shutdown period. This provides further evidence of Chinese users being able to utilise non-Chinese crypto exchanges after the shutdown.

Finally, we investigate the change in Bitcoin balances of different user types during the pre and post-shutdown period of different user types. It is possible that the shutdown caused Chinese users to wind down their use of cryptocurrency and so reduce their balances. On the other hand, Chinese users may want to hold onto Bitcoin if they think it is a good investment, despite the crypto ban. Panel E reports the total Bitcoin balances of the different user types on 31st August 2017 (pre-shutdown) and on 1st October 2017 (post-shutdown).

We find a large decline in the balances of Chinese crypto users of 63,467 Bitcoin or a 32.31% in their balances. Non-Chinese and Both users only experience modest declines in the same period. This suggests that Chinese crypto users exited the market after the crypto shutdown rather than decide to hold onto their balances.

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:

$$\text{Logit}(\text{illegal}_i{=}1) = b_0 + b_1{*}\text{ExchangeUser} + b_2{*}\text{ChinExchangeUser} + b_3{*}\text{Netseller\_pct}_i + b_4{*}\text{Reverse\_pct}_i + b_5{*}\text{Chineseonly\_pct}_i + b_6{*}\text{Capflight\_pct}_i + b_7{*}\text{Netbuyer\_pct}_i + b_8{*}\text{Logn}_i + b_9{*}\text{Logturnover}_i + b_{10}{*}\text{Logtradesize}_i + e_i \quad (3)$$

where illegal is a dummy of 1 if user i is classified as an illegal user in Foley et al. (2019), 0 otherwise. Every day for each user, we calculate net turnover to each counterparty (Chinese cryptocurrency exchanges, non-Chinese cryptocurrency exchanges and other counterparties). ExchangeUser is a dummy of 1 if the trader ever traded with a cryptocurrency exchange, 0 otherwise. ChinExchangeUser is a dummy of 1 if the trader ever traded with a Chinese cryptocurrency exchange, 0 otherwise. 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 that for days that they are net selling in both non-Chinese and Chinese cryptocurrency exchanges. Reverse_pct is the percentage of net trades that is buying in non-Chinese cryptocurrency exchanges and selling in Chinese exchanges. Chineseonly_pct is the percentage 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. Logturnover is natural log of buy and sell trades, halved, for a user. Logtradesize is the average USD trade size of a user's transactions.

We first check the extent of illegal trading by trading type classification in Table 5 Panel A. We find net seller and reverse capital flight trades are most likely groups to be illegal (92.94 and 90.06 percent respectively. In particular, the percentage of reverse trades being illegal over the years is between 87.11% to 99.30%. The lowest groups are Chinese only trades and Other trades (users that trade on non-Chinese exchanges only and/or unclassified trades) of 41.06% and 37% of trades. 52% of capital flight trades are classified as illegal which is the third lowest of all groups.

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

Table 5 Panel B reports the logistic regression results and confirms the simple statistics in Table 5 Panel A. On our control variables, trading at a Chinese exchange increases the probability of being an illegal user (unconditional on trade type), while having less trades, larger turnover and smaller average trade size increases the probability of being an illegal user.

On the trading type coefficients, users that do more net sell or reverse capital flight trades tend to be illegal users. In contrast, users that do more Chinese exchange only or capital flight trades are less likely to be illegal users. For example, the coefficient of Reverse_pct is 0.017 and statistically significant suggesting that an increase of reverse trading by 1% increases the probability of being an illegal user by 1.7%[8]. Similarly the coefficient for Capflight_pct is -0.007 and statistically significant which means an increase in capital flight trades by 1% leads to a reduction in probability the user is illegal by 0.7%. Overall our results suggest that capital flight trades are not for illegal purposes nor are they for arbitrage.

[8] Exp(0.017)= 1.017145.

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 do capital flight trades. We run the following regression:

$$\text{Chin\_net}_{jt} = \text{Intercept}_0 + b_1 * \Delta\text{chinepu}_t + b_2 * \text{chinprem}_t + b_3 * \text{ntrans}_t + b_4 * \text{usdfeespertran}_t + b_5 * \text{sqvol}_t + b_6 * \text{monthid}_t + e_{it} \quad (4)$$

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

Table 6 reports coefficient results of equation where the dependent variable is net trading over a week (Panel A), fortnight (Panel B) or month (Panel C) in USD.[9] The results are similar to our baseline results when using a weekly or fortnightly regression in the fact that capital flight trades are positively associated with changes in economic policy uncertainty and the Chinese premium in Bitcoin. For the monthly interval, 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 6 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

[9] We find qualitatively similar results in Bitcoin.

address of Chinese and non-Chinese cryptocurrency exchanges we find about a third of Chinese cryptocurrency Bitcoin buys are on sold on the same day at a non-Chinese exchange, 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. With the shutdown of Chinese crypto exchanges in Sep 2017, Chinese user holdings declined more than non-Chinese user holdings suggesting that this reduced capital flight trading. We therefore find direct evidence that Bitcoin can and is used to bypass Chinese capital control restrictions.

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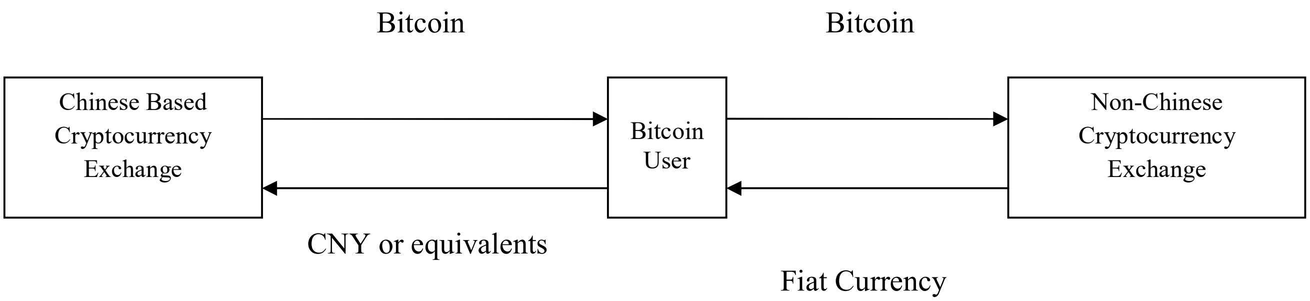
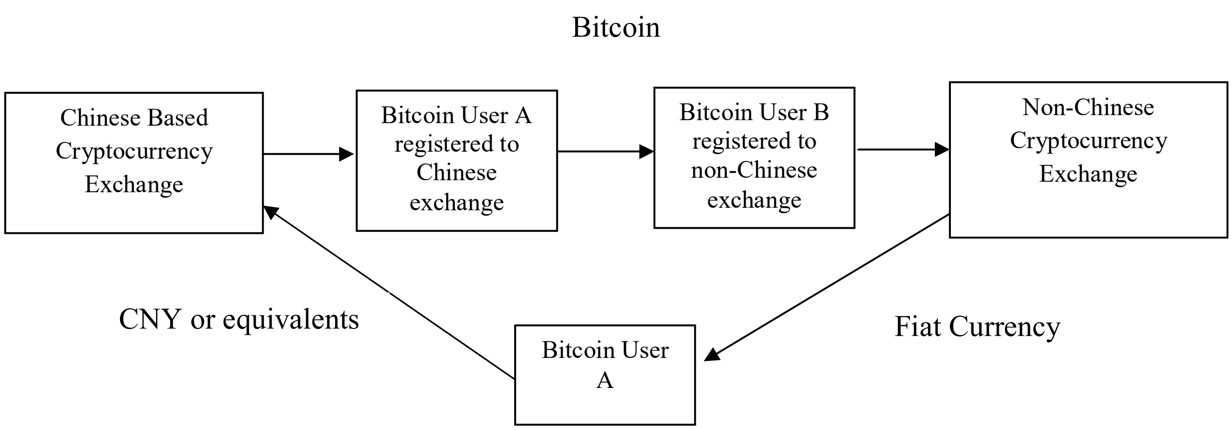
Appendix 1: Bitcoin Capital Control Circumvention

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

Panel A: Chinese Bitcoin User Registered to Both Chinese and Non-Chinese Exchanges



Panel B: Chinese Bitcoin User Only Registered to Chinese Exchange



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.
Crypto 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

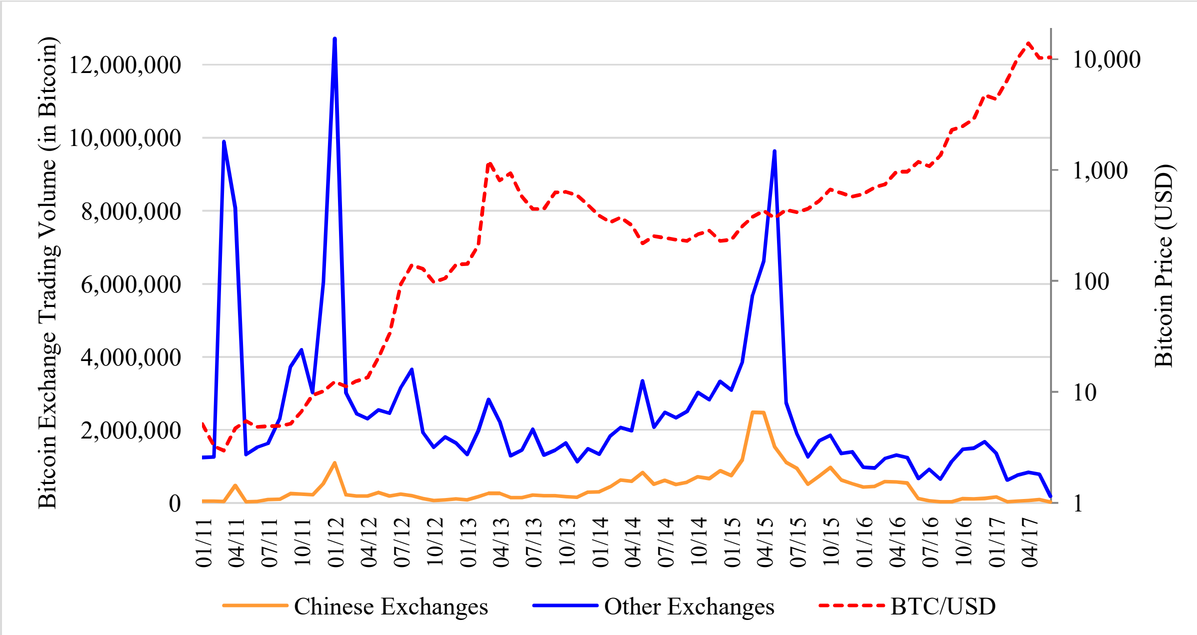
Appendix 3: Matched volume of Cryptocurrency Exchange Blockchain Trades to Self-Reported Trades

The table reports the percentage matched volume of cryptocurrency exchange volume on the Bitcoin blockchain to the volume self-reported by the exchanges. We calculate percentage matched volume as the cryptocurrency 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 cryptocurrency exchanges that have both blockchain and self-reported volume. We only keep exchange/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 cryptocurrency exchanges underreporting trades. We identify cryptocurrency exchange trades on the blockchain from known cryptocurrency exchange wallet addresses obtained from www.walletexplorer.com. Wallet Explorer collects publicly known addresses of cryptocurrency exchanges (e.g. advertised addresses) or from identifying wallets after trading with the cryptocurrency exchanges. We obtain self-reported trades from blockchain charts. Blockchain charts collects historical self-reported cryptocurrency trades from the exchange's application programming interface (API) feeds. The sample period is from 1st 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**

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

Panel A: Volume Measured in Bitcoin



Panel B: Volume Measured In USD

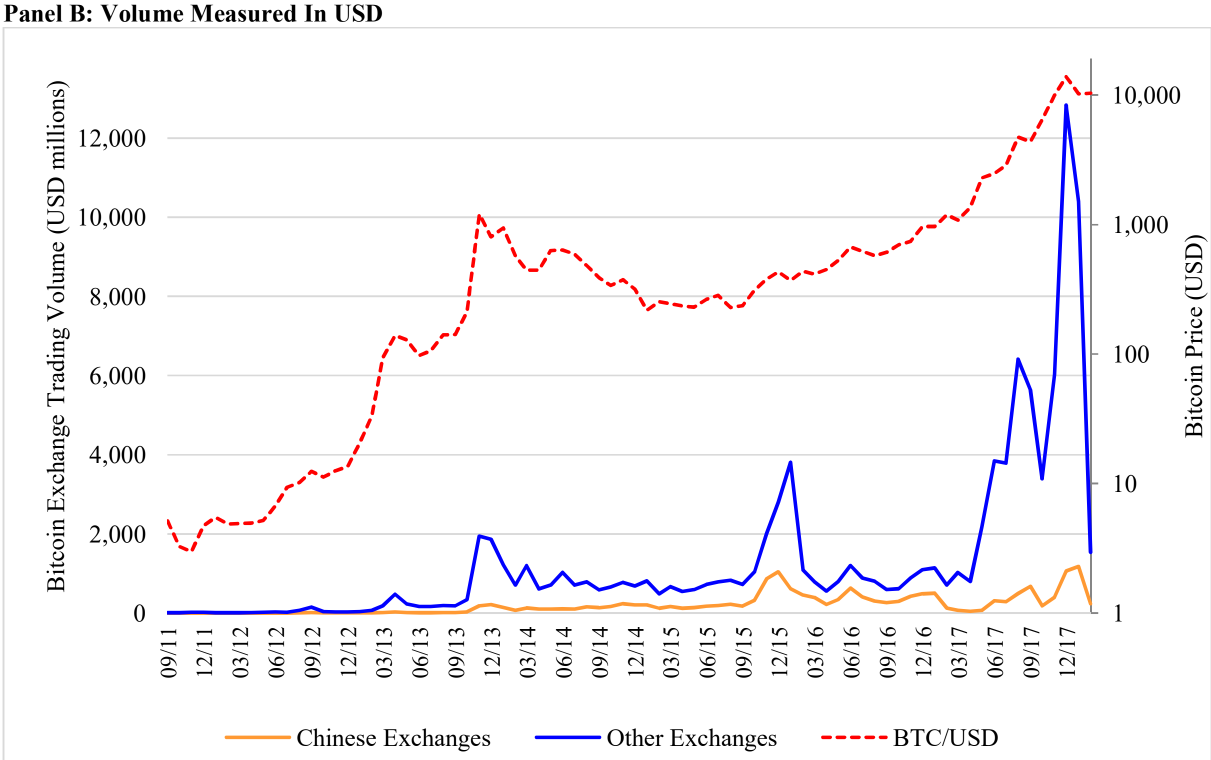
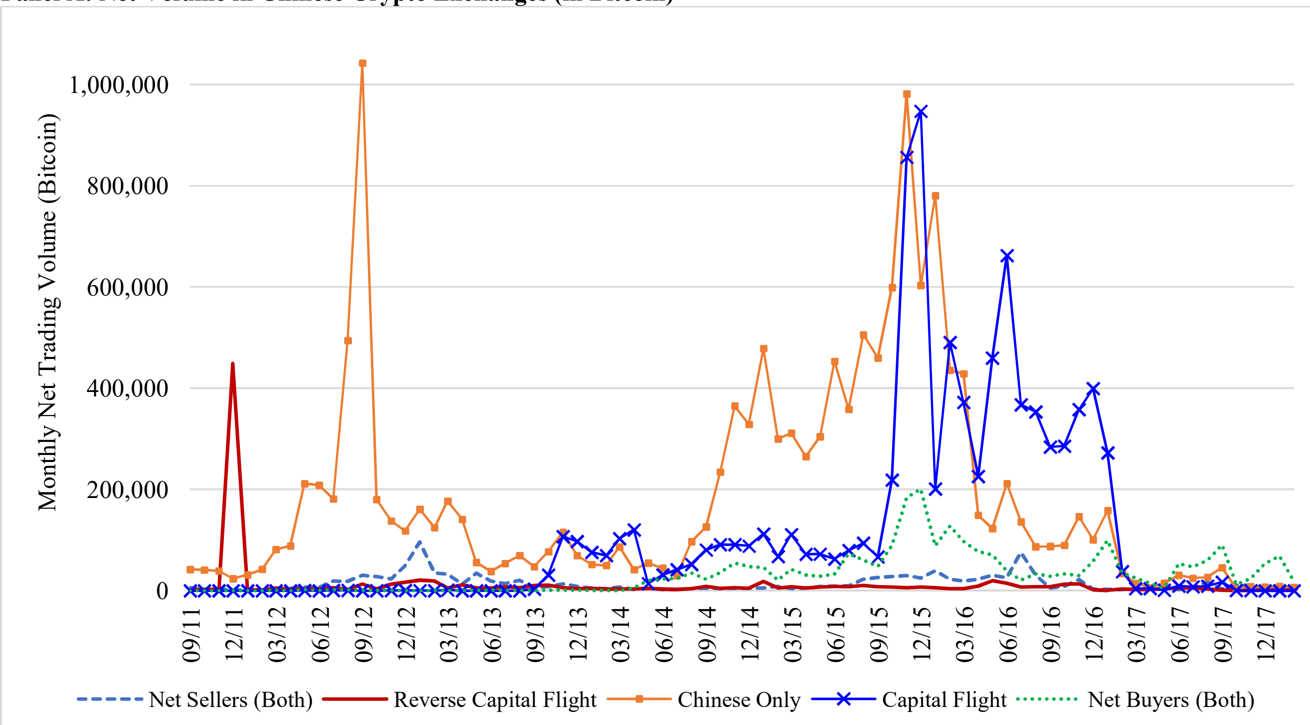


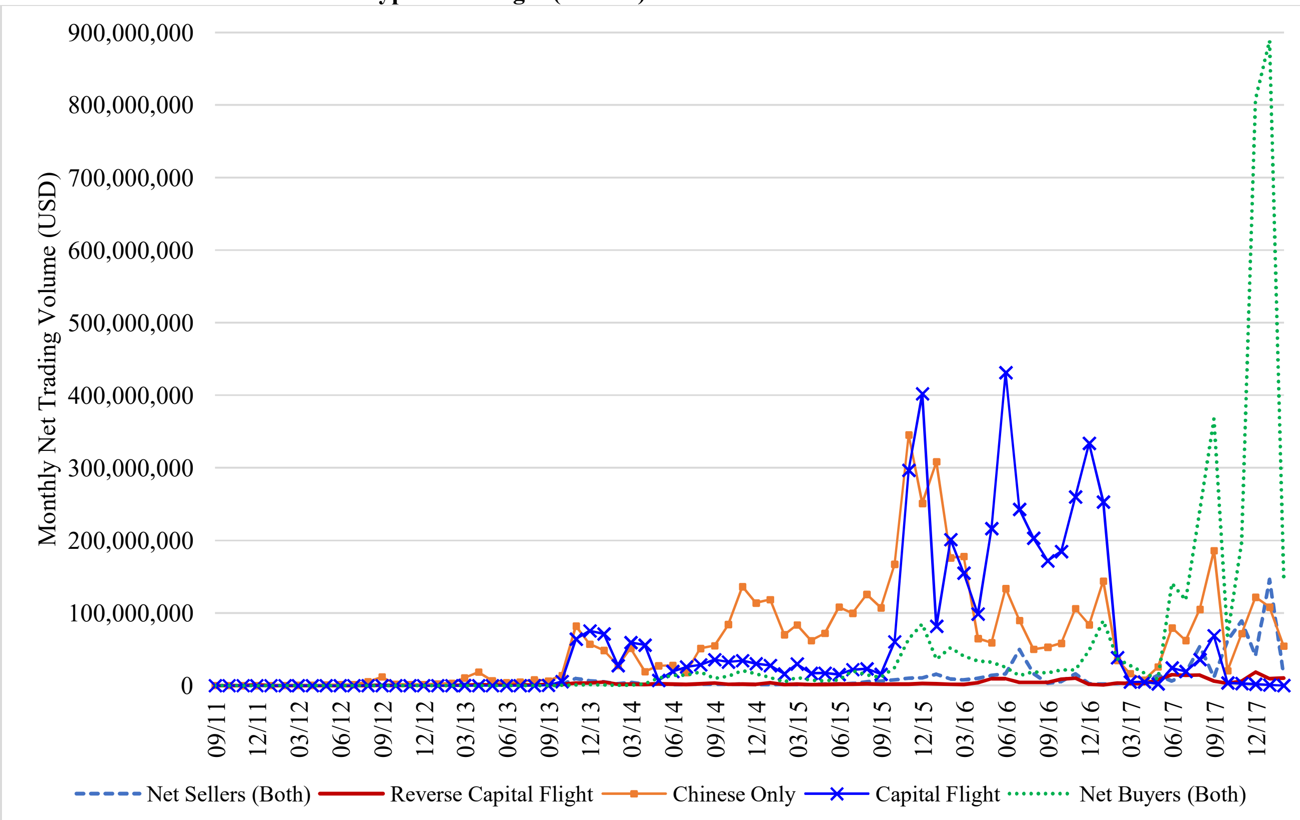
Figure 2: Monthly Absolute Bitcoin Net Volume from Chinese Crypto Exchanges by Trader Types

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



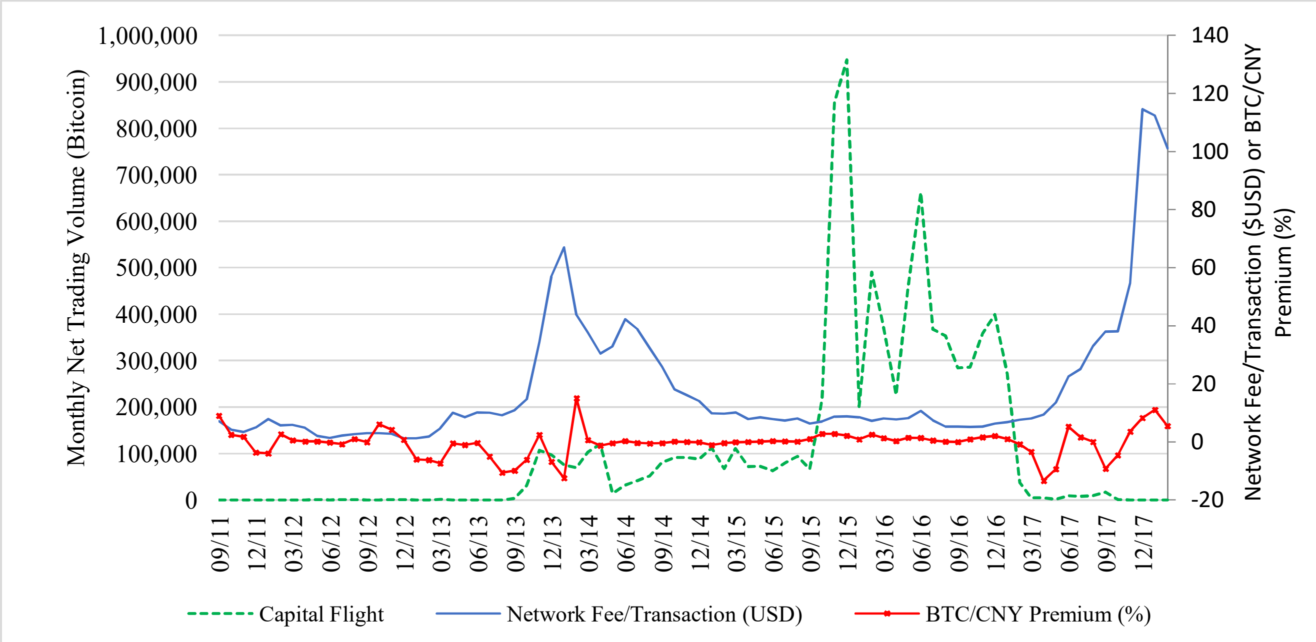
	Net Sellers (Both)	Reverse Capital Flight	Chinese Only	Capital Flight	Net Buyers (Both)
Net Volume (in Bitcoin)	1,127,618	931,877	14,394,657	8,691,273	2,452,274
% TOTAL	4.09%	3.38%	52.16%	31.49%	8.89%

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



	Net Sellers (Both)	Reverse Capital Flight	Chinese Only	Capital Flight	Net Buyers (Both)
Net Volume (in USD)	751,943,634	246,930,516	4,918,333,501	4,560,280,521	3,912,017,584
% TOTAL	5.23%	1.72%	34.18%	31.69%	27.19%

Panel C: Capital Flight Trades (in Bitcoin)



Panel D: Capital Flight Trades (in USD)

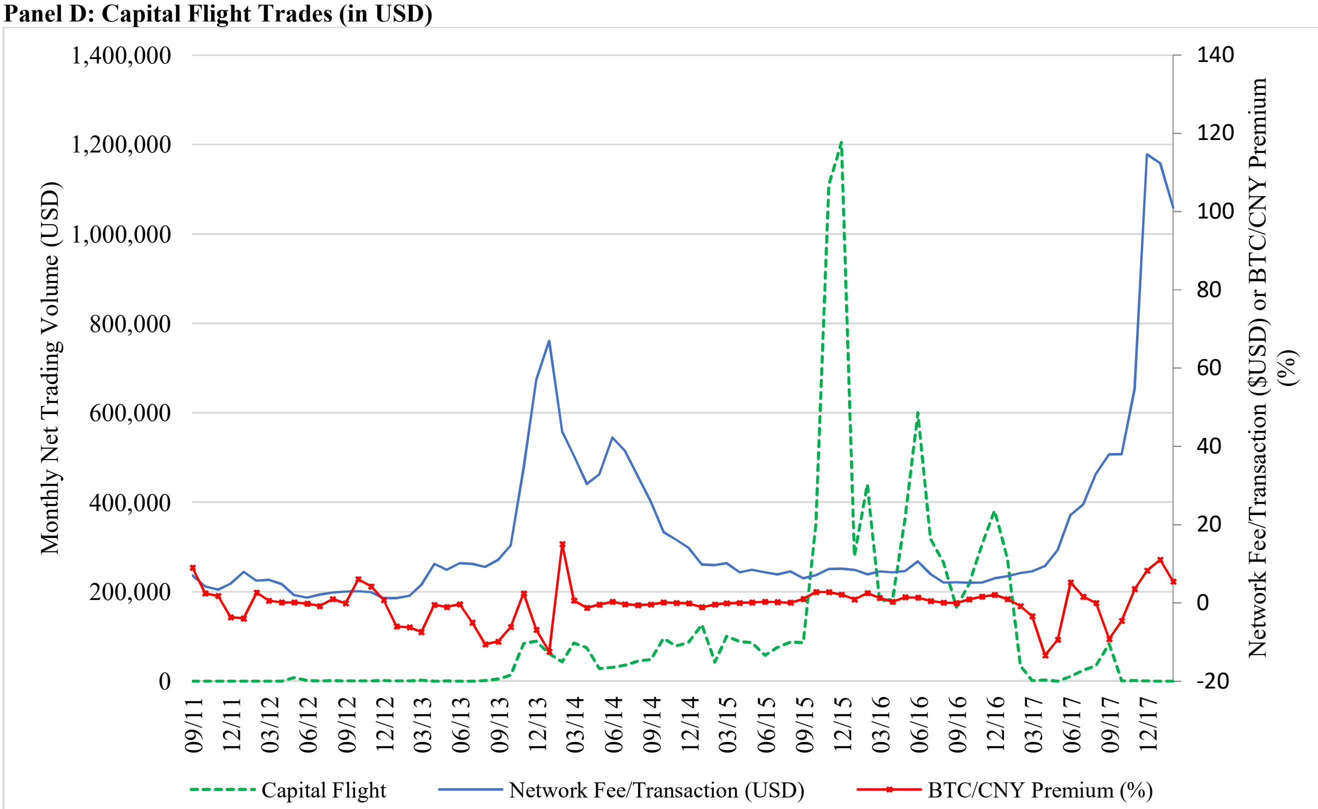


Table 1: Descriptive Statistics

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 cryptocurrency 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, *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. The sample is from 1 September 2011 to 8th February 2018. Panel A. reports various summary statistics. Panel B reports the correlation matrix of variables.

Panel A: Summary Statistics

Variable	Mean	Median	Std	P25	P75
bitcoin_return(usd)	0.54	0.21	-1.17	9.12	2.10
bitcoin_return(cny)	0.49	0.00	-0.82	6.25	1.59
Δchinepu	-0.33	0.07	-1.96	6.87	1.55
chinprem	0.64	0.26	0.11	1.09	0.68
ntrans	0.10	1.31	-50.67	97.09	64.18
usdfeespertran	1.13	0.08	0.03	4.53	0.19
sqvol	126,183.59	83,642.50	47,859.00	102,106.99	217,554.00
chin_net (net sellers)	2,405.18	872.08	326.13	5,438.62	2,354.00
chin_net (reverse capital flight)	2,356.77	1,287.02	619.36	18,548.60	2,403.30
chin_net (chinese only)	6,125.39	2,431.69	812.44	11,673.00	7,283.13
chin_net (capital flight)	4,380.87	593.70	0.01	8,195.51	4,513.32
chin_net (net_buyers)	2,546.17	1,093.33	58.66	3,840.62	3,247.42

Panel B: Correlation Matrix

No.	Variable	1	2	3	4	5	6	7	8	9	10	11	12
1	btcusd_return	1.00											
2	btccny_return	0.31	1.00										
3	chinprem	-0.14	0.09	1.00									
4	sqvol	-0.01	0.01	-0.11	1.00								
5	dchinepu	-0.02	-0.02	0.00	-0.02	1.00							
6	usdfeespertran	-0.01	0.03	0.20	-0.10	-0.10	1.00						
7	ntrans	0.00	0.03	0.06	-0.10	-0.01	0.42	1.00					
8	chin_net (net sellers)	-0.01	-0.01	0.00	-0.07	-0.02	0.00	0.15	1.00				
9	chin_net (reverse capital flight)	0.00	-0.04	-0.01	-0.01	-0.01	-0.01	-0.01	-0.00	1.00			
10	chin_net (chinese only)	-0.01	-0.02	0.07	-0.08	0.00	-0.11	-0.03	0.10	-0.01	1.00		
11	chin_net (capital flight)	-0.01	-0.00	0.13	-0.04	0.09	-0.11	0.35	0.09	-0.01	0.25	1.00	
12	chin_net (net buyers)	-0.02	-0.01	0.20	-0.19	-0.09	0.54	0.61	0.22	-0.01	0.08	0.27	1.00

Table 2: Determinants of Capital Flight Trade Volume

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

$$\text{Chin\_net}_{jt} = \text{Intercept}_0 + b_1 * \Delta\text{chinepu}_t + b_2 * \text{chinprem}_t + b_3 * \text{ntrans}_t + b_4 * \text{usdfeespertran}_t + b_5 * \text{sqvol}_t + b_6 * \text{dayid}_t + e_{it}$$

Where Chin_net is the unsigned net turnover 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, *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 1 September 2011 to 8th February 2018. Panel A reports results using Bitcoin net turnover volume (in Bitcoin). Panel B reports results using Bitcoin net turnover volume converted into USD. Panel C and Panel D calculate net turnover assuming a use of an intermediary in Bitcoin and USD, respectively. Standard errors in parentheses. ***, **, * signifies statistical significance at the 1, 5 and 10 percent level, respectively.

Panel A. Bitcoin Net Turnover Regression (in Bitcoin)

Dependant Variable:	Bitcoin Net Turnover Volume (in Bitcoin)				
	Trader Type				
	Net Sellers Both	Reverse Capital Flight	Chinese Only	Capital Flight	Net Buyers Both
Δchinepu	-1.335	-2.080	-0.998	5.83***	-1.999***
	(1.11)	(1.918)	(2.497)	(2.005)	(0.709)
chinprem	3.117	-14.736	150.864***	290.167***	63.616***
	(11.687)	(29.069)	(25.112)	(32.494)	(13.403)
ntrans	0.003	0.012	-0.02***	0.052***	0.000
	(0.003)	(0.009)	(0.005)	(0.006)	(0.002)
usdfeespertran	-94.176***	-43.395*	-381.366***	-726.954***	263.1***
	(14.484)	(23.695)	(44.754)	(77.838)	(25.118)
sqvol	-348.548***	-228.816	-954.172***	-309.429***	-396.799***
	(47.057)	(168.666)	(138.571)	(117.482)	(39.448)
dayid	1.08**	-2.174	3.597***	-2.154***	2.842***
	(0.454)	(2.182)	(0.758)	(0.792)	(0.314)
Intercept	1116.474***	3649.419*	5526.237***	2240.466***	-893.196***
	(210.94)	(1953.922)	(588.531)	(456.242)	(163.508)
Adj Rsq	0.0324	-0.0012	0.0329	0.227	0.489
N	2,343	2,318	2,350	1,786	1,981

Panel B. Bitcoin Net Turnover (in USD) Regression

Dependant Variable:	Bitcoin Net Turnover Volume (in USD)				
	Trader Type				
	Net Sellers Both	Reverse Capital Flight	Chinese Only	Capital Flight	Net Buyers Both
Δchinepu	396.686	-853.716	2,210.084***	7,940.761***	-8,676.726**
	(2,110.525)	(1,354.849)	(834.029)	(1,161.542)	(3,413.602)
chinprem	-61,532.631*	-16,860.986	51,507.087***	12,2401.542***	277,650.174**
	(35,447.283)	(17,131.633)	(9,058.628)	(17,637.146)	(111,908.324)
ntrans	5.848	10.901	-4.931***	36.847***	51.239**
	(8.569)	(7.224)	(1.675)	(3.776)	(20.295)
usdfeespertran	33,4705.981***	267,618.214***	-54,910.21***	-376,964.13***	6,215,482.055***
	(85,377.479)	(58,797.536)	(15,901.572)	(37,255.197)	(450,609.778)
sqvol	-810,288.024***	-191,752.275**	-153,406.867***	-49,634.508	-546,195.069***
	(120,053.314)	(77,517.095)	(4,4886.407)	(59,017.808)	(135,554.705)
dayid	4,175.755***	921.612	2,676.486***	-1,549.131***	-2,760.181
	(1,205.294)	(1,147.549)	(210.798)	(507.311)	(2,830.349)
Intercept	-255,5792.065***	-817,389.102**	-258,436.325***	379,757.17	-1,064,749.147
	(383,653.879)	(358,883.509)	(68,280.845)	(258,372.093)	(1,159,610.916)
Adj Rsq	0.1465	0.1708	0.1329	0.2882	0.7689
N	2,343	2,318	2,350	1,786	1,981

Panel C. Bitcoin Net Turnover with Intermediary Regression (in Bitcoin)

Dependant Variable:	Bitcoin Net Turnover Volume (in Bitcoin)				
			Trader Type		
	Net Sellers Both	Reverse Capital Flight	Chinese Only	Capital Flight	Net Buyers Both
Δchinepu	6.893	15.518	0.113	5.676	-2.266*
	(7.717)	(10.518)	(1.767)	(3.623)	(1.328)
chinprem	40.793	-192.583	136.154***	347.395***	128.953***
	(71.022)	(194.593)	(18.728)	(47.64)	(16.693)
ntrans	0.085***	0.04**	-0.031***	0.055***	0.000
	(0.012)	(0.02)	(0.004)	(0.01)	(0.004)
usdfeespertran	-161.995*	132.438	-318.205***	-871.477***	238.308***
	(95.926)	(115.729)	(36.895)	(95.709)	(28.665)
sqvol	-1,732.571***	-862.456*	-706.02***	-643.883***	-594.238***
	(444.188)	(463.743)	(90.224)	(152.222)	(77.012)
dayid	-22.351***	-13.464**	6.106***	-0.63	3.633***
	(1.957)	(5.277)	(0.609)	(1.311)	(0.585)
Intercept	27,068.443***	17,706.144***	1,892.66***	2961.62***	632.25**
	(1821.068)	(4704.324)	(371.901)	(662.838)	(268.008)
Adj Rsq	0.04268	0.01195	0.07367	0.1044	0.2557
N	2,313	2,340	2,350	1,905	1,977

Panel D. Bitcoin Net Turnover with Intermediary Regression (in USD)

Dependant Variable:	Bitcoin Net Turnover Volume (in USD)				
			Trader Type		
	Net Sellers Both	Reverse Capital Flight	Chinese Only	Capital Flight	Net Buyers Both
Δchinepu	5,859.818**	2,055.485*	1,385.07**	11,155.839***	-13,447.827***
	(2,734.809)	(1,116.85)	(562.695)	(2,161.189)	(4,353.901)
chinprem	13,399.56	-50,535.796**	43,272.408***	-1,225.086	432,391.769***
	(12,181.624)	(1,9785.33)	(6,619.817)	(48,874.167)	(123,864)
ntrans	5.679	1.081	-6.655***	31.944***	74.217***
	(3.999)	(6.907)	(1.248)	(7.61)	(22.825)
usdfeespertran	-96,464.176***	75,912.978**	-81,380.969***	-353,803.417***	8,229,390.289***
	(35,295.627)	(35,368.058)	(11,809.457)	(35,190.844)	(554,600.234)
sqvol	280,004.358*	35,091.292	-176,836.709***	-418,246.018***	-342,335.809*
	(152,039.451)	(86,307.449)	(2,7240.245)	(88,744.117)	(185,628.067)
dayid	599.407*	1,642.139	2,347.619***	2,809.441**	-7,214.545**
	(345.407)	(1,069.575)	(161.449)	(1,267.278)	(3,264.925)
Intercept	419,818.696***	-210,291.429	-147,730.775***	-2,337,967.074***	1,478,276.324
	(121,036.333)	(302,289.08)	(46,983.865)	(657,092.111)	(1,313,323.77)
Adj Rsq	0.005890	0.05552	0.1554	0.1565	0.8000
N	2,313	2,340	2,350	1,905	1,977

Table 3: Profits from Trade

The table reports the total USD profit statistics for traders from 1 January 2011 to 8th February 2018. Profits are converted into USD. Trade profit is the profit made from buying and selling the same amount of Bitcoin on the same day.

Trader Type	Intraday Profit	Intraday Profit (with Intermediary)
Net Seller	0	0
Reverse Capital Flight	420,780	524,073
Chinese Only	0	0
Capital Flight	-1,677,619	-1,890,974
Net Buyer	0	0

Table 4: Turnover Statistics by Trader Type Pre and Post Shutdown of Chinese Crypto-Exchanges

Panel A. Total Turnover by Trader Type and Venue Pre and Post Chinese Crypto Shutdown (in Bitcoin)

User Type	Pre-Shutdown			Post-Shutdown			N Users
	Chinese Exchange	Non-Chinese Exchange	Other Trading	Chinese Exchange	Non-Chinese Exchange	Other Trading	
Chinese Only	271,606	0	1,237,381	1,671	924	157,370	36,120
Non-Chinese Only	0	4,429,399	25,373,779	7,998	240,440	4,116,854	798,589
Net Buy or Sell	1,772,932	13,500,727	233,279,949	311,347	3,405,671	97,747,361	15,905
Other	0	0	4,225,081	167,187	1,701,168	20,200,844	645,058

Panel B. Average Individual User Turnover by Trader Type and Venue of Trading Pre and Post Chinese Crypto Shutdown (in Bitcoin)

User Type	Pre-Shutdown			Post-Shutdown			N Users
	Chinese Exchange	Non-Chinese Exchange	Other Trading	Chinese Exchange	Non-Chinese Exchange	Other Trading	
Chinese Only	7.52	0.00	34.26	0.05	0.03	4.36	36,120
Non-Chinese Only	0.00	5.55	31.77	0.01	0.30	5.16	798,589
Net Buy or Sell	111.47	848.84	14667.08	19.58	214.13	6145.70	15,905
Other	0.00	0.00	6.55	0.26	2.64	31.32	645,058

Panel C. Total Net Trading by Trader Type and Venue of Trading Pre and Post Chinese Crypto Shutdown (in Bitcoin)

User Type	Pre-Shutdown			Post-Shutdown			N Users
	Chinese Exchange	Non-Chinese Exchange	Other Trading	Chinese Exchange	Non-Chinese Exchange	Other Trading	
Chinese Only	40,094	0	-76,654	1,067	-275	-22,228	36,120
Non-Chinese Only	0	-1,187,564	757,274	3,058	45,739	-413,930	798,589
Net Buy or Sell	-49,810	-6,795,859	3,532,522	-27,148	-352,841	-414,553	15,905
Other	0	0	-1,410,071	-25,332	-22,952	-1,320,220	645,058

Panel D. Average Individual User Net Trading by Trader Type and Venue of Trading Pre and Post Chinese Crypto Shutdown (in Bitcoin)

User Type	Pre-Shutdown			Post-Shutdown			N Users
	Chinese Exchange	Non-Chinese Exchange	Other Trading	Chinese Exchange	Non-Chinese Exchange	Other Trading	
Chinese Only	1.11	0.00	-2.12	0.03	-0.01	-0.62	36,120
Non-Chinese Only	0.00	-1.49	0.95	0.00	0.06	-0.52	798,589
Net Buy or Sell	-3.14	-427.82	222.38	-1.71	-22.21	-26.10	15,905
Other	0.00	0.00	-2.18	-0.04	-0.04	-2.04	645,058

Panel E. Total Bitcoin Balances by User Type Pre and Post Shutdown

User Type	Pre-Shutdown Balance	Post Shutdown Balance	Change in Balance	Percentage Change in Balance (%)	N Users
Chinese Only	196,406	132,939	-63,467	-32.31	36,120
Non-Chinese Only	2,278,927	2,148,037	-130,889	-5.74	798,589
Net Buy or Sell	741,137	688,595	-52,543	-7.09	15,905
Other	3,294,641	3,323,847	29,206	0.89	645,058

Table 5: Probability of Illegal Trading by Users

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

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

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 cryptocurrency exchange, 0 otherwise. ChinExchangeUser is a dummy of 1 if the trader ever traded with a Chinese cryptocurrency exchange, 0 otherwise. Every day for each user, we calculate net turnover to each counterparty (Chinese cryptocurrency exchanges, non-Chinese cryptocurrency 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* that for days that they are net selling in both non-Chinese and Chinese cryptocurrency exchanges. Reverse_pct is the percentage of net trades that is buying in non-Chinese cryptocurrency 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. Logturnover is natural log of buy and sell trades, halved, for a user. Logtradesize is the average USD trade size of a user's transactions. 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**	**All Trades**
2011	Legal	0.28	0.02	6.79	0.00	0.00	61.13
	Illegal	0.26	3.05	0.49	0.00	0.00	49.17
	Illegal (%)	48.00	99.30	6.76	100.00	99.42	44.58
2012	Legal	1.86	0.02	12.91	0.02	0.00	109.93
	Illegal	6.02	5.61	14.74	0.14	0.54	109.44
	Illegal (%)	76.40	99.68	53.31	85.48	99.75	49.89
2013	Legal	24.64	5.60	149.00	6.48	2.03	1,105.52
	Illegal	48.40	110.97	87.80	148.29	15.31	1,075.97
	Illegal (%)	66.26	95.19	37.08	95.82	88.29	49.32
2014	Legal	23.58	21.88	498.81	10.49	20.12	1,124.24
	Illegal	72.79	352.31	196.77	461.06	227.27	1,638.23
	Illegal (%)	75.53	94.15	28.29	97.78	91.87	59.30
2015	Legal	160.31	40.81	508.99	623.83	100.68	2,014.32
	Illegal	172.56	175.98	1,137.89	438.21	279.73	1,099.29
	Illegal (%)	51.84	81.17	69.09	41.26	73.53	35.31
2016	Legal	81.47	27.86	992.22	1,800.57	130.40	2,964.08
	Illegal	562.27	359.09	465.25	1,375.42	523.05	770.32
	Illegal (%)	87.34	92.80	31.92	43.31	80.04	20.63
2017	Legal	165.76	291.64	717.89	271.28	3,581.73	8,512.58
	Illegal	5,100.40	2,591.86	200.04	524.68	9,232.80	4,940.00
	Illegal (%)	96.85	89.89	21.79	65.92	72.05	36.72
2018	Legal	37.97	36.42	150.44	1.15	3,037.41	2,669.03
	Illegal	466.30	246.14	13.01	2.21	3,530.41	1,194.76
	Illegal (%)	92.47	87.11	7.96	65.69	53.75	30.92
All	Legal	495.87	424.25	3,037.07	2,713.81	6,872.36	18,560.83
	Illegal	6,429.01	3,845.01	2,116.01	2,950.01	13,809.11	10,877.19
	Illegal (%)	92.84	90.06	41.06	52.09	66.77	36.95

Panel B. Logit Regression

Dependent Variable: Variable	Logit($illegal_i$=1) Coefficient
ExchangeUser	-0.2910
	(0.2099)
ChinExchangeUser	0.154***
	(0.0092)
Netseller_pct	0.018***
	(0.0001)
Reverse_pct	0.017***
	(0.0002)
Chineseonly_pct	-0.001***
	(0.0001)
Capflight_pct	-0.007***
	(0.0002)
Netbuyer_pct	-0.003***
	(0.0004)
logn	-0.213***
	(0.0004)
logturnover	0.373***
	(0.0002)
logtradesize	-0.377***
	(0.0002)
Intercept	1.297***
	(0.0013)
Adj Rsq	0.0821
N	64,406,044

Table 6: Capital Flight Traders Classification by Weekly, Fortnightly and Monthly

The table estimates the following regression:

$$\text{Chin\_net}_{jt} = \text{Intercept}_0 + b_1 * \Delta\text{chinepu}_t + b_2 * \text{chinprem}_t + b_3 * \text{ntrans}_t + b_4 * \text{usdfeespertran}_t + b_5 * \text{sqvol}_t + b_6 * \text{monthid}_t + e_{it}$$

Where Chin_net is the unsigned net turnover for trader type j in period t (week, fortnight or month). 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 trades over period t. USDfeespertran is the daily average fee per trade in USD over period t. Monthid is the number of months since the start of the sample period. The sample is from 1 September 2011 to 8th February 2018. Panel A reports results using weekly Bitcoin net turnover volume converted into USD. Panel B and C net 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. 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	13.679	-7.377	9.88	45.604***	-90.489*
	(40.282)	(14.56)	(9.454)	(17.573)	(47.978)
chinprem	-441.093	-230.534	530.146***	1,076.335***	2,140.13*
	(1,053.536)	(220.945)	(166.264)	(298.735)	(1,214.555)
ntrans	0.11	0.128**	-0.048**	0.233***	0.224
	(0.161)	(0.052)	(0.021)	(0.055)	(0.306)
usdfeespertran	2,525.74	2,603.804***	-509.813**	-2705.176***	47,010.313***
	(1,582.661)	(438.163)	(199.297)	(456.408)	(5,938.967)
sqvol	-8,173.615***	151.226	-530.854	740.09	-6,220.63**
	(3,025.607)	(1,227.362)	(663.752)	(1,112.289)	(2,904.314)
dayid	881.595	33.387	537.524***	-206.454	63.584
	(716.426)	(232.391)	(78.11)	(190.688)	(1,170.914)
Intercept	-1,201,624.051	-49,026.164	-722,344.804***	276,684.034	-95,886.431
	(967,208.813)	(313,736.807)	(105,246.606)	(257,284.606)	(1,579,368.919)
Adj Rsq	0.1792	0.4521	0.2041	0.3365	0.8265
N	342	342	342	317	333

Panel B. 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	-31.934	-25.894	20.103	111.286**	-246.401
	(108.437)	(37.601)	(23.276)	(46.775)	(161.183)
chinprem	-1,081.925	-610.755	1,203.799***	2,679.89***	5,049.935
	(2,842.323)	(569.008)	(448.191)	(896.241)	(3,655.196)
ntrans	0.34	0.227**	-0.132***	0.433***	0.13
	(0.402)	(0.105)	(0.051)	(0.143)	(0.515)
usdfeespertran	9,627.404	8,945.039***	-1,011.904*	-5,861.334***	122,434.313***
	(7,946.62)	(1,006.311)	(517.211)	(1,735.875)	(30,060.244)
sqvol	-18,277.942**	857.195	-121.453	3,431.474	-8,503.178
	(8,891.616)	(3,557.173)	(1604.939)	(3044.02)	(8,841.552)
dayid	1,293.483	97.264	1,154.461***	-231.674	748.801
	(1,816.142)	(506.786)	(206.114)	(489.597)	(1,853.096)
Intercept	-1,768,254.876	-137,359.073	-1,551,832.17***	307,303.462	-1,022,891.537
	(2,452,135.951)	(684,612.689)	(277,664.455)	(659,960.795)	(2,500,671.057)
Adj Rsq	0.2345	0.6111	0.2299	0.3713	0.8610
N	168	168	168	164	167

Panel C. 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	-79.007	-54.319	-143.315	167.517	-68.73
	(125.757)	(77.135)	(226.636)	(293.797)	(88.325)
chinprem	85.005	-2,089.501	7,214.32**	1,6945.509**	1,632.796
	(2,979.367)	(3,131.04)	(3,496.134)	(6,455.736)	(2,423.072)
ntrans	0.081	0.531*	-0.826	1.433*	-0.246
	(0.377)	(0.306)	(0.554)	(0.733)	(0.33)
usdfeespertran	-4,783.237**	-2,193.22	-1,2491.816**	-33,085.831***	11,871.076***
	(2,292.789)	(1,719.343)	(5,142.101)	(8,043.976)	(2,321.354)
sqvol	-1,4397.306*	-779.795	-29,894.772*	12,773.745	-16,683.088***
	(7,911.839)	(15,571.792)	(17,050.574)	(26,691.295)	(5,838.622)
dayid	1,896.903	-2,518.91	3,444.173	447.674	3,761.951**
	(1,729.911)	(2,068.854)	(2,815.265)	(2,650.298)	(1,479.592)
Intercept	-2,519,590.631	3,514,319.021	-4,457,933.762	-605,961.837	-5,067,622.434**
	(2,334,092.155)	(2,831,842.621)	(3,818,425.597)	(3,574,741.156)	(1,997,286.898)
Adj Rsq	0.1594	-0.03571	0.05121	0.3176	0.6865
N	78	78	78	78	78