Evading Capital Controls via Cryptocurrencies: Evidence from the Blockchain

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Abstract

To what extent are cryptocurrencies used to evade cross-border capital controls? We develop a new method that exploits blockchain data to identify such activities. We find that capital flight out of China is economically meaningful, accounting for over one-quarter of Chinese Bitcoin exchange volume. Capital flight increases with economic policy uncertainty and results in a Bitcoin price premium against the Chinese Yuan, ruling out alternative explanations such as arbitrage. Individuals engaging in capital flight are less likely to use Bitcoin to trade illegal goods or services, suggesting that capital flight has different motivations to other criminal activities.

Keywords: bitcoin, blockchain, capital flight, cryptocurrency, capital control

JEL Codes: G15, G18

1. Introduction

Many countries use "capital-flow management" measures (CFMs) to address the negative impacts of substantial and volatile capital flows (Forbes et al., 2015). These measures aim to mitigate the risks associated with capital flight, which can be particularly severe in countries with developing capital markets or unstable currencies. For instance, China has long imposed restrictions on its citizens, limiting their annual outbound remittance to no more than USD $50,000. Despite the existence of capital restrictions, individuals continually seek out various means to circumvent these limitations. In this paper, we examine how the emergence of cryptocurrencies has introduced a potentially fast and low-cost avenue for capital flight.

Bitcoin, as the first and most popular decentralized and pseudonymous cryptocurrency, has gained attention as a potential tool for capital flight due to its unique characteristics. First, Bitcoin transactions are conducted using cryptographic addresses that do not directly reveal the identity of the individuals involved. This feature provides a certain level of anonymity, making it challenging for authorities to trace the flow of funds or identify the parties engaging in capital flight. Second, Bitcoin operates on a global scale, allowing for relatively frictionless cross-border transactions. This capability makes it attractive for individuals seeking to move funds out of a country with capital restrictions, bypassing traditional banking channels and regulatory oversight. Third, there is no centralized control as Bitcoin operates outside the control of central banks or governments. As a result, it is not subject to traditional capital controls or regulatory measures imposed by financial authorities. This decentralized nature makes it more difficult for authorities to enforce capital restrictions effectively.

Anecdotal evidence suggests a prevailing trend of using Bitcoin to circumvent capital controls. A recent criminal prosecution involving a South Korean police officer illustrates how cryptocurrencies are employed for this purpose. The officer was indicted for orchestrating a scheme that enabled the transfer of USD $11 million of Chinese Yuan (CNY) out of China to South Korea via Bitcoin. The process involved: (i) purchasing Bitcoin with CNY from Bitcoin exchanges in China, (ii) transferring the acquired Bitcoins via the blockchain to a Bitcoin exchange in Korea, and (iii) subsequently selling the Bitcoins in Korea for a fiat currency other than CNY.[1] While such cases provide anecdotal evidence that cryptocurrencies are used to evade capital controls, little is known on the scale of such cryptocurrency-facilitated capital flight, its characteristics, and how to identify/measure it.

[1] See Helms (2017). 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). For a more recent example, see Zhao (2020).

We address these issues by developing a simple method to quantify capital flight trades using the transparency of blockchain data. We leverage a comprehensive transaction-level dataset obtained from the Bitcoin blockchain, including information about the sender and recipient wallet addresses, timestamps, block IDs, and transaction amounts. Our method involves reconstructing fund flows from one fiat currency to another across borders, via cryptocurrencies as intermediaries that circumvent capital controls. We then isolate the cross-border flows with characteristics indicative of intentional circumvention of capital controls.

One of the key features that distinguishes capital flight is that such transactions fit the notion of "uneconomical trades"[2], meaning that individuals willingly pay a premium (incur a loss) to exchange one fiat currency for another via a cryptocurrency. For example, an individual with $100,000 worth of CNY might exchange it for Bitcoins in China, transfer the Bitcoins abroad, and then sell them in an overseas exchange for $95,000, effectively paying a $5,000, or 5%, premium to obfuscate the capital outflow via a cryptocurrency compared to just exchanging CNY for USD. This characteristic enables us to rule out profit-motivated trading, speculation, and many other possibilities where one would expect the opposite flow. The premium arises from the price pressure created by capital flight itself—when there is a large demand to convert from fiat currency A to fiat currency B via cryptocurrency C, the price of C will become relatively expensive in units of A and relatively cheap in units of B, much like exchange rates appreciate or depreciate in response to currency flows. In effect, capital flight trades are the opposite of arbitrage trades—individuals lose money on the capital flight trade, which is the cost to an individual of bypassing capital control regulations.

We apply the method to quantify the extent of capital flight from China to USD via cryptocurrencies from 2011 to 2018, a period marked by stringent capital outflow restrictions. Our findings reveal a significant volume of capital flight from China throughout the sample period. Specifically, we estimate that over one-quarter of the trading volume on Chinese Bitcoin exchanges is associated with circumventing China's capital controls. In terms of monetary value, the capital flight out of China via Bitcoin during the sample period amounts to approximately USD $4.6 billion. In Bitcoin units, this corresponds to around 8.78 million Bitcoins. To put that into perspective, the total number of Bitcoins in circulation as of January 2019 was just over 18 million. This implies that nearly half of the Bitcoin supply has been utilized for evading China's capital controls.[3] These findings shed light on the

[2] The notion of "uneconomical trades"—trades that are clearly unprofitable absent some alternate motive—is often used in defining and identifying market manipulation (e.g., Ledgerwood and Carpenter, 2012; Perdue, 1987). In contrast, economical trades, such as for Bitcoin triangular arbitrage, tend to be few and made by sophisticated users (e.g., Saggese et al., 2021).

[3] It is worth noting that this comparison is made between a flow (capital flight) and a stock (Bitcoin supply).

significant scale of capital flight facilitated by cryptocurrencies, particularly Bitcoin, as a means to bypass China's capital controls. Considering the scale of these flows, it is plausible that capital flight contributes to the congestion on the blockchain, resulting in elevated fees for all users, not just those engaged in capital flight, akin to the impact observed during surges in ransomware incidents (see Sokolov, 2021).

We then examine the potential factors influencing the intensity of capital flight through Bitcoin. Prior literature documents that the tendency towards flight-to-safety is more pervasive when investors face heightened level of risk and uncertainty (Longstaff, 2004; Beber, Brandt and Kavajecz, 2009; Baele et al., 2020; Adrian, Crump, and Vogt, 2019). Consistent with investors' motive of seeking a safe haven for their domestic assets in China, we find that the intensity of capital flight out of China via Bitcoin increases during periods of elevated economic policy uncertainty in China. During episodes of heightened economic policy uncertainty in China, we observe a decrease in the demand for CNY and a simultaneous rise in the demand for USD. Consequently, more capital is channeled out of China through Bitcoin as individuals seek to safeguard their assets in a more stable currency, such as USD. This supports the notion that capital flight through Bitcoin serves as a response to economic policy uncertainty, providing investors with an avenue to diversify their holdings and mitigate potential risks.

For additional corroboration, we examine alternative explanations for the observed capital flows, specifically investigating if they can be attributed to the activities of cross-currency arbitrageurs. However, our findings rule out this explanation. On the contrary, we find the volume of trades identified as capital flight trades using our method is positively correlated with the Bitcoin premium in Chinese Yuan. This premium refers to the situation where Bitcoin tends to be relatively more expensive when purchased using CNY compared to other fiat currencies. This result rules out triangular arbitrage as an explanation for the flows from CNY to USD via Bitcoin, as the direction of the capital flight flows contradicts what would be expected in an arbitrage trade.

Instead, our findings suggest that capital flight traders are willing to accept a loss, which can be seen as a transaction fee, in order to conduct such trades. The motivation behind this willingness to incur losses is likely the desire to bypass capital restrictions and move domestic assets offshore. The positive association between the volume of identified capital flight trades and the Bitcoin premium in Chinese Yuan indicates that these trades are not driven by cross-currency arbitrage, but rather by individuals seeking to transfer their domestic assets abroad through Bitcoin, even at a cost. This underscores the notion that capital flight traders are willing to bear losses as a means of evading capital controls and achieving greater financial mobility.

The above result also highlights the importance of capital flight as a driver of the persistent and large arbitrage opportunities in cryptocurrency markets. For example, Makarov and Schoar (2020) document that there are large and recurrent arbitrage opportunities across cryptocurrency exchanges that tend to be larger across countries than within countries. Interestingly, just as capital controls give rise to the capital flight that contributes to the emergence of arbitrage opportunities, Makarov and Schoar (2020) point out that capital controls also restrict the movement of arbitrage capital and thereby limit the ability of arbitrageurs to correct the mispricing.

Another alternative explanation is that the seemingly "uneconomical" flows from CNY to USD via Bitcoin could be driven by the laundering of the proceeds of criminal activities or illegal business ventures, rather than solely evading capital controls. To investigate this potential explanation, we undertake a matching process where we compare each wallet address in our sample with a database of Bitcoin users engaged in illicit activities, such as trading illegal goods and services (Foley, Karlsen, and Putniņš, 2019). Our matching result reveals that individuals involved in capital flight are less likely to use Bitcoin for illegal activities, suggesting that the capital flight that we identify is not primarily driven by laundering proceeds from illicit businesses. Instead, it is more likely driven by other motives such as Chinese citizens seeking to deposit or invest funds in foreign countries or to purchase foreign goods. Therefore, capital flight displays different characteristics to the flows associated with trade in illegal goods.

We further investigate the destination countries that receive the majority of the capital flight out of China. Our analysis reveals several trends in the flow of capital flight. First, we show there is a tendency for capital flight to gravitate towards countries with more active cryptocurrency markets. These countries often exhibit a higher level of activity and participation in the cryptocurrency sector. Second, capital flight shows a preference for countries with less stringent capital controls and lower corruption, consistent with investors seeking destinations with a more transparent and trustworthy business environment. Third, capital flight tends to be directed towards countries that have large peer-to-peer Bitcoin exchanges that tend to have lower AML and KYC requirements, facilitating more discrete transactions.

Additionally, we conduct a placebo test by designating either the United States or Russia as the "home" country for capital flight, instead of China. In doing so, we aim to assess the robustness of our findings and ascertain whether the observed capital flight patterns are specific to China or more widely applicable. We discover a notable disparity in the volume of capital flight trades. Specifically, the volume of capital flight trades is significantly lower when considering the United States or Russia as the focal countries. This stark contrast strongly suggests that China experiences a distinct and substantially higher level of capital flight through Bitcoin when compared to other countries.

Overall, we find the average costs of undertaking capital flight trades are in the order of 2% of transaction value, which is relatively cheap compared with other methods to circumvent capital controls such as using shell companies to disguise the purchases of foreign currencies as legitimate business transactions (Yeung, 2020) or using straw agents to purchase real estate assets (Agarwal et al, 2020). Our findings suggest that cryptocurrencies provide a new way to circumvent capital controls. While capital flight has existed for a long time, cryptocurrencies provide a new means, which is cheaper and potentially more convenient than other existing methods. Additionally, the pseudo-anonymity of cryptocurrencies provides a degree of protection from law enforcement agencies.

More broadly, however, capital flight via cryptocurrencies can be considered a form of money laundering as it involves transactions conducted in a manner that deliberately conceals the origin and destination of the funds. To that extent, our study demonstrates the broader potential for cryptocurrencies to be used in money laundering. To mitigate money laundering in cryptocurrencies, a potential avenue for future research or the development of global surveillance tools is to use the concept of "uneconomic trades" underlying our identification strategy to track suspicious fund flows involved in money laundering.

Our paper contributes to several strands of literature. First, a growing number of studies document that cryptocurrencies have been used in a range of potentially illegal activities including online trade in illegal goods and services (e.g., Soska and Christin, 2015; Foley, Karlsen, and Putniņš, 2019), financing pedophilia and child exploitation (e.g., DoJ, 2019), extracting payments in ransomware attacks (Sokolov, 2021), money laundering (e.g., Barone and Masciandaro, 2019), cross-border transactions (von Luckner, Reinhard and Rogoff, 2023), and even financing terrorism (e.g., Choo, 2015). The pseudo-anonymity and low regulatory oversight are among the factors that make cryptocurrencies appealing for use in illegal activities. Our paper contributes by showing that the evasion of capital control regulations is another form of prohibited activity involving cryptocurrencies.

Second, our paper contributes to the literature on arbitrage and mispricing in the cryptocurrency markets. Several papers show that triangular arbitrage opportunities exist for long periods of time between cryptocurrency and foreign exchange pairs. For example, Choi, Lehar, and Stauffer (2018) find an average Bitcoin premium of 4.73% on Korean exchanges. Other studies also relate the persistence of the arbitrage opportunities to capital control rules, which impede the flow of arbitrage capital to exploit the mispricing (e.g., Makarov and Schoar, 2020; Choi et al. , 2018). Based on blockchain data, our study contributes direct evidence that the intensity of capital flight is positively associated with the magnitude and persistence of such arbitrage opportunities, suggesting that capital flight is one of the underlying drivers of arbitrage opportunities in Bitcoin.

Third, other studies show flight-to-Bitcoin effects, whereby investors buy Bitcoin when economic policy uncertainty increases (e.g., Yu and Zhang, 2021). These effects have similarities with "flight to safety" (e.g., Baele et al., 2020) but differ in that they are triggered by economic policy uncertainty, not financial market turmoil. While we also test the role of economic policy uncertainty, rather than examining the flight-to-bitcoin effect which involves flows *to* Bitcoin, we characterize flows between fiat currencies *via* Bitcoin as the facilitator of the cross-country capital flight. Using blockchain data, we explicitly identify and remove from our capital flight measure the flight-to-Bitcoin effects as our focus is on how cryptocurrencies can facilitate illegal capital flows as opposed to serving as a safe-haven asset.

Our paper also contributes to the literature on the evasion of capital controls and capital flight by quantifying the activities and their nature.[4] Prior studies show that capital flight, i.e., the evasion of capital controls, can be destabilizing in emerging economies. Capital flight is conducted via a variety of means, elaborated in the next section, and is often a result of political and economic instability. Our study contributes by showing that cryptocurrencies provide a new way of evading capital controls, potentially cheaper and more convenient than some of the existing methods. Cryptocurrencies undermine the effectiveness and enforceability of capital control regulations and policies. Policymakers might reconsider the necessity for such capital control policies or at least monitor the capital flight—the methods in this paper provide a means to do this monitoring.

Our method differs from, and complements, the approach taken by von Luckner et al. (2023) to analyze cross-border flows via cryptocurrency exchanges. Their approach focuses on "off-chain" transactions that happen within a cryptocurrency exchange. Specifically, they use data from two cryptocurrency exchanges (LocalBitcoins and Paxful) and match pairs of trades based on trade size and timestamp to identify instances where it appears a trader likely went from fiat currency A to bitcoin, and then to fiat currency B. Their approach does not consider cryptocurrency transfers on the blockchain as a means of shifting capital between jurisdictions or across borders. Therefore, the "facilitator" of

[4] For example, see Cuddington (1986), Claessens, Naude, and Mundial (1993), Lensink, Hermes, and Murinde (2000), and Le and Zak (2006) for cross-country analyses of capital flight and Gunter (1996, 2017) and Wong (2017) for evidence on capital flight in China. Some studies provide indirect evidence on the use of cryptocurrencies in evading capital controls, for example, Ju et al. (2016) show that the ban on financial institutions' use of Bitcoin by the Chinese government in 2013 resulted in a reduction in the Chinese Bitcoin premium to the USD, consistent with a reduction in the amount of capital outflow from China via cryptocurrencies. Unlike our paper, however, they rely on indirect proxies for Chinese Bitcoin activity due to the challenges in working with the full blockchain data, stating that "it is difficult to detect directly capital flight via Bitcoin because none of the Bitcoin transactions is traceable."

exchange between fiat currencies in their approach is the two centralized exchanges. In contrast, we focus on "on-chain" transfers of a cryptocurrency between different countries via the blockchain, providing direct evidence of capital flows between countries. In our method, centralized exchanges serve as the on- and off-ramps into the cryptocurrency, but the "facilitator" of the cross-border capital flow is the blockchain. Thus, the two different methods focus on different ways to hop between fiat currencies via a cryptocurrency – one being within an exchange, the other being via the blockchain.

These two approaches have different pros and cons. An advantage of examining within-exchange capital flows is being able to conveniently examine a sample of flows between many different fiat currencies. However, the downside is that those flows reflect only a small subset of capital flows via cryptocurrencies because the two exchanges are a small subset of the universe of over 500 cryptocurrency exchanges and the approach omits capital flows between exchanges. In contrast, our approach is better suited to estimating the full extent of capital flight from a country (e.g., as per our application to China), but is more challenging to apply on a global scale. As a result, we provide a more detailed analysis of the nature of the capital flight from one single country characterized by an active bitcoin market and stringent capital controls, and examine various aspects including its economic determinants, its impact on price premiums, its cost, and how it relates to other illegal activities including criminal financing. Additionally, by leveraging publicly available blockchain data, our method may be more accessible for researchers, particularly in cases where proprietary exchange data is not readily available. It is also less susceptible to false positives in identifying capital flight trades as a result of wash-trading on centralized exchanges (e.g., Cong et al., 2021; Le Pennec et al., 2021).

2. Institutional Detail: Capital Controls and How They are Circumvented

2.1. Capital Controls in China

China maintains stringent controls on capital outflow, including restrictions on the acquisition of foreign currencies using CNY. These capital control regulations are overseen by China's Foreign Exchange Regulatory Authority, the State Administration of Foreign Exchange (SAFE). During our sample period, individuals were limited to purchasing a maximum of USD 50,000 worth of foreign currencies per year.[5] for trade-related purposes, companies face no restrictions on cross-border currency

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

flows. Nevertheless, significant controls are imposed on cross-border flows related to investment purposes (Walsh and Weir, 2015).

According to Fernández et al. (2016)'s country capital control index, which is updated until 2017 (one year prior to the end of our sample period), China is ranked among the countries with the strictest controls on capital inflow and outflow. However, it is worth noting that these controls have been gradually relaxed from 2013 to 2017. By 2017, China had transitioned from being the strictest country to being the 13th strictest country in terms of capital controls. China's position as one of the countries with stringent capital controls underscores the importance and relevance of studying capital flight through alternative channels such as cryptocurrencies.

2.2. Circumventing Capital Controls in China

Despite China’s capital controls, capital flight from China has traditionally occurred in the following ways.

Mis-invoicing of imports/exports: According to Gunter (1996), if reported amounts of exports are much less than actual amounts of exports, the difference is highly likely to be a form of capital flight. This is achieved by under-invoicing exports and transferring the difference to some financial intermediaries such as tax haven. For example, a company may receive $1,000,000 in exports but officially declare only $200,000 as export sales, thereby allowing $800,000 to be taken out of the country and be placed in some offshore financial haven.

Alternatively, a capital flight importer may over-invoice the imports to achieve the same effect. The estimate of capital flight conducted by this means can be estimated by comparing the balance of trade amounts using Chinese data versus International Monetary Fund data. Gunter (1996) finds mis-invoicing increasing from $2.5 billion in 1984 to $44 billion in 1994 and $201 billion in 2014, suggesting the prevalence of capital flight in the form of mis-invoicing.

Incomplete foreign debt data: Debt owed to foreign banks may be underreported and as such could be a means for capital flight. Misreported debt is estimated as the difference between the amount of debt owed to foreign banks as reported by the Chinese companies and the amount of the same debt as reported by foreign banks. Gunter (1996) estimates the underreported debt is $16 billion from 1994 to 1996 and $72 billion in 2014.

Misreported travel expenses: Although Chinese nationals have individual restrictions in foreign exchange withdrawals as mentioned above, there are ways to circumvent the restrictions by masking the use of foreign currencies 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. An 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 $100 billion to $123 billion.

Other methods: These include activities such as purchasing gambling chips from Macau casinos then exchanging them for foreign currency or purchasing Hong Kong investment-related insurance policies in foreign currency (Gunter, 2017), which has since been banned (Yu, 2017).

2.3. Using Bitcoin to Circumvent Capital Controls

A typical strategy employed to bypass capital controls in China using cryptocurrencies, specifically to convert CNY to USD, follows these steps:

1) Purchase Bitcoin at a domestic Bitcoin exchange using CNY.
2) Transfer the acquired Bitcoin to an overseas Bitcoin exchange using the Bitcoin blockchain.
3) Sell the Bitcoin at a foreign exchange for USD and subsequently withdraw the USD from the foreign Bitcoin exchange.

This strategy allows individuals to circumvent the limitations imposed by CNY foreign transfer restrictions, which restrict individuals to a maximum of $50,000 per year. As the transfer of Bitcoin occurs on the blockchain, there is no effective way to prevent or control the movement of Bitcoin, enabling individuals to move funds across borders without being subject to these restrictions.

Figure 1 Panel A illustrates the flows of Bitcoin and CNY for the simple case of a single Bitcoin user engaging in direct capital flight. The process begins with the capital flight trader establishing a Bitcoin wallet. Within this wallet, they proceed to purchase Bitcoins using CNY or its equivalents at a Chinese Bitcoin exchange[6] using CNY or equivalents.[7] Subsequently, the acquired Bitcoins are transferred to a foreign Bitcoin exchange, where they are exchanged for another currency, such as USD.

In certain instances, this scheme of capital flow could be made slightly more complicated due to constraints on an individual's capacity to create accounts at both domestic and foreign Bitcoin exchanges. Some non-Chinese exchanges, which enforce registration requirements for compliance with anti-money laundering (AML) or know your client (KYC) rules, may restrict Chinese citizens from creating

[6] It is no longer possible to do this as Chinese Bitcoin exchanges were forced to close by the government in September 2017. After September 2017, users in China could still trade Bitcoin using decentralized exchanges (see Coindesk, 2020, https://www.coindesk.com/what-is-defi).

[7] Kaiser, Jurado and Ledger (2018) state 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, and so on.

accounts. For example, *Gemini*, one of the largest exchanges in the U.S., states that it operates as a New York trust company and is regulated by the New York State Department of Financial Services. They are subject to stringent cybersecurity and banking compliance standards.[8] As a consequence, the platform's policies often restrict access to non-US residents, citing the inability to verify their identities as one of the reasons for exclusion.[9] In such cases when Chinese nationals encounter restrictions accessing non-Chinese exchanges, they may need to rely on the assistance of another registered user on the blockchain. We refer to this modified version of the scheme as "indirect capital flight," which involves additional steps illustrated in Figure 1 Panel B. These steps include transferring Bitcoins between the wallets of the two users via the Bitcoin blockchain and subsequently transferring the foreign fiat currency back to the Chinese citizen's foreign account. In our analysis, we account for this additional step when categorizing capital flight trades.

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

3. Data and Sample

Our sample period spans from September 2, 2011 to February 8, 2018.[10] For a detailed overview of our data sources, please refer to Appendix 1. To acquire comprehensive data on Bitcoin blockchain transactions, we rely on the dataset provided by Kondor et al. (2014), extended up until February 8, 2018.[11] In order to obtain this data, we first install a Bitcoin client and establish a connection with the peer-to-peer network to download the blockchain data. Subsequently, we transform the data into a usable format where each transaction is accompanied by a timestamp, the amount of Bitcoin transacted, and the receiving and sending Bitcoin addresses. To link multiple Bitcoin addresses belonging to the same user, we employ the Union-Find algorithm as outlined by Meiklejohn et al. (2013). This process allows us to establish connections between various Bitcoin addresses associated with a single user. Additionally, we derive statistics on Bitcoin average network fees and the number of transactions directly from the Bitcoin blockchain data.

We identify the addresses of Bitcoin exchanges (their wallets) from Wallet Explorer.[12] This platform collects data on Bitcoin exchange wallet addresses and other relevant information from public

[8] See https://gemini.com/about
[9] For example, Gemini requires the linking of a working mobile number, a US bank account, photo ID and proof of address (see https://www.bitdegree.org/crypto/gemini-exchange-review).
[10] The start of the sample is determined based on the starting date when the CNY-denominated Bitcoin prices began in Cryptocompare.com.
[11] The data can be obtained here: https://senseable2015-6.mit.edu/bitcoin/
[12] See www.walletexplorer.com

sites as well as internal sources, particularly when conducting transactions with those exchanges. Our analysis is at the individual wallet level, considering individual blockchain transactions, which provides a high level of granularity. Wallet Explorer is used in various studies to deanonymize wallet addresses, such as Jourdan et al. (2018), Toyoda et al. (2018), and Liang et al. (2019). However, the Bitcoin exchange addresses obtained through Wallet Explorer do not constitute an exhaustive list of all wallets associated with an exchange. Additionally, Wallet Explorer may not encompass all Bitcoin exchanges. For instance, according to Liang et al. (2019), Wallet Explorer identified only 4.32% of addresses and 6.48% of total transactions in the entire Bitcoin blockchain in November 2018.[13]

We determine the country of each Bitcoin exchange based on publicly available information or data retrieved from their respective websites. In the case of exchanges categorized as Chinese, we conduct additional verification by examining their archived websites using the Internet Archive Wayback Machine[14] to confirm their initial headquarters.[15] Appendix 3 provides a comprehensive list of Bitcoin exchanges, including their country headquarters and rankings based on blockchain volume denominated in USD. Our sample contains major non-Chinese exchanges such as Bitrex and Bitfinex, as well as major Chinese Bitcoin exchanges like Huobi and BTCC.

In addition to Bitcoin transaction data, we also collect data on exchange rates, Bitcoin prices, and the economic policy uncertainty index. The daily CNY/USD exchange rate data is sourced from the Federal Reserve Economic Data (FRED). We acquire intraday Bitcoin prices in both CNY and USD from Bitconcharts.com, while end-of-day prices are obtained from Cryptocompare.com, along the same line as Yu and Zhang (2021). To capture the level of economic policy uncertainty in China, we use the monthly Chinese economic policy uncertainty index provided by policyuncertainty.com, following the method used by Baker, Bloom, and Davis (2016).

To conduct a comparison between the transaction volumes of Chinese Bitcoin exchanges and non-Chinese Bitcoin exchanges, we calculate the monthly volumes for each type of exchange based on the identified exchange trades recorded on the blockchain. By analyzing these transaction records, we can assess and contrast the trading activities and volumes between Chinese and non-Chinese Bitcoin

[13] Appendix 2 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% of self-reported transaction volume across 31 exchanges in the database. Coverage across years varies from 4.34% in 2011 to 20.12% in 2018.

[14] https://archive.org/web/web.php

[15] We use the initial headquarter country because the exchange's largest client base likely remains largely from the country where the exchange is initially headquartered. We note that some Chinese exchanges do change their headquarters over time (as seen from looking at different snapshots of their site in the Internet Archive Wayback Machine), though still cater to Chinese customers as evident from having Chinese language sites.

exchanges on a monthly basis. Figure 2 reports monthly trading volumes measured in Bitcoin (Panel A) and USD (Panel B) and the BTC/USD exchange rate. Both panels show that there is clearly more volume in non-Chinese exchanges than Chinese exchanges and the volume in the two types of exchanges are positively correlated. Based on our sample of Bitcoin transactions, the market share of Chinese exchanges is about 16% of the global Bitcoin trading volume.

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

Throughout our sample period, we observe a substantial surge in Bitcoin prices. The highest recorded price for Bitcoin within this period is $13,850.40, attained in November 2017. This price represents an increase of over 4,000 times compared to the price of $2.97 observed in March 2011. It is worth noting that although the dollar volumes of traded Bitcoins generally exhibit an upward trend over our sample period, the volumes measured in BTC tend to decrease. This decline is primarily attributed to the significant and rapid escalation in the price of Bitcoin during the same period.

4. Empirical Analysis

4.1. Identifying Capital Flight Trades

Our approach is based on the integration of data from Chinese and foreign Bitcoin exchanges, as well as the observed flows between them documented on the Bitcoin blockchain. By linking these data together, our method identifies Bitcoin flows as illustrated in Figure 1. Specifically, we identify instances where a trader first uses CNY to purchase Bitcoin, and within a short time span transfers the acquired Bitcoin to a foreign exchange, where the Bitcoin is subsequently sold for a foreign fiat currency, such as USD.

A significant portion of our analysis centers around identifying flows that are deemed “uneconomical”, which means that these flows result in a loss, making them financially unfeasible for arbitrage profit. Consequently, these flows incur higher costs compared to simply exchanging CNY for USD directly. When we observe capital flight trades occurring when Bitcoin is more expensive in CNY compared to USD, it is highly likely that these trades reflect an intention to evade capital controls. Otherwise, if alternative means of converting CNY to USD were available, they would be more cost-effective, rendering such capital flight trades unnecessary.

At the core of our approach is the complete record of Bitcoin addresses, which we consolidate at the user level following the method outlined in Kondor et al. (2014) using the Union-Find algorithm.

Additionally, we have access to the complete dataset of transactions recorded on the Bitcoin blockchain. By connecting the Bitcoin exchange address data with the blockchain transaction data, we are able to identify individuals (users) who engage in daily trading activities on one or more Bitcoin exchanges. Furthermore, we determine whether these individuals are purchasing Bitcoin from the exchange (receiving Bitcoin) or selling Bitcoin to the exchange (sending Bitcoin).

Using the linked data, we calculate the net trading amount (buy less sell) for each user on a daily basis at both Chinese and non-Chinese Bitcoin exchanges. Based on the trading activities of each user during a given day, we classify the user-day observations[16] into the following six categories:

(i) *Net Sellers*: Users with net selling of Bitcoin in both Chinese and non-Chinese exchanges.

(ii) *Net Buyers*: Users with net buying of Bitcoin in both Chinese and non-Chinese exchanges.

(iii) *Chinese Only*: Users that only trade in Chinese exchanges (with no trading records on non-Chinese exchanges).

(iv) *Capital Flight*: Users that net buy Bitcoin in Chinese exchanges and net sell Bitcoin in non-Chinese exchanges. The transactions of these users conform to the pattern in Figure 1 Panel A. In later sections we impose a further condition that isolates the uneconomical trades within this group, which we find are the majority of trades within this group.

(v) *Reverse Flight*: Users that net sell Bitcoin in Chinese exchanges and net buy Bitcoin in non-Chinese exchanges.

(vi) *Others*: Users that only trade in non-Chinese exchanges or do not trade in an exchange.

We focus on the fourth type, namely the *Capital Flight* category, which involves capital flight out of China, which we show below are predominantly "uneconomical" trades. There are 70,776 user-day observations in the *Capital Flight* trader group (or 5.34% of all categories except All Others), whereas *Reverse Flight* only makes up 39,179 (or 2.96%) of the sample.

4.2. Scale and Dynamics of Capital Flight

Figure 3 shows the monthly Chinese exchange net trading volume (in Bitcoin in Panel A and in USD in Panel B) for each trader category. The aggregate amounts and percentages are also reported in Table 1 Panel A. *Chinese Only* traders are the dominant group, accounting for about 60% of volume measured in BTC (Table 1 Panel A row 2) and 46% of volume measured in USD, followed by *Capital Flight* traders, who account for just over one-quarter of total net volume measured in either BTC or USD.

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[16] We define a day as being 24 hours in the Chinese time zone (UTC+8).

[--- INSERT FIGURE 3 ABOUT HERE ---]

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

Chinese Only trades were predominant before 2013, whereas *Capital Flight* emerged as the dominant category in 2016 and 2017. This shift suggests a growing inclination to use Bitcoin to bypass capital controls. In total, approximately BTC8.78 million, equivalent to $4.6 billion in Bitcoin blockchain transactions, meet the criteria for *Capital Flight* trades out of China. Considering that there are slightly over 18 million Bitcoins in circulation as of January 2019, these volumes account for nearly half of the total Bitcoin supply.

To delve deeper into *Capital Flight* trades, Figure 3 Panel C and D present the monthly Bitcoin net volume of *Capital Flight* trades on Chinese exchanges in Bitcoin (Panel C) and in USD (Panel D), respectively against the average daily Bitcoin network transaction fee and the daily BTC/CNY premium. We convert the Bitcoin price in CNY to USD, then compare it to the Bitcoin price in USD, and define the percentage difference as the premium. We find that the majority of the *Capital Flight* trades occur during 2013 to early 2017 with a small negative BTC/CNY average daily premium of -0.32% over this time period. However, the daily premium standard deviation is high (6.87%) but is not apparent in the relatively stable monthly premiums in Figure 3. The network fee also appears low during this period ($1.13 per transaction on average daily).

From March 2017 onwards, *Capital Flight* trades become nearly non-existent, coinciding with the period when the BTC/CNY premium experiences volatility and network fees reach their peak. Another significant factor contributing to the low trading volume observed is the anticipation of the Chinese government's announcement regarding the potential shutdown of all Bitcoin exchanges in China. This announcement, made in September 2017, likely deterred most of the trading activities on Chinese Bitcoin exchanges.

4.3. Determinants of Capital Flight

To better understand the drivers of the different trader type volumes and test whether the *Capital Flight* category involves uneconomical trading we estimate the following regression:

$$Volume_{jt} = \alpha + b_1 \Delta EPU_t + b_2 Premium_t + b_3 Trades_t + b_4 Fee_t + b_5 Volatility_t + b_6 Day_t + e_{jt} \quad (1)$$

where $Volume_{jt}$ is the net volume traded on Chinese Bitcoin exchanges by trader type j on day t. ΔEPU_t is the monthly change in the Chinese economic policy uncertainty index (standardized) obtained from Baker et al. (2016). $Premium_t$ is the Bitcoin price in CNY converted to USD expressed as a percentage over the USD Bitcoin price. $Volatility_t$ is the daily sum of squared one-minute USD Bitcoin returns. $Trades_t$ is the daily number of trades. Fee_t is the daily average fee per trade in USD. Day_t is the number of days since the start of the sample period.

Table 1 Panel B reports the summary statistics for the key variables used in the regression analysis, and Table 1 Panel C reports the correlation matrix of the main variables. From Table 1 Panel B, the average daily Bitcoin return in USD is 0.54% and in CNY it is 0.49%. The average CNY premium on Bitcoin relative to USD is 0.64%. The mean daily net trading by the *Chinese Only* category has the highest volume being 8,560 Bitcoins followed by the *Capital Flight* group with 4,410 Bitcoins. However, in dollar volumes, the highest volume group is *Net Buyers*, with a trading volume of $8.7 million.

Table 1 Panel C shows that *Capital Flight* trade volume is positively correlated with changes in Chinese economic policy uncertainty “EPU” (0.094), CNY Bitcoin premium (0.13), and net trading of *Chinese Only* (0.365). The positive correlation between *Capital Flight* volume and Chinese EPU indicates that *Capital Flight* trades are more intense when individuals face grater uncertainty in China, consistent with the flight-to-safety motivation. The positive correlation between *Capital Flight* volume and CNY Bitcoin premium suggests that there are more *Capital Flight* trades when Bitcoins are expensive in CNY (when $Premium_t$ is positive), consistent with the notion that trades in the *Capital Flight* category are not arbitrage trades. All net trades groups are negatively correlated with volatility and with fees (with the exception of *Net Buyers*), consistent with traders being risk averse and also with high transactions costs deterring trading (e.g., Easley et al., 2019; Sokolov, 2021).

The regression results in Table 2 Panel A (in BTC) and Panel B (in USD) show that *Capital Flight* net volume in Chinese exchanges tends to be high when Chinese economic policy uncertainty increases (ΔEPU), the Chinese Bitcoin premium ($Premium$) is high, and there is more trading on the Bitcoin network. *Capital Flight* volume tends to be lower when there are higher network fees (Fee). The magnitudes of the key relations are economically meaningful. For example, a one-standard-deviation increase in ΔEPU is associated with an increase in the daily *Capital Flight* by $661,147 (519 Bitcoins). A one percent premium for Bitcoin in CNY increases daily *Capital Flight* volume by $77,563 (174 Bitcoins). Given the average daily capital flight net volume in the sample from Table 1 Panel B is $3,443.76 (median $2,276.10), these effects are large.

Overall, the regression results suggests that *Capital Flight* trades are most sensitive to uncertainty in China's political climate and occur when the Chinese Bitcoin premium is high, consistent with the underlying motivation of this trade type being circumventing capital controls.

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

4.4. Classifying Indirect Capital Flight Trades

To identify *Capital Flight* trades that involve another user facilitating the trade or involve a user transferring their Bitcoin through a second account that they control before selling it, we identify trade pattern as per Figure 1 Panel B. Specifically, we apply the following algorithm[17]:

(i) Every day, for each user ID (as defined in Kondor et al. (2014)), calculate their net trading in Chinese and non-Chinese Bitcoin exchanges. Record whether they are net buying or net selling at the exchanges.

(ii) For net traders on Chinese exchanges or non-Chinese foreign exchanges, collect their non-exchange blockchain trades that are in 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.

(iii) For the trading records collected from these users, match the trades together based on the direction of the trades, where one identified Chinese exchange net trader is sending/receiving Bitcoin to/from another in the same transaction (i.e., they are trading pairs).

(iv) The volume of the indirect *Capital Flight* is calculated as the sum of all trading volume when a Chinese exchange net buyer sending Bitcoin to a non-Chinese exchange net seller. Indirect *Reverse Flight* volume is calculated as the sum of all trading volume when a Chinese exchange net seller receiving Bitcoin from a non-Chinese exchange net buyer.

(v) Halve the volume of net buying/selling by Chinese/non-Chinese exchange traders involved in indirect trades to avoid double counting.

Table 3 Panel A reports the aggregate Chinese exchange net volume of trader groups including indirect trades in Bitcoin and USD. Total net trading volume of 33.51 million Bitcoin and 17.710 billion USD is the same as not including indirect trades as in Table 1 Panel A. Instead, the *Net Buyer*, *Net Seller*

[17] Appendix 4 provides a table summarizing the indirect trade classifications between trader A (Chinese exchange trader) and trader B (non-Chinese exchange trader).

and *Chinese Only* categories have lower net volume that is reallocated to the *Capital Flight* and *Reverse Capital Flight* categories. With indirect trades, *Capital Flight* volume increases by 1.12 billion USD or about 24% compared with not including indirect *Capital Flight* trades. *Reverse Flight* net volume substantially increases by $176 million USD or 75% more than when excluding indirect trades. These results imply that indirect trades make up a substantial part of *Capital Flight* and *Reverse Flight* trades, particularly for the latter.

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

We re-estimate the regressions in Equation (1) using the trade classifications that include indirect trade volumes. The results in Table 3 Panel B (in Bitcoin) and Panel C (in USD) show similar relations as the baseline regressions. *Capital Flight* volume is positively related to the CNY premium and Chinese economic policy uncertainty with similar coefficients

4.5. Split Sample Period Regression

As shown in Figure 3, the bulk of net trading volume on Chinese Bitcoin exchanges occurs from September 2015 due to the increasing popularity of Bitcoin in China. As such, we test the sensitivity of the determinants of net trade volumes by splitting the sample into two periods: (1) before September 1, 2015 and (2) from September 1, 2015 onwards. Table 4 Panel A reports the regression results for the first period before September 1, 2015, and Panel B reports results for the second period from September 1, 2015 onwards. We again estimate the regressions separately for the five trader types although our focus is on the *Capital Flight* category.

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

Table 4 shows that our main results persist in both sample periods, with more pronounced effects in the second part of the sample. Specifically, for the *Capital Flight* category, the coefficients for ΔEPU and $Premium$ are both statistically significant at the one percent level and consistent with the full sample regression results. In the second subsample period the coefficients for ΔEPU (741.67) and $Premium$ (160.66) are larger in magnitude than in the full sample, indicating stronger effects in the later period.

The *Reverse Flight* trader group also has a weakly significant $Premium$ 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 is estimated to result in a mere \$6,370 more *Reverse Flight* trading. Before September 1, 2015, $Premium$ remains statistically significant for the $Capital\ Flight$ group but not the $Chinese\ Only$ group. ΔEPU is positive and not statistically significant for both groups.

4.6. Profitability of Capital Flight Trades

What are the costs of undertaking capital flight transactions via cryptocurrencies? Capital flight trades are driven by the desire to preserve wealth or escape economic and political uncertainties. One of the key features that distinguishes capital flight trades is that these transactions fit the notion of "uneconomical trades"[18]. That is, individuals engaged in capital flight trades may willingly pay a premium (incur a loss) to exchange one fiat currency for another via a cryptocurrency, which can be seen as the price individuals are willing to pay to maintain financial mobility, protect assets, or access better investment environments. For example, an individual with \$100,000 worth of CNY might exchange it for Bitcoins in China, transfer the Bitcoins abroad, and then sell them in an overseas exchange for \$95,000, effectively paying a \$5,000 (or 5%) premium to obfuscate the capital outflow via a cryptocurrency compared to just exchanging CNY for USD. This unique feature enables us to rule out profit-motivated trading, speculation, and many other possibilities where one would expect the opposite flow.

Capital flight trades occur during times of a high CNY Bitcoin premium, rendering them "uneconomical" trades. The premium emerges as a consequence of the price dynamics resulting from capital flight. When there is a significant demand to convert from fiat currency A to fiat currency B via cryptocurrency C, the price of C will tend to increase relative to A and decrease relative to B. This phenomenon is akin to how exchange rates appreciate or depreciate in response to currency flows. In essence, the price pressure created by capital flight causes cryptocurrency C to become relatively expensive in terms of A and relatively inexpensive in terms of B. In effect, capital flight trades are the opposite of arbitrage trades—individuals on average lose money on the capital flight trade, which is the cost to an individual of bypassing capital control regulations.

We examine the magnitude of losses for such *Capital Flight* trades and, conversely, the profits for *Reverse Flight* trades. We estimate two components of intraday profits. *Intra-exchange* profit is the profit/loss (PnL) from buying and selling within exchanges (Chinese or non-Chinese exchanges) within the same day. *Inter-exchange* profit is the PnL from net buying or selling between exchanges (for both

[18] The notion of "uneconomical trades"—trades that are clearly unprofitable absent some alternate motive—is often used in defining and identifying market manipulation (e.g., Ledgerwood and Carpenter, 2012; Perdue, 1987). In contrast, economical trades, such as for Bitcoin triangular arbitrage, tend to be few and made by sophisticated users (e.g., Saggese et al., 2021).

Chinese and non-Chinese Bitcoin exchanges). We calculate the traded price on Bitcoin exchanges every day based on the nearest one-minute Bitcoin price (in CNY or USD), using trade level data from Bitcoin exchanges. The intraday dollar profit for trader i on day t for *Capital Flight* or *Reverse Flight* traders is calculated as follows:

$$IntraExchangePnL_{it} = \frac{\min\left(QBuy_{it}^{CHINA}, QSell_{it}^{CHINA}\right)\left(PSell_{it}^{CHINA} - PBuy_{it}^{CHINA}\right)}{USDCNY_t} + \min\left(QBuy_{it}^{NONCHINA}, QSell_{it}^{NONCHINA}\right)\left(PSell_{it}^{NONCHINA} - PBuy_{it}^{NONCHINA}\right) \tag{2}$$

For *Capital Flight* traders,

$$InterExchangePnL_{it} = ChinaNet_{it}\left(PSell_{it}^{NONCHINA} - \frac{PBuy_{it}^{CHINA}}{USDCNY_t}\right) \tag{3}$$

For *Reverse Flight* traders,

$$InterExchangePnL_{it} = ChinaNet_{it}\left(\frac{PSell_{it}^{CHINA}}{USDCNY_t} - PBuy_{it}^{NONCHINA}\right) \tag{4}$$

where subscript i indexes users and t indexes days. $QBuy_{it}^{CHINA}$ and $QSell_{it}^{CHINA}$ are the quantity of Bitcoins bought or sold at Chinese Bitcoin exchanges, respectively. $PBuy_{it}^{CHINA}$ and $PSell_{it}^{CHINA}$ are the volume-weighted average prices of Bitcoins bought or sold at Chinese Bitcoin exchanges, respectively. $NONCHINA$ refers to Bitcoins bought or sold at non-Chinese Bitcoin exchanges. $USDCNY$ is the closing price of USD/CNY. $ChinaNet_{it}$ is $QBuy_{it}^{CHINA}$ minus $QSell_{it}^{CHINA}$. We calculate percentage profits as the profit divided by the net Bitcoin volume traded in Chinese exchanges converted to USD. Note that the trader categories *Net Buyers*, *Chinese Only*, and *Net Sellers* do not have inter-exchange profits as they do not buy in one exchange and net sell in the other.

Table 5 reports the aggregated profits in Panel A. We find that the intra-exchange profit is positive for all trader types except the *Capital Flight* traders. For example, *Net Sellers* make profit of 0.13% on average, whereas the profit for *Net Buyers* is 0.01%. The only group that incurs a loss in trading is the *Capital Flight* group, which loses $476,000 or -0.01% of their Chinese exchange net volume. For inter-exchange profits/losses, the *Capital Flight* group overall lost $31.6 million or -0.69% of their net volume traded, reflecting that *Capital Flight* trades were still being made even when the Chinese Bitcoin premium is high. In comparison, the *Reverse Flight* group made a profit of 0.04% of their net volume.

Overall, the 0.7% loss incurred by the average *Capital Flight* trade is reasonably low. 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 were about $1.12 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 Flight*. Such a cost is inconsequential in comparison to using import/export companies, or the cost of straw purchase of overseas real estate investments (about 4% price premium) as documented in Agarwal et al (2020). Also, provided there is sufficient liquidity on the Bitcoin exchanges, the potential amount that can be taken out of China to circumvent capital controls is scalable, unlike other means of capital flight such as using casinos or misreported travel expenses.

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

To investigate the extent of uneconomical trading, we further categorize *Reverse* and *Capital Flight* traders by their inter-exchange profitability. We categorize traders on a given day as economical if their inter-exchange return is greater than 1%, and uneconomical otherwise. Table 5 Panel B reports summary statistics. About 75% of *Reverse Flight* trader/days and 82% of *Capital Flight* trader/days are uneconomical, despite using a very conservative benchmark return of 1% for inter-exchange profits, which is unlikely to cover exchange fees and transfer costs in most cases.

Notably, the average trader/day $USD principals involved are 20 to 30 times larger for *Capital Flight* traders than *Reverse Flight* trades. As such *Reverse Flight* trader average gains/losses are much smaller when measured in dollars and are also lower as a percentage of principal traded. For example, for uneconomical traders, the average inter-exchange returns are -1.77% (median -0.69%) and -2.04% (median -1.31%) for *Reverse* and *Capital Flight* traders, respectively. This suggests that uneconomical *Capital Flight* volumes are much larger and more uneconomical than *Reverse Flight* volumes.

With these new categories of economical and uneconomical trades, we also test whether the Chinese exchange trading volume of the traders is associated with the determinants that we use in Equation (1). Table 5 Panel C reports the regression results. We find that uneconomical *Capital Flight* volumes (column 3) are again positively related with both ΔEPU and $Premium$. Economic *Capital Flight* volume however has no significant relation with ΔEPU and is negatively correlated with $Premium$. These results are consistent with uneconomical *Capital Flight* volume being associated with economic uncertainty in China, whereas economical trades may be for arbitrage purposes. The results also show that *Reverse Flight* volumes are not related to ΔEPU. Therefore, only uneconomical *Capital Flight* volumes are sensitive to higher Chinese political uncertainty.

4.7. Capital Flight Traders and Illegal Users of Bitcoin

In prior sections, we show that *Capital Flight* trades are "uneconomical" in the sense that traders appear to willingly lose money on a currency conversion between two fiat currencies. While circumventing capital controls is likely to be the dominant explanation for such uneconomical trading, in this section we test whether other illegal motivations explain such trades. 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 business or activities. It is therefore our hypothesis that such users are also more likely than others to use Bitcoin to buy or sell illegal goods and services given their experience and knowledge in using Bitcoin for illicit purposes.

To identify trades involved in illegal activities, we use the illicit user database from Foley, Karlsen, and Putniņš (2019).[19] Foley et al. (2019) estimate the probability that a Bitcoin user is involved in trading illegal goods and services by linking users to known darknet marketplaces (e.g., the Silk Road darknet marketplace), darknet forums in which illegal goods/services are traded, and FBI and other law enforcement agency seizures of Bitcoin used in criminal activities. These identified illegal users are from around the world, including China and Hong Kong (UNDOC, 2020). Foley et al. (2019) use network cluster analysis and detection-controlled estimation to probabilistically identify other illegal users based on the network characteristics of the known illegal users. They find that approximately one-quarter of Bitcoin users are involved in illegal activity.

To examine the involvement of different Chinese trader types in illegal activities, we estimate the following logit regression at the user level:

$$\begin{aligned} Logit(illegal_i = 1) = b_0 + b_1 ExchUser_i + b_2 ChinaExchUser_i + b_3 NetSeller\%_i + b_4 Reverse\%_i + \\ b_5 ChineseOnly\%_i + b_6 CapFlight\%_i + b_7 NetBuyer\%_i + b_8 LogN_i + b_9 LogTradeSize_i + \\ b_{10} Concentration_i + e_i \end{aligned} \quad (5)$$

where $illegal_i = 1$ if user i is classified as an illegal user in Foley et al. (2019) and 0 otherwise. $ExchUser_i$ and $ChinaExchUser_i$ are dummy variables for whether the user ever traded with a Bitcoin exchange or a Chinese Bitcoin exchange respectively. Every day for each user, we calculate net volume of their trades with Chinese Bitcoin exchanges, non-Chinese Bitcoin exchanges, and other counterparties. Net volume in each venue is the absolute of buy dollar volume less sell dollar volume. $NetSeller\%_i$ is the percentage of the user's trading where they are net selling in both non-Chinese and Chinese Bitcoin

[19] Foley et al. (2019) note that as their measure focuses on the buying and selling of illegal goods and services with Bitcoin, it may underestimate the prevalence of other illegal activities such as evading capital controls. We therefore test whether there is any relation between the capital flight trades and the illicit trade by buyers and sellers of illegal goods that Foley et al. (2019) identify.

exchanges. $Reverse\%_i$ is the percentage of the user's trading that is classified as *Reverse Flight* (buying in non-Chinese Bitcoin exchanges and selling in Chinese exchanges). $ChineseOnly\%_i$ is the percentage of the user's trading that is classified as *Chinese Only* trading. $CapFlight\%_i$ is the percentage of the user's trading classified as *Capita Flight* trading (buying in Chinese exchanges and selling in non-Chinese exchanges). $NetBuyer\%_i$ is the percentage of the user's trading where they are net buying in both non-Chinese and Chinese Bitcoin exchanges. $LogN_i$ is the natural log of number of trades by the user. $LogTradeSize_i$ is the average USD trade size of the user's transactions. $Concentration_{i,}$ from Foley et al. (2019), is a measure of the tendency for the 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 first check the extent of illegal trading by trading group in Table 6 Panel A. We find that those traders in the *Net Seller* and *Reverse Flight* categories are most likely to be involved in trading illegal goods and services (89.11 and 89.58 percent of net trading, respectively). In particular, the percentage of *Reverse Flight* trades being associated with illegal goods/services over the years ranges from 81.52% to 99.27%. We find 51.80% of *Capital Flight* trades are classified as belonging to a user that trade illegal goods/services, which is the third lowest of all groups. The trader categories with the lowest likelihood of being illegal are *Chinese Only* trades and *Other* trades (users that trade on non-Chinese exchanges only and/or unclassified trades) of 39.85% and 27.10% of trades, respectively.

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

Table 6 Panel B column 1 reports the logistic regression results which are consistent with the statistics by trader type in Table 6 Panel A. We find that if a Bitcoin user has ever traded at any Chinese Bitcoin exchange, the probability of being an illegal user (unconditional on trade type) is 55% higher. We also find that users that conduct more net selling of Bitcoin are more likely to be involved in illegal activities.

Turning to the trade types, users that do more *Net Seller* and *Reverse Flight* trades are more likely to be illegal users, all else equal. In contrast, users that trade within Chinese Bitcoin exchanges only or that conduct *Capital Flight* trades are less likely to be illegal users, all else equal. For example, the coefficient of $Reverse\%_i$ is 0.014 and statistically significant, suggesting that an increase of *Reverse Flight* trading by 1% would increase the probability of being an illegal user by 1.4%.[20] In contrast, the

[20] Calculated as $e^{0.017} - 1 = 0.014098$

coefficient for $CapFlight\%_i$ is -0.011 and statistically significant, suggesting that an increase in *Capital Flight* trades by 1% leads to a reduction of illegal probability by 0.11%.

Table 6 Panel B column 2 further separates trading volume of *Reverse / Capital Flight* trades by whether they are uneconomical or not based on whether the trader/day's inter-exchange profit was greater than 1%. We find uneconomical *Capital Flight* traders are even less likely to be illegal trades. In contrast, uneconomical *Reverse Flight* trades are more likely to be illegal. Overall, our results suggest that *Capital Flight* trades are not mainly for the purpose of buying/selling illegal goods and services, nor are they driven by arbitrage profit.

4.8. Destination Countries for Chinese Capital Flight

In this section, we investigate which countries are the main recipients of Chinese capital flight. We calculate the net volume traded in the non-Chinese leg of the *Capital Flight* and *Reverse Flight* trades using the exchange's headquarter country. We also look at country-specific factors that may affect destination/source countries such as overall Bitcoin trading activity, corruption, and capital controls: *Country Market Share %* is the country's monthly market share of total USD turnover in Bitcoin exchanges in our sample. This measure is a proxy for the relative size of overall Bitcoin trading in our sample. *Corruption Perceptions Index* is the country's prior year corruption perceptions index from transparency.org. The index is flipped by subtracting it from 100 so that higher values indicate high corruption perception. *Capital Control Index* is the country's prior year capital controls index from Fernández et al. (2016) where higher scores indicate more stringent controls. Our hypotheses are that *Capital Flight* traders would want to choose destination countries with high turnover, low corruption, and low capital controls.

Table 7 Panel A reports summary statistics of Chinese capital flight destinations. The statistics are ranked by total capital flight volume received by the country. Capital flight volume from China is highest to the US, Finland, Luxembourg, Russia, and Japan. These countries are also the largest in *Country Market Share %*. With the exception of Russia, these countries also have corruption and capital control (except Luxembourg which has no measure) measures below the sample average. For reverse capital flight, the same countries appear in the top five as for capital flight except now the UK replaces Finland. However, country rankings differ when we measure capital flight volume as a percentage of total volume in the country (*Capital Flight / Country Volume (%)*). For this measure, the top countries are Finland, Austria, Russia, Taiwan, and Brazil. For *Reverse Flight / Country Volume* the top countries are UK, US, Lithuania, Czech Republic, and Luxembourg.

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

The most anomalous capital flight destination is Finland which ranks second in raw volume and first in *Capital Flight / Country Volume (%)*. However, Finland has low reverse flight volume. The reason is that Finland is dominated by LocalBitcoins.com, a peer-to-peer (P2P) exchange that differs from the centralized exchanges. The P2P nature allows for discreteness and a lower standard of anti-money laundering (AML) and know-your-client (KYC) requirements when *Capital Flight* traders sell their Bitcoin and also a choice of where they sell and into what fiat currency by finding appropriate buyers. For reverse flight however, large, centralized exchanges in the US and Luxembourg (e.g., BitStamp) are preferred as they accept major fiat currencies.

Panel B reports Spearman rank correlations between monthly capital flight and reverse flight volume measures and country specific variables. *Capital Flight* trades are positively related to *Reverse Flight* (0.091) and country market share (0.255) negatively related to corruption (-0.088) and capital controls (-0.114). These results are consistent with the Panel A summary statistics where large exchanges with low corruption and capital controls tend to have more capital flight trading. Reverse flight trades are also positively correlated to market shares (0.255) and negatively related to corruption (-0.073) and capital controls (-0.075). Although the directions of these correlations are the same as capital flight volume, the magnitudes are smaller, particularly for market share. The results suggest that liquidity/size of exchange is an important consideration in both capital flight and reverse flight trade destinations/sources.

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

We examine the robustness of our daily classification of trade types by netting user trades at weekly, fortnightly, and monthly intervals instead of daily intervals. This is because traders may take longer than a day to complete *Capital Flight* trades. We estimate the same regression as in Equation (1) except the dependent variables are net trading volume over weekly, fortnightly, or monthly intervals and rather than a daily time indicator, we use weekly, fortnightly, or monthly time indicators.

Table 8 Panel A reports total net trading across groups for different frequencies while Panel B, C, and D report coefficient estimation for when the dependent variable is net trading over a week, fortnight, or month, respectively.[21] We find that total net trading is between $14.36 and $14.48 billion,

[21] We find qualitatively similar results in Bitcoin.

lower than the trading volume at daily frequency of $17.71 billion (Table 1 Panel A). This comparison implies that user trades tend to net out over longer periods, which reduces net trading volume. At these longer frequencies, *Capital Flight* trades are the largest group of between 35.42% (weekly) to 37.34% (monthly) of net trading. These percentages are higher than the *Capital Flight* proportion of 26.01% observed based on daily intervals. In contrast, the proportion of *Chinese Only* trades ranges between 24.85% (monthly) to 24.85% (weekly), down from 45.74% at the daily interval.

The regression results are similar to our baseline results when using a weekly classification window: *Capital Flight* volume is positively associated with changes in economic policy uncertainty and the Chinese premium in Bitcoin. For fortnightly and monthly classification windows, only the Bitcoin Chinese premium remains statistically significant and ΔEPU is positive but not statistically significant. The results are consistent with *Capital Flight* trades being completed in a short time frame and therefore not being as accurately captured by longer classification intervals.

[--- INSERT TABLE 8 ABOUT HERE ---]

4.10. Falsification Tests

In this section, we test whether US and Russian exchanges experience similar capital flight volume and trade characteristics as Chinese exchanges. Similarities would imply that such patterns of trading (i.e., buying in home country and selling in a foreign country) are regular patterns of trading and perhaps not due to strict capital controls imposed by the Chinese government.

We choose US and Russia as they are the largest destinations of capital flight from China. The US has no capital restrictions so should have minimal *Capital Flight* trades. Russia has a significant, although lower than China, reported capital control violation (e.g., Kar and Spanjers, 2015; Repousis, Louis and Kougioumtsidis, 2019) thus we should observe less *Capital Flight* from Russian exchanges.

We repeat the net volume analysis but using US and Russia as the home country instead of China. Our expectation is that *Capital Flight* trades in the US and Russia should represent a minority of trades and not be positively associated with Chinese economic policy uncertainty or the CNY premium on Bitcoin.

The time series plots of monthly volume of different trader types in the US (Figure 4, Panels A and B) and Russia (Figure 4, Panels C and D) show that *Capital Flight* trades constitute a small proportion of trades for those countries over time. An exception is an increase in capital flight trades from Russian exchanges in December 2013 and February 2017.

Looking at the proportion of *Capital Flight* trades in our sample, we find that they constitute at most 5% of US net trading in USD (Table 9 Panel A). For Russia, *Capital Flight* trades constitute at most 13.26% of trades in USD (Table 9 Panel B). Both countries therefore have significantly lower proportions of *Capital Flight* than the one-third of volume in Chinese exchanges, implying the *Capital Flight* trades that we identify in China are not a usual trading pattern in countries without strict capital controls.

As a further falsification test, we use the daily net volume measures for US and Russia and regress on the right-hand side the same variables as in equation 1. If the patterns of trade in China, US, and Russia are correlated, we should find ΔEPU and $Premium$ being positive and statistically significant for *Capital Flight* trades for US and Russia. The results in Table 9 Panel C (US) and Panel D (Russia) do not show positive coefficients for ΔEPU and $Premium$, implying the *Capital Flight* trades in the US and Russia are not associated with Chinese factors. The negative and statistically significant ΔEPU for *Capital Flight* trades in the US (Table 9 Panel C, column 4) implies higher Chinese uncertainty is associated with less *Capital Flight* trades in the US. Combined with the positive and statistically significant ΔEPU for *Reverse Flight* trades (Table 9 Panel C, column 2), higher Chinese uncertainty is associated with an increase in selling to US exchanges consistent with Chinese *Capital Flight* trades selling in US exchanges in times of high Chinese economic policy uncertainty.

We also find a positive and statistically significant *Premium* for *Reverse Flight* trades for both US and Russian exchanges. That implies that when the CNY price for Bitcoin is high relative to the USD, there is more buying in US and Russian exchanges and selling to other countries. This pattern is consistent with arbitrage activity.

Overall, the results show that *Capital Flight* trades in the US and Russia represent very small proportions of their trading activity and are not significantly related to the explanatory variables for China, suggesting that the Chinese *Capital Flight* trades identified in our analysis are not a usual trading pattern in countries without strict capital controls.

5. Conclusion

We show that cryptocurrencies provide a novel avenue for evading circumvent capital controls. The magnitude of capital flowing across borders via cryptocurrencies is economically meaningful and significant. Our estimates indicate that it constitutes over one-quarter of the trading volume on Chinese Bitcoin exchanges from 2011 to 2018, amounting to \$4.6 billion in dollar terms or a remarkable one-half of the total circulating supply of Bitcoins.

We examine the potential factors influencing these activities and find that the intensity of capital flight out of China via Bitcoin increases during periods of elevated economic policy uncertainty in China, which is inconsistent with triangular arbitrage and consistent with investors' motive of seeking a safe haven for their domestic assets in China. During episodes of heightened economic policy uncertainty in China, we observe a decrease in the demand for CNY and a simultaneous rise in the demand for USD. Driven by the desire to bypass capital restrictions and move domestic assets offshore, capital flight traders are willing to accept a loss, which can be seen as a transaction fee, in order to conduct such trades.

Capital flight via cryptocurrencies involves "uneconomical trading" in the underlying markets—people incur losses on trades from one fiat currency to another via a cryptocurrency for the benefit of being able to circumvent controls. This interesting feature of the trading is similar to some market manipulation strategies in which uneconomical trading in one market, for the benefit of a payoff in another market or contract, is used as a defining and identifying feature of the misconduct. Our findings contribute to understanding the drivers of the large and persistent arbitrage opportunities that have been documented in cryptocurrency markets—some of the mispricing is likely driven by a willingness to pay a premium to evade capital controls.

Our findings also indicate that individuals engaged in capital flight are less inclined to use Bitcoin for illicit trading of goods or services. This observation suggests that the capital flight identified in our study is not primarily motivated by the need to launder proceeds from illicit businesses. We show the characteristics of capital flight differ from the flows associated with the trade of illegal goods. Instead, capital flight is more likely driven by other motives, such as Chinese citizens aiming to deposit or invest funds in foreign countries or to purchase foreign goods.

One of the broader implications of our study is that it demonstrates the potential for cryptocurrencies to be used in money laundering. Converting fiat currencies via a cryptocurrency to evade capital controls has similarities with money laundering in that it involves transactions conducted in a manner that deliberately conceal the origin and destination of the funds. To that extent, our study suggests a potentially fruitful avenue for future research is to use the concept of uneconomic trades in cryptocurrencies to identify and track the global flows potentially associated with money laundering. This avenue of investigation could deepen our understanding of the dynamics and patterns associated with money laundering facilitated by cryptocurrencies.

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Appendix 1: 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 transactions per day	Calculated directly from blockchain data
User level characteristics such as trade frequency, average trade size and trading with other users	From Foley et al. (2019)

Appendix 2: Blockchain Trades Matched to Exchange Self-Reported Trades

The table reports the percentage of volume self-reported by the exchanges that is able to be matched to trades on the Bitcoin blockchain. 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%. The Matched Volume (%) is defined as total amount of Bitcoin exchange trades matched using exchanges' wallet addresses divided by reported trading volume by exchanges. 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 September 2, 2011 to February 8, 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 3: Bitcoin Exchanges Ranked by Volume Matched to the Blockchain

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

Rank	Exchange Name	HQ Country/Region	Volume (BTC thousands)	Volume (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

Rank	Exchange Name	HQ Country/Region	Volume (BTC thousands)	Volume (USD millions)
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 Republic	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

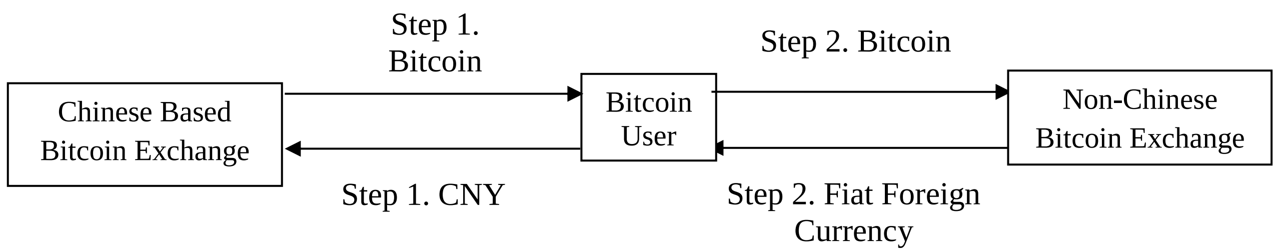
Appendix 4: Indirect Trades Classifications

The table below shows the pattern of trades involving two users, User A and User B, to identify indirect *Capital Flight* and *Reverse Flight* trades. User A trades on Chinese Bitcoin exchanges and user B trades on non-Chinese Bitcoin exchanges. Indirect trades involve two users are as depicted in Figure 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 Flight*	Net sells at Chinese exchanges	A receives Bitcoin from B	Net buys on non-Chinese exchanges

Figure 1: How Bitcoin is used to Circumvent Capital Controls
The diagrams below depict the flows of Bitcoin and fiat currency from a Bitcoin user converting CNY to a foreign currency via Bitcoin, effectively bypassing regulatory checks. Panel A shows an example of a Chinese Bitcoin user that registers in both Chinese and non-Chinese Bitcoin exchanges (direct *Capital Flight*). Panel B depicts an example of a Chinese Bitcoin user that only registers in a Chinese Bitcoin exchange and transfers Bitcoin to another user registered in a non-Chinese exchange (indirect *Capital Flight*).

Panel A: Direct Capital Flight



Panel B: Indirect Capital Flight through another User

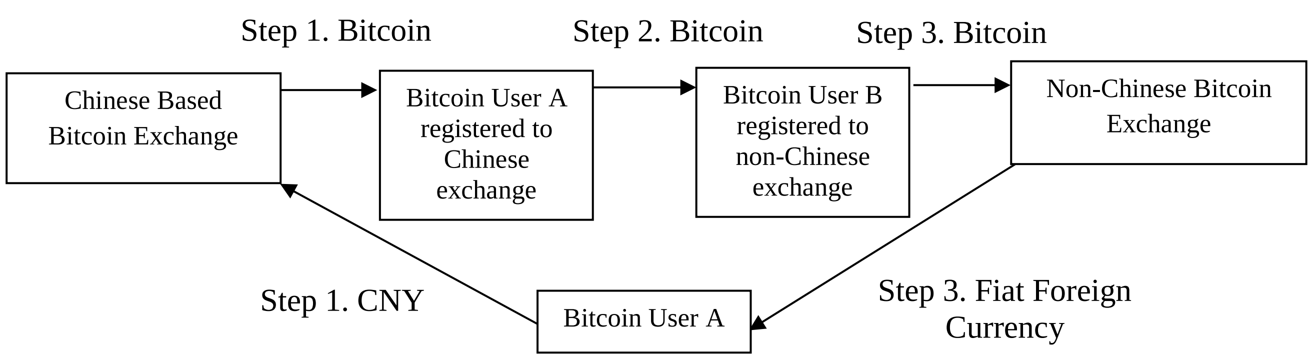
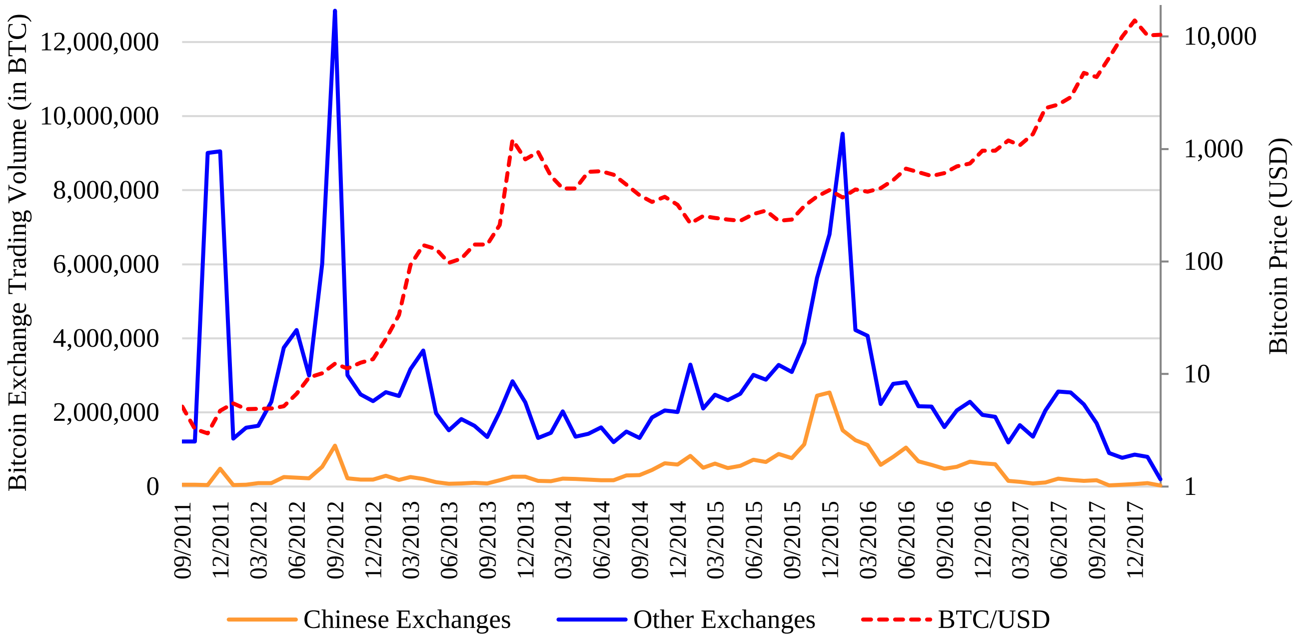


Figure 2: Monthly Bitcoin Exchange Volume

Panel A presents the monthly trading volume measured in Bitcoin on Chinese and foreign Bitcoin Exchanges against the BTC/USD exchange rate. Panel B presents the monthly trading volume measured in USD on Chinese and foreign Bitcoin Exchanges against the BTC/USD exchange rate.

Panel A: Trading Volume Measured in BTC



Panel B: Trading Volume Measured In USD

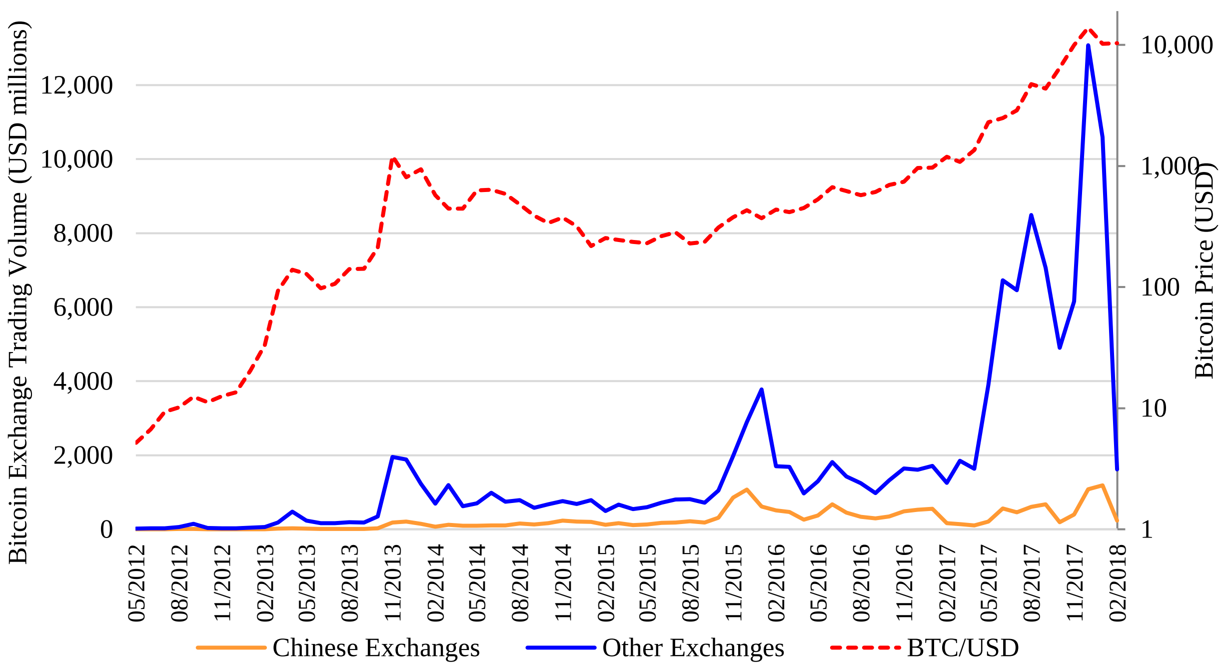
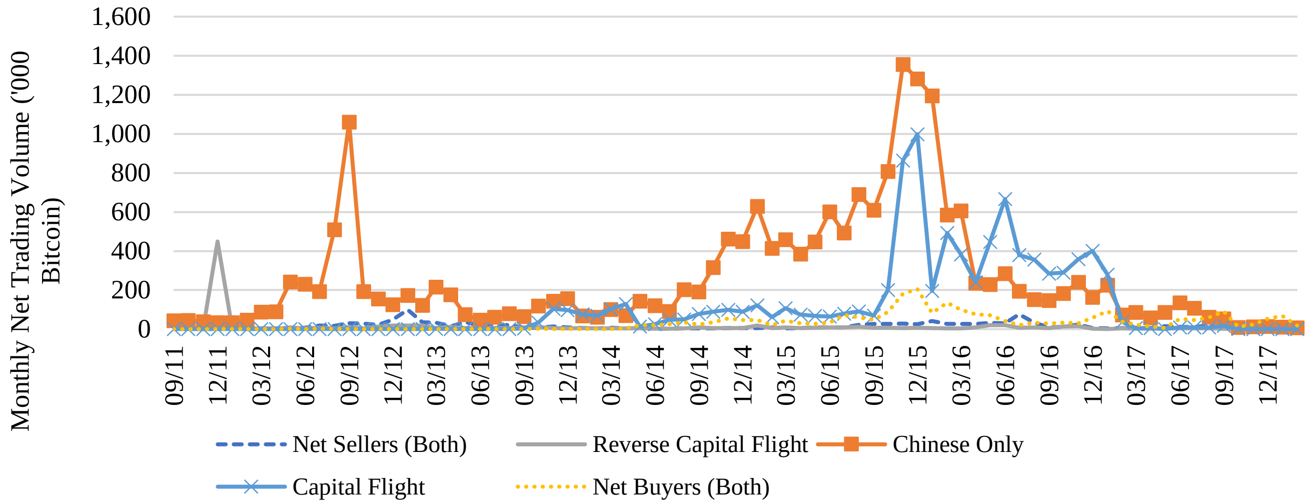


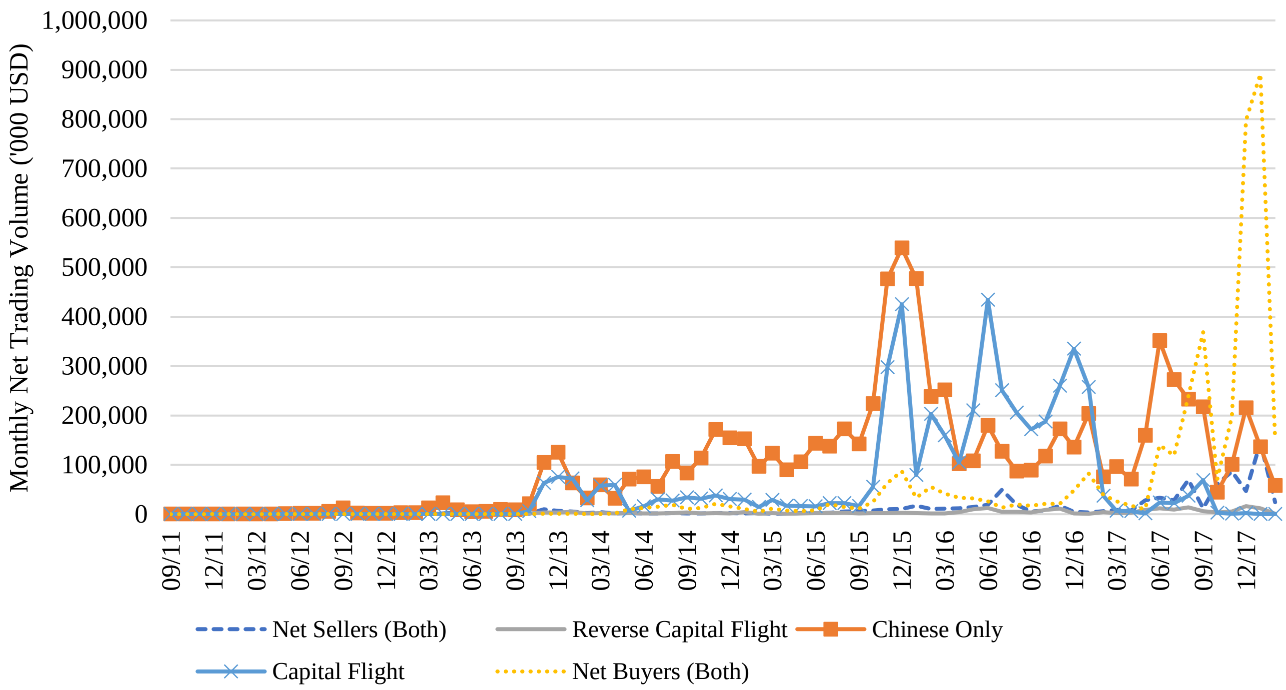
Figure 3: Bitcoin Trading Volume in Chinese Exchanges by Trader Type

Panel A presents the monthly Chinese exchange Bitcoin net trading volume in Bitcoin for each trader category, and Panel B presents the same in USD. Panel C presents the monthly Bitcoin net volume of *Capital Flight* trades on Chinese exchanges in Bitcoin, the average daily network fee in USD per transaction and the average daily BTC/CNY premium Panel D presents the same as Panel C except *Capital Flight* trades in USD.

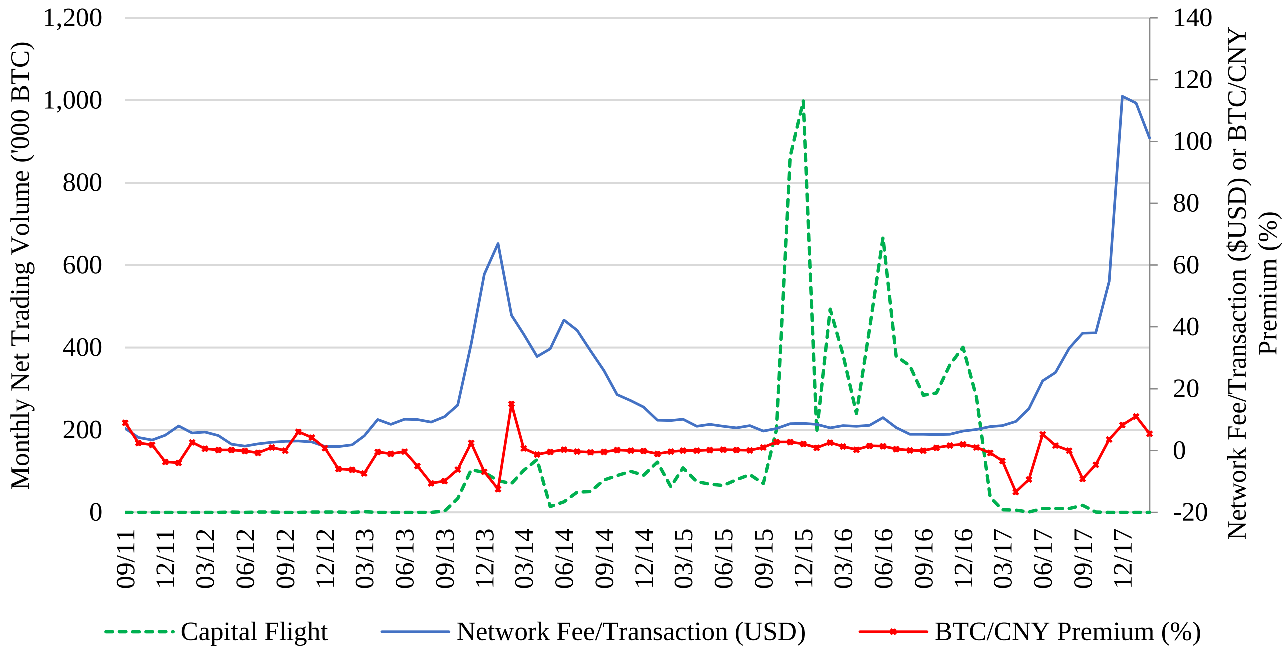
Panel A: Net Volume in Chinese Bitcoin Exchanges (in '000 BTC)



Panel B: Net Volume in Chinese Bitcoin Exchanges (in '000 USD)



Panel C: Capital Flight Volume (in '000 BTC)



Panel D: Capital Flight Volume (in USD$ millions)

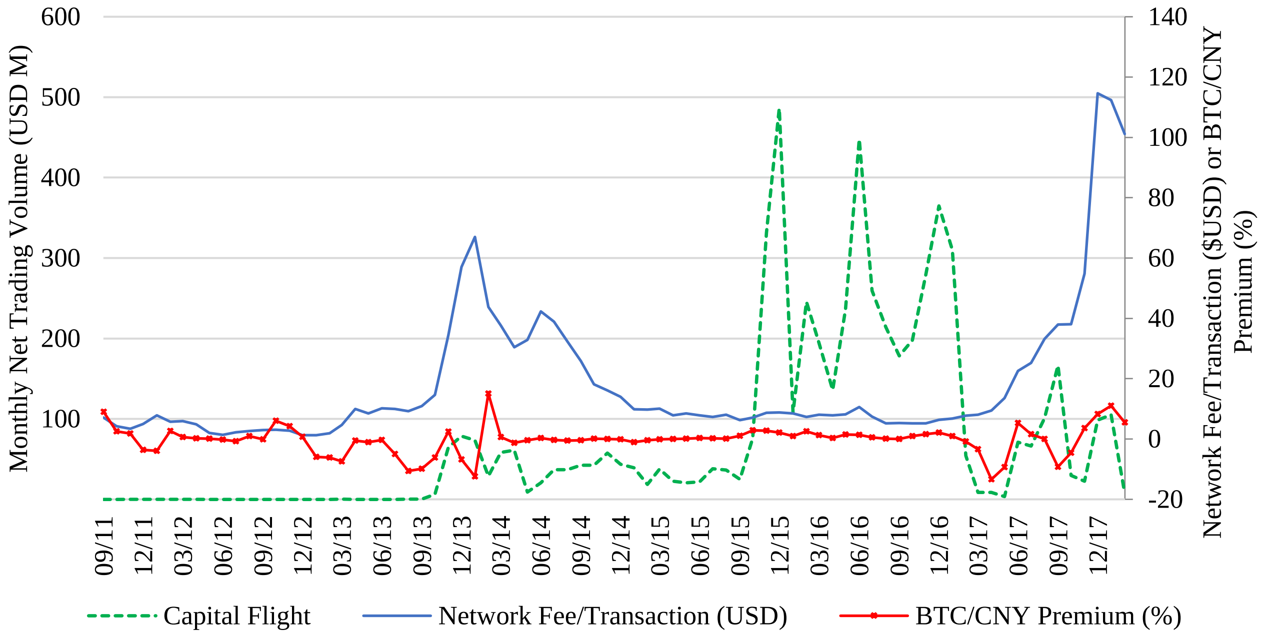
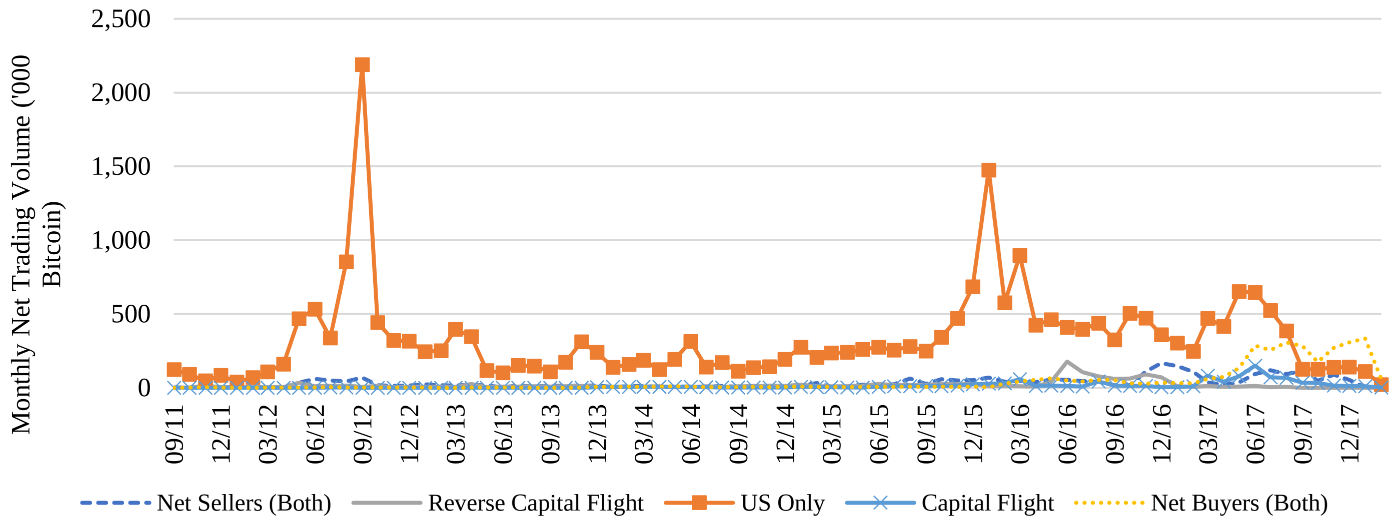


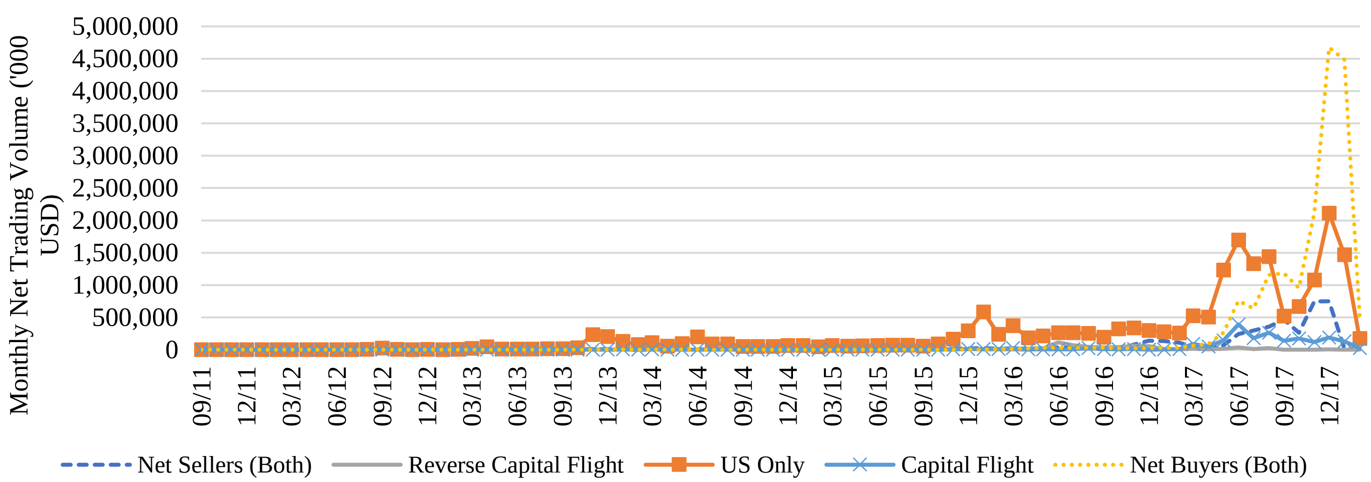
Figure 4: Monthly Bitcoin Exchange Volume (US and Russia)

Panel A and B presents the monthly US exchange Bitcoin net trading volume in Bitcoin and USD for each trader category, respectively. Panel C and Panel D presents the monthly US exchange Bitcoin net trading volume in Bitcoin and USD for each trader category, respectively.

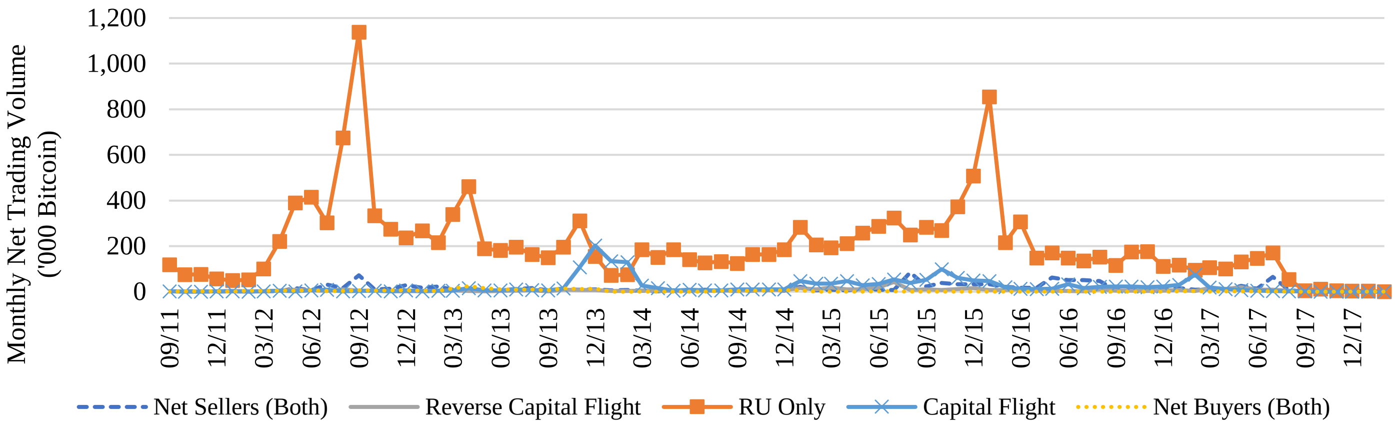
Panel A. Net Volume in US Bitcoin Exchanges (in '000 BTC)



Panel B. Net Volume in US Bitcoin Exchanges (in '000 USD)



Panel C. Net Volume in Russian Bitcoin Exchanges (in ‘000 BTC)



Panel D. Net Volume in Russian Bitcoin Exchanges (in ‘000 USD)

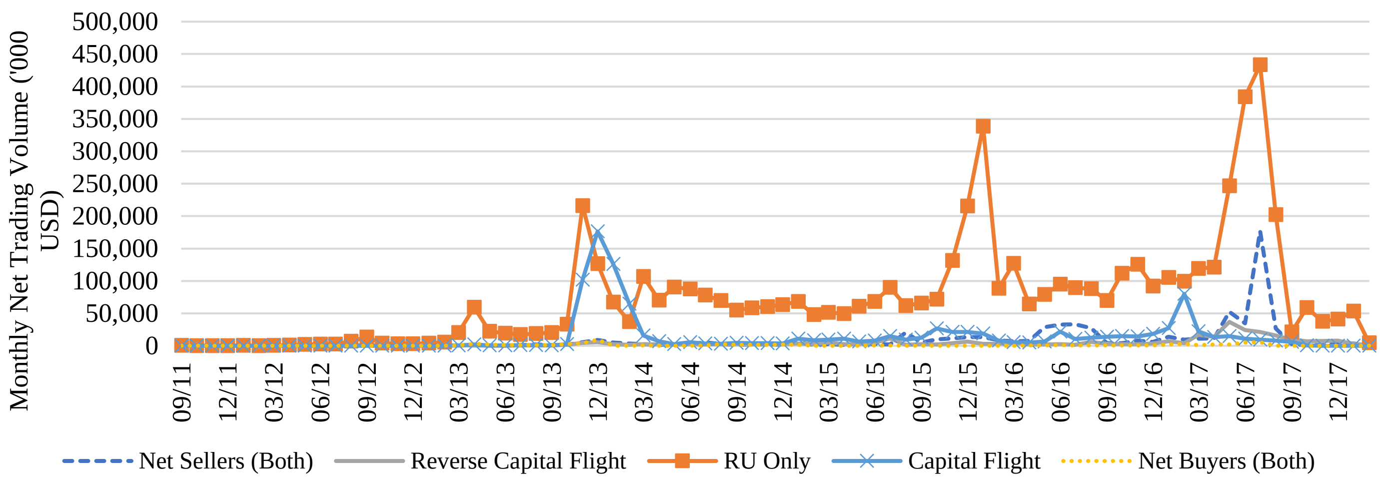


Table 1: Descriptive Statistics

The table reports descriptive statistics of daily variables. $Bitcoin\ Return$ (USD) and $Bitcoin\ Return$ (CNY) are the daily percentage Bitcoin returns in USD and CNY, respectively. ΔEPU is the monthly change in the Baker et al. (2016) Chinese economic policy uncertainty index (standardized), $Premium$ is the Bitcoin price in CNY converted to USD expressed as a percentage over the Bitcoin price in USD. $Trades$ is the daily number of Bitcoin blockchain transactions (in thousands). $Volatility$ is the daily sum of squared one-minute USD Bitcoin returns. Fee is the daily average fee per trade in USD. China Net (*category*) is the net trading volume in Chinese exchanges by the given category of traders. The sample is from September 2, 2011 to February 8, 2018. Panel A reports the total net trading volume (in Bitcoin and US$) at Chinese Bitcoin exchanges for different trade groups. Panel B reports summary statistics. Panel C reports the correlation matrix of variables.

Panel A: Net Trading by Trader Types at Chinese Bitcoin Exchanges

Measure	Net Sellers	Reverse Flight	Chinese Only	Capital Flight	Net Buyers	Total Net Trades
Bitcoin (million)	1.21	0.94	20.14	8.78	2.45	33.51
% of Total	3.60	2.82	60.10	26.19	7.30	100.00
USD (million)	864.43	235.42	8,099.73	4,605.43	3,904.48	17,709.48
% of Total	4.88	1.33	45.74	26.01	22.05	100.00

Panel B: Summary Statistics of Daily Variables

Variable	Mean	Median	Std Dev	P25	P75
$\boldsymbol{Bitcoin\ Return}$ (USD)	0.54	0.21	9.11	-1.17	2.10
$\boldsymbol{Bitcoin\ Return}$ (CNY)	0.49	0.00	6.24	-0.82	1.59
$\boldsymbol{\Delta EPU}$	0.00	0.01	0.72	-0.38	0.48
$\boldsymbol{Premium}$	-0.32	0.07	6.87	-1.96	1.55
$\boldsymbol{Trades}$	126.08	83.36	102.11	47.85	217.51
$\boldsymbol{Volatility}$	0.64	0.26	1.09	0.11	0.68
$\boldsymbol{Fee}$	1.13	0.08	4.53	0.03	0.19
China Net (*Net Sellers*) BTC '000	2.52	0.96	5.49	0.35	2.57
China Net (*Reverse Flight*) BTC '000	2.37	1.29	18.53	0.62	2.40
China Net (*Chinese Only*) BTC '000	8.56	4.17	13.28	1.64	10.62
China Net (*Capital Flight*) BTC '000	4.41	0.62	8.28	0.00	4.58
China Net (*Net Buyers*) BTC '000	2.56	1.10	3.87	0.06	3.17
China Net (*Net Sellers*) USD '000	3,056.32	233.46	11,191.87	52.73	1,168.00
China Net (*Reverse Flight*) USD '000	1,827.10	388.16	5,635.91	49.52	1,105.59
China Net (*Chinese Only*) USD '000	3,443.76	2,276.10	4,892.24	183.06	4,565.77
China Net (*Capital Flight*) USD '000	2,417.42	383.45	4,785.96	0.00	2,374.36
China Net (*Net Buyers*) USD '000	8,739.90	425.10	33,715.88	2.99	1,534.64

Panel C: Correlation Matrix

No.	Variable	1	2	3	4	5	6	7	8	9	10	11	12
1	$\boldsymbol{Bitcoin\ Return}$ (USD)	1.000											
2	$\boldsymbol{Bitcoin\ Return}$ (CNY)	0.311	1.000										
3	$\Delta\boldsymbol{EPU}$	-0.020	-0.020	1.000									
4	$\boldsymbol{Premium}$	-0.140	0.092	0.004	1.000								
5	$\boldsymbol{Trades}$	0.003	0.028	-0.010	0.061	1.000							
6	$\boldsymbol{Volatility}$	-0.010	0.007	-0.020	-0.110	-0.090	1.000						
7	$\boldsymbol{Fee}$	-0.010	0.030	-0.100	0.201	0.416	-0.100	1.000					
8	China Net (*Net Sellers*) BTC	0.000	0.004	-0.020	0.016	0.147	-0.080	0.002	1.000				
9	China Net (*Reverse Flight*) BTC	0.017	0.000	-0.010	-0.030	-0.010	-0.010	-0.010	0.000	1.000			
10	China 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	China 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	China 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 Trading Volume by Trader Type

This table reports estimates from the following regression:

$$Volume_{jt} = \alpha + b_1 \Delta EPU_t + b_2 Premium_t + b_3 Trades_t + b_4 Fee_t + b_5 Volatility_t + b_6 Day_t + e_{jt}$$

where $Volume_{jt}$ is the net volume traded on Chinese Bitcoin exchanges by trader type j on day t. ΔEPU_t is the monthly change in the Chinese economic policy uncertainty index (standardized) obtained from Baker et al. (2016). $Premium_t$ is the Bitcoin price in CNY converted to USD expressed as a percentage over the USD Bitcoin price. $Trades_t$ is the daily number of trades. Fee_t is the daily average fee per trade in USD. $Volatility_t$ is the daily sum of squared one-minute USD Bitcoin returns. Day_t is the number of days since the start of the sample period. The sample is from September 2, 2011 to February 8, 2018. Panel A reports results using Bitcoin net volume (in '000 BTC). Panel B reports results using Bitcoin net volume converted into USD (in '000). Standard errors are in parentheses. ***, **, and * signifies statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Dependent Variable: Bitcoin Net Volume (in '000 BTC)

	Trader Type				
	Net Sellers	Reverse Flight	Chinese Only	Capital Flight	Net Buyers
ΔEPU	0.028	-0.106	0.052	0.519***	-0.043
	(0.069)	(0.115)	(0.375)	(0.200)	(0.042)
$Premium$	-0.006	-0.039	0.206***	0.174***	0.029***
	(0.004)	(0.041)	(0.029)	(0.018)	(0.004)
$Trades$	0.002***	0.004	-0.026***	0.028***	0.001
	(0.001)	(0.004)	(0.006)	(0.004)	(0.001)
Fee	-0.018***	0.011	-0.604***	-0.523***	-0.046***
	(0.004)	(0.020)	(0.065)	(0.052)	(0.007)
$Volatility$	-0.036**	-0.065	-1.243***	-0.064	-0.152***
	(0.014)	(0.067)	(0.134)	(0.067)	(0.015)
Day	0.000**	-0.001	0.006***	0.001	0.001***
	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)
$Intercept$	0.562***	1.122	6.004***	0.117	-0.137***
	(0.058)	(0.891)	(0.578)	(0.138)	(0.029)
Adj R^2	0.56%	-0.01%	6.16%	20.80%	25.98%
N	2,352	2,352	2,352	2,352	2,352

Panel B: Dependent Variable: Bitcoin Volume (in '000 USD)

	Trader Type				
	Net Sellers	Reverse Flight	Chinese Only	Capital Flight	Net Buyers
ΔEPU	-4.362	5.958	209.624	661.147***	-119.699
	(49.269)	(8.495)	(132.262)	(107.371)	(77.854)
$Premium$	1.632	1.227	67.746***	77.563***	27.931**
	(4.085)	(0.91)	(10.692)	(9.637)	(13.442)
$Trades$	2.881***	0.596***	1.258	22.803***	3.071
	(0.824)	(0.159)	(2.221)	(2.486)	(2.824)
Fee	87.477***	7.84**	-107.855***	-278.407***	839.404***
	(21.082)	(3.11)	(20.307)	(26.626)	(70.915)
$Volatility$	-34.986***	1.749	-327.166***	49.967	-176.385***
	(10.947)	(3.309)	(44.94)	(36.926)	(27.463)
Day	0.015	0.02	3.483***	-0.485*	0.82**
	(0.122)	(0.022)	(0.274)	(0.272)	(0.39)
$Intercept$	-89.087**	-7.512	-374.871***	-52.036	-493.982***
	(37.342)	(7.281)	(85.608)	(70.844)	(112.591)
Adj R^2	20.80%	12.24%	24.90%	26.87%	68.63%
N	2,352	2,352	2,352	2,352	2,352

Table 3: Determinants of Capital Flight Trade Volume Including Indirect Trades

Panel A reports net trading volumes in Chinese exchanges partitioned by trader group. The trader groups are classified using the algorithm in Section 4.3 and include indirect *Capital Flight* trades. Panels B and C report estimates from the following regression:

$$Volume_{jt} = \alpha + b_1 \Delta EPU_t + b_2 Premium_t + b_3 Trades_t + b_4 Fee_t + b_5 Volatility_t + b_6 Day_t + e_{jt}$$

where $Volume_{jt}$ is the net volume traded on Chinese Bitcoin exchanges by trader type j on day t. ΔEPU_t is the monthly change in the Chinese economic policy uncertainty index (standardized) obtained from Baker et al. (2016). $Premium_t$ is the Bitcoin price in CNY converted to USD expressed as a percentage over the USD Bitcoin price. $Volatility_t$ is the daily sum of squared one-minute USD Bitcoin returns. $Trades_t$ is the daily number of trades. Fee_t is the daily average fee per trade in USD. Day_t is the number of days since the start of the sample period. The sample is from September 2, 2011 to February 8, 2018. Standard errors are in parentheses. ***, **, and * signifies statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Net Trading Volumes on Chinese Bitcoin Exchanges by Trader Type

	Trader Group							
Measure	Net Sellers	Reverse Flight	Chinese Only	Capital Flight	Net Buyers	Total Net Trades	Indirect Reverse Flight	Indirect Capital Flight
Bitcoin (million)	0.98	1.29	19.6	10.31	1.33	33.51	0.35	1.53
% of Total	2.91	3.86	58.49	30.76	3.97	100.00	1.04	4.57
USD (million)	735.28	411.72	7,827.07	5,730.19	3,005.21	17,709.48	176.30	1,124.76
% of Total	4.15	2.32	44.20	32.36	16.97	100.00	1.00	6.35

Panel B: Dependent Variable: Bitcoin Net Volume (in '000 BTC)

	Trader Type				
	Net Sellers	Reverse Flight	Chinese Only	Capital Flight	Net Buyers
ΔEPU	0.036	-0.110	0.039	0.541**	-0.056**
	(0.068)	(0.116)	(0.369)	(0.216)	(0.028)
$Premium$	-0.003	-0.041	0.198***	0.197***	0.014***
	(0.004)	(0.041)	(0.029)	(0.020)	(0.002)
$Trades$	0.002***	0.004	-0.026***	0.028***	0.001**
	(0.001)	(0.004)	(0.006)	(0.005)	(0.000)
Fee	-0.016***	0.007	-0.580***	-0.591***	0.001
	(0.004)	(0.020)	(0.063)	(0.058)	(0.004)
$Volatility$	-0.026*	-0.076	-1.235***	-0.147**	-0.077***
	(0.014)	(0.067)	(0.133)	(0.074)	(0.009)
Day	0.000*	-0.001	0.006***	0.001**	0.001***
	(0.000)	(0.001)	(0.001)	(0.001)	(0.000)
$Intercept$	0.410***	1.327	5.948***	0.102	-0.120***
	(0.053)	(0.891)	(0.576)	(0.155)	(0.019)
Adj R^2	0.41%	0.02%	5.90%	21.83%	24.72%
N	2,352	2,352	2,352	2,352	2,352

Panel B: Dependent Variable: Bitcoin Net Volume (in ‘000 USD)

	Trader Type				
	Net Sellers	Reverse Flight	Chinese Only	Capital Flight	Net Buyers
ΔEPU	-15.953	15.680	204.623	654.007***	-105.689
	(48.216)	(11.085)	(130.210)	(112.018)	(68.461)
$Premium$	2.113	0.661	65.011***	91.329***	16.984
	(3.923)	(1.124)	(10.372)	(10.756)	(11.964)
$Trades$	2.277***	1.096***	0.573	24.877***	1.787
	(0.731)	(0.282)	(2.187)	(2.759)	(2.636)
Fee	80.392***	15.74***	-97.149***	-217.557***	767.034***
	(20.283)	(4.510)	(19.968)	(25.523)	(64.945)
$Volatility$	-26.633***	-7.124*	-321.101***	-9.558	-122.404***
	(10.255)	(4.143)	(44.145)	(39.939)	(21.990)
Day	0.025	0.037	3.429***	-0.205	0.567
	(0.110)	(0.041)	(0.270)	(0.306)	(0.364)
$Intercept$	-75.65**	-18.758	-358.208***	-184.326**	-380.545***
	(34.476)	(11.912)	(83.625)	(79.765)	(102.512)
Adj R^2	17.96%	21.91%	24.09%	29.63%	68.91%
N	2,352	2,352	2,352	2,352	2,352

Table 4: Split Sample Regressions

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

$$Volume_{jt} = \alpha + b_1 \Delta EPU_t + b_2 Premium_t + b_3 Trades_t + b_4 Fee_t + b_5 Volatility_t + b_6 Day_t + e_{jt}$$

where $Volume_{jt}$ is the net volume traded on Chinese Bitcoin exchanges by trader type j on day t. ΔEPU_t is the monthly change in the Chinese economic policy uncertainty index (standardized) obtained from Baker et al. (2016). $Premium_t$ is the Bitcoin price in CNY converted to USD expressed as a percentage over the USD Bitcoin price. $Trades_t$ is the daily number of trades. Fee_t is the daily average fee per trade in USD. $Volatility_t$ is the daily sum of squared one-minute USD Bitcoin returns. Day_t is the number of days since the start of the sample period. Panel A reports results for the sample before September 1, 2015 using Bitcoin net volume in USD '000s. Panel B reports results for the sample after September 1, 2015 using Bitcoin net volume in USD '000s. Standard errors are in parentheses. ***, **, and * signifies statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Before September 1, 2015 (in '000 USD)

	Trader Type				
	Net Sellers	Reverse Flight	Chinese Only	Capital Flight	Net Buyers
ΔEPU	-7.930	7.775	36.344	25.551	21.436
	(5.808)	(6.193)	(91.851)	(38.399)	(15.901)
$Premium$	-0.257	-0.087	6.637	7.095**	1.469***
	(0.452)	(0.395)	(5.985)	(3.579)	(0.333)
$Trades$	1.574***	0.48**	22.479***	1.152	-0.105
	(0.429)	(0.191)	(4.234)	(1.871)	(0.693)
Fee	679.836***	223.59***	2,313.197**	5,502.609***	-316.428***
	(165.973)	(64.906)	(1,140.602)	(781.408)	(61.212)
$Volatility$	-0.703	3.151	-239.46***	-63.947***	-35.823***
	(2.851)	(2.319)	(25.916)	(18.463)	(3.057)
Day	-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 R^2	15.08%	10.29%	51.30%	29.91%	36.10%
N	1,460	1,460	1,460	1,460	1,460

Panel B: From September 1, 2015 (in ‘000 USD)

	Trader Type				
	Net Sellers	Reverse Flight	Chinese Only	Capital Flight	Net Buyers
ΔEPU	17.203	5.276	-9.152	741.668***	-70.730
	(72.706)	(11.562)	(165.750)	(137.005)	(101.98)
$Premium$	17.271	6.369*	108.817***	160.662***	127.610***
	(16.149)	(3.267)	(25.263)	(26.504)	(49.001)
$Trades$	1.038	0.705**	4.886	24.39***	-4.603
	(1.718)	(0.307)	(3.462)	(3.627)	(5.360)
Fee	58.794**	3.568	30.927	-148.674***	715.191***
	(25.861)	(3.610)	(22.93)	(29.716)	(79.383)
$Volatility$	-445.062***	-64.607***	-3,279.503***	-1,162.032***	-1,157.813***
	(105.723)	(20.485)	(365.642)	(269.88)	(172.666)
Day	1.115**	0.075	-9.046***	-11.157***	5.886***
	(0.489)	(0.090)	(1.345)	(0.89)	(1.450)
$Intercept$	-1,422.771**	-96.561	23,752.8***	20,359.362***	-7,333.448***
	(620.155)	(112.15)	(2,215.609)	(1,575.37)	(1,755.142)
Adj R^2	15.02%	5.83%	13.28%	28.68%	65.92%
N	892	892	892	892	892

Table 5: Profits from Bitcoin Trading

The table reports USD profits for traders from September 2, 2011 to February 8, 2018. We split intraday trading profits into two components: (1) intra-exchange trading profits from buying and selling within either Chinese or non-Chinese exchanges of the same exchange; and (2) inter-exchange profits from trading between Chinese and non-Chinese exchanges. These measures are defined in equations (2) to (4) of the paper. We calculate percentage profits as the profit divided by the net Bitcoin volume traded in Chinese exchanges converted into USD. Panel A report total profits by trader type. In Panel B and Panel C we classify *Reverse Flight* and *Capital Flight* user/days as economical if their inter-exchange profit is greater than one percent and uneconomical otherwise. Panel B reports statistics by flight type and profitability. Panel C reports estimates from the regression specified in Equation (1) by flight type and profitability.

Panel A. Total Trading Profits by Trader Type

Trader Type	Intra-Exchange (USD '000)	Intra-Exchange (%)	Inter-Exchange (USD '000)	Inter-Exchange (%)
Net Sellers	544.47	0.1344	-	-
Reverse 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 Buyers	198.77	0.0111	-	-

Panel B. Profitability of Trader Types at User/Day Level

		Inter-Exchange P/L (USD$)		Inter-Exchange P/L (%)		Principal (USD$)		
Trader Type	*Economical*	Mean	Median	Mean	Median	Mean	Median	N Users/Days
Reverse Flight	*No*	-57.76	-0.15	-1.77	-0.69	2,443.54	57.98	53,104
Reverse Flight	*Yes*	177.73	1.76	6.86	2.59	3,812.13	54.82	17,672
Capital Flight	*No*	-2,120.11	-10.60	-2.04	-1.31	111,367.02	1,849.05	32,104
Capital Flight	*Yes*	5,155.35	42.16	3.23	2.18	144,750.56	1,706.05	7,075

Panel C. Determinants of Capital Flight Net Volume by Economical/Uneconomical Trading

	Dependent Variable: Bitcoin Volume (in USD thousands)			
	Reverse Flight	Reverse Flight	Capital Flight	Capital Flight
Economical:	*No*	*Yes*	*No*	*Yes*
	(1)	(2)	(3)	(4)
ΔEPU	5.448	-10.291	437.333***	39.586
	(6.185)	(9.705)	(119.088)	(67.535)
$Premium$	-1.323**	1.971***	74.873***	-41.986***
	(0.519)	(0.53)	(13.317)	(12.656)
$Trades$	0.057	0.395**	45.089***	4.834***
	(0.095)	(0.192)	(3.596)	(1.644)
Fee	23.77**	28.339***	-1,217.073***	-207.902***
	(9.733)	(10.363)	(126.102)	(59.262)
$Volatility$	0.405	0.946	-210.884***	-57.195
	(2.494)	(2.497)	(64.85)	(34.933)
Day	0.054***	-0.003	-2.875***	0.256
	(0.012)	(0.024)	(0.487)	(0.231)
$Intercept$	-11.669**	-7.200	548.434**	-194.379
	(5.003)	(8.79)	(264.268)	(136.121)
Adj R^2	8.63%	5.37%	36.31%	7.63%
N	2,014	1,403	1,438	1,281

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:

$$Logit(illegal_i = 1) = b_0 + b_1 ExchUser_i + b_2 ChinaExchUser_i + b_3 NetSeller\%_i + b_4 Reverse\%_i + b_5 ChineseOnly\%_i$$
$$+ b_6 CapFlight\%_i + b_7 NetBuyer\%_i + b_8 LogN_i + b_9 LogTradeSize_i + b_{10} Concentration_i + e_i$$

where $illegal_i = 1$ if user i is classified as an illegal user in Foley et al. (2019) and 0 otherwise. $ExchUser_i = 1$ if the user ever traded with a Bitcoin exchange and 0 otherwise. $ChinaExchUser_i = 1$ if the user ever traded with a Chinese Bitcoin exchange and 0 otherwise. Every day for each user, we calculate net volume of their trades with Chinese Bitcoin exchanges, non-Chinese Bitcoin exchanges, and other counterparties. Net volume in each venue is the absolute of buy dollar volume less sell dollar volume. $NetSeller\%_i$ is the percentage of the user's trading where they are net selling in both non-Chinese and Chinese Bitcoin exchanges. $Reverse\%_i$ is the percentage of the user's trading that is classified as *Reverse Flight* (buying in non-Chinese Bitcoin exchanges and selling in Chinese exchanges). $ChineseOnly\%_i$ is the percentage of the user's trading that is classified as *Chinese Only* trading. $CapFlight\%_i$ is the percentage of the user's trading classified as *Capita Flight* trading (buying in Chinese exchanges and selling in non-Chinese exchanges). $NetBuyer\%_i$ is the percentage of the user's trading where they are net buying in both non-Chinese and Chinese Bitcoin exchanges. $LogN_i$ is the natural log of number of trades by the user. $LogTradeSize_i$ is the average USD trade size of the user's transactions. $Concentration_i$ is a measure of the tendency for the 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 Trader Type by Year (USD Millions)

		Trade Type Classification					
Year	Legal/Illegal User	Net Sellers	Reverse Flight	Chinese Only	Capital Flight	Net Buyers	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	167.36	26.80	712.90	1,811.42	131.34	7,903.71
	Illegal	549.27	363.97	460.62	1,388.07	528.20	769.54
	Illegal (%)	76.65	93.14	39.25	43.38	80.09	8.87
2017	Legal	367.80	314.63	1,163.66	267.89	3,284.56	14,960.95
	Illegal	5,082.03	2,549.78	193.15	508.63	9,344.43	5,191.87
	Illegal (%)	93.25	89.02	14.24	65.50	73.99	25.76
2018	Legal	37.98	35.98	146.15	0.86	3,083.06	2,460.20
	Illegal	471.91	286.80	12.73	1.07	3,540.92	1,159.63
	Illegal (%)	92.55	88.85	8.01	55.42	53.46	32.04
All	Legal	782.64	447.65	3,175.37	2,740.67	6,622.39	29,825.46
	Illegal	6,406.25	3,849.77	2,103.87	2,945.11	13,933.87	11,088.88
	Illegal (%)	89.11	89.58	39.85	51.80	67.78	27.10

Panel B: Logit Regression

	$Logit(illegal_i = 1)$	
	(1)	(2)
$ExchUser_i$	3.066***	3.066***
	(0.5124)	(0.5124)
$ChinaExchUser_i$	0.552***	0.552***
	(0.0089)	(0.0089)
$NetSeller\%_i$	0.014***	0.014***
	(0.0001)	(0.0001)
$Reverse\%_i$	0.014***	
	(0.0002)	
$Reverse\%_i$ (uneconomical)		0.016***
		(0.0002)
$Reverse\%_i$ (economical)		0.009***
		(0.0003)
$CapFlight\%_i$	-0.011***	
	(0.0002)	
$CapFlight\%_i$ (uneconomical)		-0.012***
		(0.0002)
$CapFlight\%_i$ (economical)		-0.007***
		(0.0005)
$ChineseOnly\%_i$	-0.006***	-0.006***
	(0.0001)	(0.0001)
$NetBuyer\%_i$	-0.002***	-0.002***
	(0.0004)	(0.0004)
$LogN_i$	-0.049***	-0.049***
	(0.0002)	(0.0002)
$LogTradeSize_i$	-0.087***	-0.087***
	(0.0001)	(0.0001)
$Concentration_i$	0.411***	0.411***
	(0.0011)	(0.0011)
$Intercept$	0.056***	0.056***
	(0.0008)	(0.0008)
Pseudo Adj R^2	2.66%	2.66%
N	54,469,162	54,469,162

Table 7: Destination Country for Chinese Capital Flight Volume (Source Country For Reverse Flight)

This table presents summary statistics of total monthly unsigned net volume by trader type (*Capital Flight* or *Reverse Flight*) and by exchange country headquarters for trades in the non-Chinese exchange leg of capital flight and reverse capital flight transactions. We identify trades to or from exchanges by their Bitcoin wallet addresses from walletexplorer.com. Other variables are: *Country Market Share %* is the country's monthly percentage market share of total Bitcoin turnover. *Corruption Perceptions Index* is the country's prior year corruption perceptions index from transparency.org. The index is flipped by subtracting it from 100 so that higher values indicate high corruption perception. *Capital Control Index* is the country's prior year capital controls index from Fernández et al. (2016). The sample is from September 2011 to February 2018. Panel A reports total Bitcoin volumes to/from destination/source countries capital flight and reverse flight, monthly average country Bitcoin market share, corruption perception index and capital control index. Panel B reports Spearman rank correlations of monthly volume by trader type and country variables. ***, **, and * signifies statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A. Summary Statistics

Exchange HQ Country	Reverse Flight (USD $'000)	Capital Flight (USD $'000)	Reverse Flight / Country Volume (%)	Capital Flight / Country Volume (%)	Country Market Share % (average)	Corruption Perceptions Index (average)	Capital Control Index (average)
Pakistan	9	0	1.63	0.00	0.001	**71.69**	**0.70**
Iran	113	0	3.79	0.00	0.004	**73.03**	0.54
Czech Republic	786	3	**4.66**	0.02	0.006	49.56	0.32
Korea	437	81	0.80	0.15	0.104	45.54	0.14
New Zealand	15	147	0.12	1.18	0.32	8.64	0.10
Lithuania	15,663	235	**8.12**	0.12	0.079	44.39	-
India	168	288	0.57	0.98	0.062	**63.59**	**0.95**
Netherlands	1,261	1,059	1.36	1.15	0.165	15.54	0.00
Australia	1,792	2,820	0.36	0.57	0.323	17.87	0.18
Poland	8,799	2,976	2.43	0.82	0.225	40.51	**0.62**
Canada	1,634	4,673	0.51	1.45	0.715	16.72	0.05
Singapore	1,194	5,188	0.24	1.05	0.198	13.39	0.13
Thailand	17,313	5,542	4.19	1.34	0.309	**63.87**	**0.75**
Taiwan	1,685	6,164	0.52	**1.89**	0.369	38.95	-
Malta	387	6,320	0.09	1.47	0.146	43.54	0.08
Brazil	19,070	12,654	2.28	**1.51**	0.706	59.62	**0.64**
Austria	2,036	13,809	0.40	**2.74**	0.459	26.49	0.20
HK	58,457	22,058	1.98	0.75	3.256	22.64	0.02
Germany	45,959	25,540	1.81	1.00	2.845	20.33	0.30
UK	**923,647**	76,188	**9.77**	0.81	4.673	22.00	0.03
Japan	**158,448**	**117,107**	1.92	1.42	**20.95**	24.74	0.00
Russia	**275,962**	**134,860**	3.52	**1.72**	**9.669**	**72.80**	0.41
Luxembourg	**725,041**	**179,412**	**4.31**	1.07	**9.249**	17.69	-
Finland	74,163	**320,532**	0.86	**3.73**	**9.634**	9.87	0.15
US	**2,473,817**	**577,064**	**5.52**	1.29	**19.423**	26.59	0.14
All Countries	4,807,855	1,514,721	4.54	1.43	3.356	36.38	0.29

Note: Numbers in bold are the top five countries with the largest measure.

Panel B. Spearman Rank Correlations of Monthly Turnover

	Reverse Flight (USD $'000)	Capital Flight (USD $'000)	Country Market Share (%)	Corruption Perceptions Index	Capital Control Index
Reverse Flight (USD $'000)	1.000				
Capital Flight (USD $'000)	0.091***	1.000			
Country Market Share (%)	0.255***	0.614***	1.000		
Corruption Perceptions Index	-0.073***	-0.088***	-0.174***	1.000	
Capital Control Index	-0.075***	-0.114***	-0.235***	0.770***	1.000

Table 8: Capital Flight Trade Classification Using Weekly, Fortnightly, and Monthly Windows

Panel A reports net trading volumes in Chinese exchanges partitioned by trader group. The classification of traders is conducted separately for three different classification windows (weekly, fortnightly, monthly). Panels B to D report estimates from the following regression:

$$Volume_{jt} = \alpha + b_1 \Delta EPU_t + b_2 Premium_t + b_3 Trades_t + b_4 Fee_t + b_5 Volatility_t + b_6 Period_t + e_{jt}$$

where $Volume_{jt}$ is the net volume traded on Chinese Bitcoin exchanges by trader type j on day t (in USD millions). ΔEPU_t is the monthly change in the Chinese economic policy uncertainty index (standardized) obtained from Baker et al. (2016). $Premium_t$ is the Bitcoin price in CNY converted to USD expressed as a percentage over the USD Bitcoin price. $Trades_t$ is the daily number of trades. Fee_t is the daily average fee per trade in USD. $Volatility_t$ is the daily sum of squared one-minute USD Bitcoin returns. $Period_t$ ($Week/Fortnight/Month$) is the number of weeks/fortnights/months since the start of the sample period, depending on the classification window. The sample is from September 2, 2011 to February 8, 2018. Standard errors are in parentheses. ***, **, and * signifies statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Net Trading Volumes on Chinese Bitcoin Exchanges (in USD millions) by Trader Type

	Net Sellers	Reverse Flight	Chinese Only	Capital Flight	Net Buyers	Total
Weekly	886.51	251.74	4,153.40	5,125.15	4,051.26	14,468.05
%	6.13	1.74	28.71	35.42	28.00	100.00
Fortnightly	863.18	288.01	3,937.38	5,221.13	4,165.42	14,475.12
%	5.96	1.99	27.20	36.07	28.78	100.00
Monthly	871.01	300.91	3,566.99	5,360.55	4,256.45	14,355.91
%	6.07	2.10	24.85	37.34	29.65	100.00

Panel B: Regressions Using Weekly Windows to Classify Traders

	Trader Type				
	Net Sellers	Reverse Flight	Chinese Only	Capital Flight	Net Buyers
ΔEPU	-412.941	-174.918*	-8.262	4088.838**	-523.973
	(558.581)	(98.527)	(1441.061)	(1867.782)	(1203.419)
$Premium$	63.132	11.718	337.906**	851.374***	290.435
	(41.776)	(8.338)	(145.836)	(227.691)	(234.583)
$Trades$	21.763*	2.242	-61.76***	166.551***	-12.364
	(11.842)	(1.726)	(22.89)	(43.853)	(51.889)
Fee	619.354*	43.591	-351.729*	-2269.894***	6246.567***
	(326.403)	(28.896)	(181.211)	(497.111)	(986.426)
$Volatility$	-218.177*	4.355	-1347.811**	798.224	-1404.885**
	(130.543)	(47.34)	(549.697)	(890.072)	(568.264)
$Week$	-1.157	3.188*	145.194***	-14.022	72.762
	(10.174)	(1.809)	(18.936)	(32.787)	(49.729)
$Intercept$	-453.096	-120.733	-2955.844***	-1009.862	-4690.996**
	(411.498)	(87.984)	(781.131)	(1340.009)	(2118.112)
Adj R^2	39.38%	29.81%	21.68%	32.33%	77.30%
N	336	336	336	336	336

Panel C: Regressions Using Fortnightly Windows to Classify Traders

	Trader Type				
	Net Sellers	Reverse Flight	Chinese Only	Capital Flight	Net Buyers
ΔEPU	-1,026.036	-251.926	-1,731.116	7,190.661	1,099.254
	(1,170.917)	(285.173)	(3,887.611)	(5,145.27)	(2,864.207)
$Premium$	179.696	7.33	731.898*	2,008.931***	623.13
	(109.119)	(26.398)	(398.453)	(722.936)	(755.13)
$Trades$	31.486	3.322	-145.361***	340.059***	-83.073
	(22.983)	(5.589)	(55.662)	(120.047)	(126.616)
Fee	1,034.021	342.093***	-1,000.913**	-4,911.561***	13,462.535***
	(834.123)	(109.073)	(478.243)	(1,294.59)	(20,60.667)
$Volatility$	-451.936	67.206	-2,834.598*	2,108.568	-2,809.327*
	(387.689)	(109.717)	(1,532.518)	(2,683.092)	(1,639.386)
$Fortnight$	21.422	11.69	605.162***	-56.476	390.525
	(40.452)	(10.387)	(96.224)	(184.616)	(264.917)
$Intercept$	-1,441.002	-112.838	-6176.793***	-2,316.496	-10,909.646*
	(931.101)	(227.222)	(1,904.293)	(3,747.588)	(5,991.35)
Adj R^2	43.74%	52.41%	24.65%	33.75%	81.01%
N	168	168	168	168	168

Panel D: Regressions Using Monthly Windows to Classify Traders

	Trader Type				
	Net Sellers	Reverse Flight	Chinese Only	Capital Flight	Net Buyers
ΔEPU	0.341	-0.441	-8.744	19.824	-3.561
	(2.172)	(0.727)	(10.653)	(15.818)	(6.243)
$Premium$	0.243	-0.007	1.202	6.309**	-0.04
	(0.241)	(0.082)	(1.187)	(2.73)	(2.201)
$Trades$	0.018	0.021	-0.348*	0.947***	-0.162
	(0.048)	(0.017)	(0.189)	(0.348)	(0.22)
Fee	3.309**	0.336**	-2.332	-14.139***	34.456***
	(1.646)	(0.14)	(1.537)	(2.999)	(3.431)
$Volatility$	-0.693	0.036	-5.877*	9.193	-4.299
	(0.852)	(0.267)	(3.487)	(11.093)	(4.186)
$Month$	0.228	0.022	2.743***	-0.871	1.296
	(0.214)	(0.066)	(0.724)	(1.141)	(1.042)
$Intercept$	-308.555	-29.051	-3,687.599***	1,162.51	-1,749.73
	(289.403)	(88.566)	(974.765)	(1,537.212)	(1,407.174)
Adj R^2	62.93%	40.81%	23.64%	40.14%	90.26%
N	78	78	78	78	78

Table 9. Falsification Test by Measuring US and Russian Capital Flight

This table calculates the trader type categories from the perspective of US and Russian domiciled Bitcoin investors. Panel A and B report net trading by trader types for US and Russian Bitcoin exchanges, respectively. Panel C and D report Bitcoin net volume regressions for US and Russian Bitcoin exchanges respectively using the same dependent variables as in Equation 1.

Panel A. Net Trading by Trader Types at US Bitcoin Exchanges

Measure	Net Sellers	Reverse Flight	US Only	Capital Flight	Net Buyers	Total Net Trades
Bitcoin (million)	2.66	1.42	25.61	1.06	3.33	34.07
% of Total	7.80	4.16	75.15	3.12	9.77	100.00
USD (million)	4,169.10	754.78	19,676.50	2,126.11	17,318.78	44,045.27
% of Total	9.47	1.71	44.67	4.83	39.32	100.00

Panel B. Net Trading by Trader Types at Russian Bitcoin Exchanges

Measure	Net Sellers	Reverse Flight	Russia Only	Capital Flight	Net Buyers	Total Net Trades
Bitcoin (million)	1.17	0.50	16.13	1.80	0.26	19.86
% of Total	5.87	2.52	81.24	9.08	1.28	100.00
USD (million)	665.12	301.74	5,727.75	1,033.80	66.34	7,794.76
% of Total	8.53	3.87	73.48	13.26	0.85	100.00

Panel C. US Exchange Bitcoin Net Volume Regressions

Dependent Variable: Bitcoin Net Volume (in '000 BTC)					
	Trader Type				
	Net Sellers	Reverse Flight	US Only	Capital Flight	Net Buyers
ΔEPU	-0.004	0.951***	-0.134	-0.171**	-0.245**
	(0.178)	(0.201)	(0.442)	(0.07)	(0.102)
$Premium$	0.006	0.167***	0.105**	0.004	0.028***
	(0.015)	(0.019)	(0.044)	(0.006)	(0.011)
$Trades$	0.012***	0.037***	0.079***	0.009***	0.007***
	(0.003)	(0.004)	(0.007)	(0.001)	(0.002)
Fee	-0.185***	-0.517***	-0.566***	-0.053***	0.368***
	(0.019)	(0.051)	(0.061)	(0.006)	(0.033)
$Volatility$	-0.391***	0.118	-0.905***	-0.118***	-0.603***
	(0.056)	(0.083)	(0.196)	(0.019)	(0.049)
Day	0.001*	-0.001*	-0.008***	0.000	0.002***
	(0.001)	(0.000)	(0.001)	(0.000)	(0.000)
$Intercept$	1.207***	1.603***	11.444***	-0.055	0.201
	(0.243)	(0.169)	(0.986)	(0.073)	(0.123)
Adj R^2	7.59%	22.22%	4.14%	17.78%	53.14%
N	2,352	2,352	2,352	2,352	2,352

Panel D. Russian Exchange Bitcoin Net Volume Regressions

Dependent Variable: Bitcoin Net Volume (in '000 BTC)					
	Trader Type				
	Net Sellers	Reverse Flight	Russia Only	Capital Flight	Net Buyers
ΔEPU	-0.143	0.332**	0.146	-0.100	-0.361***
	(0.168)	(0.137)	(0.261)	(0.070)	(0.058)
$Premium$	-0.003	0.073***	0.062**	0.011	0.006
	(0.012)	(0.012)	(0.031)	(0.009)	(0.005)
$Trades$	0.005*	0.017***	0.016***	0.000	0.005***
	(0.003)	(0.003)	(0.004)	(0.001)	(0.001)
Fee	-0.135***	-0.239***	-0.275***	-0.066***	-0.026***
	(0.015)	(0.027)	(0.032)	(0.008)	(0.005)
$Volatility$	-0.372***	-0.391***	-0.486***	0.324***	-0.156***
	(0.054)	(0.05)	(0.131)	(0.074)	(0.021)
Day	0.001***	0.001***	-0.004***	0.000	-0.001***
	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)
$Intercept$	0.936***	0.538***	9.907***	0.758***	1.729***
	(0.205)	(0.124)	(0.612)	(0.138)	(0.087)
Adj R^2	61.69%	23.07%	34.76%	29.78%	50.80%
N	2,352	2,352	2,352	2,352	2,352