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Flight to Bitcoin *

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Flight to Bitcoin

Abstract

This paper uncovers the role of Bitcoin (BTC) in incorporating local investors' demand shift for the domestic currency. We first show that the signed value of price discrepancies (*GAP*) of BTC across trading fiat currencies increases as the local Economic Policy Uncertainties surge. This finding is supported by difference-in-difference tests exploiting episodes of Brexit, Car Wash Operation, and India Banknote Demonetization. We then show that *GAP* has short-term predictability for Foreign Exchange (FX) returns. Last, we demonstrate that these properties do not apply to gold and American Depositary Receipts. We argue that BTC uniquely reflects information in FX because of its stateless nature and the fact that its arbitrageurs are constrained by capital controls among other forms of limits to arbitrage.

JEL code: D40, D84, G12, G14

Keywords: Cryptocurrency, Bitcoin, Capital controls, Economics policy uncertainty, Foreign exchange

1 Introduction

Bitcoin (BTC) is created by a group of developers (Nakamoto, 2008) in the wake of the Great Recession, a time of mounting distrust for financial intermediaries and resistance against government interventions. The novel concept of a decentralized ledger system underpinning BTC promises a revolutionized financial system independent of centralized clearing and central authorities. BTC appeals enormously to many people who search for an alternative to the existing financial markets which are subject to the scrutiny of regulators and socioeconomic uncertainties.

Does this stateless feature of BTC explain the trading nature of BTC? Do investors go to BTC when they lose confidence in their local central authorities? Do they resort to BTC when they are constrained by local authorities to conduct cross-border transactions? Does BTC trading incorporates investors' expectations of foreign exchange rates? What are the implications of this "flight to alternatives" behavior on BTC pricing, other financial assets and regulations?

These are the central questions this paper investigate empirically. Overall, we aim to show that "Flight to BTC" reflects investors' beliefs on the local economy. Specifically, we first analyze macroeconomic and policy drivers for investors' demand for BTC itself, and then investors' expectations about FX which is linked to BTC by an arbitrage parity.

First, investors can hold BTC due to innate hedging preferences or external constraints to transfer wealth abroad. There are several reasons why local investors opt for BTC especially during turbulence. Currency depreciations and inflations are common follow-up scenarios after episodes of uncertainties. BTC is exposed to neither. First, BTC is stateless in nature and hence not much exposed to idiosyncratic risks arising from individual country's economic and political situations. Second, BTC is inflation resistant by design because of its pre-fixed supply stipulated by the algorithms. Third, BTC is subject to non-negligible political risks only if authorities from all countries coordinate to ban its circulation. Legal restrictions from one single authority will not be fatally detrimental to the entire cryptocurrency space. For instance, the BTC market plunges in Sep, 2017 after the Chinese government enforces an end to the cryptocurrency trading platforms. However, other countries do not join the crack-down campaign, and the BTC market not only recovers but also penetrates into the futures market in CBOE and CME[1] [2]. Last but not the least, BTC can help transfer domestic funds out of regulators' watch.

Their preferences and constraints vary across countries and over time, given the heterogeneity in the banking systems, capital controls policies, and government interventions and the time-varying nature of local economic policies uncertainties among other socioeconomic factors. These cross-sectional and time-series variations in the demand for BTC are reflected in BTC prices quoted in different fiat currencies. Interestingly, these quotes do not always converge. For example, BTC is traded at a premium in South Korea than in the US, the so-called "Kimchi Premium" (Choi et al., 2018).

To capture these discrepancies in BTC pricing by different fiat currencies, we construct a measure of price gap (*GAP*) based on the foreign exchange (FX) adjusted spread between a non-USD quote of BTC and the USD quote. We build up the *GAP* measure for 23 fiat currencies and keep USD as the benchmark currency in our analysis and the base currency for the FX quote throughout this paper. We find that *GAP* rallies when the local Economic Policy Uncertainties index (*EPU* as constructed in Baker et al. 2016) rise, reflecting a higher demand for BTC in the local market than in the US. This result derives from 14 fiat currencies, whose underlying countries have *EPU* measures available. *EPU* can be interpreted as upcoming FOMC meetings, economic stimulus plans, presidential elections, political riots etc. A handful of concrete examples can illustrate this finding. As shown in Figure 3, the implied FX rates for GBP against USD from the BTC market shoots up right after the Brexit referendum result is announced on June 24, 2016. Similarly, the shadow exchange rate for Indian Rupee (INR) surges after the Government of India announces the demonetization plan on 8 November 2016.

However, BTC is not a riskless option when its ecosystem is under construction. For example, cryptocurrency exchanges are prone to hacks. Intuitively, investors may lose trust in BTC as an

[1] https://www.cmegroup.com/trading/bitcoin-futures.html
[2] http://cfe.cboe.com/cfe-products/xbt-cboe-bitcoin-futures

alternative to replace local assets when their cryptos are gone for no reasons overnight. We show that the relation between *GAP* and *EPU* weakens in the aftermath of the second largest theft of BTC on August 2, 2016 when 120,000 units of BTC are stolen from Bitfinex.

Second, the alternative interpretation of *GAP* is the deviation of the implied FX rate in the BTC market from the real FX rate in the spot market. BTC and FX are fundamentally linked by an arbitrage parity as BTC is traded in 104 fiat currencies. The demand and pricing of BTC mirrors that of FX. A higher quote of BTC in CNY reflects a lower demand for CNY against BTC. The same argument applies to the quote of BTC in USD. *GAP* effectively nets out the demand for BTC and can evaluate the relative demand for CNY against USD among BTC investors. Hence, positive values of *GAP* imply that investors in the BTC market have a lower demand about CNY vis-à-vis USD than investors in the spot FX market. In other words, positive values of *GAP* reflect higher depreciation expectations for CNY by BTC investors than by FX investors. This interpretation fits our previous argument that one trading motive of BTC is the loss of confidence in the local currency and the demand to move away from assets denoted in local currencies.

In line with this intuition, we show that the demand shift for local currencies is impounded more speedily in the BTC market than the FX market and the predictability power of our *GAP* measure in short-term FX movements. This finding may sound counterintuitive given that the daily trading volume of the FX market outsizes that of BTC by ten to hundred times with higher liquidity and pricing efficiencies. However, one overlooked fact is that the FX market is subject to heavy scrutinies and government interventions which can mask the true demand shift arising from non-government investors.

We conduct both Panel and Fama-Macbeth return predictability regressions where the dependent variable is the two-day ahead leading FX return, and independent variables are concurrent, one-day, two-day, three-day, and four-day lagged *GAP* changes. We find that the one-day lagged *GAP* change explains future FX returns significantly and positively. This predictability is true to subsamples split by dates. We then decompose *GAP* into three components, the return of BTC denoted by the home currency, the return of BTC denoted by USD, and the FX return. We find that the predictability of *GAP* for FX mainly comes from the return of BTC denoted by the home currency, which serve as a reassuring evidence that the predictability mechanism is through the local demand shift for BTC against the home currency.

The predictability of *GAP* for FX returns is complementary evidence to the finding that *GAP* jumps after *EPU* increases. Both evidence point to the key fact that the BTC market incorporates demand information about FX in a timely manner because investors opt for BTC as an alternative when losing confidence in the local currencies.

A key prerequisite for our argument that GAP reflects local demand shift is the segmentation across BTC markets. Pasquariello (2017); Gromb and Vayanos (2010) illustrate that the divergence of prices of the same underlying good across markets can reflect different local demand only when these multiple markets have segmented market making or limits to arbitrage exist. We show that capital controls policies are a form of limit to arbitrage resulting in the market segmentation in the BTC market. We follow Fernández et al. (2016) for the inflow and outflow capital controls intensity measures. For example, to reduce the positive price gap between BTC denoted by CNY and that by USD, arbitrageurs need to sell BTC into CNY and convert the proceeds in CNY back to USD in order to sustain the triangular arbitrage. If China imposes restrictions on capital outflows which prevent investors from selling CNY into foreign currencies, the arbitrageurs will not be able to complete the arbitrage trip and bring the positive price gap back to zero. Accordingly, we do find that positive *GAP* is more positive for those countries with stricter capital controls on outflows. By the same token, restrictions on capital inflows will stop arbitrageurs to respond to the negative gap between the CNY and USD price of BTC. We also show that negative *GAP* is more negative when the capital controls on inflows are more stringent.

Another concern is that our *GAP* measure only captures the transaction costs embedded in the triangular arbitrage strategy involving BTC, USD, and a third currency. There are different routes to engineer the textbook triangular arbitrage. We resort to one of them for illustration purpose, which is explained in detail in Section 4. In short, we explicitly take out the order execution charges, short selling costs, and the bid-ask spread from the price gap. Hence, transaction costs alone do not drive our empirical findings and there is an information component in the measure.

One may wonder whether these properties we identify with BTC also apply to other financial assets. For example, gold and American Depository Receipts (ADRs) are also traded in different exchanges and denoted by multiple currencies. Gold has long been labeled as the "flight to safety" commodity. So what is unique about BTC to be a sideshow for FX markets? For comparison analysis, we reconstruct *GAP* for gold and ADRs. The value of *GAP* for gold is almost negligible. *GAP* for ADR is non-zero but much closer to zero than BTC *GAP*. *GAP* for gold and ADRs do not respond to the fluctuations in *EPU*, and have no predictability power for FX returns. We conclude that the price gap across trading platforms for gold and ADRs, compared to BTC *GAP*, is not as informative about local investors' demand for local currencies.

We argue that BTC differentiates from gold in its constituent investors' access to FX markets. To instantaneously wipe out the price gap across marketplaces, arbitrageurs need sufficient amount of FX to scale up the arbitrage. Gold and other commodity trading is well and long developed with active participation from institutional investors with easy access to FX markets. Hence, the demand shift information for local currencies is wiped out by gold arbitrageurs who economize on price gaps observed. On the contrary, the BTC market, until 2017 December, primarily consists of retail investors facing constraints, administrative burden and time delay when transferring funds across currencies. For example, each Chinese resident is granted a purchase quota of 50,000 USD worth of foreign currencies per year. Facing the non-linear capital controls restrictions, retail investors are handicapped to profit from the price disparities beyond the quota limit. Institutional investors do not actively participate in crypto assets which are dubbed as unregulated and highly risky because of their fiducial duties. In the absence of sufficient arbitrage forces, the remaining price gap can persist and reflect the local demand shift for BTC as well as local currencies.

BTC differs from ADRs in its hedging role for local assets. Our evidence show that BTC can be a hedging device for local investors in both normal and crises times, regardless of the presence of capital controls. Similar empirical evidence for ADRs is so far only limited to episodes of the Argentina crisis in 2001 and the Venezuela crisis in 2003. Auguste et al. (2006) and Melvin (2003) demonstrate that ADRs serve as a tool to transfer funds abroad when restrictions on capital outflows tighten, and the ADR discount is indicative of peso devaluation expectations during the crises period. In normal times, however, ADRs are diversification assets for US investors to access non-US equity markets and do not necessarily reflect non-US investors' belief in non-US currencies. Accordingly, we do not find a correlation between *EPU* and ADR *GAP* in our sample period.

Literature and contributions We consider our contributions to the literature to be fourfold. First, this paper contributes to the understanding of the trading motives and intrinsic value of cryptocurrencies, the emerging financial asset class attracting more and more attention and capital flows. Some suggest that BTC facilitate illegal transactions such as drug dealings in "darknet" online marketplaces. Foley et al. (2018) applies a network cluster analysis to estimate the number of BTC users involved in the illegal activities and the dollar amount at stake. Some associate BTC trading with the Dutch Tulip Bubble and the Ponzi scheme. However, a bubble cannot be identified unless we know how to quantify the fundamental value of BTC. Griffin and Shams (2018) demonstrates that BTC trading is subject to manipulation by showing that the purchases of Tether follow the market downturns of BTC and result in BTC price run ups, suggesting the bubble property of BTC. These attempts focus on assessing the value of BTC from cryptocurrencies themselves. Our findings suggest that the value of cryptocurrencies not only depends on users' beliefs and acceptance about the crypto assets themselves, but also derives from investors' dissent about the fiat money and other financial assets denoted by the fiat money. This source of value is different from existing arguments which exclusively attribute BTC's value to itself serving as a store of value, payment and exchange medium, or speculation tools.

Second, we demonstrate the predictability of our *GAP* measure for FX price movements in the following days. As summarized by Rossi (2013), plenty of research works have attempted to forecast exchange rates using economic models and various econometric methodologies (Della Corte et al. (2008). Most of them investigate predictabilities at monthly, quarterly, and even yearly frequencies. Papers, which focus on daily data, mainly study the impacts of macroeconomic news announcements on exchange rates (see Faust et al. 2007; Fratzscher 2009; Della Corte and Krecetovs 2017 among others). One exception is Ferraro et al. (2015), which find that the lagged oil price shocks has short-term out-of-sample predictability for exchange rates. To our knowledge, our paper is the first to empirically evaluate and show the relative merits of the BTC pricing process relative to FX markets. We show that the implied currency exchange rate quoted in the BTC market incorporates information about a demand shift for domestic currencies.

Third, this paper contributes to the understanding of market frictions that can lead to violations of the no-arbitrage conditions on which the modern finance is built. We empirically demonstrate the institutional frictions are candidates to limits to arbitrate in the BTC and FX markets. These findings complement the existing literature which often cites behavioral and rational demand shocks as sources for limits of arbitrage (see Lamont and Thaler 2003; Gromb and Vayanos 2010, among others). A couple of papers are close to ours in this regard. Pasquariello (2017) attributes currency market fictions to government interventions. Choi et al. (2018) and Makarov and Schoar (2018) probe into the microstructure and price formation of cryptocurrencies and argue that the capital controls intensity explains the magnitude of arbitrage opportunities in the cryptocurrency space. Our paper adds to this evidence with a longer and wider panel dataset.

Last but the least, the findings in this paper are relevant for regulators. Currently, there are very few research papers that examine cryptocurrencies' externalities on the macroeconomic conditions and policies. Related works in a broader sense are Raskin and Yermack (2016) and Yermack (2017) which qualitatively evaluate the possible changes to central banking policies and corporate governance that Blockchain technology could bring. Our findings suggest investors can now choose a stateless currency to hedge country-specific risks and circumvent restrictions on capital flights, which poses a challenge to the monopoly power of central banks. Capital controls arguable curb capital flight which are accomplished through cross-listed shares (e.g., Domowitz et al. 1998; Auguste et al. 2006; Edison and Warnock 2008) or cross-border mergers and acquisitions (e.g., Di Giovanni 2005) or FDI (e.g., Alfaro et al. 2008), but wealth transfer through cryptocurrencies are intact. With cryptocurrencies in town, how should regulators ensure the effectiveness in issuing fiat currencies, controlling short-term interest rates, and implementing monetary policies? In addition to adjusting the existing regulation paradigm, regulators also face a new challenge to create a fair ecosystem for BTC that does not come at the cost of taxation avoidance, money laundering, and capital flights.

The reminder of this paper is organized as follows. In Section 2 we provide institutional details about BTC trading. In Section 3, we describe our measurements and data. We provide empirical analysis in Section 4. Section 5 compares BTC with gold and ADRs. Section 6 concludes.

2 Introduction to Bitcoin Trading

BTC is the first decentralized cryptocurrency created in 2009 by a pseudonymous developer Satoshi Nakamoto. It is open-sourced and features itself with the peer-to-peer network and proof-of-work scheme. Discussions about BTC have centered around its potential as an alternative monetary system, and a payment system to replace the existing commercial banking[3]

BTC started out as a digital cash and online payment system, with its first transaction taking place in 2010 when two pizzas were procured with 10,000 BTC. In its infant days, its user base covers mostly geeky programmers and sometimes criminals who use BTC to facilitate illegal transactions, see Foley et al. (2018). Transferring BTC between "wallets" usually takes up to one hour to find the block and confirm the transaction. In 2011 February, BTC took parity with US dollar and received increasing attention from traders and investors. As its price took off, the demand to trade BTC as an asset soared. We need further investigation as to the sophistication of BTC traders. Investors can trade BTC: 1) at over-the-counter (OTC) marketplace which offers low-fee escrow service and a

[3] Harvey (2014) and Harvey (2016) provide in-depth descriptions about the space.

marketplace to exchange currencies between PayPal and BTC[4], 2) through P2P exchanges, 3) through centralized exchanges. In this paper, we focus on the case of centralized exchanges. We choose 3) because centralized exchanges offer observable trading volumes and their data quality is higher. Ideally, the trades in OTC market should be included our analysis as well but due to data limitation we only focus on trades on exchanges.

As of July 31, 2018, BTC is traded in 104 fiat countries. Table 20 lists the top 23 fiat currencies with which BTC can be traded and the respective exchanges for each trading pair. BTC can be traded with USD across 36 exchanges and 12 exchanges provide trading platforms between CNY and BTC. Effectively, each BTC-Fiat trading pair attracts both home and international investors.

Completing BTC-Fiat trades on a chosen exchange incurs several types of fees including exchange fees, trade fees, bid-ask spread, and deposit/withdrawal fees. These transaction fees vary quite a lot across these exchanges, depending on the liquidities, market size, and service qualities of the exchanges[5]. Exchange fees are the basic fees for operations. Trade fees include a maker fee which is the cost to make an offer to sell currencies, and a taker fee which is the cost charged to take others' offer. Depositing or withdrawing cryptocurrencies incurs no charges. Fees are charged when traders deposit fiat currencies to the exchange account and withdraw fiat currencies from the exchange to bank accounts. Some exchanges allow credit card transactions.

For example, Kraken, one of the biggest European BTC trading platforms, affords BTC-USD, BTC-EUR, BTC-CAD, BTC-JPY, and BTC-GBP trading pairs. Traders can deposit or withdraw fiat currencies to their Kraken accounts with debit cards. In terms of Bank deposit and withdrawal fees, international wire incurs 0%-0.19% or fixed commission depending on the deposit and withdrawal currency. For trade fees, maker fee is 0% - 0.36% depending on volume and currency pair, while taker fee is 0.1% - 0.36%. In terms of transaction time, depositing and withdrawal fiat currencies takes 1 to 5 business days. Market or limit orders take seconds to go through, and transfer BTC in and out of the Kraken account requires 10 minutes to 1 hour depending on the traffics.

[4] See details at https://en.bitcoin.it/wiki/OTC_Exchange

[5] See details at https://crowdsourcingweek.com/blog/bitcoin-exchange-comparison/

In early 2014, Bitfinex introduces margin trading for BTC[6]. Margin trading allows investors to borrow bitcoin from exchanges or peer margin funding platforms. Investors are charged of the accrued interest embedded in the positions they take. The key difference from short-selling is that margin trading requires initial assets deposited as the collateral in the exchange. For example, Bitfinex allows users to trade with up to 3.3*leverage, meaning that investors can short-sell 3.3 Bitcoin for every 1 Bitcoin deposited. Therefore, margin trading provides a constrained short-selling possibility. The last column in Table 20 records the earliest month when at least one of BTC exchanges allows margin trading for the corresponding fiat currencies. In 2014, investors can margin trade BTC with exchanges for 11 out of 23 fiat currencies in our sample. After 2017, there are only 8 fiat currencies for which margin trading is inaccessible through exchanges. However, in practice Brazilian investors who want to short-sell BTC can still borrow BTC from peer-to-peer BTC lending platforms, such as BitBond and BTCPOP etcs. The disadvantage is that investors can not instantly borrow and trade Bitcoin as what margin trading service enables.

The infrastructure and ecosystem BTC trading is getting improved. BTC futures trading are made available at CBOE and CME Dec 2017. Although, the U.S. Securities and Exchange Commission (SEC) has so far rejected all the BTC derivatives-based ETF proposals, many believe that the new product will eventually be approved in 2019 as legal and compliance issues get resolved. Initially the majority of participants in the BTC market are individuals and retail investors, but the landscape gets shifted a bit more to small-scale institutions as the price boom peaks in 2017. 167 crypto funds are incepted in 2017, up from 19 in 2016. As of July 2018, more than 300 cryptocurrency funds collectively manage between $7.5 billion and $10 billion in assets. AUM is highly concentrated among the largest funds.

[6] See related news at http://blog.bitfinex.com/announcements/introducing-oco-orders/

3 Data

We introduce our key measure *GAP* based on price discrepancies between the BTC market and the spot foreign exchange (FX) markets in Section 3.1. We describe the data in Section 3.2 and summary statistics in Section 3.3.

3.1 Measurements

As discussed in Section 2, investors can easily convert one fiat currency to another through BTC at a fast speed and relatively low transaction costs, rather than via the traditional banking or FX channels. The construction of *GAP* is based on the triangular arbitrage strategies between BTC and FX markets. A caveat is that we proxy for the short-selling costs imperfectly. For BTC trading fiat currencies with access to margin trade, we back out the dollar costs due to possible time delay in BTC transfer by the accrued interests charged. For BTC trading fiat currencies without access to margin trade, we fill out the shorting cost with the average margin costs incurred concurrently on other currencies.

In a frictionless world, when Law of One Price is violated, arbitrageurs can step in and profit from the triangle arbitrage strategies. To complete the triangular arbitrage between BTC and two other fiat currencies, one needs to buy BTC with one fiat currency and sell instantaneously to the other currency which then gets exchanged back to the starting currency at the spot foreign exchange rate. A classic notebook riskless arbitrage requires the simultaneous realization of all trades. In reality, however, transferring across BTC exchanges if needed[7] and across countries for fiat currencies could take some time. In the period of delay, the risk of BTC price movements is non-negligible due to high volatility of BTC, while intra-day foreign exchange rate fluctuation is less of a concern. Therefore, to lock in triangular arbitrage profit, it is relatively safe to first long and (short-)sell BTC across two exchanges simultaneously and then clear the short position of BTC later.

[7] If multiple fiat-BTC pairs are listed in one exchange, then there is no delay of BTC transferring.

In the following, we describe in detail the trading strategies in two scenarios and the associated transaction costs incurred throughout the process. For illustration purpose, we take triangle arbitrage among BTC, USD and CNY as an example and make up numbers for easy calculation. To simplify notation, we define

- E_t^i = the spot exchange rate, currency i per USD
- $Ƀ_t^{USD}$ = the BTC price in USD
- $Ƀ_t^i$ = the BTC price in currency i
- $\mathbf{E}_t^i = \frac{Ƀ_t^i}{Ƀ_t^{USD}}$ the implied exchange rate

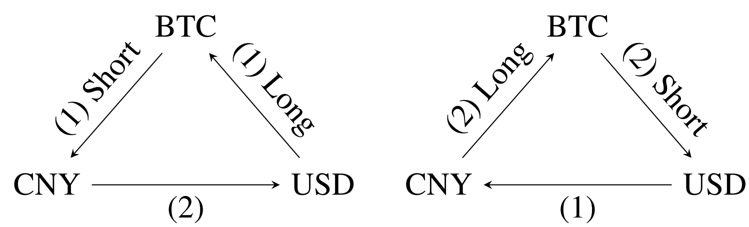
Case 1: When BTC in CNY is priced higher than in USD For instance, $Ƀ^{CNY} = 8000$, $Ƀ^{USD} = 1000$ and $E^{CNY} = 7.8$. As shown in the left panel of Figure 1, we first buy BTC in USD at exchange A and (short-)sell BTC in CNY at exchange B, then transfer BTC from A to B to close the short position, and at last exchange CNY back to USD in FX market. Without transaction costs, arbitragers get the return of $\frac{Ƀ^{CNY}}{Ƀ^{USD}} \frac{1}{E^{CNY}} - 1 = \frac{8000}{1000} \frac{1}{7.8} - 1 = 2.56\%$. In reality, the purchase of BTC at exchanges requires paying the bid-ask spread and transaction fees, and short-sale incurs additional costs of borrowing BTC from brokerages. These are the major costs associated with the triangular arbitrage. In addition, there are trivial costs to transfer BTC across exchanges and exchange currencies via FX. The highest daily transfer cost in our sample is around 5 USD per transaction[8], which is quite small. Moreover, transactions in the FX markets encounters the bid-ask spread, which is also small compared to BTC spreads[9]. Therefore, we neglect these cost and only factor in the major costs in our analysis.[10]

[8] The information is extracted from https://bitcoinfees.info/.

[9] Based on www.FX.com, pair USD/ZAR in our sample has the highest spread, around 150pip ZAR.

[10] Another procedure is to buy BTC using USD, directly send to CNY exchange through BTC network, sell it and exchange CNY back to USD. In this way, arbitragers do not pay short-sale cost but they are exposed to BTC price movement risk even in a short time window. Importantly, arbitragers choose the procedure with the lowest cost. So the profit from the short-sale procedure can be deemed as the lower boundary.

Figure 1: Triangle-arbitrage procedure for case 1 (left) and case 2 (right)



Since transaction spreads are quoted in fiat currencies while transaction and short-sale costs are quoted in percentage, we can express the trading return from triangle arbitrage as

$$(1)\quad GAP^{+} = \max\left(0, \frac{\frac{Ƀ^{CNY} - spread^{CNY}/2}{Ƀ^{USD} + spread^{USD}/2}(1 - \text{trans. fee})(1 - \text{trans. fee} - \text{short-sale cost})}{E^{CNY}} - 1\right) * 100,$$

where the short-sale cost is approximated by multiplying the average transfer time by short-sale cost per unit of time. When the profit from triangle arbitrage does not cover costs, arbitrageurs do not engage in arbitraging and get zero return. A positive profit serves as an evidence of violation of law of one price.

Case 2: When BTC in USD is priced higher than in CNY For instance, $Ƀ^{CNY} = 7600$, $Ƀ^{USD} = 1000$ and $E^{CNY} = 7.8$. As shown in the right panel of Figure 1, we first exchange USD to CNY in the FX market, then buy BTC in CNY at exchange B and (short-)sell BTC in USD at exchange A, and at last transfer BTC from B to A to close the short position. Without transaction costs, arbitragers get the return of $E^{CNY}\frac{Ƀ^{USD}}{Ƀ^{CNY}} - 1 = 7.8\frac{1000}{7600} - 1 = 2.63\%$. After considering major costs involved in this process, the profit can be expressed as

(2)

$$GAP^{-} = \min\left(0, 1 - E^{CNY} \times \frac{Ƀ^{USD} - spread^{USD}/2}{Ƀ^{CNY} + spread^{CNY}/2}(1 - \text{trans. fee})(1 - \text{trans. fee} - \text{short-sale cost})\right) * 100.$$

Combining both cases, we define GAP to study the relative depreciation of domestic currency implied in BTC market compared to that in the FX market:

$$GAP = \begin{cases} GAP^+ & \text{if } GAP^+ > 0 \\ GAP^- & \text{if } GAP^- < 0. \end{cases} \tag{3}$$

3.2 Data sources

For cryptocurrency pricing and volume data, we access the aggregating website [11] with API. The website provides open-high-low-close price and volume data from over 70 exchanges globally at daily frequencies. Price information is quoted at 00:00:00 Greenwich Mean Time (GMT) across exchanges. The website also provides aggregated price information for each currency pair as the volume-weighted average of prices on all exchanges[12]. In this study, we focus on triangle arbitrage opportunities cross currency pairs instead of across exchanges, so we directly adopt the aggregated price provided. The volume data is denoted by the number of BTC traded per day (24 hours) at each exchange.

There are three main types of costs involved in the triangle arbitrage procedure – bid-ask spread in BTC, transaction fee and short-sale cost[13]. The daily spread information across different exchanges is downloaded from bitcoinity[14] website. As our price information is aggregated across exchanges, we take the second-largest spreads across different exchanges for each fiat-BTC pair as the measure of spread[15]. We fill in missing values with the latest non-missing spread. The transaction fee is set to be 0.2%, which is usually the upper boundary cost to buy or sell BTC at exchanges. Short-sale

[11] See https://www.cryptocompare.com/

[12] Specifically,

$$Ƀ_t^i = \sum_j Ƀ_t^{i,j} W_t^{i,j},$$

where j refers to exchange j and $W_t^{i,j}$, the weight of exchange j, is the ratio of 24-hour trading volume of currency pair i-BTC to the total volume of the pair on all exchanges. Please find more details in https://www.cryptocompare.com/media/12318004/cccagg.pdf

[13] Transaction cost in FX markets is relatively small, compared to BTC market. So we do not consider it in the analysis

[14] See https://data.bitcoinity.org/markets/spread/7d/USD?c=e&f=m10&st=log&t=l

[15] The website covers some small exchanges which is denoted as other. The spread in other exchanges could be unrealistically large possibly due to low trading volume. So we consider the second-largest spread in our study

cost depends on both transaction time in BTC blockchain and short-sale fee asked by brokerages. The daily average transfer time is downloaded from Blockchain[16]. The common short-sale cost is around 0.1% per 24 hours. We approximate short-sale cost as 0.1% * average transfer time (day).

Our sample covers the period from January 01, 2012 to July 31, 2018. In total, 104 out of 162 fiats have quotes for BTC. Some trading pairs have very little trading volume. To rule out the concern of illiquidity, we only keep fiats with at least 20 units of BTC traded per day[17]. We are left with 23 fiat currencies in our analysis sample: AUD (Australia), BRL (Brazil), CAD (Canada), CNY (China), EUR (Euro Zone), GBP (United Kingdom), HKD (Hong Kong), IDR (Indonesia), ILS (Israel), INR (India), JPY (Japan), KRW (Korea), MXN (Mexico), MYR (Malaysia), PHP (Philippines), PLN (Poland), RUB (Russia), SEK (Sweden), SGD (Singapore), THB (Thailand), USD, and VND (Vietnam), ZAR (South Africa).

The FX exchange rate data is extracted from Bloomberg. To match with the timestamp of BTC data, we need FX data quoted at 00:00:00 (GMT). Bloomberg only has complete quotes at 00:00:00 (GMT) for AUD, CNY, EUR, GBP, HKD, JPY, KRW, MXN, MYR, PHP, PLN, SEK, SGD, THB, and ZAR. For incomplete dates of the remaining fiat currencies, we extract quotes at 01:00:00 (GMT).

We adopt money market inflow (outflow) restriction intensity constructed by Fernández et al. (2016). We use Economic Policy Uncertainty Index[18] constructed by Baker et al. (2016) as a proxy for demand shocks. Equity market index returns come from Datastream.

Finally, we remove entries from February 7, 2014, to February 25, 2014 when Mt. Gox, the then largest bitcoin exchange, halted all bitcoin withdrawals citing technical issues. This event results in an abnormal trading pattern and extremely high GAP in that month. After data cleaning, we have in total 32288 observations in our final sample.

[16] See https://www.quandl.com/data/BCHAIN/ATRCT-Bitcoin-Median-Transaction-Confirmation-Time

[17] Nigerian naira (NGN) satisfies the condition of at least 20 units of trading volume per day. However, the BTC is traded in NGN with a huge premium around 15%. So we exclude it in the analysis

[18] Data website: http://www.policyuncertainty.com/

3.3 Summary statistics

Table 1 presents the summary statistics of daily Volume, and daily GAP, monthly economic policy uncertainty index (EPU) and yearly money market inflow (outflow) restriction intensity in our sample. First, we notice that only CNY, EUR, GBP and JPY are traded in BTC before 2013, and these fiat currencies have greater trading volume per day than other fiats. Second, column "ratio" under panel GAP (%) show that there is a substantial amount of non-zero *GAP*s across different fiat currencies even after taking account of main transaction fees. This indicates the violations of law of one price, which is heterogeneous cross countries, and is most prominent for BRL, IDR, INR and ZAR, and least for CHF, EUR, SEK. Third, the proportion of non-zero GAP concentrates in the positive side, expect for RUB. This suggests that BTC is traded with premium in domestic countries compared to in US. Lastly, there seems to be a link between GAP and capital restrictions. Currencies with restricted exchange controls, such as CNY, THB, INR, have substantially higher price gaps than currencies with fewer restrictions, like EUR and GBP. The exact relation between GAP and money market inflow or outflow restrictions needs a further investigation.

Figure 2 presents the time series plots of daily *GAP* for four major fiats – CNY, JPY, EUR and GBP. Despite a declining trend in both the variance and the level of GAPs, GAP remains above zero, indicating the persistent difficulty to implement triangle arbitrage strategy. There exhibit structural changes in GAP for four fiats at the beginning of 2014 due to trading suspension of Mt. Gox. In September 2017, Chinese authorities ordered China-based cryptocurrency exchanges to cease trading, creating long-lasting spikes in GAP for CNY. This policy seems to have a spillover effect on BTC trading activities in Japan, but not in UK or Europe.

4 "Flight to BTC"

For two markets with a segmented market making or limit to arbitrage, the diverging prices for the same good should reflect different demands across two markets, see Pasquariello (2017). We apply this intuition in BTC markets. When the local demand for BTC surges, the BTC prices quoted in domestic currency should increase. If arbitrageurs across countries are not efficient, the price discrepancies (GAPs under the BTC setting) should reflect relative demand differences in two countries. Therefore, an increase in GAP indicates a rise in demand for BTC in local economy, relative to in the US. This section links the demand for BTC to local economic policy uncertainties and investors' expectations about FX. We postpone the discussion of inefficient arbitraging in Section 4.3.

In Section 4.1, we first provide evidence that investors "flight to BTC" when they lose confidence in their local central authorities or when they are constrained by local authorities to conduct cross-border transactions. To reveal the relation between BTC trading motives and local economic conditions, we investigate the relation between GAP and policy uncertainties (shocks) using event studies and panel regressions. In Section 4.2.1, we argue investors "flight to BTC" when they form depreciation expectations on local currencies, so GAP should exhibit predictability power for the future FX returns.

4.1 Whether GAP responds to local economic policy uncertainties?

4.1.1 Evidence from case studies

We begin our empirical analysis with three case studies that best illustrate our points. Although these events have different causes and direct consequences, they share two features in common. First, they are all unexpected to the general public without ex-ante information disclosure and anticipation. These exogenous shocks relieve us from the suspicion that some omitted factors drive both the unexpected increase in local uncertainties, bitcoin trading, and FX movements. Second, the three cases all trigger widespread concerns among local residents about the changes and uncertainties to the economic and political regimes. Following our argument before, local investors will turn to alternative assets free from local political and economic risks when they cast doubt on local socioeconomic situations. This propensity gives rise to the "flight to bitcoin" behavior. We expect to see that the excessive purchase of BTC with the local currency enlarge the wedge between quotes of BTC in the local currency and the quote in USD.

Brexit

On June 23, 2016, a majority of British voters supported leaving the EU in a referendum. The general consensus before the referendum is that chances are slim that UK will not withdrawal from EU. The voting result injects uncertainties into the future economic development path for UK and EU. Many protests follow to overturn the voting results. We examine whether Brexit has a differential effect on the BTC trading activities in UK and EU versus other countries. We estimate

$$\text{GAP}_t^i \sim \alpha_m + \beta_1 Treat + \beta_2 Post + \beta_3 Treat * Post + Controls \tag{4}$$

where i indexes currency and t indexes time, Treat is a dummy that equals one if the currency is GBP or EUR and zero if the currency is CNY, JPY or KRW, post is a dummy variable that equals one if the Brexit has taken place, and controls include Turnover_t^i (Turnover_t^{US}) defined as the trading volume divided by the number of shares outstanding on a given day,

$$\text{Turnover}_t^i = \log\left(\frac{\text{Volume}_t^i}{\text{Total coin}_t}\right), \tag{5}$$

and $\Delta\text{Index}_{t-1,t}^i$ ($\Delta\text{Index}_{t-1,t}^{US}$), which is the daily change of log-market index for country i (US). The event window covers fifteen days before and after the event. The average effect of Brexit on *GAP* is $\beta_2 + \beta_3$. The total effect of Brexit on *GAP* GBP is $\beta_1 + \beta_3$. Our coefficient of interest is β_3 which captures the average differential change in *GAP* from the pre- to post-treatment period for the treatment group relative to the change in *GAP* for the untreated group. Our conjecture is that UK investors will flight to bitcoin after Brexit more so than non-UK investors and hence we expect β_3 to be positive.

Table 2 reports this difference-in-difference test studying the impact of Brexit on the *GAP* for GBP and EUR. The significantly positive β_3 means that the event of Brexit increases the *GAP* in GBP. In terms of economic magnitude, *GAP* in GBP increases by 1.36% compared the average change of *GAP* for control currencies. The pre-verus-post estimator is also positive ($1.36 + 0.98 = 2.34$), because the event also adds to the global uncertainties and hence incentives to invest in BTC. The treatment versus control estimator is negative ($1.36 - 2.00 = -0.64$) because BTC is traded at a discount in GBP compared to the control currencies before Brexit.

Operation Car Wash

Operation Car Wash in Brazil is an ongoing criminal investigation since March 17, 2014. It started off as a money laundering investigation, and expanded to allegations of corruption against state-controlled oil company Petrobras executives who accepted kickbacks for awarding contracts to construction firms. The corruption scandal involves US$9.5 billion in briberies and a lot of business elites and politicians including the presidents. It is the largest corruption scandal in Latin America and the escalation goes beyond expectations.

Table 3 reports the difference-in-difference test exploiting this event. Treat is 1 if fiat currency is BRL, and 0 if fiat currency is CNY or EUR or KRW or GBP. We consider 15-day window around March 17, 2014. Post is 1 for dates after March 17, 2014 and 0 otherwise. Notably, the magnitude of the coefficient of interest β_3 is 10.25, ten times bigger than its value in the Brexit test. We think one reason for the magnitude difference is that this political scandal shatters local investors' trust and confidence in the Brazilian government more severely.

Indian Banknote Denomination

On 8 November 2016, the Government of India announced the demonetisation plan in an effort to combat the black money market that has been dragging down the economic growth of the economy and supporting illegal activity and terrorism. On 9 November, all 500 and 1,000 rupees banknotes of the Mahatma Gandhi Series are invalid and replaced by new issues. Cash shortage and disruptions in business transactions pose severe threats on economic outputs given the sudden nature of the announcement. An estimated 1% GDP is lost in the aftermath of the demonetization experiment.

Table 4 exploits this event as an increase in economic uncertainties and a demand shifter. Treat is 1 if fiat currency is INR, and 0 if fiat currency is CNY or EUR or JPY or KRW or GBP. We consider 15-day window around November 09, 2016. Post is 1 for dates after November 09, 2016 and 0 otherwise. Again, the coefficient of interest is the interaction term between $Treat$ and $Post$. The significantly positive coefficient means that the increase in INR *GAP* after the demonetization event is larger than the *GAP* increase during the same event window for currencies in the control group. The interpretation is that Indian investors may either exchange their banknotes for BTCs in black markets or purchase BTCs online because of their fear for future uncertainties in the country's economic and banking policies.

To sum up, we explore three events - Brexit, Car Wash Operation, and Banknote, to represent increases in political uncertainties, corruption concerns, and economic uncertainties respectively. We consistently show an incremental increase in *GAP* in the currency threatened by these uncertainties, controlling for ongoing factors common to other fiat currencies.

4.1.2 Evidence from panel regressions

To provide further evidence that demand for BTC is linked to local economy or policy, we investigate relation between GAP and Economic Policy Uncertainty Index (EPU) constructed by Baker et al. (2016). When EPU in the domestic country rises, investors lose confidence in their local economy. So they would like to transfer their local currency to other assets such as BTC or USD, hedging against local political turbulence at home. As regulations tighten in the FX market, investors could turn to BTC market to convert domestic currencies to USD. As a result, domestic currency is depreciated vis-a-vis USD in the BTC market relative to that in the FX market and price gap increases.

Since GAP is persistent in the sample, we model the relation between GAP and EPU using a dynamic panel data model in the sense that it contains one lagged GAP. As EPU measure is constructed at monthly level, we consider the following specification:

$$\mathrm{GAP}_m^i \sim \alpha_i + EPU_m^i + EPU_m^{US} + \mathrm{GAP}_{m-1}^i + Controls,$$

where α_i is fiat fixed effect, GAP^i_m is the end-of-month GAP for fiat currency i and EPU^i_m is monthly economic policy uncertainty index[19] for country i at month m. Such dynamic panel regression is subject to Nickell (1981) bias. To resolve this issue, we adopt instrument variable approach proposed by Anderson and Hsiao (1982). Specifically, we first take the first difference of the model, and then instrument lagged $\Delta GAP^i_{m-2,m-1}$ using two-lagged $\Delta\text{GAP}^i_{m-3,m-2}$, yielding the following regression specification:

$$\Delta\text{GAP}^i_{m-1,m} \sim \alpha_m + \beta_0 \Delta EPU^*_{m-1,m} + \beta_0^{US} \Delta EPU^{*,US}_{m-1,m} + \Delta\widehat{\text{GAP}}^i_{m-2,m-1} + Controls, \tag{6}$$

where α_m is month fixed effect, $\Delta\widehat{\text{GAP}}^i_{m-2,m-1}$ is instrumented lagged change of end-of-month GAP^i_{m-1} by two-lagged $\Delta\text{GAP}^i_{m-3,m-2}$. Since EPU measure is country-specific and EPU across countries may not be comparable, we standardize the change of end-of-month EPU by demeaning and dividing the standard deviation. Other control variables include $\Delta\text{Index}^i_{m-1,m}$, the change of end-of-month log-market index for country i.

Note that adopting dynamic panel model takes care of the autocorrelation structure in error terms. However, there exists potential correlation in GAP across countries. To take this feature into consideration, we use two methodologies: the panel regression with clustered Residuals at month level, and the Fama and MacBeth (1973) regression.

Table 5 presents the regression results. The coefficient β_0 and β_0^{US} in Equation (6) captures the contemporaneous impacts of domestic and US economic policy uncertainties on the price gaps, respectively. β_0 is positive and statistically significant for domestic EPU change across different specifications. This result suggests that the additional demand shift for domestic investors in the BTC market is responding to the contemporaneous economic and political uncertainty changes. On average, a one standard deviation increase of monthly domestic EPU is associated with 1.53% higher GAP, accounting for more than half of average GAP.

[19] We have monthly EPU measurements for fourteenth countries in our sample: Australia, Brazil, Canada, China, Euro Zone, Hong Kong, India, Japan, Korea, Russia, Singapore, Sweden, United Kingdom and the United States. This measurement mainly quantifies three components: newspaper coverage of policy-related economic uncertainty, the number of federal tax code provisions set to expire and disagreement among economic forecasters.

4.1.3 When does GAP respond to EPU more strongly?

The relation between *GAP* and *EPU* varies as the preference for BTC and constraints from FX markets change. This relation should get stronger when investors are more constrained to access other FX markets when losing confidence in their local currencies. In line with this intuition, we show in Table 6 that the relation becomes stronger after the Chinese government impose stricter FX controls policies in January, 2017. The model specification is the same as Equation 4. Treat is 1 if the fiat currency is CNY, and 0 otherwise. We only consider one-year window around January 2017. Post is 1 for months later thane January 2017 and 0 otherwise. The point estimate of the difference-in-difference estimator is 4.37 at the 5% significance level.

In Table 7, we exploit the sudden decrease in investors' trust about BTC after the Bitfinex hacking event on on August 2, 2016. We consider one-year window around August 2016. Post is 1 for months later than August 2016 and 0 otherwise. All fiat currencies are included and there is no separation between treatment group and control group. We report the first-difference (pre-versus-post) point estimator which is -0.53 at the 10% significance level. The negative coefficient of the interaction term between post and *EPU* indicates that the relation between *GAP* and *EPU* weakens in the aftermath of the theft of 120,000 units of BTC. This is because investors lose confidence in BTC as an alternative asset to hedge against local currency risks. In fact in the short 6-month period after the hacking even, the total effect of *EPU* on *GAP* stands around at $(0.56 - 0.53 = 0.03)$ which is negligible compared to the point estimates of 1.53 in the earlier panel regressions Table 5.

In short, we show that the relation between *GAP* and *EPU* gets stronger when the limit to arbitrage is more binding (for example, investors face stricter capital controls), and weaker when investors are concerned with governance and cybersecurity issues plaguing the BTC market.

4.2 Does GAP incorporate depreciation expectations?

4.2.1 Predictability of GAP

In Section 4, we establish the relation between BTC demand with local economy uncertainty. In this section, we take a different angle to the same question. We argue that the demand and pricing of BTC mirrors that of FX, so that an increase in demand in BTC represents a decrease demand for domestic currency. Under this view, the positive (negative) values of GAP reflect higher depreciation (appreciation) expectations for domestic currency by BTC investors than by FX investors. If GAP indeed contains depreciation or appreciation expectation, then we expect GAP to have predictive power for foreign exchange rates. Essentially, we want to test weather past daily change of GAP can predict the future FX return.

To empirically test above intuition, we define the further k-day FX log-return as

$$R^{E,i}_{t,t+k} = 100 * \Big(\log(E^i_{t+k}) - \log(E^i_t)\Big). \tag{7}$$

We first fix k at 1 and test the predictability of past GAP information for next-day FX return. We specify the predictability regression as following:

$$R^{E,i}_{t,t+1} \sim \alpha_i + \beta_1 \Delta GAP^i_{t-2,t-1} + \beta_2 \Delta GAP^i_{t-3,t-2} + \beta_3 \Delta GAP^i_{t-4,t-3} + \beta_4 \Delta GAP^i_{t-5,t-4} \tag{8}$$

where α_i is fiat currency fixed effect to control for time-invariant omitted variables, and residuals are clustered at date level. We only take the level change of GAP since GAP is already the return from triangle arbitrage strategy and its percentage change could explode if GAP in the denominator is close to 0. Moreover, since we do not have complete quotes at 00:00:00 (GMT) for all FX currency pairs, we exclude term $\Delta GAP^i_{t-1,t}$ to removes concern of overlapping time intervals.

This regression identifies the delay with which FX rates respond to GAP changes if FX returns are relatively constant over the daily horizons. This regression can answer two key questions: 1) whether past daily change of GAP can predict future spot FX return, 2) how long does it take for FX to fully absorb the information in GAP. If the current or past daily GAP change has predictive power, then some β_j will be significantly different from zero. If predictive power dies out after h day, then β_j becomes insignificant when $j > h$.

The first three columns in Table 8 report the results for panel regressions with fiat fixed effect. These regressions explore predictability of GAP in a time-series manner. Consistent with our intuition, the two-day lagged GAP change predicts FX returns in the following day. In terms of economic magnitude, one standard deviation increase in ΔGPA_{t-1} corresponds to 12.67*6.53/100 = 0.82bps increase in two days ahead FX return, $R^{E,i}_{t,t+1}$. This magnitude is non-trivial. It is roughly half of average daily FX return, which is around 1.63bps. When GAP increases from two days before, there is an additional depreciation pressure on the domestic currency in BTC market than FX market and one-day-ahead FX returns increase. An alternative interpretation of this result is that it takes two days for demand shift information in GAP to be fully incorporated into the FX market.

For robustness checks, we also consider Fama and MacBeth (1973) regressions to examine cross-sectional predictability. The last three columns in Table 8 reassures the two-day head predictability of GAP as the statistical significance remain similar as in the panel regression.

Since BTC becomes widely known and its trading becomes more and more active over the years, we expect the predictability patterns to vary over different sample periods. We split the data into two sub-sample periods. Overall, we find significant coefficients for two-day lagged GAP change. All the results are robust even if we include one-day lag GAP change, $\Delta GAP^{i}_{t-1,t}$, see Table 21. In the unreported results, we also repeated the panel regression after excluding one fiat series from the sample at one time, and found the similar results as in Table 8. This step makes sure that our results are not driven by one fiat.

4.2.2 GAP Predictability Decomposition

To further understand where the predictability comes from, we decompose ΔGAP^i_t into three parts. We start from the identical equations for BTC price quoted in fiat i and in USD:

$$1 = (Ret^{\text{Ƀ},i}_{t,t+1})^{-1}\frac{\text{Ƀ}^i_{t+1}}{\text{Ƀ}^i_t} = (Ret^{\text{Ƀ},US}_{t,t+1})^{-1}\frac{\text{Ƀ}^{US}_{t+1}}{\text{Ƀ}^{US}_t}$$

$$\frac{Ret^{\text{Ƀ},i}_{t,t+1}}{Ret^{\text{Ƀ},US}_{t,t+1}} = \frac{\text{Ƀ}^i_{t+1}}{\text{Ƀ}^{US}_{t+1}}\left(\frac{\text{Ƀ}^i_t}{\text{Ƀ}^{US}_t}\right)^{-1} = \frac{\text{Ɇ}^i_{t+1}}{\text{Ɇ}^i_t}.$$

Dividing $\frac{E^i_{t+1}}{E^i_t}$ on both sides of the equation yields:

$$\frac{Ret^{\text{Ƀ},i}_{t,t+1}}{Ret^{\text{Ƀ},US}_{t,t+1}}\left(\frac{E^i_{t+1}}{E^i_t}\right)^{-1} = \frac{\text{Ɇ}^i_{t+1}}{E^i_{t+1}}\left(\frac{\text{Ɇ}^i_t}{E^i_t}\right)^{-1} = \frac{GAP_{t+1}/100+1}{GAP_t/100+1}.$$

After taking log on both sides and expanding $\log(1+x)$ around $x = 0$, we get:

$$\Delta GAP_{t+1} \approx R^{\text{Ƀ},i}_{t,t+1} - R^{\text{Ƀ},US}_{t,t+1} - R^{E,i}_{t,t+1},$$

where $R^{\text{Ƀ},i}_{t,t+1}$ ($R^{\text{Ƀ},US}_{t,t+1}$) is log returns for BTC quoted in fiat i (USD).

Table 9 presents the FX predictability regression using all the three components of GAP^i_t. We find that the statistical significance of $R^{\text{Ƀ},i}_{t-2,t-1}$ survive, but not $R^{\text{Ƀ},US}_{t-2,t-1}$ or $R^{E,i}_{t-2,t-1}$. So BTC Return denoted by home currency drives the predictability of GAP previously found, rather than the BTC return quoted in USD or foreign exchange rate of the home currency. We interpret this evidence as in line with our conjectured mechanism that home country investors resort to BTC when expecting depreciation of home currency and thus push up the BTC price quoted in the home currency.

In summary, we find that price discrepancies in the BTC markets across currencies could predict two-day ahead foreign exchange rate, and the predictability mainly comes from the return of BTC denoted by the home currency. These results serve as complementary evidence to the finding that GAP jumps after EPU increases. Both evidence point to the key fact that the BTC market incorporates demand information about FX in a timely manner because investors opt for BTC as an alternative when losing confidence in the local currencies.

4.3 Why does GAP persist?

A key prerequisite to ensure that GAP reflects demand shift information is segmentation across BTC markets. In other words, why GAP persists without attracting arbitrageurs to take the advantage and clear up the price wedge. Transaction costs are one of frictions preventing arbitraging across markets. However, above analysis explicitly takes out trading related costs and shows that transaction costs alone do not drive our empirical findings. This section discusses an important limit to arbitrage – cross-border capital controls.

As described in Section 3, price discrepancy, GAP, can be positive or negative. Arbitragers face difference constraints when eliminating GAP. For example, to reduce the positive price gap between BTC denoted by CNY and that by USD, arbitrageurs need to sell BTC into CNY and convert the proceeds in CNY back to USD in order to sustain the triangular arbitrage. If China imposes restrictions on capital outflows which prevent investors from selling CNY into foreign currencies, the arbitrageurs will not be able to complete the arbitrage trip and bring the positive price gap back to zero. By the same token, restrictions on capital inflows will stop arbitrageurs to respond to the negative gap between the CNY and USD price of BTC. Therefore, we expect to see positive *GAP* is positively correlated with outflow capital restrictions while negative *GAP* is negatively correlated with inflow capital restrictions.

We employ the country-level money market inflow and outflow indexes constructed by Fernández et al. (2016) to approximate capital regulation restrictiveness[20]. Both indexes range from 0 to 1 and increases in the intensity of capital control policies. Even though we have yearly panel data, the time-series variation is rather small as the capital control policies are usually stable over time. In this analysis, we only focus on cross-sectional relationships.

[20] As the data ends in 2015, we fill in later years using the average of previous five years data. Note that we are interested in the cross-sectional difference and the capital control does not change much over the years. So this procedure should not affect our analysis substantially.

We attempt to test the relation between GAP and capital control restrictions using two regression approaches, panel regression with date fixed effect and Fama-Macbeth regression. The regression is specified as

$$GAP_t^{i,\cdot} \sim \alpha_t + \beta_1 InC_t^i + \beta_2 OutC_t^i + Controls$$

where $GAP_t^{i,+}$ ($GAP_t^{i,-}$) is the daily positive (negative) discrepancy between shadow foreign exchange rate for fiat currency i and the actual spot rate i/USD. Control variables include Turnover_t^i defined in equation (5), $\Delta\text{Index}_{t-1,t}^i$, the daily change of log-market index for country i. As shown in Figure 2, the spikes of GAP is likely to be clustered cross different currency pairs. In order to take care of cross-sectional correlation, we cluster standard errors at month level in panel regression. Fama-Macbeth is an alternative way to correct for cross-sectional correlation.

As shown in the first three columns in Table 10, coefficients of $OutC$, β_2, are significantly positive under three specifications, while coefficients β_1 have smaller magnitudes and are not significant in specification (3). These results indicate that arbitrageurs are constrained by outflow capital restrictions to eliminate positive *GAP*, instead of inflow capital restrictions. Specifically, as OutC index increases 0.1 (unit), the daily price discrepancy increases by 0.25% on average, based on the result in column (1). In contrast, arbitrageurs are constrained by inflow capital restrictions to eliminate negative *GAP*, as shown in the last three columns in Table 10. A visualization of the same result is presented in Figure 4.

5 Comparison Analysis with Gold and ADRs

In this section, we show that the empirical findings we have shown so far are unique to BTC but not other traditional financial assets such as commodity and cross-listed shares. For example, gold and American Depository Receipts (ADRs) are also traded in different exchanges and denoted by multiple currencies. Gold has long been labeled as the "flight to safety" commodity. For comparison analysis, we reconstruct *GAP* for gold and ADRs.

5.1 GAP for Gold

In Table 11, we tabulate the summary statistics of gold *GAP* whose magnitude is negligible regardless of the signs. Table 12 shows that the relation between gold *GAP* and *EPU* does not hold. Similarly, gold *GAP* does not predict domestic currency returns as shown in Table 13 and Table 14. Hence, price gap of gold does not hold the same property as of BTC in reflecting local demand shift for local currencies. This, however, does not mean gold is not the safety assets as the common wisdom suggests. Rather, the pricing gap across countries for gold is instantaneously wiped out when the domestic demand for gold shoots up.

To instantaneously wipe out the price gap across marketplaces, arbitrageurs need sufficient amount of FX to scale up the arbitrage. Gold and other commodity trading is well and long developed with active participation from institutional investors with easy access to FX markets. Hence, the demand shift information for local currencies is wiped out by gold arbitrageurs who economize on price gaps observed. On the contrary, the BTC market, until 2017 December, primarily consists of retail investors facing constraints, administrative burden and time delay when transferring funds across currencies. For example, each Chinese resident is granted a purchase quota of 5,000 USD worth of foreign currencies per year. Facing the non-linear capital controls restrictions, retail investors are handicapped to profit from the price disparities beyond the quota limit. Institutional investors do not actively participate in crypto assets which are dubbed as unregulated and highly risky because of their fiducial duties. In the absence of sufficient arbitrage forces, the remaining price gap can persist and reflect the local demand shift for BTC as well as local currencies.

5.2 GAP for ADRs

Table 15 presents the summary statistics of ADR *GAP* whose magnitude is not trivial but closer to zero, compared to BTC *GAP*. Table 16 shows that ADR *GAP* does not respond to *EPU* changes either. Accordingly, ADR *GAP* does not predict domestic currency returns as shown in Table 17 and Table 18. BTC differs from ADRs in its hedging role for local assets. Our evidence show that

BTC can be a hedging device for local investors in both normal and crises times, regardless of the presence of capital controls. Similar empirical evidence for ADRs is so far only limited to episodes of the Argentina crisis in 2001 and the Venezuela crisis in 2003. In normal times, however, ADRs are diversification assets for US investors to access non-US equity markets and do not necessarily reflect non-US investors' belief in non-US currencies. In a nutshell, ADR pricing does not hold the same property as BTC in incorporating local investors' preferences for local currencies in normal times.

6 Conclusion

For concluding remarks, we first propose a novel notion of "Flight to Bitcoin" by exploring the interplay among BTC market, socioeconomic conditions, and FX market. Exploiting several case studies and standard panel regressions, this paper first uncovers the function of BTC as a device to convey investors' concerns against local economic and political uncertainties, and a cross-currency wealth transfer tool. By documenting this new phenomenon that emerges as FinTech boom unfolds, we can potentially open up entire series of discussions on the interactions between traditional financial assets and innovative asset classes that are put under spotlight.

Second, based on this unique function of BTC in hedging local uncertainties, we then study the BTC market as a shadow market for FX. We argue that BTC market incorporates investors' depreciation (appreciation) expectations about local currencies and FX, and demonstrate the short-term predictability of our *GAP* measure for future FX returns. This finding may be surprising given the embedded parity link between BTC and FX. We reconcile our findings by showing the segmentation in the BTC market explained by capital controls, a form of limits to arbitrage. To our knowledge, our paper is the first to empirically evaluate and show the relative merits of the BTC pricing process. We show that the implied price formation process of fiat currencies by BTC incorporates the real demand shift for domestic currencies. Using BTC as an example, our paper speaks to the broad debate as to whether FinTech can disrupt or improve the financial market efficiency. We are not advocating for a completely free and unregulated market for FinTech, but we do suggest that policymakers and regulators should be aware that FinTech can enjoy the innate superior market efficiency and pricing formation process. Hence, monitoring of the FinTech sector can come at the cost of its advantages in market efficiency and price informativeness.

Last but not the least, we go one step further to explore the mechanisms through which BTC differentiates from other financial assets in terms of hedging and reflecting information on FX markets. We conduct comparison analysis to show that the properties we have identified for BTC do not apply to other multi-traded assets such as gold and ADRs. Thanks to the participation of institutional investors as arbitrage forces, the gold market is not as segmented, which violates the prerequisite for price gaps across trading venues to reflect local demands. Although, ADRs can serve as a tool to circumvent cross-border capital controls in crises times, they do not share the same genes as BTC in terms of conveying dissent against authorities in all times without capital controls. The uniqueness of FinTech assets such as BTC poses a challenge for regulators to improve existing regulation frameworks which are subject to new externalities. In contrast to Fintech's exponential growth, governments around the world are still in the infant stage of setting up regulations and rules for the new area.

Overall, We hope our work can provoke more thoughts and empirical work on the interactions among FinTech related new financial products, existing traditional financial assets, and macroeconomic policies. We think externalities posed by FinTech on the current financial system seem to be a fruitful and promising research theme to follow in the future.

Figure 2: Time series plots of daily GAP for CNY, EUR, JPY and GBP.

This figure present Time series plots of daily GAP for CNY, EUR, JPY and GBP. where GAP is defined in (3). The sample period is from January 1, 2012 to July 31, 2018.

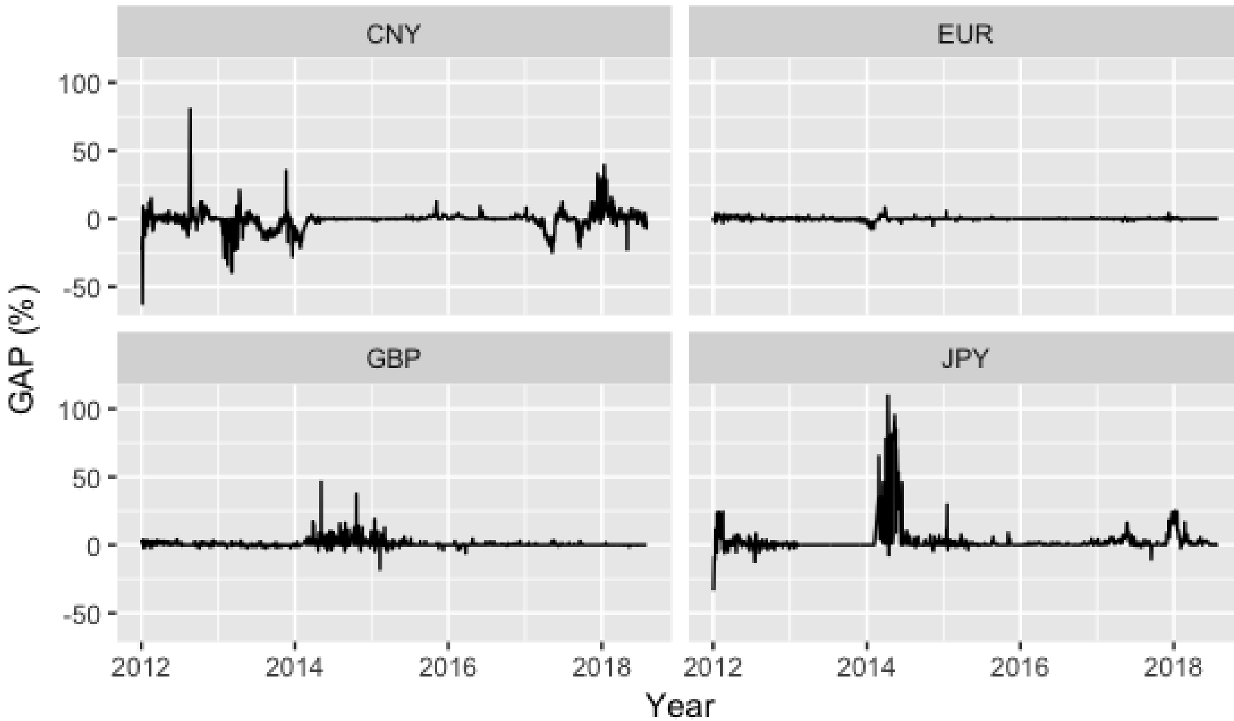


Figure 3: Shadow Exchange rate in BTC market around Brexit, India Demonetization, and Brazil operation car wash

The two figures plot shadow exchange rate, derived from BTC markets and FX exchange rate for 15-day window around the announcement of Brexit at June 24, 2016, India banknote demonetisation at November, 09, 2016 and Brazil operation car wash at March 17, 2014

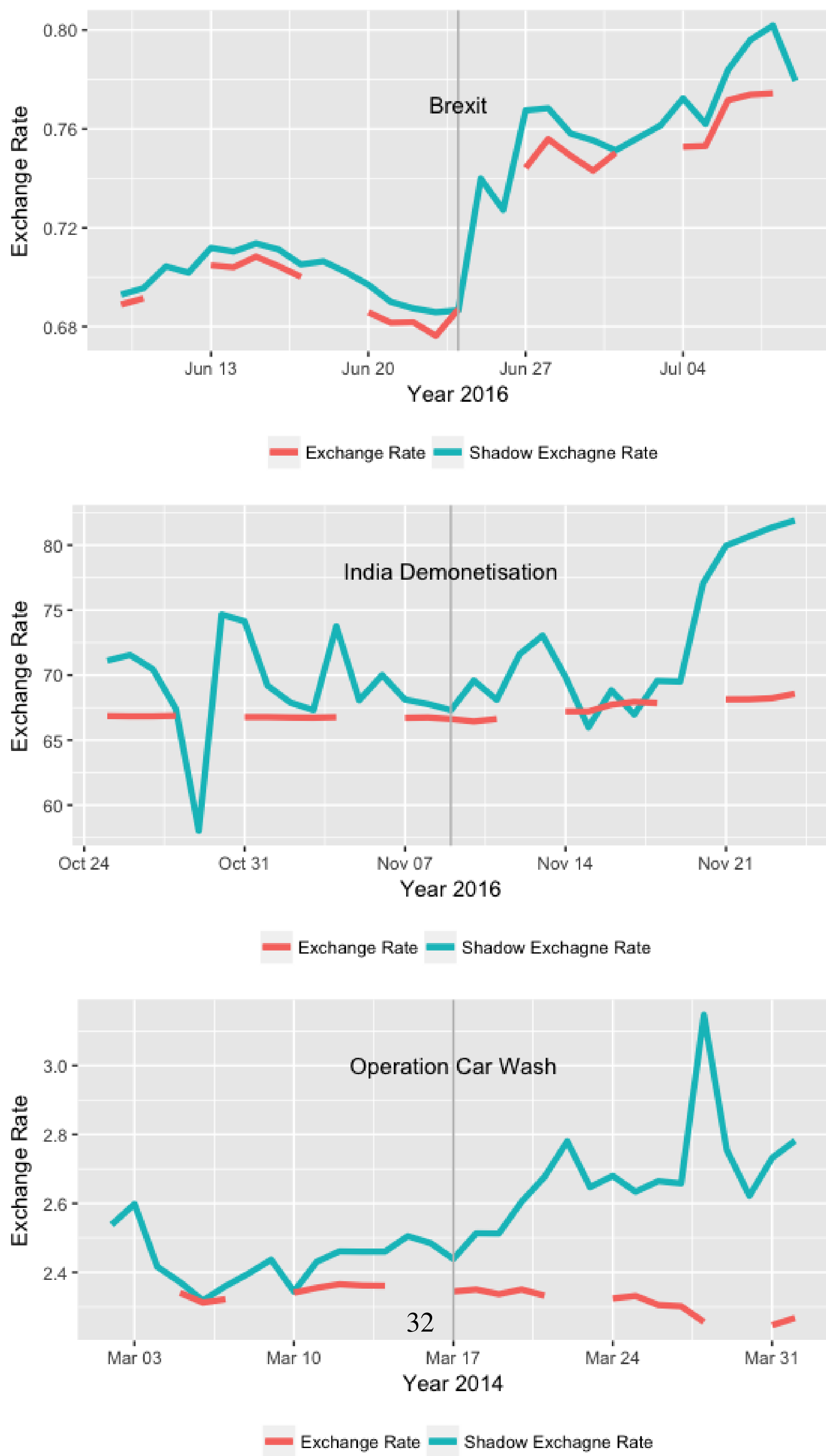


Figure 4: Scatter plots of relation between $GAP_y^{i,+}$ ($GAP_y^{i,-}$) and capital outflow (inflow) controls

The upper panel plots the linear relationship between yearly average of positive discrepancy $GAP_y^{i,+}$ and money market outflow restriction intensity measured by Fernández et al. (2016) from 2014 to 2017. The lower panel plots the linear relationship between $GAP_y^{i,-}$ and money market inflow restriction intensity. Each point represents one fiat currency and the line is OLS fit of scatter points.

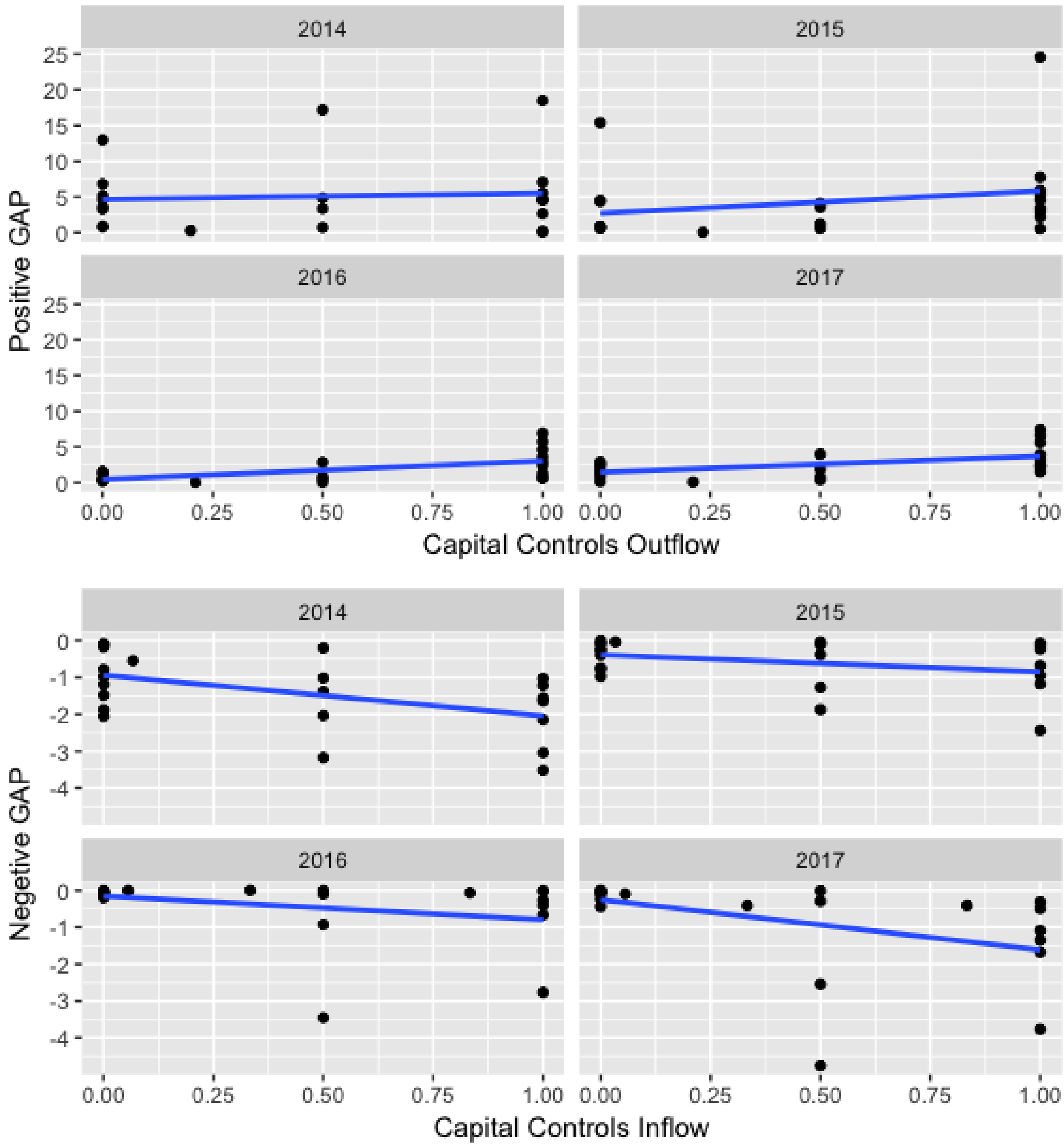


Table 1: Summary Statistics

This table presents the summary statistics of major fiat currencies traded in BTC. The sample period is from January 1, 2012 to July 31, 2018 and the frequency of BTC related variables is daily. For each fiat currency, “Start Date” records the date when BTC firstly started to trade in exchanges, “Count” records the total dates included in the sample, and “Volume” measures the average daily volume of BTC trading across exchanges. GAP, the measure of triangle arbitrage deviations, is defined in (3). GAP^{+} and GAP^{-} represent positive GAP and negative GAP, respectively. The sub-columns “mean”, “s.e.” record mean and standard error of the corresponding statistics, and sub-column “ratio” records the proportion of non-zero GAP (or GAP^{+} or GAP^{-}) in the sample. EPU is a measure of monthly Economic Policy Uncertainty constructed in Baker et al. (2016) at monthly level. “InC” (“OutC”) is yearly money market inflow (outflow) restriction intensity measured by Fernández et al. (2016).

				GAP (%)			GAP^{+} (%)			GAP^{-} (%)			EPU	InC	OutC
Fiat	Start Date	Count	Volume	Mean	s.e.	ratio	Mean	s.e.	ratio	Mean	s.e.	ratio	Mean	Mean	Mean
AUD	2013-03-11	1392	531.11	2.29	0.18	0.68	5.21	0.25	0.56	-4.82	0.49	0.13	99.45	0.00	0.00
BRL	2013-03-18	1347	206.78	4.18	0.32	0.92	6.55	0.18	0.82	-12.09	2.48	0.10	126.63	0.20	1.00
CAD	2013-03-12	1389	271.13	2.69	0.42	0.69	6.89	0.74	0.53	-6.21	0.46	0.16	126.79	0.00	0.00
CHF	2013-04-08	1345	25.98	2.44	0.38	0.34	14.49	1.18	0.24	-11.57	1.36	0.09		0.20	0.30
CNY	2012-01-02	1662	312313.98	-0.78	0.21	0.70	3.71	0.43	0.36	-6.20	0.29	0.34	139.14	1.00	1.00
EUR	2012-01-02	1701	8639.81	0.01	0.02	0.31	1.01	0.06	0.17	-1.19	0.09	0.14	123.75	0.05	0.19
GBP	2012-01-02	1701	1179.20	0.67	0.06	0.43	2.31	0.15	0.34	-1.38	0.15	0.09	123.75	0.00	0.00
HKD	2013-04-03	1374	467.07	0.57	0.27	0.67	5.54	0.30	0.44	-7.82	0.79	0.24	124.56		
IDR	2013-05-14	1303	841.87	2.77	0.50	0.84	10.69	0.54	0.57	-12.62	1.00	0.27		1.00	0.50
ILS	2013-03-15	1388	21.79	0.02	0.23	0.84	3.39	0.18	0.47	-4.22	0.52	0.37		0.00	0.00
INR	2013-03-20	1314	94.56	4.30	0.47	0.91	9.12	0.65	0.64	-5.79	0.38	0.27	94.72	1.00	1.00
JPY	2012-01-02	1700	54763.55	2.97	0.27	0.57	6.26	0.50	0.50	-2.56	0.48	0.07	101.00	0.00	0.00
KRW	2013-08-08	1284	7301.62	4.19	0.35	0.52	12.06	0.64	0.42	-9.67	0.97	0.10	106.56	0.00	0.00
MXN	2013-03-11	1390	134.60	4.52	0.62	0.84	8.29	0.86	0.68	-6.74	0.69	0.16	97.43	0.30	1.00
MYR	2013-06-26	1304	112.28	1.70	0.37	0.89	8.20	0.41	0.55	-8.14	0.62	0.34		0.50	1.00
PHP	2013-04-01	1346	129.26	1.60	0.44	0.88	9.32	0.76	0.48	-6.96	0.32	0.41		0.50	1.00
PLN	2013-06-24	1316	836.94	-0.09	0.15	0.65	2.50	0.22	0.38	-3.82	0.36	0.27		0.70	0.50
RUB	2013-03-28	1374	565.60	3.89	0.63	0.77	19.14	1.96	0.29	-3.43	0.16	0.48	126.01	1.00	0.50
SEK	2013-03-12	1389	35.74	2.01	0.43	0.31	8.71	1.51	0.27	-8.32	2.07	0.04	105.21	0.20	0.00
SGD	2013-03-25	1381	413.62	2.25	0.28	0.50	8.58	0.53	0.38	-8.02	1.00	0.12	119.92	0.00	0.00
THB	2013-03-26	1379	77.82	1.17	0.23	0.40	8.89	0.73	0.24	-5.85	0.42	0.16		1.00	1.00
VND	2014-02-27	1143	562.14	9.46	0.61	0.92	17.10	0.83	0.63	-4.93	0.35	0.28		1.00	1.00
ZAR	2013-04-15	1366	285.09	5.85	0.17	0.97	7.30	0.15	0.87	-4.93	0.38	0.10		0.50	0.90
All	2012-01-02	32288	19998.45	2.43	0.07	0.67	7.90	0.13	0.46	-6.11	0.13	0.20			

Table 2: Event study: Brexit

This table tabulates the regression results from

$$GAP_t^i \sim Treat * Post + Treat + Post + Controls$$

The dependent variable GAP_t^i is the daily discrepancy between shadow foreign exchange rate for fiat currency i and the actual spot rate i/USD. Treat is 1 if fiat currency is GBP or EUR, and 0 if fiat currency is CNY or JPY or KRW. We consider 15-day window around June 24, 2016. Post is 1 for 15 dates after June 24, 2016 and 0 for 15 days before. Other control variables include Turnover_t^i (Turnover_t^{US}) defined in equation (5), $\Delta\text{Index}_{t-1,t}^i$ ($\Delta\text{Index}_{t-1,t}^{US}$), the daily change of log-market index for country i (US).

	GAP_t^i	
	(1)	(2)
Treat:Post	1.359***	1.187***
	(0.495)	(0.399)
Treat	−2.001***	−2.836***
	(0.336)	(0.291)
Post	−0.981***	−0.715**
	(0.315)	(0.296)
Turnover_t^i		−0.361***
		(0.047)
Turnover_t^{US}		0.415*
		(0.210)
$\Delta Index_{t-1,t}^i$		−2.531
		(6.044)
$\Delta Index_{t-1,t}^{US}$		−1.584
		(10.796)
Constant	2.021***	1.784*
	(0.216)	(0.978)
Observations	108	108
R^2	0.285	0.556
Note:	*p<0.1; **p<0.05; ***p<0.01	

Table 3: Event study: Brazil operation car wash

This table tabulates the regression results from

$$GAP_t^i \sim Treat * Post + Treat + Post + Controls$$

The dependent variable GAP_t^i is the daily discrepancy between shadow foreign exchange rate for fiat currency i and the actual spot rate i/USD. Treat is 1 if fiat currency is BRL, and 0 if fiat currency is CNY or EUR or KRW or GBP. We consider 15-day window around March 17, 2014. Post is 1 for 15 dates after March 17, 2014 and 0 for 15 days before. Other control variables include Turnover_t^i (Turnover_t^{US}) defined in equation (5), $\Delta\text{Index}_{t-1,t}^i$ ($\Delta\text{Index}_{t-1,t}^{US}$), the daily change of log-market index for country i (US).

	GAP_t^i	
	(1)	(2)
Treat:Post	10.247***	11.005***
	(2.686)	(2.571)
Treat	−0.511	−0.841
	(1.975)	(1.856)
Post	3.334***	2.663*
	(1.151)	(1.419)
Turnover_t^i		−0.299***
		(0.070)
Turnover_t^{US}		1.615
		(1.757)
$\Delta Index_{t-1,t}^i$		−45.961
		(54.741)
$\Delta Index_{t-1,t}^{US}$		57.186
		(79.408)
Constant	1.982**	12.026
	(0.814)	(15.151)
Observations	108	108
R^2	0.347	0.457
Note:	*p<0.1; **p<0.05; ***p<0.01	

Table 4: Event study: India banknote demonetisation

This table tabulates the regression results from

$$GAP_t^i \sim Treat * Post + Treat + Post + Controls$$

The dependent variable GAP_t^i is the daily discrepancy between shadow foreign exchange rate for fiat currency i and the actual spot rate i/USD. Treat is 1 if fiat currency is INR, and 0 if fiat currency is CNY or EUR or JPY or KRW or GBP. We consider 15-day window around November 09, 2016. Post is 1 for dates 15 after November 09, 2016 and 0 for 15 days before. Other control variables include Turnover$_t^i$ (Turnover$_t^{US}$) defined in equation (5), ΔIndex$_{t-1,t}^i$ (ΔIndex$_{t-1,t}^{US}$), the daily change of log-market index for country i (US).

	GAP_t^i	
	(1)	(2)
Treat:Post	3.622***	3.619***
	(1.209)	(1.225)
Treat	3.306***	3.872***
	(0.836)	(0.963)
Post	0.046	−0.135
	(0.493)	(0.517)
Turnover$_t^i$		0.087
		(0.077)
Turnover$_t^{US}$		−0.959
		(0.749)
$\Delta Index_{t-1,t}^i$		17.543
		(21.470)
$\Delta Index_{t-1,t}^{US}$		−36.148
		(37.303)
Constant	0.529	−4.413
	(0.341)	(4.365)
Observations	138	138
R^2	0.376	0.395
Note:	*p<0.1; **p<0.05; ***p<0.01	

Table 5: Monthly relationship between GAP and EPU

This table tabulates the regression results from

$$\Delta \mathrm{GAP}^i_{m-1,m} \sim \alpha_m + \beta_0 \Delta EPU^*_{m-1,m} + \beta_0^{US} \Delta EPU^{*,US}_{m-1,m} + \Delta \widehat{\mathrm{GAP}}^i_{m-2,m-1} + Controls$$

The dependent variable $\Delta \mathrm{GAP}^i_{m-1,m} = \mathrm{GAP}^i_m - \mathrm{GAP}^i_{m-1}$ is the change of end-of-month GAP^i_m for fiat currency i. $\Delta EPU^*_{m-1,m}$ ($\Delta EPU^{*,US}_{m-1,m}$) is the standardized change of EPU^i_m (EPU^{US}_m) by demeaning and dividing the standard deviation. $\Delta \widehat{\mathrm{GAP}}^i_{m-2,m-1}$ is instrumented lagged change of end-of-month GAP^i_{m-1} by two-lagged $\Delta \mathrm{GAP}^i_{m-3,m-2}$. Other control variables include $\Delta \mathrm{Turnover}^i_{m-1,m}$ ($\Delta \mathrm{Turnover}^{US}_{m-1,m}$), the change of monthly turnover defined in equation (5), and $\Delta \mathrm{Index}^i_{m-1,m}$ ($\Delta \mathrm{Index}^{US}_{m-1,m}$), the change of end-of-month log-market index for country i (US). Column (1) to (4) under "*Panel*" report regression results from panel regression whose standard errors (in parentheses) are clustered at the month level. Column (5) and (6) under "FM" report results from Fama and MacBeth (1973) regression. The full sample period is January 1, 2012 to July 31, 2018.

	$\Delta \mathrm{GAP}^i_{m-1,m}$					
	Panel				FM	
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta EPU^*_{m-1,m}$	1.129**	1.103**	1.511**	1.526**	2.117***	1.437*
	(0.477)	(0.481)	(0.732)	(0.733)	(0.734)	(0.750)
$\Delta EPU^{*,US}_{m-1,m}$	−0.782	−0.766	6.800	3.435	−2.812	0.517
	(0.513)	(0.578)	(12.284)	(11.886)	(21.973)	(23.737)
$\Delta \mathrm{Index}^i_{m-1,m}$		−8.038		−8.122		−0.759
		(11.490)		(13.317)		(15.996)
$\Delta \mathrm{Index}^{US}_{m-1,m}$		−31.184		−1,476.871		
		(29.716)		(1,137.689)		
$\Delta \mathrm{Turnover}^i_{m-1,m}$		−0.829		−0.679		−0.629
		(1.177)		(0.962)		(0.769)
$\Delta \mathrm{Turnover}^{US}_{m-1,m}$		−2.358		7.885		
		(2.232)		(30.297)		
$\Delta \widehat{\mathrm{GAP}}^i_{m-2,m-1}$	0.478	0.475	0.494	0.485		
	(0.302)	(0.297)	(0.358)	(0.357)		
Constant	−0.061	0.366			0.727	−3.704
	(0.703)	(0.592)			(8.815)	(9.799)
Month FE	N	N	Y	Y	NA	NA
Observations	855	855	855	855	812	812
R^2	0.119	0.124	0.284	0.288	0.192	0.209

Note: *p<0.1; **p<0.05; ***p<0.01

Table 6: China restricts households' foreign exchange purchase from January, 2017

This table tabulates the regression results from

$$\Delta \text{GAP}^i_{m-1,m} \sim \alpha_m + \beta_0 \Delta EPU^*_{m-1,m} \times Treat \times Post + \beta_0^{US} \Delta EPU^{*,US}_{m-1,m} + \Delta\widehat{\text{GAP}}^i_{m-2,m-1}$$

The dependent variable $\Delta \text{GAP}^i_{m-1,m} = \text{GAP}^i_m - \text{GAP}^i_{m-1}$ is the change of end-of-month GAP^i_m for fiat currency i. Treat is 1 if the fiat currency is CNY, and 0 otherwise. We only consider one-year window around January 2017. Post is 1 for months later than January 2017 and 0 otherwise. $\Delta EPU^*_{m-1,m}$ ($\Delta EPU^{*,US}_{m-1,m}$) is the standardized change of EPU^i_m (EPU^{US}_m) by demeaning and dividing the standard deviation. $\Delta\widehat{\text{GAP}}^i_{m-2,m-1}$ is instrumented lagged change of end-of-month GAP^i_{m-1} by two-lagged $\Delta \text{GAP}^i_{m-3,m-2}$. Other control variables include $\Delta \text{Turnover}^i_{m-1,m}$ ($\Delta \text{Turnover}^{US}_{m-1,m}$), the change of monthly turnover defined in equation (5), and $\Delta \text{Index}^i_{m-1,m}$ ($\Delta \text{Index}^{US}_{m-1,m}$), the change of end-of-month log-market index for country i (US). We do not report coefficients for one-way and two-way interactions.

	$\Delta GAP^i_{m-1,m}$	
	(1)	(2)
$\Delta EPU^*_{m-1,m}$*Treat*Post	4.599^{**}	4.365^{**}
	(1.907)	(1.900)
$\Delta EPU^*_{m-1,m}$	−0.308	−0.109
	(0.362)	(0.374)
$\Delta EPU^{*,US}_{m-1,m}$	0.670	0.663
	(0.436)	(0.438)
$\Delta \text{Index}^i_{m-1,m}$		−3.233
		(13.569)
$\Delta \text{Index}^{US}_{m-1,m}$		-47.861^{*}
		(24.684)
$\Delta\widehat{\text{GAP}}^i_{m-2,m-1}$	-0.457^{**}	-0.440^{**}
	(0.212)	(0.210)
Constant	−0.142	0.433
	(0.539)	(0.615)
Interactions	Y	Y
Observations	143	143
R^2	0.222	0.245
Note:	*p<0.1; **p<0.05; ***p<0.01	

Table 7: Bitfinex hack in August 2016

This table tabulates the regression results from

$$\Delta\text{GAP}^i_{m-1,m} \sim \alpha_m + \beta_0 \Delta EPU^*_{m-1,m} \times Post + \beta_0^{US} \Delta EPU^{*,US}_{m-1,m} + \Delta\widehat{\text{GAP}}^i_{m-2,m-1}$$

The dependent variable $\Delta\text{GAP}^i_{m-1,m} = \text{GAP}^i_m - \text{GAP}^i_{m-1}$ is the change of end-of-month GAP^i_m for fiat currency i. We only consider one-year window around August 2016. Post is 1 for dates later than August 2016 and 0 otherwise. $\Delta EPU^*_{m-1,m}$ ($\Delta EPU^{*,US}_{m-1,m}$) is the standardized change of EPU^i_m (EPU^{US}_m) by demeaning and dividing the standard deviation. $\Delta\widehat{\text{GAP}}^i_{m-2,m-1}$ is instrumented lagged change of end-of-month GAP^i_{m-1} by two-lagged $\Delta\text{GAP}^i_{m-3,m-2}$. Other control variables include $\Delta\text{Turnover}^i_{m-1,m}$ ($\Delta\text{Turnover}^{US}_{m-1,m}$), the change of monthly turnover defined in equation (5).

	$\Delta GAP^i_{m-1,m}$	
	(1)	(2)
$\Delta EPU^*_{m-1,m}$*Post	-0.532^{*}	-0.468
	(0.290)	(0.313)
$\Delta EPU^*_{m-1,m}$	0.558^{**}	0.518^{*}
	(0.271)	(0.273)
Post	0.440	0.385
	(0.405)	(0.429)
$\Delta EPU^{*,US}_{m-1,m}$	-0.196	-0.208
	(0.200)	(0.362)
$\Delta\text{Turnover}^i_{m-1,m}$		-0.177
		(0.234)
$\Delta\text{Turnover}^{US}_{m-1,m}$		0.403
		(1.077)
$\Delta\text{Index}^i_{m-1,m}$		9.486
		(5.912)
$\Delta\text{Index}^{US}_{m-1,m}$		-2.385
		(11.706)
$\Delta\widehat{\text{GAP}}^i_{m-2,m-1}$	-0.558^{***}	-0.599^{***}
	(0.121)	(0.122)
Constant	-0.379	-0.388
	(0.284)	(0.384)
Observations	156	156
R^2	0.411	0.430
Note:	$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$	

Table 8: Daily predictability

This table presents results from prediction regression

$$10000 * R^{E,i}_{t,t+1} \sim \alpha_i + \beta_1 \Delta GAP^i_{t-2,t-1} + \beta_2 \Delta GAP^i_{t-3,t-2} + \beta_3 \Delta GAP^i_{t-4,t-3} + \beta_4 \Delta GAP^i_{t-5,t-4}$$

The dependent variable $R^{E,i}_{t,t+1}$ is one-day log return of spot exchange rate currency i/USD from date t to $t+1$. $\Delta GAP^i_{t-2,t-1} = GAP^i_{t-1} - GAP^i_{t-2}$ is the change in GAP between $t-2$ and $t-1$ for fiat currency i. We adopt pooled panel regression with fiat fixed effect to examine the time-series predictability, and adopt Fama and MacBeth (1973) regression to examine the cross-sectional predictability. Each row records the estimated coefficient, and the standard errors (in parentheses) are clustered at the date level. The full sample period is January 1, 2012 to July 31, 2018. We also report the results for sub-sample periods: June 1, 2014 to July 31, 2018 and January 1, 2016 to July 31, 2018.

	$10000 * R^E_{t,t+1}$					
	Panel			FM		
	All	>= 2014-06-01	>= 2016-06-01	All	>= 2014-06-01	>= 2016-06-01
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta GAP^i_{t-2,t-1}$	12.670**	21.084***	18.558*	42.739**	46.048*	8.221
	(6.285)	(7.584)	(9.649)	(21.125)	(26.467)	(33.764)
$\Delta GAP^i_{t-3,t-2}$	11.034	23.467**	14.234	32.157	41.387	22.972
	(7.920)	(10.001)	(9.817)	(23.073)	(28.476)	(37.425)
$\Delta GAP^i_{t-4,t-3}$	1.216	−2.069	6.421	39.888*	40.346	26.809
	(7.847)	(10.826)	(9.707)	(23.268)	(28.183)	(35.993)
$\Delta GAP^i_{t-5,t-4}$	−4.907	−9.126	−9.001	−4.194	−5.423	−10.871
	(6.155)	(7.102)	(8.579)	(18.196)	(22.859)	(30.761)
Constant				144.474	161.682	−53.158
				(91.827)	(105.255)	(132.007)
Fiat FE	Y	Y	Y	NA	NA	NA
Observations	32,130	24,702	15,250	30,874	24,693	15,241
R^2	0.001	0.001	0.001	0.254	0.250	0.273
Note:						*p<0.1; **p<0.05; ***p<0.01

Tabel 9: Decomposition of daily predictability

This table presents results from prediction regression

$$10000 * R^{E,i}_{t,t+1} \sim \alpha_i + R^{\text{₿},i}_{t-2,t-1} + R^{\text{₿},US}_{t-2,t-1} + R^{E,i}_{t-2,t-1} + R^{\text{₿},i}_{t-3,t-2} + R^{\text{₿},US}_{t-3,t-2} + R^{E,i}_{t-3,t-2} + R^{\text{₿},i}_{t-4,t-3} + R^{\text{₿},US}_{t-4,t-3} + R^{E,i}_{t-4,t-3}$$

The dependent variable $R^{E,i}_{t,t+1}$ is one-day log return of spot exchange rate currency i/USD from t to $t+1$. $R^{\text{₿},i}_{t-2,t-1}$ is the log return of BTC quoted in fiat currency i from $t-2$ to $t-1$. $R^{\text{₿},US}_{t-2,t-1}$ is the log return of BTC quoted in USD from $t-2$ to $t-1$. Each row records the estimated coefficient, and the standard errors (in parentheses) are clustered at the date level. We adopt pooled panel regression with fiat fixed effect to examine the time-series predictability, and adopt Fama and MacBeth (1973) regression to examine the cross-sectional predictability. The full sample period is January 1, 2012 to July 31, 2018. We also report the results for sub-sample periods: June 1, 2014 to July 31, 2018 and January 1, 2016 to July 31, 2018.

	$10000 * R^{E}_{t,t+1}$					
	Panel			FM		
	All	>= 2014-06-01	>= 2016-06-01	All	>= 2014-06-01	>= 2016-06-01
	(1)	(2)	(3)	(4)	(5)	(6)
$R^{\text{₿},i}_{t-2,t-1}$	17.873***	23.630***	17.826**	19.678**	24.446**	0.402
	(5.442)	(6.975)	(8.614)	(9.492)	(11.562)	(15.467)
$R^{\text{₿},i}_{t-2,t-1}$	−20.828	−39.180*	−35.602			
	(14.769)	(21.838)	(26.578)			
$R^{E,i}_{t-2,t-1}$	−35.167	−3.600	−231.419	133.300	222.121*	185.150
	(184.849)	(218.556)	(228.401)	(119.989)	(133.856)	(166.710)
$R^{\text{₿},i}_{t-3,t-2}$	14.097*	27.613***	16.887*	18.590	25.525*	10.390
	(7.746)	(10.123)	(8.635)	(11.940)	(14.650)	(19.457)
$R^{\text{₿},i}_{t-3,t-2}$	−14.054	−30.163	−46.221*			
	(14.691)	(20.990)	(23.844)			
$R^{E,i}_{t-3,t-2}$	−60.240	−110.262	−51.875	−168.356	−85.968	−45.184
	(181.231)	(209.306)	(220.296)	(142.801)	(140.638)	(171.211)
$R^{\text{₿},i}_{t-4,t-3}$	−1.813	−1.403	4.956	5.469	11.835	3.748
	(6.339)	(8.146)	(7.690)	(10.548)	(12.345)	(16.638)
$R^{\text{₿},i}_{t-4,t-3}$	−14.837	−22.771	−37.690			
	(15.028)	(22.221)	(26.111)			
$R^{E,i}_{t-4,t-3}$	−212.333	−216.154	−267.843	−242.590*	−266.919*	−368.998**
	(157.247)	(182.518)	(211.001)	(126.268)	(140.217)	(176.300)
Constant				114.388	91.280	−33.752
				(80.287)	(94.367)	(124.904)
Fiat FE	Y	Y	Y	NA	NA	NA
Observations	32,158	24,707	15,255	30,894	24,698	15,246
R^2	0.002	0.002	0.003	0.480	0.485	0.446

Note: *p<0.1; **p<0.05; ***p<0.01

Table 10: The cross-sectional regression of GAP on capital control intensities

This table presents results from the following regression

$$GAP_t^{i,\cdot} \sim \alpha_t + \beta_1 InC_t^i + \beta_2 OutC_t^i + Controls$$

The dependent variable $GAP_t^{i,+}$ ($GAP_t^{i,-}$) is the daily positive (negative) discrepancy between shadow foreign exchange rate for fiat currency i and the actual spot rate i/USD. InC_t^i ($OutC_t^i$) is money market inflow (outflow) restriction intensity measured by Fernández et al. (2016). Other control variables include Turnover_t^i defined in equation (5), $\Delta\text{Index}_{t-1,t}^i$, the daily change of log-market index for country i. Columns (1) to (2) and (4) to (5) under "Panel" report regression results from panel regression controlling for date fixed effect and clustering standard errors (in parentheses) at date level. Column (3) and (6) under "FM" report results from Fama and MacBeth (1973) regression. We only keep trading day with more than 10 observations to preserve enough cross sectional variations. The full sample period is from Jan 1, 2012 to July 31, 2018.

	$GAP_t^{i,+}$			$GAP_t^{i,-}$		
	Panel		FM	*Panel*		FM
	(1)	(2)	(3)	(4)	(5)	(6)
$OutC_t^i$	2.536***	0.987***	1.586***		0.884	1.475*
	(0.299)	(0.377)	(0.386)		(0.847)	(0.858)
InC_t^i		0.906**	0.313	−5.188***	−5.070***	−4.869***
		(0.440)	(0.471)	(0.656)	(1.162)	(1.082)
Turnover_t^i		−0.958***	−0.732***		0.433***	0.465***
		(0.051)	(0.047)		(0.072)	(0.079)
$\Delta Index_{t-1,t}^i$		−7.965	−24.365		−25.572	−1.158
		(13.976)	(25.907)		(27.013)	(32.685)
Constant	7.597***		−3.333***	−6.631***		−0.495
	(0.290)		(0.580)	(0.337)		(1.070)
Month FE	N	Y	NA	N	Y	NA
Observations	9,134	8,613	8,613	1,465	1,459	1,459
R^2	0.006	0.374	0.496	0.040	0.258	0.361

Note: *p<0.1; **p<0.05; ***p<0.01

Table 11: Summary Statistics for Gold

This table presents the summary statistics of fiat currencies traded in Gold. We consider the same sample as in BTC analysis. The frequency of observations is daily. Column "Count" records the total dates included in the sample. GAP, the measure of triangle arbitrage deviations, is defined in (3). GAP^{+} and GAP^{-} represent positive GAP and negative GAP, respectively. The sub-columns "mean", "s.e." record mean and standard error of the corresponding statistics, and sub-column "ratio" records the proportion of non-zero GAP (or GAP^{+} or GAP^{-}) in the sample.

			GAP (%)		GAP^{+} (%)			GAP^{-} (%)		
Fiat	Start Date	Count	Mean	s.e.	Mean	s.e.	ratio	Mean	s.e.	ratio
AUD	2013-03-11	1392	0.00	0.00	0.00	0.00	0.50	-0.00	0.00	0.50
BRL	2013-03-18	1358	-0.01	0.02	0.38	0.02	0.48	-0.38	0.01	0.52
CAD	2013-03-12	1391	0.00	0.00	0.00	0.00	0.59	-0.00	0.00	0.41
CHF	2013-04-08	1372	-0.00	0.00	0.00	0.00	0.53	-0.00	0.00	0.47
CNY	2012-01-03	1663	-0.01	0.01	0.23	0.01	0.50	-0.24	0.01	0.50
EUR	2012-01-03	1698	-0.00	0.00	0.00	0.00	0.48	-0.00	0.00	0.52
GBP	2012-01-03	1698	0.00	0.00	0.00	0.00	0.50	-0.00	0.00	0.50
HKD	2013-04-03	1375	-0.00	0.00	0.00	0.00	0.89	-0.00	0.00	0.11
IDR	2013-05-14	1332	-0.07	0.02	0.29	0.01	0.48	-0.40	0.02	0.52
ILS	2013-03-15	1388	-0.01	0.01	0.24	0.01	0.50	-0.26	0.01	0.50
JPY	2012-01-03	1698	-0.00	0.00	0.00	0.00	0.77	-0.00	0.00	0.23
KRW	2013-08-08	1284	0.01	0.01	0.23	0.01	0.54	-0.24	0.01	0.46
MXN	2013-03-11	1392	-0.02	0.01	0.29	0.01	0.48	-0.31	0.01	0.52
MYR	2013-06-26	1308	0.00	0.01	0.29	0.01	0.51	-0.29	0.01	0.49
PHP	2013-04-01	1374	-0.00	0.01	0.25	0.01	0.51	-0.26	0.01	0.49
PLN	2013-06-24	1317	0.00	0.01	0.21	0.01	0.52	-0.21	0.01	0.48
RUB	2013-03-28	1379	-0.05	0.03	0.32	0.02	0.49	-0.40	0.05	0.51
SEK	2013-03-12	1391	-0.00	0.01	0.21	0.01	0.50	-0.22	0.01	0.50
SGD	2013-03-25	1382	-0.01	0.01	0.20	0.01	0.50	-0.21	0.01	0.50
THB	2013-03-26	1381	-0.02	0.01	0.21	0.01	0.48	-0.22	0.01	0.52
VND	2014-02-14	1141	-0.03	0.01	0.22	0.01	0.46	-0.24	0.01	0.54
ZAR	2013-04-15	1367	-0.02	0.01	0.25	0.01	0.51	-0.30	0.01	0.49
All	2012-01-03	31081	-0.01	0.00	0.16	0.00	0.53	-0.20	0.00	0.47

Table 12: Monthly relationship between GAP of Gold and EPU

This table tabulates the regression results from

$$\Delta \text{GAP}^{i}_{m-1,m} \sim \alpha_m + \beta_0 \Delta EPU^{*}_{m-1,m} + \beta_0^{US} \Delta EPU^{*,US}_{m-1,m} + \Delta\widehat{\text{GAP}}^{i}_{m-2,m-1} + Controls$$

The dependent variable $\Delta \text{GAP}^{i}_{m-1,m} = \text{GAP}^{i}_{m} - \text{GAP}^{i}_{m-1}$ is the change of end-of-month GAP^{i}_{m} for fiat currency i, derived from gold prices. $\Delta EPU^{*}_{m-1,m}$ ($\Delta EPU^{*,US}_{m-1,m}$) is the standardized change of EPU^{i}_{m} (EPU^{US}_{m}) by demeaning and dividing the standard deviation. $\Delta\widehat{\text{GAP}}^{i}_{m-2,m-1}$ is instrumented lagged change of end-of-month GAP^{i}_{m-1} by two-lagged $\Delta \text{GAP}^{i}_{m-3,m-2}$. Other control variables include $\Delta \text{Index}^{i}_{m-1,m}$ ($\Delta \text{Index}^{US}_{m-1,m}$), the change of end-of-month log-market index for country i (US). Column (1) to (4) under "$Panel''$ report regression results from panel regression whose standard errors (in parentheses) are clustered at the month level. Column (5) and (6) under "FM" report results from Fama and MacBeth (1973) regression. The full sample period is January 1, 2012 to July 31, 2018.

	$\Delta \text{GAP}^{i}_{m-1,m}$					
	Panel regression				FM	
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta EPU^{*}_{m-1,m}$	−0.009	−0.013	−0.031*	−0.029*	−0.037*	−0.016
	(0.019)	(0.019)	(0.017)	(0.016)	(0.020)	(0.020)
$\Delta EPU^{*,US}_{m-1,m}$	0.050*	0.050	−0.123	−0.150	−2.499*	−2.514*
	(0.030)	(0.031)	(0.688)	(0.682)	(1.498)	(1.506)
$\Delta \text{Index}^{i}_{m-1,m}$		−0.230		0.489		0.380
		(0.675)		(0.462)		(0.622)
$\Delta \text{Index}^{US}_{m-1,m}$		−1.278		−65.991**		
		(0.931)		(26.897)		
$\Delta\widehat{\text{GAP}}^{i}_{m-2,m-1}$	−0.370***	−0.361***	−0.292**	−0.296**		
	(0.124)	(0.125)	(0.121)	(0.120)		
Constant	0.004	0.016			1.024*	0.914
	(0.024)	(0.026)			(0.577)	(0.630)
Month FE	N	N	Y	Y	NA	NA
Observations	793	793	793	793	749	749
R^2	0.302	0.308	0.510	0.517	0.346	0.265
Note:						*p<0.1; **p<0.05; ***p<0.01

Table 13: Daily predictability (Gold)

This table presents results from prediction regression

$$10000 * R^{E,i}_{t,t+1} \sim \alpha_i + \beta_1 \Delta GAP^{gold,i}_{t-2,t-1} + \beta_2 \Delta GAP^{gold,i}_{t-3,t-2} + \beta_3 \Delta GAP^{gold,i}_{t-4,t-3} + \beta_4 \Delta GAP^{gold,i}_{t-5,t-4}$$

The dependent variable $R^{E,i}_{t,t+1}$ is one-day log return of spot exchange rate currency i/USD from date t to $t+1$. $\Delta GAP^{gold,i}_{t-2,t-1} = GAP^i_{t-1} - GAP^i_{t-2}$ is the change in GAP between $t-2$ and $t-1$ for fiat currency i, derived from gold prices. We adopt pooled panel regression with fiat fixed effect to examine the time-series predictability, and adopt Fama and MacBeth (1973) regression to examine the cross-sectional predictability. Each row records the estimated coefficient, and the standard errors (in parentheses) are clustered at the date level. The full sample period is January 1, 2012 to July 31, 2018. We also report the results for sub-sample periods: June 1, 2014 to July 31, 2018 and January 1, 2016 to July 31, 2018.

	$10000 * R^E_{t,t+1}$					
	Panel			FM		
	All	>= 2014-06-01	>= 2016-06-01	All	>= 2014-06-01	>= 2016-06-01
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta GAP^{gold,i}_{t-2,t-1}$	−140.861	−193.524	−142.398	178.698	278.981	489.943
	(237.553)	(293.197)	(337.252)	(254.215)	(294.213)	(346.535)
$\Delta GAP^{gold,i}_{t-3,t-2}$	−68.529	−86.464	116.514	−52.661	43.436	540.171
	(277.499)	(351.402)	(447.879)	(317.764)	(365.654)	(417.939)
$\Delta GAP^{gold,i}_{t-4,t-3}$	118.990	−13.341	267.932	203.965	264.470	1,090.673**
	(290.571)	(366.113)	(492.625)	(314.473)	(357.887)	(428.515)
$\Delta GAP^{gold,i}_{t-5,t-4}$	−21.382	−98.559	228.011	−91.054	−106.669	480.576
	(219.321)	(268.823)	(355.970)	(271.779)	(315.396)	(373.191)
Constant				148.497	172.630	4.961
				(92.477)	(106.841)	(130.244)
Firm FE	Y	Y	Y	NA	NA	NA
Observations	30,949	23,538	14,540	29,691	23,538	14,540
R^2	0.001	0.001	0.001	0.422	0.422	0.398

Note: *p<0.1; **p<0.05; ***p<0.01

Tabel 14: Decomposition of daily predictability (Gold)

This table presents results from prediction regression

$$10000 * R^{E,i}_{t,t+1} \sim \alpha_i + R^{gold,i}_{t-2,t-1} + R^{gold,US}_{t-2,t-1} + R^{E,i}_{t-2,t-1} + R^{gold,i}_{t-3,t-2} + R^{gold,US}_{t-3,t-2} + R^{E,i}_{t-3,t-2} + R^{gold,i}_{t-4,t-3} + R^{gold,US}_{t-4,t-3} + R^{E,i}_{t-4,t-3}$$

The dependent variable $R^{E,i}_{t,t+1}$ is one-day log return of spot exchange rate currency i/USD from t to $t+1$. $R^{gold,i}_{t-2,t-1}$ is the log return of gold price quoted in fiat currency i from $t-2$ to $t-1$. $R^{gold,US}_{t-2,t-1}$ is the log return of gold quoted in USD from $t-2$ to $t-1$. We adopt pooled panel regression with fiat fixed effect to examine the time-series predictability, and adopt Fama and MacBeth (1973) regression to examine the cross-sectional predictability. Each row records the estimated coefficient, and the standard errors (in parentheses) are clustered at the date level. The full sample period is January 1, 2012 to July 31, 2018. We also report the results for sub-sample periods: June 1, 2014 to July 31, 2018 and January 1, 2016 to July 31, 2018.

	$10000 * R^{E}_{t,t+1}$					
	Panel			FM		
	All	>= 2014-06-01	>= 2016-06-01	All	>= 2014-06-01	>= 2016-06-01
	(1)	(2)	(3)	(4)	(5)	(6)
$R^{gold,i}_{t-2,t-1}$	−22.271	38.397	−96.602	−144.228	34.371	−44.789
	(210.772)	(268.872)	(320.255)	(254.365)	(261.778)	(323.021)
$R^{gold,US}_{t-2,t-1}$	23.302	−119.475	60.821			
	(211.314)	(274.554)	(329.025)			
$R^{E,i}_{t-2,t-1}$	−51.432	−99.988	−153.724	152.072	195.456	266.996
	(238.405)	(289.160)	(374.203)	(246.864)	(280.053)	(333.664)
$R^{gold,i}_{t-3,t-2}$	41.385	108.601	0.976	−237.504	−347.532	−318.411
	(230.642)	(297.299)	(379.049)	(332.733)	(312.617)	(376.444)
$R^{gold,US}_{t-3,t-2}$	−148.253	−320.436	−232.419			
	(238.612)	(311.741)	(398.805)			
$R^{E,i}_{t-3,t-2}$	−97.217	−250.043	−124.467	241.224	126.062	131.419
	(265.392)	(332.400)	(420.421)	(302.120)	(320.531)	(392.152)
$R^{gold,i}_{t-4,t-3}$	225.488	130.234	60.543	115.178	292.308	332.867
	(206.172)	(266.938)	(357.328)	(277.993)	(268.855)	(331.314)
$R^{gold,US}_{t-4,t-3}$	−235.997	−267.033	−291.639			
	(216.943)	(280.691)	(378.204)			
$R^{E,i}_{t-4,t-3}$	−422.050*	−371.859	−415.599	−316.419	−316.871	−500.465
	(234.415)	(294.695)	(369.875)	(256.672)	(278.564)	(345.683)
Constant				−550.748	−676.630*	−398.735
				(339.578)	(354.964)	(379.453)
Firm FE	Y	Y	Y	NA	NA	NA
Observations	30,971	23,538	14,540	29,703	23,538	14,540
R^2	0.001	0.002	0.003	0.531	0.531	0.527

Note: *p<0.1; **p<0.05; ***p<0.01

Table 15: Summary Statistics of ADRs

This table presents the summary statistics of fiat currencies traded in ADRs. We consider the same sample as in BTC analysis. The frequency of observations is daily. Column "Count" records the total dates included in the sample. GAP, the measure of triangle arbitrage deviations, is defined in (3). GAP^{+} and GAP^{-} represent positive GAP and negative GAP, respectively. The sub-columns "mean", "s.e." record mean and standard error of the corresponding statistics, and sub-column "ratio" records the proportion of non-zero GAP (or GAP^{+} or GAP^{-}) in the sample.

			GAP (%)		GAP^{+} (%)			GAP^{-} (%)		
Fiat	Start Date	Count	Mean	s.e.	Mean	s.e.	ratio	Mean	s.e.	ratio
AUD	2013-03-11	1406	-1.08	0.03	0.54	0.03	0.14	-1.35	0.03	0.86
BRL	2013-03-18	1361	0.10	0.03	0.98	0.03	0.55	-0.98	0.03	0.45
EUR	2012-01-02	1715	-0.97	0.04	0.73	0.02	0.30	-1.69	0.03	0.70
GBP	2012-01-02	1716	-0.88	0.02	0.32	0.04	0.08	-0.98	0.01	0.92
HKD	2013-04-03	1388	-0.31	0.04	1.14	0.03	0.44	-1.43	0.02	0.56
INR	2013-03-20	1327	-0.31	0.06	1.71	0.07	0.43	-1.87	0.05	0.57
JPY	2012-01-02	1716	0.23	0.03	0.88	0.05	0.54	-0.52	0.02	0.46
KRW	2013-08-08	1298	-0.16	0.04	1.17	0.05	0.44	-1.18	0.03	0.56
MXN	2013-03-11	1405	0.33	0.03	0.85	0.03	0.63	-0.55	0.02	0.37
MYR	2013-06-26	1318	-0.14	0.05	0.91	0.03	0.51	-1.24	0.07	0.49
PHP	2013-04-01	1386	0.22	0.08	1.73	0.05	0.61	-2.14	0.14	0.39
RUB	2013-03-28	1392	-1.47	0.05	0.66	0.05	0.18	-1.93	0.05	0.82
SEK	2013-03-12	1405	-0.64	0.03	0.92	0.04	0.27	-1.20	0.02	0.73
SGD	2013-03-25	1395	0.03	0.02	0.49	0.02	0.52	-0.46	0.01	0.48
THB	2013-03-26	1395	0.45	0.06	1.67	0.04	0.62	-1.50	0.07	0.38
ZAR	2013-04-15	1380	0.24	0.10	4.48	0.06	0.40	-2.57	0.04	0.60
All	2012-01-02	23003	-0.29	0.01	1.27	0.01	0.41	-1.37	0.01	0.59

Table 16: Monthly relationship between GAP of ADRs and EPU

This table tabulates the regression results from

$$\Delta \text{GAP}^i_{m-1,m} \sim \alpha_m + \beta_0 \Delta EPU^*_{m-1,m} + \beta_0^{US} \Delta EPU^{*,US}_{m-1,m} + \Delta \widehat{\text{GAP}}^i_{m-2,m-1} + Controls$$

The dependent variable $\Delta\text{GAP}^i_{m-1,m} = \text{GAP}^i_m - \text{GAP}^i_{m-1}$ is the change of end-of-month GAP^i_m for fiat currency i, derived from ADRs prices. $\Delta EPU^*_{m-1,m}$ ($\Delta EPU^{*,US}_{m-1,m}$) is the standardized change of EPU^i_m (EPU^{US}_m) by demeaning and dividing the standard deviation. $\Delta\widehat{\text{GAP}}^i_{m-2,m-1}$ is instrumented lagged change of end-of-month GAP^i_{m-1} by two-lagged $\Delta\text{GAP}^i_{m-3,m-2}$. Other control variables include $\Delta\text{Index}^i_{m-1,m}$ ($\Delta\text{Index}^{US}_{m-1,m}$), the change of end-of-month log-market index for country i (US). Column (1) to (4) under "*Panel*" report regression results from panel regression whose standard errors (in parentheses) are clustered at the month level. Column (5) and (6) under "FM" report results from Fama and MacBeth (1973) regression. The full sample period is January 1, 2012 to July 31, 2018. We exclude CNY in this analysis due to its wide variations in GAP.

	$\Delta\text{GAP}^i_{m-1,m}$					
	Panel regression				FM	
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta EPU^*_{m-1,m}$	-0.114^{*}	-0.106	-0.054	-0.053	0.0003	0.028
	(0.069)	(0.070)	(0.091)	(0.091)	(0.109)	(0.107)
$\Delta EPU^{*,US}_{m-1,m}$	0.186^{**}	0.187^{**}	2.037	1.961	2.387	6.527
	(0.077)	(0.078)	(1.721)	(1.742)	(3.138)	(5.082)
$\Delta\text{Index}^i_{m-1,m}$		2.694		2.751		6.198^{**}
		(2.384)		(2.567)		(2.494)
$\Delta\text{Index}^{US}_{m-1,m}$		-1.436		19.980		
		(3.235)		(142.774)		
$\Delta\widehat{\text{GAP}}^i_{m-2,m-1}$	0.135	0.128	0.068	0.062		
	0.068	0.064	-0.004	-0.011		
	(0.120)	(0.121)	(0.117)	(0.119)		
Constant	0.043	0.039			2.662^{**}	2.104
	(0.076)	(0.077)			(1.306)	(1.972)
Month FE	N	N	Y	Y	N	N
Observations	717	717	717	717	686	686
R^2	0.198	0.200	0.351	0.355	0.446	0.584
Note:						*p<0.1; **p<0.05; ***p<0.01

Table 17: Daily predictability (ADRs)

This table presents results from prediction regression

$$10000 * R^{E,i}_{t,t+1} \sim \alpha_i + \beta_1 \Delta GAP^{ADR,i}_{t-2,t-1} + \beta_2 \Delta GAP^{ADR,i}_{t-3,t-2} + \beta_3 \Delta GAP^{ADR,i}_{t-4,t-3} + \beta_4 \Delta GAP^{ADR,i}_{t-5,t-4}$$

The dependent variable $R^{E,i}_{t,t+1}$ is one-day log return of spot exchange rate currency i/USD from date t to $t+1$, derived from ADRs prices. $\Delta GAP^{ADR,i}_{t-2,t-1} = GAP^i_{t-1} - GAP^i_{t-2}$ is the change in GAP between $t-2$ and $t-1$ for fiat currency i. We adopt pooled panel regression with fiat fixed effect to examine the time-series predictability, and adopt Fama and MacBeth (1973) regression to examine the cross-sectional predictability. Each row records the estimated coefficient, and the standard errors (in parentheses) are clustered at the date level. The full sample period is January 1, 2012 to July 31, 2018. We also report the results for sub-sample periods: June 1, 2014 to July 31, 2018 and January 1, 2016 to July 31, 2018. We exclude CNY in this analysis due to its wide variations in GAP.

	$10000 * R^E_{t,t+1}$					
	Panel			FM		
	All	>= 2014-06-01	>= 2016-06-01	All	>= 2014-06-01	>= 2016-06-01
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta GAP^{ADR,i}_{t-2,t-1}$	77.524	75.632	47.731	96.847	95.173	89.601
	(81.977)	(97.878)	(96.907)	(68.654)	(77.013)	(89.732)
$\Delta GAP^{ADR,i}_{t-3,t-2}$	38.457	61.069	10.378	23.415	17.599	84.786
	(83.868)	(100.129)	(98.158)	(71.976)	(83.044)	(97.539)
$\Delta GAP^{ADR,i}_{t-4,t-3}$	191.885**	180.082*	187.613**	84.098	128.082	274.356***
	(81.787)	(97.380)	(95.502)	(76.043)	(87.007)	(104.034)
$\Delta GAP^{ADR,i}_{t-5,t-4}$	68.231	78.193	69.143	−32.660	−61.182	−2.347
	(72.614)	(86.411)	(88.032)	(66.567)	(76.374)	(91.057)
Constant				253.179***	326.022***	162.776
				(95.454)	(109.750)	(138.399)
Fiat FE	Y	Y	Y	NA	NA	NA
Observations	22,907	17,265	10,689	21,914	17,258	10,682
R^2	0.001	0.001	0.001	0.355	0.358	0.326

Note: *p<0.1; **p<0.05; ***p<0.01

Tabel 18: Decomposition of daily predictability (ADRs)

This table presents results from prediction regression

$$10000 * R^{E,i}_{t,t+1} \sim \alpha_i + R^{ADR,i}_{t-2,t-1} + R^{ADR,US}_{t-2,t-1} + R^{E,i}_{t-2,t-1} + R^{ADR,i}_{t-3,t-2} + R^{ADR,US}_{t-3,t-2} + R^{E,i}_{t-3,t-2} + R^{ADR,i}_{t-4,t-3} + R^{ADR,US}_{t-4,t-3} + R^{E,i}_{t-4,t-3}$$

The dependent variable $R^{E,i}_{t,t+1}$ is one-day log return of spot exchange rate currency i/USD from t to $t+1$. $R^{ADR,i}_{t-2,t-1}$ is the log return of ADR price quoted in fiat currency i from $t-2$ to $t-1$. $R^{ADR,US}_{t-2,t-1}$ is the log return of ADR quoted in USD from $t-2$ to $t-1$. We adopt pooled panel regression with fiat fixed effect to examine the time-series predictability, and adopt Fama and MacBeth (1973) regression to examine the cross-sectional predictability. Each row records the estimated coefficient, and the standard errors (in parentheses) are clustered at the date level. The full sample period is January 1, 2012 to July 31, 2018. We also report the results for sub-sample periods: June 1, 2014 to July 31, 2018 and January 1, 2016 to July 31, 2018.

	$10000 * R^{E}_{t,t+1}$					
	Panel			FM		
	All	>= 2014-06-01	>= 2016-06-01	All	>= 2014-06-01	>= 2016-06-01
	(1)	(2)	(3)	(4)	(5)	(6)
$R^{ADR,i}_{t-2,t-1}$	7.196	−35.488	−38.062	5.509	20.143	113.051
	(74.851)	(89.664)	(96.402)	(65.641)	(77.354)	(95.990)
$R^{ADR,US}_{t-2,t-1}$	−26.329	−6.491	42.344			
	(86.897)	(103.300)	(112.823)			
$R^{E,i}_{t-2,t-1}$	−88.913	−90.499	−159.702	223.037	292.322*	283.845
	(199.093)	(235.714)	(237.236)	(142.513)	(156.548)	(191.884)
$R^{ADR,i}_{t-3,t-2}$	−16.383	−15.751	−37.353	−2.633	−34.356	−59.909
	(72.823)	(87.159)	(97.159)	(67.509)	(78.604)	(91.803)
$R^{ADR,US}_{t-3,t-2}$	−42.976	−68.224	89.614			
	(71.945)	(84.140)	(86.389)			
$R^{E,i}_{t-3,t-2}$	−162.515	−238.365	−207.071	−71.990	−116.885	10.009
	(192.077)	(222.696)	(222.858)	(147.418)	(162.072)	(203.952)
$R^{ADR,i}_{t-4,t-3}$	85.948	35.374	45.994	−125.173*	−120.981	−39.807
	(75.163)	(89.083)	(102.204)	(66.508)	(75.334)	(96.336)
$R^{ADR,US}_{t-4,t-3}$	−172.230**	−179.709**	−150.349*			
	(73.906)	(86.507)	(81.801)			
$R^{E,i}_{t-4,t-3}$	−324.663*	−313.878	−379.371*	−271.218*	−302.493*	−434.482**
	(172.047)	(201.056)	(221.530)	(142.939)	(166.484)	(211.303)
Constant				176.242*	215.664**	78.610
				(91.843)	(105.890)	(128.996)
Fiat FE	Y	Y	Y	NA	NA	NA
Observations	22,923	17,265	10,689	21,921	17,258	10,682
R^2	0.002	0.002	0.003	0.520	0.530	0.480
Note:						*p<0.1; **p<0.05; ***p<0.01

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A Appendix

A.1 Tables

Table 19: Summary Statistics for EPU

This table presents the summary statistics for monthly EPU and its change over January 1, 2012 to July 31, 2018. Column "N" records the number of Observations. "Mean" and "s.d." are the average and standard deviation of the variables. We obtain EPU data from Baker et al. (2016).

		EPU_m		ΔEPU_m	
Fiat	N	Mean	s.d.	Mean	s.d.
AUD	79	108.39	52.15	-0.42	54.17
BRL	79	211.56	119.12	0.67	93.61
CAD	79	216.57	74.49	0.73	71.97
CNY	79	240.20	141.26	3.38	97.83
EUR	79	199.53	60.22	-0.47	55.20
GBP	79	199.53	60.22	-0.47	55.20
INR	79	100.49	52.07	-1.54	35.61
JPY	79	106.79	29.10	-0.65	22.81
KRW	79	140.00	67.88	-1.28	53.02
MXN	79	46.76	24.03	-0.31	20.70
RUB	79	188.37	83.02	-1.09	105.63
SEK	79	103.15	14.34	0.54	18.53
SGD	79	149.52	54.63	0.77	38.81
USD	79	117.81	30.16	0.00	25.52
All expecte USD		152.05	61.62	-0.01	53.47

Table 20: Summary for BTC exchanges

This table presents the summary for BTC exchanges in our sample. Column "Margin-trading" records the earliest date that exchange allows short-sale with margins in BTC for the corresponding fiat currency.

Fiat	N_E	Exchanges	Margin-trading
AUD	7	BitSquare, BTCMarkets, LakeBTC, LocalBitcoins, MonetaGo, Quoine, Remitano	Jan-2015
BRL	3	BitSquare, LocalBitcoins, MercadoBitcoin	N
CAD	9	BitSquare, Coinbase, Cryptsy, Kraken, LakeBTC, LocalBitcoins, MonetaGo, QuadrigaCX, Remitano	May-2015
CNY	13	BitSquare, BTCChina, BTER, CCEDK, CHBTC, Huobi, LakeBTC, LocalBitcoins, MonetaGo, OKCoin, Quoine, Remitano, Yunbi	Jun-2014
EUR	27	Abucoins, BitBay, Bitfinex, BitMarket, BitSquare, Bitstamp, BTCE, CCEDK, Cexio, Coinbase, Coinfloor, Coinroom, Cryptsy, Exmo, Gatecoin, HitBTC, itBit, Kraken, LakeBTC, LiveCoin, LocalBitcoins, Lykke, MonetaGo, Paymium, Quoine, TheRockTrading, Yacuna	Mar-2014
GBP	14	BitSquare, BTCE, CCEDK, Cexio, Coinbase, Coinfloor, Coinroom, Kraken, LakeBTC, LocalBitcoins, Lykke, MonetaGo, Remitano, Yacuna	Mar-2014
HKD	6	BitSquare, Gatecoin, LakeBTC, LocalBitcoins, MonetaGo, Quoine	May-2014
IDR	3	LocalBitcoins, Luno, Quoine	May-2014
ILS	4	Bit2C, BitSquare, LocalBitcoins, MonetaGo	N
INR	5	LocalBitcoins, MonetaGo, Quoine, Remitano, Unocoin	May-2014
JPY	11	bitFlyer, bitFlyerFX, BitSquare, Coincheck, Kraken, LakeBTC, LocalBitcoins, Lykke, MonetaGo, Quoine, Zaif	May-2014
KRW	4	Bithumb, Coinone, Korbit, LocalBitcoins	Nov-2016
MXN	3	Bitso, LocalBitcoins, MonetaGo	N
MYR	3	LocalBitcoins, Luno, Remitano	N
PHP	3	LocalBitcoins, Quoine, Remitano	May-2014
PLN	8	Abucoins, BitBay, BitMarket, BitSquare, Coinfloor, Coinroom, Exmo, LocalBitcoins	Jan-2015
RUB	6	BTCE, CCEDK, Cexio, Exmo, LocalBitcoins, MonetaGo	Aug-2014
SEK	4	BitSquare, LocalBitcoins, MonetaGo, Remitano	N
SGD	7	itBit, LakeBTC, LocalBitcoins, Luno, MonetaGo, Quoine, Remitano	May-2014
THB	3	BXinth, LocalBitcoins, MonetaGo	N
USD	36	Abucoins, BitBay, Bitfinex, bitFlyer, BitSquare, Bitstamp, BitTrex, BTCChina, BTCE, CCEDK, CCEX, Cexio, Coinbase, Coinfloor, Coinroom, Coinsetter, Cryptsy, Exmo, Gatecoin, Gemini, HitBTC, Huobi, itBit, Kraken, LakeBTC, LiveCoin, LocalBitcoins, Lykke, MonetaGo, OKCoin, QuadrigaCX, Quoine, Remitano, TheRockTrading, TrustDEX, Yobit	Mar-2014
VND	3	LocalBitcoins, Remitano, TrustDEX	N
ZAR	5	BitSquare, LocalBitcoins, Luno, MonetaGo, Remitano	N

Table 21: Daily predictability

This table presents results from prediction regression

$$10000 * R^{E,i}_{t,t+1} \sim \alpha_i + \beta_0 \Delta GAP^i_{t-1,t} + \beta_1 \Delta GAP^i_{t-2,t-1} + \beta_2 \Delta GAP^i_{t-3,t-2} + \beta_3 \Delta GAP^i_{t-4,t-3} + \beta_4 \Delta GAP^i_{t-5,t-4}$$

The dependent variable $R^{E,i}_{t,t+1}$ is one-day log return of spot exchange rate currency i/USD from date t to $t+1$. $\Delta GAP^i_{t-1,t} = GAP^i_t - GAP^i_{t-1}$ is the change in GAP between $t-1$ and t for fiat currency i. Each row records the estimated coefficient, and the standard errors (in parentheses) are clustered at the date level. Fiat fixed effect is included in all regressions. The full sample period is January 1, 2012 to July 31, 2018. We also report the results for sub-sample periods: June 1, 2014 to July 31, 2018 and January 1, 2016 to July 31, 2018.

	$10000 * R^E_{t,t+1}$		
	All	Date >= 2014-06-01	Date >= 2016-01-01
	(1)	(2)	(3)
$\Delta GAP^i_{t-1,t}$	6.105	11.078	10.232
	(6.173)	(8.482)	(8.400)
$\Delta GAP^i_{t-2,t-1}$	15.222**	27.321***	24.237**
	(7.124)	(8.739)	(10.650)
$\Delta GAP^i_{t-3,t-2}$	12.386	27.611***	18.130*
	(8.010)	(9.297)	(10.318)
$\Delta GAP^i_{t-4,t-3}$	2.013	0.557	8.801
	(8.138)	(11.579)	(9.821)
$\Delta GAP^i_{t-5,t-4}$	−4.534	−7.812	−7.832
	(6.195)	(7.314)	(8.541)
Fiat FE	Y	Y	Y
Observations	32,125	24,697	15,245
R^2	0.001	0.001	0.001
Note:			*p<0.1; **p<0.05; ***p<0.01

Tabel 22: Decomposition of daily predictability

This table presents results from prediction regression

$$10000 * R^{E,i}_{t,t+1} \sim \alpha_i + R^{Ƀ,i}_{t-1,t} + R^{Ƀ,US}_{t-1,t} + R^{E,i}_{t-1,t} + R^{Ƀ,i}_{t-2,t-1} + R^{Ƀ,US}_{t-2,t-1} + R^{E,i}_{t-2,t-1} + R^{Ƀ,i}_{t-3,t-2} + R^{Ƀ,US}_{t-3,t-2} + R^{E,i}_{t-3,t-2}.$$

The dependent variable $R^{E,i}_{t,t+1}$ is one-day log return of spot exchange rate currency i/USD from t to $t+1$. $R^{Ƀ,i}_{t-1,t}$ is the log return of BTC quoted in fiat currency i from $t-1$ to t. $R^{Ƀ,US}_{t-1,t}$ is the log return of BTC quoted in USD from $t-1$ to t. Each row records the estimated coefficient, and the standard errors (in parentheses) are clustered at the date level. Fiat fixed effect is included in all regressions. The full sample period is January 1, 2012 to July 31, 2018. We also report the results for sub-sample periods: June 1, 2014 to July 31, 2018 and January 1, 2016 to July 31, 2018.

	$10000 * R^{E}_{t,t+1}$		
	All	Date >= 2014-06-01	Date >= 2016-01-01
	(1)	(2)	(3)
$R^{Ƀ,i}_{t-1,t}$	5.399	10.459	7.888
	(5.649)	(7.498)	(8.105)
$R^{Ƀ,US}_{t-1,t}$	−7.509	−3.966	−7.833
	(14.213)	(20.733)	(22.050)
$R^{E,i}_{t-1,t}$	−331.753*	−305.997	−287.630
	(191.790)	(228.216)	(228.126)
$R^{Ƀ,i}_{t-2,t-1}$	19.236***	27.876***	18.290**
	(6.102)	(7.995)	(8.922)
$R^{Ƀ,US}_{t-2,t-1}$	−22.495	−43.042*	−35.882
	(15.125)	(22.184)	(26.959)
$R^{E,i}_{t-2,t-1}$	−44.249	−13.207	−230.975
	(185.672)	(219.323)	(227.106)
$R^{Ƀ,i}_{t-3,t-2}$	14.290*	29.361***	13.731*
	(7.828)	(11.290)	(8.286)
$R^{Ƀ,US}_{t-3,t-2}$	−16.466	−33.912	−45.647*
	(14.773)	(21.327)	(23.775)
$R^{E,i}_{t-3,t-2}$	−52.608	−105.869	−48.327
	(180.444)	(208.502)	(220.048)
Firm FE	Y	Y	Y
Observations	32,181	24,707	15,255
R^2	0.002	0.002	0.003
Note:			*p<0.1; **p<0.05; ***p<0.01