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# BITCOIN AND SHADOW EXCHANGE RATES

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## ABSTRACT

This research expands the existing literature on Bitcoin (BTC) price misalignments by incorporating transaction-level data from a peer-to-peer (P2P) exchange, LocalBitcoins.com (LB). It examines how broader economic and regulatory factors influence cryptocurrency markets and highlights the role of cryptocurrencies in facilitating international capital movements. By constructing shadow exchange rates (SERs) for national currencies against the US dollar based on BTC prices, we calculate discrepancies between these SERs and their official exchange rates (OERs), referred to as BTC premiums. We analyze various factors driving the BTC premiums on LB, including those sourced from the BTC blockchain, mainstream centralized BTC exchanges, and international capital transfer channels. Unlike in centralized markets, our results indicate that the microstructure of the BTC blockchain does not correlate with BTC premiums in the P2P market. Regarding frictions from international capital transfers, we interpret remittance costs as indicators of inefficiencies in traditional capital transfer systems. For constrained currencies subject to severe capital controls and managed exchange rate regimes, increased transaction costs in conventional currency exchange channels almost entirely translate into higher BTC premiums. Additionally, our analysis suggests that BTC premiums can serve as short-term predictors of future exchange rate depreciation for unconstrained currencies.

**Keywords** Bitcoin · Peer-to-Peer · Shadow Exchange Rates · Exchange Rate Regimes · Capital Controls · Remittance Costs · International Capital Flows

## 1 Introduction

Despite the global nature of cryptocurrency markets, violations of the law of one price are frequently observed across various markets. For instance, Bitcoin (BTC) is often traded at different prices in certain currencies when converted to U.S. dollars (USD) using official exchange rates (OERs). Notably, BTC has been traded at significantly higher prices in Korean crypto markets in South Korean won (KRW) than in US crypto markets in USD—referred to as the “Kimchi premium”—which reached as high as 54.48% in January 2018 [Choi et al., 2018]. Similarly, Makarov and Schoar [2020] documented such price deviations across Europe, the United States, and Japan, highlighting that price deviations are more pronounced between countries than within them and tend to co-move with BTC appreciation.

This phenomenon is explored to identify the potential frictions along all BTC trade flows, see Figure 1, that can lead to market segmentation of BTC across different currencies. Ideally, BTC can be acquired at lower prices in certain markets and subsequently sold at higher prices in others, with profits realized through traditional currency exchange channels. However, persistent BTC price deviations that are not immediately arbitrated away suggest underlying market frictions, which can be categorized into the following aspects: Firstly, inherent limitations within the BTC blockchain, such as microstructure frictions, can increase the risks associated with arbitrage. These limitations include such as transaction confirmation times, costs paid to miners, and the number of on-chain transactions, which may delay transfers and expose traders to price volatility. Secondly, various factors within BTC exchanges can impede arbitrage opportunities. For instance, in broader centralized markets, factors relevant to BTC prices, such as returns and volatility, can shape public expectations and demand. In peer-to-peer (P2P) markets, liquidity constraints due to the limited number of participants can pose a severe problem and significantly restrict arbitrage opportunities. Thirdly, barriers in international capital movements—such as changes in OERs, regulatory measures like capital controls, or transaction costs and frictions in

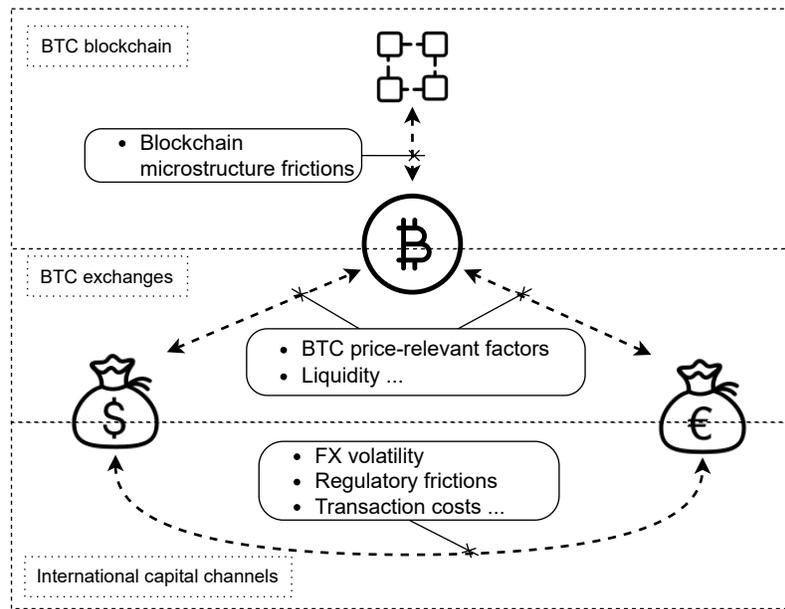


Figure 1: BTC trade flows

Notes: BTC can be purchased with national currency on centralized or P2P exchanges, and can then be utilized for various on-chain transactions such as transfers, purchases, or simply for holding. Alternatively, it can be sold on the same or different exchanges for the same or a different currency. This introduces a new mode of currency exchange known as “crypto vehicle transactions” [von Luckner et al., 2023]. With minimal regulatory oversight, these transactions can bypass the high fees and extended processing times associated with traditional currency exchange methods such as banks, credit card processors, and ATMs. Evidence suggests that digital currencies can circumvent capital controls, potentially leading to “capital flight” [Hu et al., 2020, Ju et al., 2016]. Otherwise, if used for arbitrage, profits can be repatriated via conversion in international capital channels such as FX markets, remittance channels, etc. Factors potentially influencing BTC price deviations are noted in a black box for each market.

foreign exchange (FX) markets—can make profit repatriation difficult. These barriers hinder the efficient movement of capital across borders, complicating the process of converting arbitrage profits back into the original currency.

For example, Choi et al. [2018] discussed how capital controls amplify the microstructural frictions of the BTC network and how BTC price volatility increases arbitrage risks, contributing to BTC price misalignments across different currencies. However, much of the existing research focuses on centralized exchanges such as Bitstamp, Kraken, Coinbase, and Huobi. On these platforms, traders submit bid and ask orders, and transactions are executed based on a centralized limit order book. In contrast, this paper turns its attention to P2P exchanges, whose unique trading mechanisms introduce additional variability in BTC prices. In P2P markets, transactions occur directly between users without a central intermediary, leading to frequent and significant divergences from the law of one price.

On P2P platforms such as LocalBitcoins.com (LB), users post advertisements to buy or sell BTC at customized prices and volumes, with transactions conducted bilaterally as parties respond to these offers. Transaction-level data collected from LB frequently reveals significant price deviations, sometimes even exceeding those observed on centralized platforms. These divergences between BTC prices in the USD market and those in other currency markets reveal shadow exchange rates (SERs). By analyzing the discrepancy between OERs and SERs, we can define the BTC premiums. For instance, BTC transactions on LB in countries like Iran, Angola, Ethiopia, and Argentina have seen price premiums over 100%, see Appendix B.

In response to the frictions from different BTC trade flows presented in Figure 1, BTC premiums on LB appear to exhibit both common and unique characteristics compared to centralized exchanges. For instance, they tend to co-move with BTC price-relevant factors from mainstream centralized exchanges, such as BTC price volatility and returns, aligned with Choi et al. [2018] and Makarov and Schoar [2020].

In contrast, the microstructure of the BTC network has little influence on BTC premiums on LB, likely due to its P2P nature which is not designed for instant transactions. The inherent resistance of P2P mechanisms to immediate price adjustments makes these exchanges less favorable for arbitrage. Other limitations include the absence of instruments

for shorting to lock in premiums, the price risks associated with BTC, and the extended waiting times required for offer acceptance. As a result, prices in P2P markets are less sensitive to immediate changes in the blockchain network compared to centralized exchanges, reducing the network's impact on BTC premiums.

In essence, users are drawn to LB for reasons beyond arbitrage. These include its off-chain transaction mode, a broader array of payment options, and the ability to trade in currencies that are not typically supported by centralized exchanges. With a larger panel data set acquired from LB, we can study the relationship between BTC premiums and frictions related to international capital movements. As anticipated, our findings indicate that countries with higher financial freedom generally experience lower BTC price premiums. In addition to this annual factor, we introduce a regulatory dummy variable to identify constrained currencies, namely those subject to strict capital controls and a managed exchange rate regime. We also incorporate a quantified, higher-frequency factor, remittance costs, into our panel analysis to assess the transaction costs associated with international capital transfers.

Our results show that for constrained currencies, the increase in transfer costs through traditional remittance channels<sup>1</sup> is almost entirely passed on to the BTC price premiums, suggesting that P2P exchanges may serve as indirect channels for international capital flows. These findings reinforce the conclusions of von Luckner et al. [2023] that cryptocurrencies facilitate so-called vehicle trades (fiat - crypto - fiat) to circumvent transaction frictions in traditional currency exchange corridors. Furthermore, our analysis reveals that for unconstrained currencies, OERs tend to depreciate in the short term when BTC premiums increase, shedding light on the indicative effects of BTC premiums for public expectations on currency depreciation, if this currency is allowed to adjust its exchange rate relatively freely.

Our contribution to the literature is threefold. First, we extend the study of BTC price misalignments from centralized exchanges to a P2P exchange, examining both common and unique behaviors in response to various frictions along BTC trade flows. This study goes beyond the scope of previous research, which primarily focused on BTC price-relevant factors, the impact of the microstructure of the BTC network and capital controls. We include additional frictions about international capital flows, such as exchange rate regimes, and transactional costs in remittance channels. Second, our panel data include over 80 currencies, providing a broader analysis of premium explanations. Lastly, we demonstrate that BTC premiums reveal future OER depreciation for unconstrained currencies. This study enriches the literature on BTC premium explanations, highlighting the role and impact of cryptocurrency in international capital transfers.

Our research contributes to the extensive body of literature on SERs implied by various securities. Historically, violations of the law of one price have been documented in securities markets, such as in the case of cross-listed stocks—often referred to as 'Siamese-twin' stocks—which exhibit high correlations with the status of their respective stock markets [Froot and Dabora, 1999]. Other phenomena of price deviation have been observed in closed-end country funds traded across different markets [Bodurtha et al., 1995]. Episodes of capital control, like those in Argentina (2001-2002), Malaysia (1998-1999), Venezuela (1994-1996, 2003-2007), have shown that American Depositary Receipts<sup>2</sup> and their underlying securities can create a shadow exchange premium over the controlled spot exchange rate [Eichler et al., 2009].

Our research is also closely linked to the discussion about the limits to arbitrage that explain persistent price deviations. For cross-listed stocks, the frictions of arbitrage arise from factors such as currency risks, liquidity, taxation, governance, and regulations [Rosenthal, 1990, Froot and Dabora, 1999, Jong et al., 2009]. Other than that, Gagnon and Karolyi [2010] explored how information-based barriers and holding costs contribute to deviations from price parity in cross-listed pairs. From a behavioral perspective, investor-driven demand shocks may also cause prices to diverge from fundamental values [Gromb and Vayanos, 2010, Shleifer et al., 1990]. The cryptocurrency markets share similar discussions, where Choi et al. [2018] analyzed BTC price premiums in Korea and other major markets due to capital controls and the inherent resistances in the blockchain's microstructure, such as the status of blockage on the blockchain and the fees paid to the miners. They utilize the Economic Freedom Ranking by the Fraser Institute and a sub-index on money market outflow restrictions from Fernández et al. [2016] to measure capital controls, finding that greater economic freedom correlates with lower BTC premiums with a random effects panel model. Later, Makarov and Schoar [2020] estimated the capital required to close arbitrage spreads. While these studies focus on centralized crypto exchanges, our research shifts focus to the effects of arbitrage limits in P2P crypto markets, characterized by more niche currencies and increased pricing autonomy.

Our paper also engages with discussions on capital flight via BTC as an intermediary. Ju et al. [2016] provided evidence of capital flight reflected in BTC's SERs, by controlling daily transaction volumes of BTC in Chinese Renminbi (RMB) and USD in their regressions. They employed a dummy variable to represent the announcement of BTC restriction policies by the People's Bank of China in 2013, demonstrating that these measures effectively curtailed capital flight

<sup>1</sup>According to the World Bank, recorded remittance channels include banks, money transfer operators, mobile operators, and post offices, see [urlhttps://remittanceprices.worldbank.org](https://remittanceprices.worldbank.org).

<sup>2</sup>It is a type of stocks listed in the United States but represents a specified number of shares in a foreign corporation.

immediately following their implementation. Hu et al. [2020] identified BTC-driven capital flight from China by matching wallet addresses on the blockchain, estimating that it constituted over one-quarter of Chinese BTC exchange volume. Their regressions show that the volume of capital flight trades is correlated with the countries’ economic policy uncertainty index and the BTC premium, as well as with the daily number of trades and average daily fees paid to miners, among other factors. Furthermore, von Luckner et al. [2023] developed an algorithm to detect “vehicle transactions” through a probabilistic approach, matching the exact number of BTCs traded within short-time windows. They estimated that at least 7% of all transactions on LB qualify as vehicle trades, with 20% of these transactions identified as part of international capital flows.

The structure of this paper is as follows: Section 2 provides an overview of transaction-level data from LB and the macroeconomic fundamentals used in this analysis. Section 3 presents the statistical overview of the data with specific country cases, and Section 4 elaborates on the panel data analysis and corresponding discussions. Finally, Section 5 concludes.

## 2 Data

For the analysis of BTC premiums on LB, we collect transaction data from January 1, 2017, to February 9, 2023 (the end of LB’s operations). All other variables are collected for the same timeframe to ensure consistency in our analysis and regression models.

### 2.1 Official Exchange Rates

In this analysis, OERs serve as a benchmark, particularly for comparisons with SERs derived using BTC prices in different currencies on LB, or to quantify the depreciation of a currency. We collect the foreign exchange spot rates  $e_{c,d}$ , where  $c$  stands for the currency and  $d$  the day, for our 81 currencies through the Thomson Reuters Refinitiv API, using the midpoint of bid and ask prices at the daily close. Subsequently, we calculate the percentage depreciation of currency  $c$  over the period  $h$ ,

$$depr_{c,h} = 100 * \frac{e_{c,h,close} - e_{c,h,open}}{e_{c,h,open}}. \quad (1)$$

### 2.2 Transaction Data from LB

We accessed P2P transaction data from LB through its Application Programming Interface (API). On LB, BTC was tradable for 140 currencies and 45 other cryptocurrencies. Similar to centralized exchanges, transactions on LB were executed off-chain; that is, while internal transactions within LB were not recorded on the blockchain, transactions between a private wallet and LB (and vice versa) were documented.

LB possessed several intrinsic qualities that made it an attractive platform for BTC trading globally. It had lower entry requirements than traditional banks and supports a variety of payment methods. These included cards, digital accounts, other cryptocurrencies, and even cash, enhancing its service accessibility.<sup>3</sup> LB also charged a relatively modest fee of 1%, borne by the offeror. Its global reach enabled comprehensive data collection on SERs using BTC as the intermediary.

A sample of historical transaction data is presented in Table 1. This research was conducted on trades from January 1, 2017, until LB’s last day of operation.<sup>4</sup> The focus on this period is due to the lack of sufficient liquidity on the

Timestamp	Currency	Transaction ID	Price	Amount
1649809649	EUR	55600084	40579.86	0.00418927
1649743308	CHF	55593671	34998.07	0.00145208

Table 1: Examples of historical trades

*Note:* Transactions from LB record the date of the transaction with a Unix time stamp, the currency for which Bitcoin was sold, a transaction ID, the price per unit of Bitcoin and amount of Bitcoin sold.

<sup>3</sup>Cash-settled trades were discontinued in June 2019 due to stricter regulations on money laundering. See their Twitter announcement <https://twitter.com/LocalBitcoins/status/1135872083962081281>, last accessed in Oct. 2024.

<sup>4</sup>LB ceased providing BTC trading services on February 9, 2023, due to unfavorable market conditions and regulatory pressures. For more details, see [https://localbitcoins.com/service\\_closure/](https://localbitcoins.com/service_closure/), last accessed in Oct. 2024.

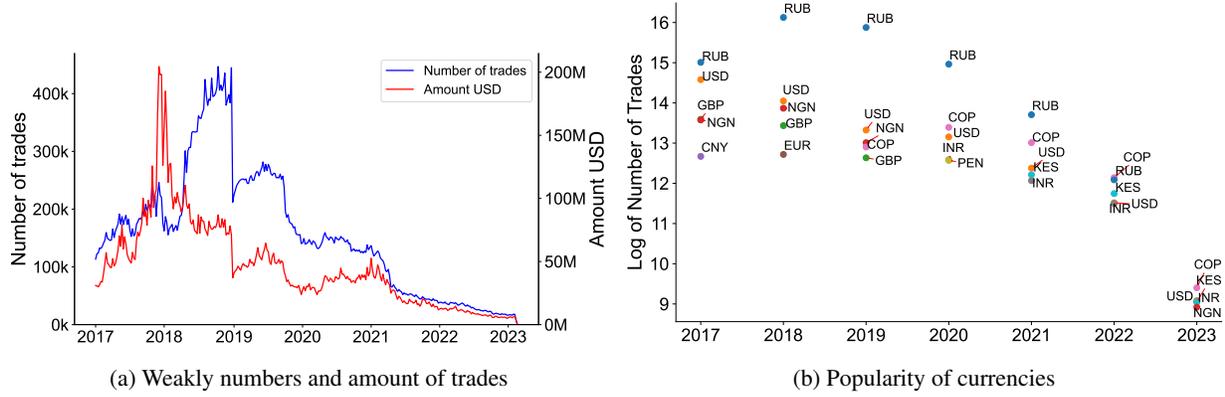


Figure 2: Transaction overview on LB from 2017

platform prior to January 1, 2017. During this timeframe, a total of 40,767,585 transactions involving 81 currencies were recorded.<sup>5</sup> The average transaction size was 0.04588548 BTC, with the largest recorded transaction being 285.25502512 BTC. An overview of its turnover (number of transactions and volume in terms of USD) is illustrated in Figure 2a. At its peak in 2018, LB processed approximately \$200 million USD in transactions per week. Subsequently, this figure gradually declined to around \$40 million USD per week by mid-2021, and between \$5.5 and \$7.5 million USD per week from 2023 until the cessation of its operations. The trend in the number of transactions is similar, but it peaked at the end of 2018, about one year later than the peak in trading volume in USD. Throughout the years, the most popular currencies for BTC trading on LB were Russian ruble (RUB), USD, British Pound sterling (GBP), Nigerian naira (NGN), and Colombian peso (COP), with a yearly breakdown of the top 5 currencies depicted in Figure 2b.

**BTC Prices on LB:** Due to the bilateral clearing of transactions on LB, we observe a wide range of prices within any given time frame. For our empirical analysis, it is necessary to aggregate this transaction-level data into one market price to reflect the value of BTC in each currency on LB. We first generate the volume-weighted value of the daily prices,

$$P_{c,d}^B = \frac{\sum_i x_i P_{i,c}^B}{\sum_i x_i}, \quad (2)$$

where  $P_{c,d}^B$  denotes the aggregated daily BTC price for currency  $c$  on day  $d$ . For each trade  $i$  within day  $d$ , we use its volume  $x_i$  and the corresponding BTC price  $P_{i,c}^B$  for the calculation of volume-weighted value.

In the aggregation process, we observe significant outliers that are challenging to explain, particularly concerning why certain bids close at notably inflated prices, despite each transaction incurring a 1% fee. Our hypothesis is that these anomalies may result from transactions between acquainted users, potentially for purposes of identification, illicit activities, or due to errors in the API log.

Weighted average daily prices are susceptible to distortion by extreme outliers, whereas median prices are more robust in this regard. Consequently, median prices could serve as a reliable market index when outsized outliers appear. Accordingly, we compute the ratio of the weighted to median prices and examine this index at the 0.01 and 0.99 quantiles, which are 0.85 and 1.08, respectively. Transactions that fall outside these quantiles indicate the dysfunction of weighted average prices, prompting us to adjust the reported weighted prices to median values for these cases.

**Shadow Exchange Rates:** We use the aggregated daily price series to compute the SERs,  $e_{c,d}^B$ , of currency  $c$  relative to USD on day  $d$ . This calculation is performed by comparing the price of BTC in currency  $c$  to its price in USD,

$$e_{c,d}^B = \frac{P_{c,d}^B}{P_{USD,d}^B}, \quad (3)$$

expressed as the price of one USD in currency  $c$ . The units are  $\frac{c}{USD}$ .

**BTC Premium:** We compare SERs from LB with the OERs. These rates are used to compute the BTC premium  $p_{c,d}$  in percentage terms, reflecting the exchange rate divergence:

$$p_{c,d} = 100 * \frac{e_{c,d}^B - e_{c,d}}{e_{c,d}}. \quad (4)$$

<sup>5</sup>We exclude 59 currencies either with fewer than 1,000 transactions over the years or without available OERs.

### 2.3 BTC Index from Blockchain and Centralized Exchanges

We collect data related to the blockchain network from blockchain.com.<sup>6</sup> Three key metrics are utilized to assess the status of the blockchain: the median confirmation time, which represents the median duration required for a transaction to be confirmed by the BTC network; the average fee in USD paid to miners for each transaction confirmed on the blockchain within a day; and the number of transactions confirmed on that day. These metrics represent network efficiency and reflect the associated risks with transaction delays and potential bottlenecks.

In order to calculate BTC price-relevant index from mainstream centralized exchanges, we obtain 5-minute BTC prices in USD from Kraken Crypto Exchange<sup>7</sup>. We then aggregated these data over various horizons,  $h$ , to compute the BTC returns as follows:

$$r_h^{B,market} = \log \left( \frac{P_{close,h}^{B,market}}{P_{open,h}^{B,market}} \right), \quad (5)$$

where  $P_{close,h}^{B,market}$  and  $P_{open,h}^{B,market}$  represent the closing and opening prices of BTC for each respective horizon  $h$ . Using the specified formula with  $h = week$ , we compute the weekly BTC returns  $r_{h=week,w}^{B,market}$  for week  $w$ . For short-term analysis, we set the horizon to hourly intervals, calculating weekly volatility as  $\sigma_{h=hour,w}^B$  for week  $w$ . This is achieved by summing the squared log-returns over the respective hourly intervals within the week,

$$\sigma_{h,w}^B = \sum_w (r_{h=hour}^{B,market})^2. \quad (6)$$

### 2.4 AREAER

In this study, we utilize data from the International Monetary Fund’s (IMF) *Annual Report on Exchange Arrangements and Exchange Restrictions (AREAER)* to represent the degree of exchange restrictions across its 190 member countries as of 2022.<sup>8</sup> To construct metrics for each currency, we average the metrics of countries that use the same currency. The country-currency pairs can be found in Appendix B. We focus on two factors: the exchange rate regime, which indicates the extent to which a currency’s exchange rate is determined by market forces, and capital controls, which regulate the flow of capital into and out of a country’s economy. We consistently update our data based on the latest *AREAER*, especially for currencies that have undergone retroactive recalibrations. By tracking the effective dates of reclassification and the annual position date of each year’s *AREAER*, we compile this data on a daily basis and aggregate it into weekly intervals to match the granularity of other data in our study.

**Exchange Rate Regime:** Rather than relying on officially announced exchange rate arrangements, we utilize the categorization provided by *AREAER*, which focuses the assessment on de facto arrangements. These may differ from official policies but reveal the actual performance of a currency. As outlined by Habermeier et al. [2009], exchange rate regimes are classified into four types—hard peg, soft peg, floating arrangements and residual<sup>9</sup>—with 10 subcategories. This classification considers observed exchange rate behavior and interventions such as monetary and foreign exchange policy actions. To indicate the stability of a currency  $c$ , we introduce a dummy variable  $Peg_{c,d}$  to denote whether a currency is under a floating exchange rate regime or not:

$$Peg_{c,d} = \begin{cases} 0 & \text{if } c \text{ in floating arrangements,} \\ 1 & \text{otherwise.} \end{cases} \quad (7)$$

**Capital Controls:** In examining capital controls, the *AREAER* offers detailed legislative information across ten asset classes, addressing both inflow and outflow controls separately.<sup>10</sup> To synthesize this data, we analyze each asset class  $i$  and its  $m_i$  corresponding subcategories, differentiating between controls impacting inflows and outflows of assets. We represent the dummy for capital control on subcategory  $j$  of asset  $i$  on day  $d$  as follows:

$$a_d^{ijk} = \begin{cases} 1 & \text{if capital controls for asset } (i, j) \text{ exist} \\ 0 & \text{otherwise,} \end{cases} \quad (8)$$

<sup>6</sup>See <https://www.blockchain.com/explorer/charts>, last accessed in Oct. 2024.

<sup>7</sup>See <https://support.kraken.com/hc/en-us/articles/360047543791-Downloadable-historical-market-data-time-and-sales->, last accessed in Oct. 2024.

<sup>8</sup>See <https://www.elibrary-areaer.imf.org/Pages/Home.aspx>, last accessed in Oct. 2024

<sup>9</sup>Countries that do not fit neatly into any specific category are grouped into a residual type, e.g., nations with frequent policy shifts within a short period.

<sup>10</sup>Less than 2.8% of observations were marked as missing for the range of data of interest (from 2017 to 2022), as per the *AREAER*.

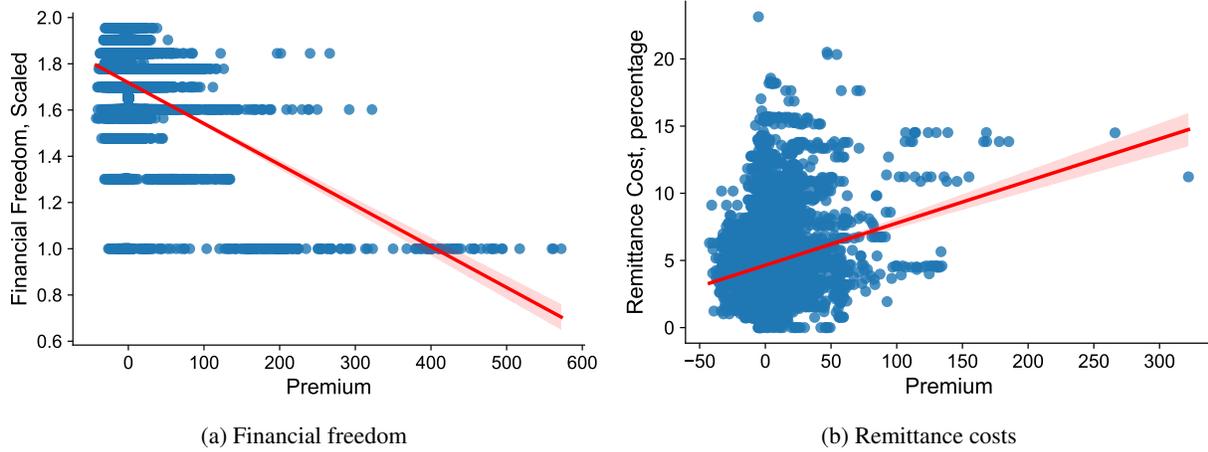


Figure 3: Premiums with financial freedom and remittance costs

where  $k \in \{\text{inflow}, \text{outflow}\}$ . By weighting all ten asset classes equally, we derive a comprehensive measure of a country’s capital control severity which ranges from 0 to 1:

$$CC_{c,d} = \frac{1}{2} \sum_k \frac{1}{10} \sum_{i=1}^{10} \frac{1}{m_i} \sum_{j=1}^{m_i} a_d^{ijk}, \quad (9)$$

We then construct a combined indicator variable,  $D_{c,t}$ , to identify constrained currencies—those that experience a combination of strict capital controls and a managed exchange rate regime. This is achieved by setting up a threshold  $\delta$  for  $CC_{c,t}$ ,

$$D_{c,t} = \begin{cases} 1 & \text{if } Peg_{c,t} = 1 \text{ and } CC_{c,t} \geq \delta \\ 0 & \text{otherwise.} \end{cases} \quad (10)$$

## 2.5 Economic Freedom Score

We utilize the annual Financial Freedom Score for currency  $c$  on year  $y$ ,  $FF_{c,y}$ , from the *Economic Freedom Index* provided by the Heritage Foundation, which highlights the openness of financial markets in each country.<sup>11</sup> This score reflects the efficiency of banks and the extent of government regulation in the financial industry. It is measured on a scale from 0 to 100, where a higher score indicates greater financial freedom. Similarly, we calculate the average score for countries using the same currency to tailor this metric for each currency.

We analyze the relationship between the Financial Freedom Score and the BTC premiums for all currencies on a yearly basis to capture changes over time. Our results are presented in Figure 3a. For better visualization, we scale the Financial Freedom Score by taking its base-10 logarithm. Our analysis reveals a negative correlation between financial freedom and premiums, with the highest premiums typically observed in currencies with exceptionally low economic freedom scores.

## 2.6 Cost of Remittances

To quantify the costs of international capital transfers for individuals, we rely on the cost of remittances from remittance channels, given their comprehensive tracking and global coverage. Remittances represent one of the largest capital inflows to emerging economies. According to the World Bank, remittance flows to low- and middle-income regions are 794 billion USD worldwide in 2023, almost doubling the size of foreign direct investment [World Bank, 2022a]. Remitting funds to many developing countries is often expensive, slow, and fraught with friction, primarily due to high transfer fees in regions with underdeveloped financial institutions. This incentivizes individuals to seek more cost-effective remittance methods. As reported by World Bank [2022b], sending \$200 incurred an average cost of 6.09% in 2023. The regions of Sub-Saharan Africa, Middle East and North Africa, and Europe and Central Asia are the

<sup>11</sup>A full description of the methodology behind the Economic Freedom Index can be found in the most recent report on their website <https://www.heritage.org/index/pages/about>, last accessed in Oct. 2024.

	Bank	MTO	Mobile operator	Post office
Cost of sending 200USD	10.94%	5.28%	2.87%	6.78%
Market share of corridors	NA	>85%	<1%	NA

Table 2: Average costs and market shares of different main corridors, worldwide [World Bank, 2022b]

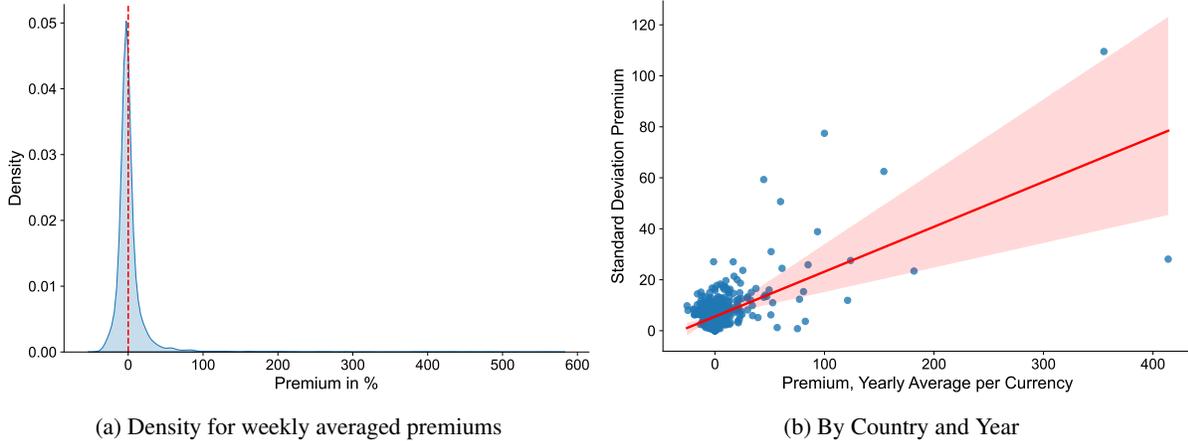


Figure 4: Overview premiums

most costly for remittance transfers. The average costs in major remittance corridors are detailed in Table 2, where Money Transfer Operators (MTOs) dominate with an 85% market share. The transfer speed varies significantly across these corridors, ranging from a few minutes to over five days. The selection of these corridors often depends on the sophistication of the financial systems, the regulatory frameworks governing capital flows in each country, and people’s payment behaviors.

We utilize the database of remittance costs monitored by Remittance Prices Worldwide (RPW) across various Remittance Service Providers (RSPs), tracking flows from 48 sending countries to 105 receiving countries.<sup>12</sup> The data spans from 2008 until February 2023 (when LB ceased operations), capturing the percentage costs associated with sending \$200 and \$500. Additional details such as sending speed, transparency, coverage of sending corridors (ranging from a few seconds to six days or more), and pick-up methods (cash, bank account, etc.) are also recorded. By considering the USD volume of each transaction on LB, we calculate the remittance costs for our study by averaging the percentage cost of sending \$500 to all parts of the world. This average serves as a quantitative factor for the cost of international capital transfer associated with each sending currency, denoted as  $C_{c,d}$  in percentage terms.

By plotting the remittance costs against BTC premiums in Figure 3b, we observe a positive correlation wherein higher remittance costs are associated with higher BTC premiums, suggesting a hypothesis that BTC may serve as an alternative channel for capital transfer. We conduct a more detailed analysis in subsection 4.2.

### 3 Descriptive Statistics

#### 3.1 Overall Statistics

For the analysis, we have constrained the dataset to transaction data from LB, spanning from January 1, 2017, to February 8, 2023, the date when LB ceased operations. All other variables have been aligned to this period as much as possible. However, some macroeconomic data, particularly those concerning capital controls and exchange rate regimes, are only available up to 2022. This delay typically results from the fact that such data are released at a lag. All data have been aggregated on a weekly basis for the analysis presented herein. For a comprehensive list of the currencies included, please refer to Appendix B.

An overview of the pooled distribution of weekly averaged BTC premiums across countries is shown in Figure 4a. Non-negative premiums account for 38.62% of the data. The lowest and highest observed premiums are -42.5% and

<sup>12</sup>The World Bank, Remittance Prices Worldwide, available at <http://remittanceprices.worldbank.org>, last accessed in Oct. 2024

Variable	N	Mean	Std. Dev.	Min	Pctl. 25	Pctl. 50	Pctl. 75	Max
Unconstrained								
Premium %	17794	1	29	-41	-6.6	-2.3	2.7	572
Depreciation %	17795	0.028	1.2	-24	-0.38	0	0.4	24
Transactions	17795	2407	15018	1	23	116	885	317864
Volume (1000 USD)	17795	599	2182	0.0053	6.3	55	362	44410
Remittance cost %	6559	5.1	3.2	0	2.8	4.7	6.3	25
Constrained								
Premium %	3096	11	32	-43	-4.9	-0.6	14	322
Depreciation %	3096	0.098	1.1	-5.8	-0.086	0.0027	0.22	26
Transactions	3096	507	1189	1	22	82	349	12297
Volume (1000 USD)	3096	485	2228	0.00069	3.8	31	130	40115
Remittance cost %	678	7.7	4.1	1.1	3.6	7.7	9.4	21

Table 3: Summary statistics

Notes: This summary table presents separate statistics for currencies categorized by their regulatory constraints on capital flows and exchange rate management, as defined in Equation 10 with the threshold  $\sigma$  set at 0.7. The table includes metrics such as the premium, as defined in Equation 4; currency depreciation, as outlined in Equation 1; the number of weekly transactions; weekly transaction volume in USD; and the average weekly cost of remitting from the respective currency. All the data are reported on a weekly basis.

572.2%, respectively. However, both the median and mean premiums are close to zero, at -1.9% and 2.5%, respectively. The distribution is right-skewed as positive premiums are theoretically unbounded, while discounts cannot exceed -100%. Yearly averages and standard deviations of premiums for each currency are plotted in Figure 4b, highlighting that premiums tend to become more volatile as they increase. The 95% confidence interval for large premiums is wide, suggesting that some large premiums can be relatively stable. Significant differences are evident between currencies, as shown in Figure 5, which plots the median BTC premium for each currency over the years. We aggregate these currency premiums at the country level, such that countries using the same currency exhibit identical premiums. North America, Latin America, parts of Europe, and parts of Asia typically exhibit negative premiums, whereas positive premiums are more common in Sub-Saharan Africa, South and Eastern Asia, the Caribbean, and other parts of Europe. 18 countries have recorded median premiums above 5% (with 31 above 0%), while only 10 have experienced discounts below -5% (50 below 0%). Notable examples include Iran (IRR, 168.4%), Ethiopia (ETB, 57.9%), Malawi (MWK, 29.3%), Angola (AOA, 26.9%), and Argentina (ARS, 24.9%) for high premiums, and Colombia (COP, -10.1%), Romania (RON, -8.8%), Costa Rica (CRC, -6.7%), Poland (PLN, -6.6%), and Serbia (RSD, -6.2%) for substantial discounts.

We also visualize the median premiums for each currency by year in a box plot Figure 6. The box outlines the median, 25th, and 75th quantiles, and is zoomed in at -30% and 30% for better visualization, as data points outside this range are sparse. Over time, the worldwide premium has demonstrated a general increase. Initially, premiums were predominantly negative in 2017, but from 2021 onward, at least half of the currencies displayed positive yearly premiums. In contrast to this trend, Figure 2a shows that, compared to other years, trading volume and the number of transactions were relatively high from 2017 to 2020. This suggests that the lower prices of Bitcoin were not due to low liquidity constraints on this specific platform. We infer that the usage of P2P platforms, in contrast to mainstream centralized exchanges, was driven by factors such as more diverse payment options, reduced traceability due to looser identity verification requirements at that time<sup>13</sup>, or the necessity to trade in currencies not supported by centralized platforms. Consequently, users were willing to sell BTC at a negative premium.

Lastly, Table 3 presents summary statistics of the variables used in our study. The number of transactions in the constrained group is approximately one-sixth that of the unconstrained group, yet the weekly transaction volume for the constrained cases is only slightly smaller than that of the unconstrained. Regarding premiums, the unconstrained transactions average a 1% premium, whereas the constrained group exhibits a higher mean premium of 11%, albeit with greater volatility. Additionally, the cost of remittances is 50% higher in constrained countries.

<sup>13</sup>Know-your-customer (KYC) verifications were introduced in 2019. Post this change, trading volumes exceeding \$1,000 US Dollars per year required ID document submission. In October 2020, LB introduced a tiered verification system based on annual transaction volumes. See <https://localbitcoins.com/blog/id-verification-update/>, accessed on Oct. 2024. Regulatory pressures increasingly impacted its operations over recent years.



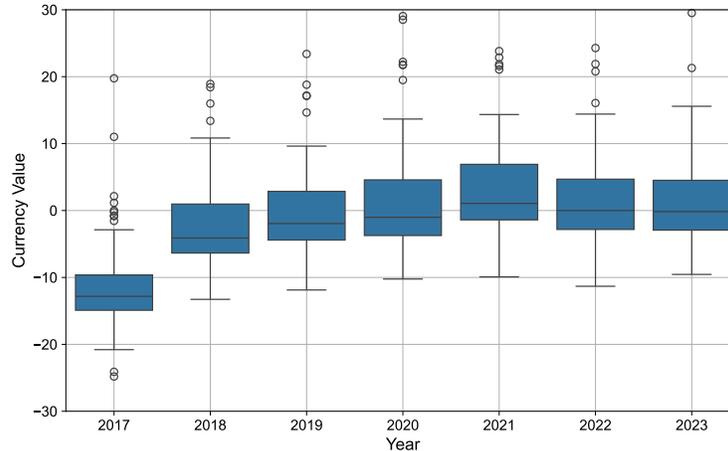


Figure 6: Premiums by year

### 3.2 Country Examples

To provide further insight, selected examples are illustrated in Figure 7. Further details about our full sample can be found in Appendix B. In Figure 7a, the example of Argentina shows that prior to the end of 2019, the SER closely tracked the OER. In mid-2019, Argentina implemented strict capital controls, including limits on USD purchases, to avert further debt defaults and stabilize its currency. Additionally, the intervention by the central bank resulted in the OER ceasing to float by the end of 2019. Since then, Argentina’s exchange rate has consistently depreciated. On LB, the number of daily transactions averaged 140 from 2018 until early 2019, increasing to 382 transactions per day following the imposition of capital controls, with a peak of over 800 transactions per day in mid-2020. Considering the increased trading volume, the widening gap between the SER and the OER signals strong pressure for further depreciation against the USD in the long run.

In Figure 7b, the NGN operates under a managed float regime, with its value stabilized relative to the USD. Around 2018, the premium on LB became persistently positive, anticipating significant depreciation against the USD by spring 2020, coinciding with the COVID-19 pandemic. In July 2020, following a USD shortage, domestic banks capped debit card spending at less than \$100 per month.<sup>14</sup> The deviations in premiums intensified thereafter, witnessing two notable depreciation of the NGN. The LB market signals indicated that the existing imbalances were unsustainable, necessitating a depreciation of the official rate.

For our last two examples, we examine Saudi Arabia and Iran, countries with fixed OERs, in Figure 7c and Figure 7d, respectively. Saudi Arabia maintains a fixed exchange rate, with the Saudi Riyal (SAR) anchored to the USD. We observe that its SER exhibits some fluctuations around the OER. Iran also has maintained a nearly constant OER, with the IRR also anchored to the USD since August 2018. In contrast, there is a large and significant divergence between the OER and SER.<sup>15</sup>

These examples underscore that premiums can be large and persistent, and the pressure indicated by the SER may take some time to be reflected in the OER for these constrained currencies. As for the impact of BTC premiums on OER depreciation in unconstrained currencies, regressions are conducted as detailed in subsection 4.3 for a rigorous analysis.

## 4 Empirical Analysis

As shown in Figure 6, premiums on LB were initially negative but have been increasing globally over the years. This trend is also evident in Appendix B. The initial negative premiums likely stemmed from users being willing to offer discounts for BTC trading on LB. Over time, the reasons for choosing P2P platforms have evolved alongside the development of the BTC market and associated laws. Factors influencing this evolution regarding P2P platforms include traceability, a wider range of payment options, and the ability to trade in currencies not supported by centralized exchanges.

<sup>14</sup>See <https://www.reuters.com/article/idUSKCN24K0E9/>, last accessed in Oct. 2024.

<sup>15</sup>The data concludes in mid-2021 when LB was banned in Iran.

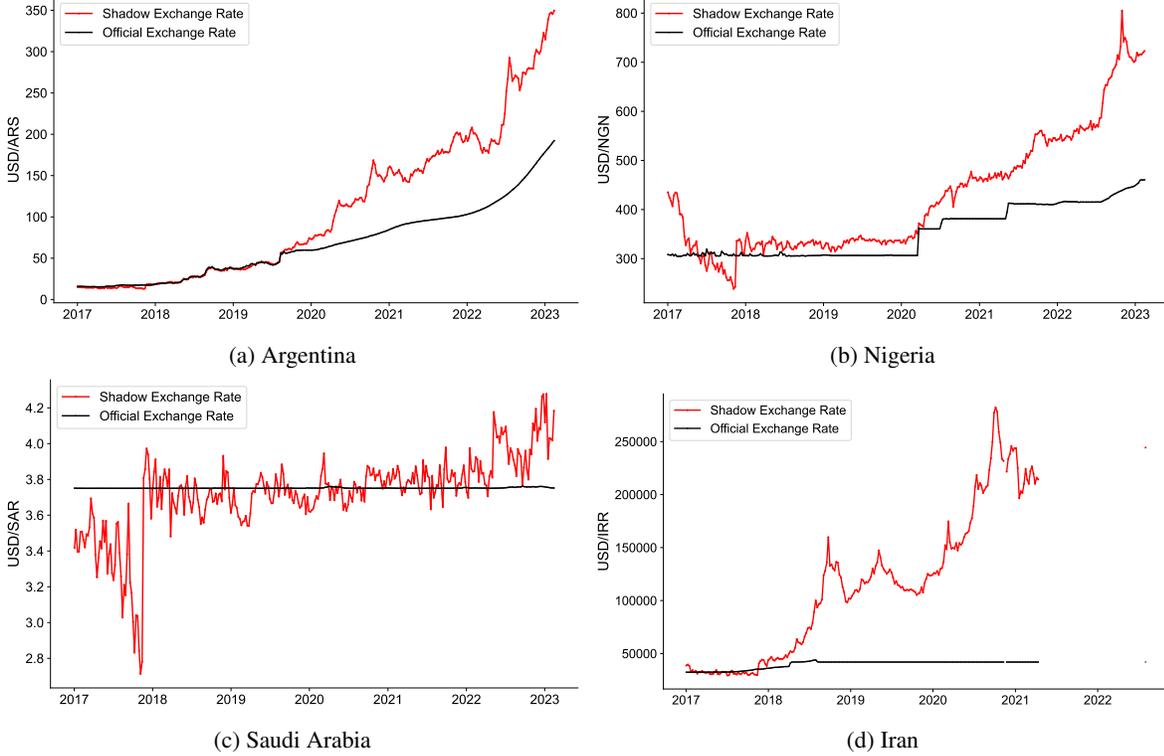


Figure 7: Official and shadow exchange rate for Argentina, Nigeria, Saudi Arabia and Iran.

The presence of BTC premiums suggests that BTC markets in different currencies are segmented. Under ideal market conditions, these premiums could be eliminated through arbitrage. This involves purchasing BTC in markets where prices are relatively low and selling it in markets where prices are higher. Profits are then repatriated through standard currency exchange channels. We analyze potential frictions related to BTC premiums on LB that can arise from various sources, as illustrated in Figure 1, to understand the role and unique characteristics of P2P trading platforms within the broader context of BTC trade flows.

#### 4.1 LB’s Premium, Blockchain, and Other Exchanges

The operational characteristics of the BTC blockchain and BTC price volatility are identified as important factors influencing BTC premiums [Choi et al., 2018]. Therefore, to assess the significance of blockchain network microstructure and BTC price-relevant factors from mainstream centralized exchanges in explaining BTC premiums on P2P exchanges, specifically LB, we conduct regressions on a weekly basis, taking the form:

$$p_{c,w} = \beta X_w + \gamma_0 p_{c,w-1} + \gamma_1 p_{c,w-2} + FE_c + TE_{2week} + \varepsilon_{c,w} \quad (11)$$

where  $X_w$  represents the treatment variables of interest at week  $w$ . We tested variables from two sources: (1) Factors reflecting the status of the BTC blockchain’s microstructure, including blockchain median confirmation time, the average cost in USD for each confirmed transaction on the blockchain, and the total number of confirmed transactions on the blockchain, and (2) indices of BTC prices in USD from mainstream centralized markets, including hourly price volatility at week  $w$ ,  $\sigma_{h=hour,w}^{B,market}$ , and the BTC return at week  $w$ ,  $r_{h=week,w}^{B,market}$ , defined by Equation 6 and Equation 5, respectively.

To control the normal dynamics of premiums, previous premiums at lag 1 and lag 2, denoted as  $p_{c,w-1}$  and  $p_{c,w-2}$ , are included in the regression. The unobserved dynamic factors affecting premiums, such as P2P liquidity and the demand for BTC in this currency, are likely to be serially correlated. Including these lagged premiums helps to mitigate autocorrelation problems, given that premiums are observed to persist over time for each currency, as shown in Appendix B.

LB only occupies a very small market share in the BTC markets. Its activities do not significantly influence the broader BTC network or centralized markets, then it’s less likely that the premiums on LB are affecting  $X_w$ . Moreover, we

	Premium <sub>w</sub>						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Premium <sub>w-1</sub>	.616*** (.045)	.617*** (.045)	.616*** (.045)	.615*** (.045)	.617*** (.045)	.615*** (.045)	
Premium <sub>w-2</sub>	.333*** (.021)	.333*** (.021)	.333*** (.022)	.334*** (.022)	.333*** (.021)	.335*** (.021)	
Blockchian median confirmation time	.048 (.112)					.083 (.121)	
Cost per transaction, USD		.003 (.019)				.014 (.020)	
Amount of transactions, Blockchain (thousands)			.003 (.007)			-.003 (.007)	
BTC hourly price volatility				21.099*** (5.605)		28.987*** (5.127)	
BTC returns					.202 (.614)	1.742*** (.617)	
R <sup>2</sup>	.942	.942	.942	.942	.942	.942	
Adj. R <sup>2</sup>	.941	.941	.941	.941	.941	.941	
Num. obs.	22856	22856	22856	22856	22856	22856	
RMSE	6.567	6.567	6.567	6.564	6.567	6.563	
N Clusters	80	80	80	80	80	80	
FEs Clustering	Currency, Bi-week Currency						

\*\*\* $p < 0.01$ ; \*\* $p < 0.05$ ; \* $p < 0.1$

Table 4: Premium explanation with factors from BTC Blockchain and other mainstream centralized BTC exchanges

perform a dynamic panel analysis with ordinary least square (OLS) estimator with currency fixed effects  $FE_c$ , and bi-weekly fixed effects  $TE_{2week}$  to control for potential omitted variable that can impact premiums and  $X_w$  at the same time, as well as short-term heterogeneity that can occur in the highly volatile, fast-paced BTC markets, while avoiding the absorption of factors that are consistent across all currencies on weekly basis.

The results are listed in Table 4. The coefficients of these two lag terms are always significant, suggesting that premiums tend to be sticky on P2P platforms, as new offers consider the prices of recent offers. However, from models (1), (2), and (3), the factors associated with the BTC blockchain are not significantly correlated with LB’s BTC premiums, unlike the phenomenon observed in centralized markets [Choi et al., 2018]. This is not surprising. For example, the median confirmation time of the BTC blockchain can be up to 25 minutes in extreme cases, with a mean value of 9.64 minutes, which is trivial in terms of the longer trading time on P2P exchanges. Similarly, the average costs paid to miners and the number of on-chain transactions both reflect the network’s congestion status. Compared to the transaction time and service fees required for transferring BTC from a P2P wallet to other centralized exchanges or a private wallet, their effects are also negligible.

BTC price-relevant factors sourced from mainstream centralized markets appear to be significant in explaining the premiums across different currencies. In model (4), we find that higher short-term BTC price volatility is significantly correlated with increased premiums, aligning with the findings of Choi et al. [2018]. This suggests that during periods of high volatility, users on LB perceive greater market uncertainty and potential for rapid price changes. As a result, they adjust their valuations to account for these risks, leading to wider price differences and higher premiums. In model (5), the coefficient of BTC return is insignificant; however, it turned out to be positively correlated with premiums while controlling for other variables, especially BTC price volatility, in model (6). This result is consistent with Makarov and Schoar [2020] who suggest that price deviations co-move and widen during large BTC appreciation. This positive correlation may stem not only from price momentum, but also from market segmentation. As BTC prices increase, the limited supply in certain markets cannot meet the increased demand, pushing premiums even higher.

## 4.2 LB’s Premium and International Capital Flow

Frictions from international capital transfer, as indicated in Figure 1 are also believed to be associated with LB’s premiums. In addition to capital controls and financial freedom scores that commonly used in the literature to measure frictions within economic and regulatory environments, we consider including another factor quantifying transaction costs from the remittance channel for international capital transfers. In this context, we establish the panel regression as below:

$$\begin{aligned}
 p_{c,w} = & \beta_0 C_{c,w} + \beta_1 D_{c,w} + \beta_2 (C_{c,w} \times D_{c,w}) \\
 & + \gamma_0 p_{c,w-1} + \gamma_1 p_{c,w-2} \\
 & + \lambda_0 FF_{c,w} + \lambda_1 depr_{c,w} \\
 & + FE_c + TE_m + \varepsilon_{c,w},
 \end{aligned} \tag{12}$$

where  $C_{c,w}$  represents the remittance cost, and  $D_{c,w}$  is the constrained dummy variable for currencies subject to strong capital controls and managed exchange rate regimes. It is defined in Equation 10 for currency  $c$  in week  $w$ , with the threshold  $\delta$  set at 0.7. A robustness check with  $\delta$  set to 0.5 is presented in appendix, Table 7. We continue to control for previous premiums as in prior models.  $FF_{c,w}$  stands for the Financial Freedom Score remaining constant within each year, while  $depr_{c,w}$  represent the depreciation of OER, as defined in Equation 1. We include controls for currency fixed effects  $FE_c$ . For time fixed effects, we choose month fixed effects  $TE_m$  to better accommodate the granularity of regulatory friction data. Although  $C_{c,w}$  is updated more frequently,  $D_{c,w}$  are updated annually and tend to show minimal changes, as they are aggregated factors for each currency and only change when regulatory alterations occur in the respective country. Month fixed effects are deemed suitable for capturing temporal variations in this setting, and regressions with bi-week fixed effects are available for robustness check in appendix, Table 8. This dynamic panel analysis employs the OLS estimator as in previous regressions, under the assumption that remittance costs and regulatory variables can be regarded as exogenous.

The regression results are presented in Table 5. Across all models, the lagged premiums remain positive and highly significant, reinforcing the persistence of premiums over time as previous regressions. In model (1), the coefficient of remittance cost indicates that a 1 percentage point increase in remittance cost is positively associated with a 0.049 percentage point increase in BTC premiums. This suggests that when remittance services are more expensive, individuals may find BTC a more attractive alternative for transferring value, leading to higher premiums in BTC markets priced in those currencies. Model (2) introduces interaction terms to examine how the effect of remittance cost on premiums varies depending on the presence of strong capital controls and a managed exchange rate regime, defined by  $D_{c,w}$ . For unconstrained currencies, remittance cost does not have a significant effect on premiums. Similarly, for constrained currencies, when the remittance cost is zero, the status of being a constrained currency does not significantly affect premiums. However, the significant interaction term reveals that for constrained currencies, increases in remittance

	Premium <sub>w</sub>			
	(1)	(2)	(3)	(4)
Premium <sub>w-1</sub>	.506*** (.021)	.466*** (.033)	.466*** (.033)	.468*** (.033)
Premium <sub>w-2</sub>	.267*** (.045)	.238*** (.026)	.238*** (.026)	.238*** (.026)
Remittance Cost <sub>w</sub>	.049* (.026)	-.050 (.074)	-.050 (.074)	-.054 (.077)
Constrained <sub>w</sub>		2.217 (6.911)	2.199 (6.913)	2.289 (7.004)
Remittance Cost <sub>w</sub> * Constrained <sub>w</sub>		.995* (.543)	.996* (.543)	.992* (.540)
Financial Freedom <sub>w</sub>			-.110*** (.028)	-.114*** (.028)
Depr <sub>w</sub>				-.353*** (.088)
R <sup>2</sup>	.734	.745	.745	.746
Adj. R <sup>2</sup>	.730	.741	.741	.742
Num. obs.	7357	6501	6501	6501
RMSE	6.667	6.752	6.752	6.738
N Clusters	43	43	43	43
FEs	Currency, Month	Currency, Month	Currency, Month	Currency, Month
Clustering	Currency	Currency	Currency	Currency

\*\*\*  $p < 0.01$ ; \*\*  $p < 0.05$ ; \*  $p < 0.1$

Table 5: Premium explanation with regulatory frictions and transaction costs, with threshold  $\delta = 0.7$  for constrained dummy.

cost are almost fully passed through to BTC premiums. This implies that in countries with capital controls and higher remittance costs, individuals potentially rely more on BTC for transferring value internationally, leading to higher premiums.

In models (3) and (4), we observe similar effects even after controlling for the Financial Freedom Score and the depreciation of OER. Holding all else constant, currencies with a higher Financial Freedom Score—which indicates greater financial openness and fewer restrictions—tend to have lower BTC premiums. This is likely because individuals in these countries have more options for capital transfer and are less dependent on BTC as an alternative means of moving funds across borders. The negative coefficient for  $depr_{c,w}$  could be due to a correction mechanism in the OER, indicating that the premiums already reflect expectations of depreciation, and as the currency depreciates, the premium adjusts downward. More detailed regressions are performed in subsection 4.3.

Model (4) demonstrates the highest  $R^2$  value, with the degree of pass-through of remittance costs to BTC premiums for constrained currencies remaining almost unchanged at 99.2%. This high degree of pass-through suggests that in constrained currencies, nearly all increases in remittance costs are reflected in higher BTC premiums. In addition to the evidence of BTC as an intermediary vehicle for international capital flow found in LB by von Luckner et al. [2023], our regressions provide similar signals from the perspective that premiums partially reflect the cost of international capital transfers via BTC for constrained currencies. Specifically, when transferring is expensive through traditional remittance channels in these currencies, BTC premiums tend to increase on platforms like LB, as individuals are willing to pay a premium for the ability to transfer value using BTC. Conversely, in economies with greater financial freedom, individuals have more options to circumvent these costs, resulting in smaller BTC premiums.

### 4.3 LB's Premium and Currency Depreciation

From the analysis of specific countries, as illustrated in Figure 7a and Figure 7b, we observe that the premiums on LB may indicate market expectations regarding the long-term depreciation of these specific constrained currencies.

	Depr <sub>w</sub> , unconstrained		Depr <sub>w</sub> , constrained	
	(1)	(2)	(3)	(4)
Depr <sub>w-1</sub>	-.0561 (.0337)	-.0741** (.0311)	.2164*** (.0699)	.2044** (.0957)
Premium <sub>w-1</sub>	.0126*** (.0043)	.0071** (.0028)	-.0077 (.0066)	-.0159 (.0380)
Depr <sub>w-2</sub>		-.0122 (.0114)		.0462 (.0501)
Premium <sub>w-2</sub>		0.0002 (.0022)		-.0121 (.0291)
N. obs.	12300	12212	2097	2081
N. Clusters	49	49	11	11
N. instruments	8	8	8	8

\*\*\* $p < 0.01$ ; \*\* $p < 0.05$ ; \* $p < 0.1$

Table 6: Dynamic panel regression for BTC premiums and OER depreciation

Subsequently, we examine their effects on unconstrained currencies as well, but in the short run. Theoretically, a freely adjustable OER is supposed to respond more timely to market reactions compared to managed OERs.

The BTC premium and OER depreciation likely influence each other over time. For example, an increase in the BTC premium could signal market expectations of future currency depreciation, while currency depreciation can, in turn, influence the BTC premium due to shifts in demand for BTC as a hedging tool. In order to have both of  $p_{c,w}$  and  $depr_{c,w}$  as endogenous variables, we conduct a two-variable vector autoregression (VAR) analysis with fixed effects, and focus on the responses of  $depr_{c,w}$  to the lag terms of BTC premiums:

$$depr_{c,w} = \sum_{i=1}^l \alpha_i depr_{c,w-i} + \sum_{i=1}^l \beta_i p_{c,w-i} + \varepsilon_{c,w,1}, \quad (13)$$

where  $l$  indicates the number of lag terms, and  $\varepsilon_{c,w}$  are the error terms. It is solved by the two-step generalized method of moments (GMM) to control for dynamic relationships over time, unobserved heterogeneity across groups, and potential endogenous variables [Sigmund and Ferstl, 2021]. Due to the unbalanced nature of our dataset, we apply the forward orthogonal deviations transformation method to remove individual fixed effects. To tackle the problem of endogeneity, instrumental variables derived from lagged terms of the variables are used. For the lagged dependent variable  $depr_{c,w-1}$  and  $p_{c,w-1}$ , their own lagged values, specifically lags 2 and 3, are used as instruments, which are assumed to be uncorrelated with the current error term. A Hansen test is performed to confirm the validity of the instruments [Hansen, 1982]. Based on the constraint dummy defined in Equation 10 with  $\delta = 0.7$ , we split the dataset into two groups: unconstrained and constrained, to distinguish whether a currency is under severe capital controls and managed exchange rate regimes. For a few currencies, it is possible to switch to the other group due to regulatory changes; however, such switches are infrequent and occur only occasionally over time. We then perform separate regressions for each group to investigate the relationship between the BTC premiums and OER depreciation. The results are presented in Table 6, with models (1), (2) and (3), (4) for the unconstrained and constrained groups, respectively. We conduct analyses using one and two lags, denoted as  $l = 1$  and  $l = 2$ , for each group.

Unlike the findings of Choi et al. [2018], who indicated that FX volatility is substantially smaller than BTC volatility—rendering the impact of FX movements trivial in the Korean BTC market—our panel analysis reveals a different pattern across a broader set of currencies in P2P markets. Specifically, for unconstrained currencies, the positive and statistically significant coefficient on the lagged BTC premium indicates that an increase in the BTC premium in the previous period is associated with an increase in the depreciation of the currency in the current period, as shown in model (1). This suggests that higher market expectations of currency depreciation or potential capital flight—signified by a higher BTC premium—can spill over into the FX markets. The BTC premium thus acts as an indicator of depreciation pressure. Without strong regulatory barriers, the OER can adjust to align with market expectations. However, this effect is only observed over a short horizon; the coefficient on the second lag of the BTC premium is not statistically significant in model (2), indicating that the predictive power of the BTC premium diminishes beyond the immediate period.

Conversely, for constrained currencies, no significant correlation is observed between the BTC premium and currency depreciation in models (3) and (4). Their OERs against the USD remain relatively stable due to government interventions

and policies aimed at maintaining exchange rate stability. Consequently, the depreciation pressure indicated by the BTC premiums does not translate to fluctuations in the OERs right away.

## 5 Conclusion

In this study, we examine the P2P market for BTC using data from LB, uncovering evidence of violations of the law of one price. Unlike centralized exchanges, LB allows users to post customized buy and sell advertisements, resulting in significant price premiums, particularly in currencies with stringent capital controls and managed exchange rate regimes.

We analyze frictions along BTC trade flows and identify factors impacting P2P BTC premiums. Unlike BTC premiums on centralized exchanges, which correlate with blockchain microstructure conditions, P2P BTC premiums are only positively associated with BTC returns and volatility. Regarding frictions from international capital transfers, we consider transaction costs (remittance costs), capital controls, exchange rate regimes, and financial freedom. For currencies subject to stringent capital controls and managed exchange rate regimes, increased transaction costs through conventional financial channels almost entirely translate into higher BTC premiums. Our analysis also suggests that an increase in BTC premium is linked to subsequent depreciation of the OER for unconstrained currencies.

In conclusion, this research sheds light on the unique dynamics of P2P Bitcoin markets, emphasizing the role of capital control frictions and alternative transfer costs in explaining price deviations. The findings underscore the importance of considering the broader economic environment and regulatory landscape when analyzing cryptocurrency markets, offering valuable insights for policymakers and investors alike. Future research could involve conducting case studies on specific countries with varying levels of capital controls and economic freedom, providing a more granular understanding and policy recommendations for managing cryptocurrency markets effectively.

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## A Robustness Check for Premium Explanation

	Premium <sub>w</sub>			
	(1)	(2)	(3)	(4)
Premium <sub>w-1</sub>	.506*** (.021)	.470*** (.032)	.470*** (.032)	.472*** (.032)
Premium <sub>w-2</sub>	.267*** (.045)	.243*** (.027)	.243*** (.027)	.243*** (.027)
Remittance Cost <sub>w</sub>	.049* (.026)	-.064 (.080)	-.064 (.080)	-.069 (.083)
Constrained <sub>w</sub>		-1.182 (5.791)	-1.209 (5.793)	-1.133 (5.844)
Remittance Cost <sub>w</sub> * Constrained <sub>w</sub>		1.078* (.574)	1.079* (.574)	1.078* (.572)
Financial Freedom <sub>w</sub>			-.107*** (.027)	-.110*** (.027)
Depr <sub>w</sub>				-.358*** (.089)
R <sup>2</sup>	.734	.744	.744	.745
Adj. R <sup>2</sup>	.730	.740	.740	.741
Num. obs.	7357	6501	6501	6501
RMSE	6.667	6.764	6.765	6.751
N Clusters	43	43	43	43
FEs	Currency, Month	Currency, Month	Currency, Month	Currency, Month
Clustering	Currency	Currency	Currency	Currency

\*\*\* $p < 0.01$ ; \*\* $p < 0.05$ ; \* $p < 0.1$

Table 7: Premium explanation with regulatory frictions and transaction costs, with threshold  $\delta = 0.5$  for constrained dummy, and month fixed effects

	Premium <sub>w</sub>			
	(1)	(2)	(3)	(4)
Premium <sub>w-1</sub>	.459*** (.026)	.415*** (.017)	.415*** (.017)	.417*** (.017)
Premium <sub>w-2</sub>	.314*** (.037)	.289*** (.026)	.289*** (.026)	.289*** (.026)
Remittance Cost <sub>w</sub>	.040 (.024)	-.071 (.074)	-.070 (.074)	-.075 (.077)
Constrained <sub>w</sub>		.779 (6.793)	.763 (6.796)	.871 (6.875)
Remittance Cost <sub>w</sub> * Constrained <sub>w</sub>		1.077* (.558)	1.078* (.559)	1.072* (.554)
Financial Freedom <sub>w</sub>			-.107*** (.026)	-.111*** (.026)
Depr <sub>w</sub>				-.377*** (.108)
R <sup>2</sup>	.755	.766	.766	.767
Adj. R <sup>2</sup>	.749	.760	.760	.761
Num. obs.	7357	6501	6501	6501
RMSE	6.426	6.494	6.494	6.479
N Clusters	43	43	43	43
FEs	currency, bi-week	currency, bi-week	currency, bi-week	currency, bi-week
Clustering	currency	currency	currency	currency

\*\*\* $p < 0.01$ ; \*\* $p < 0.05$ ; \* $p < 0.1$

Table 8: Premium explanation with regulatory frictions and transaction costs, with threshold  $\delta = 0.7$  for constrained dummy and bi-week fixed effects

## B Currencies, Countries and Exchange Rates

The currencies and corresponding countries that have been used in this paper are the following: Swiss Francs CHF (Switzerland), United Arab Emirates Dirham AED (United Arab Emirates), Angolan Kwanza AOA (Angola), Argentine Peso ARS (Argentina), Australian Dollar AUD (Australia, Kiribati, Nauru, Tuvalu), Bosnia and Herzegovina Convertible Mark BAM (Bosnia and Herzegovina), Bangladeshi Taka BDT (Bangladesh), Bulgarian Lev BGN (Bulgaria), Bolivian Boliviano BOB (Bolivia), Brazilian Real BRL (Brazil), Belarusian Ruble BYN (Belarus), Canadian Dollar CAD (Canada), Chilean Peso CLP (Chile), Chinese Yuan CNY (China), Colombian Peso COP (Colombia), Costa Rican Colón CRC (Costa Rica), Czech Koruna CZK (Czech Republic), Danish Krone DKK (Denmark), Dominican Peso DOP (Dominican Republic), Egyptian Pound EGP (Egypt), Ethiopian Birr ETB (Ethiopia), Euro EUR (Andorra, Austria, Belgium, Cyprus, Estonia, Finland, France, Germany, Greece, Ireland, Italy, Kosovo, Latvia, Lithuania, Luxembourg, Malta, Montenegro, The Netherlands, Portugal, San Marino, Slovak Republic, Slovenia, Spain), British Pound Sterling GBP (United Kingdom), Georgian Lari GEL (Georgia), Ghanaian Cedi GHS (Ghana), Guatemalan Quetzal GTQ (Guatemala), Hong Kong Dollar HKD (Hong Kong SAR), Honduran Lempira HNL (Honduras), Croatian Kuna HRK (Croatia), Hungarian Forint HUF (Hungary), Indonesian Rupiah IDR (Indonesia), Israeli New Shekel ILS (Israel, West Bank and Gaza), Indian Rupee INR (India), Iranian Rial IRR (Iran), Icelandic Króna ISK (Iceland), Jamaican Dollar JMD (Jamaica), Jordanian Dinar JOD (Jordan), Japanese Yen JPY (Japan), Kenyan Shilling KES (Kenya), South Korean Won KRW (Korea), Kuwaiti Dinar KWD (Kuwait), Kazakhstani Tenge KZT (Kazakhstan), Sri Lankan Rupee LKR (Sri Lanka), Moroccan Dirham MAD (Morocco), Mauritian Rupee MUR (Mauritius), Malawian Kwacha MWK (Malawi), Mexican Peso MXN (Mexico), Malaysian Ringgit MYR (Malaysia), Nigerian Naira NGN (Nigeria), Norwegian Krone NOK (Norway), New Zealand Dollar NZD (New Zealand), Omani Rial OMR (Oman), Panamanian Balboa PAB (Panama), Peruvian Sol PEN (Peru), Philippine Peso PHP (Philippines), Pakistani Rupee PKR (Pakistan), Polish Zloty PLN (Poland), Paraguayan Guarani PYG (Paraguay), Qatari Riyal QAR (Qatar), Romanian Leu RON (Romania), Serbian Dinar RSD (Serbia), Russian Ruble RUB (Russia), Rwandan Franc RWF (Rwanda), Saudi Riyal SAR (Saudi Arabia), Swedish Krona SEK (Sweden), Singapore Dollar SGD (Singapore), Eswatini Lilangeni SZL (Eswatini), Thai Baht THB (Thailand), Turkish Lira TRY (Türkiye), Trinidad and Tobago Dollar TTD (Trinidad and Tobago), New Taiwan Dollar TWD (Taiwan Province of China), Tanzanian Shilling TZS (Tanzania), Ukrainian

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Hryvnia UAH (Ukraine), Ugandan Shilling UGX (Uganda), United States Dollar USD (Ecuador, El Salvador, Liberia, Marshall Islands, Micronesia, Palau, Panama, Puerto Rico, Somalia, Timor-Leste, United States), Uruguayan Peso UYU (Uruguay), Vietnamese Dong VND (Vietnam), Central African CFA Franc XAF (Cameroon, Central African Republic, Chad, Republic of Congo, Equatorial Guinea, Gabon), West African CFA Franc XOF (Benin, Burkina Faso, Côte d'Ivoire, Guinea-Bissau, Mali, Niger, Senegal, Togo), South African Rand ZAR (South Africa), Zambian Kwacha ZMW (Zambia).

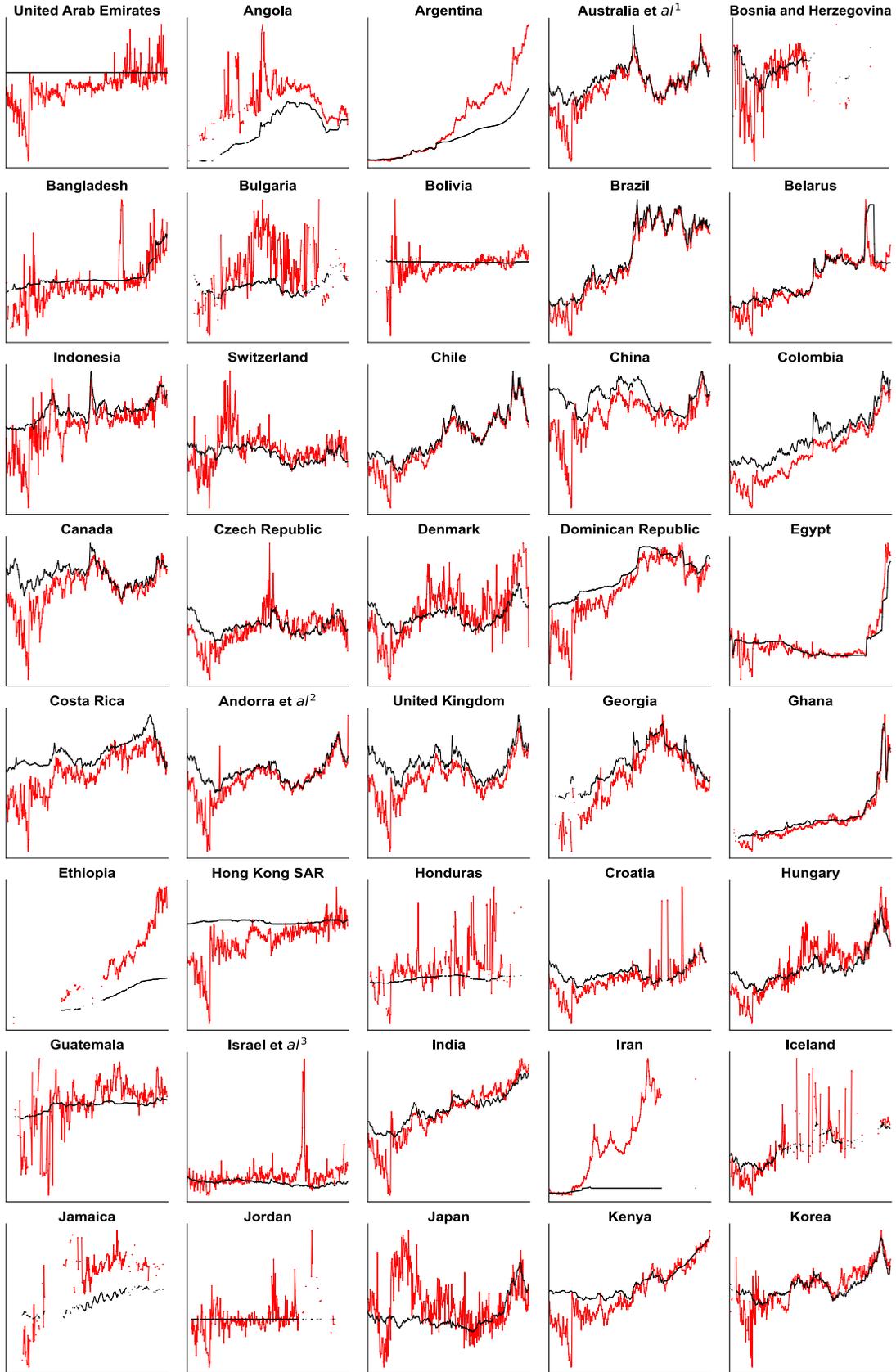


Figure 8: Overview of the official and implied exchange rates, Part 1: Red represents implied rates, and black represents official rates.

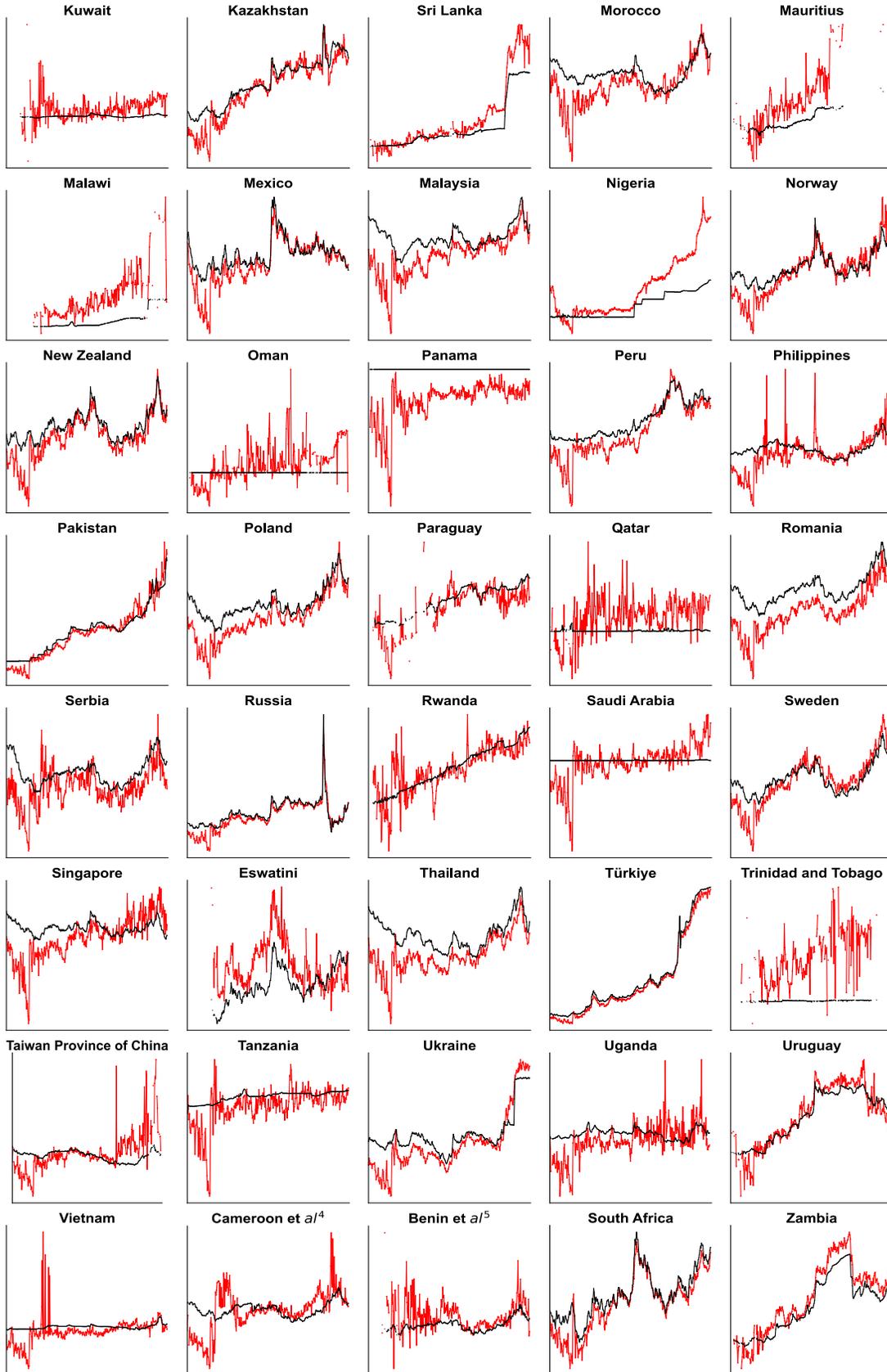


Figure 9: Overview of the official and implied exchange rate, Part 2.