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A Primer on Bitcoin Cross-Border Flows

Measurement and Drivers

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JEL Classification Numbers:	E42; E51; E58; F21; F32; F38
Keywords:	Crypto assets; Bitcoin; Cross-border flows; Capital flows
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A Primer on Bitcoin Cross-Border Flows: Measurement and Drivers*

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Abstract

The rapid growth of crypto assets raises important questions about their cross-border usage. To gain a better understanding of cross-border Bitcoin flows, we use raw data covering both on-chain (on the Bitcoin blockchain) and off-chain (outside the Bitcoin blockchain) transactions globally. We provide a detailed description of available methodologies and datasets, and discuss the crucial assumptions behind the quantification of cross-border flows. We then present novel stylized facts about Bitcoin cross-border flows and study their global and domestic drivers. Bitcoin cross-border flows respond differently than capital flows to traditional drivers of capital flows, and differences appear between on-chain and off-chain Bitcoin cross-border flows. Off-chain cross-border flows seem correlated with incentives to avoid capital flow restrictions.

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1 Introduction

The rapid growth of Bitcoin since its launch in 2009 has increased its potential macroeconomic implications. Bitcoin is the unit of account of a decentralized global digital ecosystem with public access. The technological innovation behind it—a sustainable blockchain consisting of a distributed ledger that operates and exists without any trusted parties (Halaburda et al., 2022)—has facilitated a very large number of transactions and received the attention of private and public agents. Despite its price volatility and the fact that it is not backed by any real asset or any governmental claim, the price of Bitcoin and the number of active users has increased markedly over the past decade (Auer et al., 2023). The global nature of the underlying technologies implies that a large proportion of the transactions are likely performed across national borders. Nonetheless, identifying Bitcoin cross-border transactions is far from straightforward.

While access to the Bitcoin network is public, it provides a large degree of pseudonymity because the individual users are not well identified. This pseudonymity of the users, combined with the segmentation of the Bitcoin market into on-chain (recorded on the Bitcoin blockchain) and off-chain (not recorded on the Bitcoin blockchain) transactions, has limited a comprehensive understanding of global Bitcoin cross-border flows.[1] In this paper, we tackle this challenge by using three complementary datasets to study Bitcoin transactions and cross-border flows. We discuss the pros and cons of the different approaches to estimating Bitcoin cross-border flows, present novel stylized facts using raw data that cover both on-chain and off-chain transactions, and analyse the drivers of Bitcoin cross-border flows in comparison to capital flows for a large panel of countries. Our findings suggest that Bitcoin cross-border flows respond differently than capital flows to traditional global drivers. Moreover, differences appear between on-chain and off-chain Bitcoin cross-border flows.

We start by constructing datasets on Bitcoin flows. First, we build a dataset of on-chain flows across crypto exchanges. Second, we complement this dataset with on-chain cross-country flows

[1] An on-chain Bitcoin user (i.e., any person transacting Bitcoins through the Bitcoin network) does not have an account but a wallet, which is the combination of a Bitcoin address (i.e., "an account number", also called a public key) and a private key (i.e., a password). As highlighted in the literature, wallets are relatively easy to create, users often have more than one wallet, and the way the Bitcoin system defines an address implies that there is potentially a nearly infinite number of wallets. In the words of Halaburda et al. (2022), while there is room for 2^{160} different addresses in the Bitcoin system, the estimated number of grains of sand on Earth is "only" 2^{63}. Pseudonymity of the off-chain Bitcoin user (i.e., any person transacting Bitcoins outside the Bitcoin network) is given by the privacy and characteristics of the available Bitcoin exchanges. See Section 2.1.

estimated by Chainalysis. This dataset uses information on web traffic on the crypto exchanges through which the transactions occur to identify the residency of the users. Third, we construct a dataset of off-chain cross-border flows recorded in the operations of the exchange LocalBitcoins following Graf von Luckner et al. (2023). We rely on information on the fiat currency used in the transactions as a proxy for the residency of the users. Our detailed description of these three approaches highlights their pros and cons and illustrates the complementary nature of these datasets.

A key question is to what extent Bitcoin is used for cross-border transactions. The findings in our paper put into perspective not only the relative importance and the characteristics of Bitcoin cross-border flows but also their heterogeneity, especially in terms of on-chain and off-chain transactions. The use of Bitcoin for cross-border transactions is geographically widespread, with relatively high intensities across regions both for on-chain and for off-chain flows, and some punctual differences driven by data coverage and the underlying estimation assumptions. Our usage of raw on-chain and off-chain data allows us to establish that on-chain transactions are, on average, substantially larger than off-chain transactions. This pattern likely reflects the security features that the blockchain provides and the Bitcoin blockchain fee structure. The magnitudes of the estimated Bitcoin cross-border flows are sizeable with respect to several countries' GDP, especially in those which experience relatively small traditional capital flows.

An analysis of the drivers of cross-border flows indicates that Bitcoin cross-border usage is not aligned with the same factors which drive capital flows, and that there could be some differences between on-chain and off-chain Bitcoin cross-border flows. While the levels of capital flows and estimated Bitcoin cross-border flows are not directly comparable due to methodological differences (gross vs. net concepts)[2], we gain four key insights: i) Bitcoin on-chain cross-border flows respond differently to traditional drivers than capital flows. They seem to be negatively related to broad dollar appreciation events, but unlike capital flows, react positively to changes in risk aversion as captured by the VIX; ii) On-chain cross-border flows are positively correlated with improvements in crypto-specific sentiment (crypto fear & greed)[3]; iii) Yet, neither traditional global drivers of capital flows nor sentiment towards Bitcoin affect off-chain Bitcoin cross-border flows; and iv)

[2]Capital inflows in the Balance of Payments sense are measured as net changes in non-residents' holdings of domestic assets——such as purchases net of sales of a domestic bond——instead of the gross inflows resulting from a non-resident purchasing Bitcoin from a resident. See Section 3.1

[3]The crypto fear & greed index captures crypto-specific sentiment. See Section 3.2.

While domestic factors play a less prominent role in our sample for on-chain Bitcoin cross-border flows, they seem to matter for off-chain Bitcoin flows, which exhibit a positive relationship with a Bitcoin-based measure of the parallel rate premium.

The contributions of our paper to the literature are threefold. First, we extend efforts to identify and analyze Bitcoin cross-border flows by exploring complementary datasets on global Bitcoin cross-border flows based on Bitcoin transactions. Hu et al. (2021) develop a method to identify Bitcoin on-chain cross-border flows from China. They highlight that on-chain "uneconomical" flows from CNY to USD via Bitcoin were driven by capital flight motives. Taking advantage of raw transaction off-chain data from LocalBitcoins and Paxful, Graf von Luckner et al. (2023) develop a methodology to identify cross-border flows based on matching transactions and the underlying used fiat currencies. They find that Bitcoin has become an increasingly important channel to send remittances and evade capital controls in emerging markets. Contemporaneous with our study and with a main focus on Brazil, Cardozo et al. (2024) compare authorities' estimates of crypto cross-border flows based on aggregate FX transaction data with our estimated LocalBitcoins off-chain data as well as on-chain cross-border data from commercial vendors Crystal and Chainalysis. They stress that Brazilian Bitcoin cross-border flows are not correlated with regular capital flows nor remittances, and that they are as volatile as regular Brazilian portfolio and FDI flows. Our study of the drivers of Bitcoin cross-border flows differs from theirs in that we explore a cross-country panel setup. Our direct usage of both raw on-chain and off-chain Bitcoin data allows us to identify not only the pros and cons of different approaches to estimating Bitcoin cross-border flows but also to provide insightful stylized facts.

Second, we complement the small but growing literature analyzing the drivers of crypto assets and their relationship with traditional financial assets. Benigno and Rosa (2023) find that the Bitcoin price is orthogonal to all intraday macro news that they consider (except the CPI) as well as unresponsive to unexpected changes in the short-term rate while its reaction to news about the future path of policy is not robust. Bouri et al. (2017) investigate whether Bitcoin can hedge global uncertainty, measured by the first principal component of the VIX indexes of 14 developed and developing equity markets. They show that Bitcoin prices react positively to uncertainty at both higher quantiles and shorter frequency movements of Bitcoin returns. In contrast, Adrian et al. (2022) and Iyer and Popescu (2023) find strong interconnectedness between crypto asset prices and equity prices as well as the VIX, suggesting that crypto assets behave akin to risky assets. Our cross-border results suggest that Bitcoin on-chain flows are positively related with the VIX (the opposite response of capital flows). This result also concurs with Di Casola et al. (2023) who show that an increase in the VIX results in higher Bitcoin-fiat currency trading volumes.

Third, we provide a nuanced perspective on Bitcoin and capital flow management by differentiating between on-chain and off-chain flows. Analyses of the cross-border usage of Bitcoin highlight different activities from e-commerce (Polasik et al., 2015) to money linked to illicit undertakings (Ron and Shamir, 2014).[4] Nonetheless, independent of the underlying activity, cross-border transfers through Bitcoin are thought to be motivated by high costs or government controls hindering transfers via traditional financial institutions (Biais et al., 2023). In this context, the role of capital controls has been widely highlighted in the literature. Hu et al. (2021) show how capital flight motives can explain on-chain Bitcoin flows in China. Graf von Luckner et al. (2023) stress that off-chain Bitcoin transactions can facilitate cross-border capital flight and enable the circumvention of capital flow management measures in several emerging markets. In a recent study, Graf von Luckner et al. (2024) argue that underlying capital movements still occur via traditional channels and serve as liquidity providers for crypto exchanges. They also propose that the relative price of crypto assets in an economy provides insightful information about the strength of the demand for capital flight. We contribute to this debate by providing cross-country panel evidence that off-chain cross-border outflows are positively correlated with a Bitcoin parallel premium which we interpret as a broader proxy for exchange rate pressures, reflecting macroeconomic imbalances.

The policy implications of the usage of Bitcoin for cross-border transactions are potentially ample but not definitive at this stage.[5] The volume of both on-chain and off-chain Bitcoin flows appears important. Nonetheless, Bitcoin cross-border flows respond differently than capital flows to traditional drivers. Overall, there is not much evidence that Bitcoin cross-border flows have replaced existing capital flows at this stage. This feature could be read as positive, in the sense that capital flows remain the key quantitative transmission channel of global spikes in risk aversion

[4] In November 2023, the U.S. Treasury Department found that Binance failed to report transactions associated with illicit activities and violated U.S. Anti-Money Laundering laws.

[5] More generally, IMF (2023a) recommends sound monetary policy frameworks, not granting crypto legal tender status, integrating cryptos with existing capital flow management regulations, and clarifying tax treatment of cryptos to avoid adverse implications of crypto assets on the economy. FSB and IMF (2023) highlight addressing data gaps and enhancing international cooperation and information sharing as key steps towards addressing potential macroeconomic and financial stability risk from crypto assets.

and/or flight to safety triggers. Nonetheless, crypto markets are evolving fast (e.g., the recent authorization for Bitcoin ETFs) and better data are key to evaluating the need for targeted policy responses in the future.

The remainder of the paper is organized as follows. Section 2 discusses different approaches and underlying assumptions to measure Bitcoin cross-border flows. Section 3 describes the data and presents a set of stylized facts. Section 4 introduces our empirical strategy and presents the results of the empirical analysis. Section 5 recapitulates and provides a few additional remarks on data limitations and evaluating policy implications.

2 Measuring Bitcoin Cross-Border Flows

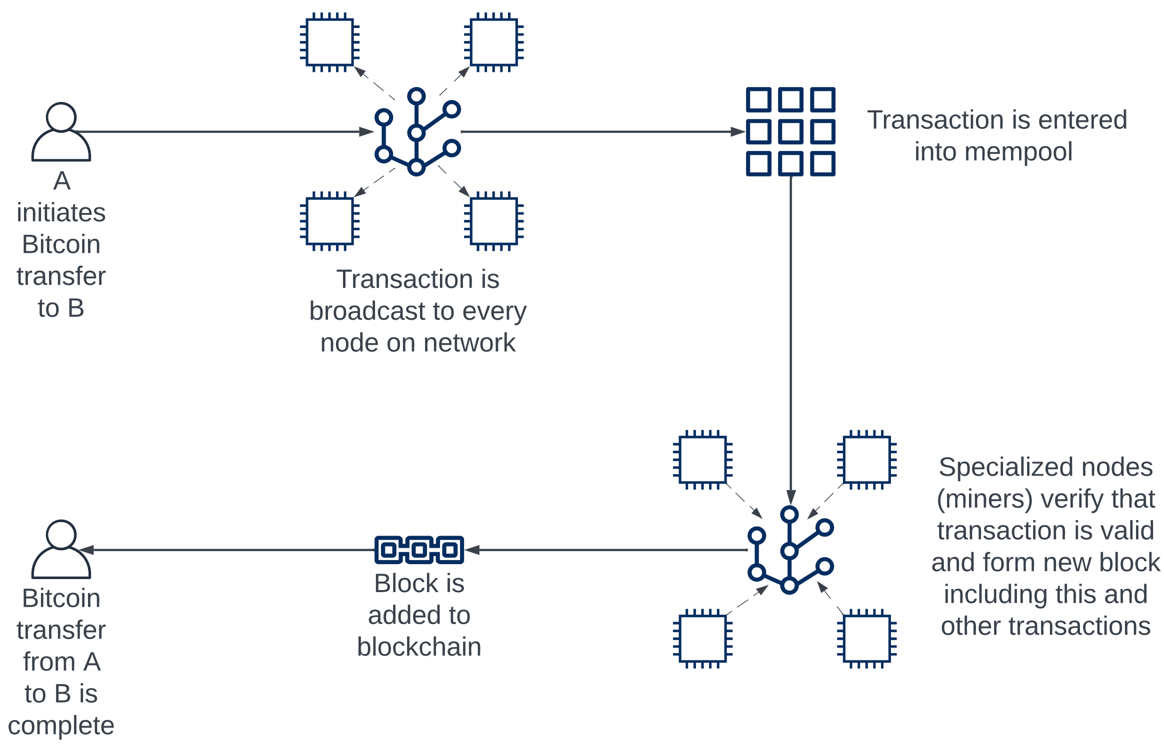
Crypto asset transactions occur on marketplaces which are different from the traditional financial system for capital flows. In this section, we provide an overview of the modalities of Bitcoin transactions, in particular the differences between on-chain and off-chain transactions. In addition, we discuss three alternative approaches to measuring Bitcoin cross-border flows and zoom in on the underlying assumptions to identify the residency of the users.

2.1 Modalities of Bitcoin Cross-Border Flows

There are two types of Bitcoin transactions: on-chain transactions, which are permanently recorded on the Bitcoin blockchain (a distributed ledger which is public as it is visible to all network participants) and are immutable, and off-chain transactions, which occur outside the blockchain. It is challenging to compare the volume of on-chain and off-chain transactions, partly due to difficulties in accounting for decentralized transactions. Nonetheless, based on a sample of 17 crypto exchanges, Makarov and Schoar (2022) find that the Bitcoin off-chain volume is somewhat larger than the on-chain volume.

Figure 1 shows an illustrative example of an on-chain Bitcoin transaction. The sender first initiates a transaction from their digital wallet. The transaction requires information on the sender's address, the recipient's address, and the amount of Bitcoin being sent. The sender then signs the transaction using the wallet's private key (a 256-bit random number akin to a digital password). Once signed, the transaction is broadcast to the Bitcoin network for validation. Next, it is entered into the mempool—the queue of pending transactions. Miners then validate transactions by solving complex cryptographic puzzles in exchange for a fee.[6] Validated transactions are stored in a block and confirmed by other miners in the network. Finally, the transaction is disseminated to the blockchain and thereby completed. Because of the immutability of the blockchain, on-chain transactions offer a high degree of security.

Figure 1: An illustrative example of an on-chain Bitcoin transaction



Off-chain transactions occur outside the blockchain network. These transactions take place, for example, through a third party, such as a crypto exchange which verifies the transaction's legitimacy and facilitates its completion. Since off-chain transactions occur without a record on the blockchain, miners are not required to validate transactions. This feature can lower fees and speed up processing time relative to on-chain transactions. However, off-chain transactions provide

[6] Fees are determined by transaction size (i.e., data volume) and block space (i.e., the desired speed.

a lower degree of security, reflecting the lack of a public record of the transaction and exchanges' vulnerability to crypto hacks.

There are three major types of crypto exchanges: centralized exchanges, peer-to-peer (P2P) exchanges, and decentralized exchanges. Centralized exchanges are similar to traditional trading platforms. They manage a central order book and are responsible for the custody of users' crypto assets (users do not have direct control over their private keys), security, maintenance, functionalities, and transaction approval. Centralized exchanges are typically regulated which implies that they must comply with Know Your Customer and Anti-Monetary Laundering regulations. These regulations require the collection and storage of customer information, including identity documents and addresses. Centralized exchanges usually provide a user-friendly interface, support a broader set of crypto assets and products for trading, and are more liquid as they have access to an extensive pool of buyers and sellers such as regulated market makers. While the ratio of trading volume on P2P and decentralized exchanges to centralized exchanges has increased, centralized exchanges still account for a substantial share of trading activity (see Makarov and Schoar (2022) and CryptoSlate). P2P exchanges are decentralized exchanges with a degree of centralization. They facilitate direct trading between clients who create public listings to match for a trade. P2P exchanges frequently provide an escrow service to secure the transaction. Decentralized exchanges, in contrast, use smart contracts to facilitate direct P2P trading without any intermediary. This feature preserves a high level of privacy and reduces the risk of hacks.

2.2 Approaches to Measuring Bitcoin Cross-Border Flows

Approach 1: Measuring Bitcoin Cross-Exchange Flows based on Exchange Wallets

We begin our analysis by measuring Bitcoin flows based on publicly available information from on-chain transactions and wallets. While this approach only provides cross-exchange flows, rather than cross-border flows, it is useful to gain a deeper understanding of the transaction-level data and the methodologies used by commercial data providers. We obtain data on on-chain transactions from Kondor et al. (2021) who extract the Bitcoin transaction data from the blockchain with an open-source client. The data contain information on sending and receiving addresses, the amount of each transaction, and a timestamp, among other details (Table 1).

Figure 2 illustrates the matching of on-chain transactions with exchange wallets. The challenge lies in identifying the location of the market participants as their wallet addresses are pseudonymous. Nevertheless, for some addresses in our dataset, we can use WalletExplorer which collects data on exchange wallets from public websites and internal transactions. We thus combine information from the blockchain and WalletExplorer to identify the exchange to which the wallet address belongs. Our approach is similar to Hu et al. (2021), although broader as we look at exchanges available globally. Due to the vast size of the Bitcoin universe, WalletExplorer cannot provide information on all available wallets and exchanges. It allows us to identify about 5 percent of the addresses in the dataset.[7] The resulting exchange-level dataset (Table 2) contains 1.6 million transactions on 80 different exchanges. About one-third of these transactions occur across exchanges.

Table 1: Blockchain: raw data

This table shows the structure of the blockchain raw data. After merging transaction IDs, in transactions, out transactions, and timestamps, the dataset contains 44.6 million transactions over Jan 12th, 2009–Feb 7th, 2020.

ID	Time	Amount (BTC))	Sending address	Receiving address
192	12 Jan 2009 07:16:40	100,000,000	15NUwyBYrZcnUgTagsm1A7M2yL2GntpuaZ	13HtsYzne8xVPdGDnmJX8gHgBZerAfJGEf
227	12 Jan 2009 14:21:00	100,000,000	1BDvQZjaAJH4ecZ8aL3fYgTi7rnn3o2thE	1LzBzVqEeuQyjD2mRWHes3dgWrT9titxvq
...				
2293	17 Sep 2012 17:00:23	1	1GsfsfwMDjeE5vqtPTto1NGZtqYYf7tc9t	1zCKhrCtwKvBXw6mNxXCC9NsngkA8hpz4
...				
44605290	07 Feb 2020 07:45:17	202,000	3LheuFinP2mDm2xFk391HGfQv6gtaLjcJK	14kLBRLM8H4HDNDUc8b8jFK1sTasPM94BC

One significant benefit of working with the raw data from the blockchain is that it allows us to explore in more detail the nature of on-chain transactions. Additionally, the dataset captures transactions on many exchanges and as such is likely more representative than transactions obtained from individual exchanges. However, it is challenging to assign exchanges to countries to obtain Bitcoin cross-border flows rather than cross-exchange flows. The location of registration does in many cases not provide reliable information on the users of the exchanges because (i) many exchanges are registered in domiciles with crypto-friendly regulations or favorable tax regimes but are global in nature[8] and (ii) users may transact on exchanges in countries other than where they reside, especially given the large concentration of exchanges.

[7] This is in line with Liang et al. (2019) who show that, as of 2018, Wallet Explorer detects 4.3 percent of addresses in the Bitcoin blockchain.

[8] For example, many exchanges are registered in the Seychelles where no regulatory framework is currently in place.

There are currently two types of datasets which add an additional layer linking exchanges to countries. Hu et al., 2021 use raw on-chain data and categorize exchanges into Chinese and non-Chinese exchanges to identify capital flight through Bitcoin from China. The focus on a single country facilitates assigning the exchange. The commercial data provider CrystalBlockchain assigns exchanges to countries based on where the exchange is registered, with a limiting focus on exchanges which the data provider expects to operate in a single country only (for an application of this dataset, see Cardozo et al., 2024). Given the global nature of many of the large exchanges in our dataset, such as Binance and Kraken, we stop short of assigning exchanges to countries.

Table 2: Blockchain: matched cross-exchange transactions

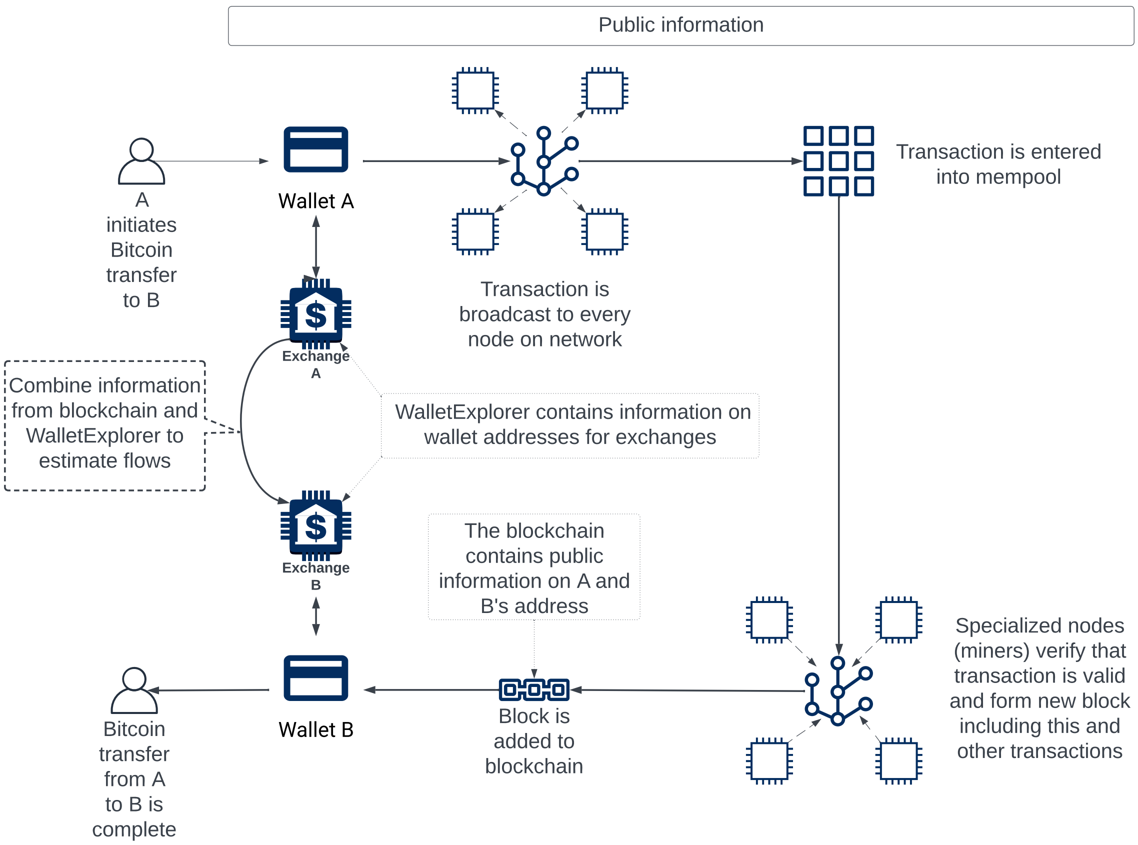
This table shows the structure of the blockchain matched transactions. The dataset contains 592,218 cross-exchange transactions over Aug 2nd, 2011–Feb 7th, 2020.

Time	Amount (BTC))	Sending address	Receiving address
2 Aug 2011 11:08:39	0.1405	Cavirtex	VirWoX
11 Sep 2011 07:25:02	7.9610	Cavirtex	BTC-e
...			
28 Mar 2018 06:25:41	147.0000	MercadoBitcoin	Poloniex
...			
07 Feb 2020 05:17:26	0.7613	Kraken	Poloniex

Approach 2: Measuring Bitcoin Cross-Border Flows based on Exchange Wallets and Web Traffic

An alternative method to measure Bitcoin cross-border flows links wallet addresses to exchanges and additionally uses web traffic information to infer the location of the market participants. Figure 3 illustrates how the commercial data provider Chainalysis implements this approach to measure on-chain cross-border flows. In the first step, Chainalysis identifies the exchanges to which wallets belong based on public data from the blockchain and information from exchanges which submit their transaction data to Chainalysis to outsource the monitoring of counterparty risk (Chainalysis Know Your Transaction). This step is conceptually equivalent to our approach 1 but broader in scope. Since exchanges submit the data using pseudonyms to conceal their users' identities, Chainalysis cannot directly assign a location to each wallet. Instead, in the second step, they assign flows to countries based on monthly web traffic patterns for each exchange. Imagine a stylized example with two exchanges, three countries, and a hypothetical transaction volume of 100 Bitcoin from exchange 1 to exchange 2 on a given day. Based on the web traffic pattern shown in Figure 3, Chainalysis would distribute this daily transaction volume as follows: 35 Bitcoin from country X

Figure 2: Matching on-chain transactions with exchange wallets



to country X, 35 Bitcoin from country X to country Z, 15 Bitcoin from country Y to country X, and 15 Bitcoin from country Y to country Z.[9]

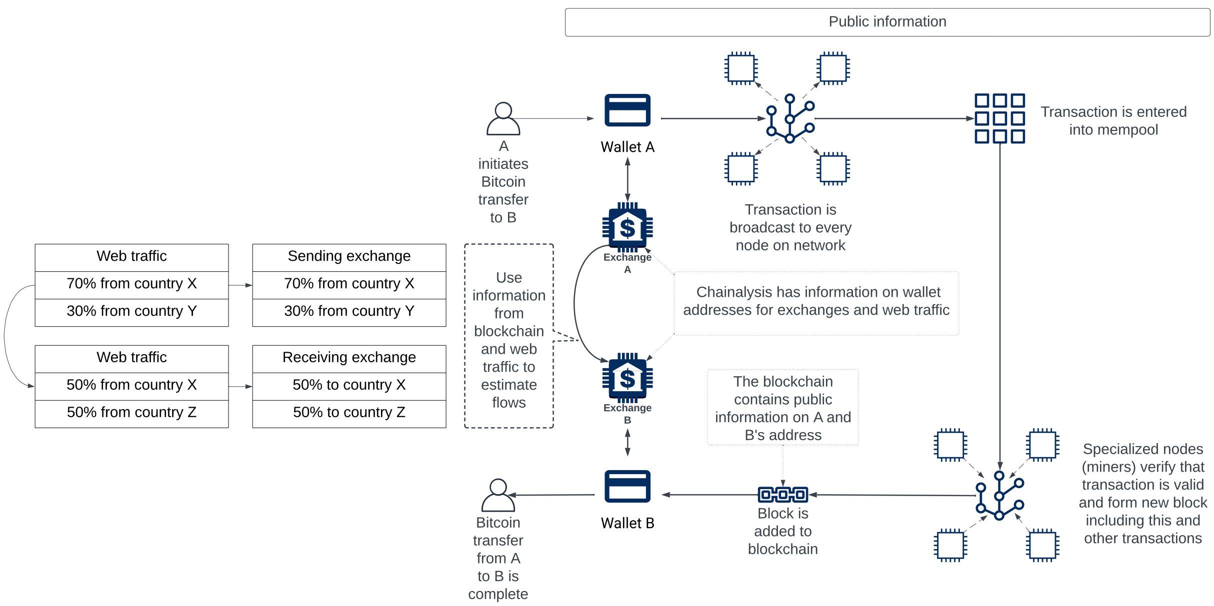
We obtain Bitcoin cross-border flows from Chainalysis over March 2019–March 2023. The identified flows rely on two key assumptions: (i) users do not mask online activity by employing virtual private networks (VPNs) and (ii) transaction amounts are, on average, broadly equal across users in different countries.[10] This approach improves upon the cross-exchange approach by using detailed exchange wallet information. Thus, it captures a larger share of the total Bitcoin on-chain transaction volume for a large number of exchanges and is therefore more representative of the on-

[9] The correlation between Chainalysis inflows and outflows is 0.99 at the country level and 0.82 at the exchange level. While applying the web traffic assumption equally to inflows and outflows might contribute to the high country-level correlation, the strong exchange-level correlation—which does not rely on any web traffic assumption—indicates that these flows are highly correlated by nature.

[10] We do not have access to the web traffic data and thus cannot apply scale web traffic by a proxy for average transaction size such as GDP per capita.

chain universe. Moreover, linking exchanges to countries through web traffic information, provides an innovative identification of cross-border flows. A caveat to this approach is that the use of VPNs to disguise users' identity may potentially impact the precision of the country identification.

Figure 3: Matching on-chain transactions with exchange wallets and web traffic



Approach 3: Measuring Bitcoin Cross-Border Flows based on Fiat Currencies

A third approach to measure Bitcoin cross-border flows relies on information on the fiat currency which is the counterpart in a Bitcoin transaction. This approach was first used by Graf von Luckner et al. (2023). It is suitable to estimate flows based on fiat-Bitcoin transactions occurring on off-chain P2P exchanges. We obtain such fiat-Bitcoin transactions from LocalBitcoins.[11]

LocalBitcoins facilitates the transfer of Bitcoin by matching buyers and sellers without intermediating the payment. It offers an escrow service which holds the Bitcoin associated with an ongoing transaction until both parties confirm that the agreed fiat currency transfer—which takes place

[11]LocalBitcoins only represents one node on the blockchain while its users can use different addresses associated with this node to transact Bitcoin. LocalBitcoins had emerged as one of the largest P2P Bitcoin exchanges but has discontinued its services in February 2023, after operating for more than ten years. Several factors may have contributed to its closure, including high fees relative to other crypto exchanges (Graf von Luckner et al., 2023), the introduction of the 5th Anti-Money Laundering Directive in the European Union, and more recently the growing popularity of stablecoins. This approach to identify cross-border Bitcoin flows can also be applied to transactions on other off-chain market places such as Paxful (see Graf von Luckner et al., 2023).

outside the platform—has been completed. The transfer of Bitcoin is off chain as individuals buy and sell their claims on Bitcoin that the exchange holds on the blockchain, without any Bitcoin being transferred between wallet addresses on the blockchain (Figure 4). For each transaction, we observe a unique transaction ID, timestamp, amount in Bitcoin up to eight digits, the counterpart fiat currency, and the price paid in local, fiat currency (Table 3). Our LocalBitcoins dataset encompasses over 40 million transactions in 136 fiat currencies over the period March 15th, 2017 to February 28th, 2023.[12]

Table 3: LocalBitcoins: raw data

This table shows the structure of the LocalBitcoins raw data. The dataset contains 40.6 million transactions over March 15th, 2017–February 28th, 2023.

ID	Time	Amount (BTC)	Currency	Price (LCU)
6277278	15 Mar 2017 00:00:13	0.07550000	MXN	26490.07
6277265	15 Mar 2017 00:00:15	0.65740001	USD	1292.97
...				
54420534	09 Nov 2021 12:16:44	0.00824622	BRL	358,443.00
...				
56378709	29 Aug 2022 17:12:51	0.00560198	RUB	1,303,111.00
...				
57009997	28 Feb 2023 17:12:51	1.24521100	EUR	19,973.26

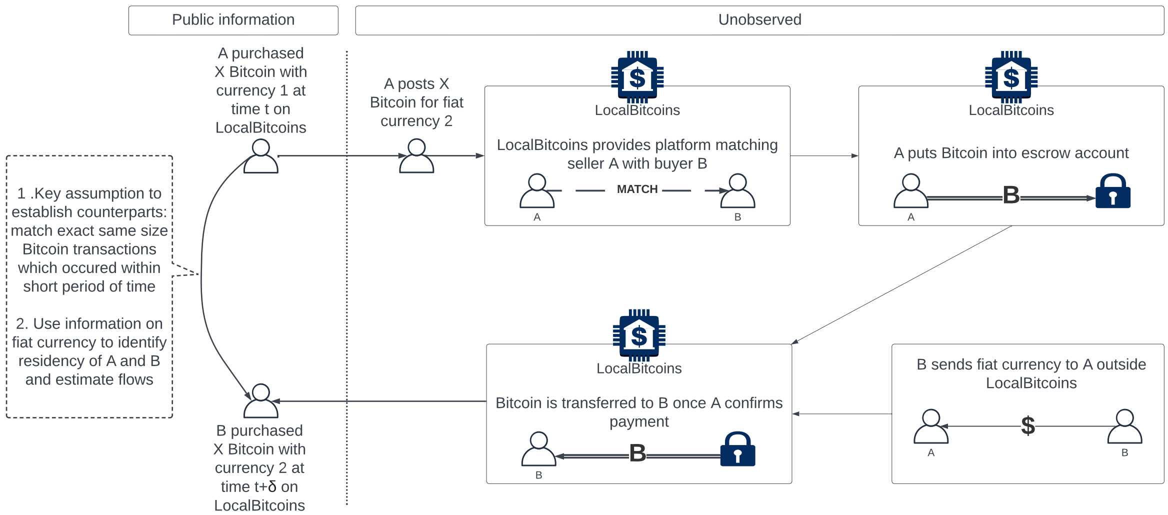
We match these transactions following the novel probabilistic algorithm for detecting cross-border crypto vehicle transactions developed by Graf von Luckner et al. (2023). Figure 4 illustrates the matching of LocalBitcoins transactions. Intuitively, the algorithm matches transactions which are of the exact same size, X, and occur within a short period of time (between time t and $t+\delta$). For example, imagine market participant A purchases X Bitcoin with Nigerian naira and shortly thereafter sells the same amount of Bitcoin for Canadian dollars to market participant B. The algorithm identifies these two transactions as a crypto vehicle trade and relies on the fiat currency used in the transactions as a proxy for the residency of the market participants.

Formally, the algorithm estimates the probability that two matching transactions within a given window of time constitute a crypto vehicle transaction at a specified confidence level. Its reliability relies on two conditions. First, transactions sizes must be not too common. This is indeed the case as the probability of observing two transactions of the same size within a short period of

[12]Following Graf von Luckner et al. (2023), we begin our analysis in March 2017 when the LocalBitcoins changed its data format.

Figure 4: Matching off-chain transactions

This figure shows the modalities of off-chain Bitcoin transactions and the key assumptions for the matching.



time is extremely low. Second, market participants relying on Bitcoin as a vehicle to exchange fiat currencies must have incentives to minimize holding time given heightened price volatility. We follow Graf von Luckner et al. (2023) in choosing a five-hour window.[13]

Define n_i the number of times the transaction size x_i occurs within the five-hour window, N_i the total number of transactions within the five-hour window, and p_i the probability that transaction size x_i occurs in the data. Under the null hypothesis (H_0), transactions of the same size within a five-hour window are random matches:

$$H_{0,i} : \hat{\theta}_i^* > \Theta_o, \qquad i = 1, ..., I \tag{1}$$

where $P(n_i > 1|N_i) = \hat{\theta}_i^* \approx 1 - (1 - \hat{p}_i)^{N_i}$. We choose $\Theta_o = 0.05$, implying that the estimated matches represent a vehicle transaction with a 95 percent confidence level. Two matching transactions of size x_i are thus classified as a vehicle transaction, if

$$n_i > 1 \quad \text{and} \quad \hat{\theta}_i^* \leq \Theta_o \tag{2}$$

[13] LocalBitcoins charges a one percent fee, however, this fee does not affect the reported transaction amount and price.

There is a possibility that we miss some matches if transactions are apart longer than five hours. As highlighted by Graf von Luckner et al. (2023), this conservative window suggests that the matched transactions represent a lower bound estimate of crypto vehicle transactions. At the same time, some of the estimated crypto vehicle transactions are potentially false positive matches. We can compute the false positive rate by averaging $\hat{\theta}_i^*$ over the the identified vehicle transactions in our sample. This calculation suggests that 0.9 percent of our crypto vehicle transactions are random.

Our matching identifies 2.1 million crypto vehicle transactions. Reflecting the large number of currencies traded on decentralized P2P exchanges, we observe transactions in over 100 currencies. About 180 thousand transactions occur across two different fiat currencies (Table 4). Measuring cross-border Bitcoin flows based on decentralized P2P exchanges such as LocalBitcoins has advantages but also some potential drawbacks. On the one hand, the identification of residency through fiat currency is straightforward. On the other hand, transactions from individual decentralized P2P exchanges are not fully representative as they capture only a share of the off-chain universe and preferences for different exchanges may differ across countries depending on regulation and other factors. In addition, the measurement of flows may be imprecise for transactions relying on globally dominant currencies such as the U.S. dollar.

Table 4: LocalBitcoins: matched cross-fiat transactions

This table shows the structure of the LocalBitcoins matched transactions. The dataset contains 187,701 cross-fiat transactions over March 15th, 2017–February 16th, 2023. One matched transaction involves two separate fiat-bitcoin transactions.

Time	Amount (BTC)	Sending currency	Receiving currency
15 Mar 2017 00:30:46	0.14079999	RUB	CAD
15 Mar 2017 00:46:37	0.51999998	GBP	NZD
...			
09 Nov 2021 06:56:14	0.00131279	KES	THB
...			
29 Aug 2022 04:18:47	0.00197678	CLP	PEN
...			
16 Feb 2023 07:33:38	0.00153023	BWP	NGN

Summary of Approaches to Measuring Bitcoin Cross-Border Flows

The three different approaches to measuring Bitcoin cross-border (cross-exchange) flows complement each other as they capture different types of flows and market participants (off chain vs. on chain) and rely on vastly different assumptions. Table 5 summarizes the Bitcoin flow datasets and the underlying assumptions to measure cross-border flows. It also recapitulates the pros and cons of each approach.

While we do not map exchanges to countries for the blockchain dataset, it serves as a useful starting point to build a deep understanding of transactions in the Bitcoin network and their key features, including pseudonymity and security. The Chainalysis dataset complements this transaction-level data by using web traffic on exchanges to establish the residency of the market participants. It benefits from information on many exchanges and a large share of the Bitcoin on-chain market volume. Nonetheless, country identification can be imprecise in cases where market participants use VPNs. Moreover, the approach assumes that transactions are, on average, equal across market participants in different countries which may impact the precision of the estimated cross-border flows. Finally, the LocalBitcoins dataset comes with the advantage of transaction-level data and a relatively long sample. The lack of representativeness of the broader Bitcoin off-chain market is a potential caveat. Moreover, the matching assumption is only valid for currencies which are not used in third countries.

Table 5: Overview of Bitcoin cross-border flows

This table provides an overview of the Bitcoin cross-border flows datasets, including the key assumptions to identify the residency of market participants and their pros and cons.

	Blockchain	Chainalysis	LocalBitcoins
Type	On chain	On chain	Off chain
Key assumptions		Web traffic = residency	Fiat currency = residency
Pros	Transaction-level data	Many exchanges	Transaction-level data
		Representative of on-chain volume	Relatively long sample
Cons	No country mapping	Imprecise for VPN use	Not representative of off-chain volume
		Web traffic assumption simplified	Imprecise for dominant currencies

3 Data and Stylized Facts of Bitcoin Cross-Border Flows

This section introduces the data for our empirical analysis and presents a set of novel stylized facts on both Bitcoin transactions and cross-border flows.

3.1 Bitcoin Cross-Border Flows and Capital Flows

To compare the determinants of Bitcoin cross-border flows to those of capital flows, we rely on two sources for high-frequency portfolio flows. First, we obtain portfolio flows from EPFR Global (EPFR) which measure net flows into investment funds (defined as purchases minus redemptions). EPFR flows are thus a proxy for investment fund flows. Second, we collect portfolio flows from the Institute of International Finance (IIF) which tracks flows for emerging markets based on national sources that are broadly in line with official Balance of Payments (BoP) data. The granularity of EPFR and IIF data allows us to explore heterogeneity between debt and equity inflows.

We aim to define Bitcoin cross-border flows in line with capital flows. For the LocalBitcoins dataset, an inflow corresponds to the flow of fiat money from the source to the destination with Bitcoin acting as the vehicle. The Chainalysis dataset captures the flow of Bitcoin from the source to the destination. To ensure comparability with the LocalBitcoins and capital flows datasets, we switch Chainalysis "inflows" and "outflows" in the subsequent analysis such that an inflow corresponds to the unobserved flow of the payment from the source to the destination.

Yet, Bitcoin cross-border flows and capital flows are not fully comparable. Both EPFR and IIF flows are conceptually comparable to gross inflows in a BoP sense, and we thus refer to them as inflows in the remainder of the paper. That is, non-resident purchases of domestic assets are netted against non-resident sales of domestic assets to compute gross inflows.[14] In contrast, the Bitcoin cross-border flow datasets provide an estimate of gross flows (we have both inflows and outflows) without any netting out.[15] Therefore, the estimated Bitcoin flows are not fully comparable to the observed portfolio inflows. As we discuss later, this conceptual difference may explain some of our findings.

We document three key stylized facts on Bitcoin transactions and cross-border flows. First, we zoom in on the transaction-level data from the blockchain and LocalBitcoins which show that

[14] Since EPFR inflows are based on dealer transactions, recorded inflows are not always consistent with the residency criteria used to record transactions in the BoP data. See Cerutti et al. (2019) on comparing BoP and EPFR data.

[15] In the IMF BoP methodology, Bitcoin-like crypto assets and digital tokens without counterpart liabilities are classified as produced non-financial assets since they are assets that do not constitute liabilities of an issuing counterparty. In this context, an inflow resulting from a sale of Bitcoin by a resident to a non-resident would be accounted as an export in official statistics. The BoP treatment is not relevant for our study which is just focusing on the direction of the flows.

on-chain transactions are, on average, significantly larger than off-chain transactions (Table 6). The average transaction size amounts to 13.3486 Bitcoin on the blockchain compared with 0.0178 Bitcoin on LocalBitcoins. To put this into perspective, at a Bitcoin price of US$10,000—the price of one Bitcoin in the summer of 2020—the average transaction amounts to US$133,486 on the blockchain compared with US$178 on LocalBitcoins. Likewise, at the same Bitcoin price, the maximum transaction amounts to US$300,000,000 on the blockchain compared with US$1,875,000 on LocalBitcoins.[16] Our data also show that the average transaction size tends to decrease over time both for off-chain and for on-chain transactions. It is likely that this decline relates to the large increase in the price of Bitcoin over time. The difference in off-chain and on-chain transaction sizes may reflect distinct groups of market participants. Evidence suggests that circumvention of capital flow restrictions and transfers of remittances are major incentives behind cross-border off-chain transactions on P2P exchanges (Graf von Luckner et al., 2023). On-chain transactions, in contrast, may be more suitable for market participants moving larger sums of money with a preference for the security features that the blockchain provides. The fee structure for LocalBitcoins and on-chain transactions likely also plays a role: LocalBitcoins fees are based on transaction amounts whereas on-chain fees depend on the data volume of the transaction and desired speed.

Table 6: Key descriptives of transaction-level data

This table shows the key descriptives for the matched blockchain and LocalBitcoins transactions. For LocalBitcoins, one match based on two transactions is counted as a single transaction.

	Blockchain	LocalBitcoins
Number of matched transactions	1,632,049	2,107,509
Average transaction size (BTC)	13.3486	0.0178
Largest transaction size (BTC)	30,000.0	187.5
Number of currencies/exchange countries (destination)	86	104
Number of currencies/exchange countries (source)	78	106
out of which		
Number of cross-currency/exchange country transactions	592,218	182,204
Average transaction size (BTC)	8.6170	0.0205
Largest transaction size (BTC)	20,000.0	25.0
Number of currencies/exchange countries (destination)	86	94
Number of currencies/exchange countries (source)	75	100

[16] The blockchain and LocalBitcoins dataset time coverage in Table 6 are not equivalent (see Tables 2 and 4). When we restrict both samples to the overlapping period of March 2017–February 2020, the average (maximum) transaction size is 32.1284 (30,000) Bitcoin on the blockchain compared with 0.0204 (187.5) Bitcoin on LocalBitcoins.

Second, the use of Bitcoin for cross-border transactions is geographically widespread with relatively high intensities across regions both for off-chain and for on-chain flows. Figures 5 and 6 depict monthly Bitcoin inflows (as a share of average annual GDP) for the Chainalysis and LocalBitcoins datasets, respectively. The magnitude of inflows, relative to other countries, is particularly high in some Latin American countries such as Argentina and Venezuela which fall within the top inflow quartile both for Chainalysis and LocalBitcoins. We also observe relatively large inflows in a number of countries in Africa, Asia, and Eastern Europe. The relative intensity of inflows shows a broadly similar pattern for Chainalysis and LocalBitcoins inflows. Nevertheless, some differences stand out, including for Nigeria where LocalBitcoins played an important role.

Third, magnitudes of Bitcoin cross-border flows are sizeable in some countries, especially in those which experience small capital flows. Conversely, countries which tend to see relatively large capital flows (Figures 7 and 8), typically have lower Bitcoin flows. This is also shown in Figure 9 which plots Bitcoin inflows against EPFR inflows. The latter are the largest in advanced economies with sophisticated financial markets whereas Bitcoin flows are typically larger in emerging and developing markets. While this comparison focuses on investment fund inflows from EPFR rather than BoP portfolio inflows, it suggests that Bitcoin flows have so far not replaced existing capital flows. The upper quartile of 2019–2022 average monthly Chainalysis inflows ranges from 0.1–2.5 percent of average annual GDP compared with 0.01–0.1 percent for EPFR inflows and 0.07–0.4 percent for IIF inflows on average over 2017–2022. As discussed above, Bitcoin cross-border flows and capital flow are conceptually not fully comparable as Bitcoin flows are measured on a gross basis. This may partly explain the relatively high estimates for Chainalysis flows. LocalBitcoins flows are smaller in magnitude, reflecting that they capture transactions from a single exchange only. They can still be sizeable, however, for some countries with the upper quartile ranging from 0–1.7 percent of average annual GDP over 2017–2022. It is worth noting that the distribution of Bitcoin cross-border flows is skewed to the right with the Seychelles registering the largest monthly Chainalysis inflows of 2.5 percent of average annual GDP followed by Venezuela with 0.8 percent and Moldova with 0.7 percent on average over 2019-2022. Likewise, monthly LocalBitcoins inflows amounted to 1.7 percent of average annual GDP in Venezuela, followed by 0.0005 percent in Nigeria on average over 2017–2022.

Figure 5: Chainalysis cross-border Bitcoin inflows

This figure shows the average of 2019–2022 monthly cross-border Chainalysis inflows as a share of (2017–2022) average annual GDP. The four buckets represent the quartiles of the distribution.

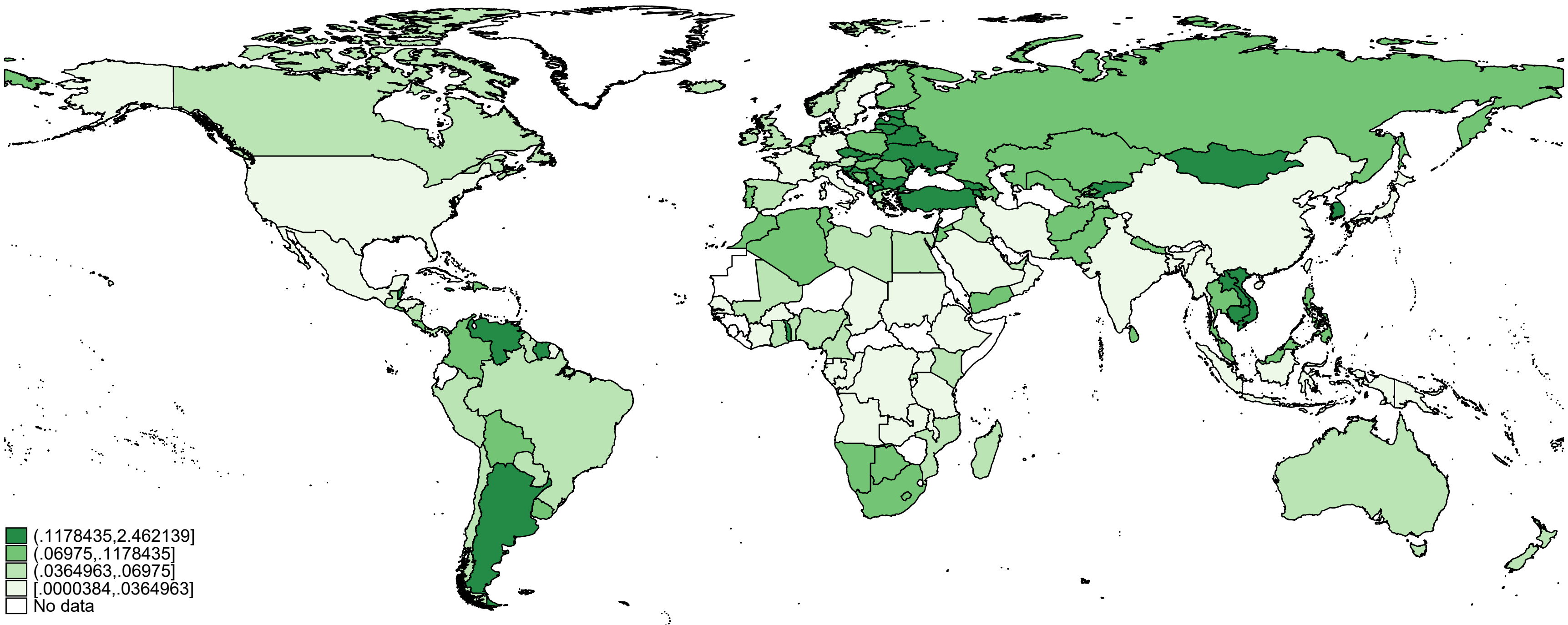


Figure 6: LocalBitcoins cross-border Bitcoin inflows

This figure shows the average of 2017–2022 monthly cross-border LocalBitcoins inflows as a share of average annual GDP. The four buckets represent the quartiles of the distribution. The dataset excludes euro area flows as we cannot allocate them to individual euro area countries.

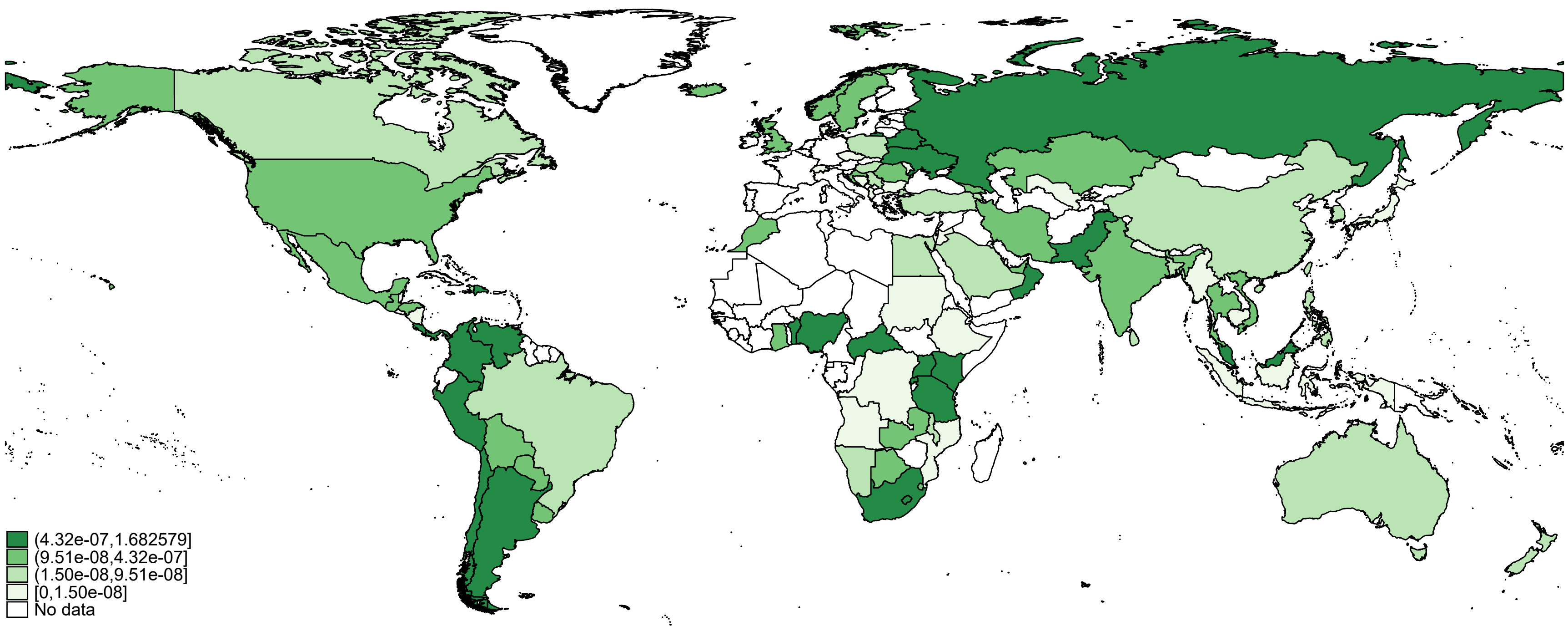


Figure 7: EPFR investment fund inflows

This figure shows the average of 2017–2022 monthly cross-border total (bond and equity) EPFR inflows as a share of average annual GDP. The four buckets represent the quartiles of the distribution.

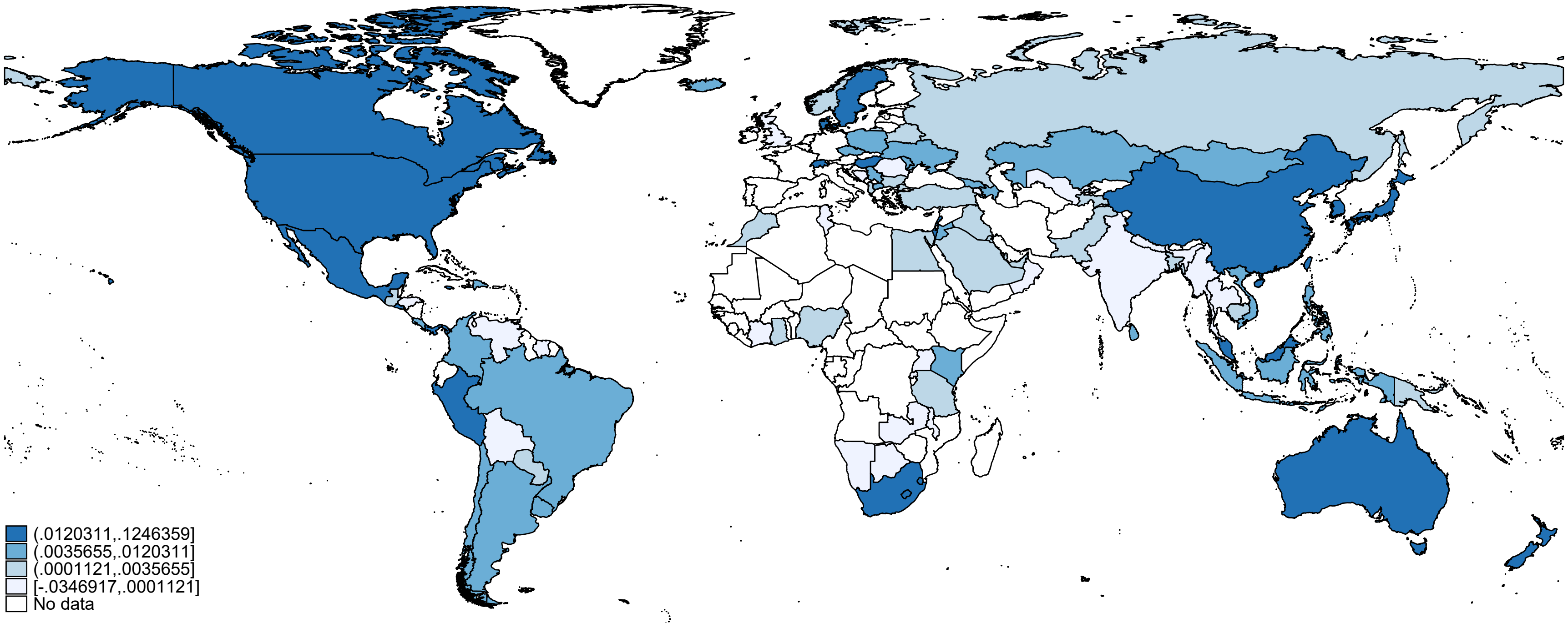


Figure 8: IIF portfolio inflows

This figure shows the average of 2017–2022 monthly cross-border total (debt and equity) IIF inflows as a share of average annual GDP. The four buckets represent the quartiles of the distribution.

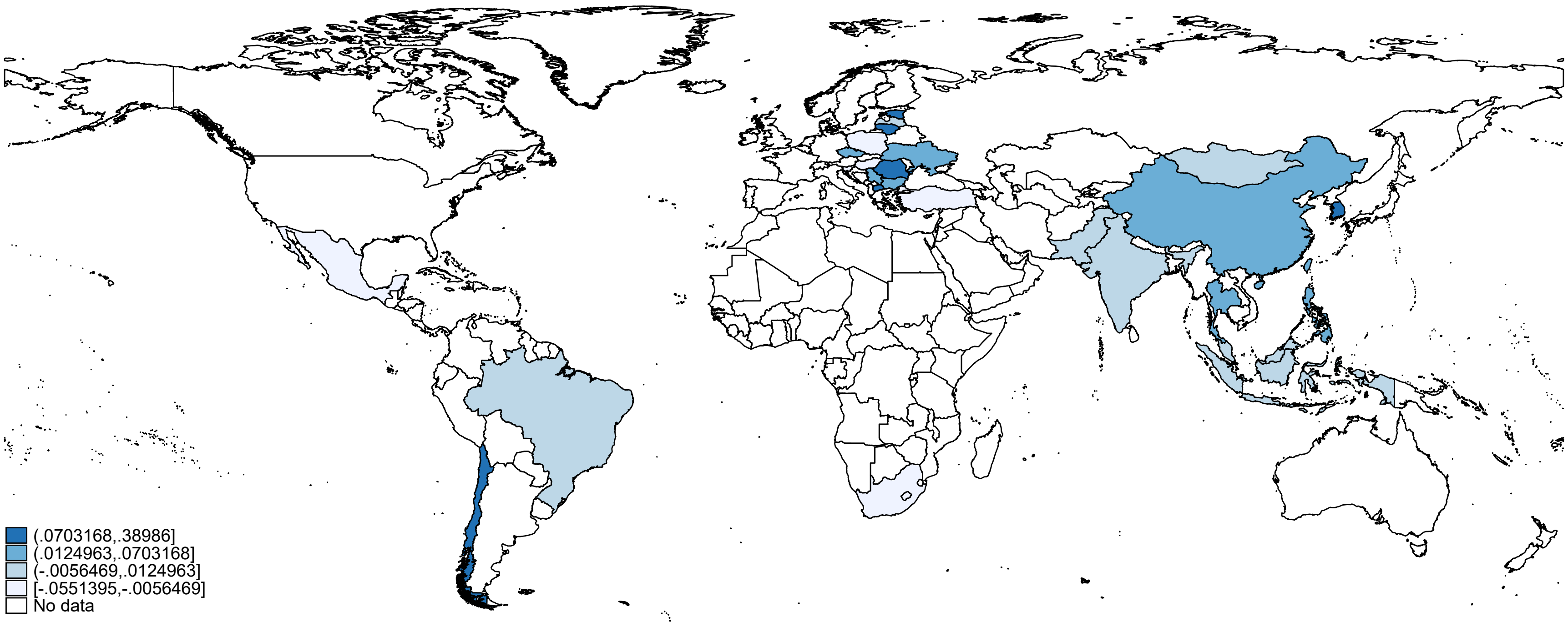
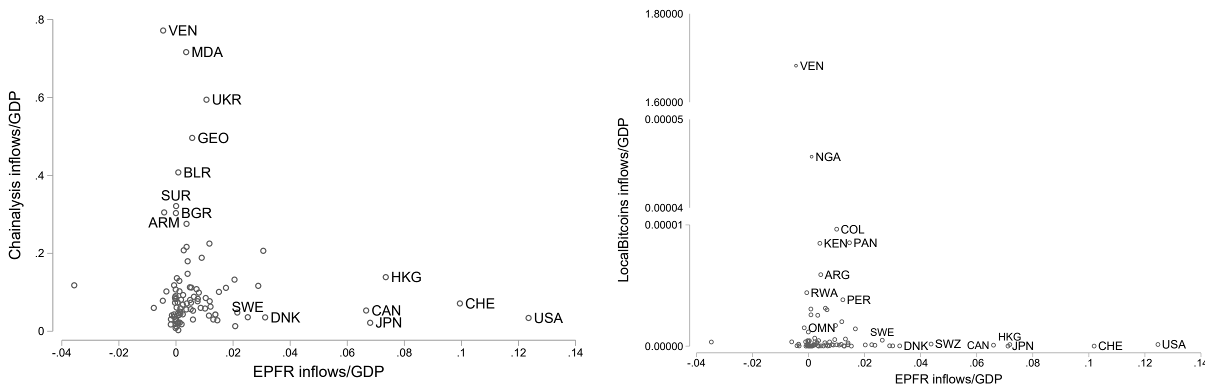


Figure 9: Bitcoin and EPFR inflows

The LHS figure shows the average of 2019–2022 monthly cross-border Chainalysis inflows as a share of (2017–2022) average annual GDP and the average of 2017–2022 monthly EPFR inflows as a share of average annual GDP. The RHS figure shows the average of 2017–2022 monthly cross-border LocalBitcoins inflows as a share of average annual GDP and the average of 2017–2022 monthly EPFR inflows as a share of average annual GDP.



3.2 Other Data

To explore the determinants of Bitcoin cross-border flows and capital flows, we collect data on global and domestic macro fundamentals. The set of global drivers consists of the VIX and the broad dollar index which proxy for global risk aversion (IMF, 2023b) and global financial conditions, respectively. As shown by Bruno and Shin (2014) and Obstfeld and Zhou (2023), the strength of the U.S. dollar has attributes akin to a barometer of dollar credit conditions, whereby a stronger dollar correlates with tighter global dollar credit conditions. In addition, we obtain information on inflation (year-over-year) and the interest differential to the U.S. (based on overnight rates) to study domestic drivers of cross-border flows.

Crypto flows may be driven not only by traditional fundamentals but also by developments which are specific to the crypto market. To explore this hypothesis, we add Bitcoin-specific global and domestic fundamentals to our set of controls. The crypto fear & greed index captures crypto-specific sentiment by summarizing Bitcoin volatility, market momentum, social media interest, dominance vis-à-vis the rest of the crypto market, and Google Trends.[17] Sentiment in the crypto market can range from extreme fear (corresponding to a value of zero) to extreme greed (cor-

[17]See Crypto Fear & Greed Index for further details.

responding to a value of 100). An increase in the crypto fear & greed index thus implies an improvement in crypto-specific sentiment. Moreover, similar to Graf von Luckner et al. (2023), we compute a country-specific measure of a parallel rate premium based on Bitcoin transaction prices. Specifically, we define the parallel rate premium as the percent deviation between the average local currency–U.S. dollar exchange rate on LocalBitcoins and the official exchange rate.[18]

4 Empirical Analysis

An important question is whether Bitcoin cross-border flows behave in a similar fashion to capital flows. We thus explore the drivers of Bitcoin cross-border flows and compare them with those of capital flows. We focus on both traditional drivers of capital flows and Bitcoin-specific drivers.

4.1 Empirical Strategy

We study the role of global and domestic factors, similar to a longstanding body of work on the determinants of capital flows (among others, Cerutti et al., 2019; Forbes and Warnock, 2012; Fratzscher, 2012; Milesi-Ferretti et al., 2011). Our analysis considers both traditional drivers and well as Bitcoin-specific drivers. We estimate the following baseline specification at a monthly frequency using a panel OLS estimation as a starting point:

$$Y_{c,t} = \alpha Y_{c,t-1} + \Gamma_1 \text{GLOBAL}_t + \Gamma_2 \text{DOMESTIC}_{c,t} + \eta_{c,y} + e_{c,t} \tag{3}$$

where $Y_{c,t}$ represents alternatively Bitcoin cross-border flows or capital flows in country c in month t. We scale local currency cross-border/capital flows by average GDP over 2017–2022 to capture the dynamics of the average country in our sample. Next, we divide flows-to-GDP by their standard deviation[19]. The dependent variable is the resulting ratio scaled by 10^6. The set of global factors includes the VIX, the broad dollar index, and the crypto fear & greed index. Domestic factors

[18]Due to some data gaps, we interpolate missing values to have longer time series. We truncate the resulting series at zero. When available, we compared the local currency–U.S. dollar exchange rate from LocalBitcoins and a parallel market exchange rate series (e.g., for Argentina). The two series are highly correlated, suggesting that both capture domestic macroeconomic imbalances.

[19]We calculate the standard deviation for the sample starting in 2017m1 or later, depending on data availability.

include inflation, the interest rate differential to the U.S., and the Bitcoin parallel rate premium. Our specification includes country-year fixed effects, $\eta_{c,y}$, to control for time-invariant and slow-moving domestic factors.

While the first real-world Bitcoin transaction took place in 2010, most market participants started learning about Bitcoin and engaged in transactions only later in the decade. Our baseline sample starts in 2017m3 which corresponds to the start of our LocalBitcoins dataset and the time around which Bitcoin began to gain mainstream acceptability. Due to limited data availability, the Chainalysis sample starts in 2019m4. Appendix A details the countries included in the Chainalysis, LocalBitcoins, EPFR and IFF samples. Our sample does not include the U.S. since we compute the interest differential relative to the U.S, and also because the LocalBitcoins key assumption to identify the residency of market participants may not be precise for Bitcoin-U.S. dollar transactions.

Finally, to ensure that Nickell bias stemming from the dynamic panel specification does not drive our results, Appendix B presents a robustness analysis using difference GMM.

4.2 Results

We begin our analysis by focusing on traditional global and domestic determinants of capital flows. We estimate the following model:

$$\begin{aligned} Y_{c,t} = \alpha Y_{c,t-1} + \beta_1 \text{VIX}_t + \beta_2 \text{Broad dollar}_t + \\ \beta_3 \text{Inflation}_{c,t} + \beta_4 \text{Interest differential}_{c,t} + \eta_{c,y} + e_{c,t} \end{aligned} \tag{4}$$

where $Y_{c,t}$ corresponds to alternatively flows from Chainalysis, LocalBitcoins, EPFR, or IIF, and all other variables are defined as in Equation (3).

Table 7 shows that global risk aversion—as proxied by the VIX—and broad dollar movements are key drivers of portfolio flows. An increase in the VIX and a strengthening of the U.S. dollar lead to lower EPFR inflows (columns 5 and 6) and IIF inflows (columns 7 and 8) both for debt and equities. The broad dollar also plays a significant role for Chainalysis flows (columns 1 and 2). We do not find any significant impact of global drivers on the dynamics of LocalBitcoins flows (columns 3 and 4). This finding may relate to the fact that the off-chain and on-chain datasets capture different market participants. As discussed above, LocalBitcoins transactions are smaller on average, likely reflecting transaction motives such as sending remittances or evading capital flow restrictions. Flows may therefore not be as closely linked to traditional drivers of capital flows.

Among domestic factors, we find that higher inflation results in lower portfolio flows but does not affect Bitcoin flows. An increase in the interest rate relative to the U.S. seems to be associated with lower LocalBitcoins inflows, but this result is not robust as shown below. Moreover, the interest rate differential does not appear to determine Chainalysis flows or portfolio flows. This finding may be partially driven by the synchronization of global monetary policy cycles during a large part of our sample.

Next, we add Bitcoin-specific drivers to our analysis. These allow us to study whether sentiment in the Bitcoin market as well as the Bitcoin-based parallel rate premium impact cross-border flows. We estimate the following specification:

$$\begin{aligned} Y_{c,t} = \alpha Y_{c,t-1} + \beta_1 \text{VIX}_t + \beta_2 \text{Broad dollar}_t + \beta_3 \text{Crypto fear\&greed}_t + \\ \beta_4 \text{Inflation}_{c,t} + \beta_5 \text{Interest differential}_{c,t} + \beta_6 \text{BTC parallel premium}_{c,t} + \eta_{c,y} + e_{c,t} \end{aligned} \tag{5}$$

where Crypto fear&greed$_t$ reflects the crypto fear & greed index, BTC parallel premium$_{c,t}$ captures the Bitcoin-based measure of the parallel rate premium, and all other variables are defined as in Equation (4).

The results in Table 8 suggest that increases in the VIX and broad dollar continue to negatively impact EPFR and IIF portfolio inflows (columns 5–8). While the effect of the broad dollar on Chainalysis flows remains negative but is no longer significant, we find that the VIX now plays a role (columns 1 and 2). An increase in the VIX is associated with higher Chainalysis inflows and outflows. This significant, positive response may reflect increased activity via the Bitcoin market as investors move away from other, traditional risky assets.[20] Likewise, an improvement in sentiment in the crypto market is associated with higher Chainalysis flows. Interestingly, better crypto sentiment is also associated with higher IIF equity inflows (column 8).

Domestic drivers appear more relevant for off-chain flows. We find that a higher interest rate differential to the U.S. is associated with higher LocalBitcoins inflows, in line with the traditional

[20] This finding is in line with the literature analyzing the interconnectedness between crypto assets and traditional financial assets. See Adrian et al. (2022) and Iyer and Popescu (2023).

view that flows are determined, among other factors, by relative interest rates. Nevertheless, the interest rate differential does not appear to determine EPFR or IIF flows in our sample. An increase in the parallel premium is associated with higher LocalBitcoins outflows (column 4). This finding indicates that Bitcoin may be used to circumvent capital controls. Supporting the idea that the Bitcoin-based measures of the parallel rate premium is a useful proxy for broader exchange rate pressures (see Graf von Luckner et al., 2023), an increase in the Bitcoin parallel premium also matters for portfolio flows, resulting in lower IIF equity inflows. Finally, an increase in inflation is associated with lower EPFR inflows and, somewhat puzzling, with lower LocalBitcoins outflows, but these trends are not robust across specifications as shown below.

In addition to the opposite impact of the VIX on Bitcoin flows and capital flows, it is also interesting that the (absolute) magnitude of the response to a change in the VIX is larger for capital flows than for Bitcoin flows.[21] Monthly EPFR and IIF inflows decline in the range of 0.2–0.7 standard deviations in response to a one standard deviation increase in the VIX.[22] Chainalysis inflows and outflows increase by 0.05 standard deviations in response to a one standard deviation increase in the VIX. This is not the case for the Bitcoin parallel premium. A one standard deviation increase in the Bitcoin parallel premium is associated with a 0.04 standard deviation increase in LocalBitcoins outflows and a 0.03 standard deviation decline for IIF equity inflows, respectively.

Overall, our analysis suggests that Bitcoin cross-border flows respond differently than capital flows to traditional drivers. The response of EPFR and IIF inflows is in line with our expectations. That is, we find that an increase in risk aversion and a strengthening of the dollar lead to lower inflows. Unlike capital flows, Chainalysis flows respond positively to changes in the VIX. This result appears in line with the positive correlation of the VIX and Bitcoin returns as broadly highlighted in the literature (e.g., Bariviera and Merediz-Solà, 2021; Bouri et al., 2017). Chainalysis flows are also positively correlated with crypto sentiment. While the role of global fundamentals appears limited for LocalBitcoins flows, we find a significant increase in outflows in response to a higher Bitcoin parallel rate premium.

Finally, we explore whether global drivers determine blockchain cross-exchange flows by esti-

[21] As previously noted, flows refer to monthly flows scaled by average annual GDP.

[22] We calculate the magnitude of the response by dividing the estimated coefficient by 100 and multiplying with the standard deviation of the regressor.

mating the following model:

$$Y_{e,t} = \alpha Y_{e,t-1} + \beta_1 \text{VIX}_t + \beta_2 \text{Broad dollar}_t + \beta_3 \text{Crypto fear\&greed}_t + \eta_{e,y} + e_{e,t} \tag{6}$$

where $Y_{e,t}$ corresponds to flows in exchange e at time t, $\eta_{e,y}$ are exchange-year fixed effects, and all other variables are defined as in Equation (5). The results in Table 9 suggest that an increase in the broad dollar lowers cross-exchange Bitcoin inflows and outflows. We interpret this result with caution as cross-exchange flows do not allow controlling for domestic factors.

4.3 Robustness Checks

To ensure that our results are not driven by Nickell bias stemming from the dynamic panel estimation, we implement a GMM estimation. We decide to employ a difference GMM estimator rather than a system GMM estimator based on the Bond et al. (2001) rule of thumb. Table B.1 shows that the results on the global drivers remain very similar and qualitatively unchanged. Among the domestic drivers, the impact of an increase in the Bitcoin parallel rate premium remains positive and significant for LocalBitcoins outflows and negative for IIF inflows. The results for inflation and the interest rate differential are not robust as suggested by the negative relationship between the interest differential and LocalBitcoins inflows and the insignificance of the coefficient on inflation for LocalBitcoins outflows.

We also explore whether there is any difference between Bitcoin cross-border flow values (the amount of Bitcoin times the average global Bitcoin price[23]) and Bitcoin cross-border flow volumes (the amount of Bitcoin). First, we use Bitcoin volumes as our dependent variable (Table C.2, columns 1–4). Second, we use Bitcoin values as the dependent variable (as we do in our baseline regressions) but control for the global Bitcoin price (Table C.2, columns 5–8). Our results are broadly similar to the baseline results in Table 8 for both approaches and are in fact unchanged when we control for the Bitcoin price (columns 5–8). For the volume regressions (columns 1–4), the VIX remains significant for Chainalysis flows while the broad dollar remains insignificant. The crypto fear&greed index is not significant. On the domestic side, the interest differential to the

[23]The global Bitcoin price may differ from the local Bitcoin prices at which LocalBitcoins transactions are made.

U.S. continues to be significant for LocalBitcoins inflows. As expected, an increase in inflation is associated with lower LocalBitcoins inflows, while the negative impact on outflows is no longer significant. Finally, the BTC parallel rate premium is not significant for LocalBitcoins volume outflows but instead turns significant for Chainalysis volume flows.

5 Conclusion

The adoption of Bitcoin has grown rapidly over the last decade. The global nature of Bitcoin raises questions about the relative importance and characteristics of Bitcoin cross-border flows. The sheer amount of Bitcoin transactions both on the blockchain and outside the blockchain as well as their pseudonymous nature complicate the task of studying cross-border flows facilitated by Bitcoin.

In this paper, we use three complementary datasets to obtain a comprehensive picture of global Bitcoin transactions and cross-border flows for a large set of countries. We explain the modalities of the underlying cross-border transactions and discuss the pros and cons of the assumptions needed to proxy the residencies of Bitcoin users. Based on these Bitcoin cross-border flow datasets, we show that the use of Bitcoin for cross-border transactions is geographically very widespread, with relatively high intensities across regions both for off-chain and for on-chain flows, and some punctual differences driven by the underlying data coverage and estimation assumptions. The magnitudes of the estimated Bitcoin cross-border flows are sizeable with respect to several countries' GDP, especially in those which experience smaller capital flows.

Our analysis highlights some differences between on-chain and off-chain Bitcoin cross-border flows. Cross-border on-chain transactions are, on average, considerably larger than off-chain transactions. Off-chain data also suggest that an increase in a Bitcoin-based measure of the parallel rate premium is associated with higher outflows. These findings are in line with a recent body of work suggesting that Bitcoin facilitates the circumvention of capital flow restrictions (Graf von Luckner et al., 2024, 2023; Hu et al., 2021). As highlighted by IMF (2023a), policymakers aiming to manage capital flows should ensure that capital flow management regulations cover crypto assets. From a more structural perspective, it is certainly also important to address the underling imbalances which manifest in exchange rate pressures, since the usage of crypto assets would represent just symptoms of the imbalances.

We also show that countries with relatively large capital inflows tend to have lower Bitcoin inflows, and vice versa. Moreover, Bitcoin cross-border flows respond differently than capital flows to traditional drivers. On-chain flows seem to be negatively correlated with broad dollar appreciation events, but unlike capital flows, they react positively to changes in the VIX. While capital flows and Bitcoin cross-border flows are—due to methodological differences—not directly comparable, we conjecture that Bitcoin cross-border flows have at this point not yet replaced existing capital flows. Capital flows thus remain the most important quantitative channel for the transmission of global spikes in risk aversion and/or flight to safety triggers. Yet, crypto markets are evolving fast. The recent authorization of spot Bitcoin ETFs in the U.S. indicates that Bitcoin may increasingly be used—even if indirectly—by more mainstream financial operators. This and other potential future Bitcoin developments could make the response of Bitcoin cross-border flows more similar to traditional capital flows, as the average user bases for both types of assets get closer. This user convergence could certainly complicate policy responses.

Reflecting the decentralized and pseudonymous technology facilitating crypto transactions, measuring Bitcoin cross-border flows is challenging, and currently only possible with a series of non-trivial assumptions. Although we provide a comprehensive approach exploring both on-chain and off-chain flows to study global cross-border flows, our datasets do not capture the entire universe of Bitcoin cross-border transactions. Improvements in the measurement of flows and identification of the residency both for on-chain and for off-chain cross-border flows—based on transaction level data—are thus key for gaining a deeper understanding of Bitcoin cross-border dynamics and for evaluating the need for and designing adequate policy responses in the future.

Table 7: Traditional global and domestic drivers of capital flows

	(1) CA in	(2) CA out	(3) LB in	(4) LB out	(5) EPFR bond in	(6) EPFR equity in	(7) IIF debt in	(8) IIF equity in
Global drivers								
VIX	0.47	0.48	0.02	0.03	-8.52***	-2.09***	-1.99***	-3.05***
	[0.346]	[0.359]	[0.100]	[0.225]	[2.411]	[0.660]	[0.324]	[1.002]
Broad dollar	-2.20**	-2.15**	-0.01	-0.25	-1.72	-5.25***	-2.24*	-0.68
	[0.857]	[0.880]	[0.229]	[0.640]	[1.456]	[1.637]	[1.144]	[2.874]
Domestic drivers								
Inflation	-0.02	-0.03	-0.29	-1.74	-0.41	-0.32*	0.04	-0.67***
	[0.024]	[0.028]	[0.475]	[1.074]	[0.381]	[0.166]	[0.211]	[0.135]
Interest differential	0.07	0.04	-1.74***	-0.33	0.96	0.76	-2.18	3.75
	[0.359]	[0.397]	[0.547]	[0.436]	[0.866]	[0.742]	[2.956]	[3.074]
Observations	1,741	1,741	2,098	2,098	2,630	2,630	917	1,159
R2	0.86	0.85	0.93	0.70	0.37	0.47	0.25	0.20

Robust standard errors in brackets
*** p<0.01, ** p<0.05, * p<0.1

Notes: We scale monthly flows by country-level average annual GDP. Next, we divide flows-to-GDP by their standard deviation. The dependent variable is the resulting ratio scaled by 100. CA in columns 1–2 refers to Chainalysis while LB in columns 3–4 refers to LocalBitcoins. All columns control for the lagged dependent variable and country-year fixed effects. All regressions are estimated with double clustered standard errors at the country and month level.

Table 8: Traditional and Bitcoin-specific global and domestic drivers of capital flows

	(1) CA in	(2) CA out	(3) LB in	(4) LB out	(5) EPFR bond in	(6) EPFR equity in	(7) IIF debt in	(8) IIF equity in
Global drivers								
VIX	0.66***	0.67***	0.02	0.09	-8.98***	-2.52***	-2.26***	-2.30*
	[0.22]	[0.23]	[0.07]	[0.23]	[2.55]	[0.81]	[0.72]	[1.10]
Broad dollar	-0.55	-0.54	0.41	0.48	-0.52	-5.67***	-2.55*	-1.45
	[1.05]	[1.09]	[0.32]	[0.77]	[1.92]	[1.69]	[1.25]	[4.30]
Crypto fear&greed	0.54***	0.52**	0.04	0.14	0.28	0.27	0.04	0.77**
	[0.19]	[0.20]	[0.03]	[0.15]	[0.30]	[0.22]	[0.32]	[0.32]
Domestic drivers								
Inflation	-0.61	-0.58	-2.22	-3.62*	-9.98*	-5.42*	-6.11	2.17
	[0.86]	[0.84]	[1.57]	[1.88]	[5.38]	[2.72]	[4.37]	[5.14]
Interest differential	0.91	0.90	2.53**	0.65	3.32	2.37	3.05	1.67
	[0.62]	[0.63]	[1.23]	[0.85]	[2.34]	[1.70]	[4.25]	[5.94]
BTC parallel premium	-0.04	-0.04	-0.01	0.06**	-0.03	0.02	-0.48	-0.05**
	[0.11]	[0.12]	[0.01]	[0.03]	[0.02]	[0.02]	[0.38]	[0.02]
Observations	929	929	1,253	1,253	1,221	1,221	531	629
R2	0.88	0.87	0.93	0.80	0.33	0.40	0.24	0.21

Robust standard errors in brackets
*** p<0.01, ** p<0.05, * p<0.1

Notes: We scale monthly flows by country-level average annual GDP. Next, we divide flows-to-GDP by their standard deviation. The dependent variable is the resulting ratio scaled by 100. CA in columns 1–2 refers to Chainalysis while LB in columns 3–4 refers to LocalBitcoins. All columns control for the lagged dependent variable and country-year fixed effects. All regressions are estimated with double clustered standard errors at the country and month level.

Table 9: Traditional and Bitcoin-specific global drivers of cross-exchange and cross-country flows

	(1) Blockchain in	(2) Blockchain out	(3) EPFR bond in	(4) EPFR equity in	(5) IIF debt in	(6) IIF equity in
Global drivers						
VIX	-0.08	-0.01	0.00	0.00	-0.02	0.00
	[0.077]	[0.056]	[0.022]	[0.021]	[0.015]	[0.018]
Broad dollar	-0.23**	-0.12**	-0.17***	-0.14***	0.02	-0.04
	[0.082]	[0.050]	[0.059]	[0.031]	[0.024]	[0.027]
Crypto fear&greed	-0.01	0.01	0.00	0.01***	-0.00	0.01
	[0.016]	[0.020]	[0.005]	[0.004]	[0.005]	[0.005]
Observations	243	259	1,852	1,573	460	460
R2	0.51	0.73	0.92	0.94	0.81	0.85

Robust standard errors in brackets
*** p<0.01, ** p<0.05, * p<0.1

Notes: Blockchain flows are transformed to ln USDt. EFPR and IIF flows are transformed to ln USD. All columns control for the lagged dependent variable. Columns 1–2 control for exchange-year fixed effects while columns 3–7 control for country-year fixed effects. Columns 1–2 are estimated with double clustered standard errors at the exchange and month level and columns 3–7 are estimated with double clustered standard errors at the country and month level.

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Appendix

A Regression sample

To ensure that our empirical analysis covers the largest number of countries possible, we include all countries for which we have data on cross-border flows and regressors in our sample. The sample for the Chainalysis, LocalBitcoins, EPFR, and IIF regressions are thus somewhat different. We choose to keep the larger, although different, samples to ensure our results are not driven by the selection of countries.

Sample for the regressions presented in Table 7

Chainalysis (43 countries): Bahrain, Belarus, Brazil, Canada, Chile, China, Colombia, Croatia, Egypt, Hong Kong, Hungary, Iceland, India, Israel, Japan, Jordan, Korea, Lebanon, Malaysia, Mauritius, Mexico, Morocco, Namibia, Nigeria, Norway, Oman, Paraguay, Poland, Qatar, Russia, Saudi Arabia, Serbia, South Africa, Sri Lanka, Sweden, Switzerland, Tanzania, Trinidad & Tobago, Tunisia, Turkey, Uganda, U.K., Vietnam.

LocalBitcoins (41 countries): Belarus, Brazil, Bulgaria, Canada, Chile, China, Colombia, Croatia, Egypt, Hong Kong, Hungary, Iceland, India, Indonesia, Israel, Japan, Korea, Malaysia, Mauritius, Mexico, Morocco, Namibia, Nigeria, Norway, Oman, Paraguay, Poland, Qatar, Russia, Saudi Arabia, Serbia, South Africa, Sri Lanka, Sweden, Switzerland, Tanzania, Trinidad & Tobago, Turkey, Uganda, U.K., Vietnam.

EPFR (46 countries): Bahrain, Belarus, Brazil, Bulgaria, Canada, Chile, China, Colombia, Egypt, Hong Kong, Hungary, Iceland, India, Indonesia, Israel, Japan, Jordan, Korea, Lebanon, Malaysia, Mauritius, Mexico, Morocco, Namibia, Nigeria, North Macedonia, Norway, Oman, Paraguay, Poland, Qatar, Russia, Saudi Arabia, Serbia, South Africa, Sri Lanka, Sweden, Switzerland, Tanzania, Trinidad & Tobago, Tunisia, Turkey, Uganda, U.K., Vietnam, Zambia.

IIF (20 countries: Brazil, Bulgaria, Chile, China, Hungary, India, Indonesia, Korea, Lebanon, Malaysia, Mexico, North Macedonia, Poland, Qatar, Saudi Arabia, Serbia, South Africa, Sri Lanka, Turkey, Vietnam.[24]

Sample for the regressions presented in Table 8

Chainalysis (29 countries): Belarus, Brazil, Canada, Chile, China, Colombia, Egypt,Hungary, India, Korea, Malaysia, Mexico, Morocco, Nigeria, Norway, Paraguay, Poland, Russia, Saudi Araba, Serbia, South Africa, Sri Lanka, Sweden, Switzerland, Tanzania, Turkey, Uganda, U.K., Vietnam.

LocalBitcoins (30 countries): Belarus, Brazil, Canada, Chile, China, Colombia, Egypt, Hungary, India, Indonesia, Korea, Malaysia, Mexico, Morocco, Nigeria, Norway, Paraguay, Poland, Russia, Saudi Arabia, Serbia, South Africa, Sri Lanka, Sweden, Switzerland, Tanzania, Turkey, Uganda, U.K., Vietnam.

EPFR (29 countries): Belarus, Brazil, Canada, Chile, China, Colombia, Egypt, Hungary, India, Indonesia, Korea, Malaysia, Mexico, Morocco, Nigeria, Norway, Paraguay, Poland, Russia, Saudi Arabia, Serbia, South Africa, Sri Lanka, Sweden, Switzerland, Tanzania, Turkey, U.K., Vietnam.

IIF (16 countries): Brazil, Chile, China, Hungary, India, Indonesia, Korea, Malaysia, Mexico, Poland, Saudi Arabia, Serbia, South Africa, Sri Lanka, Turkey, Vietnam.[25]

[24] For equity flows. Debt flows exclude Qatar, Saudi Arabia, Sri Lanka, Vietnam.

[25] For equity flows. Debt flows exclude Saudi Arabia, Sri Lanka, Vietnam.

B GMM Estimation

Table B.1: Traditional and Bitcoin-specific global and domestic drivers of capital flows: GMM estimation

	(1) CA in	(2) CA out	(3) LB in	(4) LB out	(5) EPFR bond in	(6) EPFR equity in	(7) IIF debt in	(8) IIF equity in
Global drivers								
VIX	0.40***	0.36**	-0.04	-0.10	-7.36***	-1.79*	-2.57***	-2.89***
	[0.137]	[0.157]	[0.090]	[0.128]	[2.149]	[1.028]	[0.537]	[1.103]
Broad dollar	1.04	1.53*	-0.51	-0.17	-11.27	-15.00***	-5.39***	-4.13
	[0.774]	[0.899]	[0.806]	[1.193]	[7.272]	[3.711]	[1.331]	[4.884]
Crypto fear&greed	0.53***	0.52***	-0.03	-0.04	-0.10	0.62***	-0.40	0.41
	[0.127]	[0.126]	[0.093]	[0.131]	[0.403]	[0.191]	[0.301]	[0.302]
Domestic drivers								
Inflation	2.00	2.12	0.07	0.19	-1.99	-2.60	3.61	3.61
	[1.444]	[1.437]	[1.088]	[1.691]	[3.252]	[2.387]	[4.295]	[10.033]
Interest differential	0.69	0.54	-0.52**	0.35	0.34	-0.17	-0.44	-1.64
	[0.538]	[0.550]	[0.241]	[0.876]	[0.878]	[0.934]	[4.845]	[10.210]
BTC parallel premium	0.09	0.10	-0.01	0.17**	0.04	0.00	-4.23***	-0.06**
	[0.145]	[0.201]	[0.008]	[0.079]	[0.075]	[0.115]	[1.335]	[0.027]
Observations	879	879	1,190	1,190	1,162	1,162	491	585
Number of countries	29	29	30	30	29	29	13	16
p-value AR(2)	0.652	0.763	0.330	0.263	0.266	0.139	0.658	0.387
p-value Hansen test	0.323	0.255	0.0948	0.142	0.253	0.801	0.557	0.178

Robust standard errors in brackets
*** p<0.01, ** p<0.05, * p<0.1

Notes: We scale monthly flows by country-level average annual GDP. Next, we divide flows-to-GDP by their standard deviation. The dependent variable is the resulting ratio scaled by 100. CA in columns 1–2 refers to Chainalysis while LB in columns 3–4 refers to LocalBitcoins. All columns control for the lagged dependent variable and country-year fixed effects. All regressions are estimated with cluster robust standard errors.

C Exploring Bitcoin cross-border flow volumes

Table C.2: Traditional Bitcoin-specific global and domestic drivers of capital flows: volumes

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	CA in	CA out	LB in	LB out	CA in	CA out	LB in	LB out
Global drivers								
VIX	1.390***	1.401***	-0.012	-0.052	0.626***	0.624***	0.015	0.068
	[0.287]	[0.276]	[0.059]	[0.154]	[0.219]	[0.224]	[0.074]	[0.248]
Broad dollar	-0.617	-0.438	0.271	0.534	-0.276	-0.235	0.434	0.773
	[1.131]	[1.158]	[0.178]	[0.452]	[1.238]	[1.297]	[0.338]	[0.710]
Crypto fear&greed	0.036	0.040	0.011	-0.170	0.469***	0.445***	0.034	0.042
	[0.133]	[0.139]	[0.013]	[0.155]	[0.155]	[0.159]	[0.047]	[0.164]
BTC price					0.000	0.000	0.000	0.001
					[0.000]	[0.001]	[0.000]	[0.001]
Domestic drivers								
Inflation	1.471	1.426	-0.387*	-1.567	-0.559	-0.519	-2.201	-3.469*
	[1.052]	[1.077]	[0.226]	[1.260]	[0.835]	[0.800]	[1.550]	[1.899]
Interest differential	-0.130	-0.145	0.731**	-0.021	0.612	0.565	2.511**	0.470
	[0.595]	[0.582]	[0.328]	[0.328]	[0.465]	[0.445]	[1.225]	[0.898]
BTC parallel premium	0.511***	0.453***	0.002	-0.007	0.018	0.023	-0.006	0.065**
	[0.106]	[0.089]	[0.002]	[0.016]	[0.074]	[0.087]	[0.013]	[0.025]
Observations	929	929	1,253	1,253	929	929	1,253	1,253
R2	0.86	0.84	0.87	0.826	0.883	0.869	0.928	0.803

Robust standard errors in brackets
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Notes: We scale monthly flows by country-level average annual GDP. Next, we divide flows-to-GDP by their standard deviation. The dependent variable is the resulting ratio scaled by 100. CA in columns 1–2 and 5–6 refers to Chainalysis while LB in columns 3–4 and 7–8 refers to LocalBitcoins. Flows in columns 1–4 are volumes (the amount of Bitcoin) while flows in columns 5–8 are values (the amount of Bitcoin times the price). All columns control for the lagged dependent variable and country-year fixed effects. All regressions are estimated with double clustered standard errors at the country and month level.

PUBLICATIONS

A Primer on Bitcoin Cross-Border Flows: Measurement and Drivers

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