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*DeFi*ying Gravity? An Empirical Analysis of Cross-Border Bitcoin, Ether and Stablecoin Flows*

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Abstract

We investigate trends and drivers of cross-border flows of the two major native cryptoassets (Bitcoin and Ether) and the two major asset-backed stablecoins (Tether and USD Coin) between 184 countries from 2017 to 2024. These flows are substantial, peaking at around USD 2.6 trillion in 2021, with stablecoins accounting for close to half the volume. The unique bilateral data allow us to estimate the drivers of these flows in a gravity framework, and how they differ across different types of crypto assets. Our findings highlight speculative motives and global funding conditions as key drivers of native crypto asset flows. Transactional motives play a significant role in cross-border flows for stablecoins and low-value Bitcoin transactions, where we further find a strong association with higher costs of traditional remittances. Geographic barriers play a diminished role compared to traditional financial flows, and capital flow management measures appear ineffective.

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Keywords: Cryptocurrency; payments; cross-border flows; blockchain; decentralised finance; capital flow management; Bitcoin; Ether; USD Coin; Tether; stablecoins; remittances.

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1 Introduction

Gauging cryptoasset flows across borders remains a huge gap in international finance. The crypto and decentralised finance (DeFi) ecosystem has grown rapidly, spurred by speculation and rising acceptance of cryptoassets in mainstream finance. Cryptoassets are increasingly being integrated into exchange-traded funds, futures and other conventional financial instruments. However, despite total market capitalisation exceeding that of large national stock markets, the macroeconomic implications of cryptoassets – including their underlying use cases and risks during market turmoil – remain poorly understood. A key challenge is that cryptoassets operate on decentralised infrastructure transcending national boundaries, unlike conventional financial networks governed by intermediary institutions and established regulations. In this context, new types of often elusive intermediaries have emerged in crypto markets.

In this paper, we shed light on a key type of crypto flows: cross-border transactions. We investigate the trends and drivers of these flows using novel bilateral cross-country data covering both native cryptoassets and asset-backed stablecoins across up to 184 countries from Q1 2017 to Q2 2024. The data allow us to document the geography of crypto flows and to uncover the underlying drivers of crypto transactions across distinct cryptoassets. Specifically, the dataset encompasses Bitcoin (BTC), Ethereum's native asset Ether (ETH) and the two largest stablecoins by market capitalisation: Tether (USDT) and USD Coin (USDC). Including these heterogeneous cryptoassets makes it possible to capture distinct use cases.[1]

We begin by documenting the magnitude, time variation and geography of global crypto flows. Across the four cryptoassets, international flows reached a peak of US$ 2.6 trillion in 2021, roughly equivalent to 12% of global trade in goods at the time. Of this amount, US$ 1.2 trillion was accounted for by stablecoins. Although transaction volumes fell back to US$ 1.8 trillion in 2023, they have since resurged, indicating a continued, albeit uneven, expansion of the crypto ecosystem. We show that the United States, United Kingdom and major emerging markets represent key nodes in the different crypto networks. We also document significant geographical shifts in cross-border activity, particularly from China to other major emerging markets like India, Indonesia and Türkiye, amidst tighter crypto regulation in China. We find that network concentration varies across cryptoassets but is notably lower than for cross-border banking, whereas network density is considerably higher.

Building on a gravity framework as our analytical lens, we investigate various drivers to shed light on the multifaceted nature of cryptoassets' utility as both a speculative financial asset and a medium of exchange. Comparing with traditional financial flows

[1] For this analysis, we rely on two datasets that have been complied by commercial data providers and specify aggregated quarterly flows between major crypto exchanges. These entity-level flows are then allocated to individual countries based on statistics on the location of app usage or web traffic.

across borders and its determinants, we highlight the diminishing significance of geographical proximity in crypto flows, particularly for stablecoins, which appear to largely "defy" these traditional frictions. Concurrently, we observe that tighter global funding conditions, known to curtail risk-taking in traditional asset classes, are associated with reduced flows. This indicates increasing interconnectedness between cryptoassets as speculative assets and mainstream finance. Furthermore, we identify crypto market-specific risk factors alongside heightened public awareness of cryptoassets as strong drivers of crypto flows, illustrating cryptoassets' role for speculation.

Our analysis points to cryptoassets also being used as a transactional medium. This is most apparent for stablecoins and low-value BTC payments. Higher opportunity costs of fiat currency usage, such as high inflation, spur bilateral cross-border transactions in both unbacked cryptoassets and stablecoins. Likewise, greater economic activity within both sender and receiver countries is often linked to increased crypto flows in most cases. Moreover, high costs of remittance payments through traditional financial intermediaries are associated with significantly larger cross-border flows in stablecoins and low-value BTC payments from advanced economies to emerging market and developing markets.

Finally, on the efficacy of capital flow management measures (CFMs) governing cross-border transactions, our analysis suggests that CFMs targeting the reduction of outflows from the sender country and the limitation of inflows into the recipient country have little impact on crypto flows. Indeed, CFMs may even correlate with an increase in cross-border flows of some cryptoassets, hinting at circumvention.

Our contribution to the literature is twofold. First, we present a comprehensive dataset of the four most important cryptoassets, covering both the leading unbacked cryptoassets and stablecoins. This allows us to investigate differences and commonalities across drivers of cross-border crypto flows, indicative of the varied use cases of different cryptoassets.

In doing so, our analysis of the global network of cross-border flows in cryptoassets expands the scope fo prior research focussing on individual market segments. Measurement of cross-border crypto flows can be done based on off-chain transactions (e.g. through external channels like exchanges) or on-chain transactions (i.e. directly on the blockchain). Our work complements analysis in von Luckner et al. (2023), who explore off-chain BTC activity using data from two peer-to-peer crypto exchanges. Their findings suggest usage of BTC for remittances and evading capital controls, resonating with our on-chain data results. We broaden the analysis by assessing on-chain flows, which are several orders of magnitude larger, and including additional cryptoassets. The addition of stablecoins is particularly relevant since these serve different use cases than unbacked cryptoassets.[2]

[2] von Luckner et al. (2023) identify cross-border flows by the fiat currency used in the transaction to determine origination and destination. Fiat currencies approximate locations reasonably well for emerging market currencies but are less suitable for global currencies like the US dollar. Weighting business entity flows in our approach gauges global user engagement, including for the United States,

Our work also complements related studies of on-chain BTC activity.[3] We show that on-chain cross-border flows are negatively related to broad dollar appreciation but react positively to changes in global risk aversion. One of our datasets includes BTC flows categorised by transaction sizes, which allow us to examine the role of cryptoassets as a potential alternative to low-value remittances processed by traditional financial intermediaries. Leveraging the richness of the two datasets, we assess drivers and policy measures affecting the network of directional bilateral flows between countries.

Our second contribution leverages the unique bilateral nature of the data, which allows for a novel empirical approach to uncover drivers of bilateral relations.[4]

We unpack the key drivers of bilateral cross-border crypto transactions, drawing a comparison with the established determinants of traditional flows, namely, trade in goods, interbank lending and remittances. In this regards, our paper combines insights from the literature on international capital flows (e.g. Coppola et al., 2021, Miranda-Agrippino and Rey, 2020, Hoffmann et al., 2019 and Forbes and Warnock, 2012) and on global factors (e.g. Obstfeld and Zhou, 2023 and Bruno and Shin, 2015) and in applications of gravity models to finance (e.g. Badarinza et al., 2022, Brei and von Peter, 2018, and Portes et al., 2001). By examining crypto-specific drivers, we link our paper to the research in Pagnotta (2022), Liu and Tsyvinksi (2021) and, in particular, Liu et al. (2022), who identify a set of factors specific to crypto markets that help predict returns. We provide a detailed discussion of determinants and respective data sources in Section 2.2.

Moreover, we provide two specific applications that build on bilateral flow data: a comparison to traditional remittances and an assessment of the impact of CFMs. In this regard, our findings contribute to the literature on remittance flows, as discussed among others by Yang (2011) and in the context of financial development by Aggarwal et al. (2011). In a similar empirical vein to work on remittances by Lueth and Ruiz-Arranz (2008), we employ a gravity framework leveraging bilateral flows. We estimate determinants of crypto flows likely to reflect remittances. In particular, we find signs that crypto transactions emerge as a substitute for remittance payments. Country corridors

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one of the largest crypto markets.

[3] See, for example, Makarov and Schoar, 2021 for an analysis of the BTC network at the entity level, and Cerutti et al. (2024), who explore cross-border BTC inflows and outflows at the country level to examine differences in on-chain and off-chain flow patterns. Cardozo et al. (2024) explore global crypto flows and associated measurement challenges.

[4] From a broader perspective, our paper also relates to the growing body of literature on the economics of cryptoassets. Böhme et al. (2015) provide a comprehensive overview of BTC's economic significance. Athey et al. (2016) investigate early adoption and usage patterns, predicting that an increase in users correlates with a rise in BTC's price. Halaburda et al. (2022) provide an overview of the literature, focusing on the microeconomics of cryptoassets including drivers of trading and pricing. Using a theoretical model, Hinzen et al. (2022) demonstrate that BTC's limited adoption is an equilibrium outcome resulting from its design. Another strand of literature focuses on the returns and pricing of BTC. Schilling and Uhlig (2019b), for example, analyse BTC pricing and its implications for monetary policy within a currency competition model. Biais et al. (2023) develop a framework to model BTC prices in relation to transactional benefits and extrinsic volatility.

characterised by high remittance costs or slow processing exhibit larger cryptoasset flows. This relationship is more pronounced for stablecoins than for unbacked cryptoassets. It is also more pronounced for low-value BTC transfers than for large value ones (BTC is the only cryptoasset for which we have data by transaction bands).

Our findings on the ineffectiveness of CFMs resonate with prior research on traditional capital flows (e.g. Forbes et al., 2015) and associated risks of policy circumvention (e.g. Cerutti et al., 2017). They also relate to the nascent literature on the impact of policy measures on crypto activity. Hu et al. (2023) estimate that capital flight accounts for over one-quarter of Chinese BTC exchange volume, with transactions motivated by circumvention of restrictions on capital outflows rather than trade in illegal goods or services. Other studies infer the impact of capital controls from the persistence of arbitrage opportunities across BTC markets (e.g. Makarov and Schoar, 2021, Choi et al., 2022).

The remainder of this paper is organised in four sections. In Section 2, we map out global crypto flows, discuss their key characteristics, and identify potential drivers to guide our selection of control variables. Section 3 details the key specifications of the gravity equations central to our empirical approach. Section 4 presents the results, starting with gravity and global drivers, moving to country-specific drivers and a comparative analysis of remittances, and concluding with an assessment of the impact of policy interventions on crypto flows. Section 5 concludes.

2 Global crypto maps and underlying drivers

2.1 Cross-border crypto flows

Mapping cryptoasset flows to countries presents a unique challenge for two reasons. First, addresses in borderless blockchain networks are public but the ultimate owners are unknown, making them "pseudonymous". Second, entities such as crypto exchanges operate globally. However, they are often elusive in terms of both their geographic domicile and the location of their customers.[5]

To bridge these two gaps, we combine two types of data to derive cross-border flows between countries. First, we use flows in cryptoassets between crypto exchanges from external data providers.[6] These data providers link pseudonymous blockchain addresses and their transactions to entities such as crypto exchanges using proprietary attribution data.[7] In a second step, we allocate entity flows to locations based on statistics on their

[5] For a more detailed discussion of measurement challenges in this context see, for instance, Cardozo et al. (2024). Notably, the presence of global firms in the traditional financial system brings about similar attribution challenges as studied in Coppola et al. (2021).

[6] The datasets are provided by Chainalysis and Iknaio and have been prepared for this study. These do not include transaction-level data but instead offer aggregated flows at the quarterly and entity-to-entity level, along with a breakdown by value bands in the case of Iknaio.

[7] In addition, they rely on clustering heuristics to support attribution by grouping addresses that

user base.[8] To calculate the geographic profile of crypto flows, the entity-to-entity data are complemented by the geographic distribution of app usage of the respective exchange or the web traffic of a crypto exchange's website. For example, if 56% of usage of the app of a specific exchange originates from the US, 56% of all crypto in- and outflows to this exchange are allocated to the US. By aggregating over all crypto exchanges, bilateral cross-country data are obtained.

The first dataset we create in this manner – covering aggregate bilateral BTC flows and low-value BTC flows – combines exchange-to-exchange flows from Iknaio with SensorTower app usage statistics.[9] SensorTower provides aggregate app download and usage statistics by country for crypto exchanges. This dataset captures flows within and between exchanges and includes a breakdown of transfers below US$ 500 and US$ 200 per transaction. The data vendor (Iknaio) employs restrictive assumptions for on-chain exchange flows to reduce false identification, which limits the covered volume and number of countries. We allocate crypto exchange flows to countries using app usage statistics and the weighting methodology detailed in Annex A.2.

The second dataset draws on entity flow data from Chainalysis, which allocates country weights based on web traffic. The resulting dataset encompasses all four major cryptoassets: BTC and ETH, the two largest unbacked cryptoassets with freely floating values, and USDT and USDC, the two largest stablecoins with a peg to the US dollar.[10] While BTC and ETH are native assets on their respective blockchains, USDC and USDT are issued as tokens via smart contracts across multiple chains. Chainalysis data cover USDC flows on the Ethereum blockchain and USDT flows on both the Ethereum and Tron blockchains, covering about 67% of USDC issuance and 98% of USDT issuance.[11] The entity data construction applies less restrictive assumptions on clustering addresses and includes a wider range of business entities, such as miners and other services.[12]

Figure A.2 in the Annex provides graphical evidence to affirm the accuracy of the approximated flows. Clearly, the pseudo-anonymity of the ledgers implies that a comprehensive attribution of transactions to users is impossible, such that a mapping of flows to countries will always remain an approximation. Even so, our measure of cross-border flows is tightly linked to the number of crypto exchange users at the country-level, with

belong to the same entity (see Möser and Narayanan, 2022). Cerutti et al. (2024) provide a non-technical overview of how on-chain or off-chain flows can be allocated to exchanges and similar entities.

[8] This approach differs from assigning locations based on entities' headquarters, as is done in the preparation of international banking statistics. Headquarters are often strategically chosen according to the regulatory environment and other factors. Our approach better reflects the global reach of crypto exchanges and other services and where flows originate.

[9] SensorTower gathers app usage and download statistics. However, not all crypto exchanges offer an app, and data may not always be available for all apps via SensorTower.

[10] As of January 2025, USDT and USDC accounted for almost 90% of the global market capitalisation of issued stablecoins, according to data from DeFiLlama.

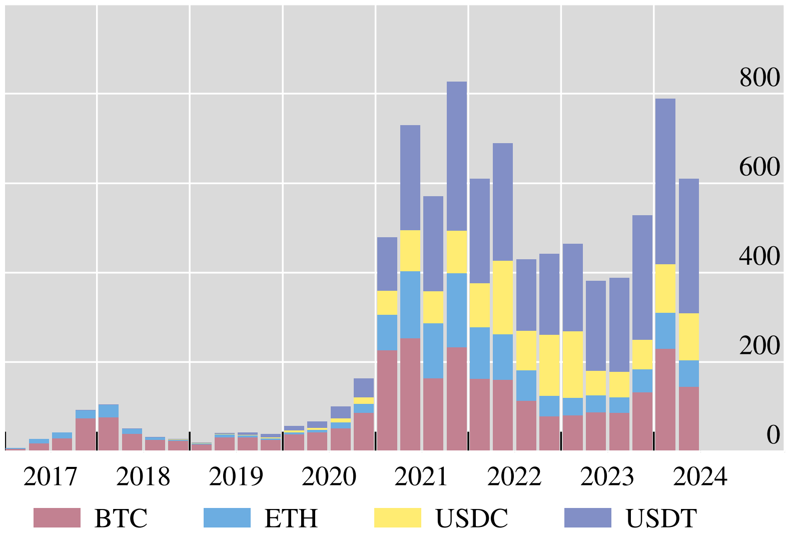
[11] According to data from Circle and Tether as of January 2025.

[12] Crypto exchanges account, on average, for about 80% of entity flows in BTC. See also Figure A.1 for a graphical comparison of the aggregate BTC flows obtained from the two data sources.

variation in the latter accounting for about 64% of the variation in country-level flows. Moreover, flows show a highly significant and positive correlation with the level of cryptoasset adoption across countries obtained from survey data.[13]

The resulting country-level data highlight the significant growth of cross-border flows for the major cryptoassets, particularly at the start of 2021 (Figure 1, which is based on the Chainalysis data). These flows started from less than US$7 billion in Q1 2017 and surged to over US$800 billion by Q4 2021. After declining back to approximately US$400 billion in 2022 amidst crypto market turmoil, flows picked up again, amounting to about US$600 billion at the end of our observation period in Q2 2024. Initially, BTC dominated transaction volumes, accounting for roughly 80% up to Q2 2019. By Q2 2024, however, its share fell to less than 25% as transactions in stablecoins expanded strongly.

Figure 1: Cross-border crypto flows (US$ billions)

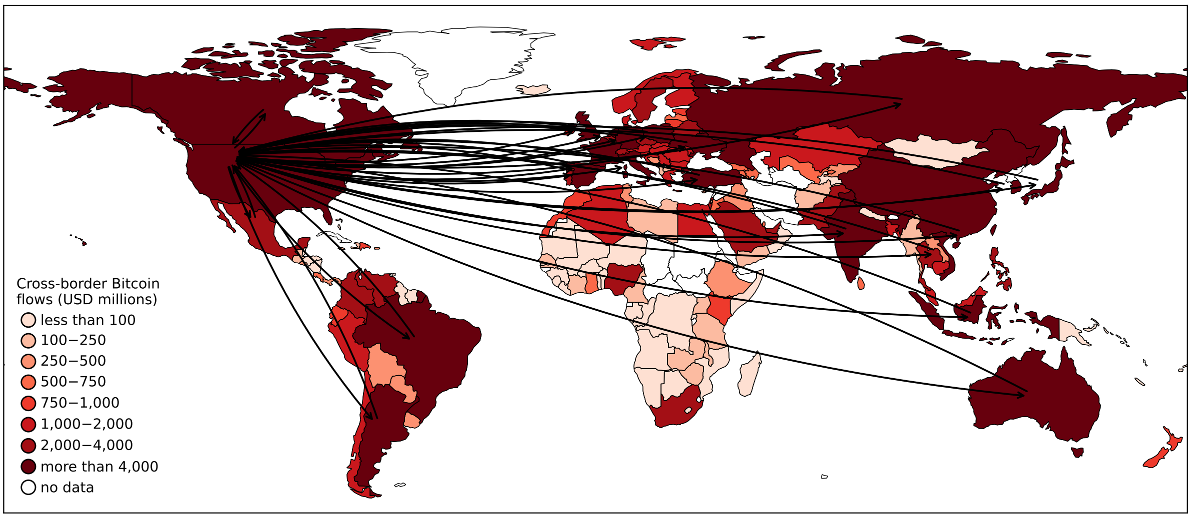


Note: The graph presents quarterly aggregates of cross-border flows for four cryptoassets from Q1 2017 to Q2 2024.

We map out a global network of cross-border BTC and USDT flows to visualise the key nodes and edges, i.e. directional links between two countries, in the first half of 2024, the two most recent quarters of our period of observation (Figure 2 and Figure 3). Corresponding maps for the other two cryptoassets are provided in Figure A.3 and Figure A.4 in Annex A.1. This BTC network spans 180 countries spread across all continents, nearly all the 184 countries with non-zero flows in at least one of the cryptoassets in our dataset. We highlight flows of at least one billion US dollars with black arrows to indicate important edges. These flows accounted for nearly 25% of the total cross-border transaction volume, even though they represented only 0.15% of the total number of flows. In comparison to BTC, the global USDT map is less centered on the United States, with flows more evenly spread across a few large countries as discussed below.

[13]Given that survey data on cryptoasset adoption captures ownership and general usage of these assets rather than the intensity of activity, it is intuitive that the correlation with flows is weaker compared to measures of crypto exchange usage.

Figure 2: A Global Bitcoin Map



Note: Country colours represent the total US$ equivalent of Bitcoin (BTC) sent abroad in the first half of 2024, with countries grouped into eight categories. The arrows represent bilateral flows equivalent to at least $US 1 billion.

Figure 3: Global Tether (USDT) Map

Note: Country colours represent the total US$ equivalent of USDT sent abroad in the first half of 2024, with countries grouped into eight categories. Black arrows represent bilateral flows equivalent to at least $US 1 billion.

The United States, the United Kingdom and major emerging markets represent key nodes of the networks in leading cryptoassets. BTC flows between the United States and the United Kingdom grew about tenfold from 2019 (bottom panel of Table 1) to 2023–24 (top panel), outpacing the overall increase in BTC cross-border volumes. These bilateral links were also the two largest edges in the ETH and USDC network in 2023–24, respectively. Overall, the United States and the United Kingdom accounted for about 20% of cross-border activity in BTC and USDC, and close to 30% for ETH (Table 2). Common across all three networks was the geographical shift in flows during this time. Cross-border activity has moved from China to other major emerging markets, notably India and Indonesia, against the backdrop of tighter crypto regulation and bans imposed by Chinese authorities (Auer and Claessens, 2018 and Auer et al., 2022b).

Table 1: Largest bilateral flows point to changing geographical patterns

Q3 2023 to Q2 2024											
BTC			ETH			USDC			USDT		
Pair	Flows	Share	Pair	Flows	Share	Pair	Flows	Share	Pair	Flows	Share
GB→US	9.89	1.7	US→GB	2.23	1.0	US→GB	6.33	1.9	US→TR	5.89	0.5
US→GB	9.28	1.6	GB→US	2.09	0.9	GB→US	6.23	1.8	US→RU	5.47	0.5
CA→US	4.94	0.8	US→ID	1.30	0.6	IN→US	4.21	1.2	TR→US	5.24	0.5
DE→US	4.89	0.8	US→TR	1.27	0.6	US→IN	4.18	1.2	RU→US	5.00	0.4
US→CA	4.87	0.8	RU→US	1.26	0.6	ID→US	3.85	1.1	GB→US	4.79	0.4
All	592.99	100.0	All	225.54	100.0	All	338.14	100.0	All	1,158.56	100.0
Q1 2019 to Q4 2019											
BTC			ETH			USDC			USDT		
Pair	Flows	Share	Pair	Flows	Share	Pair	Flows	Share	Pair	Flows	Share
US→GB	1.02	1.0	US→KR	0.15	0.9	CN→US	0.19	3.2	US→CN	0.08	0.6
CN→US	1.01	1.0	KR→CN	0.14	0.8	US→CN	0.13	2.3	CN→US	0.08	0.6
US→CN	0.91	0.9	KR→US	0.14	0.8	GB→US	0.10	1.8	US→RU	0.07	0.6
GB→US	0.91	0.9	CN→KR	0.13	0.8	US→GB	0.10	1.8	CN→RU	0.07	0.5
RU→US	0.77	0.7	RU→US	0.11	0.7	US→RU	0.06	1.1	US→IN	0.06	0.5
All	105.38	100.0	All	17.00	100.0	All	5.72	100.0	All	12.71	100.0

Note: The top and bottom panels present, for each cryptoasset, the five largest bilateral flows and the sum of all flows in US$ billions as well as the corresponding percentage share of total flows for the period from Q3 2023 to Q2 2024 and for the four quarters of 2019, respectively. For USDT, flows are available from Q2 2019. Country abbreviations are based on the official (ISO 3166-1) alpha-2 codes.

Geographical patterns differ for USDT, with a stronger presence of Türkiye and Russia (Figure 3). As cross-border volumes jumped from US$ 13 billion in 2019 to more than US$ 1,100 billion in 2023–24, Türkiye became the second largest sender and receiver of USDT according to the Chainalysis data. Together with Russia, it represented about 12% of USDT cross-border volume (Table 1 and Table 2). Overall, these observations highlight the dynamic nature of the global crypto market, with significant changes in the geographical distribution and volume of cross-border flows over the observed period.

Table 2: Major participants (flows in US$ billions, shares in %)

BTC	**Flows sent**	**Share**	**Flows received**	**Share**	**USDC**	**Flows sent**	**Share**	**Flows received**	**Share**
US	102.3	17.3	110.9	18.7	US	30.4	13.5	27.4	12.2
GB	29.6	5.0	30.2	5.1	GB	10.8	4.8	10.5	4.6
RU	23.1	3.9	20.8	3.5	TR	9.9	4.4	10.2	4.5
TR	21.3	3.6	20.1	3.4	RU	9.7	4.3	9.9	4.4
KR	19.2	3.2	21.7	3.7	ID	8.1	3.6	8.9	3.9
ETH					**USDT**				
US	82.3	24.3	81.8	24.2	US	98.1	8.5	92.5	8.0
GB	18.5	5.5	18.3	5.4	TR	67.9	5.9	69.5	6.0
IN	13.2	3.9	12.9	3.8	RU	66.1	5.7	66.8	5.8
ID	11.8	3.5	11.6	3.4	VN	44.1	3.8	45.1	3.9
CA	9.9	2.9	9.6	2.8	GB	42.9	3.7	41.2	3.6

Note: The panel depicts the top-5 countries in terms of cross-border flows sent in BTC, ETH, USDC and USDT, respectively, from Q3 2023 to Q2 2024. It reports the amount of flows sent and received for these countries in US$ billions and as a percentage share of the total amount of flows, respectively. Country abbreviations are based on the official (ISO 3166-1) alpha-2 codes.

Following years of expansion, network density has recently declined in all four crypto networks. We record non-zero flows for around 55% of all possible directional links in 2024, down from more than 60% in 2023 (see Table 3). This follows years of rising density, with stablecoins experiencing a particularly rapid increase immediately after their inception.

As such, crypto network density is comparable to the density of the global trade network and significantly more dense than the cross-border banking network (Table 3).[14]

Network concentration varies across cryptoassets but is notably lower than for cross-border banking. The top-5 bilateral flows, for instance, accounted for around 2% and 7% of cross-border transaction volume in USDT and USDC, respectively (Table 3), compared to around 9% and 15% for exports and cross-border interbank claims at the end of our sample period. Moreover, all top-10 interbank claims were among large advanced economies, in contrast to the comparatively strong footprint of major emerging market economies in each of the four cryptoasset networks. These differences motivate our analysis of the various drivers of cross-border crypto flows in comparison to those underpinning traditional finance.

Table 3: Network density and concentration (in %)

	BTC	ETH	USDC	USDT	Exports	IB claims
Network density						
Q1 2018	52.3	51.6	NA	38.3	53.5	12.8
Q1 2019	53.0	52.4	49.0	43.6	53.8	12.7
Q1 2020	53.0	52.6	51.0	50.8	53.6	12.7
Q1 2021	60.9	60.0	58.5	59.3	54.4	12.4
Q1 2022	59.0	57.6	57.5	57.7	55.0	12.2
Q1 2023	63.4	62.4	61.3	61.1	54.9	12.0
Q1 2024	56.6	55.1	53.7	54.5	53.8	11.8
Concentration (2023–24)						
Top-5	5.7	3.6	7.3	2.3	9.4	15.1
Top-10	9.2	6.2	12.1	4.1	14.6	23.0
Top-50	24.4	18.2	33.1	13.5	32.4	50.8

Note: The top panel depicts the network density for each cryptoasset, defined as the number of non-zero flows as a percentage share of the maximum number of possible directional flows between the 225 reporting countries in the network. The bottom panel presents the flows accounted for by the top-5, top-10 and top-50 directional country-pair links, respectively, as a percentage share of all flows from Q3 2023 to Q2 2024. For interbank (IB) claims, we report the shares based on the average stock of claim from Q3 2023 to Q1 2024 (the latest available data point).

2.2 Potential drivers of cross-border crypto flows

Cryptoassets can serve multiple purposes, which in turn affect drivers of cross-border flows. Unbacked cryptoassets can be viewed as financial assets, sought after for investment or speculation, but also as a digital medium of exchange offering transactional benefits (Biais et al., 2023, Schilling and Uhlig, 2019b). Stablecoins like USDC and USDT derive stability by being pegged to the US dollar via off-chain reserves. They often serve as substitutes for fiat currencies in DeFi protocols, such as token swaps, liquidity pools and lending platforms. This gives rise to their different geographic profiles in cross-border flows compared to unbacked cryptoassets.

[14]For consistency, we calculate network density based on 225 countries, which yields $225 \times 224 = 50,400$ theoretically possible directional flows. For inclusion in the sample, we require that a country reports at least one non-zero cross-border crypto flow, export flow, or cross-border interbank claim. Non-zero crypto flows were reported by 184 countries during the period of observation.

The sensitivity of cross-border flows to different drivers is expected to vary with their usage patterns. Speculative activity, for instance, would likely depend on global conditions for funding in major crypto markets. Conversely, use of cryptoassets as a medium of exchange could depend more strongly on conditions in the sending and receiving country, such as the stability of the local fiat currencies. Policy interventions, such as capital controls, could also influence cryptoasset usage, either by constraining cross-border activity as generally intended by the measures or by incentivising circumvention of the controls on traditional financial flows through cryptoassets. To determine drivers of cross-border crypto flows, we therefore consider a broad range of metrics at global, country, and country-pair levels. Table 4 provides summary statistics of the crypto flow variables and controls used in our regression analysis in the next sections.

First, we supplement our dataset with measures of financial activity through traditional intermediaries to benchmark against crypto flows. Specifically, we gather data on bilateral interbank cross-border claims from the BIS international banking statistics. We also estimate annual bilateral remittances following the World Bank's methodology.[15] For a subset of countries, bilateral data on remittance cost is available from the World Bank's remittance prices database. High costs of processing transactions through traditional intermediaries provide additional incentives to rely on cryptoassets for cross-border payments, in particular related to remittances (Schilling and Uhlig, 2019a). We also use quarterly bilateral merchandise exports from the IMF's Direction of Trade dataset to compare crypto flows with cross-border flows in goods.

We consider traditional measures of frictions, such as physical distance or information asymmetry. The impact of these measures is a priori unclear. On the one hand, they could be expected to have little impact on cross-border crypto activity, given the design and ambition of the decentralised ledger technology that underpins these networks. On the other hand, if seen from the perspective of crypto networks as facilitators of transactions tied to real economic activity, offering substitutes for traditional payment methods in the financial system (Athey et al., 2016; von Luckner et al., 2023), factors that hinder cross-border economic activity, such as physical distance or language barriers, would similarly influence cross-border crypto flows that mimic the payment leg of economic transactions. To examine these dynamics, we include proxies for frictions in bilateral flows widely used in international trade and capital flow studies, so-called "gravity" measures (Badarinza et al., 2022, Brei and von Peter, 2018, Portes et al., 2001). Specifically, we use the log distance between the most populated cities of each country pair, a binary variable indicating shared borders, and a binary variable for common official or primary languages. These data are sourced from the CEPII gravity database (Conte et al., 2022).

[15] The methodology in Ratha and Shaw (2007) converts aggregate data on remittances received at the country level into bilateral remittance flows based on migrant stocks and income levels in the origin and destination country.

Global factors influence investors' risk-taking capacity and sentiment in other asset classes. Tightening global financial conditions, such as US dollar appreciation (Obstfeld and Zhou, 2023, Bruno and Shin, 2015) or rising corporate credit spreads (Gelos et al., 2022), could reduce cross-border crypto flows. Rising market volatility may attract speculative traders and boost transaction volumes. Accordingly, we examine several global factors (Miranda-Agrippino and Rey, 2020) to assess their impact on crypto flows. We use the log of the CBOE Volatility Index (VIX), which reflects expected volatility in US equity markets, as a proxy for global financial market volatility. Additionally, we control for changes in credit risk pricing using option-adjusted spreads tracked by the ICE BofA BBB US corporate index (Gelos et al., 2022). We also test the effect of a rise in the broad nominal dollar index. Global monetary conditions are gauged via the Federal funds rate, and quarterly real US GDP growth approximates the global economic backdrop.

Crypto's usage as a speculative asset implies that risk factors driving cryptoasset returns (Liu et al., 2023, Liu and Tsyvinksi, 2021) likely affect transaction volumes. These factors are distinct from other macroeconomic factors (Liu et al., 2023), providing complementary explanatory power. We thus expand global factors to include "crypto risk factors". We calculate the relative volatility of the BTC price in US dollars over the past quarter. Additionally, we utilise the three global crypto risk factors developed by Liu et al. (2023) – market, size, and momentum – which explain significant cross-sectional variation in cryptoasset returns.

Economic factors specific to the sending or receiving country could also incentivise the use of cryptoassets, particularly for payments. High exchange rate volatility, for instance, could drive such usage. To assess the relevance of these country-specific factors, we consider CPI inflation and real GDP growth rates compiled by the World Bank and the BIS based on national statistics.[16] We also obtain from the BIS bilateral exchange rate volatility for each country-pair over the past quarter. Additionally, we use BIS bilateral exchange rate volatility for each country-pair over the past quarter and measure cryptoasset awareness through country-level Google search indices for "Bitcoin", "Ethereum," and "Stablecoin" (see e.g. Liu et al., 2022). These factors are expected to influence crypto flows when exceptionally high, such as during local currency pressures or surges in public interest. To capture this, we define a binary variable set to one (zero otherwise) for quarters where the factor exceeds the 75th percentile of its pooled distribution. For Google searches, standardised nationally, we set the binary variable to one for observations surpassing the 75th percentile of the country's own time series.

[16] For countries without quarterly data, we interpolate quarterly inflation and GDP growth rates from annual figures.

Table 4: Summary statistics

	Mean	St.dev.	P10	P25	P50	P75	P90	N
Cross-border crypto flows								
BTC ($ '000)	3,267.38	29,039.10	0.08	2.16	40.67	501.00	3,686.17	846,414
ETH ($ '000)	1,569.45	15,913.54	0.02	0.62	13.40	189.49	1,520.53	833,470
USDC ($ '000)	2,162.38	27,509.73	0.00	0.26	10.07	198.80	1,830.66	637,874
USDT ($ '000)	4,816.42	33,386.86	0.00	0.31	21.07	526.28	5,363.44	704,617
BTC between exchanges ($ '000)	3,128.56	22,221.52	0.95	27.59	226.22	1,158.15	4,537.51	205,309
of which < $500 ($ '000)	5.05	39.10	0.00	0.04	0.32	1.68	6.58	205,309
of which < $200 ($ '000)	1.97	15.81	0.00	0.01	0.11	0.60	2.47	205,309
Gravity								
Distance (log km)	8.71	0.80	7.57	8.36	8.91	9.27	9.54	30,937
Common border (binary)	0.02	0.13	0.00	0.00	0.00	0.00	0.00	30,937
Common language (binary)	0.14	0.34	0.00	0.00	0.00	0.00	1.00	29,935
Traditional finance								
Interbank claims ($ mn)	2,698.37	18,757.36	0.09	1.45	26.80	306.00	2,350.00	182,508
Exports ($ mn)	189.14	1,944.40	0.00	0.02	0.56	12.10	131.70	819,932
Remittances ($ mn)	61.84	646.15	0.00	0.02	0.46	6.02	52.48	79,190
Remittance cost (log of pp of transaction)	1.53	0.59	0.83	1.16	1.52	1.92	2.25	10,692
Capital flow measures (categorical)	−0.01	0.21	0.00	0.00	0.00	0.00	0.00	896,525

	Mean	St.dev.	P10	P25	P50	P75	P90	N
Global factors								
VIX (log)	2.89	0.32	2.45	2.65	2.83	3.21	3.28	30
High-yield spread (log of %)	0.44	0.19	0.18	0.36	0.43	0.55	0.63	30
Federal funds rate (%)	1.83	1.75	0.12	0.17	1.35	2.38	5.17	30
U.S. growth (%)	2.49	2.94	0.13	2.09	2.44	3.24	4.50	30
Dollar index (log)	4.59	0.04	4.54	4.57	4.59	4.63	4.65	30
Crypto risk factors								
BTC-USD volatility (coeff. of variation)	0.17	0.10	0.07	0.09	0.14	0.23	0.28	30
Crypto market	0.02	0.04	−0.04	−0.01	0.01	0.03	0.08	26
Crypto size	0.03	0.05	−0.02	0.00	0.02	0.05	0.12	26
Crypto momentum	0.01	0.02	−0.01	−0.00	0.01	0.02	0.04	26
Country-level factors								
Inflation (%)	143.16	5,162.72	0.42	1.45	3.26	6.72	13.39	5,200
GDP growth (%)	2.64	7.58	−3.09	0.41	2.92	5.10	7.37	5,915
Bilateral FX volatility (coeff. of variation)	3.55	15.10	0.40	0.90	1.63	2.86	5.31	256,174
Google searches: Bitcoin (index)	25.56	18.20	7.00	12.33	21.00	34.67	52.67	6,043
Google searches: Ethereum (index)	15.00	18.64	0.00	0.00	8.00	23.33	44.00	6,262
Google searches: Stablecoin (index)	4.38	11.18	0.00	0.00	0.00	0.00	18.33	3,809

Note: The table presents summary statistics for the dependent variables and controls. Data sources are reported in parentheses at the end of each definition in the following. *Cross-border crypto flows:* US$ equivalent of all quarterly country-to-country flows in Bitcoin (BTC), Ether (ETH), USD Coin (USDC) and Tether (USDT), respectively (Chainalysis). The table also reports the cross-border BTC flows including only transactions among crypto exchanges, including for transactions of less than *US$ 500* or *US$ 200*, respectively (Iknaio, SensorTower, World Bank; see also Annex A.2). *Distance:* log distance in kilometers between the most populated city of each country (CEPII). *Common border (language):* binary variable equal to one and zero otherwise for countries with common border (official or primary language) (CEPII). *Interbank claims:* total amount of cross-border interbank claim, e.g. loans, deposits (BIS). *Exports:* quarterly value of country-to-country merchandise exports (IMF). *Remittances:* annual bilateral remittances, estimated based on the methodology in Ratha and Shaw (2007), using migrant stocks and remittances (World Bank). *Remittance cost:* log of the average percentage total cost of the transaction (World Bank – Remittance Prices Worldwide). *Capital flow measures:* categorical variable that is equal to +1 (−1) if either the sending country tightened (loosened) net outflow restrictions or the receiving country tightened (loosened) inflow restrictions or both occurred in a given quarter; and zero otherwise. CFM data are from Binici et al. (2023). *VIX:* CBOE Volatility Index (FRED). *High-yield spread:* ICE BofA BBB US Corporate Index option-adjusted spread (FRED). *Federal funds rate:* quarterly average Federal funds rate (FRED). *US growth:* US real GDP growth rate (FRED). *Dollar index*: log of the broad (i.e. covering 64 economies) effective nominal US dollar exchange rate index, normalised to an average of 100 units in 2020 (BIS). *BTC-USD volatility:* quarterly coefficient of variation of the US$ price of BTC (Investing.com). *Crypto risk factors:* common risk factors for *market*, *size* and *momentum* as provided by Liu et al. (2022). *Inflation:* consumer price inflation rate (BIS and World Bank). *GDP growth:* real GDP growth rate (BIS and World Bank). *Bilateral FX volatility:* quarterly coefficient of variation of the bilateral exchange rate of the sending and receiving country-pair (BIS). *Google searches:* national index of Google searches of the term "Bitcoin", "Ethereum", and "Stablecoin", respectively (Google).

The pseudo-anonymity of the crypto network could be exploited to circumvent policy measures restricting cross-border capital flows, such as CFMs. Transactions motivated by evading these measures are driven by alternative incentives, with senders and recipients willing to incur additional costs to move funds across borders (Hu et al., 2023). That said, even if policy measures predominantly target traditional financial flows, limits to cross-border arbitrage in crypto markets (e.g. Makarov and Schoar, 2020) suggest that national restrictions on capital flows could nevertheless hamper crypto activity.

We investigate the impact of policy measures on crypto flows by considering CFMs, using the dataset by Binici et al. (2023). We calculate quarterly changes in sending (receiving) countries' measures to control capital outflows (inflows). Based on this, we construct a categorical variable measuring directional changes in CFM tightness for each country-pair. Values for CFM_t of $+1$ indicate a net tightening of outflow restrictions by the sending country or inflow restrictions by the receiving country (or both) in quarter t. Conversely, values of -1 indicate loosening of restrictions by either the sending or receiving country (or both). All other observations are assigned a zero value.[17]

3 Empirical approach

Our empirical approach leverages the directed bilateral flow data to investigate the drivers of cross-border crypto flows. This allows us to take advantage of the richness of the network data and to examine factors at the global, country and country-pair level.

We assess these drivers building on the extant literature on gravity equations (e.g. Anderson and Yotov, 2016 and Anderson and van Wincoop, 2003) and assume that cross-border crypto flows, f_{ijt}, from sending country i (henceforth "senders") to receiving country j (henceforth "receivers") in quarter t can be represented as follows:

$$f_{ijt} = \frac{f_{it}}{\Pi_{it}^{-\theta}} \frac{f_{jt}}{P_{jt}^{-\theta}} \tau_{ijt}^{-\theta}, \tag{1}$$

where $f_{it} \coloneqq \sum_j f_{ijt}$ and $f_{jt} \coloneqq \sum_i f_{ijt}$ represent the total cross-border transaction volume of the two countries, respectively. The term τ_{ijt} accounts for bilateral frictions that could hinder cross-border crypto transactions, whereas θ is the associated transaction elasticity. Π_{it} and P_{jt} represent the Anderson and van Wincoop (2003) outward and inward multilateral resistance terms, which follow from the workhorse general equilibrium gravity model as (e.g Weidner and Zylkin, 2021):

[17] Unlike indices that track the cumulative number of measures implemented or lifted, changes in CFMs capture shifts in the policy stance without assuming the relative tightness or importance of individual measures.

$$\Pi_{it}^{-\theta} = \sum_{j=1}^{N} \frac{f_{jt}}{P_{jt}^{-\theta}} \tau_{ijt}^{-\theta}, \quad P_{jt}^{-\theta} = \sum_{i=1}^{N} \frac{f_{it}}{\Pi_{it}^{-\theta}} \tau_{ijt}^{-\theta}. \tag{2}$$

Applied to the case of crypto flows, Π_{it} summarises the sender's ability to transact in cryptoassets with more crypto-affine receivers, whereas P_{jt} captures the receiver's ability to transact with more crypto-affine senders. Seen through the lens of cryptoassets being used as a medium of exchange, the corresponding flows represent the payment leg of real and financial transactions, providing a direct analogue to the application of gravity equations in trade (e.g. Anderson and Yotov, 2016 or Anderson and van Wincoop, 2003) and finance (e.g. Badarinza et al., 2022, Brei and von Peter, 2018 or Portes et al., 2001).

Following the literature, we parameterise the bilateral frictions τ_{ijt} as an exponential function of observable explanatory variables, x_{ijt}, and the unobservable ω_{ijt}:

$$\tau_{ijt}^{-\theta} = \exp\left(x_{ijt}\,\beta\right)\omega_{ijt}. \tag{3}$$

Substituting the above into (1) and defining sender-time and receiver-time fixed effects as $\alpha_{it} = \ln\left(f_{it}/\Pi_{it}^{-\theta}\right)$ and $\gamma_{jt} = \ln\left(f_{jt}/P_{jt}^{-\theta}\right)$, respectively, yields the two-way gravity equation:

$$f_{ijt} = \exp\left(\alpha_{it} + \gamma_{jt} + x_{ijt}\,\beta\right)\omega_{ijt}. \tag{4}$$

We estimate equation (4) based on the Poisson pseudo maximum likelihood (PPML) estimator, which accommodates the presence of zero flows and accounts for heteroskedasticity (Santos Silva and Tenreyro, 2006), and has therefore become the preferred choice for gravity analysis (Anderson and Yotov, 2016).

We employ several specifications of equation (4) to assess drivers of crypto flows at the global, country, and country-pair level, respectively.

We begin by gauging the impact of global factors, including global risk factors that pertain to crypto markets (e.g. Liu et al., 2023). By determining global funding conditions (e.g. Miranda-Agrippino and Rey, 2020) and investor sentiment, these factors could have a first-order impact on cross-border crypto flows. Since factors that are common across all countries, x_t, are absorbed by the fixed effects in equation (4), we consider a less restrictive specification with fixed effects only at the sender and receiver level, α_i and γ_j, while controlling for time-invariant bilateral frictions, x_{ij}, based on a standard set of gravity controls (as discussed below):

$$f_{ijt} = \exp\left[\alpha_i + \gamma_j + \left(x_{ij} + x_{t-1}\right)\beta\right]\omega_{ijt}. \tag{5}$$

To err on the side of caution, we lag x_t by one quarter to address potential endogeneity concerns that could relate to cross-border crypto flows affecting global factors, notwithstanding the still modest scale of transaction volume if compared with global traditional finance activity. In this specification, the impact on crypto flows of variation in country-specific factors over time will be subsumed by the effect attributed to the global factors.

As a natural extension of (5), we add to the global factors (lagged) time-varying controls at the sender level, x_{it-1}, and receiver level, x_{jt-1}, respectively:

$$f_{ijt} = \exp\left[\alpha_i + \gamma_j + (x_{ij} + x_{t-1} + x_{it-1} + x_{jt-1})\,\beta\right]\omega_{ijt}. \tag{6}$$

We estimate the effect of time-varying bilateral frictions based on exploiting the richness of remittances data. Specifically, we employ directional country-pair information, x_{ijt}, available for the cost of sending remittances. This allows us to saturate the model with sender-time, α_{it}, and receiver-time, γ_{jt}, fixed effects. We then estimate the model:

$$f_{ijt} = \exp\left[\alpha_{it} + \gamma_{jt} + (x_{ij} + x_{ijt-1}\beta)\right]\omega_{ijt}. \tag{7}$$

Finally, we move to the fully saturated specification in order to assess the impact of policy interventions. Specifically, we assess the impact of CFMs on crypto flows. Recent empirical research on network analysis has underscored the importance of accounting for time-invariant sender-receiver ("pair") fixed effects, η_{ij}, in order to address any potential bias that may arise from the endogeneity of policy choices (e.g. in the case of trade policy Head and Mayer, 2014, Baier and Bergstrand, 2007). CFMs, for instance, are often imposed to address financial imbalances, such as excessive capital flows, violating the assumption of exogeneity in a regression on these flows.

Formally, we expand the parameterisation of the friction term, τ, in (3) as:

$$\tau_{ijt}^{-\theta} = \exp\left(\eta_{ij} + x_{ijt}\,\beta\right)\omega_{ijt}. \tag{8}$$

For expositional clarity, we replace the controls, x_{ijt}, with a measure of the direction of (lagged) bilateral policy interventions, cfm_{ijt-1}. This measure can take on values of 1 or -1 to indicate a tightening and loosening of policy measures, respectively, and is zero otherwise. Building on (4), this yields the three-way gravity equation:

$$f_{ijt} = \exp\left(\alpha_{it} + \gamma_{jt} + \eta_{ij} + cfm_{ijt-1}\beta\right)\omega_{ijt}. \tag{9}$$

Here, all global and national drivers as well as any time-invariant determinants of bilateral crypto flows are absorbed by the comprehensive set of fixed effects. Any impact of policy interventions will therefore be identified from time-variation in flows within a sender-receiver pair.

4 Results

4.1 Gravity and global factors as drivers of international crypto flows

We start our analysis by examining how, based on gravity equations following the specification in equation (5), measures of geographical and linguistic distance affect cross-border BTC flows, as the predominant cryptoasset (Table 5).[18]

Cross-border interbank claims (column 1) and exports (column 2) serve as our initial benchmark. Consistent with prior research emphasising the importance of informational frictions in international finance (e.g. Brei and von Peter, 2018, Portes et al., 2001), banks from more distant countries maintain lower claims on each other, whereas banks from neighbouring countries or countries that share a common language exhibit higher claims. The effects are economically significant: a 1% increase in distance is associated with a 0.6% decline in claims, whereas countries with a common border and common language exhibit higher claims than otherwise of around 84% (calculated as $\exp[0.608]-1$) and 44%, respectively. The impact of distance is even more pronounced for exports, consistent with it implying greater frictions for physical trade than for financial transactions. Here, we estimate an elasticity of -0.75% and more than a doubling of trade volumes for countries that share a common border.

Since overcoming information asymmetry is at the core of the decentralised ledger technology, we expect a diminished role of geographical and linguistic factors on cross-border BTC flows. In line with this, the estimated elasticity of distance declines to less than -0.1% and the common border effect becomes both quantitatively and statistically insignificant (columns 3 to 7 of Table 5). At around 13%, the impact of an increase in BTC flows associated with a common language is less than one third of the effect observed in cross-border banking.[19]

The influence of global factors on cross-border BTC flows tallies with an increasing integration of the BTC ecosystem into traditional finance (columns 4 to 7). High expected financial market volatility, as gauged by the VIX, consistently exhibits a strong positive relationship with BTC flows with an elasticity of around 2%. This finding tallies with speculative trading motives and also accords with off-chain BTC activity (e.g. Di Casola et al., 2023) as well as markets dominated by institutional investors, such as FX markets (e.g. Cespa et al., 2021). Tighter global funding conditions, in turn, hamper cross-border

[18] To ensure consistency, the regressions are conducted using data from Q1 2017 to Q2 2023, the period for which all control variables were available at the time of writing

[19] For our alternative measure of BTC flows based on the more narrow sample of exchange-to-exchange flows and alternative locational weighting (see Annex A.2), we estimate a stronger impact of sharing a common language, comparable to the estimate for interbank claims. This accords with crypto exchanges with strong interconnections catering to users with similar native languages, e.g. by advertising their services in the same language.

Table 5: Gravity, global and crypto risk factors as drivers of Bitcoin flows

	IB claims	Exports	Bitcoin flows				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Gravity							
Distance	-0.582^{***}	-0.750^{***}	-0.080^{***}	-0.084^{***}	-0.084^{***}	-0.084^{***}	-0.084^{***}
	(0.041)	(0.027)	(0.013)	(0.014)	(0.014)	(0.014)	(0.014)
Common border	0.608^{***}	0.757^{***}	0.002	-0.001	-0.001	-0.001	-0.001
	(0.161)	(0.083)	(0.033)	(0.035)	(0.035)	(0.035)	(0.035)
Common language	0.364^{***}	-0.029	0.124^{***}	0.126^{***}	0.126^{***}	0.126^{***}	0.126^{***}
	(0.110)	(0.072)	(0.027)	(0.028)	(0.028)	(0.028)	(0.028)
Global factors (t–1)							
VIX				2.244^{***}	1.699^{***}	2.086^{***}	2.229^{***}
				(0.028)	(0.019)	(0.028)	(0.025)
High-yield spread				-3.390^{***}		-3.781^{***}	-3.355^{***}
				(0.035)		(0.032)	(0.031)
Dollar index					-10.525^{***}		
					(0.136)		
Federal funds rate						-0.037^{***}	-0.023^{***}
						(0.003)	(0.003)
US growth						-0.045^{***}	0.005^{***}
						(0.002)	(0.002)
Crypto risk factors (t–1)							
BTC-USD volatility				1.472^{***}	0.870^{***}	1.139^{***}	
				(0.037)	(0.035)	(0.033)	
Crypto market							7.470^{***}
							(0.061)
Crypto size							-2.330^{***}
							(0.080)
Crypto momentum							-4.981^{***}
							(0.178)
N	146,014	582,171	671,794	668,467	668,467	668,467	668,467
Pseudo R2	0.882	0.928	0.992	0.936	0.889	0.938	0.947
FE: sender$\times t$ & receiver$\times t$	Yes	Yes	Yes				
FE: sender & receiver				Yes	Yes	Yes	Yes

Note: $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$. The dependent variable is the quarterly US dollar amount of bilateral (1) cross-border interbank (IB) claims; (2) merchandise exports; and (3–7) bilateral cross-border Bitcoin (BTC) flows. To ensure comparability across the different specifications, the regressions are estimated based on using observations from Q1 2017 up to Q2 2023, consistent with the last available quarter of observation for the crypto risk factors (i.e. Q1 2023) at the time of writing. Robust standard errors, clustered by country pairs, in parentheses.

BTC activity. For one, a 1% increase in the credit spread on high-yield debt is associated with a decline in cross-border BTC transaction volume of more than 3%. Likewise, a 1% appreciation of the US dollar index is associated with a more than 10% decline in BTC cross-border flows BTC (column 5). This supports the notion of increased funding of BTC activity through investors susceptible to financial losses from dollar appreciation, such as those from major emerging markets with a strong footprint in the BTC network.[20]

A tightening of global monetary conditions is associated with a reduction in cross-border BTC transaction volumes. Controlling for variation in the VIX and spreads, we estimate that an increase in the Federal funds rate by the typical increment of 25 basis points is associated with a statistically significant but quantitatively modest decline of about 1% (columns 6 and 7).[21] In the same vein, we find that an increase in US growth

[20] See e.g. Bruno and Shin (2015) for a discussion of how US dollar appreciation constrains local currency borrowers' leverage capacity.

[21] Based on column 6 of Table 5, the impact of a 25 basis point change is given by $\exp(-0.037 \times 0.25) - 1$.

rates, a closely watched indication of future monetary policy tightening during the observation period, is associated with a reduction in cross-border BTC transaction volumes by 4.5% for a one percentage point rise in the US GDP growth rate (column 6).

We augment our specification by adding risk factors that have been shown to explain the cross-sectional variation of crypto returns. For one, we find a positive contribution to cross-border transaction volumes from higher volatility of BTC prices in US$ terms, indicative of speculation being a driving force of international BTC flows (column 4 to 6).

Building on this, we assess the inclusion of market, size, and momentum factors, all highly statistically significant (column 7). Cross-border BTC transaction volumes increase following periods of excess crypto market returns, with a positive, significant loading on the lagged market factor. Interpreting the size factor as a liquidity premia gauge per Liu et al. (2022), we observe that volumes decline after episodes of high liquidity demand in crypto markets. As BTC is among the most liquid cryptoassets, this likely reflects a reversal in elevated BTC transaction volumes during such episodes.[22] The negative momentum factor impact, capturing the investor overreaction premium, indicates a reversal in transaction volumes after quarters of elevated crypto returns.

We compare these findings to estimates based on flows of the other cryptoassets to gain insights on potential similarities and differences in their underlying use cases.

Cross-border ETH flows exhibit a similar relationship with the above factors for BTC (Table 6). This accords with the similarity of their network characteristics (recall Table 1 and Table 2) and the pairwise correlation of bilateral flows of nearly 0.9. Based on the most comprehensive specifications in columns 6 and 7 of Table 5, we find that the impact of gravity factors and crypto risk factors declines only modestly for ETH flows compared to BTC flows. At about 3% and −5%, the estimated elasticities with respect to the VIX and to high-yield spreads are also broadly equivalent to those for BTC flows. Differences arise in terms of the impact of increases in US policy rates, for which we do not observe a decline in ETH flows, whereas our estimates for the impact of US growth on ETH flows suggest a positive, although quantitatively small, relationship.

Flows in stablecoins across borders share a number of characteristics with unbacked cryptoassets but differ in several important ways (columns 3 to 6 of Table 6). Common among all four cryptoassets, and particularly pronounced for stablecoins, is the positive association of flows with an increase in the VIX and a negative one with a tightening of global credit conditions as approximated by high-yield spreads. Gravity factors, by contrast, play a subdued role for stablecoin flows. For one, USDT flows exhibit no apparent link to linguistic proximity, consistent with none of the top country-pairs of the USDT network sharing a common language (Table 1).

[22]Consistent with this, the coefficient on the contemporaneous (but potentially endogenous) size factor is positive, aligning with high size factor values during elevated BTC transaction volumes. Results are available upon request.

Table 6: Drivers of cross-border flows in ETH, USDC and USDT

	ETH (1)	ETH (2)	USDC (3)	USDC (4)	USDT (5)	USDT (6)
Gravity						
Distance	-0.048^{***}	-0.048^{***}	-0.000	-0.000	-0.025^{***}	-0.025^{***}
	(0.008)	(0.008)	(0.004)	(0.004)	(0.004)	(0.004)
Common border	-0.020	-0.020	0.018	0.018	0.003	0.003
	(0.019)	(0.019)	(0.012)	(0.012)	(0.012)	(0.012)
Common language	0.107^{***}	0.107^{***}	0.025^{***}	0.025^{***}	0.003	0.003
	(0.020)	(0.020)	(0.008)	(0.008)	(0.008)	(0.008)
Global factors (t–1)						
VIX	3.139^{***}	3.244^{***}	6.811^{***}	6.553^{***}	6.810^{***}	6.964^{***}
	(0.039)	(0.035)	(0.050)	(0.069)	(0.032)	(0.038)
High-yield spread	-5.173^{***}	-4.777^{***}	-6.403^{***}	-7.471^{***}	-7.757^{***}	-8.668^{***}
	(0.039)	(0.046)	(0.037)	(0.115)	(0.039)	(0.057)
Federal funds rate	-0.005	0.033^{***}	0.446^{***}	0.508^{***}	0.492^{***}	0.566^{***}
	(0.006)	(0.005)	(0.007)	(0.008)	(0.003)	(0.003)
US growth	0.008^{***}	0.061^{***}	0.081^{***}	0.037^{***}	0.066^{***}	0.058^{***}
	(0.001)	(0.001)	(0.003)	(0.002)	(0.002)	(0.002)
Crypto risk factors (t–1)						
BTC-USD volatility	0.502^{***}		-5.556^{***}		-4.022^{***}	
	(0.045)		(0.089)		(0.054)	
Crypto market		7.513^{***}		-5.672^{***}		0.629^{***}
		(0.074)		(0.342)		(0.091)
Crypto size		-2.688^{***}		-6.576^{***}		-6.747^{***}
		(0.061)		(0.130)		(0.096)
Crypto momentum		-2.842^{***}		12.625^{***}		2.083^{***}
		(0.191)		(0.426)		(0.218)
N	657,913	657,913	484,419	484,419	547,740	547,740
Pseudo R2	0.936	0.943	0.927	0.923	0.912	0.913
FE: sender & receiver	Yes	Yes	Yes	Yes	Yes	Yes

Note: $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$. The dependent variable is the quarterly US dollar equivalent of bilateral cross-border flows in (1–2) ETH (Ether); (3–4) USDC (USD Coin); (5–6) and USDT (Tether), respectively. To ensure comparability across the different specifications, the regressions are estimated based on using observations from Q1 2017 up to Q2 2023, consistent with the last available quarter of observation for the crypto risk factors (i.e. Q1 2023) at the time of writing. Robust standard errors, clustered by country pairs, in parentheses.

Unlike BTC and ETH, stablecoin flows show a strong negative association with BTC-USD volatility. Crypto risk factors also exhibit significant loadings for stablecoins, with reversed signs for the momentum factor (USDC and USDT) and market factor (USDC) compared to unbacked cryptoassets. This aligns with the positive correlation between BTC-USD volatility and the market factor. Large price movements in unbacked cryptoassets may erode investor confidence in stablecoins' peg or divert speculative investment. When market momentum in unbacked cryptoassets reverses, stablecoin transactions rise, aligning with the positive momentum factor coefficients for stablecoins.

Moreover, stablecoin flows are tightly linked to US monetary conditions, reflecting their close ties to the currency they are pegged to. A 25 basis point rise in the Federal funds rate is associated with an increase in cross-border USDC flows of about 12% and 15% for USDC and USDT, respectively. Moreover, as for ETH, we find a positive association of flows with US growth, with semi-elasticities of around 4% to 8%.[23]

[23] To affirm the robustness of our findings, we assess flows aggregated at the country level in Annex A.3. Overall, the findings of this analysis is consistent with the findings presented in our main analysis based on the much more detailed bilateral country flows.

4.2 Country-specific drivers

We next assess the importance of country-specific drivers of crypto flows at the sending and receiving country, respectively. Our focus is on conjunctural macroeconomic factors since slower-moving structural factors, such as demographics and the level of financial development will be largely absorbed by the comprehensive set of fixed effects we employ to control for potential confounding factors. In all our specifications, we account for the global factors and the bilateral gravity controls discussed above (reported in column 6 of Table 5).[24]

Table 7: How are crypto flows related to country-specific factors?

	BTC (1)	ETH (2)	USDC (3)	USDT (4)	USDC (5)	USDT (6)
Sender (t–1)						
High inflation	0.033**	0.162***	0.428***	0.146***	0.533***	0.176***
	(0.014)	(0.013)	(0.036)	(0.016)	(0.052)	(0.018)
High GDP growth	0.103***	0.062***	0.008	0.063***	0.013	0.059***
	(0.013)	(0.012)	(0.018)	(0.014)	(0.022)	(0.019)
High Bitcoin awareness	0.096***					
	(0.017)					
High Ethereum awareness		0.261***	0.361***	0.312***		
		(0.020)	(0.037)	(0.024)		
High stablecoin awareness					0.133***	0.146***
					(0.023)	(0.018)
Receiver (t–1)						
High inflation	0.009	0.159***	0.436***	0.157***	0.547***	0.174***
	(0.015)	(0.012)	(0.036)	(0.016)	(0.053)	(0.018)
High GDP growth	0.107***	0.096***	−0.020	0.075***	−0.010	0.061***
	(0.013)	(0.012)	(0.016)	(0.014)	(0.018)	(0.019)
High Bitcoin awareness	0.082***					
	(0.018)					
High Ethereum awareness		0.273***	0.327***	0.319***		
		(0.020)	(0.038)	(0.024)		
High stablecoin awareness					0.080***	0.161***
					(0.023)	(0.018)
High bilateral FX volatility	−0.002	−0.015	0.072*	0.016	0.056	0.076***
	(0.013)	(0.013)	(0.038)	(0.015)	(0.047)	(0.020)
N	225,833	221,705	167,386	195,529	27,984	32,896
Pseudo R2	0.905	0.911	0.916	0.868	0.882	0.795
Gravity controls	Yes	Yes	Yes	Yes	Yes	Yes
Global factors	Yes	Yes	Yes	Yes	Yes	Yes
FE: sender & receiver	Yes	Yes	Yes	Yes	Yes	Yes

Note: $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$. The dependent variable is the quarterly US dollar equivalent of bilateral cross-border flows in the cryptoasset reported in the top row. Robust standard errors, clustered by country pairs, in parentheses. All regressions include controls for gravity (distance, common language and common border), lagged global factors (VIX, high-yield spreads, US policy rate change and US growth) as defined in Table 4. High inflation and high GDP growth are binary variables equal to one (zero otherwise) for values in the top quartile of the sample distribution. High awareness is a binary variable equal to one (zero otherwise) if the number of Google searches for "Bitcoin" (column 1), for "Ethereum" (columns 2 to 4), and for "Stablecoin" (columns 5 and 6), respectively, are in the top quartile of the country's own time series of searches.

[24] We do not account for crypto risk factors in order to make use of the full sample length since these factors were only available up to Q1 2023 at the time of writing.

High inflation in both the sending and, in most specifications, the receiving country is associated with more use of cryptoassets in cross-border transactions (Table 7). In line with our conjecture on the use of cryptoassets as a medium of exchange, we find that high inflation in the sending or receiving country is associated with an increase in transaction volumes to the tune of about 50% for USDC and nearly 20% for USDT and ETH. Our findings for USDC resonate with the attractiveness of stablecoins for international transactions among countries facing inflationary pressure.[25] In line with this, we also observe increased stablecoin flows following periods of elevated volatility in the bilateral exchange rate of the sending and receiving country in some of our specifications (columns 3 and 6). This accords with the major emerging market economies representing key nodes in the USDT network (see Table 2) having experienced bouts of volatility in their home currencies' exchange rate during the period of observation.

High economic growth, by comparison, only modestly adds to cross-border crypto activity. The associated increase is largest for BTC, with an estimated impact of around 10% for high-growth sending and receiving countries, respectively.[26] For ETH and stablecoins, our estimates indicate increased transaction volumes of about 6% if the sending or the receiving country exhibited high GDP growth in the previous quarter.

Notwithstanding indications of crypto usage for transactional purposes, we find that cross-border activity also hinges on public awareness of cryptoassets, indicative of swings in investor interest driving transaction volumes. Following quarters of particularly large search interest in "Ethereum", volumes increase by up to 30% for ETH as well as for USDC and USDT, which operate on the Ethereum blockchain (columns 2 to 4 of Table 7). For BTC, with its longer history of existence and more widespread coverage in media, periods of higher awareness are associated with an increase in cross-border transactions of close to 10% (column 1). High search interest in stablecoins, for which data coverage is more limited, is associated with increased cross-border activity in these coins of around 15% (columns 5 and 6).

4.3 Relation between cross-border crypto flows and remittances

The use case for cryptoassets as a cross-border medium of exchange is particularly evident for financial transactions burdened by high costs in the traditional financial system. Remittance fees are a case in point. While international efforts have contributed to reducing fees over the past decade, the cost of sending remittances remains high on average due to, among other factors, incumbent intermediaries' market power Beck et al. (2022).

[25] High inflation implies an increase in the CPI of at least 6.7% on an annual basis, the threshold for the top quartile in our sample (see Table 4). Intuitively, raising the threshold to, for instance, the 90th percentile (equivalent to inflation exceeding 13.4%) yields higher coefficient estimates, indicating a stronger impact for countries with particularly high inflation. The results are available upon request.

[26] High economic growth implies an increase in real GDP of at least 5.1% on an annual basis, which is the threshold for the top quartile in our sample (see Table 4).

We test whether high costs of remittances are associated with increased reliance on cryptoassets for cross-border transactions. In addition to studying the impact on the total volume of flows, we zoom in on BTC flows related to low-value transactions, i.e. transfers below the equivalent of US$ 500 and US$ 200, respectively. Despite limitations, these flows can serve as a proxy of remittances channelled through the BTC network. Our regressions, presented in the top panel of Table 8, are based on annual flows, consistent with the available data on remittances. The bottom panel provides the corresponding estimates for the crypto flows based on quarterly observations. Time-varying information on the bilateral cost of remittances (as a log percentage share of the transaction value) allows us to control for confounding factors based on sender-year and receiver-year fixed effects in addition to pairwise gravity factors as per equation (7). To sharpen our analysis, we focus on flows from advanced economies to emerging market and developing economies in all our regressions, in line with the main direction of traditional remittance payments.

Table 8: Crypto as an emerging substitute for remittances?

Annual data	Remittances (1)	BTC (2)	ETH (3)	USDC (4)	USDT (5)	BTC<$500 (6)	BTC<$200 (7)
Remittance cost$_{t-1}$	-0.453^{*}	0.066	0.043	0.084^{**}	0.243^{***}	0.253^{**}	0.257^{**}
	(0.243)	(0.041)	(0.031)	(0.039)	(0.068)	(0.123)	(0.112)
Distance	-0.553^{***}	-0.082^{***}	-0.012^{*}	0.006	-0.029	-0.286^{***}	-0.280^{***}
	(0.188)	(0.026)	(0.007)	(0.015)	(0.030)	(0.069)	(0.059)
Common border	-0.156	-0.001	-0.008	0.045	-0.041	-0.517^{***}	-0.491^{**}
	(0.324)	(0.062)	(0.025)	(0.039)	(0.044)	(0.189)	(0.191)
Common language	1.116^{***}	0.145^{***}	-0.003	0.030^{*}	-0.034	0.611^{***}	0.648^{***}
	(0.157)	(0.033)	(0.015)	(0.017)	(0.027)	(0.087)	(0.080)
N	1,038	1,043	1,043	751	895	701	701
Pseudo R2	0.928	0.998	0.999	1.000	0.998	0.995	0.995
FE: sender×year, receiver×year	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarterly data		(8)	(9)	(10)	(11)	(12)	(13)
Remittance cost$_{t-1}$		0.001	0.014	0.055^{**}	0.127^{***}	0.228^{**}	0.283^{***}
		(0.034)	(0.024)	(0.023)	(0.030)	(0.107)	(0.106)
Distance		-0.087^{***}	-0.009	0.010	-0.032^{**}	-0.295^{***}	-0.296^{***}
		(0.027)	(0.007)	(0.015)	(0.015)	(0.077)	(0.062)
Common border		-0.030	-0.008	0.036	-0.035	-0.496^{***}	-0.470^{***}
		(0.060)	(0.022)	(0.039)	(0.026)	(0.192)	(0.181)
Common language		0.139^{***}	0.009	0.035^{*}	-0.005	0.583^{***}	0.622^{***}
		(0.030)	(0.012)	(0.018)	(0.012)	(0.088)	(0.081)
N		4,451	4,451	3,429	3,965	2,994	2,994
Pseudo R2		0.998	0.999	0.999	0.999	0.995	0.994
FE: sender×quarter, receiver×quarter		Yes	Yes	Yes	Yes	Yes	Yes

Note: $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$. The dependent variable is the annual US dollar amount of bilateral remittances in column (1) and the annual (quarterly) cross-border crypto flows in columns (2) to (7) ((8) to (13)), respectively. Robust standard errors, clustered by country pairs, in parentheses. Remittance costs are measured based on the log of the (lagged) mean of the total percentage of the transaction value charged for payments.

We find signs of cross-border crypto transactions emerging as a substitute for remittance payments through traditional intermediaries. Remittance volumes exhibit a highly negative cost elasticity, close to −45% (column 1). This tallies with a lack of competition within the traditional financial system, allowing intermediaries to maintain high fees in remittance corridors with limited activity.[27] Conversely, higher costs of sending remittances through traditional channels are associated with larger cross-border flows in stablecoins, notably USDT, and low-value BTC transactions, with elasticities of around 25% (columns 5 to 7 for annual estimates and columns 11 to 13 for quarterly estimates Table 8). By comparison, BTC flows comprising all transactions as well as flows in ETH, likely reflecting a variety of user motives, do not exhibit any significant relation to the cost of sending remittances.

4.4 Impact of policy interventions on crypto flows

As cryptoassets become more integrated with the broader financial system, there is a growing concern about the emergence of financial stability risks. Policymakers have noted that risks could be particularly relevant in emerging markets, where cryptoassets could provide avenues to bypass capital flow management measures (CFMs) and other exchange restrictions (Financial Stability Board, 2022). Hu et al. (2023), for instance, estimate that capital flight could account for over one-quarter of Chinese BTC exchange volume, with transactions motivated by circumvention of restrictions on capital outflows.

We explore how CFMs affect cross-border crypto flows by investigating the combined effects of outflow restrictions in the sending country and of inflow restrictions in the receiving country. We construct a time-varying country-pair measure of CFM stringency by combining these restrictions. The measure equals $+1$ and -1 to indicate a tightening and loosening, respectively, and zero otherwise. To address endogeneity concerns related to policy interventions responding to flows, we saturate our specification with the most comprehensive set of fixed effects, as detailed in equation (8). This accounts for time-invariant country-pair level effects in addition to fixed effects at the sender-quarter and receiver-quarter level.

Prior research has pointed to the risk of leakage effects, suggesting that CFMs can often be circumvented in highly developed markets, whereas they are more effective in less financially developed countries (e.g. Başkaya et al., 2024). To account for this, we run our regressions not only on the full sample but also on subsamples that consist only of flows between emerging market economies (EMEs). Indeed, for cross-border interbank claims, our estimates suggest that CFMs constrain activity between EMEs, whereas we find no statistically significant effect in our specification that also includes claims related to advanced economies (column 2 versus 1 of Table 9).

We find some evidence of circumvention of CFMs through crypto networks (Table 9). Specifically, a tightening of CFMs is associated with an increase in cross-border transactions in BTC of up to 25% (columns 3 and 4). For USDC, we detect a modest increase at

[27] These corridors may also be costly to serve for banks (e.g. due to obstacles to maintaining correspondent banking relationships), which would also explain higher transaction costs.

Table 9: Effect of capital flow management measures

	IB claims (1)	IB claims (2)	BTC (3)	BTC (4)	ETH (5)	ETH (6)	USDC (7)	USDC (8)	USDT (9)	USDT (10)
CFMs_{t-1}	-0.071	-0.102^{**}	0.249^{*}	0.235^{**}	0.049	0.055	0.048^{**}	0.027	-0.042	-0.031
	(0.048)	(0.050)	(0.138)	(0.118)	(0.061)	(0.059)	(0.024)	(0.023)	(0.029)	(0.028)
H_0 strict exogeneity:										
p-value	0.661	0.261	0.403	0.256	0.634	0.686	0.701	0.075^{*}	0.145	0.793
N	132,647	31,127	573,331	315,204	564,168	309,746	375,061	208,561	439,883	243,780
Pseudo R2	0.992	0.992	0.996	0.995	0.998	0.997	0.998	0.996	0.999	0.999
Fixed effects:										
pair, sender$\times t$, receiver$\times t$	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sample	All	EMEs	All	EMEs	All	EMEs	All	EMEs	All	EMEs

Note: $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$. The dependent variable is the quarterly US dollar equivalent of bilateral cross-border interbank (IB) claims (columns 1 and 2) and the quarterly US dollar equivalent of cross-border flows in the cryptoasset reported in the top row (columns 3 to 10). Robust standard errors, clustered by country pairs, in parentheses. The bottom row indicates the sample composition, distinguishing between regressions based on all flows and those based on flows between EMEs, respectively. Capital flow measures (CFMs) are given by a categorical variable with values -1, 0, and $+1$, to indicate a loosening, no change, and tightening of CFMs at the country-pair level, respectively. All coefficient estimates are corrected for potential bias in three-way gravity equations based on the approach in Weidner and Zylkin (2021). Strict exogeneity of CFMs is tested as in Baier and Bergstrand (2007), based on regressing crypto flows or IB claims, respectively, on the next period's capital flow measures (CFM_{t+1}). The null of strict exogeneity can only be rejected at the 10% level for USDC in specification (8) but not in any other specification.

around 5%. For ETH and USDT the effects are statistically insignificant. This suggests that these cryptoassets are not responsive to – but also little affected by – CFMs.

To affirm the robustness of our findings, we test for strict exogeneity of CFMs by using the methodology outlined in Baier and Bergstrand (2007). Our results support the assumption of exogeneity, as we observe that future changes in CFMs are uncorrelated with contemporaneous flows. This conclusion holds for all specifications for where a significant impact of CFMs on flows is identified. These findings align with the notion that capital controls primarily target cross-border services facilitated by traditional financial intermediaries.

5 Conclusion

This paper maps bilateral flows of major cryptoassets to uncover drivers of cross-border activity in both unbacked cryptoassets and stablecoins from 2017 to 2024. We document key nodes and edges of the country-to-country networks, highlighting the central role of the United States and the pivotal role of major emerging markets. Additionally, we observe substantial geographical shifts in activity amid significant growth in cross-border transaction volumes.

We next use a gravity framework to assess whether cross-border transactions in cryptoassets can be linked to drivers commonly associated with traditional financial activity. Our findings reveal that geographical distance curbs cross-border crypto flows far less than it does traditional financial flows. Indeed, cryptoassets used in decentralised networks appear to largely defy traditional frictions in capital flows. Conversely, a tightening of global funding conditions correlates with a decline in cross-border crypto flows, indicative of the use of cryptoassets as a risky investment. At the same time, we also find evidence of stablecoins and low-value BTC payments being used for transactions in the context of remittances. This is indicative of the multifacetted use cases of different cryptoassets.

Finally, our assessment highlights a continuing need for future research to understand the dynamics of global crypto flows. Our analysis indicates that policy measures designed to dampen traditional financial flows may have limited impact on constraining cross-border crypto activity. Yet, as cryptoassets become more integrated with mainstream finance, understanding the systemic risks and potential contagion effects between these markets will be essential for policymakers and market participants alike. At the same time, the socio-economic implications of increased crypto adoption, particularly in emerging market and developing countries, warrant a deeper examination. This includes assessing the impact on financial inclusion and economic stability, and the potential for cryptoassets to serve as a hedge against local currency volatility and weakness.

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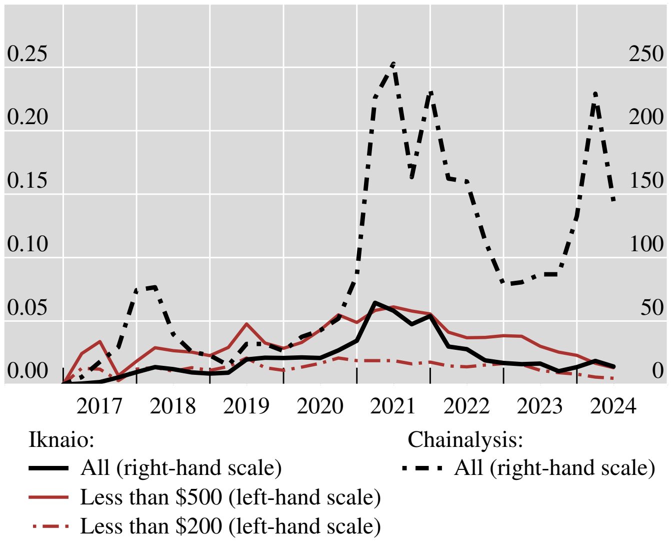
A Appendix

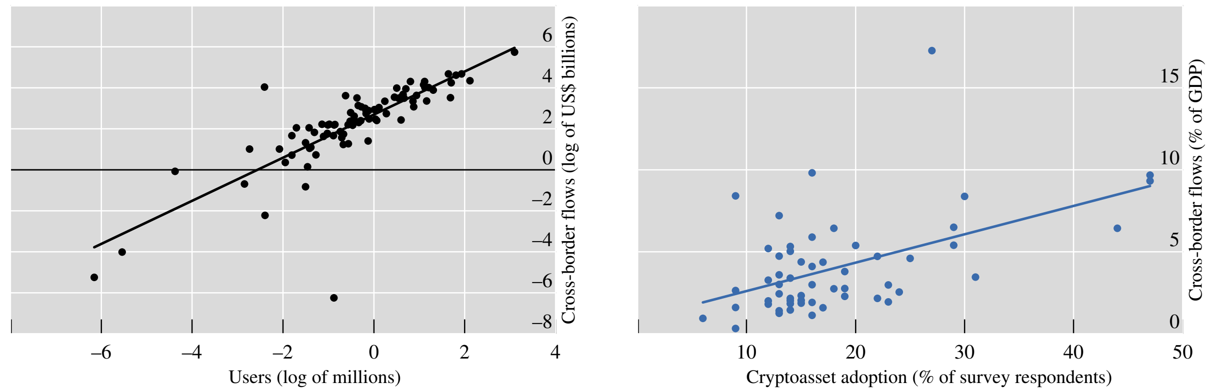
A.1 Figures

Figure A.1: Comparison of cross-border Bitcoin (BTC) flows (US$ billions)



Note: The graph presents quarterly cross-border BTC flows in US dollar equivalents from Q1 2017 to Q2 2024. The black dashed line shows total flows from Chainalysis, while the black solid line shows exchange-to-exchange flows from Iknaio, derived using the matching and weighting procedure in Annex A.2. The red solid and dashed lines represent flows for transactions below US$ 500 and US$ 200, respectively.

Figure A.2: Gauging the accuracy of approximated cross-border flows

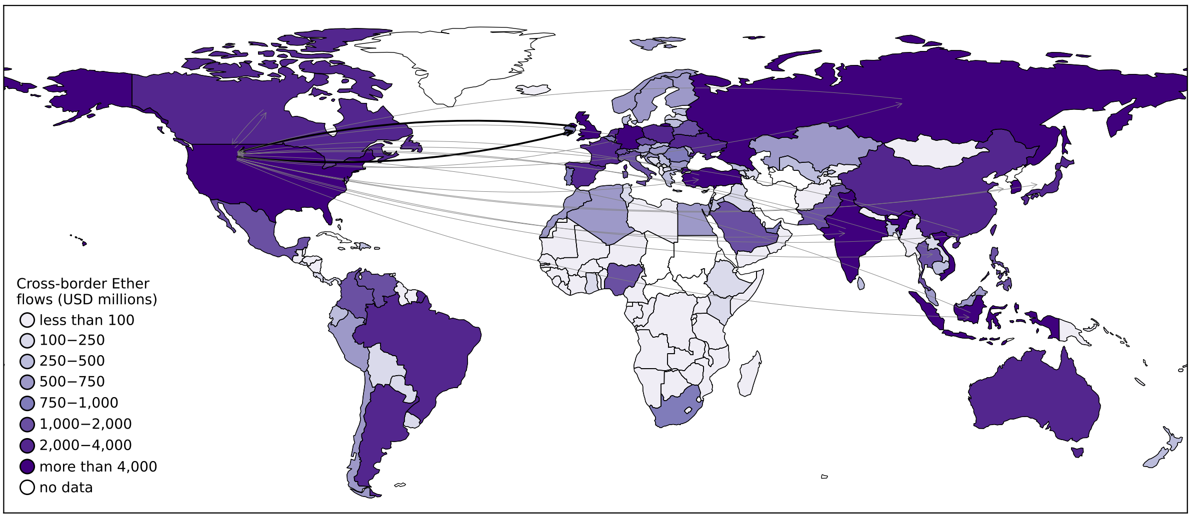


(A) Flows vs users

(B) Flows vs crypto adoption

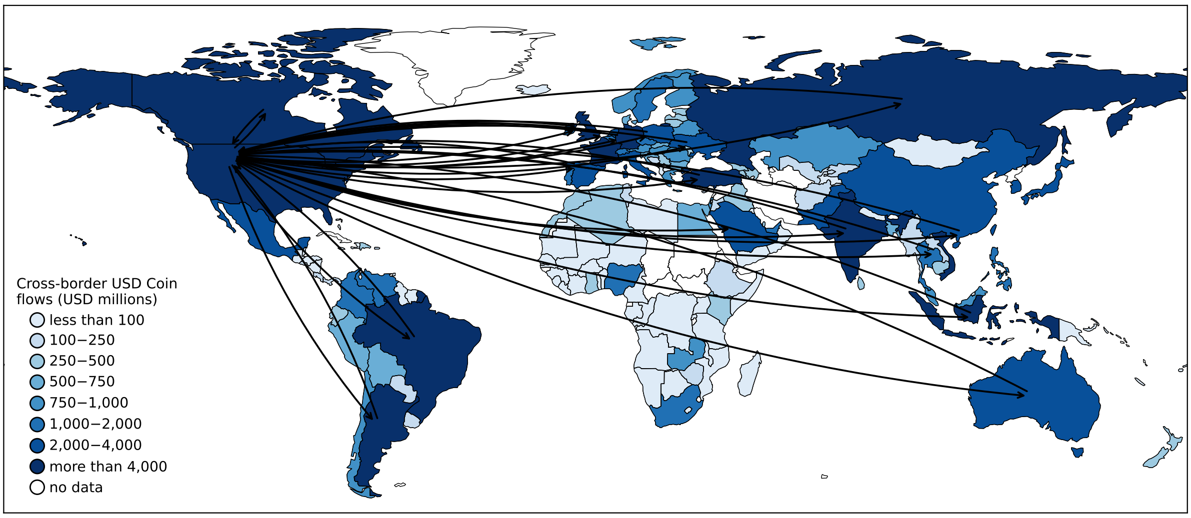
Note: Panel A shows the relationship, by country, between the log of average cryptoexchange users (in millions, x-axis) and the log of total cross-border flows (in US$ billions) of BTC, ETH, USDC, and USDT (y-axis) during Q3 2023 to Q2 2024. The log number of users explains approximately 64% of the variation in log flows, with a statistically significant pairwise correlation coefficient of 0.8. Panel B illustrates, by country, the percentage of survey respondents owning or using cryptoassets in 2023 (or the latest available year, x-axis) against cross-border flows of BTC, ETH, USDC, and USDT (as a percentage of GDP, y-axis) over the same period. Cryptoasset adoption accounts for roughly 26% of the variation in flows, with a statistically significant pairwise correlation coefficient of 0.5. Sources: Chainalysis (flow data); SensorTower (user statistics); Statista (survey data).

Figure A.3: Global Ether (ETH) Map



Note: Country colours represent the total US$ equivalent of ETH sent abroad in the first half of 2024, with countries grouped into eight categories. Black arrows represent bilateral flows equivalent to at least $US 1 billion, light grey arrows represent flows equivalent at least $US 500 million but less than $US 1 billion.

Figure A.4: Global USD Coin (USDC) Map



Note: Country colours represent the total US$ equivalent of USDC sent abroad in the first half of 2024, with countries grouped into eight categories. The arrows represent bilateral flows equivalent to at least $US 1 billion.

A.2 Alternative measures of cross-border Bitcoin flows

This annex describes the construction of the alternative measure of cross-border Bitcoin (BTC) flows used in the analysis of low-value flows in columns 6 and 7 of Table 8.

This measure is based on data provided by Iknaio, from which we obtain daily data on BTC flows between up to 303 crypto exchanges. The dataset contains times series for the US dollar equivalent of all flows, flows with a transaction value of less than US$ 500, and those of less than US$ 200, respectively. To address concerns about an artificial inflation of transaction volumes by individual crypto exchanges (so-called "wash trading"), we exclude daily flows within the same exchange that exceed the 99$^{\text{th}}$ percentile of flows in the sample.

We employ usage statistics on the crypto exchanges' smartphone applications from SensorTower (see Auer et al., 2022a, for a discussion) to allocate the BTC flows to countries. Specifically, we match country-level information on SensorTower's estimated number of active exchange users to each crypto exchange-month observation. For the period of observation (2017–24), our data record up to 170 million active users in a given month, suggesting broad coverage.

For each exchange, e, we calculate weights for country i in month t as follows:

$$weight_{ei,t} = \frac{Active\ users_{ei,t} \times GDP_{i,t}}{\sum_{j \in \Omega_e} (Active\ users_{ej,t} \times GDP_{j,t})}, \tag{10}$$

where Ω_e represents the set of all countries j with active users for crypto exchange e. $GDP_{i,t}$ is country i's GDP per capita in month t, which we interpolate from annual data to avoid jumps at year-end. For the months in 2024, we use the year-end value of 2023, the latest available data point at the time of writing. Weighting by GDP per capita accounts for differences in wealth and income across users.

As a final step, we employ the weights of the sending and receiving crypto exchanges to map flows pro rata to the corresponding bilateral flow from country to country. With user weight $weight_{ei,t}$, for country i at exchange e and weight $weight_{fj,t}$ for country j at exchange f, flows from exchange e to f in period t, $flow_{ef,t}$, yield an approximated flow from i to j equal to:

$$flow_{ij,t} = flow_{ef,t} \times weight_{ei,t} \times weight_{fj,t}. \tag{11}$$

We aggregate flows at quarterly and annual frequency to align them with the available frequency of our controls (see Table A.1) and of the remittances data (see Table 8).

This approach yields cross-border BTC flows for 84 countries, for which we plot total quarterly US dollar amounts (see the black solid line) alongside those from Chainalysis (black dashed line) in Figure A.1. On average, the Iknaio data account for about 35% of the transaction volume reported by Chainalysis, with coverage varying over time.

To assess the robustness of our main analysis using Chainalysis data, we repeat the regressions in Table 5 based on using total BTC flows from Iknaio. The results, presented in Table A.1, affirm the robustness of our main results with two exceptions: First, flows among crypto exchanges exhibit a tighter link to physical and linguistic proximity than those based on the broader Chainalysis dataset. Second, we find that a tightening of the Federal funds rate is associated with an increase in flows among crypto exchanges, consistent with our findings for stablecoins in Table 6.

Table A.1: Alternative measure of Bitcoin flows: gravity and key global drivers

	(1)	(2)	(3)	(4)	(5)
Gravity					
Distance	−0.207***	−0.217***	−0.218***	−0.217***	−0.217***
	(0.024)	(0.025)	(0.025)	(0.025)	(0.025)
Common border	0.282**	0.302**	0.302**	0.302**	0.302**
	(0.127)	(0.131)	(0.131)	(0.131)	(0.131)
Common language	0.418***	0.433***	0.433***	0.433***	0.433***
	(0.059)	(0.062)	(0.062)	(0.062)	(0.062)
Global factors (t–1)					
VIX		2.003***	1.757***	1.793***	2.001***
		(0.080)	(0.055)	(0.072)	(0.070)
High-yield spread		−2.469***		−2.811***	−2.387***
		(0.095)		(0.080)	(0.063)
Federal funds rate				−0.071***	−0.073***
				(0.008)	(0.007)
US growth				−0.048***	−0.005**
				(0.002)	(0.003)
Crypto risk factors (t–1)					
BTC-USD volatility		0.965***	0.214***	0.567***	
		(0.065)	(0.054)	(0.055)	
Crypto market					6.188***
					(0.169)
Crypto size					−0.885***
					(0.105)
Crypto momentum					−7.347***
					(0.458)
Dollar index			−10.797***		
			(0.332)		
N	160,712	163,369	163,369	163,369	163,369
Pseudo R2	0.950	0.848	0.826	0.852	0.860
FE: sender×t & receiver×t	Yes				
FE: sender & receiver		Yes	Yes	Yes	Yes

Note: $^{***}p < 0.01,^{**} p < 0.05,^{*} p < 0.1$. The dependent variable is the quarterly US dollar amount of bilateral cross-border Bitcoin (BTC) flows based on measure discussed in Appendix A.2. Robust standard errors, clustered by country pairs, in parentheses.

A.3 Aggregate flow measures

This annex uses an alternative empirical approach to assess the robustness of our main findings. Following the international capital flows literature (see e.g. Koepke, 2019 for a discussion). we aggregate the flows, f_{it}, received by each country, i, across all sending countries and scale this measure by the receiving country's GDP, gdp_{it}. Taking logs, we regress the following specification:

$$\ln\left(\frac{f_{it}}{gdp_{it}}\right) = \alpha_i + (x_{it-1} + x_{t-1})\,\beta + \varepsilon_{it}. \tag{12}$$

x_{it-1} represents the country-level factors and x_{t-1} the global factors and crypto risk factors employed in our main analysis above, whereas α_i accounts for time-invariant country-level effects and ε_{it} is the error term.

Table A.2: Drivers of aggregate crypto flows

	BTC (1)	BTC (2)	ETH (3)	ETH (4)	USDC (5)	USDC (6)	USDT (7)	USDT (8)
Global factors (t–1)								
VIX	2.707***	2.873***	3.683***	4.071***	9.602***	7.870***	15.378***	15.955***
	(0.141)	(0.157)	(0.200)	(0.207)	(0.486)	(0.397)	(0.290)	(0.260)
High-yield spread	−4.232***	−3.831***	−5.725***	−5.254***	−10.568***	−8.037***	−11.491***	−8.854***
	(0.154)	(0.154)	(0.227)	(0.218)	(0.471)	(0.412)	(0.337)	(0.348)
Federal funds rate	−0.029	−0.022	−0.066**	−0.005	0.427***	0.358***	0.685***	0.977***
	(0.022)	(0.026)	(0.028)	(0.028)	(0.043)	(0.041)	(0.033)	(0.032)
US growth	−0.013*	0.050***	0.035***	0.142***	0.107***	0.209***	0.314***	0.628***
	(0.007)	(0.010)	(0.007)	(0.010)	(0.012)	(0.018)	(0.011)	(0.018)
Country-level factors (t–1)								
High inflation	0.355***	0.312***	0.759***	0.650***	0.991***	1.220***	0.707***	0.391*
	(0.084)	(0.084)	(0.122)	(0.121)	(0.144)	(0.140)	(0.218)	(0.235)
High GDP growth	0.060	0.067	0.168**	0.185**	0.107	0.265*	0.093	0.292
	(0.064)	(0.061)	(0.083)	(0.076)	(0.149)	(0.159)	(0.197)	(0.193)
Crypto risk factors (t–1)								
BTC-USD volatility	1.206***		1.831***		−6.757***		−8.863***	
	(0.100)		(0.121)		(0.486)		(0.692)	
Crypto market		12.970***		19.376***		8.698***		28.744***
		(0.474)		(0.527)		(1.286)		(2.256)
Crypto size		−3.623***		−4.929***		−7.638***		−14.938***
		(0.329)		(0.357)		(0.728)		(0.958)
Crypto momentum		−7.660***		−4.620***		28.107***		41.900***
		(0.721)		(0.888)		(2.707)		(2.786)
N	3,767	3,767	3,760	3,760	2,755	2,755	3,271	3,271
Adjusted R2	0.857	0.873	0.812	0.836	0.766	0.763	0.611	0.624
Fixed effects: country	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$. The dependent variable is the log of the quarterly US dollar equivalent of country-level cross-border crypto flows as a share of GDP. Robust standard errors, clustered by country, in parentheses. High inflation and high GDP growth are binary variables that are equal to one (zero otherwise) if the country's inflation and GDP growth, respectively, are above the 75$^{\text{th}}$ percentile of the sample distribution in a given quarter.

Overall, the findings based on aggregated flows (Table A.2) are qualitatively consistent with the estimates obtained from the bilateral flows in our main analysis, but quantitative differences underscore the additional insights that can be inferred from using more granular data.

The estimated effect of global factors on aggregate crypto flows generally tallies with the estimates based on using bilateral flows. The impact of the VIX and of high-yield spreads is qualitatively the same for the aggregate flows. The relative size of the elasticities across cryptoassets is also similar, with USDT flows most sensitive to changes in these global factors.

Country-level factors confirm the positive association of crypto flows and receiving countries' inflation. Likewise, estimates of the impact of high GDP growth point to a supportive, although statistically often insignificant, effect on flows.

Crypto risk factors, finally, exhibit a qualitatively similar effect on crypto flows when considered at the country-level and at the more granular bilateral level. Most notably, our estimates confirm the negative association of flows in unbacked cryptoassets with past periods of strong crypto momentum based on aggregate data, in difference to the positive association found for stablecoins.

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