The Drivers of Cross-border Bitcoin, Ether, and Stablecoin Flows*

Raphael Auer†, Ulf Lewrick‡, Jan Paulick§

March 20, 2025

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 United States and major emerging markets serve as central nodes in the global crypto network. 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 standard capital flow measures appear ineffective.

JEL Codes: F24, F32, F38, G15, G23

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

*For helpful comments, we thank seminar participants at the Bank for International Settlements (BIS), the UC Santa Barbara, and at the Bank of Canada and Deutsche Bundesbank international conference on payments and securities settlement. We thank Sally Dubach, Maximilian Schrader and Violeta Vuletic for expert assistance with the data. The views expressed in this paper are those of the authors and not necessarily those of the BIS. The use of any maps in this paper does not constitute, and should not be construed as constituting, an expression of a position by the BIS regarding the legal status of, or sovereignty of any territory or its authorities, to the delimitation of international frontiers and boundaries and/or to the name and designation of any territory, city or area.

†BIS and CEPR. raphael.auer@bis.org

‡BIS and University of Basel. ulf.lewrick@bis.org (corresponding author)

§BIS and Deutsche Bundesbank. jan.paulick@bis.org

1 Introduction

Gauging cryptoasset flows across borders remains a huge gap in international finance. The crypto and decentralized 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 decentralized 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 2017 to 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. 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, 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. Drawing comparisons with traditional financial flows across borders and its determinants, we highlight the diminishing significance

[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.

of geographical proximity in crypto flows, particularly for stablecoins. 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 its role for speculation.

Our analysis in particular shows that cryptoassets are being used as a transactional medium. This is true for stablecoins and low-value Bitcoin 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 Bitcoin payments from advanced economies to emerging 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.

Our contribution to the literature is twofold. First, we offer 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. Second, the unique bilateral nature of the data allows for a novel empirical approach that helps uncover drivers of bilateral relations. We provide two applications of this: a comparison to traditional remittances and an assessment of the impact of CFMs.[2]

The bilateral nature of our dataset allows a novel approach to measuring the global network of cross-border flows in cryptoassets. Measurement of cross-border crypto flows can be done based on off-chain (through external channels) or on on-chain (i.e., directly on the blockchain) transactions. 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 con-

[2]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. Utilizing 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.

trols, resonating with our on-chain data results. We broaden the analysis by focusing on on-chain flows, which are several orders of magnitude larger and on additional cryptoassets. In particular the addition of stablecoins is relevant, as these serve different use cases than bitocin.[3]

Our work also complements related studies of on-chain Bitcoin activity.[4] 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.

The unique bilateral nature of our dataset also allows us to unpack the key drivers of cross-border crypto transactions, drawing a comparison with the established determinants of traditional flows, namely, trade in goods, interbank lending, and remittances. Our paper combines insights from the literature on international capital flows (e.g., Miranda-Agrippino and Rey (2020), Goldberg and Krogstrup (2023), and Hoffmann et al. (2019)) and in applications of gravity models to finance (e.g., Portes et al. (2001), Brei and von Peter (2018)). 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.

To examine drivers of crypto flows, our approach considers determinants identified in international trade and capital flow studies, for example in Badarinza et al. (2022), Brei and von Peter (2018) and Portes et al. (2001) and global factors employed by Bruno and Shin (2015) and Obstfeld and Zhou (2023). We provide a detailed discussion of determinants and respective data sources in 2.2.

Our findings complement 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 payment. Country corridors characterized 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

[3] von Luckner et al. (2023) identify cross-border flows based on the fiat currency used in the transaction to determine origination and destination. Fiat currencies provide a reasonable location approximation 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, one of the largest crypto markets.

[4] 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.

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).[5]

The remainder of this paper is organised into 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.

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 user base.[8] To calculate the geographic profile of crypto flows, the entity-to-entity data is complemented by the geographic distribution of 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

[5]These results 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).

[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 belong to the same entity 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.

in- and outflows to this exchange are allocated to the US. By aggregating over all crypto exchanges, bilateral cross-country data are obtained.

A first dataset we create – covering aggregate bilateral BTC flows as well as aggregate bilateral low-value BTC flows – in this manner combines exchange-to-exchange flows from Iknaio with SensorTower app usage statistics.[9] SensorTower offers aggregate downloads and usage statistics of apps offered by crypto exchanges by country of the users. This dataset constructs flows within and between crypto exchanges. It additionally offers a breakdown of transfers below the equivalent of US$ 500 and US$ 200 per transaction. The methodology employed by the data vendor (Iknaio) for these on-chain exchange flows relies on restrictive assumptions to mitigate false identification, resulting in a smaller covered volume and number of countries. We subsequently allocate crypto exchange flows to countries based on app usage statistics based on the weighting methodology explained in Annex A.2.

Our 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 covers 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 broader assumptions on clustering addresses and includes a wider range of business entities, such as miners and other services. [12]

The resulting country level data highlights the significant growth of cross-border flows for the major cryptoassets. The data reveal that growth of cross-border flows for the four major cryptoassets has been remarkable, 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 of 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 decreased to less than 25% as transactions in stablecoins expanded strongly.

We map out a global network of cross-border BTC and USDT flows to visualise the key

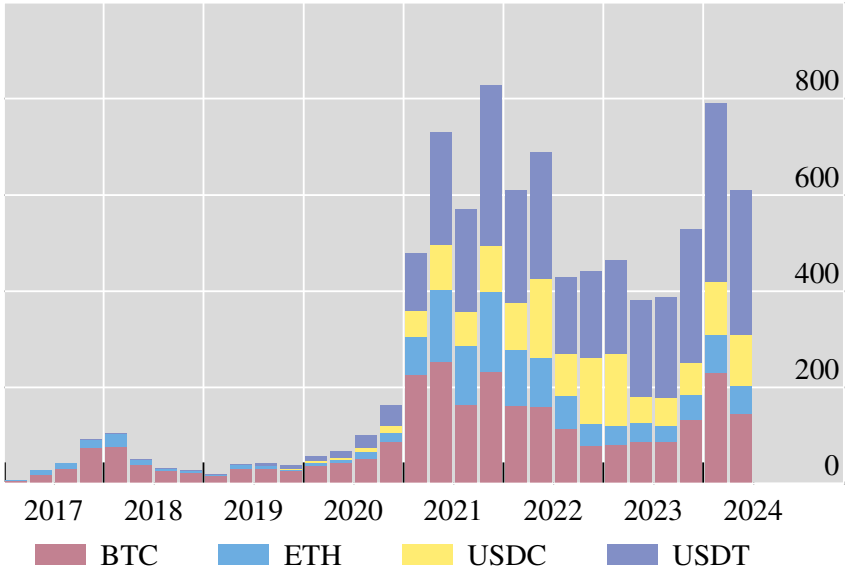
[9] We employ app usage statistics obtained from SensorTower where possible. However, not all crypto exchanges offer an app or data may not be available for all apps via SensorTower.

[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 for 80% of entity flows in BTC. BTC flows, including other services and broader assumptions, are roughly five times the size of those covered by the Iknaio dataset.

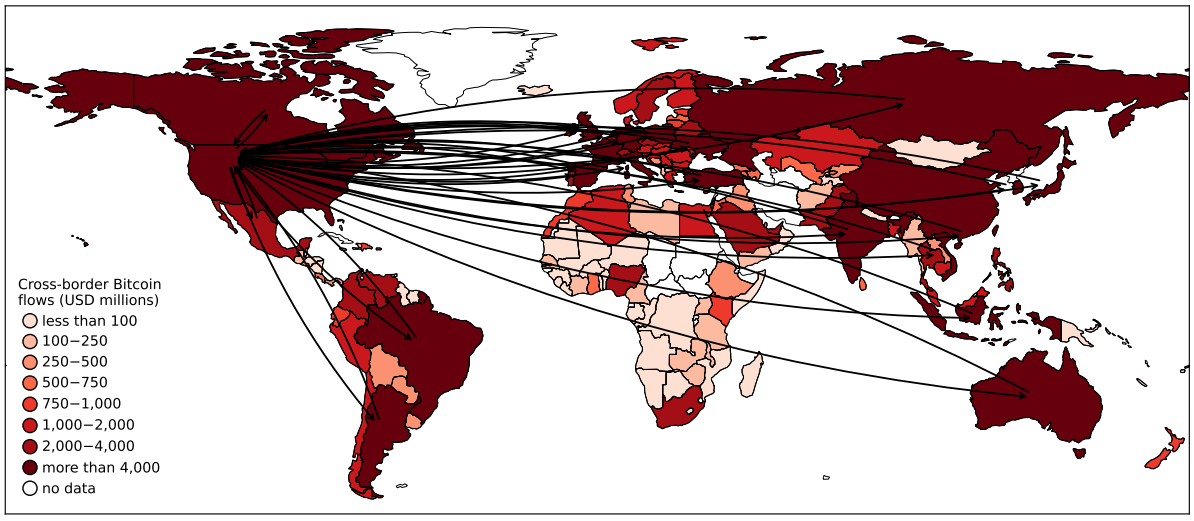
Figure 1: Cross-border crypto flows (US$ billions)



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

nodes and edges, i.e. directional links between two countries, for the period from Q3 2023 to Q2 2024, the last four quarters of our period of observation (Figure 2 and Figure 3). Corresponding maps for the other two cryptoassets are provided in Figure 5 and Figure 6 in Annex A.1. This BTC network spans 180 countries spread across all continents. We highlight flows of at least one billion US$ 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, the global USDT map is less centered on the United States, with flows more evenly spread across a few large countries as discussed below.

Figure 2: A Global Bitcoin Map



Note: Country colours represent the total US$ equivalent amount 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.

The United States, the United Kingdom and major emerging markets represent key

Figure 3: Global Tether (USDT) Map



Note: Country colours represent the total US$ equivalent amount 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.

nodes of the networks that underpin 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 during this period. These bilateral links also represented 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, respectively (Table 2). Common across these three networks is the geographical shift in cross-border flows during this period. Cross-border activity has moved from China to other major emerging markets, most notably India and Indonesia, against the backdrop of tighter crypto regulation and bans imposed by Chinese authorities (e.g. Auer and Claessens, 2018 and Auer et al., 2022b).

Geographical patterns differ for USDT, with a stronger presence of Turkey 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, Turkey 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.

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.[13]

[13]For consistency, we calculate network density based on the 225 countries included in our sample,

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.

Table 2: Major participants (flows in $ 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.

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.

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 are reported by 184 countries during the period of observation.

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, in turn affecting 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, likely giving rise to their different geographic profiles in cross-border flows compared to unbacked cryptoassets.

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, national, 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.[14]

[14]The methodology in Ratha and Shaw (2007) converts aggregate data on remittances received at the

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).

Global factors determine investors' risk-taking capacity and sentiment in other asset classes. Tightening global financial conditions, such as US dollar appreciation (Bruno and Shin, 2015, Obstfeld and Zhou, 2023) or rising corporate credit spreads (Gelos et al., 2022), could decrease crypto flows across borders. Rising market volatility may attract speculative traders and increase transaction volumes. We inspect several global factors of traditional capital flows (Miranda-Agrippino and Rey, 2020) to measure their impact on crypto flows. We consider the log of the CBOE Volatility Index (VIX) to capture expected volatility in US equity markets. Additionally, we control for changes in credit risk pricing based on option-adjusted spreads tracked by the ICE BofA BBB US corporate index (Gelos et al., 2022). We also test the impact of a rise in the broad nominal dollar index. We gauge global monetary conditions from the Federal funds rate and include quarterly real US GDP growth to approximate the global economic backdrop.

country level into bilateral remittance flows based on migrant stocks and income levels in the origin and destination country.

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 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 amount 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). *Bilateral FX volatility:* quarterly coefficient of variation of the bilateral exchange rate of the sending and receiving country-pair (BIS). *GDP growth:* real GDP growth rate (BIS and World Bank). *Google searches:* national index of Google searches of the term "Bitcoin", "Ethereum", and "Stablecoin", respectively (Google).

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 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 in the context of their usage for payments. High exchange rate volatility, for instance, could motivate the use of cryptoassets. To estimate 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.[15] We also obtain from the BIS bilateral exchange rate volatility for each country-pair over the past quarter. We also measure awareness of cryptoassets based on country-level indices of "Bitcoin", "Ethereum", and "Stablecoin" searches on Google (Liu et al., 2022). For all these factors, we expect an impact on crypto flows when their values are particularly high, e.g. when the local currency is under particular pressure or public interest in cryptoassets is exceptionally high. Therefore, we define a binary variable equal to one (zero otherwise) for each quarter in which the factor exceeds the 75$^{\text{th}}$ percentile of its pooled distribution. For Google searches, which are standardised at the national level, we set to one (zero otherwise) those observations that exceed the 75$^{\text{th}}$ percentile of the country's own time series of searches.[16]

The pseudonymity 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

[15] We interpolate quarterly inflation and GDP growth rates from annual figures for countries that do not report quarterly data.

[16] Our results are robust to using the corresponding indices of "stablecoin" searches for USDC and USDT, respectively. These indices, however, are available only for a much smaller subset of observations, and we therefore employ "Ethereum" searches for these two cryptoassets, which run on the Ethereum blockchain.

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.

3 Empirical approach

Our empirical approach leverages the directed bilateral flows data (corridors) 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, national and corridor 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):

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

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. Brei and von Peter, 2018 or Portes et al., 2001).

Following the literature, we parameterize 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, national, and corridor 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.

Thus, 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:

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

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:

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

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 parameterization 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 measures of geographical and linguistic distance affect cross-border BTC flows, as the predominant cryptoasset. Cross-border interbank claims and exports serve as our initial benchmark, and we estimate gravity equations following the specification in equation (5).[17]

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%

[17] 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

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×t & receiver×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.

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 (column 1 of Table 5). 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 (column 2).

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.[18]

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 volatility in equity markets, as gauged by the VIX, consistently exhibits a strong positive relationship with BTC flows with an elasticity of around 2%. Tighter global funding conditions, in turn, hamper cross-border 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 around 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 dollar appreciation, such as those from major emerging markets with a strong footprint in the BTC network.

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).[19] In the same vein, we find that an increase in US growth 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, 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 the market, size, and momentum factors. Each of these factors proves to be highly statistically significant (column 7). We find that cross-border BTC transaction volume increases following periods of excess returns in crypto markets, with a positive and statistically significant loading on the lagged crypto market factor. Following Liu et al. (2022), who interpret the size factor in terms of a liquidity premium, this suggests that cross-border BTC activity declines following an episode of high liquidity demand in crypto markets. Since BTC is one of the most liquid cryptoassets this finding likely reflects a reversal in elevated BTC transaction volumes during episodes of high liquidity premia.[20] The negative impact of the momentum factor,

[18] For our alternative measure of BTC flows based on the more narrow sample of exchange-to-exchange flows and alternative locational weigthing (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.

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

[20] In line with this interpretation, we find that the coefficient on the contemporaneous (but possibly

a gauge of the investor overreaction premium, points to a reversal in transaction volumes following quarters in which crypto returns were pushed to elevated levels.

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 changes little 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).

In difference to BTC and ETH, there is a strong negative association of stablecoin flows with BTC-USD volatility. Likewise, crypto risk factors show significant loadings for both stablecoins with a reversal of signs for the momentum factor (USDC and USDT) and market factor (USDC) if compared with the unbacked cryptoassets. This tallies with the positive correlation of BTC-USD volatility with the market factor. One interpretation is that large movements in the price of unbacked cryptoassets could weigh on investor confidence in the stablecoin's ability to maintain their peg. Alternatively, such movements could attract speculative investment at the expense of stablecoins. Once market momentum in the unbacked cryptoassets reverses, transactions in stablecoins pick up again, consistent with the positive signs of the coefficients on the momentum factor for the stablecoins.

Moreover, stablecoin flows are tightly linked to US monetary conditions, reflecting their close ties to the currency they are pegged to. We estimate that a 25 basis point increase 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,

endogenous) size factor is positive. This accords with high values of the size factors at times of high BTC transaction volumes. The results are available upon request from the authors.

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 amount 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.

we find a positive association of flows with US growth, with semi-elasticities of around 4% to 8%.[21]

4.2 Country-specific drivers

We turn to country-specific factors to assess the importance of national 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

[21] 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.

(reported in column 6 of Table 5).[22]

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

	BTC	ETH	USDC	USDT	USDC	USDT
	(1)	(2)	(3)	(4)	(5)	(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 amount 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", respectively, are in the top quartile of the country's own time series of searches.

High inflation is associated with more use of stablecoins and ETH 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 to nearly 20% for USDT and ETH. Our findings for USDC resonate with the attractiveness of stablecoins for international transactions among countries facing inflationary pressure.[23] 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 of the USDT network (see Table 2) having experienced bouts of volatility in their home currencies' exchange rate during the period of observation.

[22]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.

[23]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).

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.[24] 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. Indeed, 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). 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).

We test whether high costs of remittances is 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 amount 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 and developing markets in all our regressions, in line with the direction of traditional remittance payments.

[24] 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).

Table 8: Crypto as an emerging substitute for remittances?

	Remittances	BTC	ETH	USDC	USDT	BTC<$500	BTC<$200
Annual data	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Remittance cost$_{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 −60% (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. 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 close to 30% (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, respectively. We construct a time-varying country-pair measure of CFM stringency by combining these restrictions, which equals +1 and −1 to indicate a tightening and loosening, respectively, and is 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), which 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 samples but also on subsamples that consist only of flows between emerging market economies (EMs). Indeed, for cross-border interbank claims, our estimates suggest that CFMs constrain activity between EMs, 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).

Table 9: Effect of capital flow management measures

	IB claims	IB claims	BTC	BTC	ETH	ETH	USDC	USDC	USDT	USDT
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(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×t, receiver×t	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sample	All	EMs	All	EMs	All	EMs	All	EMs	All	EMs

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 EMs, 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.

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%. For ETH and USDC, we detect a modest, although mostly statistically insignificant, increase at around 5%, with no significant effect found

for USDT. 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 using the approach in Baier and Bergstrand (2007), which confirms that future changes in CFMs are uncorrelated with concurrent flows. This holds for all specifications for which we find a significant effect of CFMs on flows, consistent with capital controls focussing predominantly on cross-border services provided 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 in some networks and the pivotal role of major emerging markets in others. Additionally, we observe substantial geographical shifts in activity amid significant growth in cross-border transaction volumes.

Using 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 decentralized 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 cryptoasset usage 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, indicative of the multifacetted use cases of differtn 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 developing countries, warrant a deeper examination. This includes assessing the impact on financial inclusion, economic stability, and the potential for cryptoassets to serve as a hedge against local currency volatility and weakness.

References

Aggarwal, R., Demirgüç-Kunt, A., Pería, M.S.M., 2011. Do remittances promote financial development? Journal of Development Economics 96, 255–264.

Anderson, J., van Wincoop, E., 2003. Gravity with gravitas: a solution to the border puzzle. American Economic Review 93, 170–192.

Anderson, J., Yotov, Y., 2016. Terms of trade and global efficiency effects of free trade agreements, 1990-2002. Journal of International Economics 99, 279–298.

Athey, S., Parashkevov, I., Sarukkai, V., Xia, J., 2016. Bitcoin pricing, adoption, and usage: theory and evidence. Stanford University Graduate School of Business Research Paper, no 16-42.

Auer, R., Claessens, S., 2018. Regulating cryptocurrencies: assessing market reactions. BIS Quarterly Review.

Auer, R., Cornelli, G., Doerr, S., Frost, J., Gambacorta, L., 2022a. Crypto trading and Bitcoin prices: evidence from a new database of retail adoption. BIS Working Papers 1049.

Auer, R., Farag, M., Lewrick, U., Orazem, L., Zoss, M., 2022b. Banking in the shadow of Bitcoin? The institutional adoption of cryptocurrencies. BIS Working Papers, no 1013.

Başkaya, Y., Shim, I., Turner, P., 2024. Financial development and the effectiveness of macroprudential an capital flow management measures. BIS Working Papers, no 1158.

Badarinza, C., Ramadorai, T., Shimizu, C., 2022. Gravity, counterparties, and foreign investment. Journal of Financial Economics 145, 132–152.

Baier, S., Bergstrand, J., 2007. Do free trade agreements actually increase members international trade? Journal of International Economics 71, 72–95.

Beck, T., Janfils, M., Kpodar, K., 2022. What explains remittance fees? Panel evidence. IMF Working Papers 2022/063. International Monetary Fund.

Biais, B., Bisière, C., Bouvard, M., Casamatta, C., Menkveld, A., 2023. Equilibrium bitcoin pricing. Journal of Finance 78, 967–1014.

Binici, M., Das, M., Pugacheva, E., 2023. The incidence of capital flow management measures: observations from a new database. IMF Economic Review, June.

Brei, M., von Peter, G., 2018. The distance effect in banking and trade. Journal of International Money and Finance, 81, 116–137.

Bruno, V., Shin, H.S., 2015. Capital flows and the risk-taking channel of monetary policy. Journal of Monetary Economics 71, 119–132.

Böhme, R., Christin, N., Edelman, B., Moore, T., 2015. Bitcoin: Economics, technology, and governance. Journal of Economic Perspectives 29, 213–38.

Cerutti, E., Chen, J., Hengge, M., 2024. A primer on Bitcoin cross-border flows. IMF Working Paper, WP/24/85.

Choi, K., Lehar, A., Stauffer, R., 2022. Bitcoin microstructure and the Kimchi premium. mimeo.

Conte, M., Cotterlaz, P., Mayer, T., 2022. The CEPII gravity database. CEPII Working Paper, no 2022-05.

Financial Stability Board, 2022. Assessment of risks to financial stability from crypto-assets. February.

Gelos, G., Gornicka, L., Koepke, R., Sahay, R., Sgherri, S., 2022. Capital flows at risk: Taming the ebbs and flows. Journal of International Economics 134, 103555.

Goldberg, L., Krogstrup, S., 2023. International capital flow pressures and global factors. Journal of International Economics 146, 103749.

Halaburda, H., Haeringer, G., Gans, J., Gandal, N., 2022. The microeconomics of cryptocurrencies. Journal of Economic Literature 60, 971–1013.

Head, K., Mayer, T., 2014. Gravity equations: workhorse, toolkit, and cookbook, in: Gopinath, G., Helpman, E., Rogoff, K. (Eds.), Handbook of International Economics. Elsevier, pp. 131–195.

Hinzen, F.J., John, K., Saleh, F., 2022. Bitcoin's limited adoption problem. Journal of Financial Economics 144, 347–369.

Hoffmann, M., Krause, M., Tillmann, P., 2019. International capital flows, external assets and output volatility. Journal of International Economics 117, 242–255.

Hu, M., Lee, A., Putniņš, T., 2023. Evading capital controls via cryptocurrencies: evidence from the blockchain. Mimeo.

Koepke, R., 2019. What drives capital flows to emerging markets? A survey of the empirical literature. Journal of Economic Surveys 33, 516–540.

Liu, Y., Tsyvinksi, A., 2021. Risks and returns in cryptocurrency. Review of Financial Studies 34, 2689–2727.

Liu, Y., Tsyvinksi, A., Wu, W., 2022. Common risk factors in cryptocurrency. Journal of Finance 77, 1133–1177.

Liu, Z., Spiegel, M., Zhang, J., 2023. Capital flows and income inequality. Journal of International Economics 144, 103776.

von Luckner, C., Reinhart, C., Rogoff, K., 2023. Decrypting new age international capital flows. Journal of Monetary Economics, 138, 104–122.

Lueth, E., Ruiz-Arranz, M., 2008. Determinants of bilateral remittance flows. The B.E. Journal of Macroeconomics 8.

Makarov, I., Schoar, A., 2020. Trading and arbitrage in cryptocurrency markets. Journal of Financial Economics 135, 293–319.

Makarov, I., Schoar, A., 2021. Blockchain analysis of the Bitcoin market. NBER Working Paper, no 29396.

Miranda-Agrippino, S., Rey, H., 2020. U.S. monetary policy and the global financial cycle. Review of Economic Studies 87, 2754–2776.

Möser, M., Narayanan, A., 2022. Resurrecting address clustering in bitcoin, in: Eyal, I., Garay, J. (Eds.), Financial Cryptography and Data Security, Springer International Publishing, Cham. pp. 386–403.

Obstfeld, M., Zhou, H., 2023. The global dollar cycle. NBER Working Paper Series, no 31004.

Pagnotta, E., 2022. Decentralized money: Bitcoin prices and blockchain security. Review of Financial Studies 35, 866–907.

Portes, R.P., Rey, H., Oh, Y., 2001. Information and capital flows: the determinants of transactions in financial assets. European Economic Review 45, 783–796.

Ratha, D., Shaw, W., 2007. South-south migration and remittances. World Bank Working Paper, 102.

Santos Silva, J., Tenreyro, S., 2006. The log of gravity. The Review of Economics and Statistics 88, 641–658.

Schilling, L., Uhlig, H., 2019a. Currency substitution under transaction costs. AEA Papers and Proceedings 109, 83–87.

Schilling, L., Uhlig, H., 2019b. Some simple bitcoin economics. Journal of Monetary Economics 106, 16–26.

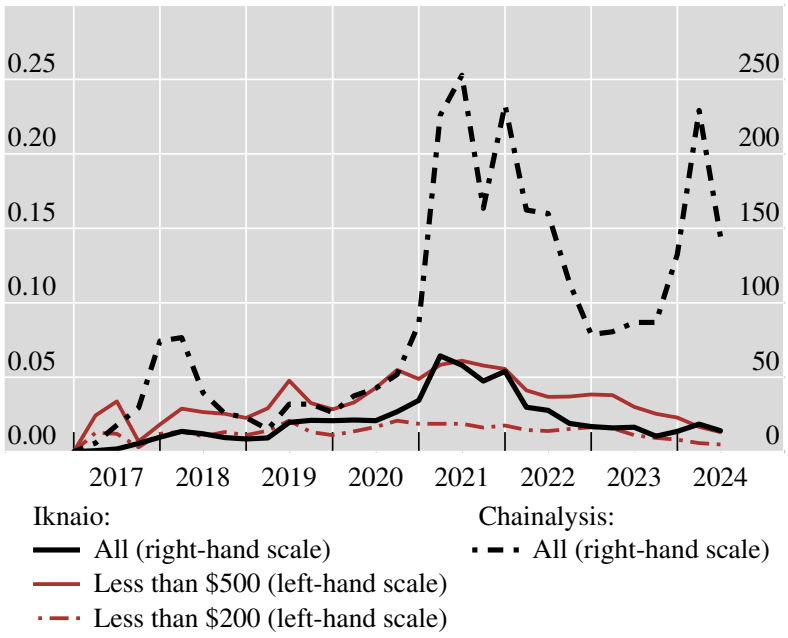
Weidner, M., Zylkin, T., 2021. Bias and consistency in three-way gravity models. Journal of International Economics 132, 103513.

Yang, D., 2011. Migrant remittances. Journal of Economic Perspectives 25, 129–52.

A Appendix

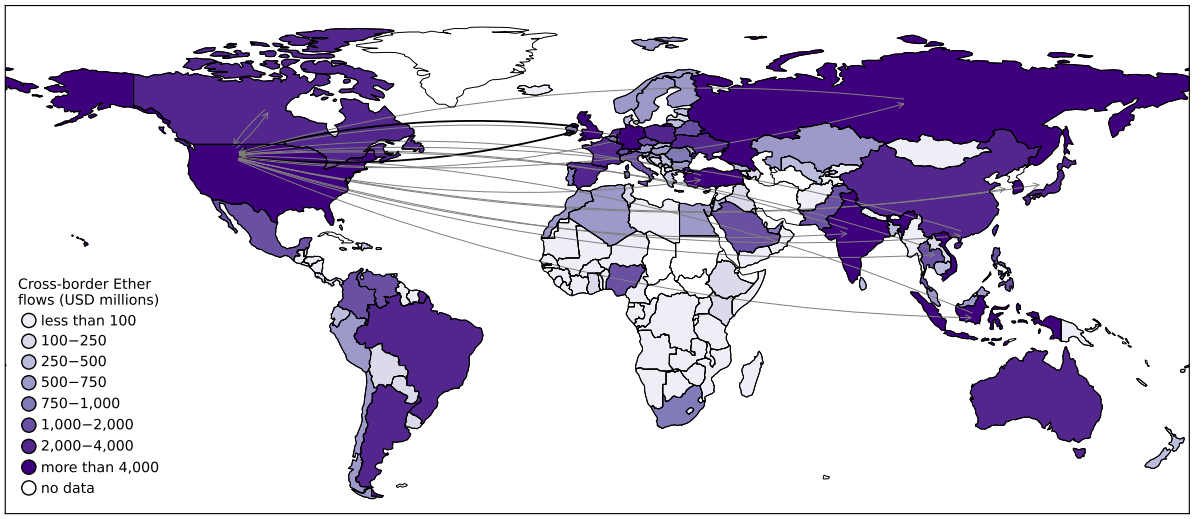
A.1 Figures

Figure 4: Comparison of cross-border Bitcoin (BTC) flows (US$ billions)



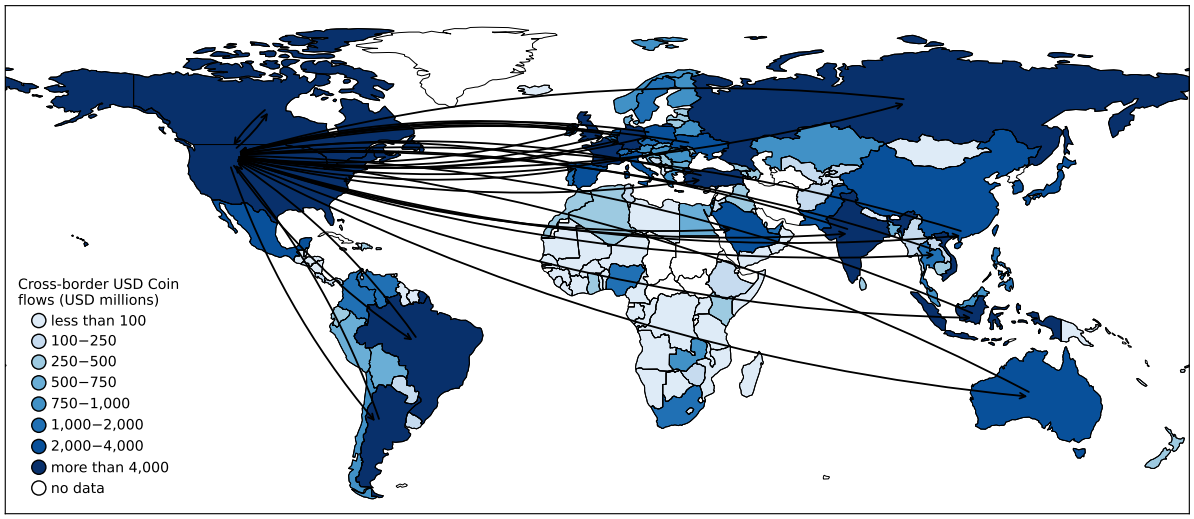
Note: The graph presents the US dollar equivalent of quarterly aggregates of cross-border BTC flows from Q1 2017 to Q2 2024. The black dashed line represents all flows obtained from Chainalysis. The black solid line depicts all exchange-to-exchange flows obtained from Iknaio based on applying the matching and weighting procedure detailed in Annex A.2. The solid and dashed red lines represent the corresponding flows for transactions equivalent to less than US$ 500 and less than US$ 200, respectively.

Figure 5: Global Ether (ETH) Map



Note: Country colours represent the total US$ equivalent amount 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 6: Global USD Coin (USDC) Map



Note: Country colours represent the total US$ equivalent amount 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 amounts 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^{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. 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 or annual frequency to align them with the available frequency of our controls (see below) or 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 4. Overall, the Iknaio data account, on average, for about 35% of the transaction volume reported by Chainalysis.

To assess the robustness of our main analyis using Chainalysis data, we repeat the regressions in Table 5 based on using total BTC flows from Iknaio. The results, presented

in Table 10, 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 10: 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$\times t$ & receiver$\times t$	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

We affirm the robustness of our main findings based on using an alternative empirical approach. Following the international capital flows literature,[25] 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 11: 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 11) 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

[25] See e.g. Koepke, 2019 for a discussion.

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.

A.4 Mapping flows based on cryptoexchange domiciles

Table 12: Flows based on cryptoexchange domiciles

	BTC (1)	BTC (2)	BTC (3)	ETH (4)	ETH (5)	ETH (6)	USDC (7)	USDC (8)	USDC (9)	USDT (10)	USDT (11)	USDT (12)
Gravity												
Distance	0.192***	0.161**	0.161**	0.171***	0.157***	0.157***	0.522***	0.484**	0.484**	0.181***	0.152**	0.152**
	(0.066)	(0.066)	(0.066)	(0.061)	(0.061)	(0.061)	(0.196)	(0.203)	(0.203)	(0.063)	(0.063)	(0.063)
Common border	0.708***	0.762***	0.762***	0.763***	0.879***	0.879***	1.220**	1.058*	1.058*	−0.162	0.037	0.037
	(0.261)	(0.260)	(0.260)	(0.265)	(0.246)	(0.246)	(0.576)	(0.541)	(0.541)	(0.372)	(0.389)	(0.389)
Common language	1.080***	1.101***	1.101***	1.793***	1.774***	1.774***	3.747***	3.799***	3.799***	1.682***	1.590***	1.590***
	(0.385)	(0.390)	(0.390)	(0.458)	(0.465)	(0.465)	(0.610)	(0.628)	(0.628)	(0.379)	(0.367)	(0.367)
Global factors (t-1)												
VIX		0.917***	1.102***		2.552***	2.670***		7.376***	8.440***		5.879***	5.804***
		(0.147)	(0.150)		(0.276)	(0.254)		(0.193)	(0.244)		(0.358)	(0.401)
High-yield spread		−3.099***	−2.758***		−4.529***	−4.043***		−7.822***	−10.911***		−6.526***	−6.488***
		(0.090)	(0.087)		(0.246)	(0.272)		(0.384)	(0.330)		(0.382)	(0.666)
Federal funds rate		−0.187***	−0.195***		−0.131***	−0.095*		0.361***	0.551***		0.302***	0.343***
		(0.027)	(0.031)		(0.046)	(0.049)		(0.129)	(0.104)		(0.079)	(0.083)
US growth		−0.080***	−0.042***		−0.010	0.045***		0.090***	0.028***		0.035	0.058***
		(0.010)	(0.009)		(0.016)	(0.008)		(0.011)	(0.006)		(0.022)	(0.014)
Crypto risk factors (t-1)												
BTC-USD volatility		1.537***			1.750***			−4.194***			−3.501***	
		(0.179)			(0.388)			(0.437)			(0.499)	
Crypto market			6.844***			7.765***			−4.623***			3.230***
			(0.345)			(0.961)			(0.780)			(0.779)
Crypto size			−1.449***			−1.813***			−8.778***			−4.586***
			(0.289)			(0.392)			(0.388)			(0.842)
Crypto momentum			−9.593***			−3.727*			0.659			0.170
			(1.029)			(2.102)			(1.916)			(2.090)
N	76,459	84,500	84,500	59,117	72,982	72,982	29,464	68,302	68,302	34,008	69,680	69,680
Pseudo R2	0.929	0.861	0.866	0.949	0.882	0.885	0.983	0.933	0.937	0.943	0.878	0.878
FE: sender×t & receiver×t	Yes			Yes			Yes			Yes		
FE: sender & receiver		Yes	Yes		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 amount of bilateral cross-border flows in the cryptoasset reported in the top row. Robust standard errors, clustered by country pairs, in parentheses.