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Patterns and Determinants of Global Cryptocurrency Flows

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Patterns and Determinants of Global Cryptocurrency Flows*

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Abstract

In this paper, we examine the patterns and determinants of cross-border cryptocurrency flows. While our analysis focuses primarily on Bitcoin flows, the cryptocurrency with the largest market capitalization, we show that our key results also extend to four major stablecoins. After documenting global patterns of cross-border Bitcoin flows and contrasting them with those of traditional capital flows, we employ a cross-country panel approach to identify the key drivers of cross-border crypto flows for up to 162 countries. Our results provide evidence for the presence of multiple coexisting motives. The most significant motives comprise strategies to adjust to unfavorable macro and financial developments, as well as the need to conduct international payment and remittance transfers. Moreover, by conducting a case study of cross-border Bitcoin flows after the COVID-19 shock, we find that these motives were particularly relevant at a time when economic conditions were weak and the need for remittances appeared high. Gaining a better understanding of the motives behind cross-border cryptocurrency transactions is crucial for informing the public debate on cryptocurrencies and their potential use cases.

Keywords: Cryptocurrency flows, Bitcoin, stablecoins, traditional capital flows, determinants

JEL Classification: E4, F3, F32, F38, F51, G15, G23

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1 Introduction

Over the past decades, the economic profession has developed a deep understanding of the determinants and consequences of traditional international capital flows. By now, we have obtained a clear picture of their dynamics in normal and crisis times, a rich understanding of their global and domestic drivers, as well as a good idea of their consequences for the economy and the financial system. However, we cannot say the same about cross-border cryptocurrency flows yet (henceforth *crypto flows*). Do crypto flows follow the same patterns? Are they subject to the same determinants and drivers?[1] What are the implications for the economy and the financial system? Using a new and extensive dataset on cross-border crypto flows, this paper aims to provide a first set of answers to these questions.

Our analysis is based on a recently released cross-border crypto flow dataset from Chainalysis. The dataset is derived from publicly available blockchain transactions, spans multiple cryptocurrencies, and covers a broad range of crypto exchanges (including non-peer-to-peer exchanges) and other crypto service providers. By clustering crypto addresses with similar behaviors, mapping them into real-world entities, and linking the likely user-bases of these real-world entities to specific countries, Chainalysis converts the blockchain information into analyzable data. At this point, the Chainalysis dataset is arguably the richest source of cross-border cryptocurrency flows available.

In this paper, we focus mostly on cross-border crypto flows of *Bitcoin* (BTC), the largest cryptocurrency with a market capitalization of \$2.49 trillion US dollars (USD) at its peak in late 2025, and four major stablecoins, namely *Tether* (USDT; peak market capitalization of \$187 billion USD), *USD Coin* (USDC; \$79 billion USD), *Binance USD* (BUSD; \$23 billion USD, now discontinued), and *Dai* (DAI; \$10 billion USD).[2] Overall, our crypto data cover crypto in- and outflows for up to 162 countries over the period from 2020Q3 to 2023Q3.

We make four contributions to the literature. First, we document the patterns of global cross-border Bitcoin flows and contrast these patterns with those of traditional international capital flows.[3] Second, using a cross-country panel approach at annual frequency, we conduct a systematic and comprehensive assessment of the key determinants and motives of cross-border Bitcoin flows. Third, we conduct an event study based on the COVID-19 pandemic, which serves as a natural experiment

[1] In this paper, we use the terms *determinants* and *drivers* interchangeably. Moreover, we refer to a group of similar determinants/drivers as a *motive*.

[2] All market capitalization data are taken from CoinMarketCap (2026). The dates for the peak values are: Bitcoin (October 2025), Tether and USD Coin (December 2025), Binance USD (November 2022), and Dai (February 2022).

[3] In this paper, we treat cryptocurrencies as assets and not as money. We discuss this assumption in Section 2.3.

during which the relevance of several previously identified motives may have been amplified. And fourth, we apply our determinant analysis to the cross-border flows of four major stablecoins. We conclude by discussing the implications of our findings for the economy and the financial system.

Our results are as follows. First, we document several key patterns of global cross-border Bitcoin flows. Starting at around $40 billion USD in mid-2020, the total value of global cross-border Bitcoin flows rises quickly and peaks at around $160 billion USD in the first half of 2021. While cross-border Bitcoin flows are still relatively small for the average country in our sample (the sum of Bitcoin in- and outflows amounts to 1.6% of quarterly GDP), several countries in Eastern Europe, Latin America, and Asia have experienced more sizable cross-border Bitcoin flows (up to 14 % of quarterly GDP). When turning to net flows (i.e., the difference between in- and outflows), we find that net outflows generally originate from emerging market economies, while net inflows are mostly recorded by advanced economies. Next, we contrast these patterns with those of traditional capital flows. When comparing means and standard deviations of Bitcoin flows and traditional capital flows in net terms, we find limited evidence that Bitcoin flows behave in a similar way to traditional capital flows, suggesting that they possibly respond to a different set of drivers. When computing shares of Bitcoin flows relative to portfolio investment flows and other investment flows, respectively, we find that Bitcoin flow shares amount to around 3-4% at the 75^{th} percentile of the share distribution, and thus, are relatively small for most sample countries. For several countries, however, Bitcoin flow shares are more sizeable (e.g., up to 61% of portfolio investment flows), suggesting that, at least in some cases, Bitcoin flows have become a notable alternative to traditional capital flows.

In our annual panel analysis, where we assess the determinants of cross-border cryptocurrency transactions more formally, we identify seven distinct motives that serve as drivers for such transactions. These motives include strategies to adjust to unfavorable macro and financial developments in the present and the past, weak institutions, underdeveloped financial systems, the need to conduct international payment and remittance transfers, as well as the possible circumvention of capital controls and international sanctions. Using the example of Bitcoin again, our analysis indicates that the most significant motives are strategies to adjust to unfavorable macro and financial developments, as well as the need to conduct international payment and remittance transfers. Overall, our findings highlight that there is a wide range of motives for cross-border cryptocurrency transactions that are likely of varying appeal to policymakers. On the one hand, the international payments and remittances motive, which appears to take advantage of a more favorable cost structure of cryptocurrencies compared to many traditional cross-border payment services, seems to be worthy of support. On the other hand, the potential use of cryptocurrencies to circumvent capital controls or international sanctions may foster discussions about closer monitoring and possibly also tighter regulation of cryptocurrencies.

Next, we conduct an event study of cross-border Bitcoin flows during the COVID-19 period that highlights the robustness of our previously identified motives. By comparing the impact of the COVID-19 shock on countries with high vs. low pre-COVID-19 motive exposures, we find that, in particular, pre-COVID-19 exposures related to unfavorable macro and financial developments, as well as the need to conduct international payment and remittance transfers, have supported cross-border Bitcoin transactions during episodes of high COVID-19 intensity. Taken together, our findings suggest that these two motives played a central role precisely during times when they were expected to be important, further strengthening the external validity of our results.

Finally, when applying the baseline specification of our determinant analysis to four major stablecoins, we show that our Bitcoin findings also extend to the stablecoin ecosystem. This reinforces the economic significance of our results and provides a richer information set to policymakers.

Our work relates to the existing literature as follows. First, we build on an extensive and mature literature on traditional capital flows that focuses in particular on documenting the *patterns* (or dynamics) and *determinants* (or drivers) of international capital flows. Early work by Calvo, Leiderman and Reinhart (1993) highlights the relevance of external (or *push*) factors—such as global or US economic and financial developments—as key drivers of international capital flows. These external factors were then placed in contrast to domestic (or *pull*) factors—such as the economic and financial conditions in the capital-flow-receiving country—which subsequently shifted the focus of the literature to an assessment of their relative contributions (e.g., Fernandez-Arias, 1996). Hannan (2018) and Koepke (2018) provide reviews of this large literature. Both reviews identify global risk aversion, global or US interest rates, and global or US economic growth as important push factors. According to Hannan (2018), pull factors can be further divided into cyclical and structural factors. Cyclical factors, on the one hand, include in particular macroeconomic variables, such as the domestic interest rate and economic growth. Structural factors, on the other hand, capture slow-moving variables that represent specific features of the economy, especially those that attract foreign investors to a particular country. Examples of these factors are institutional quality, financial account openness, trade openness, financial development, foreign reserves, and the exchange rate regime. The literature has also extensively studied the role of policies impacting capital flows, most notably monetary policy (e.g., Rey, 2015; Miranda-Agrippino and Rey, 2020) and capital controls (e.g., Magud, Reinhart, and Rogoff, 2018; Rebucci and Ma, 2019).[4] Throughout the paper, we rely extensively on the literature on traditional capital flows, such as when documenting the patterns of cross-border crypto flows, when comparing them to traditional capital flows, and, most notably, when conducting our analysis of the determinants of cross-border cryptocurrency transactions.

While the literature examining the corresponding cross-border flows of cryptocurrencies is still in its infancy, several studies have taken a first look at the topic.[5] One of the key challenges for this literature is having access to comprehensive and reliable data, in particular data on the location of the entities involved in a transaction, as well as on the contractual terms under which a transaction takes place.[6] Obtaining such data are particular challenging, however, as cryptocurrencies are largely operated decentralized, anonymously, and are often not regulated.[7]

Graf von Luckner, Reinhart, and Rogoff (2023) make an early innovative contribution by relying on off-chain (i.e., within exchange) transaction-level data from the Bitcoin peer-to-peer exchanges *Localbitcoins.com* and *Paxful.com* over the period from 2017 to 2022.[8] The authors identify cases of *crypto vehicle transactions*, i.e., transactions in which cryptocurrency is used to exchange one fiat currency for another. As the data contain information on the fiat currencies involved in each trade, the authors develop an algorithm that compares the digits of the Bitcoin amount (with up to eight digits) in the purchase leg of the trade to the digits in the sale leg of the trade. If the algorithm identifies matching pairs of digits within a five-hour window, the authors treat this as a crypto vehicle transaction. As the share of identified crypto vehicle trades in all transactions amounts to 11.1%, the authors conclude that a significant share of Bitcoin users has a transactional motive and does not necessarily use Bitcoin for speculative purposes. The analysis further indicates that countries

[4] Related streams of literature include an explanation of the capital flow dynamics during the 2007/8 Global Financial Crisis (e.g., Milesi-Ferretti and Tille, 2011; Fratzscher, 2012), an assessment of large waves of capital flows (e.g., Calvo, 1998, Forbes and Warnock, 2012, and Ghosh et al., 2012) and a discussion of the consequences for the economy (e.g., Kose et al., 2010).

[5] It should be noted that the focus of this paper is on flows of cryptocurrencies (i.e., on quantities) and not on their prices. Graf von Luckner, Reinhart, and Rogoff (2023) list several papers in their literature that focus on analyzing the price of Bitcoin, as well as its drivers. See, for example, Liu and Tsyvinski (2021).

[6] E.g., by just observing a transaction on the blockchain, it would not be possible to distinguish between a transfer of funds between two wallets of the same owner and a collateralized loan transaction between two different individuals.

[7] To tackle the underlying data gap, especially in the availability of non-commercial data, the Bank for International Settlements (BIS) has launched *Project Atlas* (BIS, 2023a), an initiative to document the global use of crypto asset markets and decentralized finance. As part of this project, the BIS has created a data platform that includes a proof-of-concept focusing on the identification and visualization of cross-border flows of crypto assets in a similar spirit as the Chainalysis dataset.

[8] Taken together, both exchanges offer trade in Bitcoin with the fiat currencies of more than 160 countries.

most involved in these trades are located predominantly in Latin America and Africa. As several of these countries are regular users of capital controls, the authors further suggest that crypto vehicle transactions are frequently used to circumvent capital controls. In contrast to Graf von Luckner, Reinhart, and Rogoff (2023), who use data from only two peer-to-peer crypto exchanges, our dataset covers a broad range of crypto exchanges (including non-peer-to-peer exchanges) and other crypto service providers, which are more representative of the overall crypto market. Moreover, our data come from on-chain transactions, which allow us to better capture the crypto flows between entities (instead of within entities), resulting in possibly higher external validity.

Cardozo et al. (2024) and Cerutti, Chen, and Hengge (2024) both discuss the measurement of cross-border crypto flows (e.g., including comprehensive comparisons across data sources, covering, among others, the Chainalysis dataset as well), present stylized facts about their relationship with traditional capital flows, and conduct small-scale empirical analyses regarding their drivers. In addition, using crypto data reported to the Brazilian Central Bank, Cardozo et al. (2024) estimate a Structural Vector Autoregressive (SVAR) model to disentangle the effects of different macroeconomic and financial push and pull factors. The authors find that about one third of the variance in cross-border crypto flows is explained by push factors, which is significantly higher than for traditional capital flows. Moreover, Cerutti, Chen, and Hengge (2024) conduct a similar analysis in panel format using data on cross-border Bitcoin flows from different sources. Also, these authors find that cross-border crypto flows respond differently than traditional capital flows. While Cardozo et al. (2024) and Cerutti, Chen, and Hengge (2024) dedicate a significant share of their analysis to valuable insights into the measurement of cross-border crypto flows, we focus primarily on an assessment of the drivers of crypto flows and, as such, examine a considerably wider range of potential determinants.

Our work is most closely related to Auer et al. (2025), who document the patterns of bilateral cross-border flows for the largest cryptocurrencies (in particular, Bitcoin, Ether, Tether, and USD Coin) and employ a gravity model to examine their drivers. While the authors rely on Chainalysis data for considerable parts of their analysis as well, the focus of their analysis differs notably. The authors are particularly interested in the role of traditional gravity variables (e.g., distance, common border, or language), global factors (e.g., US financial and macroeconomic variables), and crypto risk factors (e.g., Bitcoin price volatility, crypto market/return, size, and momentum factors), allowing them to highlight the paper-title-inspiring *gravity-defying* nature of cryptoflows, and to document a potential speculation motive associated with the dynamics of past crypto prices and returns.

Our analysis, on the other hand, has a stronger focus on explaining differences in cross-border crypto flows *across countries* by drawing on a wide range of structural, financial, macroeconomic, and socioeconomic explanatory variables at the country-level, thus offering a more granular assessment of possibly competing motive explanations. Lastly, in an extension of their main analysis to country-specific drivers and policy interventions, Auer et al. (2025) examine both a transaction motive related to remittances and a capital control circumvention motive, as discussed by Graf von Luckner, Reinhart, and Rogoff (2023), which also feature prominently in our own study. While our determinants analysis shares some findings with this extension of Auer et al. (2025)—such as higher remittance costs increase cross-border stablecoin transactions and a tightening of capital controls increases Bitcoin transactions—we undertake a substantially deeper dive into understanding both motives. For example, by conducting an extensive analysis of capital controls in Tables 10 through 12 in Section 3 and our COVID-19 event study with a key focus on the payments and remittances motive in Section 4.

More broadly, several papers that do not examine the cross-border aspect of crypto flows relate to our work, for example, by providing innovative solutions to reduce data gaps or by attempting to uncover the motives for using cryptocurrencies more generally. Alnasaa et al. (2022) use data from the Global Consumer Survey to conduct a small-scale analysis of the determinants of cryptocurrency use. The Global Consumer Survey was conducted in 55 countries (with 2,000-12,000 respondents in each country), and the crypto-related question asked participants whether they owned or used crypto assets in the year 2020. The authors then correlate the use of crypto assets with indicators of corruption, capital controls, a history of high inflation, and several development-related variables, and find that both corruption and capital controls are positively related to crypto asset use. The paper concludes that these motives for crypto asset use support the case for regulating crypto assets.

Additional evidence on potential motives comes from Pourpourides (2023), Foley, Karlsen and Putniņš (2019), and Anadu et al. (2023). Pourpourides (2023) examines the long-run effects of macroeconomic and financial fundamentals on the market capitalizations and prices of several cryptocurrencies. The author includes these outcome variables separately in a Vector Error Correction Model (VECM), each time together with proxies for the fundamentals, such as the federal funds rate, a US dollar index (DXY), the S&P 500, and the gold price. In particular, the gold price and the US dollar index have a significant (negative) long-run relationship with the outcome variables. The author interprets these findings as that cryptocurrencies (in particular Bitcoin) act as a substitute for gold and therefore as a store of value.[9] Foley, Karlsen, and Putniņš (2019) focus on quantifying the amount of illegal online trade that uses Bitcoin as a transaction currency. The authors state that about one-quarter of Bitcoin users and 46% of all Bitcoin transactions appear to be associated with illegal activities during their sample period from 2009 to 2017. However, the authors also note that their classification algorithm is not error-free and the share of illegal activity has declined as mainstream interest in cryptocurrencies has started to increase. Lastly, Anadu et al. (2023) focus specifically on the behavior of stablecoins. They show that during periods of stress in crypto markets, safer stablecoins experience net inflows and riskier ones suffer net outflows. Moreover, if the price of a stablecoin falls below $1, even by only one cent, investor redemptions accelerate significantly. The authors compare both features to the response of money market funds in crises.

The remainder of this paper proceeds as follows. After this introduction, Section 2 introduces our crypto flow dataset, which we use to document global Bitcoin flow patterns as well as their relation to traditional capital flows. Section 3 then analyzes the determinants and motives of Bitcoin flows empirically, and Section 4 presents our COVID-19 event study. Section 5 then extends our determinant analysis to four major stablecoins. Finally, Section 6 concludes and discusses possible policy implications of our findings.

2 Patterns of Global Bitcoin Flows

2.1 Crypto Data

In this section, we document the patterns of global cryptocurrency flows using the example of Bitcoin, the cryptocurrency with the largest market capitalization. Our dataset on cross-border cryptocurrency flows comes from Chainalysis (see Chainalysis, 2023) and is derived from publicly available blockchain transactions (also referred to as *on-chain* data).[10] Blockchains are distributed ledgers that serve as a venue to publicly record the transactions of most cryptocurrencies. Blockchains usually contain information on the timing and the amount of the transaction, as well as information on the alphanumeric addresses involved in the transaction. They do not, however, contain information about the individuals or entities involved in these transactions. The underlying

[9]A similar argument is put forward by Biais, Rochet, and Villeneuve (2025), who construct a general equilibrium model in which agents can use cryptocurrencies to buffer productivity shocks while avoiding public currency hyperinflation.

[10]The dataset also serves as an input into Chainalysis' Global Crypto Adoption Index, which is frequently cited in policy publications on crypto assets (e.g., BIS, 2023b; FSB, 2023; OECD, 2022).

challenge is then to convert individual transactions on the blockchain into more meaningful metrics for economic analysis, such as, in our case, cross-border crypto flows. Chainalysis uses a two step procedure to match alphanumeric addresses to real-world entities (see Chainalysis, 2022a). In a third step, Chainalysis then links the real-world entities to specific countries based on web traffic to these entities as a proxy for the country of residence of the users interacting with these entities (see Chainalysis, 2022b). A detailed explanation of the three steps, including a numerical example for the last step, is provided in Appendix A.

This procedure results in a bilateral crypto flow allocation for all sample countries at a daily frequency. As with all studies in this nascent field, including those discussed in the introduction, the approach to extract meaningful information from the blockchain data (or from off-chain data) requires assumptions that can have limitations. As discussed in Chainalysis (2022b), web traffic data are recorded at a monthly frequency. As we conduct our analysis at a quarterly and an annual frequency, we avoid confounding updates of the web traffic data with actual changes in crypto flows that could possibly occur if we had used the data at the weekly or even daily frequency, for example. Moreover, Chainalysis (2022b) states that the usage of virtual private networks (VPNs) and other products that potentially mask online activity can impact the country allocation of crypto flows to individual countries. However, given the large set of blockchain transactions, Chainalysis expects that VPN usage would have to be extremely widespread to meaningfully skew the data. A recent analysis by Forbes (2023) suggests that VPNs usage ranges from 0.71% in Japan to 25.72% in the United Arab Emirates.[11] Moreover, there are various reasons for using VPNs that are not related to circumventing geo-restrictions, such as increasing online privacy or cybersecurity, so we would expect the actual impact of VPNs on our data to be considerably smaller (moreover, even a circumvention of a geo-restriction does not automatically relate to the trade of cryptocurrency, which should mitigate the issue further). Lastly, we aggregate the bilateral data on crypto flows to the country-level. While we conduct this step mostly to increase the analytical tractability, it can help alleviate any remaining biases potentially associated with individual country pairs.

Before presenting our set of stylized facts for cross-border Bitcoin flows and focusing on our comparison with traditional capital flows, we perform several checks to validate the crypto data. We compute a ranking of the sum of Bitcoin in- and outflows in % of quarterly GDP for 142 sample

[11]The second and third highest VPN usage rates occur in Qatar (24.03%) and Russia (23.94%).

countries for each year of our sample (i.e., for 2020 to 2023).[12] We now use these rankings to discuss the relative prominence and dynamics of specific countries.

Our first exercise focuses on the level of the ranking. Panel a) of Figure 1 shows the ranking of Venezuela, Ukraine, and Georgia among 142 countries over time. They occupy ranks between 1 to 6, 2 to 6, and 3 to 7, respectively, which suggests that all three countries are highly exposed to cross-border Bitcoin flows. This pattern is, in fact, mirrored by anecdotal evidence. Reuters (2021), for example, states that Venezuelan workers frequently rely on cryptocurrency to send remittances to their families and that Venezuelan businesses use cryptocurrency to overcome the challenges of a high inflation rate. Moreover, the Economist Intelligence Unit (2023) writes that the Ukrainian government partially relies on cryptocurrency flows to facilitate international transfers and donations supporting the country's defense efforts. As part of this process, the government legalized the previously unregulated cryptocurrency market, which allows crypto exchanges to operate. Lastly, IMF (2019) states that in 2018, Georgia's share in global Bitcoin mining amounted to 15%, which is a multiple of its share in global GDP and highlights the importance of Bitcoin for Georgia. Hence, in light of the anecdotal evidence presented above, it is not surprising to find Venezuela, Ukraine, and Georgia taking the top ranks of cross-border crypto exposures among the 142 sample countries of this exercise.[13]

Our second and possibly more ambitious exercise focuses on verifying the dynamics of the ranking over time. Panel b) of Figure 1 shows the ranking for Latvia and Laos over time. While Latvia's trajectory shows a significant drop from rank 1 in 2021 and 2022 to rank 24 in 2023, Laos' trajectory shows the opposite pattern, with a sizable increase from rank 43 in 2020 to rank 4 in 2023. Reassuringly, these dynamics match anecdotal evidence well. In the case of Latvia, Cointelegraph (2023) writes that, according to a financial stability report by the Latvian central bank, crypto asset investment in Latvia declined by 50% over the past year. As such, it appears intuitive that the rank of Latvia in our sample has also fallen significantly during this time period. Laos, on the other hand, experienced the opposite dynamics. The Laotian Times (2021) states that the government authorized a cryptocurrency trial program in 2021, where six companies can engage in mining and trading cryptocurrencies. This was seen as a *shift in stance* of the government towards

[12] In the process of making the comparison of the data across countries and over time more systematic, the number of countries in this exercise decreases from 162 to 142. For more information on the construction of the underlying series, see Section 2.2.

[13] Some smaller nations, such as Andorra, reach even higher average ranks in our sample. While their cases are supported by anecdotal evidence as well (e.g., see Advantia, 2024, on possibly favorable regulatory changes for cryptocurrencies in Andorra), they are less prominent examples, and their high ranking could be driven in part by relatively small GDP values in the denominator.

the legalization of cryptocurrencies by market observers (e.g., Bitcoin Magazine, 2021). As a result, a steady and considerable increase in ranks for Laos in our sample since 2021 seems to reflect these events.

Lastly, Reuter (2025) estimates stablecoin flows between self-custodial wallets across world regions (rather than countries) based on an innovative artificial intelligence and machine learning technique. The author finds that the magnitudes of stablecoin flows across world regions obtained through this approach are broadly comparable to those recorded in the Chainalysis dataset. Moreover, gross outflow data in both datasets show a high degree of comovement over time with a correlation (averaged across world regions) of around 0.93.[14]

Overall, we have demonstrated that—despite the fact that several assumptions were required to construct the cross-border cryptocurrency dataset—the resulting country rankings of cross-border Bitcoins flows in the dataset are well supported by anecdotal evidence from independent sources[15] and key features of the stablecoin data match those of alternatively obtained estimates. In the next subsection, we therefore proceed by establishing several stylized facts based on the Chainalysis data.

2.2 Bitcoin Flow Facts

This section aims at identifying the key patterns of Bitcoin flows and highlighting their dynamics across countries and over time. Our final sample in this exercise covers 142 countries and ranges from 2020Q3 to 2023Q3. This reflects several adjustments to the raw data to make our data comparable across countries and time: After aggregating the cross-border Bitcoin flow data from a bilateral structure to the country-level, we also aggregate the data from daily to quarterly frequency (each time by taking the respective sums).[16] Next, to obtain a balanced sample, we require countries to have non-missing Bitcoin data and non-missing GDP data for the full 2020Q3 to 2023Q3 period. The latter two requirements reduce our sample size from 162 to 142 countries. Lastly, we construct the variables *sum of Bitcoin in- and outflows in % of quarterly GDP* and *net Bitcoin in- and outflows* (i.e., the difference between Bitcoin in- and outflows) *in % of quarterly GDP*.[17]

We start by documenting the dynamics of global Bitcoin flows over time. Panel (a) of Figure

[14] There are, however, differences across both datasets regarding the estimates for China (possibly due to VPN use), when focusing on net flows, and when disaggregating flows into direct and indirect categories.

[15] While Economist Intelligence Unit (2023) cites a (different) dataset from Chainalysis as one of its sources, the article includes information from other sources as well.

[16] While for some countries, Bitcoin data are already available for June 2020, we discard in this exercise all data prior to 2020Q3 in order to avoid ending up with partially summed quarters.

[17] As quarterly GDP data are not available for many of our sample countries, we create an auxiliary quarterly GDP series to normalize both variables. We construct this auxiliary series by calculating a moving average of annual GDP data over time and dividing this moving average by 4 to reflect its quarterly nature.

2 shows the sum of Bitcoin in- and outflows in million USD, aggregated over all countries in our sample, for each quarter of our sample period.[18] Starting at around \$40 billion USD in mid-2020, the total value of Bitcoin flows rises rapidly and peaks at around \$160 billion USD in the first half of 2021. The peak is followed by a significant drop to around \$90 billion USD in 2021Q3 and a rebound to around \$120 billion in 2021Q4. Afterwards, Bitcoin flows experience a gradual decline and reach a total value close to their starting level in late 2023. These dynamics appear to resemble the trajectory of the Bitcoin price during this time, which peaked in March and November 2021, respectively. While changes in the Bitcoin price seem to materially affect the valuation of Bitcoin flows, it should be noted that the Bitcoin price is public information, and Bitcoin users are likely to review it before conducting a transaction. As such, it seems reasonable to expect that Bitcoin users deliberately choose the value of their transactions, and changes in transaction values are not predominantly driven by price changes.[19] Moreover, the cross-country dimension of our dataset allows us in Section 3 to explore differences in cross-border Bitcoin transactions across countries while keeping the Bitcoin price constant. Next, we turn to Panel b) of Figure 2. This panel shows the same aggregation of the sum of Bitcoin flows over in- and outflows across all sample countries as Panel a) but reports flows in % of quarterly GDP (henceforth, simply referred to as *in % of GDP*) instead of in million USD. The pattern looks very similar, with the total value of Bitcoin flows at the sample-level ranging from 0.2% to 0.7% of GDP.

Subsequently, Panels c) and d) show the *average* sum of Bitcoin in- and outflows for our sample countries at each point in time, highlighting a similar trajectory as Panels a) and b). These panels suggest that, for the average country in our sample, the sum of Bitcoin in- and outflows over the entire sample period amounts to around 1,04 billion USD (1.6% of quarterly GDP) with a peak of around \$2.25 billion USD (3.6% of quarterly GDP) in 2021Q2.[20] Altogether, these numbers are a first indication that Bitcoin flows are still nascent but not negligible.

In the next step, we exploit the rich cross-country nature of our dataset by averaging Bitcoin flows over time for each country. We conduct this exercise first for the sum of in- and outflows and then for net inflows, each time in % of GDP. Panel a) of Figure 3 shows the distribution of the sum

[18]For Panels a) and b), we divide the sum of Bitcoin in- and outflows across all sample countries by 2 in order to account for the fact that one country's inflows are another country's outflows.

[19]As such, it is unlikely that someone would repeat at the current Bitcoin price the famous 2010-anecdote of purchasing two pizzas for 10,000 Bitcoin, which would amount to \$100 millions of USD these days (see CoinDesk, 2024).

[20]See Columns 3 and 1 of Table 1 for details. Note that the slight difference in trajectories across Panels b) and d) results from the fact that, in the case of the former, Bitcoin flows and GDPs are aggregated to the sample-level before their ratio is taken. In the case of the latter, the ratios of Bitcoin flows to GDP are computed at the country-level before their average is taken.

of Bitcoin in- and outflows in % of GDP across countries. A darker red color shade represents a higher exposure of a country to cross-border Bitcoin flows. Most notably, we observe the highest Bitcoin exposures in Eastern Europe, followed by Latin America and selected countries in South East Asia. Advanced economies in North America, Europe and Oceania, as well as China and India feature mostly a lower exposure. The evidence in Africa is mixed. Related to this, the first column of Table 1 shows a further breakdown of the exposure information for individual countries at the top and the bottom of the list. The country with the highest sum of Bitcoin in- and outflows in % of GDP is Latvia with a value of 14.35. Andorra follows with 13.11% of GDP, Moldova ranks third with a value of 9.85% of GDP, and Venezuela ranks fourth with 8.34% of GDP. Other Eastern European countries also appear high up on the list, with Georgia (7.12% of GDP) and Ukraine (6.90% of GDP) in positions 5 and 6. Table 1 also shows the countries at the bottom of the list, which are most notably located in Africa and the Middle East but also include China.

Panel b) of Figure 3 shows the distribution of net Bitcoin in- and outflows in % of GDP across countries. Positive net inflows are represented by a green color scheme, and negative net inflows are represented by a red color scheme. Again, a darker color shading reflects a higher exposure. Interestingly, a clear pattern emerges. Eastern Europe, Latin America, and most of Asia experience significant net Bitcoin outflows, while advanced economies in North America, Western Europe, and Oceania record strong net Bitcoin inflows. Also India and major parts of (Southern) Africa experience net Bitcoin inflows. Column 2 of Table 1 shows the corresponding breakdown at the country-level again.

In addition, Table 1 highlights which countries carry the highest exposure to Bitcoin flows in absolute terms (i.e., without a normalization by GDP). The ranking of the sum of in- and outflows is topped by the United States with around $21 billion USD, followed by Korea (around $9 billion USD) and the United Kingdom (around $7 billion USD). In the net in- and outflow ranking, the United States and the United Kingdom remain in their respective positions, with Australia taking the second spot. Countries experiencing the highest net outflows (i.e., negative net inflows) are China, Russia, Venezuela, and the Ukraine. These developments can possibly be explained by regulatory actions regarding the use of Bitcoin in China as well as the Russian-Ukrainian war.

2.3 Comparison of Bitcoin Flows with Traditional Capital Flows

We then turn to a comparison between cross-border Bitcoin flows and traditional capital flows. In particular, we compare the cross-border Bitcoin flow data in net terms against net *portfolio invest-*

ment flows, which mostly comprise equity and bond flows, and net *other investment* flows, which include, for example, bank credit, trade credit, as well as currency and deposit flows. Appendix B provides more detailed information about the underlying challenges and our data choices for this exercise.

The results are shown in Table 2. We highlight the key messages of this table using graphical representations. First, (number) Columns 1-3 of the table focus on a comparison of the mean of flows. In particular, they highlight the mean (by country, over time) of net Bitcoin in- and outflows in % of GDP in Column 1, as well as the means of portfolio investment flows in % of GDP in Column 2 and other investment flows in % of GDP in Column 3. Panels a) and b) in Figure 4 show corresponding scatter plots between the mean of crypto flows on the vertical axis and the mean of traditional capital flow measures on the horizontal axis. The cloud of dots in each panel does not indicate a close association between the means of Bitcoin flows and traditional capital flows. Hence, there is limited evidence that cross-border Bitcoin flows respond to the same drivers as traditional capital flows.

Second, Columns 4-6 of Table 2 show a comparison of the standard deviation of flows. Column 4 of the table focuses on the standard deviation (again, by country, over time) of net Bitcoin in- and outflows in % of GDP, Columns 5 and 6 show the corresponding concepts for portfolio investment flows in % of GDP and other investment flows in % of GDP, respectively. Panels c) and d) present the same information in graphical form again. Similar to the mean comparison, there seems to be no clear association between the standard deviations of Bitcoin and traditional capital flows. This suggests that also the dynamics of both flows might differ.[21]

Third, Columns 7 and 8 of Table 2 show the share of net Bitcoin in- and outflows in traditional capital flows, represented by portfolio investment flows and other investment flows, respectively. We calculate these Bitcoin flow shares for each country by dividing a country's time mean of the absolute values of its Bitcoin flows by the time mean of the absolute values of its traditional capital flows (and multiplying the result by 100). For most sample countries, Bitcoin flow shares are still relatively small. For example, at the 25th percentile of the share distribution, they amount to 0.40% for portfolio investment flows and to 0.42% for other investment flows. At the 75th percentile, the shares increase somewhat to 3.82% for portfolio investment flows and to 2.52% for other investment flows. For several countries, however, the Bitcoin flow shares are more sizeable, suggesting that

[21] Overall, this supports evidence from Cardozo et al. (2024) and Cerutti, Chen, and Hengge (2024), which suggests that the drivers of cross-border crypto flows and traditional capital flows are different.

Bitcoin flows have become a notable alternative to traditional capital flows in some cases. Figure 5 highlights all countries with Bitcoin flow shares relative to portfolio investment flows for values greater than 10% in Panel a)—a list that is topped by Vietnam (61.26%), Belarus (47.49%), and Mozambique (44.34%). Bitcoin flow shares relative to other investment flows, on the other hand, appear to be an order of magnitude smaller, and are shown for values greater than 5% in Panel b). Countries with the highest Bitcoin flow shares in this category are Latvia (25.51%), Ukraine (7.69%), and Argentina (6.98%).[22]

Fourth, Columns 9 and 10 of Table 2 show the correlation between net Bitcoin in- and outflows on the one hand, and portfolio investment flows or other investment flows on the other hand. There does not appear to be a clear pattern in the data that would consistently suggest that Bitcoin flows and traditional capital flows act as complements (positive correlation) or substitutes (negative correlation). Panels a) and b) of Figure 6 therefore highlight all countries with a correlation coefficient greater than or smaller than a certain threshold for the two types of capital flows.[23] Countries with a significantly positive correlation are Mozambique, Hungary, and Namibia for the correlation with portfolio investments, and Israel, Austria, and Macedonia for the correlation with other investments. The most negative correlations are shown by Angola, Netherlands, and Thailand for portfolio investment flows, as well as by China, Mozambique, and India for other investments. This notable heterogeneity of correlations across countries suggests that some of the drivers of crypto flows are likely of country-specific nature. We will learn more about their role in the next section.

3 Determinants of Cross-Border Bitcoin Flows

In this section, we examine the determinants and motives of cross-border Bitcoin flows more formally. In particular, we employ a panel approach at annual frequency that allows us to identify the key determinants of Bitcoin transactions across countries and over time. We will conduct a corresponding exercise for cross-border stablecoin flows in Section 5.

[22]It should be noted that Bitcoin flow shares become larger when either the mean and/or the standard deviation of Bitcoin flows is particularly high, or the mean and/or the standard deviation of traditional capital flows is particularly low. The first six columns of Table 2 provide more information about these sample statistics for each country.

[23]The thresholds are greater than 0.5 or smaller than -0.5 for Panel a); and greater than 0.4 or smaller than -0.4 for Panel b).

3.1 Motivation

We identify seven distinct motives—defined as a group of similar determinants—for cross-border cryptocurrency use, which apply to both cross-border Bitcoin and stablecoin transactions. These motives are:

Current Macro and Financial Conditions: As discussed in previous sections, anecdotal and previous empirical evidence suggests that cryptocurrency can serve as a store of value in countries with weak macroeconomic fundamentals (e.g., Reuters, 2021; Alnasaa et al., 2022; Pourpourides, 2023) or depreciating official currencies. As such, cryptocurrency use would be *negatively* related to favorable economic and financial outcomes, such as high economic growth or strong stock market performance, and *positively* related to adverse outcomes, such as uncertainty, unemployment, or high inflation. It should be noted, however, that there is some element of ambiguity in this interpretation, as positive economic and financial outcomes may lead to increases in income and wealth, which, in turn, could strengthen cryptocurrency use through either transaction or investment motives. Eventually, only an empirical analysis can provide clarity as to which interpretation dominates.

Past Macro and Financial Conditions: Instead of focusing on current conditions, past macro and financial conditions can also determine cryptocurrency use. In particular, unfavorable experiences with economic or financial crises in the past can serve as an incentive to store value in alternative ways, such as through cryptocurrencies. As such, we would expect the past occurrence of economic and financial crises to be *positively* related to cross-border cryptocurrency transactions.

Institutional Quality: Besides the influence of macroeconomic and financial drivers, the institutional environment can also matter for cryptocurrency use (e.g., Alnasaa et al., 2022). If institutional quality is poor, as when the state is weak and policies are poorly designed or enforced, inefficiencies, corruption, or even violence can emerge as a result. In such an environment, it can be attractive to store value abroad or in venues that are not directly controlled by the government—such as cryptocurrencies. Hence, we would expect a *negative* correlation between institutional quality and cross-border cryptocurrency transactions.

Structure of the Financial System: The structure of the financial system can impact cryptocurrency use through its function of providing a competing form of financial intermediation. If access to finance is widespread in the economy (e.g., to bank accounts, loans, and mortgages), it is less likely that the population resorts to cryptocurrencies to fulfill its banking needs. However, it would not necessarily require a lack of banking services to encourage more cryptocurrency use, as the degree of efficiency and competition can already matter for such choices (e.g., high banking fees, unfavorable borrowing rates). As such, we would expect a *negative* correlation between the efficiency and services provided by the banking system on the one hand, and cross-border cryptocurrency transactions on the other.

International Payments and Remittances: A central motive for cryptocurrency use is the frequent lack of convenient and affordable options to conduct cross-border payments (e.g., Reuters, 2021; Graf von Luckner et al., 2023). This is particularly relevant in countries that send or receive considerable amounts of remittances. A key advantage of cryptocurrencies is that transactions can be conducted anywhere there is an internet connection, and one does not have to visit a bank branch or the physical location of an international payment service. Moreover, the associated costs of a cryptocurrency transaction are significantly cheaper in most cases. We therefore expect a *positive* relationship between cross-border cryptocurrency transactions and the demand for international payments, as well as the costs of sending or receiving such payments.

Circumventing Capital Controls: Cryptocurrency use has frequently been linked to intentions of circumventing capital controls (e.g., Alnasaa et al., 2022; Graf von Luckner et al., 2023). If a government imposes capital controls that tax, restrict, or even prevent the flow of capital across borders, the use of unregulated cryptocurrencies can provide an alternative avenue to conduct such transactions. As such, we would expect a *positive* relationship between the use of capital controls and cross-border cryptocurrency transactions. However, there is some uncertainty as to whether capital controls targeting inflows or outflows are more affected.

Circumventing International Sanctions: Lastly, we discuss the possibility that cryptocurrencies can be used to circumvent international sanctions. Sanctions are usually imposed on countries in response to their governments taking actions that are not justified in the view of the global community. As such, we would expect a positive *positive* relationship between the use of sanctions and cross-border cryptocurrency transactions. As opposed to the circumvention of capital controls, where such actions would undermine the domestic government's own policies, however, the circumvention of international sanctions could be more favorably viewed by the domestic government, as it opposes the enacted sanctions in the first place.

3.2 Methodology

In this section, we describe the empirical specification and the data for our empirical analysis.

3.2.1 Empirical Specification

We first test our seven motives of cross-border cryptocurrency use by assessing the relationship between selected measures of cross-border cryptocurrency transactions and a wide range of explanatory variables that capture the underlying transmission channels of each motive. We rely on the following specification:

$$y_{i,t} = \alpha + \beta x_{i,t-1} + \delta Z_{i,t-1} + \varepsilon_{i,t} \tag{1}$$

where $y_{i,t}$ is a measure of cross-boder cryptocurrency transactions, $x_{i,t}$ is the explanatory variable of interest, $Z_{i,t}$ is a vector of two control variables, α is the regression constant, and $\varepsilon_{i,t}$ is the error term. All explanatory and control variables are lagged and standard errors are estimated heteroscedasticity-robust.

This leads to our baseline specification, which resembles Equation (1) but includes a *vector* of explanatory variables, $X_{i,t-1}$. Moreover, we add time fixed effects, γ_t, to one of our robustness specifications:

$$y_{i,t} = \alpha + \beta X_{i,t-1} + \delta Z_{i,t-1}(+\gamma_t) + \varepsilon_{i,t} \tag{2}$$

Again, all explanatory and control variables are lagged, and standard errors are estimated to be heteroskedasticity-robust. In one of our robustness analyzes, we relax this assumption and cluster the standard errors at the country-level instead.

3.2.2 Data

The dependent variable of our empirical analysis in this section is the *Sum of Bitcoin In- and Outflows in % of GDP*, which has been extensively discussed in Section 2. We rely on the sum of Bitcoin in- and outflows in % of GDP instead of the corresponding net flow measure, as the former captures the total cross-border Bitcoin flows of a given country. Hence, this measure allows us to capture all relevant aspects of cross-border Bitcoin flows when identifying their motives. Moreover, we cover the same sample period as in the previous section—2020 to 2023—but this time at an annual frequency.

Compared with Section 2, we modify our dependent variable in three ways. First, when aggregating the Bitcoin data from quarterly to annual frequency for this exercise, we take the *average* instead of the sum in order to keep the years 2020 and 2023, for which the Bitcoin data are incomplete, in the sample.[24] Second, we winsorize our dependent variable at the 1% level on each side of the distribution in order to reduce the impact of outliers on our regression results. And third, we do not require countries to have a balanced sample for either the dependent variable or the explanatory variables, which increases the number of sample countries from 142 to up to 162.

In our empirical analysis, we use a rich set of explanatory variables from a wide range of sources. Table 3 provides a detailed list of these explanatory variables, together with their sources and selected summary statistics.[25] The variables in each section of the table correspond to a distinct motive for cryptocurrency use, which we identified and discussed in Section 3.1. We review these motives and their corresponding variables briefly. Variables associated with the *Current Macro and Financial Conditions* motive are both global and country-specific. The global ones comprise the VIX (i.e., the Volatility Index of the Chicago Board Options Exchange), as well as two US stock market indices. Country-specific variables include unemployment, inflation, the interest rate, real GDP growth, and the government budget balance. We construct a composite interest rate based on the central banks' policy rate, a market-based interest rate, and the government bond yield (whichever has the highest sample coverage for a country). Variables related to the motive *Past Macro and Financial Conditions* include indicator variables for banking, currency, and sovereign debt crises. We use crisis indices from Laeven and Valencia (2018) for data on crises starting dates and from Nguyen et al. (2022) for data on the entire crises periods. As most crisis events are rare and often fall outside of our sample period, we construct indicator variables that take on the value of 1 when a crisis event took place during the period 2010 to 2019 (and zero otherwise). Variables associated with the motive *Institutional Quality* include various World Governance Indicator variables, such as Control of Corruption, Regulatory Quality, or Political Stability and Absence of Violence/Terrorism. The variables associated with the *Structure of the Financial System* motive cover financial performance and risk measures for the banking sector, such as banks' net interest margin or overhead costs, as well as banks' z-scores. Moreover, we include variables that are intended to capture the development

[24] As our sample period in Section 2 ranges from 2020Q3 to 2023Q3, year 2020 is missing data for Q1 and Q2, and year 2023 is missing data for Q4.

[25] Explanatory variables available at higher frequencies are aggregated to annual frequency using averages.

of the broader financial system, such as stock or bond market capitalization. As data coverage for these financial variables is limited, we construct their average over the period 2010 to 2019. The next motive is *International Payments and Remittances* and comprises variables, such as personal remittances received and the average transaction costs of sending remittances from a specific country. We also include variables that measure the need to self-insure through remittances in this section, such as coverage of social protection and labor programs or the coverage of unemployment benefits. Moreover, receipts and expenditures related to international tourism can provide alternative sources of foreign currency transactions. We capture our next motive, *Circumventing Capital Controls*, by both the Chinn-Ito index (see Chinn and Ito, 2006), where a higher value represents more financial openness, as well as by a wide range of capital flow restrictions from Fernández et al. (2016), where a lower value represents more openness. Also the capital control variables are defined as indicator variables over the 2010-2019 period. Our last motive is *Circumventing International Sanctions*. We capture this motive by a variety of indicator variables from the Global Sanctions Database that we aggregate (from the original bilateral data) to the country-level. The set of sanctions covers military, arms, trade, financial, travel, and other sanctions. As with our dependent variable, all explanatory variables (except for the indicator variables) are winsorized at the 1% level on each side of the distribution.

3.3 Results

3.3.1 Identifying Cross-Border Cryptocurrency Motives Based on Bitcoin Data

We first present the results of estimating Equation (1) using cross-border Bitcoin flow data on our sample of 162 countries over the period from 2020 to 2023 at annual frequency. Before we turn to the test of different motives of cryptocurrency use, we derive the empirical specification for this section. As discussed in Section 3.2.1, we include two control variables in each specification. They are a country's nominal GDP in USD and a measure of internet access via broadband/high-speed connections[26] and serve as basic controls regardless of the explanatory variable of interest. In particular, the nominal GDP variable may capture important factors such as income and/or the level of economic development of a country, and the degree of broadband access may proxy for the technological ability of residents to engage in cryptocurrency transactions. Omitting controls for

[26]The variables are *Gross Domestic Product (GDP), Current Prices; in U.S. Dollars* and *Fixed Broadband Subscriptions (per 100 People)*, respectively.

these factors from the specifications may bias our results.[27] However, we demonstrate below that the choice of these two control variables is robust to a variety of sensible alternatives.

Table 4 presents the results of this exercise. We start with Specification (1), which includes only the controls for nominal GDP and broadband use. The nominal GDP variable is highly significant at the 1% level and carries a negative sign. This may reflect the fact that the share of Bitcoin use in high-income countries or countries with larger markets is relatively smaller than in low income countries or smaller markets. The broadband variable is also highly significant and carries a positive sign. The positive sign supports the interpretation that access to advanced telecommunication infrastructure is positively associated with cross-border Bitcoin transactions. The remaining specifications in this table highlight the robustness of our choice of control variables. Specifications (2) and (3) replace the nominal GDP variable with a purchasing power parity GDP variable and a measure of population size. In line with the sign on the nominal GDP variable, both alternative measures are highly significant and carry a negative sign. Specifications (4) to (7) feature alternatives to the broadband variable, such as cell and fixed phone use, general internet access, and access to secure internet servers. Again, all four alternative telecommunication variables are significant and carry a positive sign, suggesting a close association between telecommunication infrastructure and cryptocurrency use. Having demonstrated the relevance and robustness of our two control variables, we now proceed to empirically identify the different motives for cross-border Bitcoin transactions.

Table 5 presents the results of all variables associated with the Current Macro and Financial Conditions motive. We first focus on the three global variables, the VIX, the S&P 500 and the Dow Jones Industrial Average. All three variables are highly significant. In Specification (1), we find a positive sign on the coefficient for the VIX, suggesting that an increase in the VIX raises the sum of Bitcoin in- and outflows in % of GDP for the average country in our sample. In particular, a 1-unit increase in the VIX is associated with a 0.0870 percentage point increase in the sum of Bitcoin in- and outflows in % of GDP. Hence, an increase in the VIX by 1-standard deviation (about 4.5 units in Specification (1) of Table 5) results in a corresponding increase in Bitcoin in- and outflows by 0.39% of GDP. Given that the sample median of our dependent variable in this specification amounts to 0.67% of GDP, an increase of 0.39% of GDP corresponds to almost 60% of that value,

[27] E.g., an insignificant coefficient on a explanatory variable of interest may be wrongly attributed to the lack of relevance of the corresponding motive if the underlying empirical specification does not take into account that an underdeveloped telecommunication infrastructure would make it more difficult for residents to engage in cryptocurrency activities in the first place.

indicating that the impact of the VIX on cross-border Bitcoin flows appears to be of considerable economic significance. Moreover, the sign of the coefficient is consistent with the first interpretation of the Current Macro and Financial Conditions motive outlined in Section 3.1. As an increase in the VIX may signal the emergence of financial stress, and hence strengthen the need to store values in countries with weak macroeconomic fundamentals or depreciating official currencies, it becomes more likely that cross-border Bitcoin transactions are used to achieve this objective.

In line with the results for the VIX, we find in Specifications (2) and (3) that both the coefficients on the S&P 500 and the Dow Jones Industrial Average are highly significant and carry a negative sign. Due to their inverse correlation with the VIX, the negative sign is consistent with the previous interpretation. If increases in the S&P 500 and the Dow Jones Industrial Average represent an improvement in global economic and financial conditions, one would expect the need to resort to Bitcoin as a store of value to diminish. This interpretation also highlights the relevance of opportunity costs associated with Bitcoin investments. If traditional investments experience a period of growth, it might be less appealing to engage with possibly riskier alternatives, such as Bitcoin investments.

The remaining specifications in Table 5 focus on country-specific macro variables and feature highly significant coefficients as well. Specifications (4) to (6) feature the unemployment rate, the inflation rate, and the interest rate—three variables, for which high values are often associated with adverse macroeconomic conditions. In each case, an increase in the macro variable results in an increase in the sum of Bitcoin in- and outflows in % of GDP. Specifications (7) and (8) contain real GDP growth and the government budget balance—two variables, for which high values are generally associated with a favorable macro environment. In both cases, an increase in the macro variable leads to a decrease in the sum of Bitcoin in- and outflows in % of GDP. Hence, in line with the global variables, the country-specific variables also support the hypothesis that a deterioration of macroeconomic and financial conditions increases the cross-border flows of Bitcoin.

Next, we turn to the closely related motive of Past Macro and Financial Conditions. Instead of current conditions, as discussed in the context of the first motive, this motive postulates that past conditions, in particular the presence of past financial or macroeconomic crises, are key drivers of cross-border cryptocurrency flows. In Table 6, we test this hypothesis by assessing the impact of past banking, currency, and (sovereign) debt crises on the sum of Bitcoin in- and outflows in % of GDP. We find positive coefficients on the crisis indicator variables in seven cases, five of which are statistically significant. In particular, we find the coefficients on banking crises in Specifications

(1) and (4) to be highly significant, regardless of whether we capture their starting dates (taken from Laeven und Valencia, 2018) or the entire crisis period (taken from Nguyen et al., 2022). This suggests that cross-border Bitcoin flows respond particularly to the existence of (past) banking crises. There is also evidence that currency and debt crises matter for cross-border Bitcoin flows (e.g., Specifications (3) and (5)) but it is less pronounced than for banking crises. Moreover, the joint crises indicator in Specification (7) also shows significance.

Our third motive for cross-border cryptocurrency use is a low level of Institutional Quality in a country. Not only the macro and financial conditions, as discussed in the context of the previous motives, but also the structural features of the economy can be important drivers of cross-border cryptocurrency use. In Table 7, we test a range of six different proxies for institutional quality, comprising control of corruption, rule of law, regulatory quality, government effectiveness, political stability and the absence of violence, and voice and accountability—each time, a higher value in the variable is associated with a greater level of institutional quality. In all six cases, we find highly significant and negative coefficients, suggesting that an increase in institutional quality is associated with a decrease in the sum of Bitcoin in- and outflows in % of GDP. This, in turn, supports the interpretation that in countries with low levels of institutional quality, it becomes more attractive to store values abroad or in venues that are not directly controlled by the local government—such as cryptocurrencies.

In a similar vein, our fourth motive Structure of the Financial System focuses on the structural features of the financial system. In Table 8, we assess the impact of a host of financial system variables, such as the interest rate margin or overhead costs in Specifications (1) and (2), and z-score in Specification (3). Consistent with previous results, an increase in the (from the customer-perspective) less favorable variables, such as interest rate margin and overhead costs, is positively associated with cross-border Bitcoin use, while an increase in the more favorable variable z-score is negatively associated. Moreover, a well-developed banking system, indicated by the presence of foreign loans or a high share of bank credit or bank deposits in % of GDP, carries a negative association. Similarly, a well developed stock or bond market leads to fewer cross-border Bitcoin transactions. This again confirms our hypothesis of a negative correlation between the efficiency and services provided by the banking and/or financial system on the one hand, and cross-border cryptocurrency use on the other hand.

The fifth motive constitutes International Payments and Remittances, and is examined in Table 9. Specification (1) shows that an increase in the volume of remittances (i.e., measured by the share of personal remittances received in % of GDP) is associated with an increase in the sum of Bitcoin in- and outflows in % of GDP. Moreover, Specification (2) shows that an increase in the costs of sending remittances also increases cross-border Bitcoin use. Together, these findings support the hypothesis that a greater need for remittance transfers across borders and the absence of convenient and affordable options to conduct such payments lead to a greater use of cryptocurrencies. In the remaining four specifications, we highlight several factors associated with remittance transfers that support the findings from our first two specifications. Specifications (3) and (4) depict the impact of tourism income and expenditures, respectively. A country's involvement with tourism suggests the exposure of its population to foreign (and potentially stronger) currencies—a channel that shares a certain overlap with the objective of remittances. We also show in Specifications (5) and (6) that a higher share of social protection or unemployment insurance coverage is associated with fewer instances of cross-border cryptocurrency use, suggesting that alternative insurance schemes reduce the urgency of receiving remittances and thus the need for resorting to Bitcoin transactions.

Our sixth motive is Circumventing Capital Controls, which we analyze in Tables 10 to 12. To motivate this exercise, Specifications (1) and (2) in Table 10 highlight that trade openness, measured by a high share of imports and exports in % of GDP, respectively, is negatively associated with cross-border Bitcoin use. In a similar vein, Specifications (3) and (4) show that financial openness, captured by two different versions of the Chinn-Ito index (see Chinn and Ito, 2006),[28] produce a similar result: An increase in financial openness is associated with a lower cross-border use of cryptocurrencies. In Specifications (5) to (7), we rely on capital control measures by Fernández et al. (2016).[29] Specification (5) contains an aggregate measure that captures all types of capital controls. In line with our previous findings, the positive coefficient on this variable suggests that an increase in restrictions on the flow of capital is associated with more cross-border Bitcoin transactions. As such, this finding supports the hypothesis that the use of (unregulated) cryptocurrency may serve as an alternative to traditional capital flows when a government imposes capital controls that tax, restrict, or even prevent these flows. A breakdown of the aggregate measure into in- and outflow restrictions in Specifications (6) and (7), respectively, reveals that most of the effect stems from restrictions on capital inflows. The next two tables then break down the impact of capital controls on cross-border Bitcoin flows further and assess the impact on different instruments. Table 11 focuses on bond market restrictions and Table 12 on money market restrictions. With 11 out of 14

[28] A first version relies on the traditional Chinn-Ito index, and a second one normalizes the range between zero and one.

[29] These measures capture the inverse of financial openness; therefore, we would expect the opposite sign to appear.

specifications across these tables showing significant coefficients for the capital control variables, it appears that restrictions to short-term portfolio investment flows are key drivers of this channel.

The seventh and last motive for cross-border cryptocurrency use is Circumventing International Sanctions. Table 13 contains a range of sanction measures from the Global Sanctions Database that comprise military, arms, trade, financial, travel, and other sanctions. While all coefficients are positive, suggesting a positive association between the imposition of sanctions on a country and the increased use of cross-border Bitcoin transactions, only the coefficients on military sanctions and travel sanctions are statistically significant. However, since our sanctions data span only four years and sanctions are imposed rather infrequently, the variation in the sanctions variable makes it challenging to identify a strong effect. Hence, if a longer sample becomes available, other forms of sanctions, in particular, financial sanctions could become more relevant as well.

To conclude this section, using Bitcoin flows, we have identified seven distinct motives of cross-border cryptocurrency use. These motives comprise strategies to adjust to unfavorable macro and financial developments both in the present and in the past, weak institutions, underdeveloped financial systems, the need to conduct international payment and remittance transfers, as well as the possible circumvention of capital controls and international sanctions. In all cases, we presented a wide range of evidence supporting the motives, increasing our confidence that the motives are, in fact, driving the results. However, so far, we have considered each motive individually. We therefore examine the different motives jointly in the next section.

3.3.2 Baseline Specification and Robustness

Using the example of Bitcoin again, we now combine the seven different motives for cross-border cryptocurrency use from the previous section into a single baseline specification that builds on Equation (2). For each motive, we include a representative variable from the individual regressions. In particular, we select variables that show a high statistical significance and are characterized by broad sample coverage (to avoid unnecessarily restricting the sample coverage of our baseline specification).

The list of representative variables is as follows: real GDP growth to reflect the Current Macro and Financial Conditions motive, an indicator variable for a past banking crisis to capture the Past Macro and Financial Conditions motive, control of corruption as a measure of the Institutional Quality motive, net interest margin as a proxy for the Structure of the Financial System motive, personal remittances received in % of GDP to represent the International Payments and Remittances motive, the Chinn-Ito index to represent the Circumventing Capital Controls motive (noting that an increase in the index is associated with more financial openness and, thus, a lower level of capital controls), and an indicator variable for the existence of travel sanctions to capture the Circumventing International Sanctions motive. We also include the two controls nominal GDP in USD and broadband use again.

Specification (1) in Table 14 presents the results of our baseline specification. All coefficients are statistically significant and carry the same sign as when they were included individually in the specifications in the previous section. We find that higher real GDP growth, more corruption control, and a higher Chinn-Ito index all lead to lower cross-border Bitcoin use. Moreover, past banking crises, a greater net interest rate margin in the banking system, more personal remittances received, and the existence of travel sanctions lead to greater cross-border Bitcoin use. These results are therefore consistent with the interpretation that the seven motives of cross-border cryptocurrency use which we have identified in this paper are distinct from one another and, as such, do not appear to simply be a reflection of the same underlying drivers. We also observe that the two motives with the highest level of statistical significance in our baseline specification are the Current Macro and Financial Conditions motive and the International Payments and Remittances motive, possibly suggesting that these two motives are the most prevalent ones.

Next, we conduct a set of robustness and sensitivity checks for our baseline specification. The results are shown in Specifications (2) to (9) of Table 14. Specification (2) excludes the variable that captures corruption control, which is not available for the year 2023 and thus slightly reduces the number of observations in our baseline specification. By removing this variable, the number of observations increases from 422 to 541 while retaining the signs and magnitudes of the coefficients on the other variables. There are only smaller changes in statistical significance, such as an increase in statistical significance for the net interest rate margin and the capital control coefficients and a reduction in significance for the international sanctions coefficient.

Specification (3) adds time fixed effects to the baseline specification, which absorb the effects of global time-varying influences on the dependent variable, such as a change in the price of Bitcoin, for example. While several coefficients lose significance (which, for the coefficient on real GDP growth, may be associated with the global synchronization of the COVID-19 shock), the majority of motives remains statistically significant, and all coefficients retain their signs. Specification (4) clusters the standard errors at the country-level instead of relying on heteroskedasticity robust standard errors. Although, again, the signs for all motives remain the same as in our baseline specification, only the previously most significant motive variables, associated with the Current Macro and Financial Conditions motive and the International Payments and Remittances motive, remain significant (both at the 1% level).

Specifications (5) to (7) exclude selected countries and time periods from our analysis. Specification (5) excludes the US from our sample, as it is the country with the highest cross-border Bitcoin use when flows are measured in USD. The results show that the sign and significance levels of the motive coefficients are very stable and therefore do not seem to be driven exclusively by the US. Specification (6) addresses a potential shortcoming of our Chainalysis dataset, which does not take VPN usage into account (as discussed in Section 2.1). To demonstrate that this is not a key driver of our results either, we exclude Qatar and Russia, two countries with the highest share of VPN coverage from our sample.[30] The results show that the signs and significance levels on all motive coefficients remain the same again. Lastly, in Specification (7), we exclude the year 2020 because it aligns with the initial COVID-19 shock. As the COVID episode constitutes a considerable part of the variation in our relatively short sample, we want to ensure that not all of our results are an artifact of this shock. While we see some motive coefficients losing significance, we still observe that the majority of the coefficients remain significant and, again, that the signs remain stable. This supports the interpretation that our findings are not simply the result of the COVID-19 pandemic.

Lastly, in Specifications (8) and (9), we split our data into an advanced economy and an emerging market economy sample, respectively.[31] While the coefficients for the key motive variables are highly significant across both samples, it becomes clear that certain motives are mostly driven by developments in a specific country group. For example, we observe significant coefficients associated with the occurrence of banking crises and capital account openness (measured by the Chinn Ito index) only in the emerging market sample, which aligns with the traditionally more frequent occurrence of banking crises and use of capital controls in this country group.[32] Moreover, Specifications (8) and (9) create two homogeneous country samples and thus serve as evidence that potential correlations between Chainalysis' measures of web-traffic (used to allocate crypto flows

[30]According to Forbes (2023) the United Arab Emirates, Qatar, and Russia, are the countries with the highest VPN adoption in 2022, of which the latter two are part of our baseline regression sample.

[31]We rely on the country classifications in the IMF's World Economic Outlook Database from April 2025. Our advanced economy sample corresponds to the classification *Advanced Economies*, and our emerging market economy sample to the classification *Emerging Market and Developing Economies*.

[32]We also run two specifications where we replace the control variables in our baseline specification with alternatives from Table 4. The first specification includes a measure of population instead of nominal GDP in USD to control for country or market size, and the second specification relies on a measure of cell phone use instead of the broadband subscription variable. Both variables carry the same sign as the variables that they replace, and most of the motive variables remain unaffected. These results are available on request.

across countries) and country-specific characteristics, such as income or wealth levels, are not a notable driver of our results.

Overall, using the example of cross-border Bitcoin flows, we have shown in this section that there are at least seven distinct motives of cross-border cryptocurrency use and that they are robust to a variety of alternative explanations.

4 COVID-19 Event Study for Bitcoin Flows

4.1 Motivation and Background

Next, we use the COVID-19 pandemic as a natural experiment to demonstrate the robustness of our previously identified motives for cross-border cryptocurrency transactions. The idea behind this event study is that the relevance of any motive linked to a country's economic environment is likely to increase notably during times of economic or financial stress, such as those caused by the COVID-19 shock. The motives expected to be impacted the most are the Current Macro and Financial Conditions motive and the International Payments and Remittances motive. For the former, deteriorating economic and financial conditions (e.g., lower incomes or higher unemployment rates, depreciating emerging market currencies, and elevated inflation rates) may increase the appeal of relying on cross-border cryptocurrency transactions with the objective of storing value abroad. Similarly, for the latter, the economic and health situation (e.g., wide-spread COVID-19 infection rates) may increase the need to use cross-border cryptocurrency transactions to send or receive financial transfers to/from family members abroad.

The COVID-19 shock and its economic and financial repercussions were largely unanticipated and can be considered reasonably exogenous in the context of our research question. Given that our research question is defined at the country-level and centers on cross-border cryptocurrency use as a result of the pandemic's adverse economic impact, it is not essential to disentangle the relative contributions of the economic impact's underlying causes (e.g., being unable to work due to sickness, layoffs in response to weak demand, or government-mandated lockdowns, etc.), provided they can be plausibly linked to the pandemic.[33] Moreover, besides absorbing a wide range of

[33] It could be more challenging to make this argument for more granular research questions, especially when focusing on smaller units of observation, as they are likely prone to a wider range of confounding factors occurring at the same time. For example, a question that asks about the impact of the COVID-19 pandemic on agents' mental health could have a variety of different explanations—e.g., adverse health impact from being sick, the economic impacts from being unable to work, or the social impact of having to self-isolate at home, etc.—and each explanation could give rise to a different policy conclusion.

potentially confounding factors through the inclusion of country and time fixed effects in our event study, we also control for the full set of cross-border cryptocurrency use motives, which rules out many alternative explanations. Lastly, the cross-country nature of our study and our extensive country sample are more likely to average out the impact of any (unaccounted) country-specific developments or institutional factors that might potentially adversely impact the external validity of single-country studies.

4.2 Empirical Specification and Data

Our empirical analysis follows a difference-in-difference strategy, where we compare the impact of the COVID-19 shock on countries with high vs. low pre-COVID-19 exposures to the most relevant motives for engaging in cross-border Bitcoin transactions. One challenge of our analysis is that our Bitcoin data only start in June 2020 (and, after calculating the growth rate of our dependent variable, effectively in July 2020), which makes it more difficult to capture the early stages of the COVID-19 shock and does not provide us with the opportunity to identify the pre-COVID-19 trends of the treatment and the control groups. To take this feature of our data into account, we adapt our empirical specification as follows. First, instead of identifying our coefficients of interest based on a pre- vs. post-COVID-19 comparison, we focus on differences in the *intensity* of the COVID-19 shock over the 24-month period from July 2020 to June 2022. In particular, we expect the motives to engage in cross-border cryptocurrency transactions to matter more when the intensity of the COVID-19 shock is high compared to when the intensity is low. The use of time-varying and country-specific COVID-19 case count data allow us to determine periods of low and high intensity on a country-specific basis. Second, we use pre-COVID-19 values for our motive variables so that they are not impacted by the COVID-19 shock itself. Third, we run a series of robustness checks that support our identification strategy, such as adding additional control variables, excluding lower intensity observations after the intensity peak, and conducting several placebo tests.

We estimate the following empirical specification for 152 countries over the period July 2020 to June 2022:

$$\hat{y}_{i,t} = \alpha + \beta Dcovid_{i,t} \times DX_i + \mu Dcovid_{i,t} + \delta_i + \gamma_t + \varepsilon_{i,t} \tag{3}$$

where $\hat{y}_{i,t}$ represents our dependent variable, which is defined as the month-over-month growth rate of the sum of Bitcoin in- and outflows.[34] $Dcovid_{i,t}$ corresponds to an indicator variable that takes on the value of 1 when the intensity of COVID-19 is high (and 0 otherwise), DX_i is a vector of indicator variables that signals a high exposure to the motives in question prior to COVID-19, α is the regression constant, and $\varepsilon_{i,t}$ is the error term. The baseline specification also includes country fixed effects (δ_i) and time fixed effects (γ_t) that absorb time-invariant country-specific and time-varying global factors, respectively.[35] Standard errors are clustered at the country-level. Our two key explanatory variables are created as follows:

Measure of COVID-19 Intensity ($Dcovid_{i,t}$): An indicator variable that takes on the value of 1 in the month when a country's COVID-19 cases reach their peak during the period from July 2020 to June 2022, as well as in the five months prior to this date (and 0 otherwise). This six month window is characterized by rising growth rates of COVID-19 cases and thus represents the period when COVID-19 appears to have hit hardest. We measure COVID-19 cases based on the variable *new cases per million (people)* from Mathieu et al. (2020), which we convert to *new cases per thousand (people)*.[36]

Measure of Pre-COVID Motive Exposure (DX_i): A vector of indicator variables that take on the value of 1 (and 0 otherwise) when a country had a high exposure to a motive for engaging in cross-border Bitcoin transactions prior to the COVID-19 pandemic.[37] We construct a separate indicator variable for each motive included in the baseline specification of Section 3.3.2. For motives represented by continuous variables, the pre-COVID exposure indicator variables take on the value of 1 (and 0 otherwise) when a country's value was greater than the sample median prior to the pandemic. For motives captured by indicator variables, we set the pre-COVID exposure indicator variable to 1 (and 0 otherwise) when a country's value was greater than 0 prior to the pandemic. For the two main motive variables analyzed in this section, a higher motive exposure

[34] In this exercise, we rely on the growth rate of our dependent variable instead of scaling it by GDP, as monthly GDP values are often unavailable or heavily interpolated. In addition, we winsorize our dependent variable at the 1% level on each side.

[35] Note that the inclusion of country fixed effects absorbs the direct effect of DX_i.

[36] Our approach takes into account potential measurement differences of COVID-19 cases across countries in two ways. First, by relying on an intensity measure that focuses on a country's peak of cases instead of a continuous measure capturing a country's count of individual cases, we focus on the major COVID-19 dynamics and abstract from smaller changes over time. And second, by including country fixed effects in our baseline specification, we are able to absorb the impact of (time-invariant) differences in case numbers across countries (e.g., due to differences in medical systems or reporting requirements).

[37] The basis for determining the motive exposure *prior* to the pandemic for the variables related to personal remittances, institutional quality, and sanctions is represented by their 2019 values. For the remaining variables—either because 2019 data are not available or not particularly meaningful (e.g., the occurrences of banking crises are better captured over a longer time horizon)—this basis is represented by the average values for continuous variables (or by positive values for indicator variables) over the period from 2010 to 2019.

prior to the pandemic was present when personal remittances were high or when the growth rate of real GDP was low. For the remaining motives, a high exposure was present when banks' net interest rate margins were high, institutional quality was low, capital openness was low, a banking crisis occurred, or a country was subject to travel sanctions.

4.3 Results and Robustness

Table 15 presents the results of estimating Equation (3) on Bitcoin data for 152 countries over the period July 2020 to June 2022. The first three specifications represent the build-up of our baseline specification for this exercise. Specification (1) does not include any fixed effects, Specification (2) contains time fixed effects, and Specification (3) includes country fixed effects.[38] Our baseline specification, Specification (4), subsequently includes both country and time fixed effects.

The first four specifications show the same pattern: First, the direct effect of COVID-19 intensity, represented by coefficient $Dcovid$, is negative and significant. This implies that the growth rate of cross-border Bitcoin transactions is, on average, lower during periods of high COVID-19 intensity than during periods of low intensity. A possible explanation for this observation is that the adverse economic effects of COVID-19 (e.g., lower income, (temporary) unemployment) could reduce the funds available for any Bitcoin activity, and thus lower the volume of cross-border Bitcoin transactions. Moreover, the widespread nature of COVID-19 infections during this period, and the associated physical limitations (e.g., sickness, need to isolate) may further reduce the opportunity to participate in such activities. Next, are the two main coefficients of interest, the interaction terms between the effect of COVID-19 intensity and the two pre-COVID motive exposure variables ($Dcovid \times HighRemittances$ and $Dcovid \times LowGDPGrowth$, respectively). In both cases, the interaction terms are positive and significant, suggesting that the growth rate of cross-border Bitcoin transactions during periods of high COVID-19 intensity falls by relatively less in countries with high pre-COVID motive exposures, characterized by an above-median value of personal remittances received and a below-median value of GDP growth rates prior to the COVID-19 shock, respectively. This supports our findings in Section 3.3.2 that both the International Payments and Remittances motive and the Current Macro and Financial Conditions motive are key determinants of cross-border Bitcoin transactions.

[38] In the absence of country fixed effects, we additionally include the direct effects of the pre-COVID motive exposure variables, $HighRemittances$ and $LowGDPGrowth$, in Specifications (1) and (2). Note that all subsequent specifications include country fixed effects, which absorb the variation of these direct effects, and thus do not require their additional inclusion any longer.

The remaining specifications in Table 15 constitute robustness checks that highlight the robustness of our empirical analysis. First, Specification (5) additionally controls for the other five motives that were included in our baseline specification of Section 3.3.2 by creating a separate interaction term (between the COVID-19 intensity measure and the corresponding pre-COVID motive exposure variable) for each of them. This action even strengthens the results by increasing the coefficient size of the two interaction terms of interest, as well as their significance.[39] Specification (6) corresponds to Specification (4) but focuses only on the observations up until the COVID-19 peak (setting all post-peak observations to missing). The idea of this exercise is to exclude all post-treatment observations from the control group, as they could be impacted by a behavioral change during the treatment period (e.g., regularly conducting a remittance transaction with relatives abroad that started as a one-time payment during the COVID-19 peak period). Again, the coefficients remain positive and significant, with the significance of the remittances interaction term even increasing considerably. Specification (7) then adds a control variable for *policy stringency* to the specification.[40] This robustness check aims to control for differences (across countries and over time) in the *hardship* that derives from a given number of COVID-19 cases. The outcome of this exercise indicates that even with the inclusion of this variable, our results remain very similar to those of the previous specifications. Lastly, Specifications (8) and (9) constitute *placebo* specifications. Specification (8) selects the minimum instead of the maximum month of COVID-19 cases during the period from July 2020 to June 2022 (plus the corresponding window of the previous five months) and Specification (9) shifts the 6-month window identified in our baseline specification by one year into the future.[41] In both cases, the interaction terms of interest turn out to be *insignificant*, as expected, suggesting that an arbitrary placement of the treatment period does not produce the same outcome as the identification strategy used in our baseline specification. This again supports the robustness of our empirical analysis and highlights the relevance of the identified motives.

[39] None of the interaction terms for other included motives is significant in this specification. This is, however, not unexpected, as most of them are less likely to interact with the COVID-19 shock.

[40] This variable is taken from the Oxford Covid-19 Government Response Tracker (variable: *stringencyindex_average*; dataset: *OxCGRT_compact_national_v1.csv*) and captures, among others, school or workplace closures, gathering and travel restrictions, as well as public information campaigns.

[41] To keep countries with later case number peaks in the sample, we extended the sample period for this exercise from June 2022 to the latest available data point, which is September 2023.

5 Extension to Stablecoin Flows

Lastly, this section extends the results of our baseline specification for Bitcoin in Section 3 to four major stablecoins. Stablecoins are a type of cryptocurrency that aims to maintain a stable value relative to a trusted reference asset, which, for most stablecoins, is the US dollar. Stablecoins have experienced rapid growth in recent years, particularly since the COVID-19 pandemic, and have reached a joint market capitalization of around $255 billion USD in 2025 (Aldasoro et al., 2025). Our analysis covers four of the largest stablecoins by market capitalization (in order of relevance): Tether (USDT), the largest stablecoin by market capitalization and trading volume; USD Coin (USDC), the second largest stablecoin; followed by Binance USD (BUSD), the third largest stablecoin historically but discontinued in 2023; and Dai (DAI, also SAI), which frequently ranks among the top 5 stablecoins as well. While the first three stablecoins are directly pegged to the US dollar, Dai relies on overcollateralized crypto loans instead of fiat money as a backing mechanism but still aims for a 1:1 relationship to the US dollar.

Figure 7 illustrates the evolution of the sum of in- and outflows for each of these stablecoins across our sample countries over the period from 2020 to 2023.[42] Cross-border stablecoin flows started to increase in mid-2020, with Tether and USD Coin emerging as the most dominant assets. Notably, cross-border transactions for USD Coin and Dai increased several-fold in 2022Q3, likely as investors pivoted toward fiat- and cryptocurrency-backed stablecoins following the collapse of the algorithmic (and thus, unbacked) stablecoin TerraUSD in May 2022. As Tether briefly deviated from its 1:1 peg to the US dollar during this event itself, it was possibly considered a less-appealing alternative at that time, reflecting the absence of an increase in cross-border Tether flows during this episode.

We then estimate our baseline specification—Equation (2) in Section 3—together with several robustness checks for each of these stablecoins (i.e., following the structure of Table 14 in Section 3, where we conduct this analysis for Bitcoin).[43] Table 17 replicates the entire Table 14 (i.e., Specifications (1)-(9)) for Tether, and Table 18 presents the first three specifications of Table 14 (i.e., (1) the baseline specification, (2) maximizing the sample length, and (3) adding time fixed effects to the specification) for the remaining three stablecoins.

The results for Tether in Table 17 are very much in line with our Bitcoin results in Table 3.

[42] While the country sample of the chart covers 164 countries, the following empirical analysis covers up to 145 countries due to the limited availability of some of the control variables.

[43] Table 16 presents the corresponding summary statistics for each stablecoin.

For Specification (1), the baseline specification, the coefficients on all seven motive variables carry the same signs, and five out of seven coefficients are statistically significant.[44] In particular, the variables representing the Current Macro and Financial Conditions motive (*real GDP growth*) and the International Payments and Remittances motive (*personal remittances received in % of GDP*), show the same high levels of significance as in our Bitcoin analysis. Moving through the remaining eight robustness specifications of the table, the two key motives remain statistically significant in all cases and often show a high degree of significance at the 1% level. This appears to suggest that Tether users follow a largely similar set of motives as Bitcoin users when engaging in cross-border crypto transactions.

Next, Table 18 presents the results for USD Coin, Binance USD, and Dai, focusing on the first three specifications in each case. While we still observe relatively similar patterns in coefficients and significance levels in the baseline specifications for USD Coin and Binance USD (with three and two coefficients being insignificant relative to our Bitcoin baseline specification, respectively), the baseline specification for Dai reveals only two significant coefficients.[45] However, for all stablecoins, the two key motives, Current Macro and Financial Conditions motive and International Payments and Remittances motive, remain significant in their respective baseline specifications. The least significance is shown by Dai in the robustness specification with time fixed effects (i.e., Specification (9) of Table 18), where only a single motive variable turns out significant: the International Payments and Remittances motive. A possible explanation for the somewhat weaker results for Dai could be that its alternative pegging mechanism and its less widespread use may make it less feasible for cross-border transactions associated with certain motives.

Overall, the results of this section highlight that the key motives of using Bitcoin for cross-border transactions, namely the Current Macro and Financial Conditions motive and the International Payments and Remittances motive, carry over to the largest stablecoins as well. While our sample is too short to conduct a meaningful subsample analysis, a possible explanation for this extensive overlap could be that Bitcoin may have been seen as the most stable cryptocurrency in the early stages of the crypto market and this role has increasingly been taken on by dedicated stablecoins. However, Bitcoin's substantially larger market capitalization could still make it appealing for a variety of use cases.

[44]The two exceptions are the coefficients on the indicator variable for banking crises and the variable capturing control of corruption. Moreover, the two standard controls, a country's nominal GDP in USD and a measure of internet access via broadband/high-speed connections, remain significant and carry the same signs as well.

[45]The baseline specifications are shown in columns (1), (4), and (7) of Table 18, respectively.

6 Conclusion

In this paper, we have examined the patterns and determinants of cross-border cryptocurrency flows, using data on Bitcoin and four major stablecoin flows for up to 162 countries during the years 2020 to 2023. We have made several contributions to the literature. First, we have documented the patterns of global cross-border Bitcoin flows and contrasted these patterns with those of traditional international capital flows. Second, using a cross-country panel approach at annual frequency, we have conducted a systematic and comprehensive assessment of the key determinants and motives of cross-border Bitcoin flows. Third, we have devised an event study for Bitcoin flows during the COVID-19 pandemic, which serves as a natural experiment that reinforced the relevance of several previously identified motives. And fourth, we have applied our determinant analysis to the cross-border flows for four major stablecoins.

Our results are as follows. First, we document several key patterns of global cross-border Bitcoin flows. While cross-border Bitcoin flows are still relatively small for the average country in our sample (the sum of Bitcoin in- and outflows amounts to 1.6% of quarterly GDP), several countries in Eastern Europe, Latin America, and Asia have experienced more sizable cross-border Bitcoin flows (up to 14 % of quarterly GDP). Similarly, when computing the shares of Bitcoin flows in net terms compared with correspondingly recorded portfolio investment flows and other investment flows, respectively, we find that Bitcoin flow shares amount to around 3-4% at the 75$^{\text{th}}$ percentile of the share distribution, and thus, are relatively small for most sample countries. For several countries, however, these shares are more sizeable (e.g., up to 61% of portfolio investment flows), suggesting that, at least in some cases, Bitcoin flows have become a notable alternative to traditional capital flows.

In our annual panel analysis, where we assess the determinants of cross-border cryptocurrency transactions more formally, we identify seven distinct motives that serve as drivers for such transactions. These motives include strategies to adjust to unfavorable macroeconomic and financial developments in the present and in the past, weak institutions, underdeveloped financial systems, the need to conduct international payment and remittance transfers, as well as the possible circumvention of capital controls and international sanctions. Using the example of Bitcoin, our analysis indicates that the most significant motives are strategies to adjust to unfavorable macro and financial developments, as well as the need to conduct international payment and remittance transfers.

Moreover, we conduct an event study of cross-border Bitcoin flows during the COVID-19 period that highlights the robustness of our previously identified motives. By comparing the impact of the COVID-19 shock on countries with high vs. low pre-COVID-19 motive exposures, we find that, in particular, pre-COVID-19 exposures related to unfavorable macro and financial developments, as well as the need to conduct international payment and remittance transfers have supported cross-border Bitcoin transactions during episodes of high COVID-19 intensity. Taken together, our findings suggest that these two motives played a central role precisely during times when they were expected to be important—further strengthening the external validity of our results.

Lastly, when applying the baseline specification of our determinant analysis for cross-border crypto flows to four major stablecoins, we demonstrate that our Bitcoin findings extend to the stablecoin ecosystem as well. This reinforces the economic significance of our results and provides a richer information set to policymakers.

The findings of our paper provide several inputs into the policy discussions on cryptocurrencies. First, the presence of several motives for cross-border cryptocurrency transactions shows that there is a wide range of use cases. On the one hand, there is an international payments and remittances motive, which seems to take advantage of a more favorable cost structure of cryptocurrencies compared to many traditional cross-border payment services. As these activities serve a vital purpose for workers with foreign ties, in particular one that traditional banks may not be able to provide (or provide at this price), policymakers may want to consider preserving or even supporting the possibility of using cross-border cryptocurrency flows in line with this motive. On the other hand, the intention to use cryptocurrencies to circumvent international sanctions or capital controls, where more cryptocurrency use would have considerable side effects, may trigger discussions about closer monitoring and tighter regulation of cryptocurrencies. The other motives are possibly more ambiguous, such as the macro and financial conditions motive and the weak institutions motive, where cross-border cryptocurrency can play a role in storing value. A recurring theme in this context, however, appears to be that cryptocurrency use is rather a symptom than a cause, and addressing the underlying macroeconomic challenges directly seems to be of higher priority.

While the current focus of our paper is on the patterns and determinants of cross-border cryptocurrency use, the consequences and implications of cross-border cryptocurrency use are also of significant interest to policymakers. For example, are cryptocurrency transactions large enough to move a country's exchange rate? Do cross-border cryptocurrency flows impact the allocation of capital? Or do they increase financial stability risks? With cryptocurrency flows gaining more economic relevance and higher-quality data becoming increasingly available, such questions can likely be answered in a more satisfying way in the near future.

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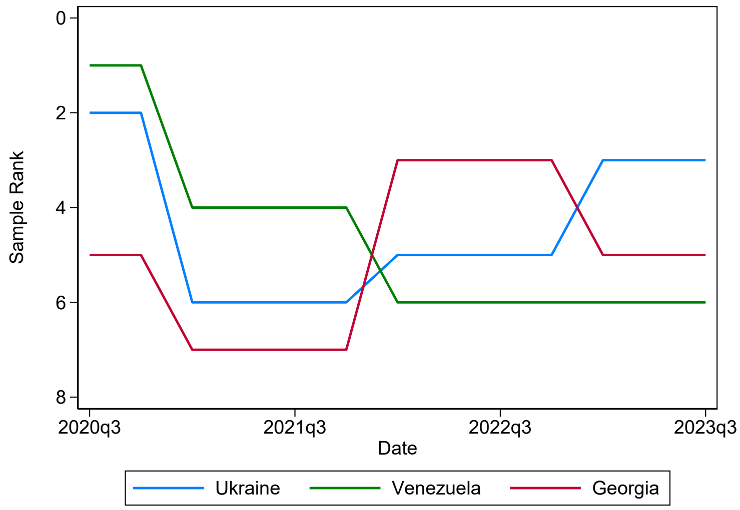
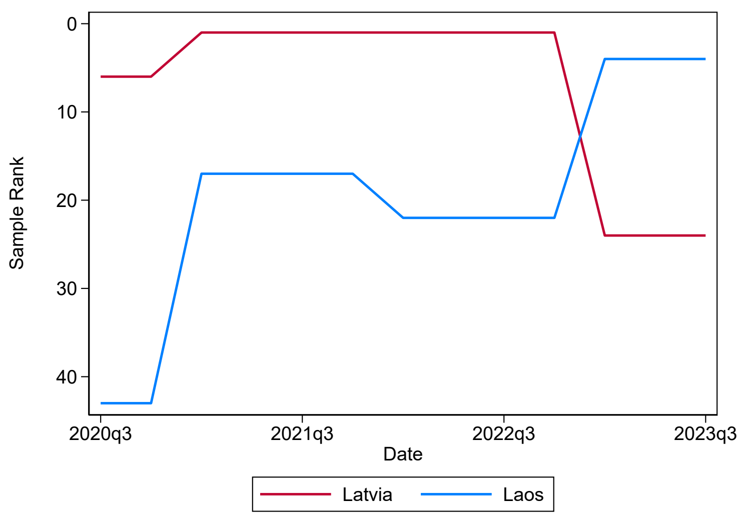
8 Figures and Tables

Figure 1: Sample Rank of Bitcoin Flows over Time

(a) Countries with High Bitcoin Exposure Levels



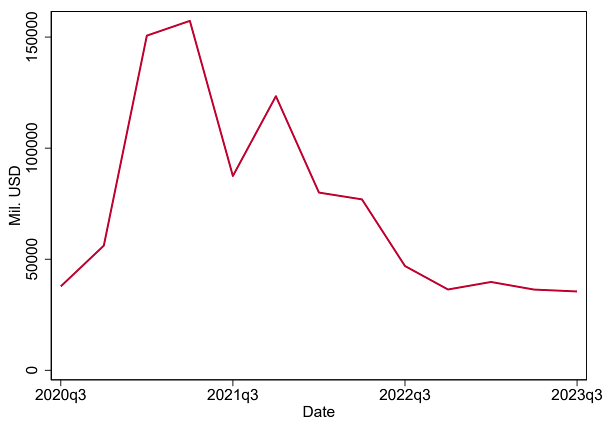
(b) Countries with Strong Bitcoin Exposure Dynamics



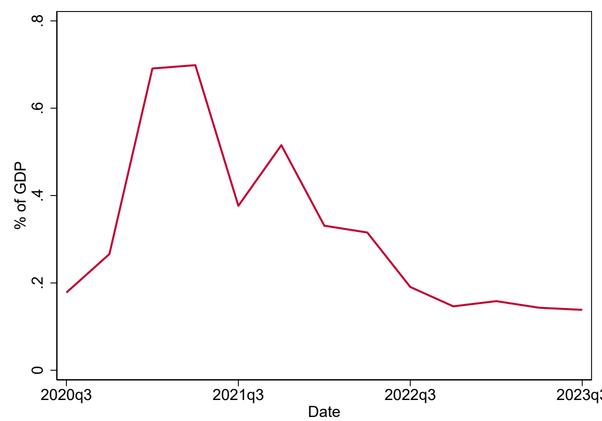
Note: This figure shows the sample rank of the variable sum of Bitcoin in- and outflows in % of GDP for each country over time. Sample rank ranges from 1 (highest) to 142 (lowest). Plot a) shows the values for Venezuela, Ukraine and Georgia. Panel b) shows them for Latvia and Laos.

Figure 2: Dynamics of Bitcoin Flows over Time: Sum of In- and Outflows

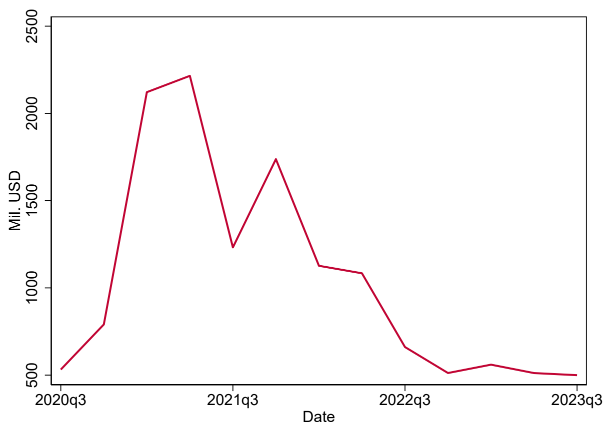
(a) Sum across Sample Countries (in Mil. USD)



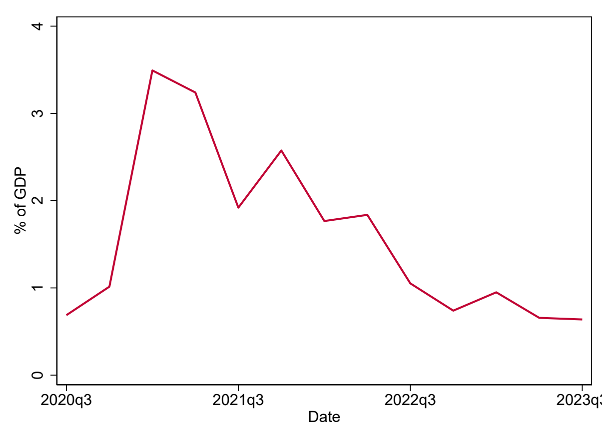
(b) Sum across Sample Countries (in % of GDP)



(c) Mean of Sample Countries (in Mil. USD)



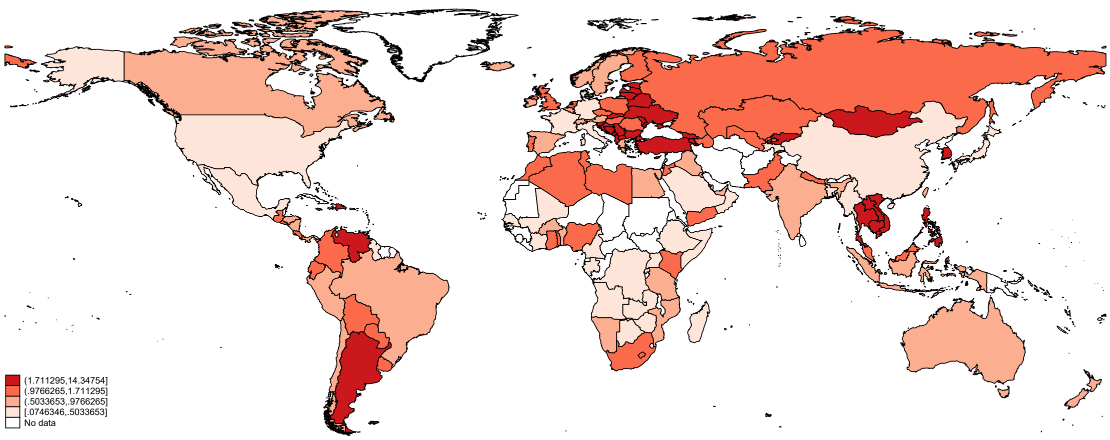
(d) Mean of Sample Countries (in % of GDP)



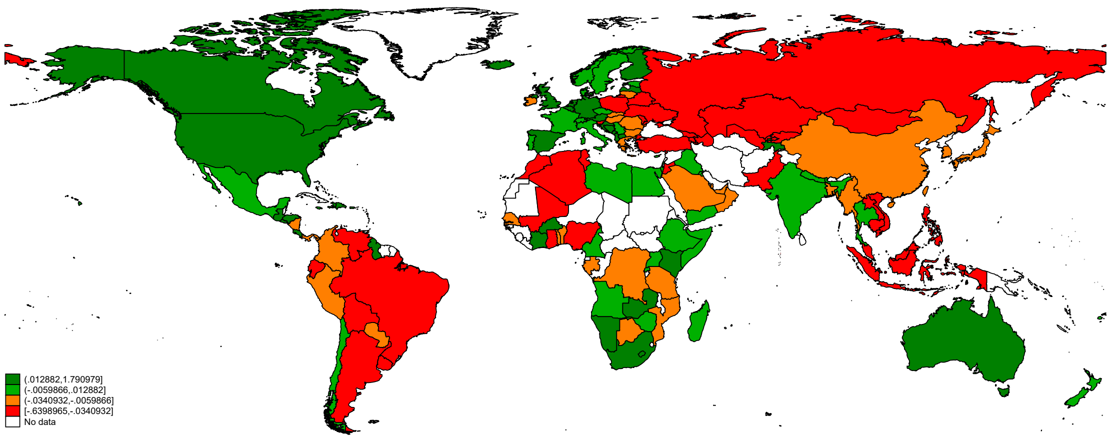
Note: This figure plots the sum of Bitcoin in- and outflows in four different ways. The panels in the first row, Panels (a) and (b), present these flows as the sum of in- and outflows across all sample countries, whereas the panels in the second row, Panels (c) and (d), show these flows for the average country in our sample. For Panels (a) and (b), we divide the sum of Bitcoin in- and outflows across all sample countries by 2 in order to account for the fact that one country's inflows are another countries outflows (we do not make this adjustment for Panels (c) and (d) as these panels focus on the country-level). Moreover, panels in the first column, i.e., Panels (a) and (c), present the data in Million USD, and panels in the second column, Panels (b) and (d), in % of GDP. The patterns in Panels (b) and (d) differ slightly, as in the case of the former, Bitcoin flows and GDPs are aggregated to the sample-level before their ratio is taken. In the case of the latter, the ratios of Bitcoin flows to GDP are computed at the country-level before their average is taken.

Figure 3: Distribution of Bitcoin Flows across Countries

(a) Sum of Bitcoin In- and Outflows



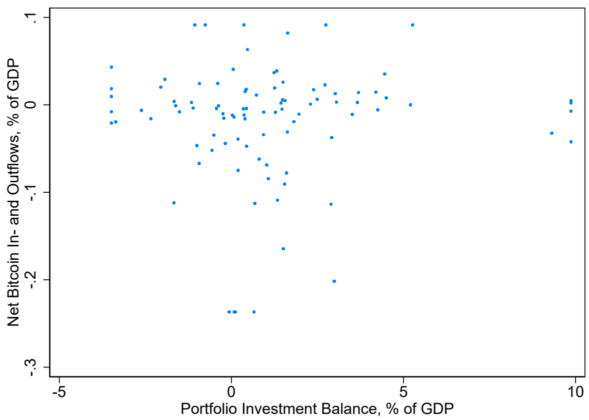
(b) Net Bitcoin In- and Outflows



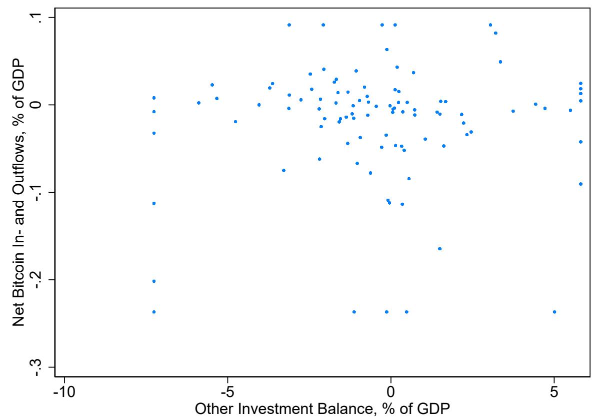
Note: This figure shows the global distribution of Bitcoin flows in two ways. Panel (a) presents the sum of Bitcoin in- and outflows in % of GDP for each country. Darker red colors imply a higher exposure. Panel (b) shows net Bitcoin in- and outflows in % of GDP for each country. Green colors represent net inflows and red colors represent net outflows. Countries without data are shown in white. All data are based on averages over the period 2020q3 to 2023q3.

Figure 4: Comparison of Mean and Standard Deviation between Bitcoin and Traditional Capital Flows

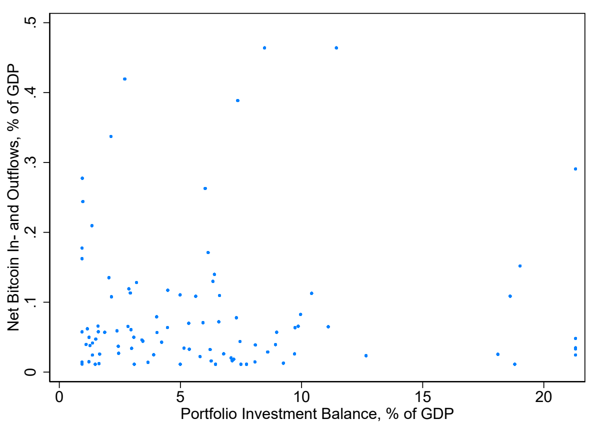
(a) Mean: Bitcoin vs. Portfolio Flows



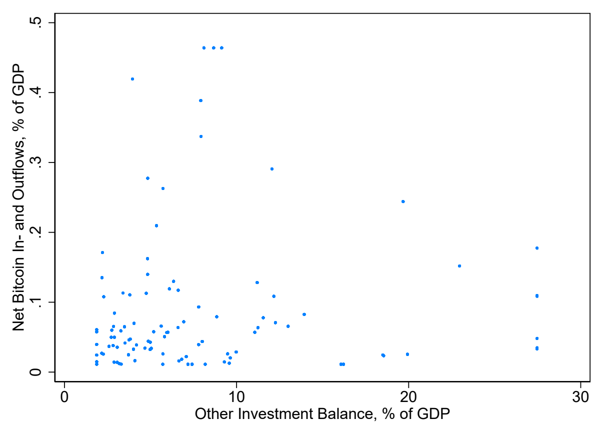
(b) Mean: Bitcoin vs. Other Flows



(c) Standard Deviation: Bitcoin vs. Portfolio Flows



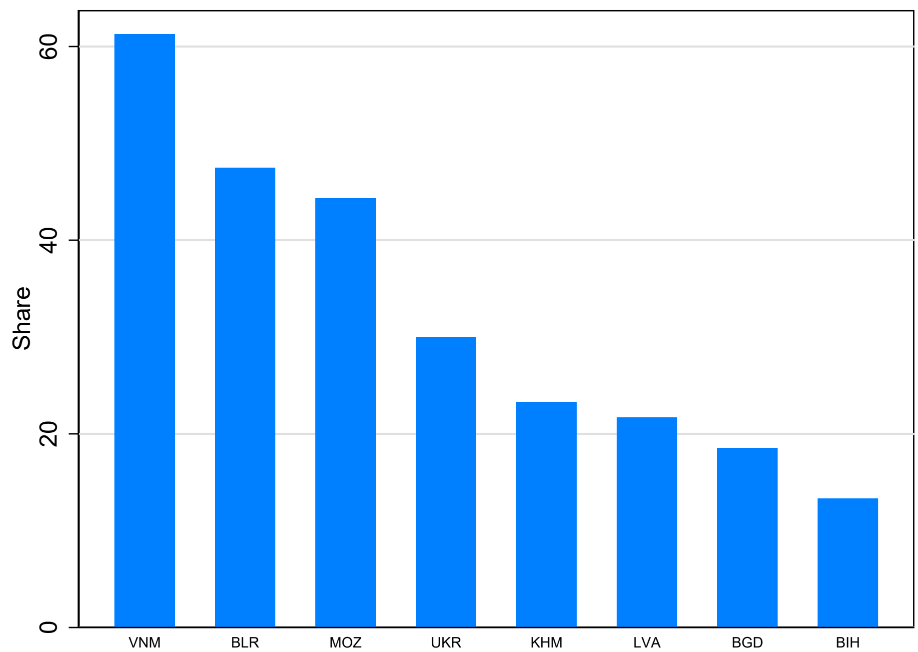
(d) Standard Deviation: Bitcoin vs. Other Flows



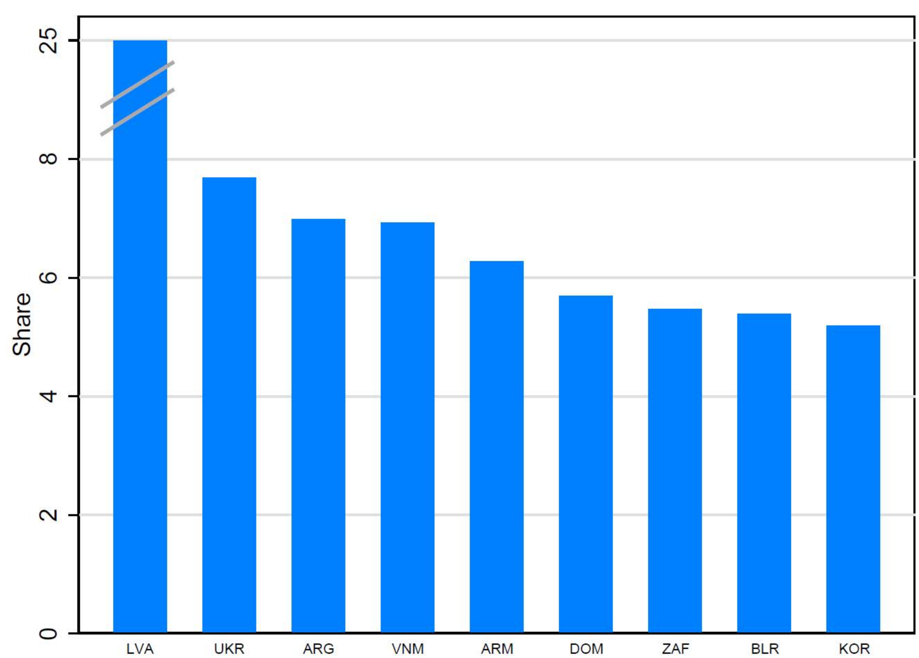
Note: Bitcoin flows in this figure are defined as net Bitcoin in- and outflows in % of GDP. Portfolio flows are the balance of portfolio investment flows in % of GDP from the Balance of Payments (BoP). Other flows are the balance of other investment flows in % of GDP from the BoP. Mean and standard deviation are calculated for each country over the period 2020q3 to 2023q3. Means and standard deviations are winsorized at the 5% and 95% level respectively.

Figure 5: Share of Bitcoin Flows in Traditional Capital Flows

(a) Share of Bitcoin Flows in Portfolio Flows



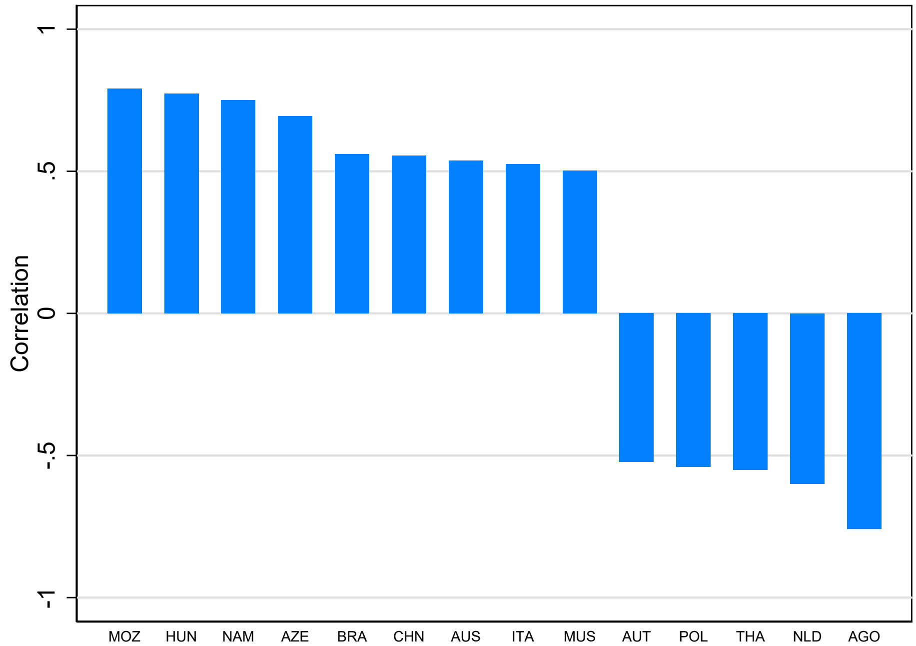
(b) Share of Bitcoin Flows in Other Flows



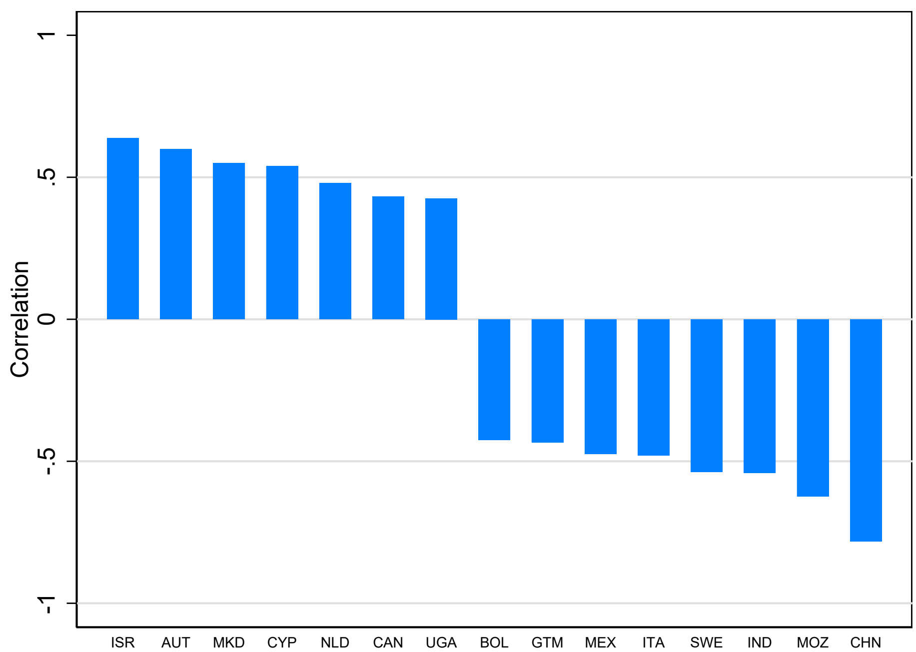
Note: The figure shows Bitcoin flows as a share of traditional capital flows from the Balance of Payments (BoP). Bitcoin flows in this figure are defined as net Bitcoin in- and outflows in % of GDP. Portfolio flows are the balance of portfolio investments in % of GDP from the BoP. Other flows are the balance of other investment flows in % of GDP from the BoP. The shares correspond to the share of the means of the absolute values over the period 2020q3 to 2023q3. Panel (a) shows only shares with values above 10% and Panel (b) with values above 5%. The bar for Latvia in Panel B is adjusted for size purposes.

Figure 6: Correlation between Bitcoin Flows and Traditional Capital Flows

(a) Correlation between Bitcoin and Portfolio Flows

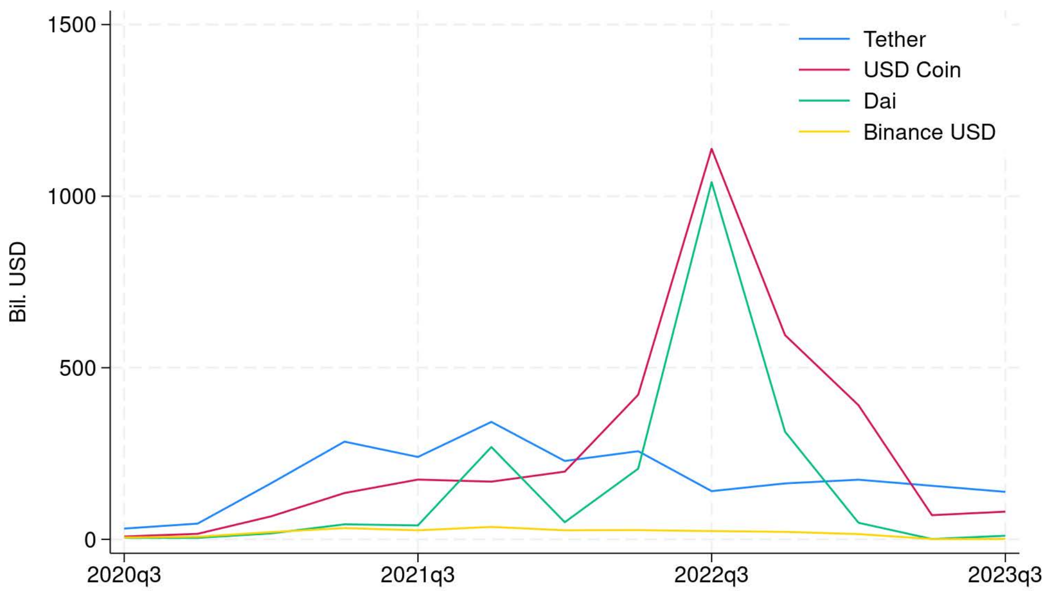


(b) Correlation between Bitcoin and Other Flows



Note: Bitcoin flows in this figure are defined as net Bitcoin in- and outflows in % of GDP. Portfolio flows are the balance of portfolio investments in % of GDP from the Balance of Payments (BoP). Other flows are the balance of other investments in % of GDP from the BoP. Correlations are computed over the period 2020q3 to 2023q3. Panel (a) shows only correlations that are greater than 0.5 or smaller than -0.5, and Panel (b) shows only correlations that are greater than 0.4 or smaller than -0.4.

Figure 7: Sum of Stablecoin In- and Outflows



Note: This figure plots the sum of in- and outflows, in billion USD, across all sample countries of our analysis for the four stablecoins Tether, USD Coin, Binance USD, and Dai.

Table 1: Summary Statistics for Bitcoin Flows

	Sum of In- and Outflows *% of GDP*		**Net In- and Outflows** *% of GDP*		**Sum of In- and Outflows** *Mil. USD*		**Net In- and Outflows** *Mil. USD*	
Sample:								
	Mean	1.58	Mean	0.00	Mean	1044.97	Mean	0.73
	Std. Dev.	2.12	Std. Dev.	0.24	Std. Dev.	2257.03	Std. Dev.	154.82
	25th Percentile	0.50	25th Percentile	-0.03	25th Percentile	55.17	25th Percentile	-11.47
	Median	0.98	Median	-0.01	Median	285.96	Median	-0.82
	75th Percentile	1.69	75th Percentile	0.01	75th Percentile	1034.12	75th Percentile	1.76
Top 10:								
1	Latvia	14.35	Andorra	1.79	United States	20971.72	United States	1629.60
2	Andorra	13.11	Latvia	1.71	Korea	9080.54	Australia	244.49
3	Moldova	9.85	Barbados	0.37	United Kingdom	7693.37	United Kingdom	180.51
4	Venezuela	8.34	Namibia	0.18	Türkiye	5985.76	Germany	177.23
5	Georgia	7.12	South Africa	0.14	Russia	5198.14	Latvia	166.00
6	Ukraine	6.90	Malta	0.11	China	5186.25	South Africa	131.91
7	Slovenia	5.62	Guatemala	0.10	India	4588.61	Canada	100.55
8	Belarus	4.55	Bosnia and Herzeg.	0.09	Germany	4374.80	Spain	48.86
9	Kyrgyz Republic	4.28	Montenegro	0.08	Japan	4318.09	Netherlands	46.45
10	Barbados	4.21	Australia	0.06	Canada	3891.64	Belgium	28.89
Bottom 10:								
1	Oman	0.22	Mongolia	-0.16	Mali	14.96	Venezuela	-81.29
2	Botswana	0.22	Georgia	-0.20	Madagascar	12.13	Japan	-95.14
3	Qatar	0.16	Kyrgyz Republic	-0.24	Somalia	10.80	Argentina	-106.12
4	Gabon	0.16	Vietnam	-0.28	Botswana	9.58	Indonesia	-114.00
5	Uganda	0.15	Belarus	-0.30	Rwanda	9.22	Brazil	-143.82
6	Congo, Dem. Rep.	0.14	Lao P.D.R.	-0.31	Tajikistan	8.38	Türkiye	-161.32
7	Ethiopia	0.14	Armenia	-0.38	Gabon	7.47	Ukraine	-220.69
8	China	0.13	Ukraine	-0.51	Maldives	5.59	Vietnam	-264.84
9	Guyana	0.10	Venezuela	-0.55	Fiji	2.60	Russia	-298.88
10	Angola	0.07	Moldova	-0.64	Guyana	1.70	China	-457.08

Note: This table provides the summary statistics for the 142 countries covered in our stylized facts section sample and more information for the top and bottom 10 countries of this sample. All statistics are computed over the period 2020q3 to 2023q3.

Table 2: Comparison of Bitcoin and Capital Flows

Country	**Mean, % of GDP**			**Std. Dev., % of GDP**			**Share of Bitcoin**		**Corr. of Bitcoin**	
	Bitcoin	*Portf.*	*Other*	*Bitcoin*	*Portf.*	*Other*	*Portf.*	*Other*	*Portf.*	*Other*
Albania	0.04	1.32	-1.06	0.11	4.99	3.80	1.93	2.92	-0.05	0.08
Algeria	-0.05	.	-0.28	0.06	.	2.75	.	2.93	.	-0.07
Angola	0.00	-0.43	4.72	0.01	1.48	5.72	0.94	0.11	-0.76	0.32
Argentina	-0.08	1.07	0.55	0.06	0.91	1.53	6.82	6.98	0.16	-0.26
Armenia	-0.38	0.11	-1.13	0.46	8.47	8.67	7.99	6.28	0.19	0.02
Australia	0.06	0.47	-0.12	0.07	5.34	4.04	1.51	2.21	0.54	-0.31
Austria	0.02	0.43	-2.43	0.02	7.09	9.63	0.40	0.26	-0.52	0.60
Azerbaijan	-0.09	1.55	9.78	0.06	1.87	11.06	4.35	0.75	0.69	-0.01
Bangladesh	-0.01	0.08	-1.37	0.01	0.04	3.30	18.51	0.47	0.11	0.19
Belarus	-0.30	0.08	5.01	0.28	0.95	4.84	47.49	5.39	-0.08	-0.1
Belgium	0.02	1.26	-3.71	0.04	8.93	7.80	0.33	0.35	0.25	-0.12
Bolivia	-0.05	-0.56	0.41	0.05	1.23	2.72	6.25	3.10	0.18	-0.42
Bosnia and Herzeg.	0.09	0.36	-2.07	0.21	1.35	5.35	13.33	3.38	0.00	0.29
Brazil	-0.03	-0.51	-0.14	0.03	1.66	2.25	3.97	2.50	0.56	-0.09
Bulgaria	-0.01	1.97	1.50	0.08	4.02	8.85	1.43	0.77	-0.25	-0.03
Cambodia	-0.11	0.68	-12.25	0.24	0.97	19.68	23.29	0.96	0.16	0.22
Cameroon	0.01	0.73	-3.11	0.04	1.37	3.52	2.57	0.73	-0.32	0.00
Canada	0.02	-2.05	-0.81	0.02	6.27	6.65	0.48	0.47	-0.44	0.43
Chile	0.01	-5.02	-0.73	0.04	8.09	4.18	0.36	0.79	0.09	0.08
China	-0.01	0.37	0.73	0.01	1.22	1.43	1.09	1.01	0.55	-0.78
Colombia	-0.02	0.40	-1.55	0.05	3.08	2.90	1.92	1.39	-0.10	-0.29
Costa Rica	0.04	4.45	-2.47	0.06	1.61	5.18	1.20	1.25	0.23	0.04
Croatia	0.04	1.24	0.69	0.07	5.93	12.26	1.29	0.57	0.21	0.25
Cyprus	0.01	3.02	19.65	0.11	18.61	31.64	0.62	0.35	-0.45	0.54
Czech Republic	0.00	1.56	-0.96	0.03	6.78	9.48	0.37	0.29	-0.12	0.13
Denmark	0.00	2.30	4.43	0.01	6.45	8.18	0.17	0.13	-0.44	0.16
Dominican Republic	0.04	-3.66	0.19	0.17	6.14	2.21	2.67	5.69	0.29	-0.14
Ecuador	-0.03	0.93	2.33	0.05	1.50	3.82	2.99	1.75	-0.07	0.03
Egypt	0.00	0.35	-2.20	0.03	5.37	4.01	0.71	0.76	0.26	-0.10
El Salvador	0.04	0.05	-2.05	0.12	4.48	6.61	3.07	1.54	0.20	0.11
Estonia	0.00	3.05	-0.69	0.08	9.96	13.93	0.73	0.56	-0.45	-0.21
Ethiopia	0.00	.	-0.45	0.01	.	1.17	.	0.56	.	-0.38
Finland	0.02	2.72	-5.47	0.07	9.86	13.00	0.58	0.43	-0.05	0.01
France	0.00	-1.16	0.23	0.01	9.25	9.58	0.16	0.15	-0.23	0.18
Georgia	-0.20	2.99	-7.26	0.26	6.02	5.72	5.08	3.45	0.48	0.11
Germany	0.02	2.39	0.13	0.01	7.50	7.42	0.32	0.33	0.08	0.02
Ghana	-0.05	.	1.62	0.04	.	3.06	.	1.69	.	-0.40
Greece	-0.03	9.31	-13.12	0.06	9.73	11.24	0.40	0.27	-0.35	0.36
Guatemala	0.10	-0.76	3.05	0.42	2.70	3.95	6.33	2.90	0.13	-0.43
Honduras	0.03	1.50	-1.73	0.03	2.99	5.05	1.48	0.78	0.33	-0.30
Hong Kong SAR	-0.04	18.33	5.81	0.15	19.02	22.96	0.50	0.57	-0.09	0.25
Hungary	-0.02	-2.34	-2.03	0.03	5.15	4.67	0.65	0.77	0.77	-0.16
Iceland	0.01	4.20	-1.32	0.06	8.97	6.01	0.40	0.61	-0.11	0.14
India	0.00	-0.37	-1.16	0.02	1.37	1.81	1.83	1.09	0.47	-0.54
Indonesia	-0.04	0.19	1.05	0.04	1.11	1.16	3.76	2.96	0.31	-0.08
Ireland	-0.01	-2.61	5.50	0.03	28.52	28.76	0.08	0.08	0.22	-0.08
Israel	0.00	-1.66	1.53	0.01	3.66	3.06	0.37	0.42	-0.38	0.64
Italy	0.00	5.21	-4.04	0.01	4.99	7.17	0.09	0.08	0.52	-0.48
Jamaica	0.01	1.49	-2.76	0.06	4.46	6.60	1.47	1.13	-0.27	0.14
Japan	-0.01	-1.51	0.36	0.02	7.20	6.81	0.24	0.28	0.07	-0.18
Kazakhstan	-0.11	1.34	-0.09	0.13	6.34	6.34	2.28	2.53	0.13	-0.07
Korea	-0.01	1.28	0.05	0.11	2.15	2.28	4.49	5.19	-0.10	-0.18
Kuwait	0.00	30.69	-5.89	0.03	18.10	19.93	0.06	0.14	0.02	-0.26
Latvia	1.71	2.74	-0.27	2.74	11.44	9.14	21.66	25.51	-0.14	0.13
Lithuania	-0.03	1.63	2.46	0.08	7.31	11.55	1.10	0.69	-0.07	0.01
Luxembourg	-0.01	-94.86	-20.36	0.03	240.35	191.54	0.01	0.01	0.13	-0.20
Malaysia	-0.08	1.60	-0.62	0.04	3.45	4.87	2.53	1.81	0.36	-0.31
Mauritius	0.01	4.50	-48.80	0.05	112.13	50.64	0.05	0.07	0.50	0.04
Mexico	0.00	1.47	0.06	0.01	1.64	3.19	0.56	0.45	0.37	-0.47
Moldova	-0.64	.	-14.31	0.49	.	8.10	.	4.48	.	-0.20
Mongolia	-0.16	1.51	1.50	0.13	3.19	11.20	6.33	1.92	0.26	-0.22
Montenegro	0.08	1.64	3.21	0.29	21.31	12.06	1.50	1.63	0.17	0.32

Table 2: Comparison of Bitcoin and Capital Flows (cont'd)

Country	**Mean, % of GDP**			**Std. Dev., % of GDP**			**Share of Bitcoin**		**Corr. of Bitcoin**	
	Bitcoin	*Portf.*	*Other*	*Bitcoin*	*Portf.*	*Other*	*Portf.*	*Other*	*Portf.*	*Other*
Morocco	-0.07	-0.94	-1.03	0.07	2.83	2.85	4.48	3.29	0.23	-0.10
Mozambique	-0.01	0.03	-0.71	0.18	0.37	27.60	44.34	0.63	0.79	-0.62
Namibia	0.18	-1.06	-3.12	0.14	6.40	4.83	3.74	4.02	0.75	-0.14
Nepal	0.01	.	-5.33	0.08	.	2.90	.	1.01	.	-0.12
Netherlands	0.02	-6.11	10.14	0.02	33.38	18.50	0.13	0.16	-0.60	0.48
New Zealand	0.00	-1.11	0.11	0.02	7.14	4.09	0.27	0.46	0.11	0.01
Nicaragua	-0.01	-0.24	-1.19	0.07	1.60	5.62	3.52	0.97	0.45	-0.21
Nigeria	-0.05	-1.00	0.14	0.06	2.38	3.28	3.05	2.21	-0.05	-0.13
North Macedonia	0.02	0.40	0.24	0.11	10.42	4.75	1.15	2.42	-0.43	0.55
Norway	0.00	12.76	1.68	0.01	18.80	16.07	0.04	0.06	-0.17	-0.05
Pakistan	-0.04	-0.18	-1.33	0.04	1.27	2.83	6.84	1.97	0.25	0.27
Panama	-0.02	-0.22	-1.14	0.03	9.71	5.72	0.30	0.44	0.06	-0.25
Paraguay	-0.02	.	-2.14	0.05	.	5.81	.	1.00	.	0.03
Peru	-0.02	-3.49	2.23	0.03	6.23	4.98	0.54	0.77	0.15	0.01
Philippines	-0.06	0.81	-2.18	0.06	2.96	1.87	4.14	3.18	-0.16	0.30
Poland	-0.05	0.44	0.33	0.03	2.45	2.17	2.37	2.69	-0.54	-0.02
Portugal	0.00	3.66	0.50	0.04	7.46	8.01	0.47	0.52	-0.43	0.33
Qatar	-0.01	9.87	3.74	0.01	7.73	16.21	0.07	0.06	0.13	0.00
Romania	-0.02	-3.36	-1.58	0.02	3.89	3.72	0.61	0.83	-0.21	0.10
Russia	-0.07	1.03	.	0.06	1.16	.	6.21	.	-0.23	.
Saudi Arabia	-0.01	3.51	2.17	0.01	3.09	7.41	0.30	0.23	0.42	0.01
Serbia	0.00	-1.62	-0.03	0.06	4.03	5.95	1.62	1.06	0.41	-0.07
Singapore	0.00	18.20	16.89	0.11	6.61	27.46	0.41	0.31	0.26	-0.38
Slovak Republic	-0.02	1.81	-4.76	0.07	6.59	6.93	0.84	0.73	0.05	0.00
Slovenia	-0.11	2.89	0.35	0.39	7.37	7.92	4.23	3.74	-0.27	0.18
South Africa	0.14	5.26	0.13	0.06	11.10	3.49	2.46	5.48	-0.32	-0.07
Spain	0.01	3.69	-1.62	0.02	5.81	7.08	0.36	0.34	0.14	-0.25
Sweden	0.01	2.49	-2.16	0.01	8.08	9.29	0.22	0.17	0.01	-0.54
Switzerland	-0.01	4.25	0.73	0.02	12.66	18.55	0.20	0.14	0.13	0.10
Tajikistan	0.05	.	3.35	0.09	.	7.80	.	1.03	.	-0.23
Thailand	0.00	1.44	-1.68	0.11	2.93	3.40	2.95	3.02	-0.55	0.11
Trinidad and Tobago	-0.01	0.94	1.42	0.05	3.41	3.75	1.32	1.21	0.15	0.31
Türkiye	-0.07	0.19	-3.28	0.14	2.05	2.18	8.23	3.59	0.33	0.18
Uganda	0.00	0.44	-3.13	0.01	0.94	2.88	1.12	0.33	0.46	0.43
Ukraine	-0.51	0.66	-0.13	0.34	2.13	7.94	30.02	7.69	0.12	0.24
United Kingdom	0.02	-0.93	-3.63	0.03	8.60	9.98	0.44	0.38	0.10	-0.14
United States	0.03	-1.93	-1.67	0.04	2.44	2.59	1.41	1.46	0.07	-0.30
Uruguay	-0.04	2.92	-0.94	0.04	4.22	4.99	1.15	1.19	0.35	0.11
Uzbekistan	-0.11	-1.67	-0.04	0.12	2.87	6.10	8.35	2.85	0.30	0.25
Vietnam	-0.28	-0.06	0.48	0.16	0.54	4.83	61.26	6.93	-0.38	0.25
Zambia	0.02	-0.40	10.77	0.11	5.63	12.17	1.65	0.57	-0.18	-0.25

Sample	**Mean, % of GDP**			**Std. Dev., % of GDP**			**Share of Bitcoin**		**Corr. of Bitcoin**	
	Bitcoin	*Portf.*	*Other*	*Bitcoin*	*Portf.*	*Other*	*Portf.*	*Other*	*Portf.*	*Other*
Mean	-0.01	0.63	-0.78	0.11	9.62	9.83	4.52	1.85	0.06	-0.02
Std. Dev.	0.20	10.93	6.89	0.28	26.76	19.67	9.84	2.94	0.33	0.27
25th Percentile	-0.04	-0.40	-2.05	0.03	2.15	3.49	0.40	0.42	-0.17	-0.20
Median	0.00	0.70	-0.28	0.05	5.07	5.77	1.36	0.90	0.11	0.00
75th Percentile	0.01	2.32	0.73	0.11	7.81	9.43	3.82	2.52	0.26	0.15

Note: This table shows a comparison between Bitcoin flows (defined as net Bitcoin in- and outflows in % of GDP) and traditional capital flows (defined as the balance of portfolio investment flows in % of GDP and other investment flows in % of GDP from the BoP) for all countries of our sample. The first three data columns show the mean of Bitcoin flows, portfolio flows and other flows. The next three columns show their respective standard deviations. The next two columns show Bitcoin flows as a share of traditional capital flows; first, as a share of portfolio flows and then of other flows. The share measures are calculated by dividing a country's time mean of the absolute values of its Bitcoin flows by the time mean of the absolute values of its traditional capital flows (and multiplying the result by 100). The final two columns show the correlation between Bitcoin and portfolio flows as well as between Bitcoin and other flows. All statistics are computed over the period 2020q3-2023q3. The summary statistics at the bottom of the table cover 103 countries (out of the 142 countries of our stylized facts section sample), which have data for at least one of the two traditional capital flows.

Table 3: Variables and Sources

Variable	**Description**	**Source**	**Mean**	**Std. Dev.**	**Min.**	**Max.**
Dependent Variable						
Sum of Bitcoin In- and Outflows	In % of quarterly GDP. See Section 2 for details.	Chainalysis (2023)	1.51	2.04	0.00	13.40
Control Variables						
Nom GDP	Gross Domestic Product (GDP), Current Prices; in U.S. Dollars	WEOD, Oct. 2023	569.61	1819.32	1.50	14340.60
Broadband Use	Fixed Broadband Subscriptions (per 100 People)	WDI	17.98	15.19	0.00	49.55
Alternative Control Variables						
PPP GDP	GDP per Capita, Const. Prices, Purch. Power Parity; 2017 Int'l Dollar	WEOD, Oct. 2023	22415.78	20783.83	1099.28	108036.10
Population	Population; in Million Persons	WEOD, Oct. 2023	51.77	168.541	0.10	1383.11
Cell Phones	Mobile Cellular Subscriptions (per 100 People)	WDI	116.40	30.50	37.97	212.22
Fixed Phones	Fixed Telephone Subscriptions (per 100 People)	WDI	15.24	14.71	0.00	59.04
Internet Access	Individuals Using the Internet (% of Pop.)	WDI	72.15	23.03	6.50	100.00
Sec Int Servers	Secure Internet Servers (per 1 Million People)	WDI	15926.03	30990.10	3.72	132241.60
Current Macro and Financial Conditions						
VIX, Lev	Volatility Index (VIX)	CBOE	24.69	3.86	19.72	29.08
SP500, Lev	Standard & Poor's 500 Stock Price Index	Haver	3875.32	457.17	3212.74	4261.95
Dow Jones, Lev	Stock Price Averages: Dow Jones 30 Industrials, NYSE	Haver	31369.52	3099.78	26876.00	33985.77
Unemp	Unemployment Rate; Percent of Total Labor Force	WEOD, Oct. 2023	7.89	4.93	1.78	29.18
Inflation	Inflation, Average Consumer Prices; Percent Change	WEOD, Oct. 2023	9.01	19.76	-2.09	193.40
Comp Int Rate	Composite Interest Rate – See Details in Table Notes	IFS	4.05	5.06	-0.54	29.25
Real GDP Gr	Gross Domestic Product (GDP), Constant Prices; Growth Rate	WEOD, Oct. 2023	2.08	6.71	-23.59	19.27
Gov Bud Bal	General Government Net Lending/Borrowing; Percent of GDP	WEOD, Oct. 2023	-4.62	4.45	-19.83	15.14
Past Macro and Financial Conditions						
D Bank Crisis Start	Banking Crises Start Date	L&V	0.02	0.15	0	1
D Curr Crisis Start	Currency Crises Start Date	L&V	0.16	0.36	0	1
D Debt Crisis Start	Sovereign Debt Crises Start Date	L&V	0.05	0.22	0	1
D Bank Crisis	Indicator Variable for Banking Crises	Nguyen et al. (2022)	0.11	0.32	0	1
D Curr Crisis	Indicator Variable for Currency Crises	Nguyen et al. (2022)	0.19	0.39	0	1
D Debt Crisis	Indicator Variable for Debt Crises	Nguyen et al. (2022)	0.24	0.43	0	1
D Any Cri Ind	Indicator Variable for Any Crises	Nguyen et al. (2022)	0.42	0.49	0	1
Institutional Quality						
Cont of Corr	Control of Corruption	WGI	0.02	0.98	-1.69	2.17
Rule of Law	Rule of Law	WGI	0.04	0.94	-1.86	1.94
Regulatory Qual	Regulatory Quality	WGI	0.10	0.92	-2.18	1.88
Gov Effect	Government Effectiveness	WGI	0.09	0.92	-2.25	2.00
Pol Stab and No Viol	Political Stability and Absence of Violence/Terrorism	WGI	-0.10	0.86	-2.65	1.49
Voice and Acc	Voice and Accountability	WGI	0.01	0.94	-1.93	1.60
Structure of the Financial System						
Int Margin	Net Interest Margin (%)	FDSD	4.47	2.43	0.83	10.87
Overhead Costs	Bank Overhead Costs to Total Assets (%)	FDSD	3.47	2.43	0.54	19.15
Zscore	Bank Z-Score	FDSD	13.81	8.41	2.22	42.71
Foreign Loans	Loans from Non-Resident Banks (Amt. Outstanding) to GDP (%)	FDSD	20.41	28.21	0.34	154.43
Bank Credit, % of GDP	Private Credit by Deposit Money Banks to GDP (%)	FDSD	53.59	39.97	4.64	199.30
Deposits, Banks	Bank Deposits to GDP (%)	FDSD	55.46	44.10	8.05	324.81
Stock Market Cap	Stock Market Capitalization to GDP (%)	FDSD	47.13	49.34	0.36	249.02
Bond Market	Private Bond Market Capitalization to GDP (%)	FDSD	34.15	33.07	0.10	164.50

Table 3: Variables and Sources Cont'd

Variable	Description	Source	Mean	Std. Dev.	Min.	Max.
International Payments and Remittances						
Pers Remit Rec'vd, % of GDP	Personal Remittances, Received (% of GDP)	WDI	4.53	6.61	0.00	31.14
Costs of Remit Sent, %	Avg. Trans Cost of Sending Remit. from a Spec. Country (%)	WDI	8.14	4.28	1.94	19.73
Tourism, Income	International Tourism, Receipts (% of Total Exports)	WDI	3.46	2.96	0.48	19.48
Tourism, Expend	International Tourism, Expenditures (% of Total Imports)	WDI	6.51	9.80	0.20	78.87
Soc Prot, Share	Coverage of Social Protection and Labor Programs (% of Pop.)	WDI	-	-	-	-
Unemp Cov, Share	Coverage of Unemployment Benefits and ALMP (% of Pop.)	WDI	-	-	-	-
Capital Controls						
Imports, % of GDP	Volume of Imports of Goods and Services; Percent Change	WEOD, Oct. 2023	3.14	14.30	-32.74	44.86
Exports, % of GDP	Volume of Exports of Goods and Services; Percent Change	WEOD, Oct. 2023	4.26	19.90	-55.60	92.80
Chinn Ito, Cont	Chinn-Ito index	C&I	0.50	1.55	-1.93	2.31
Chinn Ito, 0-1	Chinn-Ito index, normalized between 0 and 1	C&I	0.57	0.37	0	1
Fernández et al., All Restr	Overall Restrictions Index	FER	0.39	0.33	0	0.98
Fernández et al., In Restr	Overall Inflow Restrictions Index	FER	0.35	0.30	0	0.99
Fernández et al., Out Restr	Overall Outflow Restrictions Index	FER	0.42	0.38	0	1
Bo Avg Restr	Average Bond Restrictions	FER	0.42	0.38	0	1
Bo In Restr	Bond Inflow Restrictions	FER	0.34	0.39	0	1
Bo Out Restr	Bond Outflow Restrictions	FER	0.50	0.43	0	1
Bo Loc Purch by NonRes Restr	Purchase Locally by Nonresidents (Bonds)	FER	0.27	0.41	0	1
Bo Loc Sale/Issue by NonRes Restr	Sale or Issue Locally by Nonresidents (Bonds)	FER	0.50	0.49	0	1
Bo Abr Purch by Res Restr	Purchase Abroad by Residents (Bonds)	FER	0.51	0.47	0	1
Bo Abr Sale/Issue by Res Restr	Sale or Issue Abroad by Residents (Bonds)	FER	0.42	0.48	0	1
MM Avg Restr	Average Money Market Restrictions	FER	0.40	0.38	0	1
MM In Restr	Money Market Inflow Restrictions	FER	0.32	0.38	0	1
MM Out Restr	Money Market Outflow Restrictions	FER	0.47	0.42	0	1
MM Loc Purch by NonRes Restr	Purchase Locally by Nonresidents (Money Market Instr.)	FER	0.28	0.41	0	1
MM Loc Sale/Issue by NonRes Restr	Sale or Issue Locally by Nonresidents (Money Market Instr.)	FER	0.45	0.48	0	1
MM Abr Purch by Res Restr	Purchase Abroad by Residents (Money Market Instr.)	FER	0.50	0.47	0	1
MM Abr Sale/Issue by Res Restr	Sale or Issue Abroad by Residents (Money Market Instr.)	FER	0.35	0.46	0	1
International Sanctions						
D Milit Sanc	Indicator Variable for Military Assistance Sanctions	GSD	0.09	0.29	0	1
D Arms Sanc	Indicator Variable for Arms Sanctions	GSD	0.18	0.39	0	1
D Trade Sanc	Indicator Variable for Trade Sanctions	GSD	0.51	0.50	0	1
D Fin Sanc	Indicator Variable for Financial Sanctions	GSD	0.49	0.50	0	1
D Travel Sanc	Indicator Variable for Travel Sanctions	GSD	0.38	0.49	0	1
D Other Sanc	Indicator Variable for Other Sanctions	GSD	0.14	0.34	0	1

Note: The overall regression sample covers up to 162 countries over the period 2020 to 2023. For an easier comparison, all summary statistics in this table are based on the sample of the baseline specification (Specification (1) in Table 14), which includes 146 countries. For two variables (*Soc Prot, Share* and *Unemp Cov, Share*), these samples do not overlap, and hence, no summary statistics are shown. CBOE = Chicago Board Options Exchange; C&I = Chinn and Ito (2006); FDSD = Financial Development and Structure Database (by Beck, Demirgüç-Kunt, and Levine, 2000; Beck, Demirgüç-Kunt, and Levine, 2009; and Čihák, Demirgüç-Kunt, Feyen, and Levine, 2012); FER = Fernández et al. (2016); GSD = Global Sanctions Database (by Felbermayr et al., 2020, Kirilakha et al., 2021, and Syropoulos et al., 2024); IFS = International Financial Statistics; L&V = Laeven and Valencia (2018); WEOD = World Economic Outlook Database; WDI = World Development Indicators; WGI = World Governance Indicators (by Kaufmann and Kraay, 2023). The composite interest rate is constructed based on the central bank policy rate, a short-term money market rate, and the government bond yield. For each country, it is based on the series with the highest sample coverage and uses the remaining series to fill in any missing values.

Table 4: Alternative Control Variables

Sum of Bitcoin In- and Outflows in % of GDP	(1) Bitcoin, Sum	(2) Bitcoin, Sum	(3) Bitcoin, Sum	(4) Bitcoin, Sum	(5) Bitcoin, Sum	(6) Bitcoin, Sum	(7) Bitcoin, Sum
L.Nom GDP	-0.0002***			-0.0001***	-0.0002***	-0.0002***	-0.0002***
	(0.000)			(0.000)	(0.000)	(0.000)	(0.000)
L.Broadband Use	0.0310***	0.0611***	0.0239***				
	(0.006)	(0.009)	(0.006)				
L.PPP GDP		-0.0000***					
		(0.000)					
L.Population			-0.0011***				
			(0.000)				
L.Cell Phones				0.0046**			
				(0.002)			
L.Fixed Phones					0.0281***		
					(0.007)		
L.Internet Access						0.0138***	
						(0.003)	
L.Sec Int Servers							0.0000**
							(0.000)
R2	0.06	0.09	0.04	0.02	0.05	0.04	0.03
Observations	600	600	600	603	600	505	311
Countries	162	162	162	162	162	155	162

Note: The empirical specification, based on Equation (1) in Section 3.2.1, is estimated for up to 162 countries over the period 2020 to 2023. The dependent variable, the *Sum of Bitcoin In- and Outflows in % of GDP*, is introduced in Section 2.2 and the explanatory variables are discussed in Section 3.2.2. For all specifications: A constant is included but not reported. Standard errors are in parentheses. * $= p < 0.10$, ** $= p < 0.05$, *** $= p < 0.01$.

Table 5: Motive I: Current Macro and Financial Conditions

Sum of Bitcoin In- and Outflows in % of GDP	(1) Bitcoin, Sum	(2) Bitcoin, Sum	(3) Bitcoin, Sum	(4) Bitcoin, Sum	(5) Bitcoin, Sum	(6) Bitcoin, Sum	(7) Bitcoin, Sum	(8) Bitcoin, Sum
L.Nom GDP	-0.0002***	-0.0002***	-0.0002***	-0.0002***	-0.0002***	-0.0002***	-0.0002***	-0.0002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
L.Broadband Use	0.0301***	0.0320***	0.0324***	0.0190**	0.0337***	0.0229***	0.0305***	0.0350***
	(0.006)	(0.006)	(0.006)	(0.009)	(0.006)	(0.006)	(0.006)	(0.006)
L.VIX, Lev	0.0870***							
	(0.015)							
L.SP500, Lev		-0.0004***						
		(0.000)						
L.Dow Jones, Lev			-0.0001***					
			(0.000)					
L.Unemp				0.0492**				
				(0.022)				
L.Inflation					0.0131*			
					(0.007)			
L.Comp Int Rate						0.0492**		
						(0.023)		
L.Real GDP Gr							-0.0815***	
							(0.018)	
L.Gov Bud Bal								-0.0739***
								(0.016)
R2	0.11	0.07	0.08	0.04	0.08	0.04	0.13	0.09
Observations	600	600	600	397	600	400	600	600
Countries	162	162	162	105	162	106	162	162

Note: The empirical specification, based on Equation (1) in Section 3.2.1, is estimated for up to 162 countries over the period 2020 to 2023. The dependent variable, the *Sum of Bitcoin In- and Outflows in % of GDP*, is introduced in Section 2.2 and the explanatory variables are discussed in Section 3.2.2. For all specifications: A constant is included but not reported. Standard errors are in parentheses. * $= p < 0.10$, ** $= p < 0.05$, *** $= p < 0.01$.

Table 6: Motive II: Past Macro and Financial Conditions

Sum of Bitcoin In- and Outflows in % of GDP	(1) Bitcoin, Sum	(2) Bitcoin, Sum	(3) Bitcoin, Sum	(4) Bitcoin, Sum	(5) Bitcoin, Sum	(6) Bitcoin, Sum	(7) Bitcoin, Sum
L.Nom GDP	-0.0002***	-0.0002***	-0.0002***	-0.0002***	-0.0002***	-0.0002***	-0.0002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
L.Broadband Use	0.0217***	0.0278***	0.0246***	0.0186***	0.0283***	0.0265***	0.0276***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)	(0.005)
L.D Bank Crisis Start	4.5226***						
	(1.141)						
L.D Curr Crisis Start		0.3134					
		(0.247)					
L.D Debt Crisis Start			1.7778***				
			(0.645)				
L.D Bank Crisis				0.9378**			
				(0.452)			
L.D Curr Crisis					0.6321**		
					(0.250)		
L.D Debt Crisis						0.1691	
						(0.226)	
L.D Any Cri Ind							0.3915**
							(0.180)
R2	0.14	0.05	0.09	0.07	0.06	0.05	0.06
Observations	545	545	545	592	582	594	594
Countries	146	146	146	159	156	160	160

Note: The empirical specification, based on Equation (1) in Section 3.2.1, is estimated for up to 162 countries over the period 2020 to 2023. The dependent variable, the *Sum of Bitcoin In- and Outflows in % of GDP*, is introduced in Section 2.2 and the explanatory variables are discussed in Section 3.2.2. For all specifications: A constant is included but not reported. Standard errors are in parentheses. * $= p < 0.10$, ** $= p < 0.05$, *** $= p < 0.01$.

Table 7: Motive III: Institutional Quality

Sum of Bitcoin In- and Outflows in % of GDP	(1) Bitcoin, Sum	(2) Bitcoin, Sum	(3) Bitcoin, Sum	(4) Bitcoin, Sum	(5) Bitcoin, Sum	(6) Bitcoin, Sum
L.Nom GDP	-0.0002***	-0.0002***	-0.0003***	-0.0002***	-0.0003***	-0.0003***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
L.Broadband Use	0.0751***	0.0811***	0.0715***	0.0728***	0.0520***	0.0528***
	(0.011)	(0.012)	(0.014)	(0.012)	(0.010)	(0.010)
L.Cont of Corr	-0.7073***					
	(0.145)					
L.Rule of Law		-0.8326***				
		(0.181)				
L.Regulatory Qual			-0.6361***			
			(0.204)			
L.Gov Effect				-0.6659***		
				(0.183)		
L.Pol Stab and No Viol					-0.3182**	
					(0.135)	
L.Voice and Acc						-0.3205**
						(0.131)
R2	0.12	0.13	0.10	0.10	0.08	0.08
Observations	468	468	468	468	468	468
Countries	162	162	162	162	162	162

Note: The empirical specification, based on Equation (1) in Section 3.2.1, is estimated for up to 162 countries over the period 2020 to 2023. The dependent variable, the *Sum of Bitcoin In- and Outflows in % of GDP*, is introduced in Section 2.2 and the explanatory variables are discussed in Section 3.2.2. For all specifications: A constant is included but not reported. Standard errors are in parentheses. * = $p < 0.10$, ** = $p < 0.05$, *** = $p < 0.01$.

Table 8: Motive IV: Structure of the Financial System

Sum of Bitcoin In- and Outflows in % of GDP	(1) Bitcoin, Sum	(2) Bitcoin, Sum	(3) Bitcoin, Sum	(4) Bitcoin, Sum	(5) Bitcoin, Sum	(6) Bitcoin, Sum	(7) Bitcoin, Sum	(8) Bitcoin, Sum
L.Nom GDP	-0.0002***	-0.0002***	-0.0002***	-0.0002***	-0.0002***	-0.0002***	-0.0001***	-0.0001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
L.Broadband Use	0.0441***	0.0336***	0.0301***	0.0418***	0.0439***	0.0327***	0.0140**	-0.0001
	(0.008)	(0.007)	(0.006)	(0.007)	(0.009)	(0.006)	(0.006)	(0.006)
L.Int Margin	0.1404***							
	(0.043)							
L.Overhead Costs		0.0451*						
		(0.026)						
L.Zscore			-0.0293***					
			(0.009)					
L.Foreign Loans				-0.0143***				
				(0.002)				
L.Bank Credit, % of GDP					-0.0105***			
					(0.003)			
L.Deposits, Banks						-0.0048***		
						(0.002)		
L.Stock Market Cap							-0.0067***	
							(0.002)	
L.Bond Market								-0.0087***
								(0.003)
R2	0.08	0.06	0.07	0.08	0.07	0.06	0.06	0.10
Observations	594	594	594	580	572	571	420	194
Countries	160	160	160	156	154	154	109	49

Note: The empirical specification, based on Equation (1) in Section 3.2.1, is estimated for up to 162 countries over the period 2020 to 2023. The dependent variable, the *Sum of Bitcoin In- and Outflows in % of GDP*, is introduced in Section 2.2 and the explanatory variables are discussed in Section 3.2.2. For all specifications: A constant is included but not reported. Standard errors are in parentheses. * = $p < 0.10$, ** = $p < 0.05$, *** = $p < 0.01$.

Table 9: Motive V: International Payments and Remittances

Sum of Bitcoin In- and Outflows in % of GDP	(1) Bitcoin, Sum	(2) Bitcoin, Sum	(3) Bitcoin, Sum	(4) Bitcoin, Sum	(5) Bitcoin, Sum	(6) Bitcoin, Sum
L.Nom GDP	-0.0002***	-0.0001***	-0.0003***	-0.0003***	-0.0001	0.0001
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
L.Broadband Use	0.0419***	0.0108**	0.0382***	0.0404***	0.0507**	0.0244
	(0.007)	(0.005)	(0.010)	(0.010)	(0.021)	(0.021)
L.Pers Remit Rec'vd, % of GDP	0.0689***					
	(0.014)					
L.Costs of Remit Sent, %		0.0421*				
		(0.024)				
L.Tourism, Income			-0.0696***			
			(0.021)			
L.Tourism, Expend				-0.0197***		
				(0.005)		
L.Soc Prot, Share					-0.0106*	
					(0.006)	
L.Unemp Cov, Share						-0.0241*
						(0.011)
R2	0.11	0.06	0.09	0.09	0.53	0.30
Observations	574	95	239	227	16	11
Countries	156	48	128	121	16	11

Note: The empirical specification, based on Equation (1) in Section 3.2.1, is estimated for up to 162 countries over the period 2020 to 2023. The dependent variable, the *Sum of Bitcoin In- and Outflows in % of GDP*, is introduced in Section 2.2 and the explanatory variables are discussed in Section 3.2.2. For all specifications: A constant is included but not reported. Standard errors are in parentheses. * = $p < 0.10$, ** = $p < 0.05$, *** = $p < 0.01$.

Table 10: Motive VI: Circumventing Capital Controls – Aggregate Flows (Part A)

Sum of Bitcoin In- and Outflows in % of GDP	(1) Bitcoin, Sum	(2) Bitcoin, Sum	(3) Bitcoin, Sum	(4) Bitcoin, Sum	(5) Bitcoin, Sum	(6) Bitcoin, Sum	(7) Bitcoin, Sum
L.Nom GDP	-0.0002***	-0.0002***	-0.0002***	-0.0002***	-0.0002***	-0.0002***	-0.0002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
L.Broadband Use	0.0262***	0.0250***	0.0400***	0.0400***	0.0151***	0.0151***	0.0136**
	(0.005)	(0.005)	(0.007)	(0.007)	(0.006)	(0.005)	(0.006)
L.Imports, % of GDP	-0.0329***						
	(0.007)						
L.Exports, % of GDP		-0.0208***					
		(0.006)					
L.Chinn Ito, Cont			-0.2209***				
			(0.075)				
L.Chinn Ito, 0-1				-0.9360***			
				(0.320)			
L.Fernandez et al., All Restr					0.6504*		
					(0.332)		
L.Fernandez et al., Infl Restr						0.7352**	
						(0.345)	
L.Fernandez et al., Outfl Restr							0.4664
							(0.307)
R2	0.10	0.08	0.07	0.07	0.03	0.03	0.03
Observations	568	568	563	563	386	386	386
Countries	153	153	151	151	100	100	100

Note: The empirical specification, based on Equation (1) in Section 3.2.1, is estimated for up to 162 countries over the period 2020 to 2023. The dependent variable, the *Sum of Bitcoin In- and Outflows in % of GDP*, is introduced in Section 2.2 and the explanatory variables are discussed in Section 3.2.2. For all specifications: A constant is included but not reported. Standard errors are in parentheses. * = $p < 0.10$, ** = $p < 0.05$, *** = $p < 0.01$.

Table 11: Motive VI: Circumventing Capital Controls – Bond Flows (Part B)

Sum of Bitcoin In- and Outflows in % of GDP	(1) Bitcoin, Sum	(2) Bitcoin, Sum	(3) Bitcoin, Sum	(4) Bitcoin, Sum	(5) Bitcoin, Sum	(6) Bitcoin, Sum	(7) Bitcoin, Sum
L.Nom GDP	-0.0002***	-0.0002***	-0.0002***	-0.0002***	-0.0002***	-0.0002***	-0.0002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
L.Broadband Use	0.0182***	0.0189***	0.0138**	0.0147***	0.0166***	0.0088	0.0164***
	(0.006)	(0.006)	(0.006)	(0.005)	(0.006)	(0.006)	(0.006)
L.Bo Avg Restr	0.8102**						
	(0.342)						
L.Bo Infl Restr		0.9424***					
		(0.339)					
L.Bo Outfl Restr			0.4330				
			(0.268)				
L.Bo Loc Purch by NonRes Restr				0.8396***			
				(0.300)			
L.Bo Loc Sale/Issue by NonRes Restr					0.5545**		
					(0.237)		
L.Bo Abr Purch by Res Restr						0.0829	
						(0.236)	
L.Bo Abr Sale/Issue by Res Restr							0.5679**
							(0.255)
R2	0.04	0.05	0.03	0.05	0.04	0.02	0.04
Observations	386	386	386	386	386	386	386
Countries	100	100	100	100	100	100	100

Note: The empirical specification, based on Equation (1) in Section 3.2.1, is estimated for up to 162 countries over the period 2020 to 2023. The dependent variable, the *Sum of Bitcoin In- and Outflows in % of GDP*, is introduced in Section 2.2 and the explanatory variables are discussed in Section 3.2.2. For all specifications: A constant is included but not reported. Standard errors are in parentheses. * = $p < 0.10$, ** = $p < 0.05$, *** = $p < 0.01$.

Table 12: Motive VI: Circumventing Capital Controls – Money Market Flows (Part C)

Sum of Bitcoin In- and Outflows in % of GDP	(1) Bitcoin, Sum	(2) Bitcoin, Sum	(3) Bitcoin, Sum	(4) Bitcoin, Sum	(5) Bitcoin, Sum	(6) Bitcoin, Sum	(7) Bitcoin, Sum
L.Nom GDP	-0.0002***	-0.0002***	-0.0002***	-0.0002***	-0.0002***	-0.0002***	-0.0002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
L.Broadband Use	0.0165***	0.0149***	0.0153**	0.0122**	0.0178***	0.0090	0.0140**
	(0.006)	(0.005)	(0.006)	(0.005)	(0.006)	(0.006)	(0.006)
L.MM Avg Restr	0.6963**						
	(0.307)						
L.MM Infl Restr		0.6290**					
		(0.264)					
L.MM Outfl Restr			0.5457*				
			(0.285)				
L.MM Loc Purch by NonRes Restr				0.4737*			
				(0.266)			
L.MM Loc Sale/Issue by NonRes Restr					0.6929***		
					(0.256)		
L.MM Abr Purch by Res Restr						0.0912	
						(0.245)	
L.MM Abr Sale/Issue by Res Restr							0.4692*
							(0.252)
R2	0.04	0.04	0.03	0.03	0.05	0.03	0.03
Observations	386	386	386	386	386	386	386
Countries	100	100	100	100	100	100	100

Note: The empirical specification, based on Equation (1) in Section 3.2.1, is estimated for up to 162 countries over the period 2020 to 2023. The dependent variable, the *Sum of Bitcoin In- and Outflows in % of GDP*, is introduced in Section 2.2 and the explanatory variables are discussed in Section 3.2.2. For all specifications: A constant is included but not reported. Standard errors are in parentheses. * = $p < 0.10$, ** = $p < 0.05$, *** = $p < 0.01$.

Table 13: Motive VII: Circumventing International Sanctions

Sum of Bitcoin In- and Outflows in % of GDP	(1) Bitcoin, Sum	(2) Bitcoin, Sum	(3) Bitcoin, Sum	(4) Bitcoin, Sum	(5) Bitcoin, Sum	(6) Bitcoin, Sum
L.Nom GDP	-0.0002***	-0.0002***	-0.0002***	-0.0002***	-0.0002***	-0.0002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
L.Broadband Use	0.0359***	0.0334***	0.0290***	0.0331***	0.0308***	0.0305***
	(0.007)	(0.007)	(0.007)	(0.006)	(0.006)	(0.007)
L.D Milit Sanc	0.8388**					
	(0.353)					
L.D Arms Sanc		0.2632				
		(0.221)				
L.D Trade Sanc			0.1897			
			(0.200)			
L.D Fin Sanc				0.2474		
				(0.159)		
L.D Travel Sanc					0.4063**	
					(0.194)	
L.D Other Sanc						0.1873
						(0.335)
R2	0.07	0.06	0.06	0.06	0.07	0.06
Observations	600	600	600	600	600	600
Countries	162	162	162	162	162	162

Note: The empirical specification, based on Equation (1) in Section 3.2.1, is estimated for up to 162 countries over the period 2020 to 2023. The dependent variable, the *Sum of Bitcoin In- and Outflows in % of GDP*, is introduced in Section 2.2 and the explanatory variables are discussed in Section 3.2.2. For all specifications: A constant is included but not reported. Standard errors are in parentheses. * = $p < 0.10$, ** = $p < 0.05$, *** = $p < 0.01$.

Table 14: Baseline Specification and Robustness

Sum of Bitcoin In- and Outflows in % of GDP	(1) Bitcoin, Sum	(2) Bitcoin, Sum	(3) Bitcoin, Sum	(4) Bitcoin, Sum	(5) Bitcoin, Sum	(6) Bitcoin, Sum	(7) Bitcoin, Sum	(8) Bitcoin, Sum	(9) Bitcoin, Sum
L.Nom GDP	-0.0002***	-0.0002***	-0.0002***	-0.0002***	-0.0003***	-0.0002***	-0.0003***	-0.0002***	-0.0002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
L.Broadband Use	0.0653***	0.0497***	0.0651***	0.0653***	0.0668***	0.0648***	0.0754***	-0.0793**	0.0914***
	(0.012)	(0.010)	(0.011)	(0.015)	(0.012)	(0.012)	(0.015)	(0.036)	(0.013)
L.Real GDP Gr	-0.0746***	-0.0793***	-0.0150	-0.0746***	-0.0742***	-0.0748***	-0.0719***	-0.1630***	-0.0620***
	(0.016)	(0.015)	(0.016)	(0.014)	(0.016)	(0.016)	(0.017)	(0.045)	(0.016)
L.D Bank Crisis	1.1105**	1.0162**	1.1030**	1.1105	1.0493*	1.0976**	1.3798*	0.7598	2.0208**
	(0.520)	(0.424)	(0.508)	(0.755)	(0.541)	(0.520)	(0.741)	(0.545)	(0.967)
L.Cont of Corr	-0.2227*		-0.2661**	-0.2227	-0.2302*	-0.2240*	-0.2851*	-0.0102	0.0812
	(0.128)		(0.121)	(0.183)	(0.128)	(0.133)	(0.170)	(0.302)	(0.173)
L.Int Margin	0.0956*	0.1026**	0.0680	0.0956	0.0923*	0.0940*	0.1107	0.0967	0.0720*
	(0.051)	(0.040)	(0.049)	(0.072)	(0.051)	(0.052)	(0.069)	(0.295)	(0.042)
L.Pers Remit Rec'vd	0.0586***	0.0584***	0.0600***	0.0586***	0.0582***	0.0576***	0.0694***	0.5155**	0.0599***
	(0.016)	(0.014)	(0.015)	(0.022)	(0.016)	(0.016)	(0.020)	(0.244)	(0.014)
L.Chinn Ito, Cont	-0.1697**	-0.1929***	-0.1553**	-0.1697	-0.1760**	-0.1638**	-0.1706	0.3167	-0.1677**
	(0.078)	(0.071)	(0.074)	(0.106)	(0.079)	(0.081)	(0.105)	(0.585)	(0.071)
L.D Travel Sanc	0.3720*	0.1640	0.3251	0.3720	0.3848*	0.3993*	0.2170	1.1420**	0.2109
	(0.218)	(0.165)	(0.210)	(0.282)	(0.219)	(0.231)	(0.266)	(0.559)	(0.197)
Time Fixed Effects	No	No	Yes	No	No	No	No	No	No
Standard Errors	Het. Robust	Het. Robust	Het. Robust	By Country	Het. Robust	Het. Robust	Het. Robust	Het. Robust	Het. Robust
R2	0.24	0.22	0.30	0.24	0.24	0.24	0.25	0.37	0.36
Observations	422	541	422	422	419	416	288	105	317
Countries	146	146	146	146	145	144	146	35	111

Note: The empirical specification, based on Equation (2) in Section 3.2.1, is estimated for up to 162 countries over the period 2020 to 2023. The dependent variable, the *Sum of Bitcoin In- and Outflows in % of GDP*, is introduced in Section 2.2 and the explanatory variables are discussed in Section 3.2.2. For all specifications: A constant is included but not reported. Standard errors are in parentheses. * = $p < 0.10$, ** = $p < 0.05$, *** = $p < 0.01$.

Table 15: COVID-19 Event Study

Growth Rate of Sum of Bitcoin In- and Outflows	(1) Buildup	(2) Buildup	(3) Buildup	(4) Baseline	(5) Other Motives	(6) No Post Peak	(7) Str. Contr.	(8) Placebo: Min	(9) Placebo: +1 yr
D Covid × High Remittances	0.1043**	0.0798*	0.1076**	0.0838*	0.1000**	0.1094***	0.0746*	-0.0690	0.0180
	(0.046)	(0.044)	(0.046)	(0.044)	(0.047)	(0.038)	(0.044)	(0.058)	(0.041)
D Covid × Low GDP Growth	0.1287***	0.1326***	0.1276***	0.1331***	0.1460***	0.0730*	0.1353***	-0.0477	-0.0421
	(0.046)	(0.044)	(0.046)	(0.045)	(0.048)	(0.039)	(0.045)	(0.063)	(0.045)
D Covid	-0.1635***	-0.1175***	-0.1634***	-0.1181***	-0.1014**	-0.0951	-0.1042**	0.0329	-0.0042
	(0.039)	(0.045)	(0.039)	(0.045)	(0.047)	(0.062)	(0.045)	(0.049)	(0.036)
High Remittances	-0.0195	-0.0133							
	(0.017)	(0.016)							
Low GDP Growth	-0.0253	-0.0315*							
	(0.016)	(0.016)							
Policy Stringency							0.0010		
							(0.001)		
Time Fixed Effects	No	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes
Country Fixed Effects	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls for Other Motives	No	No	No	No	Yes	No	No	No	No
R2	0.00	0.10	0.01	0.11	0.10	0.15	0.11	0.11	0.11
Observations	3464	3464	3464	3464	3273	2488	3352	3464	5276
Countries	152	152	152	152	144	151	147	152	152

Note: The empirical specification, based on Equation (3) in Section 4.2, is estimated for up to 152 countries over the period July 2020 to June 2022. The dependent variable is the *Growth Rate of Sum of Bitcoin In- and Outflows*. The explanatory variables are explained in Section 4.2. For more details on the COVID-19 case study, see Section 4. For all specifications: A constant is included but not reported. Standard errors are in parentheses. * = $p < 0.10$, ** = $p < 0.05$, *** = $p < 0.01$.

Table 16: Dependent Variables for the Stablecoin Analysis

Variable	**Description**	**Mean**	**Std. Dev.**	**Min.**	**Max.**
Dependent Variable					
Sum of Tether (USDT) In- and Outflows	In % of quarterly GDP	0.45	0.68	0.00	4.34
Sum of USD Coin (USDC) In- and Outflows	In % of quarterly GDP	0.18	0.24	0.00	1.31
Sum of Binance USD (BUSD) In- and Outflows	In % of quarterly GDP	0.04	0.06	0.00	0.32
Sum of Dai (DAI) In- and Outflows	In % of quarterly GDP	0.02	0.06	0.00	0.47

Note: The regression sample covers up to 145 countries over the period 2020 to 2023. The summary statistics in this table are based on the sample of the respective baseline specification for each stablecoin (i.e., Specification (1) in Table 17 and Specifications (1), (4), and (7) in Table 18). All variables are taken from the Chainalysis dataset discussed in Section 2. See Section 5 for more details on stablecoins.

Table 17: Replication of the Baseline Specification for Tether

	(1) Tether, Sum	(2) Tether, Sum	(3) Tether, Sum	(4) Tether, Sum	(5) Tether, Sum	(6) Tether, Sum	(7) Tether, Sum	(8) Tether, Sum	(9) Tether, Sum
L.Nom GDP	-0.0001***	-0.0001***	-0.0001***	-0.0001***	-0.0001***	-0.0001***	-0.0001***	-0.0000***	-0.0001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
L.Broadband Use	0.0176***	0.0138***	0.0168***	0.0176***	0.0184***	0.0173***	0.0225***	-0.0193*	0.0311***
	(0.004)	(0.003)	(0.004)	(0.005)	(0.004)	(0.004)	(0.005)	(0.011)	(0.005)
L.Real GDP Gr	-0.0225***	-0.0224***	-0.0159**	-0.0225***	-0.0223***	-0.0227***	-0.0175***	-0.0340***	-0.0205***
	(0.006)	(0.005)	(0.007)	(0.004)	(0.006)	(0.006)	(0.006)	(0.013)	(0.006)
L.D Bank Crisis	0.1165	0.1134	0.1436	0.1165	0.0831	0.1124	0.2007	0.2240	0.2214
	(0.151)	(0.120)	(0.146)	(0.204)	(0.158)	(0.151)	(0.214)	(0.160)	(0.290)
L.Cont of Corr	-0.0436		-0.0628	-0.0436	-0.0476	-0.0420	-0.0825	0.0822	0.0687
	(0.042)		(0.039)	(0.056)	(0.042)	(0.043)	(0.055)	(0.073)	(0.066)
L.Int Margin	0.0361*	0.0366**	0.0284	0.0361	0.0343*	0.0354*	0.0399	0.0487	0.0198
	(0.020)	(0.015)	(0.019)	(0.025)	(0.019)	(0.020)	(0.026)	(0.043)	(0.016)
L.Pers Remit Rec'vd	0.0197***	0.0199***	0.0196***	0.0197***	0.0195***	0.0194***	0.0258***	0.1396*	0.0209***
	(0.005)	(0.004)	(0.004)	(0.006)	(0.005)	(0.005)	(0.006)	(0.073)	(0.005)
L.Chinn Ito, Cont	-0.0619**	-0.0610***	-0.0532**	-0.0619*	-0.0655**	-0.0594**	-0.0727**	0.2018*	-0.0579**
	(0.027)	(0.022)	(0.025)	(0.032)	(0.027)	(0.028)	(0.034)	(0.116)	(0.026)
L.D Travel Sanc	0.2071***	0.1477***	0.1079	0.2071**	0.2138***	0.2179***	0.1200	0.5145***	0.1371*
	(0.074)	(0.055)	(0.073)	(0.095)	(0.074)	(0.078)	(0.089)	(0.191)	(0.073)
Time Fixed Effects	No	No	Yes	No	No	No	No	No	No
Standard Errors	Het. Robust	Het. Robust	Het. Robust	By Country	Het. Robust	Het. Robust	Het. Robust	Het. Robust	Het. Robust
R2	0.17	0.16	0.27	0.17	0.17	0.17	0.18	0.34	0.28
Observations	422	540	422	422	419	416	287	105	317
Countries	145	145	145	145	144	143	145	35	110

Note: The empirical specification, based on Equation (2) in Section 4.2, is estimated for up to 145 countries over the period 2020 to 2023. The dependent variable, the *Sum of Tether In- and Outflows in % of GDP*, is introduced in Section 5 and the explanatory variables are discussed in Section 3.2.2. For all specifications: A constant is included but not reported. Standard errors are in parentheses. * = $p < 0.10$, ** = $p < 0.05$, *** = $p < 0.01$.

Table 18: Replication of the Baseline Specification for USD Coin (USDC), Binance USD (BUSD), and Dai (DAI)

	(1) USDC, Sum	(2) USDC, Sum	(3) USDC, Sum	(4) BUSD, Sum	(5) BUSD, Sum	(6) BUSD, Sum	(7) DAI, Sum	(8) DAI, Sum	(9) DAI, Sum
L.Nom GDP	-0.0000***	-0.0000***	-0.0000***	-0.0000***	-0.0000***	-0.0000***	-0.0000**	-0.0000**	-0.0000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
L.Broadband Use	0.0063***	0.0048***	0.0058***	0.0020***	0.0011***	0.0019***	0.0009***	0.0005**	0.0009***
	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
L.Real GDP Gr	-0.0068***	-0.0064***	-0.0084***	-0.0020***	-0.0023***	-0.0013**	-0.0032***	-0.0032***	-0.0016
	(0.002)	(0.002)	(0.003)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
L.D Bank Crisis	-0.0110	0.0211	0.0063	-0.0088	-0.0032	-0.0059	-0.0065	-0.0031	-0.0065
	(0.034)	(0.031)	(0.029)	(0.009)	(0.007)	(0.008)	(0.008)	(0.006)	(0.007)
L.Cont of Corr	-0.0118		-0.0205	-0.0105***		-0.0126***	-0.0036		-0.0046
	(0.015)		(0.014)	(0.004)		(0.004)	(0.006)		(0.005)
L.Int Margin	0.0109	0.0110*	0.0087	0.0025	0.0024*	0.0017	0.0003	0.0003	-0.0005
	(0.007)	(0.006)	(0.006)	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
L.Pers Remit Rec'vd	0.0110***	0.0097***	0.0108***	0.0015***	0.0015***	0.0015***	0.0029**	0.0025***	0.0030**
	(0.003)	(0.002)	(0.002)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)
L.Chinn Ito, Cont	-0.0187*	-0.0169**	-0.0146	-0.0063**	-0.0055**	-0.0054**	0.0023	0.0020	0.0027
	(0.010)	(0.008)	(0.009)	(0.003)	(0.002)	(0.003)	(0.003)	(0.002)	(0.003)
L.D Travel Sanc	0.0624***	0.0466**	0.0061	0.0120*	0.0050	0.0014	0.0101	0.0047	0.0082
	(0.024)	(0.020)	(0.021)	(0.007)	(0.005)	(0.006)	(0.009)	(0.006)	(0.009)
Time Fixed Effects	No	No	Yes	No	No	Yes	No	No	Yes
Standard Errors	Het. Robust	Het. Robust	Het. Robust	By Country	Het. Robust	Het. Robust	Het. Robust	Het. Robust	Het. Robust
R2	0.19	0.16	0.39	0.16	0.13	0.29	0.16	0.15	0.20
Observations	422	540	422	422	540	422	422	540	422
Countries	145	145	145	145	145	145	145	145	145

Note: The empirical specification, based on Equation (2) in Section 4.2, is estimated for up to 145 countries over the period to June 2023. The dependent variables, the *Sum of USDC In- and Outflows in % of GDP*, the *Sum of BUSD In- and Outflows in % of GDP*, and the *Sum of DAI In- and Outflows in % of GDP*, are introduced in Section 5 and the explanatory variables are discussed in Section 3.2.2. For all specifications: A constant is included but not reported. Standard errors are in parentheses. * = $p < 0.10$, ** = $p < 0.05$, *** = $p < 0.01$.

9 Appendix A: Dataset Construction

This appendix provides more details regarding the construction of the dataset on cross-border flows of cryptocurrencies compiled by Chainalysis. Chainalysis constructs the dataset in three steps:

- First, crypto addresses, which are observed at the wallet level, are grouped into *clusters* based on common characteristics or joint behaviors. Chainalysis relies on different heuristics to complete the clustering step. For example, *co-spend heuristics* identify co-ownership of addresses by identifying Unspent Transaction Outputs (UTXOs) that are spent as inputs in the same crypto transaction. *Deposit heuristics* follow initial crypto deposits to consolidation addresses, which are used by a crypto exchange to hold and combine funds from different users. And *event-based heuristics* focus on monitoring specific events carried out by the protocol, the set of rules that govern the cryptocurrency, on certain blockchains.[46]

- Second, clusters are identified by assigning them to specific entities. When clusters become sufficiently large, Chainalysis tries to attribute real-world entities to these clusters. Similarly to the clustering step, there are a number of strategies employed to identify an entity including, but not limited to, leveraging data from third party partners and employing verification techniques, such as ground truth data collection, where directly observable empirical evidence is collected that demonstrates that an address belongs to a specific service or wallet.[47] Chainalysis aims to document the identification step to support the auditability of the information.

- Third, the identified real-world entities are then linked to specific countries as follows. As entities can have links to multiple countries, Chainalysis uses the geographic origin of web traffic to these entities as a proxy for the country of residence of the users interacting with these entities. More specifically, Chainalysis assigns the value of a blockchain transaction proportionally to the origin countries of the web traffic that is associated with the participating entities (see below for a numerical example). A typical example where this assumption seems intuitive is the trade between two crypto exchanges. If the webpage of a crypto exchange is visited particularly often by users residing in a specific country, it is reasonable to assume that these users frequently rely on this exchange to engage in the crypto transactions. If the counterparty exchange is visited mostly by users residing in a different country, it is equally reasonable to assume that those users are involved in the crypto transaction of the counterparty exchange. One should also keep in mind that the transaction between the two exchanges—including its value—is very likely recorded correctly (i.e., it is recorded correctly on the blockchain with certainty and it is allocated correctly to the respective entities with a high probability), so the underlying crypto flow does indeed exist.

[46] See Chainalysis (2024) for details.
[47] See Chainalysis (2024) for details.

Numerical example of how web traffic is used to link real-world entities to countries: Chainalysis assigns the value of a blockchain transaction proportionally to the origin countries of the web traffic that is associated with the participating entities. The following numerical example helps illustrate the allocation procedure:

If a transaction over 100 units involves Entity 1 (visited to 70% by web users of Country A and to 30% by users of Country B) and Entity 2 (visited to 60% by web users of Country C and to 40% by users of Country D), the transaction value is distributed among Countries A to D as follows:

- A cross-border flow from Country A to Country C of 42 units (= 100 units * 70% * 60%).
- A cross-border flow from Country A to Country D of 28 units (= 100 units * 70% * 40%).
- A cross-border flow from Country B to Country C of 18 units (= 100 units * 30% * 60%).
- A cross-border flow from Country B to Country D of 12 units (= 100 units * 30% * 40%).

10 Appendix B: Comparison with Traditional Capital Flows

Our data on traditional capital flows come from the balance of payments (BoP) statistics, which are published by the International Monetary Fund (IMF). The BoP consists of the current account, the capital account, and the financial account.[48] By definition, the sum of the balances on the current and capital accounts represents the net lending (surplus) or net borrowing (deficit) of an economy vis-à-vis the rest of the world. This sum is conceptually equal to the net balance of the financial account and frequently used in the literature as a measure of international capital flows. Next, the financial account can be broken down into five functional categories: direct investment, portfolio investment, financial derivatives, other investment, and reserve assets. For our analysis, we are primarily interested in *portfolio investment* flows, which mostly comprise equity and bond flows, and *other investment* flows, which include, for example, bank credit, trade credit as well as currency and deposit flows.[49]

Transactions in the financial account are shown separately for financial assets and liabilities. Moreover, in contrast to the current and the capital account, it is important to note that the financial account records the underlying transactions in *net terms*. The netting takes place between acquisitions/purchases and disposal/sales of assets (= net acquisitions of assets) as well as between incurrences and reductions of liabilities (= net incurrences of liabilities). This netting should not

[48] The following definitions are based on IMF (2010), p. 9, paragraph 2.18.

[49] We do not consider the flows in the other functional categories in our analysis as direct investment flows have a longer-term focus and are driven by other considerations, financial derivative flows are complex and opaque, and reserve asset flows are usually not market-driven.

be confused with a netting of assets against liabilities, which is discussed at the end of this paragraph.[50] The concept of net acquisitions of assets and net incurrences of liabilities is consistent with the academic literature and directly translates into the definition of gross capital flows. From the perspective of the domestic economy, a net acquisition of foreign assets by domestic investors corresponds to a gross capital outflow, and a net acquisition of domestic assets by foreign investors corresponds to a gross capital inflow.[51] Correspondingly, a net incurrence of foreign liabilities by domestic investors constitutes a gross capital inflow and a net incurrence of domestic liabilities by foreign investors is a gross capital outflow. In addition, assets and liabilities in the financial account can also be netted against each other. Taking the difference between the sum of assets and the sum of liabilities in the financial account[52] yields the *balance of the financial account* or, in other words, a measure of *net* capital flows. However, one can also take the difference between assets and liabilities for each functional category of the financial account separately. For example, in case of the functional category *portfolio investment flows* this would result into the *balance of portfolio investment flows.* Henceforth, for simplicity, we refer to the balances of the functional categories simply by their functional category names, such as *portfolio investment flows.*

The situation for crypto flows is more complex, however, as when we downloaded our data, there was still a debate regarding how crypto activities should be classified in macroeconomic statistics as well as in the BoP.[53] However, this should not prevent us from asking the question of how the patterns of cross-border crypto flows compare to the patterns of traditional cross-border capital flows. Moreover, a positive side effect of crypto flows not being recorded in the BoP yet is that we do not need to be concerned about the potential presence of crypto flows in the comparison/control group of our analysis.

To proceed with our comparison between crypto and traditional capital flows, we require a convention of how crypto flows relate to traditional capital flows. Cross-border cryptocurrency transactions typically involve a fiat money leg (transfer of the fiat money) and a cryptocurrency leg (transfer of the cryptocurrency units). However, conceptually, either of these legs could be considered as a *capital flow.* For consistency with the literature on traditional capital flows, we treat the fiat money leg as the flow of *capital* and the cryptocurrency leg as the exchange of an asset.[54] This interpretation is supported by the fact that, in most cases, cryptocurrencies have not materially rivalled fiat money as the primary medium of exchange yet.

Crypto flow data from Chainalysis are derived from the blockchain anonymously and contain information on the inflow and outflow of cryptocurrency units from one country to another. The units are then multiplied by the cryptocurrency price in USD at the time of the transaction to

[50] See IMF (2010), p. 10, paragraph 2.19.

[51] See Forbes and Warnock (2012). For example, their Footnote 6 states that *"Net foreign purchases of domestic assets are gross capital inflows, whereas net purchases of foreign assets by domestic investors are gross outflows."*

[52] Which, in turn, would correspond to a netting along both dimensions discussed above.

[53] See IMF (2019). The document suggests to classify most crypto assets as *produced nonfinancial assets.*

[54] This is consistent with the recommendation in IMF (2019) to consider most cryptocurrencies as assets (albeit a produced and non-financial asset according to IMF, 2019).

obtain the measure of crypto flows in USD terms. While this recording format does not provide more detailed information (e.g., whether a crypto transaction relates to the asset or the liability side), a netting of crypto inflows and crypto outflows still delivers the same type of aggregate information as the balance of the financial account (or the balance of its functional categories). Hence, we use net crypto in- and outflows in our comparison with the net measure of traditional capital flows.