Decrypting Crypto: How to Estimate International Stablecoin Flows.*

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Abstract

This paper presents a new methodology to estimate the geographic distribution of international stablecoin flows, addressing the anonymity of crypto assets. Analyzing 2024 stablecoin transactions totaling $2 trillion, our findings show: (1) USDT dominates in emerging economies (Africa, Asia, Latin America), while USDC leads in advanced economies (Europe, North America); (2) Binance facilitates stablecoin inflows into emerging markets; (3) advanced economies lead in absolute flows, whereas Africa and Latin America show higher flows relative to GDP, underscoring stablecoin adoption in emerging markets; (4) North America exhibits net outflows of stablecoins, with evidence suggesting these flows meet global dollar demand, increasing during periods of volatility and dollar appreciation against other currencies.

Keywords: blockchain, capital flight, capital flow management measures (CFMs), capital flows, crypto assets, currency substitution, dollar dominance, stablecoins
JEL codes: F31, G15, C58

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1 Introduction

Policymakers are increasingly wary of the popularity of crypto assets and have called for better means of monitoring crypto transactions and international crypto asset flows (BIS (2023), EU (2023), G7 (2023) , FATF (2023), FSB (2023), IMF (2023), US Treasury (2023)). Recent research shows that crypto assets are increasingly used for international transactions, particularly when capital flow measures make it difficult to use traditional channels (von Luckner et al. (2023), von Luckner et al. (2024)), and could potentially be sizable (Cardoza et al. (2024), Cerutti et al. (2024)). However, estimating international crypto asset flows remains challenging due to the opaque nature of crypto assets.

The main contribution of this paper is the development of a novel method that enables the estimation of the geography of crypto asset flows and to then apply it to estimate international stablecoin[1] flows. Before detailing our method, we address a common misconception: that crypto asset transactions provide anonymity. In reality, the vast majority of crypto asset transactions do not offer anonymity. Every transaction is publicly recorded on a freely accessible ledger known as a blockchain. The perception of anonymity arises because blockchain data is pseudonymized; rather than recording personal information such as names or residences, blockchains log only the wallet addresses of senders and receivers. A wallet address, typically a long hexadecimal string such as `'0xdFDEe1155E1dd7c017745 60C6E98C41B7da945dB'`, reveals no personal information about the user.

The key challenge in mapping the geography of crypto asset flows is supplementing blockchain data with useful information about senders and receivers. Our methodology addresses this challenge by enabling the estimation of the geographic region of *any arbitrary* self-custodial wallet address in the Ethereum ecosystem.

To estimate the geographic region of self-custodial wallets, our methodology involves obtaining geographic information for a subset of wallets through two distinct approaches, dividing the world into five regions: Africa and the Middle East, Asia and the Pacific, Europe, North America, and Latin America and the Caribbean. First, we leverage domain names assigned to wallets purchased through systems such as the Ethereum Name System (ENS). We employ ChatGPT to infer linguistic and cultural markers—such as language, script, or regional references—that suggest a wallet's likely region. Second, we identify wallets that frequently transact with centralized exchanges (CEXs) targeting specific regional

[1] A stablecoin is a crypto asset with its value pegged to a fiat currency, most often the US dollar. The most popular stablecoins are Tether's USDT and Circle's USDC, boasting a combined market capitalization of close to $200 billion (February 2025).

markets, assuming that a wallet predominantly interacting with, for example, a Latin American-focused exchange is likely from that region. These two methods provide an ad hoc regional classification for a subset of wallets, which we then use as labeled training data to develop a machine learning model for classification of arbitrary wallets.

The core of our approach lies in leveraging this training data to train a machine learning model to recognize patterns in on-chain activity that are indicative of a wallet's geographic origin. We construct features capturing wallets' behavioral and transactional characteristics, including time-of-day activity patterns, adherence to daylight savings time, interactions with certain centralized exchanges, and engagement with popular ERC-20 tokens and smart contracts. By learning region-specific patterns the trained model can estimate the geographic region of any arbitrary self-custodial wallet. The identifying assumption of the methodology is, that conditional on the features we selected to train the model, wallets that are in the training set and those outside the training set exhibit the same patterns. The methodology then enables us to map the geographic distribution of wallets, which we can then leverage to map international stablecoin flows.

Using this approach, we analyze almost 6 million domain names and billions of on-chain transactions to construct the training dataset. Some examples of regions assigned by analyzing domains names with ChatGPT are, "pijiu" (Chinese for "beer") which is assigned to Asia and the Pacific, and الكيماويات (Arabic for "chemicals") which is assigned to Africa and Middle East. We validate these ad hoc classifications through time-of-day based activity profile analysis. By adjusting wallet transaction timestamps to regional time zones (e.g., UTC+8 for Asia and the Pacific, UTC-6 for North America), we observe distinct peaks in activity during local daytime hours (e.g., 10 AM to 10 PM) and lows during nighttime, confirming the accuracy of our regional assignments. Additionally, we document differences in activity patterns due to daylight savings time (DST) in regions like North America (where DST is common) and a lack of such differences in regions where DST is rare, like Asia and the Pacific.

We then train a Gradient Boosted Decision Tree mode on this dataset, which achieves an overall accuracy of 65% in prediction geographic regions. For context, note that random guessing yields 20% per region. We then apply the model to predict the region of any arbitrary self-custodial wallet.

Using these predictions, we map international stablecoin flows for 2024. Our analysis captures approximately 138 million transactions totaling $2,019 billion, with an average transaction size of $14,630. These transactions involve 14.6 million

wallets, comprising 10.4 million wallets belonging to centralized exchanges, such as Binance or Coinbase, and 4.2 million self-custodial wallets. The total volume can be broken down into three categories: $309 billion in flows between self-custodial wallets, $1,141 billion in flows between self-custodial wallets and CEXes, and $569 billion in flows between CEXes. This distribution underscores the pivotal role of self-custodial wallets and estimating their geographic distribution, as they are involved in 72% of the transaction volume.

We document regional heterogeneity in stablecoin usage. Tether's USDT is more popular in regions with more emerging economies—Africa and the Middle East, Asia and the Pacific, and Latin America and the Caribbean—while Circle's USDC is more prevalent in regions with more advanced economies, i.e., Europe and North America. Similarly, we document regional heterogeneity in the customer bases of the largest crypto exchanges, Binance and Coinbase. We find that Binance is preferred in emerging market regions, whereas Coinbase leads in North America.

Next, we describe the stablecoin flow patterns between self-custodial wallets. They show Asia and the Pacific and North America leading in absolute terms, while as a fraction of GDP, Africa and the Middle East (1.5%) and Latin America and the Caribbean (1.4%) exhibit higher stablecoin activity, emphasizing the relative popularity of stablecoins in emerging markets. Notably, within-region flows are smaller typically than between-region flows, suggesting that stablecoins may be particularly useful for international payments or remittances—an area with significant frictions in traditional financial markets.

Calculating bilateral net flows highlights North America as the primary source of stablecoin outflows into all other regions of the world. This suggests that stablecoins could increasingly be serving as an instrument to meet global demand for dollars, particularly in regions where access to traditional dollar markets is constrained (see e.g., Calvo and Reinhart (2002), Gopinath and Stein (2021) for global demand on dollars, and Aramonte et al. (2022) for evidence on stablecoin demand in emerging markets). To further substantiate this hypothesis, we provide evidence that net stablecoin flows from North America into other geographic regions increase both during periods of increased volatility and when the dollar appreciates relative to other currencies. Additionally, we show that a similar pattern holds for stablecoin flows into China. That is, they increase significantly when the US dollar appreciates vis-à-vis the Chinese Renminbi.

Focusing on flows between centralized exchanges (CEXes) and self-custodial wallets reveals that Binance facilitates significant inflows of stablecoins into self-custodial wallets, while Coinbase is more associated with outflows, reflecting dis-

tinct "on-ramping" (i.e., moving capital from fiat to crypto) and "off-ramping" (i.e., moving capital from crypto to fiat) patterns.

Further, we provide a more in-depth analysis of Asia and the Pacific, the region with the largest stablecoin flows. Our analysis reveals significant centralized exchange (CEX) interactions, notably with $32 billion in inflows from Binance and net inflows from North America ($7 billion). We then train an additional model to distinguish China from the rest of Asia, enabling some more detailed country-level analysis. We consider China particularly interesting due to the largely banned status of crypto and issues with measuring crypto activity based on web-traffic in China as in the Chainalysis dataset. Our data shows that China accounts for roughly one-third of the activity within Asia and the Pacific. Despite its website being inaccessible without a VPN, we document that Binance drives $11 billion in net inflows to Chinese self-custodial wallets.

To compare our approach to the existing measurements of international crypto capital flows, which largely leverages data provided by Chainalysis, we briefly explain their methodology. Chainalysis infers the geographic origin and destination of stablecoin transactions by focusing on transactions involving centralized exchanges. To assign regions, Chainalysis uses web traffic data associated with CEXs. That is, they obtain data about the number of users that access the corresponding websites of the CEX, broken down by country. They assume that the geographic distribution of a platform's website visitors reflects its user base. For instance, if a significant share of a CEX's web traffic originates from Brazil, Chainalysis attributes a proportional share of that exchange's stablecoin transactions to Brazilian users. For identification, they assume that users do not use VPNs when accessing these websites, as VPNs misrepresent the true country of origin. Further, this approach assumes that transaction sizes are uniform across users, regardless of their country or region.

In contrast, our approach focuses on estimating the geographic region of self-custodial wallets. For identification, we assume that conditional on the features we selected in the machine learning model, wallets that are in the training set and those outside the training set exhibit the same patterns. Advantages of our approach are that we do not assume that users do not use VPNs or that users in different regions, on average, have the same transaction size. A disadvantage of our approach however, is the lower granularity of the estimates. While we can (largely) only provide region-level estimates, the Chainalysis dataset can provide estimates on a country-level basis.

Related Literature. This paper contributes in particular to the literature that has focused the measurement of crypto capital flows, and in general to the literature that studies the impact of crypto assets on macroeconomic variables.

Most closely related to our methodology is Athey et al. (2016). They estimate the region of self-custodial Bitcoin wallets in 2015 on a small scale, by identifying the region of 2,858 addresses scraped from online forums, and train a random forest model for classification, to generate some empirical evidence in support of their theoretical model on Bitcoin adoption. Relative to their work, we contribute by (1) generating a much larger dataset (∼350,000 wallets) by analyzing wallet domain names, which had yet to be invented in 2015; by (2) leveraging this dataset to train a model that can be used to estimate the region of any arbitrary self-custodial wallet and by (3) applying the estimates to map international crypto asset flows. Other papers (Meiklejohn et al. (2013) and Makarov and Schoar (2021)), have used heuristic clustering and behavior-based classification to link wallets, but have not attempted to specifically make geographic predictions about wallets.

Recently, a literature on crypto capital flows has emerged (Cardoza et al. (2024), Cerutti et al. (2024), and Friedrich and Zhao (2024)), that has largely focused on Bitcoin as a vehicle for crypto capital flows, leveraging the dataset by Chainalysis as the basis for their analysis. Relative to these papers, we contribute by introducing a novel methodology to estimate crypto capital flows that does not rely on the Chainalysis dataset and its assumptions (no VPN usage, same transaction size in every country). Further, our paper focuses on mapping stablecoin flows, which combine features of crypto assets and the dollar. Particularly, we find supporting evidence that stablecoins may be used for both global capital flows, payments and remittances and also to satisfy some of the global demand for dollars. Other papers, such as, von Luckner et al. (2023) and von Luckner et al. (2024) have focused on providing qualitative evidence that crypto assets are used for circumventing capital controls and to facilitate capital flight. Relative to these, we contribute by providing quantitative estimates. Further, von Luckner et al. (2023) had to exclude dollar denominated flows from their analysis of peer-to-peer transactions for identification, which we specifically focus on by analyzing stablecoins.

There is also a growing body of literature linking macroeconomic conditions and crypto usage more generally. Cong et al. (2023) provide evidence that households adopt crypto assets and stablecoins when they expect higher inflation. Our data indirectly supports this finding by showing that stablecoin usage in regions with more emerging economies is relatively higher as a fraction of GDP. Alnasaa

et al. (2022) show that crypto usage is positively correlated with perceived corruption and capital controls, while Arbalik et al. (2021) document correlation between Bitcoin volatility and capital flows. Focusing on China, Hu et al. (2021) find evidence of capital flight through Bitcoin in China, a finding that our country-specific analysis on China supports, extends to stablecoins, and is able to quantify.

The rest of the paper is structured as follows: section 3 provides an overview of the data used, section 4 explains the methodology used, section 5 explains the results of the classification model, section 6 maps international stablecoin flows, section 7 analyzes economic drivers of stablecoin flows.

2 Background

In this section, we offer some background information about how crypto capital flows operate in practice. For that, we break down the typical transaction chain, identifying which legs of the are observable in our data, and distinguishing how different underlying motives may lead to different patterns in the data.

Typically, the initial step in any crypto capital flow involves exchanging fiat currency for a crypto asset. By far, the dominant channel for this is the use of centralized exchanges (CEXs) such as Binance or Coinbase. Users transfer fiat currency to a CEX, which then facilitates the conversion into a crypto asset—for example a stablecoin like Tether's USDT or Circle's USDC—either by acting as the counterparty or by matching the user with another participant in a peer-to-peer transaction. These initial exchanges occur within the traditional fiat banking system (i.e., "off-chain"), implying that we do not observe them in our data.

Once a user acquires a stablecoin, their subsequent actions depend on their motive. For this paper, we focus on of two types of motives for stablecoin use: cross border capital flows and flight into a (perceived by the user) more stable asset, without the intent of transferring capital abroad. For cross border flows, the user aims wants to send capital to another region, often to exchange it back into a different fiat currency. Several pathways exist after having transferred fiat currency to a CEX: (1) The user withdraws fiat directly from the same CEX to a bank account in another country. No on-chain crypto transaction takes place. Arguably, this is a traditional fiat-based capital flow facilitated by the CEX and not a crypto capital flow. As there is no on-chain transaction is not observed in our data. (2) The user transfers the stablecoin from one CEX to another CEX (and from there, exchanges for fiat and possibly withdraws into a bank account).

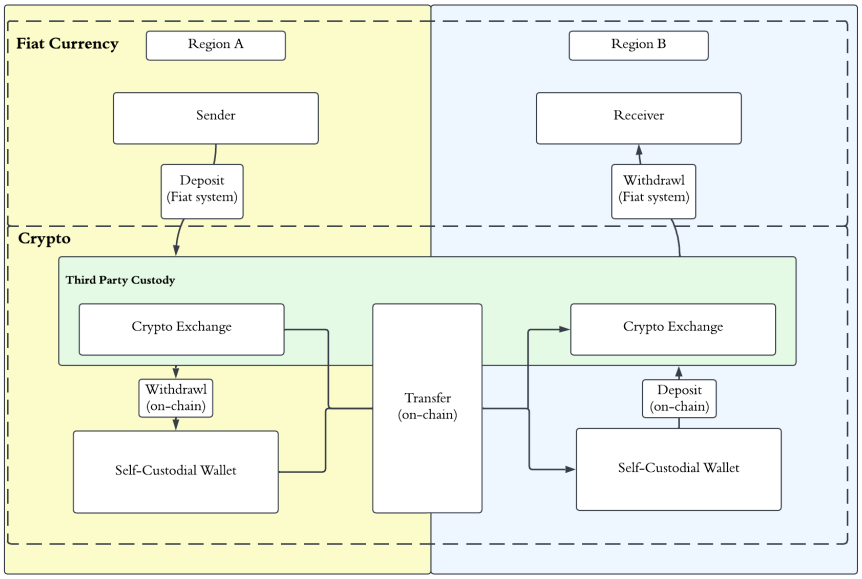


Figure 1: Schematic Overview of Crypto Capital Flows

The transfer of asset between CEXes is recorded on-chain and thus observable. (3) The user withdraws the stablecoin to a self-custodial wallet for use in another region, which is also observable. (4) The user withdraws to a self-custodial wallet and subsequently sends it to another CEX, which is recorded on-chain. All cases where the stablecoin moves on-chain can be observed in our dataset.

If a user is, for example, concerned about the stability of the local currency and wants to exchange money for a more stable asset, the chain or transactions looks different. In this case, the user transfers fiat to a CEX, exchanges it for a stablecoin, and then either (1) leaves the stablecoin in the CEX's trusting them to custody the asset on behalf of the user, or (2) withdraws it to a self-custodial wallet. We do not observe transactions that follow (1) in our data, as there is no on-chain transaction. However, (2) involves an on-chain transaction and is captured in our dataset. Unlike cross-border flows, the intent is not necessarily to relocate capital but to preserve its value domestically. As such, sending the stablecoin to another CEX or self-custodial wallet for use abroad is not necessary.

Thus, we might expect that transactions motivated by cross border flows show up more often in transactions between CEXs and transactions between self-custodial wallets. In contrast, transactions that facilitate flows from CEXs to self-custodial wallets might be more indicative of the second motive. To offer a graphical summary, figure 1 provides a schematic overview that summarizes the options outline above, describing how crypto capital flows work in practice.

3 Data

Blockchain data. We obtained full copies of the Ethereum, Binance Smart Chain, Optimism, Arbitrum, Base and Linea blockchains by synchronizing a node with the respective network and extracted the data using the Ethereum ETL package for Python (Medvedev and the D5 team (2018)). For every blockchain, the data spans the period from the genesis block[2] until the last block that has been recorded in 2024. Thus, the data spans from July 30th 2015, when Ethereum began operating, until December 31st 2024, with other blockchains joining throughout the sample period. The data is transaction level data, exceeding 12 billion transactions and more than 20 terabytes of storage. Transactions are interactions of a wallet with the blockchain, such as transferring crypto assets and interacting with smart contracts.[3] This data also includes all transfers of stablecoins, which we use to map stablecoin cross border flows after estimating the geographic region of wallets.

We combine transaction level data from the different blockchains in our sample to enlarge our data set, exploiting a peculiarity of different EVM-compatible[4] blockchains. That is, wallet addresses carry over between all the different EVM-compatible blockchains. If we observe that the same wallet address executed transactions on different blockchains, we can be certain that those have been initiated by the same user. This allows us to track the same wallet throughout the whole data set, no matter the specific blockchain a transaction took place on.

Domain name data. A wallet address for the blockchains in our sample is a 42-character hexadecimal string that starts with '0x', such as '0xd8dA6BF26964aF9D7eEd9e03E53415D37aA96045'. Because these strings are cumbersome to handle, domain name systems have been developed that allow users to effectively replace these strings with human-readable domain names, such as 'vitalik.eth'[5], when interacting with blockchains. Users can purchase these domain names from service providers, with the most popular being the *Ethereum Name Service*, henceforth ENS. Purchase prices for these domains typically range from single to triple digit dollar amounts. These purchases are recorded as on-chain transactions and thus data for all purchases is public. For simplicity, we

[2]The genesis block refers to the first block of a blockchain.

[3]A transaction is issued by a wallet whenever a user wants to change the state of the blockchain. A transaction can, but does not necessarily have to, include the transfer of assets.

[4]The Ethereum Virtual Machine (EVM) is a virtual machine for executing code that has been adopted by other blockchains to guarantee compatibility.

[5]vitalik.eth is an ENS domain owned by Vitalik Buterin, co-founder of Ethereum.

obtain our data through queries in Dune Analytics.[6]

Supplementary data from Dune Analytics. We obtain some further supplementary data from Dune Analytics. First, a list of wallets that belong to centralized exchanges such as Binance or Coinbase, totalling 10,072 wallets among 333 entities. We use this data to identify further wallets belong to exchanges in a procedure described in appendix C.

Second, wallets that belong to certain types of bots (i.e. MEV bots). We exclude these wallets because our method would likely mispredict their geographic location, as they are systematically different from the wallets in the training data set that we build. Third, data on smart contracts for the different blockchains, including the contract addresses and a categorization of the type of contract (e.g., NFTs or decentralized exchanges), and finally, data on different stablecoins which includes their contract addresses on different blockchains.

3.1 Descriptive Statistics

Description of blockchain data. Ethereum is the longest running blockchain in the sample, with its genesis block on July 30th 2015, while the genesis of Linea has been the most recent on July 6th 2023. The latest blocks for the respective chains are both determined by how long the blockchain has been operational and by how fast it produces blocks. Even though Ethereum is the longest running blockchain in the sample, it has produced less blocks than more recent blockchains such as Optimism or Arbitrum, as it produces them at a slower pace.[7] The number of wallets (for intuition the reader may wish to think of wallets as 'accounts')

Blockchain	Genesis Block	Latest Block	#Wallets	#Transactions
Ethereum	2015, Jul 30	21,525,890	216,376,711	2,639,611,278
Binance Smart Chain	2020, Aug 29	45,369,482	214,081,622	6,523,262,103
Optimism	2021, Jan 14	130,045,411	13,562,366	432,212,106
Arbitrum	2021, May 28	290,687,173	39,852,439	1,222,934,534
Base	2023, Jun 15	24,450,126	106,582,545	1,419,068,646
Linea	2023, Jul 06	14,022,234	6,317,923	240,821,235
Total			**545,267,859**	**12,477,909,902**

Table 1: Overview of Blockchain Data

[6] Dune Analytics is a commercial blockchain data provider.

[7] For example, Ethereum produces a new block approximately every 12 seconds, while Arbitrum produces a block every 0.25 seconds.

on each blockchain is a measure for its number of users and ranges from a few million (e.g., Linea) to hundreds of millions (e.g., Ethereum, Binance Smart Chain). Though, it is an imperfect measure of the number of users, and an upper bound, as one user might own multiple wallets, which we do not explicitly observe. The total number of wallets is counted as the number of distinct wallets on the union of all blockchains in the sample. That is, if the same wallet is active on multiple chains, it only counts once towards the total. The number of transactions for each blockchain ranges from hundreds of millions to several billion, with the total number exceeding 12 billion transactions.

Description of domain name data. The following table provides an overview of our domain name data:

Name Service	**# of Registered Domains**
Ethereum Name Service	3,413,426
Uxlink	875,564
Spaceid	474,021
Basenames	437,329
Linea ENS Subdomains	429,956
Arbid	303,632
Total	**5,933,958**

Table 2: Overview of Domain Name Services

4 Methodology for estimating the geographic region of self-custodial wallets

We divide the world into five regions: Africa and the Middle East, Asia and the Pacific, Europe, North America, and Latin America and the Caribbean. To estimate the geographic region of self-custodial wallets, our methodology involves obtaining geographic information for a subset of wallets through two distinct approaches. First, we leverage domain names assigned to wallets purchased through systems such as the Ethereum Name System (ENS). We employ ChatGPT to infer linguistic and cultural markers—such as language, script, or regional references—that suggest a wallet's likely region. Second, we identify wallets that frequently transact with centralized exchanges targeting specific regional markets, assuming that a wallet predominantly interacting with, for example, a Latin American-focused exchange is likely from that region. These two methods provide an ad hoc

regional classification for a subset of wallets, which we then use as labeled training data to develop a machine learning model for classification of arbitrary wallets.

We then use this data to train a Gradient Boosted Decision Tree (for background on the method see e.g., Hastie et al. (2017)) leveraging the *Yggdrasil Decision Forests (YDF)* library in Python (Guillame-Bert et al. (2023)) to classify the region of a wallet by recognizing patterns that are characteristic for the respective regions. For this, we construct features capturing wallets' behavioral and transactional characteristics, including time-of-day activity patterns, adherence to daylight savings time, interactions with certain centralized exchanges, and engagement with popular ERC-20 tokens and smart contracts. By learning region-specific patterns the trained model can estimate the geographic region of any arbitrary self-custodial wallet.

4.1 Generating training data

4.1.1 By analyzing domain names

A significant advantage of using a large language model such as ChatGPT for inferring the region, country, or language of Ethereum Name System domains is its ability to scale, as it can analyze millions of domains quickly and efficiently. Moreover, ENS supports Unicode Technical Standard 51, which allows users to register domains that employ a diverse range of characters—including those from Arabic, Chinese, Korean, Japanese scripts, and even emojis. This facilitates classification of domain names by providing clear linguistic markers. In some cases, inferring the region can be more straightforward than pinpointing a specific country, as demonstrated by instances where regional characteristics are more pronounced than national ones. However, while making inferences about a country's identity can work particularly well for nations with distinct scripts and large populations—such as China—it tends to be less reliable for smaller countries and countries where linguistic markers may not be as clear-cut.

Despite these advantages, several limitations warrant consideration. One notable challenge is that users might reside in one region while choosing a name that is culturally or linguistically associated with another. For instance, users around the world may select English names or incorporate references to U.S. culture, even if they are not based in the United States. Similarly, migrant populations in Europe or the U.S. might opt for domain names that evoke their country of origin rather than their current locale. Additionally, ChatGPT can sometimes misinterpret inputs or exhibit biases—for example, when processing German domain

names, it may default to associating them with Germany rather than recognizing that they might equally belong to Austria or Switzerland. Finally, achieving precise, full country-level estimates remains challenging given the inherent ambiguity and variability in user-selected domain names.

For every domain name in our sample, we query ChatGPT through its API interface and instruct model version ChatGPT 4.o mini[8] to analyze the domain name and make a guess about the country, language, and region the user is from and to provide a short reason for the classification. In essence, our prompt reads

> "You are trained to classify ENS domain names by country, language, region, and provide a short reason for the classification. Consider references to culture, language, localities, memes. Be creative. Be mindful of the language commonly used in crypto and web3; and of languages that are spoken in many parts of the world, such as English, French and Spanish. If you cannot classify any of these, output 'unclassified' for that particular attribute. Classify the domain: {domain name}."

including some further instructions for ChatGPT to restrict its answers for the region to the set {Africa and the Middle East, Asia and Pacific, Europe, Latin America and Caribbean, North America, unclassified}. We restrict the maximum number of tokens of the reply to 150 and set the temperature and "top_p" to 0.4 each. A reply of 150 tokens equals roughly 110-120 words in the English language, while setting ChatGPT's temperature and top_p to 0.4 makes its responses more deterministic and focused by reducing randomness (temperature) and narrowing the range of token probabilities considered (top_p), leading to safer and more predictable outputs. Some wallets have more than one domain name registered to them. In these cases, we assign the region as the region that was assigned by the majority of ChatGPT guesses, excluding "unclassified" responses. That is, a wallet which owns 10 domains, 6 of which have been left unclassified, 3 assigned to Europe and 1 assigned to North America will be assigned to Europe.

4.1.2 By linking wallets to regional exchanges

Some centralized exchanges focus on particular markets that often are restricted to a region or a country. For example, the exchange "Indodax" markets itself as an "Indonesian Bitcoin and Crypto Exchange" and its website is written entirely

[8]We selected ChatGPT 4.o mini to balance performance and cost. Our analysis does not require very deep reasoning and processing millions of domains with more advanced models would have incurred significant expenses.

in Indonesian. We exploit this fact to classify wallets as belonging to a particular region, if they interact particularly frequently with exchanges that focus on that region. The idea is, that a self-custodial wallet that frequently receives and send money to an exchange that is focused on a regional market is likely to belong to a user from that market. The following table defines the exchanges that we have manually assigned as being indicative of a particular region

Region	**Exchanges**
Africa and Middle East	Altcointrader, Arzpaya.com, Artis Turba Exchange, Bit2c, Bitoasis, Luno, Nobitex, Valr
Asia and Pacific	Bitbank, Bitkub, Bithumb, Coindcx, Coincheck, Coinhako, Coinone, Coins.ph, Gdac, GMO Coin, Gopax, Indodax, Korbit, Maicoin, Tokocrypto, Upbit, Wazirx
Europe	Anycoin Direct, Bitpanda, Bitvavo, Btcturk, Coinmetro, Exmo, Firi, Norwegian Block Exchange, Paribu, Swissborg
Latin America and Caribbean	Bitso, Brasil Bitcoin, C-Patex, Lemon Cash, Mercado Bitcoin, Orionx, Panda Exchange
North America	Binance US, Bitbuy, Coinsquare, Netcoins, Quadrigacx, Shakepay

Table 3: Regional Cryptocurrency Exchanges

We classify a wallet as belonging to a particular region, if more than 90% of its transactions with centralized exchanges (including the regional exchanges listed above and non-regional exchanges) are with centralized exchanges of that particular region.

4.2 Training the classification model

To achieve our goal of estimating the geographic region for any self-custodial wallet, we take the regional classification through domain names and regionally focused centralized exchanges from the two previous sections at face value and use them as training data to develop a model that recognizes patterns that are predictive of what region a self-custodial wallet is from. To ensure that we have enough observations on a per wallet basis, we restrict the sample to only include wallets that have initiated at least 50 transactions.

We now proceed to describe the features that we use to train the classification model:

Time of Day Features. For every wallet, we calculate the percentage of transactions that are conducted within every hour of the day. To condense the data and avoid potential over fitting issues, we estimate a third degree polynomial (to be able to accompany both a minimum and a maximum in the activity profile) and use the coefficients as features.

Daylight Savings Time Features. For every wallet, we calculate its activity profile during the months of daylight savings time and during the remainder of the year. This feature exploits regional heterogeneity in the use of daylight savings time. While DST is common in Europe and North America, it is not common in many other regions and non-existent in Asia.

Top 5 Centralized Exchanges. For every wallet, we count the number of transactions with a centralized exchange (i.e., withdrawals and deposits). We then sort descending by exchange name and create a categorical variable for the most used centralized exchange, second most used centralized exchange and so on.

Top 10 ERC-20 Tokens and Smart Contract Namespaces. These are two similar features. For the top 10 ERC-20 tokens, we count, for every wallet, the number of transactions using ERC-20 contracts, sort them descending by county and create a categorical variables for the top 10 most used ERC-20 contracts. For smart contracts in general, we count, for every wallet, the number of transactions with smart contracts of the same "namespace"[9] as determined by Dune, sort them in descending order by count and create categorical variables for the top 10 most interacted namespaces. While the first feature offers some more granularity exploiting heterogeneity on the ERC-20 level, the second feature groups smart contracts based on functionalities and exploits heterogeneity along this dimension.

Training and Evaluation. To train and evaluate the model, we split the data into a training data set (90% of the data) and a testing data set (10% of the data). We then train 3 models that we combine to assign a region from the set {Africa and Middle East, Asia and Pacific, Europe, Latin America and Caribbean, North America} to wallets. The process is illustrated by the following decision tree:

That is, we first train a model that assigns one of the following three classifications to an address: {North America, Latin America and Carribbean} or {Africa and Middle East, Europe} or Asia and Pacific. Instead of assigning North America or Latin America and Caribbean, the model assigns the classification that the wallet could be in either region. This approach maximizes the usefulness of the

[9]The "namespace" groups smart contracts that offer similar functionalities.

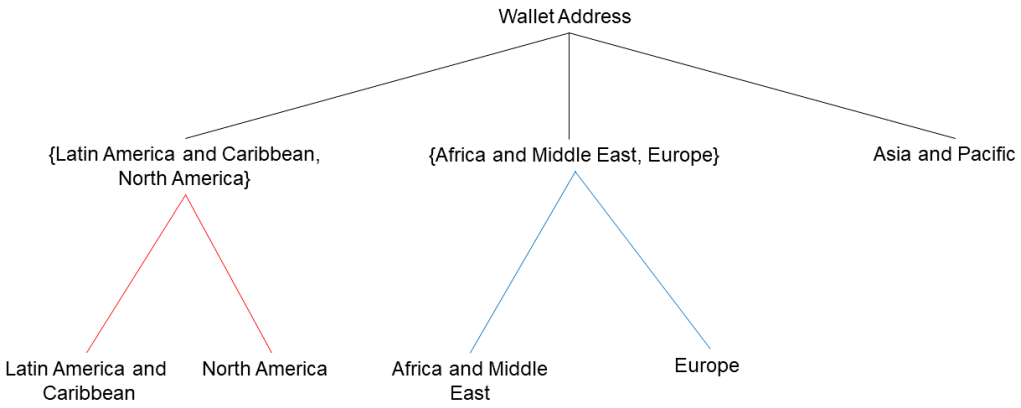


Figure 2: Decision Tree Structure of Classification Models

time of day based features, as the grouped regions largely share the same time zones. We then proceed to train two more models. One that splits {North America, Latin America and Carribbean} into its elements and one that splits {Africa and Middle East, Europe} into its respective elements. These further models then largely exploit the other features to distinguish between the respective regions. For each of the three models trained, the *Ydf* package automatically splits off some of the data for validation to avoid over fitting any given model. To address imbalance in the training data, we calculate balanced sample weights—that is, each observation is weighted inversely proportional to its class frequency, ensuring that underrepresented classes contribute equally to the estimation process (see e.g., King and Zeng (2001)).

Classification of Arbitrary Self-Custodial Wallets. To classify arbitrary self-custodial wallets, we calculate the same features that are used in training the model for wallets that have not been part of the training data and restrict the sample to only include wallets that have at least 50 transactions, to align we the restriction we made in training the model. We then apply the trained model to predict the most likely region the wallet belongs to.

Identifying assumption. Our key identifying assumption is that, conditional on the features used to train the model, wallets of a particular region in the subset

that was used to train the model follow the same data generating process as the wallets out of sample that the model is used on to predict regions. For example, we assume that there is no systematic difference between a North American wallet in the subset used to train the model an out of sample North American wallet with respect to the hours of the day during which they are typically active.

5 Results

5.1 Training Data

5.1.1 Domain Names

Before providing summary statistics of the results, we provide some example classifications of domain names by ChatGPT to allow the reader to evaluate the procedure better. In table 4, we present one example for each of the possible regions. The possible region outputs are "unclassified", when ChatGPT does not find sufficient evidence to assign the domain to a particular region; and "Africa and Middle East", "Asia and Pacific", "Europe", "Latin America and Caribbean", and "North America".

Of course, there is no guarantee that any given guess that ChatGPT makes is in fact true. Thus, before we use the output of ChatGPT as input for the training data, we proceed to validate whether this methodology produces reasonable training data. For validation, we collect the timestamps of every single transaction of the wallets that ChatGPT has classified from our blockchain data. For each wallet, we then aggregate the data by counting the hour of the day during which the transaction has occurred and normalize by the total number of transactions to derive the % of transactions that have occurred within a particular hour. We then aggregate these wallet-specific activity profiles by region. Since all timestamps in the data are recorded in UTC time, we offset the timestamps for the different regions to convert them to regional timestamps.

For Africa and the Middle East, we use use UTC+2, corresponding to the Central African time zone; for Asia and Pacific, we use UTC+8, corresponding to the time zone that is centered on China, parts of Indonesia, Malaysia, Singapore and Western Australia; for Europe we use UTC+2, which corresponds to Central European Summer Time; for Latin America and Caribbean we use UTC-4, centering on parts of Brazil, Chile and Venezuela; and for North America, we use UTC-6, which corresponds to Central Time in the US. Our intention behind picking these

Name	Region	Country	Language
vucoworld	unclassified	unclassified	unclassified
Reason: The term 'vucoworld' does not clearly reference a specific country, language, or region. It appears to be a coined term possibly related to virtual or digital worlds, which are universal concepts in the crypto and web3 space.			
الكيماويات	Africa and Middle East	unclassified	Arabic
Reason: The domain name is in Arabic, which is widely spoken in the Middle East and North Africa, and it translates to 'chemicals', indicating a potential relevance to industries in those regions.			
pijiu	Asia and Pacific	China	Chinese
Reason: 'Pijiu' means 'beer' in Chinese, reflecting a popular beverage in Chinese culture.			
philippzinner	Europe	Germany	German
Reason: The name 'philippzinner' suggests a German origin, likely a personal name, which is common in Germany and associated with the German language.			
laplazart	Latin America and Caribbean	Mexico	Spanish
Reason: The name 'laplazart' suggests a connection to 'La Plaza', which is Spanish for 'The Square', a common term in many Latin American countries, particularly in Mexico, where plazas are central to community life and culture.			
lakings	North America	United States	English
Reason: The term 'lakings' likely refers to the Los Angeles Kings, a professional ice hockey team based in Los Angeles, California, which is a significant part of American sports culture.			

Table 4: Example of domain name classifications.

time zones is not to take a stance on which time zone is the most appropriate to capture an entire region that spans multiple different time zones, but to offset the UTC based timestamps by a reasonable amount as such to convert UTC time to a reasonable proxy of "local time" for the different regions, balancing out parts of the region that are further ahead or further behind the specific choice of time zone that we made.

We then plot the activity profiles that are derived from the ChatGPT classification of the wallets as depicted in figure 3. The activity pattern of all regions in the graph exhibits a distinctive dip in activity during the nighttime, which intuitively makes sense, as we would expect activity to be lower when most people are sleeping. Further, the times of the highest activity span from roughly 10 AM to 10 PM, which correspond roughly correspond to times of the day where most people could reasonably be expected to be engaging with crypto. Our interpretation of the figure is that it is evidence that the classification of domain names by ChatGPT, on aggregate, is successful in assigning the correct regions based on the domain names.

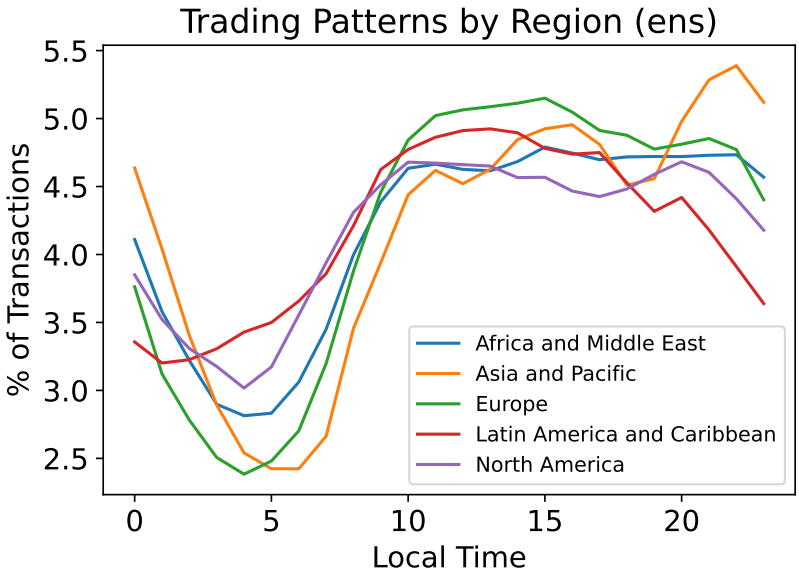


Figure 3: Activity profile by region for ChatGPT classified domain names

5.1.2 Regional Exchange Users

We validate our methodology using the same activity profile idea that has been outlined in the section on domain names above. The corresponding activity profiles are depicted in figure 4. To offer some further validation of our methodology in

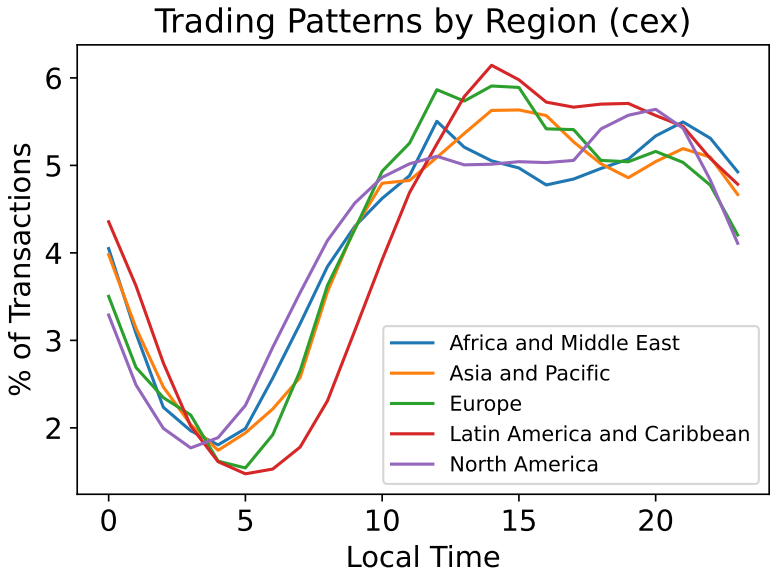
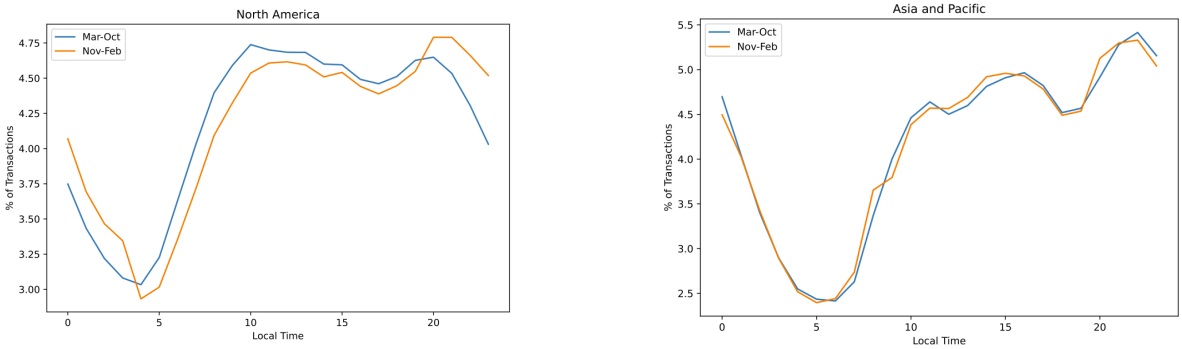


Figure 4: Activity profile by region for wallets identified as regional exchange customers

creating the training data (both through domain names and regional exchange

users), we provide Figure 5 below, that shows that it is also possible to detect the effect of daylight savings time in the classified wallets. In the left hand side



(a) DST in North America

(b) DST in Asia and Pacific

Figure 5: Regional Stablecoin Gross and Net Flows
(in billion dollars)

figure, we plot the activity patterns of wallets that we have identified to be from North America. We fix the x-axis to correspond to the typically assigned time zone for the region (e.g. UTC-6 for North America). Then, we split the data into the time period from March to October, which corresponds to Standard Time in the United States, and the time from November to February, which corresponds to Daylight Savings Time in the United States. The figure clearly shows, that the activity profile is offset by roughly one hour, as one would expect due to the one hour shift due to Daylight Savings Time. In contrast, the figure on the right hand side shows that there is no significant difference in activity by time of day for the wallets that we have classified to be from Asia and Pacific. This is to be expected, as, with the exception of Australia and New Zealand, no countries in Asia and Pacific observe daylight savings time. We see this as further strong evidence that the classification of wallets in our training data is, on average, correct. Further DST graphs for the other regions can be found in appendix B.

Finally, we present summary statistics of the training data that is generated by our methodology in Table 5 below.

Region	Domain	Regional CEX	Total	% of Total
Africa and Middle East	19,159	10,466	29,625	8.6%
Asia and Pacific	124,727	49,988	174,715	50.5%
Europe	90,509	2,291	92,800	26.8%
Latin America and Caribbean	3,723	2,090	5,813	1.7%
North America	22,537	20,711	43,248	12.5%
Total	**260,655**	**85,546**	**346,201**	**100.0%**

Table 5: Overview of Training Data with Percentage of Total

5.1.3 Classification Model

To describe the performance of the classification model, we first discuss the confusion matrix in figure 6 below. It displays the true region of the testing data in the rows and the predicted region of the model in the columns. The data in the matrix has been normalized, such that all rows add up to 100%. To help interpret

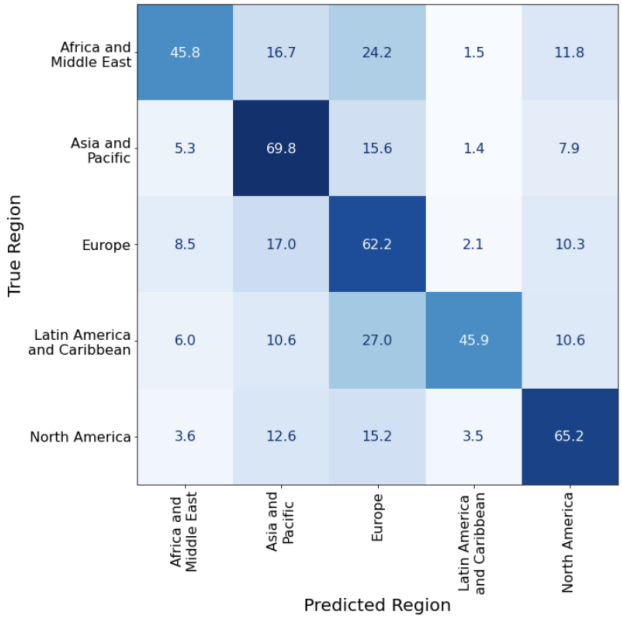


Figure 6: Confusion Matrix of Classification Model

the matrix, it is useful to think of some special cases. A model that perfectly classifies the regions would display 100% along its main diagonal, and all off diagonal entries would be 0. A model that uniformly guesses at random would display 20% everywhere in the confusion matrix. Keeping this in mind, we can see that the model has significant predictive power, performing best in predicting Asia and Pacific (69.8%) and worst at predicting Africa and the Middle East (45.8%). Even

the predictions for the worst performing region are still significantly better than random guesses. A good performance in prediction indicates two things. First, users in the respective region have relatively distinctive on-chain behavior that the classification model can recognize and use for prediction. Second, it is indicative about the performance of ChatGPT in classifying the underlying domain names correctly.

To dig further into the model performance, we discuss some of the errors in prediction regions, i.e., the off-diagonal elements of the matrix. If the model makes random errors, then off-diagonal elements should be symmetric. That is, the proportion of domains from region X that were incorrectly classified as region Y should be equal to the proportion of misclassified domains from region Y as region X. Examining the off-diagonal entries of the confusion matrix, we can see that errors do largely appear to not be random. First, there is a tendency for wallets to be more likely to be misclassified as being in Asia and Pacific, and in Europe. This likely stems from the fact that those two regions contain the majority of observations in the training data, and is a type of bias that we would prefer to avoid. Second, there is a tendency of the model to "misclassify" domains in a fashion that potentially undoes misclassification of the region by ChatGPT when generating the training data (hence the quotation marks around "misclassify"). To explain this intuitively, note that for example, the proportion of wallets with the true region Africa and Middle East that is classified as North America (11.8%) far exceeds the proportion of wallets with the true region North America that is classified as Africa and Middle East (3.6%). We think that this likely reflects the fact that there is a large immigrant population from Africa and the Middle East in North America (who may have chosen domain names that reflect their heritage), which is correctly recognized by the classification model. In contrast, there is not a significant immigrant population from North America that resides in Africa and the Middle East. Therefore, these "misclassifications" of the model are a desirable bias that potentially undoes some incorrect classifications by ChatGPT when generating the training data. A similar observation can be made for misclassifications of Latin America and North America; and for misclassifications of Africa and Latin America vis-a-vis Europe. With respect to misclassifications of Asia and Pacific, a region that also likely has a significant number of immigrants in Europe and North America, we observe that errors are much more symmetric. This is likely due to the fact that the misclassifications towards Asia and Pacific, which stem from it being a majority class, are balanced by the countervailing bias due to immigration flows.

In appendix D, we also provide more details (ROC, AUC, a variety of graphs) about the performance of the three individual classification models that are used.

5.2 Estimating the Region of Arbitrary Self-Custodial Wallets

For calculating stablecoin flows, we do not take the most likely label that is predicted by the classification model, but the predicted probabilities of each region. Using the whole distribution of the prediction should make the results more accurate and stable. We then calculate the counts of wallets by region by aggregating regional probabilities over all wallets. The results are given in table 6. Finally, we

Region	# of Wallets
Africa and Middle East	3,010,170
Asia and Pacific	6,945,933
Europe	3,231,460
Latin America and Caribbean	2,556,156
North America	4,431,223

Table 6: Predicted Regions for Self-Custodial Wallets

manually assigned a handful of wallets that belong to notable entities, as outlined in appendix E.

6 Estimating International Stablecoin Flows

We present some summary statistics for stablecoin flows in 2024, before showing detailed breakdowns of stablecoin flows in the following subsections. The total number of stablecoin transactions that we map is around 138 million, totalling a volume of $2,019 billion, implying an average transaction size of $14,630.[10] The total number of wallets involved in these transactions is 14.6 million, which can be subdivided into 10.4 million that belong to centralized exchanges and 4.2 million self-custodial wallets. The total volume of $2,019 billion can be split into three categories: $309bn in flows entirely between self-custodial wallets, $1,141bn in flows between self-custodial wallets and centralized exchanges and $569bn in flows between centralized exchanges. This breakdown highlights the importance of

[10]We exclude stablecoin transactions where the sender and receiver is the *same* centralized exchange, as these are typically due to operational needs. That is, they are flows from deposit addresses to hot wallets and flows between hot wallets and cold storage wallets.

determining the geographic region of self-custodial wallets, as they are present in at least one side of the transaction in 72% stablecoin transactions as measured by volume. There is considerable heterogeneity in the regional useage of the different stablecoins, as outlined in Table 7 below.

Region	Stablecoin	Volume (USD bn)	Percentage
Africa and Middle East	USDC	85	42.7
Africa and Middle East	USDT	115	57.3
Asia and Pacific	USDC	179	42.0
Asia and Pacific	USDT	247	58.0
Europe	USDC	167	50.0
Europe	USDT	167	50.0
Latin America and Caribbean	USDC	68	43.3
Latin America and Caribbean	USDT	88	56.7
North America	USDC	273	61.3
North America	USDT	172	38.7

Table 7: Volume and Percentage of Stablecoins by Geographic Region

As shown in the table, USDT is more popular in regions that feature more emerging markets (i.e., Africa and Middle East, Asia and Pacific, Latin America and Caribbean), while USDC is more popular in regions that feature more advances economies (Europe, North America).

Further, we present regional heterogeneity in the preference for interacting with Binance and Coinbase, as outlined in Table 8 below:

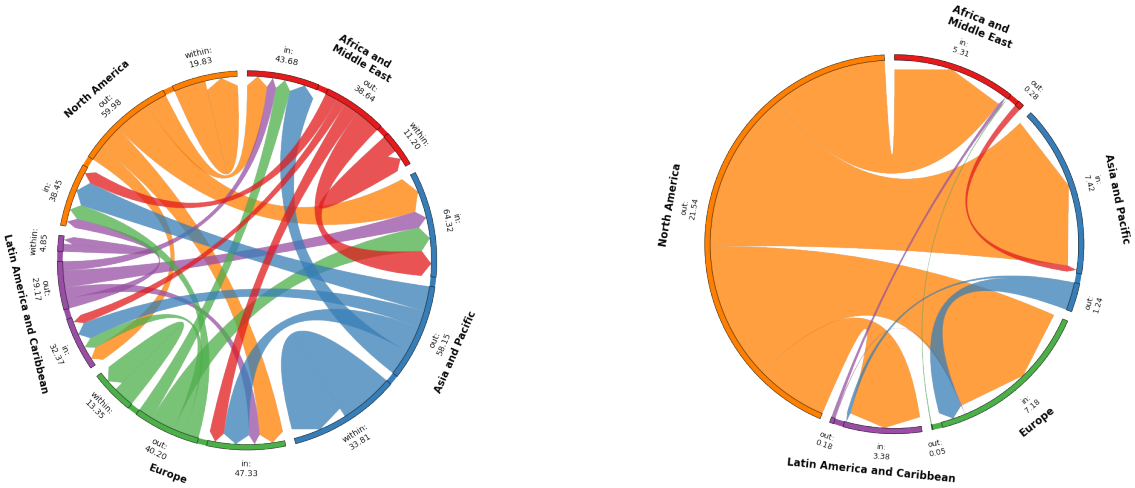
Region	Coinbase (% Volume)	Binance (% Volume)
Africa and Middle East	25.7	74.3
Asia and Pacific	16.9	83.1
Europe	33.7	66.3
Latin America and Caribbean	27.7	72.3
North America	54.0	46.0

Table 8: Percentage of Volume with Coinbase and Binance by Region

The popularity of Binance and Coinbase across regions follows a similar trend to the popularity of USDT and USDC across regions. That is, regions with more emerging markets tend to favor interactions with Binance, while Coinbase's popularity increases in regions with more advanced economies.

6.1 Stablecoin Flows Between Self-Custodial Wallets

This section focuses on estimation and description of stablecoin flows between self-custodial wallets of different geographic regions. In figure 7, we present our estimates of both gross and (bilateral) net flows of stablecoins between regions. We



(a) Regional Stablecoin Gross Flows

(b) Regional Stablecoin Net Flows

Figure 7: Regional Stablecoin Gross and Net Flows
(in billion dollars)

begin with the figure displaying gross flows on the left hand side. For each region, we split flows into three categories. Inflows, outflows and within flows (where both the sender and receiver are in the same region). The largest regions in terms of stablecoin flows are Asia and Pacific ($156.28 bn), followed by North America ($118.26 bn), while Latin America and Caribbean has the smallest stablecoin flows ($66.39 bn). However, relative to GDP, both Africa and Middle East (1.5%) and Latin America and Caribbean (1.4%) exhibit significantly higher stablecoin flows than the other regions (Asia and Pacific: 0.4% , Europe 0.4%, North America: 0.4%), hinting at the popularity of stablecoins and crypto assets, particularly in emerging markets, that has been described in the literature (see e.g., von Luckner et al. (2023), Cardoza et al. (2024), Cerutti et al. (2024), Friedrich and Zhao (2024)).[11]

[11]Percentages calculated as (inflows + outflows + within flows)/GDP. Regional GDP numbers aggregated from country level World Economic Outlook 2023 data (in trillion dollars): Africa and Middle East: 6.31, Asia and Pacific: 38.35, Europe: 27.1, Latin America and Caribbean: 4.89, North America: 33.35

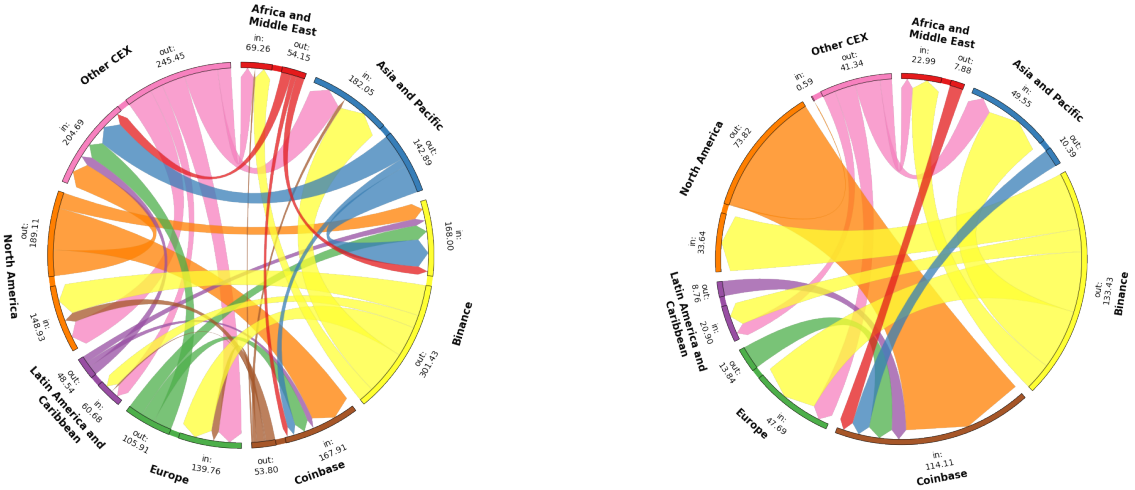
As a general pattern, within region flows are sizably smaller than between region flows. This is in line with the idea that stablecoins are particularly attractive for international payments and remittances, an area in which traditional transfers are particularly slow and costly (see e.g., World Bank (2024)). In contrast, within region (and in particular, within country) payments are typically significantly more efficient than their international counterparts, making stablecoins less attractive as an instrument to conduct such payments. Further, within country payments are also much more likely to be denominated in local currency rather then dollars, contributing to limited utility of stablecoins for domestic payments in economies that are not dollarized.

We now turn towards the right hand side figure depicting net stablecoin flows. We calculate net flows by netting out stablecoin flows for every bilateral link between regions. Virtually all stablecoin net flows are outflows from North American wallets ($21.54 bn) to the other regions.

6.2 Stablecoin Flows Between Centralized Exchanges and Self-Custodial Wallets

In this section, we investigate stablecoin transactions between self-custodial wallets and centralized exchanges. Centralized exchanges take a special role in the crypto system, as they offer the most prominent venues for users to exchange fiat currencies and crypto assets. That is, when a user wants to buy a crypto asset with fiat currency, typically the transaction is intermediated by a centralized exchange. Similarly, when a user wants to sell a crypto asset for fiat currency, the transaction is typically intermediated by a centralized exchange.

In figure 8, we present our estimate of stablecoin flows between centralized exchanges and the geographic regions. We begin with the figure on the right hand side, depicting gross flows. For centralized exchanges, we separately depict Binance and Coinbase as the two individual exchanges that are involveved in the largest amount of flows. All other exchanges are grouped into the "Other CEX" category. In terms of volumes, the critical role of centralized exchanges in bridging the fiat and crypto system becomes obvious. Binance alone processes more volume than any single geographic region of self-custodial wallets. As a general pattern, Binance and the Other CEX facilitate the vast majority of inflows of stablecoins into self-custodial wallets for all geographic regions. In contrast, Coinbase receives far more inflows of stablecoins from self-custodial wallets than outflows. This pattern hints at the possibility that Binance and other exchanges typically facilitate



(a) Gross Flows

(b) Net Flows

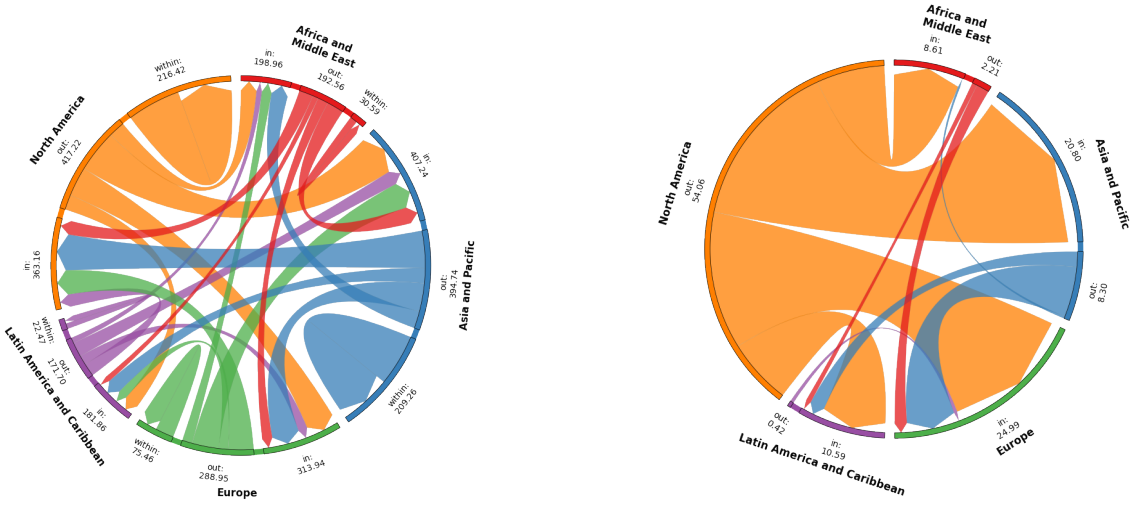
Figure 8: Stablecoin Flows between Self-Custodial Wallets and Centralized Exchanges (in billion dollars)

"on-ramping", that is the exchange of fiat currency for stablecoins, some of which are then further transferred into self-custodial wallets. In contrast, Coinbase may be used more frequently by users wanting to "off-ramp", that is, exchanging stablecoins back into fiat currency. This may also be an expression of the geographic focus of different exchanges. While Binance has stronger ties to regions with more emerging economies, where capital flight motives may be more acute, Coinbase has stronger ties to the American market, and might be better suited for transferring capital into the American financial system.

6.3 Dividing Centralized Exchange Flows into Regional Flows

In this section, we enhance our analysis of region-to-region stablecoin flows by incorporating centralized exchanges. To achieve this, we allocate each centralized exchange's stablecoin flows to specific geographic regions based on the proportion of its trading volume associated with each region. Specifically, for each exchange, we calculate the percentage of its total stablecoin flow volume that is transacted with self-custodial wallets in each region. We then use these percentages to distribute all flows involving the exchange among the regions. This method relies on the assumption that the geographic distribution of self-custodial wallets interact-

ing with the exchange approximates the geographic distribution of the exchange's users. A key advantage of this approach over the web traffic-based assumption employed by Chainalysis is that it does not assume that CEX users do not use VPNs and that the average transaction sizes across regions are uniform. By utilizing volume data, our method inherently accounts for regional differences in transaction sizes. The resulting allocation of stablecoin flows is illustrated in Figure 9. The left-hand side figure illustrates gross stablecoin flows, while the right



(a) Regional Stablecoin Gross Flows

(b) Regional Stablecoin Net Flows

Figure 9: Regional Stablecoin Gross and Net Flows
(in billion dollars)

hand-side illustrates net flows. The relative breakdown of the flows is very similar to the breakdown of flows between self-custodial wallets depicted in 7. This indicates that the interactions of self-custodial wallets with CEXs, which we have used to assign the CEX flows, is not meaningfully different from the interactions of self-custodial wallets with self-custodial wallets.

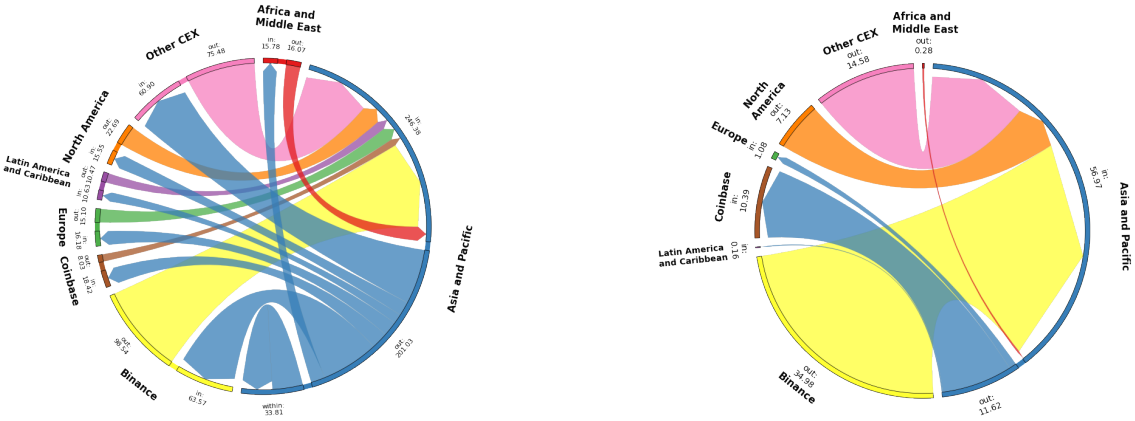
As before, North America and Asia and Pacific are the largest regions in terms of absolute stablecoin flows, while Africa and Middle East, and Latin America and Caribbean exhibit larger flows relative to GDP (6.7% and 7.7% respectively). Inter region flows again are more important than within-region flows, supporting the narrative that stablecoins are used for international capital flows and remittances.

For net flows, the most significant flow is an outflow from North America totalling $54.06bn, flowing into all other regions, satisfying some of the global demand for dollars. Furthermore, the operational mechanics of stablecoin issuance

may structurally position North America as a natural "exporter" of stablecoins. Specifically, (eligible) users—likely more often located in North America due to greater access to fiat dollars—transfer $1 in fiat currency to issuers, who then mint an equivalent value in stablecoins. Price stability is maintained through arbitrage: when a stablecoin's market price exceeds $1, North American participants can profitably exchange fiat dollars for newly issued stablecoins and sell them on secondary markets, reinforcing the region's net outflow position (see Makarov and Schoar (2022)).

6.4 Regional Focus: Asia and Pacific

In this section, we focus on the region of Asia and Pacific, which we estimate to have the largest stablecoin flows among the geographic regions, with $246bn inflows, $201bn outflows and $34bn within-region flows. To focus on the Asia and Pacific region, we plot the flow diagrams under the restriction that the sender or receiver region must be Asia and Pacific. That is, we exclude flows that do not involve Asia and Pacfic. The resulting diagrams are depicted in Figure 10 below.



(a) Gross Flows

(b) Net Flows

Figure 10: Stablecoin Flows Involving Asia and Pacific (in billion dollars)

Beginning with gross flows in the left hand side figure, the importance of CEXs is immediately obvious. Flows between Asian self-custodial wallets and centralized exchanges account for a large fraction of the overall flows. Binance is the single most important centralized exchange, facilitating $32bn dollars in flows out of Binance into Asia and Pacific self-custodial wallets, while only $21bn dollars flows back from self-custodial wallets into Binance. Noticeably, Coinbase plays a minor

role in the region, contrary to its importance on a global scale involving other regions (cf. Figure 8). That said, the general pattern that Binance facilitates flows into self-custodial wallets, while Coinbase facilitates flows out of self-custodial wallets persists. In terms of flows with other regions, flows are biggest with North America. It is also noticeable that flows with Africa and Middle East are relatively sizable, possibly spurred by large migrant populations from India and Pakistan working in the Middle East, and by Chinese FDI activity in Africa.

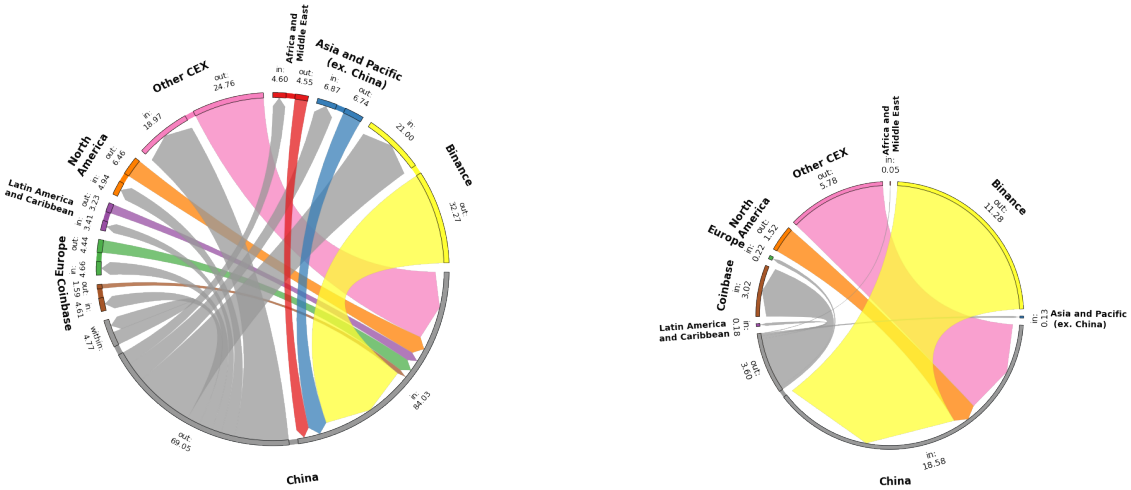
In terms of net flows, depicted in the right hand side figure, there are significant flows into Asia and Pacific self-custodial wallets. Most importantly, facilitated through Binance ($35bn), other CEXs ($15bn) and from North American self-custodial wallets ($7bn). There are outflows into Coinbase ($10bn) and to Europe ($1bn), while net flows involving Africa and Middle East, and Latin America and Caribbean are largely balanced.

6.5 Country Focus: China

Within this section, we offer country level stablecoin flow analysis for China. The reason we take a closer look at China is two-fold. One the one hand, China has anecdotally been described as very active in crypto assets, even though they have officially been banned. On the other hand, current data about crypto capital flows involving China primarily stem from use of the Chainalysis dataset, which assumes that, on average, users do not use VPNs when interacting with CEXs. An assumption that is likely systematically violated when it comes to China. For example, the website Binance.com is not accessible from China without use of a VPN and Binance even hosts a blog post on how to access Binance via VPN as a Chinese user.[12] In fact, our analysis shows that Binance is *the* most important CEX in China in terms of stablecoin flows, despite being accessible by VPN only.

To separate self-custodial wallets in the categories China and Asia and Pacific (ex. China), we train an additional model to separate wallet addresses that have been estimated to be in Asia and Pacific into these sub-categories. The classification model achieves 79% accuracy, and more detailed evaluation metrics are offered in appendix D. We present all stablecoin flows that involve Chinese as the receiver or sender in Figure 11 below. We begin by describing gross flows on the left hand side of the figure. First, we note that Chinese stablecoin flows are in general estimated to be roughly one third of Asia and Pacific flows (all

[12] https://www.binance.com/en/square/post/17293683766001



(a) Gross Flows (b) Net Flows

Figure 11: Stablecoin Flows Involving China (in billion dollars)

comparisons cf. Figure 10). That is Chinese inflows are $84.03bn, while Asia and Pacific inflows are $246.38bn, and Chinese outflows are $69.05bn, while Asia and Pacific outflows are $201.03bn. The only exception is flows within the Asia and Pacific region, that is, flows within China ($4.77bn) and vis-a-vis Asia and Pacific (ex. China) ($13.64bn) represent roughly 54% of the within Asia and Pacific flows ($33.81bn), indicating that stablecoin use within Asia may be more important for Chinese users than other users within the Asia and Pacific region. This signifies the importance of stablecoin use in China within Asia and Pacfic, and more generally, on a global scale. Further, the observation that China represents roughly one third of the flows of Asia and Pacific extends towards the estimates vis-a-vis centralized exchanges, and self-custodial wallets of the other regions. That is, our estimates indicate that stablecoin usage in China is, on average, not different from stablecoin usage in Asia and Pacific as a region.

Logically, net flows (as depicted in the right hand side figure) thus also exhibit a similar pattern compared to Asia and Pacific as a whole region, with inflows into Chinese self-custodial wallets from Binance ($11.28bn), Other CEXs ($5.78bn) and North American self-custodial wallets ($1.52bn). Outflows from Chinese self-custodial wallets mostly flow to Coinbase ($3.02bn).

7 Economic Drivers of Stablecoin Flows

While prior sections described patterns in stablecoin flows, the economic forces driving these movements remain underexplored. Existing literature suggest links to capital flow management (CFM) measures, sanctions evasion, and capital flight (e.g., von Luckner et al. (2024), Cerutti et al. (2024), Cardoza et al. (2024)). This section investigates economic drivers of stablecoin demand, focusing on stablecoins' role in meeting global dollar demand, and their sensitivity to systemic shocks, such as the March 2023 U.S. banking crisis.

7.1 Are Stablecoins a Channel for Global Dollar Demand?

Stablecoins are typically minted in the U.S., where issuers convert fiat dollar deposits into digital tokens. Taken together with our previous analysis that showed that stablecoin net flows are largely outflows from North America, we thus hypothesize that net outflows from North America to other regions reflect their demand for U.S. dollars. To test this hypothesis, we generate a panel time series of daily net stablecoin flows from North America to the other geographic regions from January 1, 2021, to December 31, 2024. Then, we estimate the following regression:

$$\text{Net Flows vs NA}_{r,t} = \beta_1 \text{VIX}_t + \beta_2 \text{Broad Dollar}_t + \beta_3 \text{Crypto F\&G}_t + \alpha_{r,m} + \text{Weekend} + \epsilon_{r,t}$$

Here, Net Flows vs $\text{NA}_{r,t}$ denotes net flows between North America and region r on day t. The VIX index measures market volatility, signaling safe-haven dollar demand, while the Broad Dollar Index tracks the U.S. dollar's value against a currency basket, reflecting store-of-value motives. The Crypto Fear & Greed Index captures sentiment in crypto markets, potentially affecting stablecoin demand. We include region-by-month fixed effects ($\alpha_{r,m}$) to account for regional and temporal variation, and a weekend dummy to control for cyclical patterns—stablecoin flows tend to be significantly lower during weekends. For the VIX and Broad Dollar Index, weekend or otherwise missing values are interpolated linearly to align with the 24/7/365 nature of stablecoins. Flows are converted to Flows/GDP and divided by their standard deviation for normalization. Standard errors are clustered at the time level, but not at the region level due to the sample only having 4 regions besides North America.

Results. (Table 9) show that a stronger U.S. dollar (higher Broad Dollar In-

dex) significantly increases outflows and that higher volatility (VIX) also boosts outflows, though with marginal significance. Both results provide support to the hypothesis that stablecoin serve to satisfy some of the global dollar demand. Conversely, bullish crypto sentiment (higher Crypto Fear & Greed Index) reduces outflows, hinting at possible substitution toward riskier crypto assets like Bitcoin.

Variable	**Estimate**
VIX	0.0127*
	(0.0076)
Broad Dollar	0.0058***
	(0.0022)
Crypto Fear & Greed	-0.0042***
	(0.0016)
Region × Month FE	✓
Weekend FE	✓
Observations	5,844

*p<0.10, **p<0.05, ***p<0.01

Table 9: Are Stablecoins Satisfying Global Dollar Demand?

Next, we extend this analysis to China. For this, we create a time series using our China specific estimates, as outlined in section 6.5. The data consists of daily observations from January 1, 2021 to December 31, 2024. In addition to net flows between North America and China, we consider net flows between Binance and China. We add net stablecoin flows vis-a-vis Binance as figure 11b indicates that they are the most important centralized exchange in facilitating net stablecoin flows into Chinese self-custodial wallets. Further, we replace the Broad Dollar Index with the USD/CNY exchange. The resulting regression is:

$$\text{Net Flows vs (NA+Binance)}_t = \beta_1 \text{VIX}_t + \beta_2 \text{USD/CNY}_t + \beta_3 \text{Crypto F\&G}_t + \alpha_m + \text{Weekend} + \epsilon_t$$

Results (Table 10) confirm that a stronger dollar versus the Rinmimbi (higher USD/CNY) drives inflows to China, with volatility (VIX) showing a positive, marginally significant effect. The negative Crypto Fear & Greed coefficient again suggests substitution effects.

These results collectively indicate that stablecoins channel dollar demand, particularly when the dollar strengthens or markets turn volatile—a pattern consistent across global and China-specific analyses.

Variable	Estimate
VIX	0.0177*
	(0.0104)
USD/CNY	0.1149***
	(0.0529)
Crypto Fear & Greed	-0.0049***
	(0.0020)
Month FE	✓
Weekend FE	✓
Observations	1,461

*p<0.10, **p<0.05, ***p<0.01

Table 10: Are Stablecoins Satisfying Chinese Dollar Demand?

7.2 Did the March 2023 Banking Crisis Disrupt Stablecoin Flows?

To further highlight the utility of datasets that can be derived through the methodology laid out in this paper, we present novel evidence of the impact of the March 2023 US banking crisis on stablecoin flows. Stablecoin issuers rely on banks to manage fiat reserves and to settle the fiat leg of stablecoin issuance and redemption transactions. During stablecoin issuance, customers have to send fiat to stablecoin issuers, while during redemption stablecoin issuers have to return fiat to their customers—transactions that have to be facilitated by banks. The March 2023 banking crisis exhibited failures of several crypto-related institutions (Silicon Valley Bank, Signature Bank, Silvergate) that provided banking services to both stablecoin issuers and centralized crypro exchanges. When these banks failed, the fiat currency side of stablecoin issuance was disrupted. As a consequence, we hypothesize that this shock caused a distruption in North American stablecoin flows. Using a difference-in-differences approach, we compare weekly flows originating from North America (treated group) to weekly flows originating from other regions (controls) over five weeks pre- and post-crisis. We set the treatment day to be March 10th 2023, the day Silicon Valley Bank collapsed and was put under FDIC receivership. We estimate the event study style differences in differences regression:

$$\text{Flows from Region}_{r,t} = \alpha_r + \alpha_t + \sum_{\substack{\tau=-5,\\ \tau\neq -1}}^{\tau=5} (1\{\text{Treated}\}1\{\tau = t\}) + \epsilon_{r,t}$$

Flows are demeaned and divided by their standard deviation for normalization. **Results** (Figure 12, Table 13 in appendix F) show parallel pre-trends with a slight upward bias, highlighting that the other geographic regions are reasonable controls for North America. On impact of the shock, stablecoin flows originating from North American drop dramatically, exhibiting a decrease of nine standard deviations relative to controls. While there are signs of recovery over time, the effect persists up to five weeks later at a reduction in stablecoin flows of around 3 standard deviations. This underscores the banking sector's critical role in stablecoin markets and the disruption that the March 2023 banking crisis has caused for the sector.

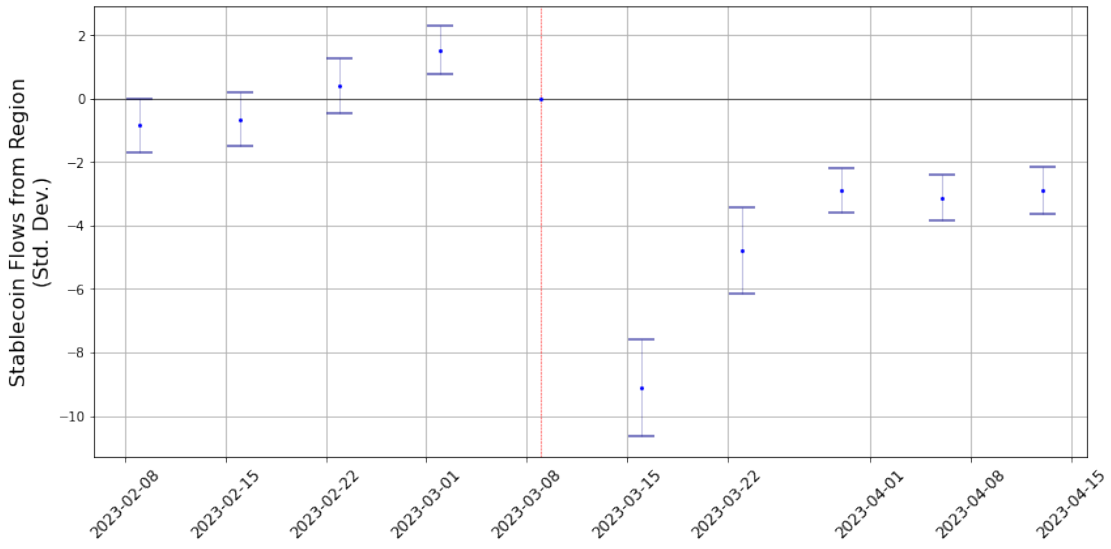


Figure 12: Impact of March 2023 Banking Crisis on Stablecoin Flows

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A Regional Centralized Exchanges

Region	Exchange	Rationale
Africa and Middle East	Altcointrader	Headquartered in South Africa
Africa and Middle East	Arzpaya.com	Focused on Iran region
Africa and Middle East	Artis Turba Exchange	Headquartered in Middle East
Africa and Middle East	Bit2c	Headquartered in Israeli region
Africa and Middle East	Bitoasis	Regulated in Middle East
Africa and Middle East	Luno	Operating in South Africa
Africa and Middle East	Nobitex	Licensed in Iran region
Africa and Middle East	Valr	South Africa based service
Asia and Pacific	Bitbank	Mainly Japan market focus
Asia and Pacific	Bitkub	Licensed in Thailand region
Asia and Pacific	Bithumb	Operating in South Korea
Asia and Pacific	Coindcx	Headquartered in India region
Asia and Pacific	Coincheck	Based in Japan market
Asia and Pacific	Coinhako	Licensed in Singapore region
Asia and Pacific	Coinone	South Korea market focus
Asia and Pacific	Coins.ph	Operating in Philippine market
Asia and Pacific	Gdac	South Korea service focus
Asia and Pacific	GMO Coin	Operating in Japanese market
Asia and Pacific	Gopax	Licensed in South Korea
Asia and Pacific	Indodax	Focus on Indonesian market
Asia and Pacific	Korbit	South Korea regulatory focus
Asia and Pacific	Maicoin	Based in Taiwan market
Asia and Pacific	Tokocrypto	Indonesian market primary focus
Asia and Pacific	Upbit	Primary market: South Korea
Asia and Pacific	Wazirx	Operating in Indian market
Europe	Anycoin Direct	Licensed in Netherlands region
Europe	Bitpanda	Based in Austria region
Europe	Bitvavo	Operating in Netherlands market
Europe	Btcturk	Licensed in Turkey region
Europe	Coinmetro	Headquartered in Malta region
Europe	Exmo	Focus on Eastern Europe
Europe	Firi	Based in Spain region
Europe	Norwegian Block Exchange	Headquartered in Norway region
Europe	Paribu	Operating in Turkey market
Europe	Swissborg	Licensed in Switzerland region
Latin America and Caribbean	Bitso	Based in Mexico region
Latin America and Caribbean	Brasil Bitcoin	Operating in Brazil market
Latin America and Caribbean	C-Patex	Focus on Latin America
Latin America and Caribbean	Lemon Cash	Serving Latin America clientele
Latin America and Caribbean	Mercado Bitcoin	Licensed in Brazil region
Latin America and Caribbean	Orionx	Brazil market regulatory focus
Latin America and Caribbean	Panda Exchange	Primarily Latin America focus
North America	Binance US	Based in United States
North America	Bitbuy	Headquartered in Canada region
North America	Coinsquare	Licensed in Canadian market
North America	Netcoins	Operating in Canadian market
North America	Quadrigacx	Based in Canada region
North America	Shakepay	Licensed in Canada region

Table 11: Exchanges by Region with Brief Rationale

B Daylight Savings Time Graphs

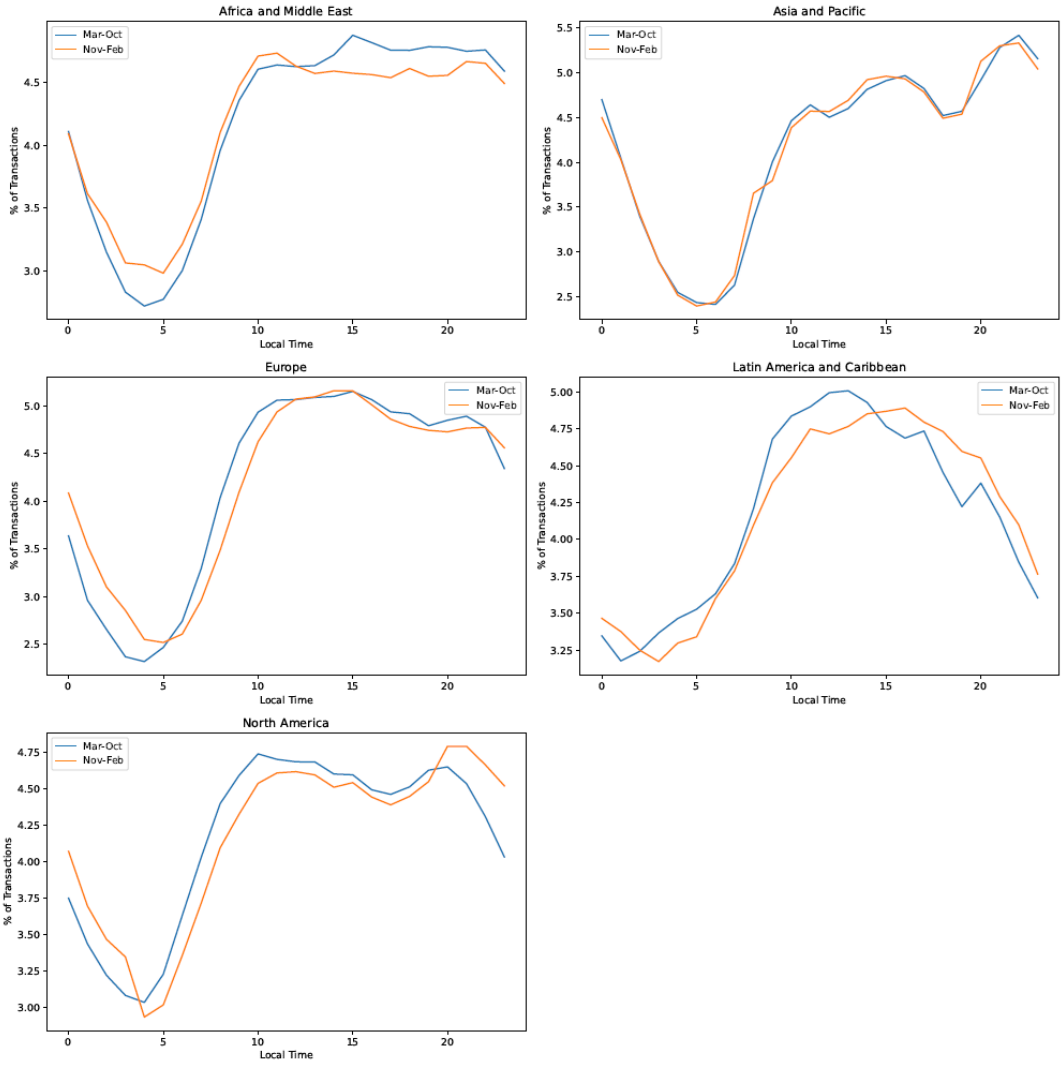


Figure 13: Figures Decpicting Activity During DST and no-DST Months.

C Identifying Additional Centralized Exchange Wallets

We briefly describe how centralized exchanges structure their wallets. There are 4 different types: hot wallets, cold wallets, deposit wallets and gas supplier wallets. Hot wallets are wallets that hold pooled customer funds and are used to send out funds from the exchange to other wallets in on-chain transactions. Cold wallets are

wallets that exchange use for long term storage of funds, are not relevant for our analysis. Last, there are gas supplier wallets that provide gas[13] These addresses are present in the dataset that we get from Dune.

Deposit wallets are wallets that are specifically created for customers when they want to deposit funds into the exchange. These wallets are absent from the Dune dataset. Typically, these addresses immediately forward deposits into the exchange's hot wallets and do not engage in any other activities. We identify and tag these wallets in the data if they (1) only forward funds to hot wallets of an exchange or (2) have receives gas from a gas supplier wallet.

D Model Evaluation

[13]Gas measures the computational effort needed to process on-chain transactions. Users must pay for gas used, typically with the native protocol crypto asset, which for the blockchains in our sample is Ether, except on Binance Smart Chain which uses Binance Coin.

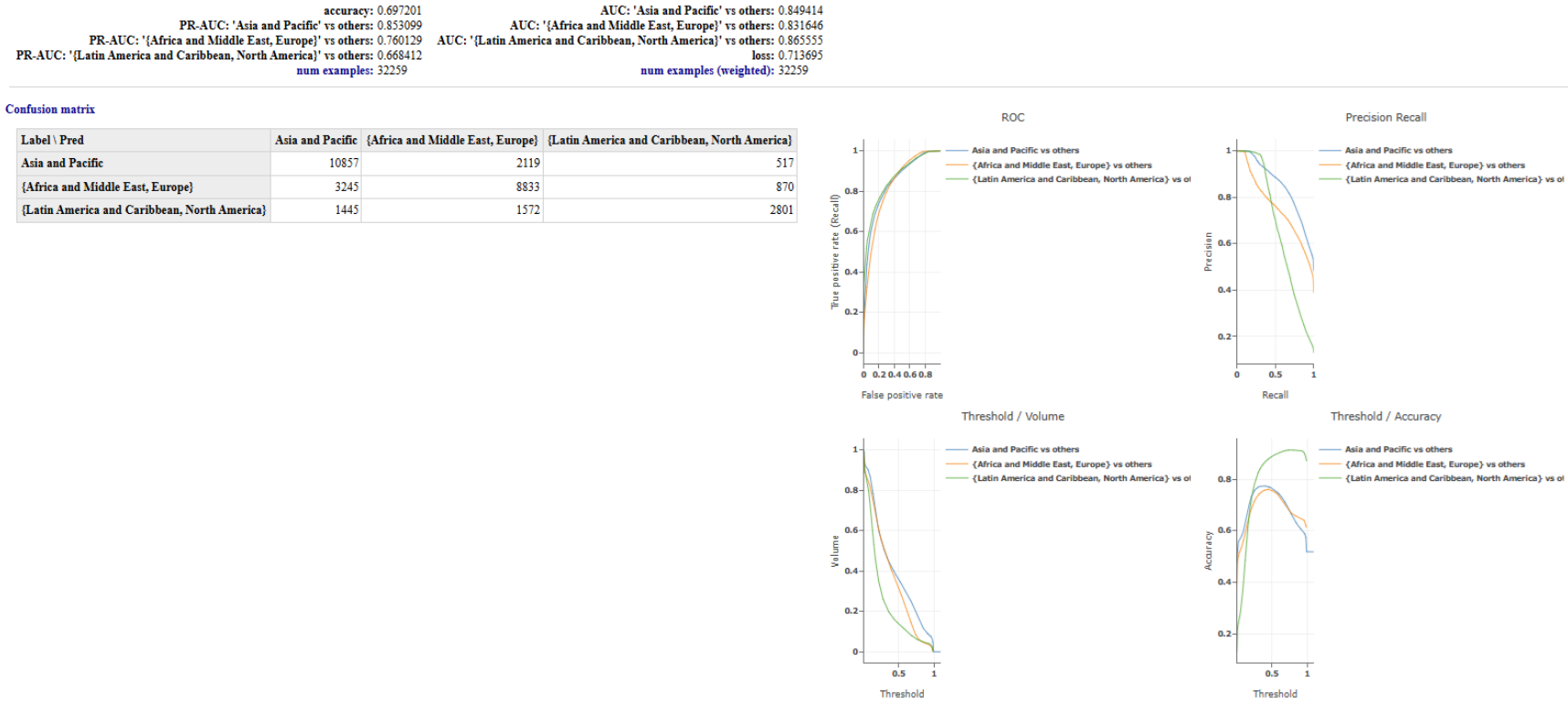


Figure 14: Model Evaluation for First model

accuracy: 0.844556 **AUC: 'North America' vs others:** 0.894665
PR-AUC: 'North America' vs others: 0.979059 **loss:** 0.334371
num examples: 4188 **num examples (weighted):** 4188

Confusion matrix

Label \ Pred	Latin America and Caribbean	North America
Latin America and Caribbean	428	475
North America	176	3109

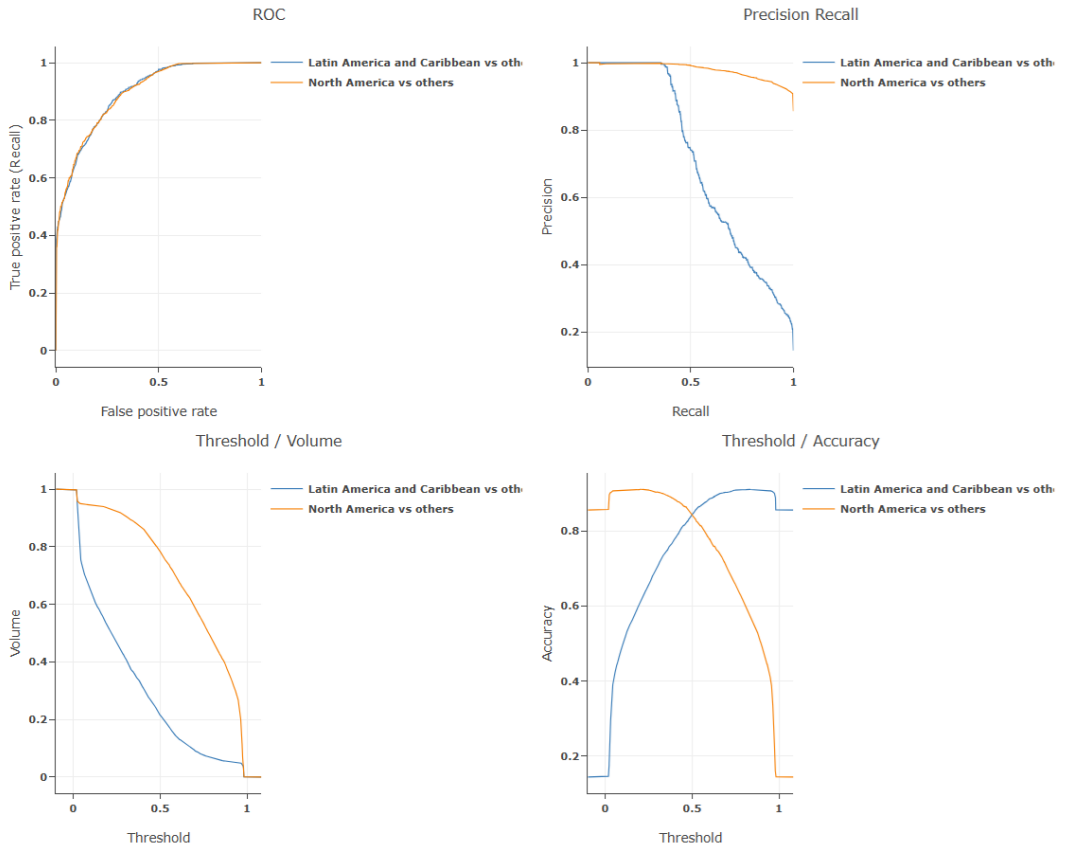


Figure 15: Model Evaluation to Distinguish Latin America and Caribbean from North America

accuracy: 0.782098 **AUC: 'Europe' vs others:** 0.805675
PR-AUC: 'Europe' vs others: 0.930036 **loss:** 0.476119
num examples: 12524 **num examples (weighted):** 12524

Confusion matrix

Label \ Pred	Africa and Middle East	Europe
Africa and Middle East	1641	1808
Europe	921	8154

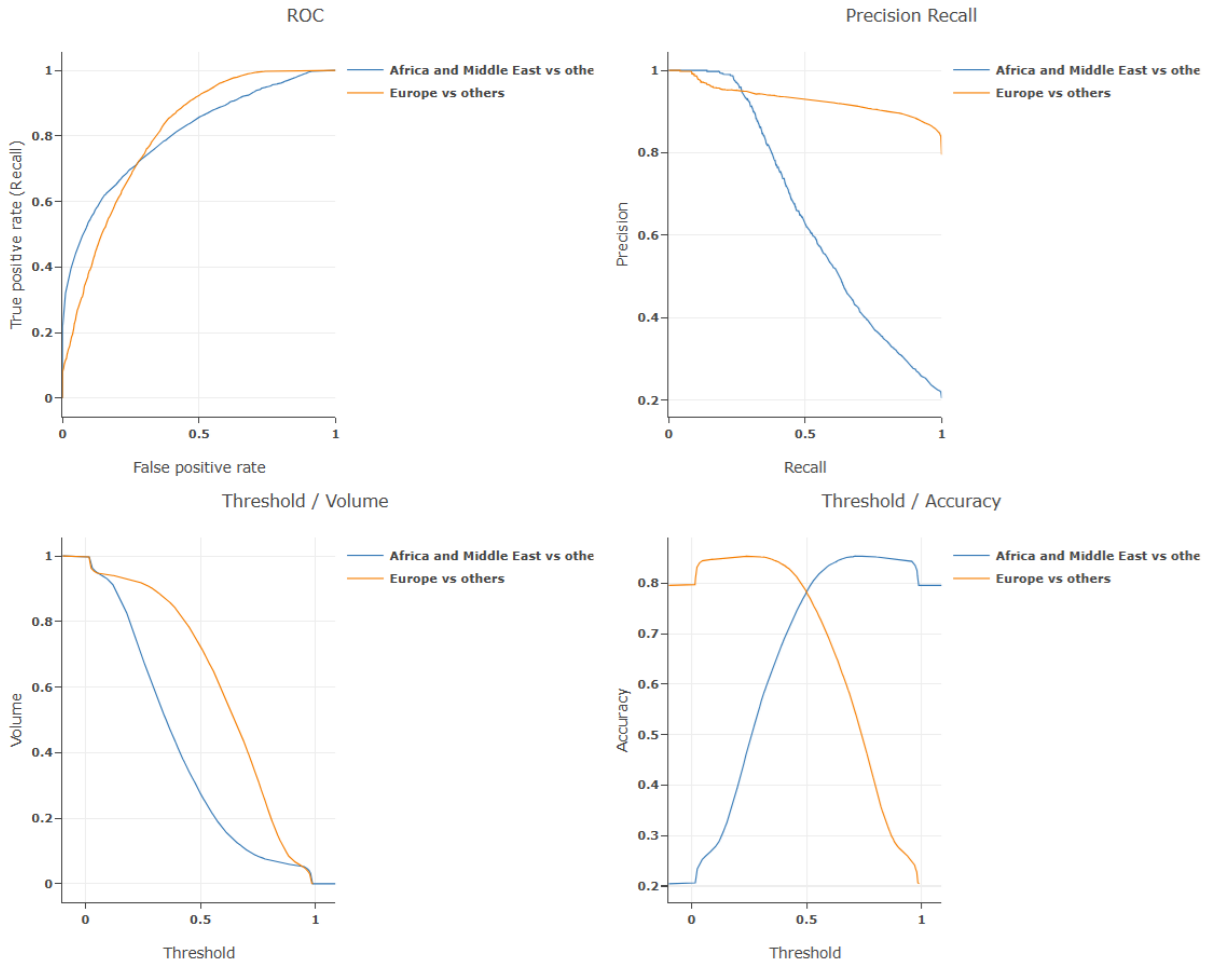


Figure 16: Model Evaluation to Distinguish Africa and Middle East from Europe

accuracy: 0.823239 **AUC: 'non-China' vs others:** 0.911902
PR-AUC: 'non-China' vs others: 0.96429 **loss:** 0.392763
num examples: 155464 **num examples (weighted):** 155464

Confusion matrix

Label \ Pred	China	non-China
China	37068	20940
non-China	6540	90916

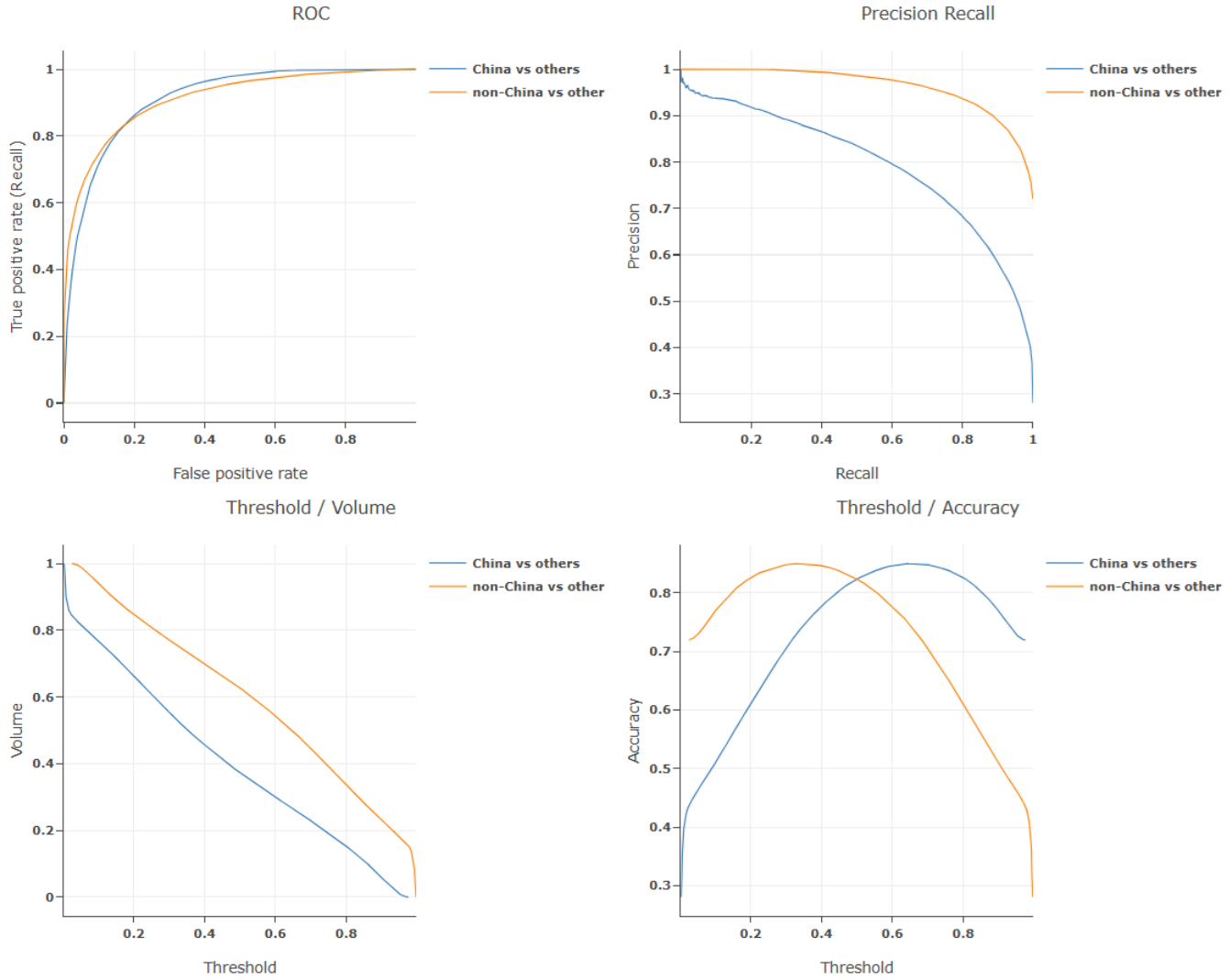


Figure 17: Model Evaluation to Distinguish China from the Rest of Asia

E Manually Assigned Wallets

Address	Region	Entity
0x55fe002aeff02f77364de339a1292923a15844b8	North America	Circle
0xad6eaa735d9df3d7696fd03984379dae02ed8862	North America	Cumberland
0x87b49a99cbce4a9030e67919b776aa97d538adda	North America	Cumberland
0xf584f8728b874a6a5c7a8d4d387c9aae9172d621	North America	Jump Trading
0x0548f59fee79f8832c299e01dca5c76f034f558e	North America	Genesis Trading
0xd628f7c481c7dd87f674870bec5d7a311fb1d9a2	North America	Genesis Trading
0x84d34f4f83a87596cd3fb6887cff8f17bf5a7b83	North America	Alameda Research
0xe31a9498a22493ab922bc0eb240313a46525ee0a	North America	Alameda Research
0x17d70306956a6a4b4f9319ad9b9de43e98382f5e	North America	Alameda Research
0x2f2be7c998a2abcf0caa32d1b7da714ea0a0e2d2	North America	Alameda Research
0x83a127952d26ced22410cb1dbe4bfe2676bc63bd	North America	Alameda Research
0xb560da83a2c351fca35e5ebadba2a82fd525d4c3	North America	Alameda Research
0x1d77f556ee0dbd8b07a7bd4fa461ad24d35543ba	North America	Alameda Research
0x0ae80df72ad0620b1d34d1ec31fa43415bfe0afc	North America	Alameda Research
0x882a8127d5aee37c82ba1449f28e1252e3ee6620	North America	Alameda Research
0x82a505ad68bc9a10a96f807df60078ef75bd5e56	North America	Alameda Research
0x01811f428f03682d43db8d1bbf242dcd05acbe9f	North America	Alameda Research
0x8be32560a42a378d349ba0d69d54b210b31d9efb	North America	Alameda Research
0xa8553cfb14d2321f0cf2cadae36bf2d607a552ed	North America	Alameda Research
0x9ea14a8379152f42d39d24239100ca4546722d92	North America	Alameda Research
0x75ec94e298dc0e3b00c30955c94edb40049a2a44	North America	Alameda Research
0x4a9f2de50756c756fad90c3037bf1f39676ff701	North America	Alameda Research
0x67dce0c45fc2e38812a8602ea6ff7b4eb90c839b	North America	Alameda Research
0xb9bd20ec7b4d24bc115ef24724ad04d851b2b9b0	North America	Alameda Research
0x0a4d88a90b0b9c53bd2d167fede915ffbe2238fe	North America	Alameda Research
0x7a66dc0da224955e8256d9c289ef345c7cb8d229	North America	Alameda Research
0x875b7f1d8f1986f369dd08c801ef47f64e8c320a	North America	Alameda Research
0x7cf4ce48bf3b7e3139c25c017978a71b2ba293be	North America	Alameda Research
0x84806f88e475f556883a607e1d9b0c3fe79ef15f	North America	Alameda Research
0x30da8f270a92a2ab076392b4ab72bfaa476ca1d1	North America	Alameda Research
0xa8cfec07a38c5b3fa0b5ae7fe1f71412ced385fa	North America	Alameda Research
0x3507a4978e0e83315d20df86ac0b976c0e40ccb	North America	Alameda Research
0x83a127952d266a6ea306c40ac62a4a70668fe3bd	North America	Alameda Research
0xdbf5e9c5206d0db70a90108bf936da60221dc080	Europe	Wintermute
0x8aceab8167c80cb8b3de7fa6228b889bb1130ee8	Europe	Celsius
0x4862733b5fddfd35f35ea8ccf08f5045e57388b3	Asia and Pacific	Three Arrows Capital
0x3ddfa8ec3052539b6c9549f12cea2c295cff5296	Asia and Pacific	Justin Sun

Table 12: Blockchain addresses manually assigned to regions

F Results of Differences in Differences Regression for 2023 US Banking Crisis

Variable	Estimate
Pretrend at t=-5	-0.8559**
	(0.4055)
Pretrend at t=-4	-0.6594
	(0.4115)
Pretrend at t=-3	0.3869
	(0.4229)
Pretrend at t=-2	1.5221***
	(0.3698)
Pretrend at t=-1	[Normalized to 0]
Treatment Effect at t=0	-9.1013***
	(0.7456)
Treatment Effect at t=1	-4.7942***
	(0.6650)
Treatment Effect at t=2	-2.8943***
	(0.3391)
Treatment Effect at t=3	-3.1306***
	(0.3485)
Treatment Effect at t=4	-2.9062***
	(0.3624)
Time FE	✓
Region FE	✓
Observations	50

*p<0.10, **p<0.05, ***p<0.01

Table 13: Effect of March 2023 Banking Crisis on Stablecoin Flows