Bridge the Gap: Geography of Cryptocurrency Flows and Access to the Banking System

Abstract

This study examines the interplay between cryptocurrency and banks in cross-border payment markets. This study uses the on-chain data to analyze the impact of a shock to the cross-border bank payment system on the estimated geographic distribution of cryptocurrency flows. A difference-in-differences design reveals that, following the SWIFT ban on Russian banks, Bitcoin inflows to cryptocurrency exchanges from Russia increased more than those from other countries. Concurrently, Bitcoin outflows from cryptocurrency exchanges to treated countries increased more than those to untreated countries. In the cross-section, the disparities in Bitcoin outflows from exchange platforms to treated versus control countries after the SWIFT ban are more pronounced in countries with lower banked populations and lower costs of bank-intermediated cross-border payments. The evidence highlights the potential of blockchain-powered cryptocurrency in providing a digital cross-border payment option and lowering cross-border payment costs.

Keywords: banking; cryptocurrency; cross-border payment; blockchain; on-chain; off-chain

JEL codes: F24; G15; G23; O33

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1. Introduction

Cryptocurrencies represented an overall market capitalization of about $2 trillion as of December 2023, with participation from both institutional and retail investors. Globally, the number of cryptocurrency users has increased from 5 million in 2016 to 516 million in 2023 (Statista, 2023). However, more is needed to know about the user segments that cryptocurrency serves. Does cryptocurrency meet the demand that would otherwise be unmet by banks and traditional financial intermediaries or compete with banks for the same clientele? Does cryptocurrency disproportionately benefit the population with access to banking services or those without financial access? This issue is essential for assessing the economic implications of cryptocurrency adoption. If cryptocurrencies complement banks, cryptocurrency expands access for the unbanked population or individuals underserved by the existing financial system. If cryptocurrencies compete directly with banks, cryptocurrency adoption is mainly limited to the banked population.

Compared with a traditional payment system, where a third-party financial intermediary makes sure funds are sent and received correctly and where banks of the sender and the receiver validate transactions, only the sender and the recipient participate in a peer-to-peer (P2P) payment system using cryptocurrencies. In theory, cryptocurrency could complement or substitute for the existing banking system. On the one hand, because bank accounts are *unnecessary* for storing, sending, and receiving cryptocurrency in crypto wallets, the payment system using cryptocurrencies allows the unbanked population to bypass the conventional banking system. On the other hand, existing banking customers could switch to cryptocurrencies as substitutes for bank payments due to greater convenience and lower costs.

This study uses the ban of Russian banks from the Society for Worldwide Interbank Financial Telecommunication (SWIFT) as an exogenous shock to investigate the interplay between banks and cryptocurrency in the cross-border payment market. SWIFT sends more than 40 million messages daily, and 1% of those messages involve Russian payments. Notably, significant movements of people out of Russia and associated physical cash transfers likely changed the overall need (demand) for cross-border payments after the SWIFT ban. In light of this shift in demand, it becomes uncertain whether cross-border cryptocurrency payments will increase or decrease after the SWIFT ban.

As cryptocurrency is not a widely accepted payment method, most users convert cryptocurrencies to fiat currencies through cryptocurrency exchanges. Using the on-chain data from CryptoQuant, this study finds an overall marked increase in Bitocin inflows (outflows) to (from) cryptocurrency exchanges during the week after initiating the SWIFT ban on February 26th, 2022, compared to the week before. On March 25, 2024, the U.S. imposed secondary sanctions on foreign crypto platforms that partnered with various sanctioned Russian banks to evade the SWIFT ban. This study finds a marked *decrease* in Bitocin inflows (outflows) to (from) cryptocurrency exchanges during the week after the secondary sanction compared to the week before. Furthermore, this study observes a marked *increase* in the number of Bitcoin (Stablecoins) active sending and receiving addresses in the week after initiating the SWIFT ban compared to the week before. Assuming that the *average* number of addresses per user stays intact within the two-week window, the increase in active sending and receiving addresses indicates an increased number of users that transfer money on the blockchain in response to the SWIFT ban, highlighting the potential of blockchain-powered cryptocurrency in broadening financial access.

A more pointed question is the *geographical distribution* of the change in Bitcoin flows in response to the SWIFT ban. Due to the pseudo-anonymity of users on the blockchain, it is rather challenging to obtain the *precise* amount of cryptocurrency inflows (outflows) to (from) individuals and entities residing in a particular country. This study uses a combination of on-chain data and web traffic analytics to overcome this significant empirical difficulty in estimating the more granular cryptocurrency inflows (outflows) to (from) a country. In particular, I take the following two steps to estimate the on-chain Bitcoin inflow (outflow) to (from) entities and individuals residing in country *i* via exchange platform *p* on day *t*. First, this study obtains the on-chain Bitcoin inflow (outflow) to (from) exchange platform *p* on day *t* from CryptoQuant. Second, this study uses SimilarWeb, which provides the *geographical* distribution of web traffic for the platform's URL address, to allocate this platform's Bitcoin inflow(outflow) to various countries. For instance, Binance received 13,159 Bitcoin on the day when seven Russian banks were removed from the SWIFT. Based on SimilarWeb, Russia, Belarus, and Turkey account for 4.7%, 0.6%, and 6.7% of web traffic on Binance.com, respectively. Accordingly, the Bitcoin inflow from Russia, Belarus,

and Turkey to Binance is estimated at 618 (4.7% of 13,159), 79 (0.6% of 13,159), and 908 (6.7% of 13,159), respectively.

The sample includes 19,656 country-platform-day observations that cover 78 countries and 18 major exchange platforms. These eighteen cryptocurrency platforms have the most significant flows on the blockchain, whose combined inflows (outflows) account for 92% (91%) of total inflows (outflows) to (from) *all* cryptocurrency exchanges during the corresponding period. Using the more granular *country-level* inflows (outflows) to (from) an exchange platform, this study employs a difference-in-differences design to identify the effect of the SWIFT ban on the geographical distribution of Bitcoin flows. This study finds a *marked* increase in Bitcoin inflows from Russia to cryptocurrency exchanges after initiating the SWIFT ban. In contrast, Bitcoin inflows from other (non-banned) countries increase *moderately* during the corresponding period. The wedge in Bitcoin inflows from Russia versus other countries widened sharply after the SWIFT ban. Specifically, during the week after the SWIFT ban, there are substantial increases in Bitcoin inflows from Russia to the following four exchange platforms: FTX, Bitfinex, Kucoin, and OKX. Then, this paper uses a difference-in-difference design to identify the effect of the SWIFT ban on the destinations of Bitcoin outflows from cryptocurrency exchanges. I classify countries receiving bank-intermediated remittances from Russia in the pre-shock period as treated countries and the remaining countries as the control group. After controlling for migration, technological, and regulatory factors, this study finds that Bitcoin outflows from exchange platforms to treated countries are significantly higher than those to the control group *after* the SWIFT ban. As some treated countries received more bank-intermediated remittances from Russia than others, this study uses a recipient country's share of bank-intermediated remittances sent from Russia before the SWIFT ban as a *continuous* proxy for the *intensity* of the treatment effect. When the treatment effect is continuous, Bitcoin outflows from cryptocurrency exchanges to treated countries remain significantly higher after the SWIFT ban.

In summary, the difference-in-differences results in Bitcoin flows indicate that more users in Russia switched from banks to cryptocurrency for cross-border payments after the SWIFT ban. On one side, Bitcoin inflows from Russia to cryptocurrency exchanges increased more than from other countries after

the SWIFT ban. On the other side of the flow, after the SWIFT ban, Bitcoin outflows from cryptocurrency exchanges to countries that received more bank-intermediated remittances from Russia in the pre-shock period are significantly higher than those to countries that received less Russian outward remittances.

A more intriguing question is how the effect of the SWITT ban varies with the destination country's access to the banking system in the *cross-section*. To address this question, similar to Tang (2019), this study first develops a conceptual framework in which the relation between banks and cryptocurrency is defined by the clientele they serve in equilibrium. Cryptocurrency provides the banked population with a substitute product if the user segments that cryptocurrencies serve are individuals with banking access. If cryptocurrencies operate as *perfect* substitutes for banks, the effect of the SWIFT ban will be *more* pronounced in treated countries with higher *banked* populations. However, cryptocurrency complements banks if the user segments that cryptocurrencies serve are individuals *without* banking access. If cryptocurrencies operate as *perfect* complements for banks, the effect of the SWIFT ban will be *more* pronounced in treated countries with higher *unbanked* populations. Empirically, after controlling for migration and migrants' differential sensitivity to bankruptcy/crash risks, this study finds that the disparities in Bitcoin outflows from cryptocurrency exchanges to treated versus control countries after the SWIFT ban are *more pronounced* in countries with *lower* banked populations. Moreover, such disparities remain more pronounced for countries with lower banked populations when a country's share of bank-intermediated remittances sent from Russia in the pre-shock period is used to proxy for the intensity of the treatment effect. The cross-sectional variation suggests that some users without banking access used cryptocurrency for digital cross-border payments *even before* the shock. It implies a more robust complementarity between banks and cryptocurrency in countries with more limited access to the banking system.

A related cross-sectional question is how the effect of the SWITT ban varies with the costs of bank-intermediated cross-border payments. Empirically, this study finds that the disparities in Bitcoin outflows from cryptocurrency exchanges to treated versus control countries after the SWIFT ban are *more pronounced* when the costs of bank-intermediated cross-border payments are *lower* in the pre-shock period. When the treatment effect is continuous, such disparities remain more pronounced when the costs of bank-

intermediated cross-border payments are higher. The comparative statistic suggests that more users were incentivized to use cryptocurrency for cross-border payments when the costs of bank-intermediated payments were higher *even before* the SWIFT ban. As a result, the SWIFT ban has a less pronounced effect because users in those countries experienced a more *subdued* shift from bank payments to cryptocurrency.

Next, this study calibrates the economic significance of cross-border remittances for cryptocurrency inflows (outflows) to (from) cryptocurrency exchanges. Survey evidence suggests that 23 percent of respondents used at least one type of cryptocurrency for online cross-border remittances (PYMNTS, 2021). While Bitcoin has a limited adoption problem due to the need for consensus and the existence of network delay (e.g., Hinzen, John, and Saleh, 2022), remittance is a natural use case because cryptocurrency helps mitigate significant frictions in bank remittances, including high fees, slow processing times, and regulatory barriers. This study estimates that the decline in bank-intermediated remittances sent from Russia (16.8 billion in 2022 relative to 5.8 billion in 2021) accounts for 18% of the total value of $61.3 billion worth of Bitcoin outflows from exchange platforms to all treated countries in 2022. As banks do not directly exchange Bitcoin for U.S. dollars, the most common method is to trade Bitcoin for a stablecoin, such as USDT, on a centralized exchange and then convert it into fiat currency. The value of Stablecoins outflows from cryptocurrency exchanges to all treated countries was estimated at $4.6 billion during the *week* immediately after the SWIFT ban.

Moreover, as the percentage of the banked population is not exogenous, this study uses a change specification (equivalent to including country-fixed effects) to alleviate the concern for time-invariant omitted correlated variables. This study finds that, after controlling for contemporaneous changes in economic, technological, and regulatory factors, annual on-chain cryptocurrency flows (deflated by GDP) decrease in the percentage of the banked population, corroborating the documented complementarity between banks and cryptocurrency based on the short-window event studies. To further substantiate the bank-cryptocurrency interplay, this study finds that a lack of trust in financial institutions discourages financial account ownership but increases the reliance on blockchain-powered control systems to mitigate counterparty risks, thereby increasing the *on-chain* cryptocurrency flows. Interestingly, as a placebo test, a

lack of trust in financial institutions cannot explain the geography of *off-chain* crypto transactions that continue to rely on third-party financial intermediation, such as buying and selling Bitcoin via centralized exchange platforms.

This study contributes to the literature on financial institutions and financial intermediation. It provides *new* insights into the interplay between cryptocurrency and banks in cross-border payment markets by using the on-chain data to analyze the impact of a shock on the cross-border bank payment system on the geographic distribution of cryptocurrency flows. It provides the first large-sample *cross-country* evidence that the SWIFT ban has a more pronounced effect on Bitcoins and Stablecoins outflows from cryptocurrency exchanges to treated countries with lower banked populations. The comparative statistic suggests that unbanked users could benefit from cryptocurrency as a digital cross-border payment option, implying a more robust bank-cryptocurrency complementarity in countries with limited access to the banking system. Furthermore, this study documents that the SWIFT ban has a less pronounced effect on cryptocurrency outflows from exchange platforms to treated countries when the costs of bank-intermediated cross-border payments are higher before the shock. The less pronounced effect suggests that higher costs of the bank-intermediated cross-border payments incentivized more users to switch from bank to cryptocurrency transfers *even before* the negative shock to the cross-border bank payment system. Overall, the evidence highlights the potential of blockchain-powered cryptocurrency in providing services to the unbanked population and lowering costs in the cross-border payment market.

This study differs from prior studies in several aspects. Conceptually, much of the emerging literature focuses on the use case of cryptocurrency as a vehicle for investment and speculation (e.g., Makarov and Schoar, 2020; Liu and Tsyvinski, 2021) and the verification mechanism of cryptocurrency (e.g., Easley, O'Hara, and Basu, 2019; Cong, He, and Li, 2020). While Huberman, Leshno, and Moallemi (2021) analyze the Bitcoin payment system in a theoretical model, this paper is among the first empirical studies to focus on the use case of cryptocurrency as an option for cross-border payments. This study investigates the interplay between banks and cryptocurrency in the previously under-explored cross-border payment market. Moreover, this study is related to but distinct from prior studies on fintech platforms (e.g., Buchak

et al., 2018; Fuster et al., 2019; Berg et al., 2020). First, previous studies typically use a fintech platform in a specific country as the setting and focus on the *distribution* of fintech-enabled financial access among participants with differing socioeconomic statuses and credit scores *within* the country. In contrast, this study emphasizes the distribution of on-chain cryptocurrency inflows (outflows) to (from) exchange platforms *across* countries with varying *percentages* of banked populations and differing *costs* of bank-intermediated remittances in response to the SWIFT ban. Second, as documented in previous studies, enhanced financial access typically relies on the financial intermediation of fintech platforms. In contrast, this study uncovers a distinct mechanism by focusing on on-chain cryptocurrency flows that operate independently of financial intermediaries.

Furthermore, this study provides insights into the evolving regulatory process for sanctions against Russia and its effectiveness. This is the first study to systematically *quantify* the cross-country distribution of cryptocurrency inflows and outflows on the blockchain before and after the SWIFT ban on Russian banks. On-chain cryptocurrency flows indicate that more users in Russia switched from banks to cryptocurrency for cross-border payments after the SWIFT ban. Specifically, this study documents a marked increase in Bitcoin inflows from Russia to exchange platforms during the week after the SWIFT ban, especially to platforms dominated by non-U.S. users, such as FTX, Bitfinex, Kucoin, and OKX. On-chain data reveals a more substantial Bitcoin and Stablecoins outflow from exchange platforms to treated countries than to the control group after the SWIFT ban. Interestingly, this study also documents a *decrease* in overall cryptocurrency inflows (outflows) to (from) exchange platforms after the U.S. imposed secondary sanctions against foreign exchange platforms that partnered with sanctioned Russian banks to evade sanctions. The evidence collectively underscores the effectiveness of the *proposed* legislation that imposes secondary sanctions on foreign exchange platforms or "transaction facilitators" that assist or support transactions with sanctioned Russian entities. The proposed secondary sanctions could level the playing

field for U.S. cryptocurrency firms by requiring foreign crypto platforms to comply with U.S. sanctions (or risk losing access to the U.S. market and financial system).[1]

2. Institutional Background and the Conceptual Framework

2.1. Institutional background on cross-border payments and cryptocurrency

Cross-border payments are financial transactions where the sender and the recipient are based in different countries. Wholesale cross-border payments are typically between financial institutions to support customers' or cross-border operating activities. Retail cross-border payments are usually made among individuals and businesses, and the key types include person-to-person, person-to-business, and business-to-business. Digital payments far exceed cash payments in the cross-border person-to-person payment market. Figure 1 depicts the flow chart of the bank-intermediated cross-border payment process. The system's basic structure consists of four main components: sender, recipient, payment service provider, and payment system. The sender is the person who initiates the transfer of funds to the recipient, and the recipient is the person who receives the funds in another country. The payment service provider is the entity that facilitates the transfer of funds between the sender and the recipient, such as a bank, a money transfer operator (MTO), or a mobile money provider. The payment system is the network of institutions and mechanisms that enable the transfer of funds between service providers in different countries, such as correspondent banking or payment platforms. However, high fees, slow processing times, foreign exchange settlement risk, and regulatory barriers are significant frictions in the bank-intermediated cross-border payment process. First is the additional foreign exchange settlement risk. In the receiving country, an MTO must buy the receiving currency from their correspondent bank and sell equivalent foreign currency. The exchange rate may deteriorate during this process, increasing foreign exchange settlement risk. Second is the complicated regulatory environment. Each country issues a separate set of guidelines on issuing licenses

[1] Several cryptocurrency exchanges have adopted know-your-customer (KYC) measures that facilitate the enforcement of sanctions. For example, in March 2022, Coinbase, the largest U.S. cryptocurrency exchange, blocked 25,000 accounts and wallets tied to suspected Russian entities.

for MTOs to send and receive money out of the country, transaction processing, and settlement mechanisms. Third is the risk of illicit activities and money laundering. Financial institutions are expected to ensure due diligence of cross-border transactions and stakeholders regarding business models, know-your-customers checks, anti-money laundering (AML), and combating the financing of terrorism (CTF). With strict regulations concerning AML/CFT, financial institutions cut MTO partnerships and increase transaction fees. All those factors make the bank-intermediated cross-border payment process more complex and expensive.

Cryptocurrencies like Bitcoin enable value transfer directly between the sender and receiver without financial intermediaries. Blockchain is a distributed ledger technology that supports cryptocurrencies. A decentralized network of "miners" secures the authenticity of past transactions but also prevents the double-spending problem (the possibility that an individual could duplicate and spend the cryptocurrency simultaneously at two or more places) via the consensus mechanism known as Proof of Work (PoW). Easley, O'Hara, and Basu (2019) and Cong, He, and Li (2020) study the mechanism and the incentives for Bitcoin mining. Miners use hashes (long strings of numbers) to detect tampering, and confirmed transactions are posted to a universal ledger. While users can navigate the blockchain and review transactions for *quantity*, the identities of the buyer and seller are protected by encryption. PoW makes it extremely difficult to change any aspect of the blockchain, as such a change would require remining all subsequent blocks. Blockchain uses a technology-based mechanism to ensure the independent verifiability of transactions and the pseudo-anonymity in the identities of counterparties.

Conceptually, blockchain is a technology-based control system that can remove the need for a trusted third-party intermediary. Although blockchain-based control systems could substitute for trust in financial institutions, blockchain does not *eliminate* the need for trust because blockchain does not solve human problems. Even if the computer codes that provide the foundation for blockchain-powered control systems work flawlessly, humans design, implement, and use blockchains. Crypto markets are fraught with fraudulent and illegal activities, such as money laundering and terrorist financing (Amiram, Jorgensen, and Rabetti 2022), price manipulation (Griffin and Shams 2020), illicit activities (Foley, Karlsen, and Putniņš

2019), and frauds. Blockchain helps remove intermediaries in the money transfer process and has the potential to reduce costs and increase transaction speeds. Cryptocurrency significantly cuts the cost of sending money internationally. For instance, sending Bitcoin to another wallet costs an average of $1.50 per transaction (Cointelegraph, 2021). In contrast, the average cost of bank-intermediated cross-border remittance is $14.80 in the United States (PYMNTS, 2021). Preliminary data from a limited-scope pilot run by the Stellar Development Foundation suggests that fees for remittances sent on a blockchain were half those paid for traditional remittances. Furthermore, while bank-intermediated cross-border payments take between one and three days to settle, cryptocurrency payments take, on average, just minutes or hours. Accordingly, cryptocurrency provides a cheaper but faster alternative in the cross-border payment market.

A unique feature of cryptocurrency as a cross-border payment option is that bank accounts are *not* required to store, send, or receive cryptocurrency in crypto wallets. For instance, Local Bitcoins, with over 1 million active users, is one of the largest P2P crypto platforms and offers several payment methods, such as cash and prepaid mobile phone cards, for buying Bitcoin with *no* bank account. Users without bank accounts can also use Bitcoin ATMs to convert between Bitcoin and local fiat currency. Anecdotally, Bitcoin ATMs installed in small pizza places in Kyrgyzstan transformed remittances (Guardian, 2014). According to Tradingbrower.com, while the percentage of the unbanked population is 60% in Mexico, it ranks third in the number of Bitcoin ATMs installed. Thus, a P2P payment system using cryptocurrencies bypasses the traditional banking system, potentially enabling the 1.7 billion unbanked population globally to participate in the cross-border payment market. A related advantage of cryptocurrency is its accessibility. Anyone with a smartphone and access to the internet can transfer funds across borders. Therefore, families of migrant workers who live in less developed areas and may not have access to traditional banking services could quickly receive cross-border remittances via cryptocurrency.

Remittances, a subset of cross-border payments, refer to money that immigrants transfer from the host country to their home countries. Remittances are economically substantial and a vital source of foreign income for many developing countries, sometimes surpassing foreign direct investment and overseas development assistance. According to the World Bank, global remittances sent to low-income and middle-

income countries totaled $626 billion. The top five countries are Tonga (44.9%), Lebanon (37.8%), Samoa (33.7%), Tajikistan (32%), and Kyrgyz Republic (31.2%) in terms of remittances received as a percentage of gross domestic product. While MTOs, such as Western Union, MoneyGram, and Ria, dominated the *overall* cross-border payment market, immigrants *mostly* use bank wire transfer services for remittances. The bank-intermediated cross-border remittance process charges high fees and takes more time. Globally, the average cost of sending $200 was 6.5% in 2022, which doubles the Sustainable Development Goal target of 3%. The excessive costs of bank remittances impose disproportionately higher financial burdens on immigrants who are underserved or excluded by traditional financial institutions.

The PYNMTS survey provides insights into using cryptocurrency for cross-border remittances (PYNMTS, 2021). First, 23 percent of respondents used at least one type of cryptocurrency for online cross-border remittances. Cryptocurrency was the most used payment method for 13 percent of respondents. Second, 46% of those using cryptocurrency for cross-border payments send remittances directly into a mobile wallet. By comparison, only 30 percent of those who make bank transfer remittances send them to mobile wallets. Third, half of those who make cryptocurrency cross-border P2P payments are motivated to choose a specific provider if the option of sending or receiving payments in cryptocurrency is available.

Despite the rise in cryptocurrency, bank transfers and credit cards are the most frequently used payment methods for sending cross-border remittances online. Autonomous Research estimated that cryptocurrency accounts for approximately 1% of cross-border remittance transfers as of June 2021 (Reuters, 2021). The ability for users to transfer value from local fiat currencies to cryptocurrency or vice versa has historically been a challenge. Crypto-to-fiat offramps are the gateways that allow customers to convert cryptocurrency into fiat currency *easily* without the need for *technical* expertise. Once a user registers with an offramp service provider and goes through the verification process through an app, the person deposits cryptocurrency into the account and converts the deposited cryptocurrency into the desired fiat currency. Then, the user can withdraw the converted fiat currency to selected destinations. For instance, a service provider, payouts. cash launched a product where cryptocurrency sent is instantly converted to the receiver's local fiat currency and provides liquidity to customers in 3 minutes. With these new developments, a sender

could transfer money in their local currency, and instantaneously, the recipient could receive remittances in their local currency without exposure to cryptocurrency price volatility. Blockchain makes cross-border remittances more accessible and cheaper, and the ability to send and receive money cross-border instantaneously is transformative.[2] Thus, cryptocurrency will likely account for a *larger* share of global remittances in the foreseeable future.

2.2. Conceptual framework for the interplay between banks and cryptocurrency

To guide the empirical investigation of the interplay between banks and cryptocurrency in the cross-border payment market, this study develops a simple conceptual framework in which cryptocurrency and the bank-intermediated payment system coexist and compete. Each payment channel via bank or cryptocurrency offers a service menu specifying payment instruments and costs. The market reaches an equilibrium when each user, with or without access to banking services, chooses the optimal instrument-cost combination offered. The bank-cryptocurrency relation is defined by the clientele they serve in equilibrium. Considering the percentage of the population with access to banking services is γ, let $\alpha(\gamma) \in [0,1]$ be the fraction of the banked population who use *cryptocurrencies* for cross-border payments and $1-\alpha(\gamma)$ be the fraction of the banked population who use *banks* for cross-border payments. For a given user, the two channels are perfect substitutes if $0 < \alpha(\gamma) < 1$ and perfect complements if $\alpha(\gamma)$ is either 0 or 1.

SWIFT is a global financial messaging network that enables banks to exchange electronic messages and financial transactions securely. Financial institutions use SWIFT in over 200 countries, and it is the most influential infrastructure in financial services regarding the volume and value of money transferred. Russia is ranked second globally in terms of the number of users of SWIFT in 2021. Seven Russian banks were banned from SWIFT in the initial phase. Another three Russian banks, including

[2] Besides banks and traditional MTOs, online money transfer platforms have emerged as new players in cross-border payment markets. However, the innovation for online money transfer platforms primarily focuses on the *front-end (the client-facing)* side, such as providing better customer services. The *back end* of online money transfer platforms still uses the legacy *banking* infrastructure such as clearing (NSCC), payment (ACH), and messaging (SWIFT) systems, which is in sharp contrast to blockchain-powered cryptocurrency payments.

Sberbank, the largest bank in Russia, were banned in the second phase. A direct effect of the SWIFT ban is a decrease in cross-border bank payments from and to Russia via SWIFT.

Now, consider the SWIFT ban's impact on cryptocurrency inflows (outflows) to (from) cryptocurrency exchanges. It is uncertain whether cryptocurrency flows will increase or decrease after the SWIFT ban for *several* reasons. The SWIFT ban likely forced more users in Russia to switch from banks to cryptocurrency for cross-border remittances to families overseas and more users outside of Russia to send cryptocurrency remittances to families in Russia. The Department of Treasury and a private-sector blockchain analytic firm find little evidence that wealthy Russians or the Russian government successfully use cryptocurrencies for *large-scale* sanctions evasion (CRS 2022). While the crypto market's *inherent* capacity constraints limit *large-scale* sanctions evasion, cryptocurrency provides some avenues for *small-scale* sanctions evasion, such as through unregulated wallets and exchanges. Notably, there were significant movements of people out of Russia and associated physical cash transfers after the outbreak of the war. Emigrants from Russia surged almost threefold, rising from 238,020 in 2021 to 668,433 in 2022. The surge in emigration likely changed the overall need (demand) for cross-border payments out of Russia via either banks or cryptocurrency after the SWIFT ban. Moreover, the SWIFT ban and the trade embargo have altered correlation dynamics in business-to-business cross-border flows. For instance, to bypass the SWIFT ban, Russian businesses could use alternative methods for international payment transfers, such as utilizing banks in non-sanctioning countries. Several major economies, including Brazil, China, India, Mexico, Saudi Arabia, and the United Arab Emirates, have not imposed sanctions on Russia.

Under the assumption that the cross-border payment market reaches a new equilibrium within a reasonable period after the SWIFT ban, I derive predictions about how the effect of the SWIFT ban on cryptocurrency flows on the blockchain varies with the percentage of the banked population in the destination country. To streamline the discussion, I first consider two polar cases—where banks and cryptocurrencies are either perfect substitutes or perfect complements—and then discuss an intermediate case. Each case is characterized by γ (the percentage of the banked population) and α (the fraction of the banked population that cryptocurrencies serve) in the destination country.

First, let us consider cryptocurrencies operating as perfect substitutes for banks. In this case, cryptocurrency provides banked users with a substitute product and does *not* serve the "unbanked" population before the SWIFT ban. That is, $0 < \alpha(\gamma) < 1$. Given that the percentage of the banked population is γ and that cryptocurrencies solely serve the segment of individuals with banking access, the fraction of the *entire* population that cryptocurrencies served *before* the SWIFT ban is $\alpha*\gamma$. The SWIFT ban affects the banked population *only*. If the fraction of individuals with banking access in destination countries that received cryptocurrency from Russia via exchange platforms increases by β after the SWIFT ban, the fraction of the *entire* population that cryptocurrency serves increases by $\beta*\gamma$. Therefore, after the SWIFT ban, the fraction of the banked population in the destination country that receives cryptocurrency from Russia is $(\alpha + \beta)$, and the fraction of the *entire* population that receives cryptocurrency from Russia is $(\alpha +\beta) *\gamma$. As $(\alpha + \beta)$ is positive, cryptocurrency outflows from exchange platforms to destination countries *increase* in the percentage of the banked population (γ). Accordingly, when the segments that cryptocurrencies serve are primarily users with banking access, i.e., banks and cryptocurrency are perfect substitutes, the effect of the SWIFT ban on cryptocurrency outflows from exchange platforms is more pronounced in recipient countries with *higher* banked populations.

Second, let us consider the case of cryptocurrencies operating as perfect complements for banks. In this case, banks serve users with banking access (the "banked" population), whereas cryptocurrency solely serves users without banking access (the "unbanked" population) before the SWIFT ban. That is, $\alpha(\gamma) = 0$. Assume that the fraction of the "unbanked" population that cryptocurrency serves is π. Given that the percentage of the unbanked population is $(1-\gamma)$, the faction of the *entire* population that cryptocurrencies served before the SWIFT ban is $(1- \gamma) *\pi$. If the fraction of individuals with banking access in destination countries that received cryptocurrency from Russia via exchange platforms increases by β after the SWIFT ban, the fraction of the *entire* population that cryptocurrency serves increases by $\beta*\gamma$. Therefore, after the SWIFT ban, the fraction of the *entire* population that cryptocurrency serves is $[(1-\gamma)*\pi+\beta*\gamma]$, which is equivalent to $[\pi+(\beta-\pi)*\gamma]$. As cryptocurrency primarily serves the "unbanked" population, it is reasonable to assume that the increase in the fraction of the banked population that received cryptocurrency after the

SWIFT ban (β) is less than the fraction of the unbanked population that received cryptocurrency before the ban (π). As (β-π) is negative, cryptocurrency outflows from exchange platforms to destination countries *decrease* with the percentage of the banked population (γ). Accordingly, when the user segments that cryptocurrencies serve are primarily users *without* banking access, i.e., banks and cryptocurrency are perfect complements, the effect of the SWIFT ban on cryptocurrency outflows from exchange platforms is more pronounced in recipient countries with *lower* banked populations.

The comparison indicates that the SWIFT ban has the same effect on the *quantity* of cryptocurrency outflows from exchange platforms under these two cases. However, the two contrasting cases have opposite effects on how the effect of the SWIFT ban on cryptocurrency outflows *varies* with the percentage of the *banked* population in the destination country. If the user segments that cryptocurrencies serve are individuals *with* access to banking services, the SWIFT ban will likely have a more pronounced effect on cryptocurrency outflows to recipient countries with *higher* banked populations. However, if the user segments that cryptocurrencies serve are individuals *without* banking access, the SWIFT ban will likely have a more pronounced effect on cryptocurrency outflows to recipient countries with *lower* banked populations. Those opposite predictions help distinguish between the perfect substitute and complement cases. Moreover, the conceptual framework accommodates intermediate cases between perfect substitutes and complements. For instance, cryptocurrency may serve a small fraction of banked users while primarily catering to unbanked users. In this case, compared to banks, cryptocurrency serves a more extensive range of users. The cross-sectional variation of the effect of the SWIFT ban on cryptocurrency outflows depends on the *relative* extent of substitution and complementarity between banks and cryptocurrency.

3. Identifying the SWIFT Effect on Cryptocurrency Inflows to Exchange Platforms

3.1. Overall trend in Bitcoin inflows to cryptocurrency exchanges

Using an event-study methodology, this study first examines the overall Bitcoin inflows to *all* cryptocurrency exchanges in response to the SWIFT ban. Figure 2 graphs the cumulative 7-day Bitcoin flows before and after three key events associated with the SWIFT ban. I use the cumulative 7-day window

to account for the potential anticipation of upcoming sanctions after the outbreak of the Russian-Ukaine war on February 20, 2022. First, on February 26, 2022, the European Union, the United States, the United Kingdom, Canada, and Japan agreed to ban selected Russian banks (*unnamed* at this point in time) from SWIFT. Seven Russian banks were named and removed from the SWIFT on March 2, 2022. As illustrated in Panel A, based on the blockchain data provided by CryptoQuant, there is a marked increase in Bitcoin inflows to all cryptocurrency exchanges after initiating the SWIFT ban. Second, on May 4, 2022, three additional Russian banks, including Sberbank, the Credit Bank of Moscow, and the Russian Agricultural Bank, were removed from the SWIFT. This second phase of the SWIFT ban is potentially significant because Sberbank, the largest bank, accounted for one-third of banking services in Russia. As illustrated in Panel B, based on the blockchain data provided by CryptoQuant, there was a further increase in Bitcoin inflows to all cryptocurrency exchanges after those three banks were added to the sanctioned list. Then, on March 25, 2024, the U.S. imposed secondary sanctions on foreign cryptocurrency platforms that assist targeted Russian entities in evading sanctions. Targeted cryptocurrency platforms include Joint Stock Company B-Crypto and Masterchain, both of which partnered with multiple sanctions Russian banks to facilitate cross-border settlements. As illustrated in Panel C, based on the blockchain data provided by CryptoQuant, there was a marked *decline* in Bitcoin inflows to all cryptocurrency exchanges after the secondary sanctions on cryptocurrency platforms. The patterns illustrate an overall increase in Bitcoin transferred to cryptocurrency exchanges on the blockchain in response to the SWIFT ban and an overall *decline* in Bitcoin inflows to cryptocurrency exchanges in response to secondary sanctions on cryptocurrency platforms that assist targeted Russian entities in evading sanctions.

3.2. Difference-in-differences design in inflows to cryptocurrency exchanges

A more pointed question is whether the increase in Bitcoin inflows during the week after the SWIFT ban is driven by an *abnormal* increase in Bitocin inflows *from Russia* to cryptocurrency exchanges. It is impossible to calculate the *exact* number of Bitcoin inflows from a particular country to cryptocurrency exchanges due to the pseudo-anonymity of users on the blockchain. To *estimate* Bitcoin inflows at the more granular *country* level, I obtained the on-chain Bitcoin inflow to a particular cryptocurrency exchange

and the geographical distribution of web traffic for this platform. Specifically, I take the following two steps to estimate the on-chain Bitcoin inflow from entities and individuals residing in country *i* to an exchange platform *p* on day *t*. First, I obtain the on-chain Bitcoin inflow to exchange platform *p* on day *t* from CryptoQuant. Second, I use SimilarWeb, which provides the *geographical* distribution of web traffic for the platform's URL address, to allocate the platform's on-chain Bitcoin inflow from various countries. For instance, Binance received 13,159 Bitcoin on the day when seven Russian banks were removed from the SWIFT. Based on SimilarWeb, Russia, Belarus, and Turkey account for 4.7%, 0.6%, and 6.7% of web traffic on Binance.com, respectively. Accordingly, the Bitcoin inflow from Russia, Belarus, and Turkey to Binance is estimated at 618 (4.7% of 13,159), 79 (0.6% of 13,159), and 908 (6.7% of 13,159), respectively. The estimation methodology has one caveat: web traffic tools cannot *precisely* identify the URL address and the user's location if a user uses mixers or VPN services. Notably, the estimated Bitcoin inflow captures the volume of Bitcoin *transferred* from country *i* to cryptocurrency exchange *p* on the blockchain. The estimated on-chain Bitcoin inflows are distinct from the volume of buying and selling cryptocurrencies on centralized exchange platforms carried out *off* the blockchain.

Specifically, I use the following difference-in-difference design to identify the disparity in on-chain inflows from Russia versus other countries to cryptocurrency exchanges during the two-week window before and after the initiation of the SWIFT ban on February 26, 2022:

$$Ln(INFLOWTOEXCHANGE)ipt = \alpha + \beta 1 * RUSSIAi + \beta 2 * POSTt + \boldsymbol{\beta 3 * RUSSIAi * POSTt} + \beta 4 * UKRAINEi + \beta 5 * UKRAINEi * POSTt + Platform\ Fixed\ Effect + \varepsilon \qquad Equation\ (1)$$

where *i* denotes countries, *p* denotes exchange platforms, and *t* indexes time. The dependent variable is the natural log of $INFLOWTOEXCHANGE_{ipt}$, the number of Bitcoin inflow from country *i* to crypto exchange platform *p* on day *t*. The panel is perfectly balanced, with half of those observations during the 7-day window leading up to the initiation of the SWIFT ban on February 26th, 2022, and the remaining half during the 7-day window *after* the ban. In order to mitigate the influence of confounding factors, such as other types of sanctions imposed on Russia, the starting date of the event window is deliberately set to be February 20th, 2022 to ensure that both the pre-window and the post-window fall *after* the outbreak of the Russian-

Ukraine war. $RUSSIA_i$ is a dummy variable set to 1 for Russia and 0 otherwise. $POST_t$ is a dummy variable set to 1 for the week after the SWIFT ban and 0 for the week leading up to the ban. The model includes the indicator variable for Ukraine ($UKRAINE_i$) as a control variable to account for the possibility that people in Ukraine are also worried about their savings in banks or security markets and thus purchase more cryptocurrencies (as safe assets).

Panel B of Table 1 presents the sample formation. The sample used in the analysis includes 19,656 country-platform-day observations that capture Bitocin inflows from 78 countries to 18 cryptocurrency exchanges over the 14-day window. CryptoQuant provides *exchange*-level data on Bitcoin inflows to 21 cryptocurrency exchanges, and SimilarWeb provides data on web traffic analytics for 31 cryptocurrency exchanges during the sample period. The following 18 exchanges have information on both on-chain Bitcoin inflows and web traffic analytics: Binance, Binance.us, Bitfinex, Bitflyer, Bithumb, Bitstamp, Bittrex, CeX, Coinbase, Ftx, Gemini, Hitbtc, Korbit, Kraken, Kucoin, Okx, Poloniex, and Yobit. The combined Bitcoin inflow to those 18 exchange platforms accounts for 91% of the total inflow to *all* cryptocurrency exchanges during the corresponding period. With a short panel of one week before the SWIFT ban and another week after the SWIFT ban, clustering standard errors by week is subject to the "too few clusters" issue, which biases standard errors downwards (Angrist and Pischke, 2009; Cameron et al., 2008; Cameron and Miller, 2015). Therefore, standard errors in the estimation are cluster-adjusted by country-platform pairs, equivalent to 1404 (78*18) clusters. The variable of interest is the slope coefficient on $RUSSIA_i*POST_t$, which is expected to be positive if the wedge in Bitcoin inflows to cryptocurrency exchanges from Russia versus other countries widens after initiating the SWIFT ban.

Table 2 provides descriptive statistics of the main variables. The mean (median) Bitcoin inflow from country *i* to exchange platform *p* on day *t* is 22.16 (0.55). However, the cross-exchange and cross-country variation is substantial: the standard deviation is 256.6 with a minimum of 0 and a maximum of 15,104. This study then sums up Bitcoin inflows from country *i* across 18 cryptocurrency exchanges on day *t* and uses this aggregated value as the daily on-chain Bitcoin inflow from this particular country. Figure 3 graphs the estimated rolling 7-day average Bitcoin inflows to cryptocurrency exchanges from Russia versus other

countries on the blockchain. The rolling 7-day average Bitcoin inflow from Russia to cryptocurrency exchanges is consistently higher than from other countries before and after the SWIFT ban. However, the SWIFT ban triggered a differential pattern between Russia and other countries. There is a marked increase in Bitcoin inflows from Russia to cryptocurrency exchanges starting two days before the announcement of the SWIFT ban. In contrast, the increase in Bitcoin inflows from other (non-banned) countries is relatively moderate after the SWIFT ban. Compared to the period before, the wedge in Bitcoin inflows between Russia and other countries widened sharply after the SWIFT ban. Regarding specific exchange platforms, this study observes the *largest* increase in Bitcoin inflows from Russia to the four exchanges: Ftx, Bitfinex, Kucoin, and OKx.

Table 3 reports the difference-in-differences results in cryptocurrency inflows to exchange platforms. As noted in column 1, when the dependent variable is Bitcoin inflows, the slope coefficient on $RUSSIA_i*POST_t$ is 0.056 and statistically significant with a *p*-value of 0.01. The positive coefficient on the interaction term suggests that Bitcoin inflows to cryptocurrency exchanges from Russia were 5.75% higher than those to other countries *after* the SWIFT ban, compared with the prior week. The higher Bitcoin inflows from Russia to exchange platforms imply a substitution effect between banks and Bitcoin when the cross-border banking system is disrupted. Additionally, this study examines the Ethereum and Stablecoins inflows to exchange platforms during the corresponding period. As reported in column 2, the slope coefficient on *RUSSIAi*POSTt* is not statistically significant when the dependent variable is Ethereum inflows to cryptocurrency exchanges. Similarly, as reported in column 3, the slope coefficient on *RUSSIAi*POSTt* is not statistically significant when the dependent variable is Stablecoins inflows to cryptocurrency exchanges.

4. Identifying the SWIFT Effect on Cryptocurrency Outflows from Exchange Platforms

4.1. Overall trend in cryptocurrency outflows

Using an event-study methodology, this study examines the overall Bitcoin outflows from *all* cryptocurrency exchanges in response to the SWIFT ban. Panel B of Figure 2 illustrates a marked increase

in Bitcoin outflows from all cryptocurrency exchanges after initiating the SWIFT ban on February 26, 2022. Panel D of Figure 2 illustrates a marked increase in Bitcoin outflows from all cryptocurrency exchanges after instituting the second phase of the SWIFT ban. Panel F of Figure 2 shows a marked *decline* in Bitcoin outflows from all cryptocurrency exchanges after imposing secondary sanctions on cryptocurrency platforms that assisted sanction-evading Russian banks. The patterns illustrate an *overall* increase in Bitcoins transferred out of exchange platforms on the blockchain in response to the SWIFT ban and an overall decline in Bitcoin outflows from cryptocurrency exchanges in response to secondary sanctions on cryptocurrency platforms that assist targeted Russian entities in evading sanctions.

4.2. Overall trend in active sending and receiving addresses

Section 3.1 and section 4.1 explore the overall trend in the number of *Bitcoins* transferred to and from cryptocurrency exchanges on the blockchain, but not the number of *users* on the blockchain. Assuming that the average number of addresses *per user* on the blockchain does not change over a short window, the number of active sending and receiving addresses of all cryptocurrency exchanges is a reasonable proxy for the number of unique users on the blockchain during the two-week window before and after the initiation of the SWIFT ban. Panel A of Figure 4 graphs the rolling 7-day average number of active Bitcoin sending and receiving addresses on the blockchain before and after initiating the SWIFT ban. There was a marked increase in the number of addresses that *sent* Bitcoin on the blockchain after initiating the SWIFT ban. Similarly, there was a marked increase in the number of addresses that *received* Bitcoin on the blockchain after initiating the SWIFT ban. The largest increase in sending and receiving addresses coincided with the three-day window immediately after the initiation of the SWIFT ban on February 26, 2024.

As banks do not directly exchange Bitcoin for U.S. dollars, the most common method is to transfer cryptocurrencies to a centralized exchange and then trade for a stablecoin. A stablecoin, such as USDT, can be converted into fiat currency, which then moves to a local bank account. Panel B of Figure 4 graphs the rolling 7-day average number of active Stablecoins sending and receiving addresses on the blockchain before and after initiating the SWIFT ban. After initiating the SWIFT ban, there was a marked increase in the number of addresses that either sent or received all types of Stablecoins on the blockchain. The largest

increase in the number of sending addresses occurred within two days immediately after the announcement of a SWIFT ban on (unnamed) Russian banks on February 26, 2022. The largest increase in receiving addresses occurred within three days immediately after initiating the SIFT ban. In summary, the overall trend in active sending and receiving addresses highlights increased users and possibly broader participation on the blockchain after the SWIFT ban.

4.3. Geographical distribution of outflows from cryptocurrency exchanges

A more intriguing question is the *geographical distribution* of *destinations* of the increase in Bitcoin inflows from Russia to cryptocurrency exchanges after the SWIFT ban. Accordingly, this section uses a difference-in-differences design to identify the impact of the SWIFT ban on Bitcoin outflows from cryptocurrency exchanges. Based on the cross-border bilateral transfer estimated by the World Bank, I classify countries that received at least 0.1% of bank-intermediated remittances originating from Russia and Belarus in 2021 (the last year before the SWIFT ban) as treated countries. The World Bank data captures remittances sent and received through formal channels like banks and money transfer operators. Bank-intermediated remittances sent from Russia in 2021 totaled $16.4 billion. Treated countries include Armenia, Azerbaijan, Belarus, China, Czech, Estonia, France, Georgia, Germany, Hungary, Israel, Kazakhstan, Kyrgyzstan, Latvia, Lithuania, Moldova, Mongolia, Poland, Russia, Tajikistan, Ukraine, and Uzbekistan. The remaining countries are classified as the control group. As a sensitivity check, I exclude Russia, Ukraine, and Belarus from the analysis to eliminate confounding factors for the three countries. $TREATED_i$ is a dummy variable set to 1 for countries that received at least 0.1% of outward remittances from Russia in 2021 and 0 otherwise.

Figure 5 graphs the estimated rolling 7-day average Bitcoin outflows from cryptocurrency exchanges to treated versus control countries on the blockchain. Treated countries received at least 0.1% of bank-intermediated cross-border payments from Russia before the SWIFT ban in 2021. There was a *parallel* uptick in Bitcoin outflows from treated and control countries *two days* before initiating the SWIFT ban, which implies a certain level of market anticipation of the SWIFT ban. However, the rolling average Bitcoin outflows from treated countries were consistently higher than those from control countries by 40 Bitcoins

during the one-week window *before* the SWIFT ban, suggesting that the parallel assumption underlying the DID design holds. Starting the official announcement of the SWIFT ban, this study observed a *widened* wedge in on-chain Bitcoin outflows from cryptocurrency exchanges to treated versus control countries the entire week after the SWIFT ban. For instance, the wedge in Bitcoin outflows from cryptocurrency exchanges to treated versus control countries grew to 43 Bitcoins on the official announcement day of the ban. Then the wedge peaked at 67 Bitcoins four days after the SWIFT ban.

Specifically, to control for other factors that could influence Bitcoin outflows from cryptocurrency exchanges, I use the following model to identify the impact of the SWIFT ban on Bitcoin outflows from cryptocurrency exchanges to treated versus control countries during the two-week window before and after the initiation of the SWIFT ban:

$$\boldsymbol{Ln(OUTFLOWFROMEXCHANGE)ipt} = \alpha + \beta 1 * TREATED(RUSBANKREMIT)i + \beta 2 * POSTt + \boldsymbol{\beta 3 * TREATED(RUSBANKREMIT)i * POSTt} + \beta 4 * BANKEDSHAREi + \beta 5 * POSTt * BANKEDSHAREi + \beta 6 * Ln(IMMIGRANTi) + \beta 7 * POSTt * Ln(IMMIGRANTi) + \beta 8 * INTERNETi + \beta 9 * SMARTPHONEi + \beta 10 * MOBILEMONEYi + \beta 11 * CAPITALCONTROLi + + \beta 12 * INFLATIONi + \beta 13 * FOREXi + \beta 14 * Ln(POP)i + \beta 15 * Ln(GDP)i + \beta 16 * AMLSCOREi + \beta 17 CHGPRRICEt + Platform\ Fixed\ Effects + \varepsilon \qquad Equation\ (2)$$

The dependent variable is the natural log of $OUTFLOWFROMEXCHANGE_{ipt}$, the number of Bitcoin outflow from crypto exchange platform p to country *i* on day *t*. The model includes the proportion of the banked population in country *i* as an explanatory variable ($BANKEDSHARE_i$), obtained from the Global Findex Database (Demirgüç-Kunt et al. 2022). The higher the share of the banked population in country *i*, the greater the potential impact of the SWIFT ban. $POST_t$*$BANKEDSHARE_i$ is also included to account for the possibility that the banked population's share correlates with the SWIFT ban's treatment intensity. The model also includes the number of people who moved from Russia to country *i* as another explanatory variable to account for physical money transfers associated with emigration. *Ln (IMMIGRANT)*$_i$ is the natural log of people migrating from Russia to country *i*. $POST_t$*$Ln(IMMIGRANT)_i$ is included to account for the possibility that the outflow of people changes the overall demand for cross-border payments after the SWIFT ban.

The first control variable is a *time-series* variable that measures the Bitcoin return on day *t*, $CHGPRICE_t$, to capture Bitcoin outflows driven by price movements. Equation (2) includes three sets of *country-level* control variables. The first set of control variables captures policies related to capital controls and regulations against money laundering and illicit activities. Hu, Lee, and Putniņš (2021) find that capital flight volume is one-quarter of Chinese Bitcoin exchange volume. Makarov and Schoar (2022) suggest that crypto adoption could increase with the opportunity of sidestepping regulation. Accordingly, I include the restrictiveness on capital flows ($CAPITALCONTROL_i$), using data obtained from Fernández et al. (2016), the same measure as that used by Makarov and Schoar (2020). Moreover, it is crucial to control the effectiveness of laws and procedures against money laundering and illicit activities because cryptocurrency remains appealing to illegal activities, primarily due to its anonymity and the ease with which it allows users to send funds anywhere in the world. For instance, one-quarter of Bitcoin users were involved in illegal activities up to 2017 (e.g., Foley, Karlsen, and Putniņš, 2019). Amiram, Jorgensen, and Rabetti (2022) find that cryptocurrencies are used in informal money transfer markets for terrorism financing (e.g., the Hawala markets). The Basel Institute on Governance provides a *country-level* score that quantifies the effectiveness of anti-money-laundering policies and procedures instituted by country *i* ($AMLSCORE_i$). By construct, a higher $AMLSCORE_i$ is associated with less money laundering and fewer dark markets.

The second set of control variables relates to technological factors, including internet penetration, mobile phone ownership, and money account ownership. $INTERNET_i$ and $SMARTPHONE_i$ are the numbers of individuals with access to internet services and mobile phones out of 100 adults for country *i*, respectively. Both variables are included because internet access and mobile phones provide the technological support for using cryptocurrency. Users without bank accounts but with smartphones can also load cash into digital wallets and use a mobile device to transfer money by short messaging service technology (e.g., Jack and Suri, 2014). For instance, users have adopted mobile money transfer platforms like M-PESA in Kenya to facilitate faster payments. Mobile money account ownership ($MOBILEMONEY_i$) is the percentage of the population owning a mobile money account for country *i*. All three technology-related variables are obtained from the Global Findex Database.

The third set of control variables is related to economic factors and population size. The first economic variable is GDP per capita (*GDP*), which is included because GDP per capita captures the innate demand for inward remittances and the available funds for cross-border payments. The second economic variable is the inflation rate (*INFLATION*). As pundits in Bitcoin claim, Bitcoin could hedge against the debasement of fiat currencies and inflation. If so, the higher the inflation rate, the higher the demand for cryptocurrency as a store of value. The third economic variable is the foreign exchange rate of the local currency against the U.S. dollar (*FOREX*). I include the foreign exchange rate as a control variable because some users, especially users in emerging markets, may turn to cryptocurrency to preserve their savings in the face of currency devaluation (Chainalysis 2021). The population size (*POP*) is also included because it captures the upper bound on a country's share of the web traffic on exchange platforms. Those variables are all obtained from the World Bank Development Indicator Series.

As reported in Table 2, 18% of sample countries are classified as treated countries, and the remaining 82% are control countries. On average, a treated country received about 4.42% of remittances from Russia and Belarus. As a country's average share of the web traffic on cryptocurrency exchanges is 1.26%, the mean Bitcoin outflow from exchange platform p to country i on day t is 22.11. However, the cross-exchange and cross-country variation is significant: the standard deviation is 268.48 with a minimum of 0 and a maximum of 16,150. On average, 71% of the population has at least one account in a financial institution during the sample period. However, there is a significant cross-country variation, as evidenced by the standard deviation of 28%, with a maximum of 100% and a minimum of 9%. on average, GDP per capita is $26,715, the inflation rate is 6.87%, and the population size is 65.55 million. Out of 100 adults, 71 individuals have access to the Internet, and the average number of mobile phones is 119. The average mobile money account ownership is 11%, and the standard deviation is 17%.

Panel A of Table 4 reports the difference-in-differences results on Bitcoin outflows from exchange platforms when the treatment effect is dichotomous. Again, standard errors in the estimation are cluster-adjusted by country-platform pairs. As noted in column 1, after controlling for capital control measures and technological and economic factors, the slope coefficient on $POST_t*TREATED_i$ is 0.004, but it is not

statistically significant. As reported in column 2, when $AMLSCORE_i$ is included as an additional control variable, the slope coefficient on $POST_t*TREATED_i$ is 0.008 but statistically insignificant. The number of observations, as reported in column 2, declines by 28% to 14,112 because the Basel Institute on Governance coverage for $AMLSCORE_i$ is much more limited. Regarding control variables, the coefficient on $BANKEDSHARE_i$ is positive and statistically significant, consistent with the intuition that the Bitcoin outflow from cryptocurrency exchanges to country *i* increases with the country's share of the banked population. The slope coefficient on $Ln(IMMIGRANT)_i$ is positive and statistically significant, consistent with the intuition that the Bitcoin outflow from cryptocurrency exchanges to country *i* increases with the number of Russian immigrants. Consistent with Foley, Karlsen, and Putniņš (2019) and Makarov and Schoar (2020), the slope coefficients on $CAPITALCONTROL_i$ and $AMLSCORE_i$ are negative. As reported in column 3, the results are qualitatively similar when the sample excludes Russia and Ukraine.

However, the SWIFT ban's potential effect varies among treated countries because some treated countries received more bank-intermediated cross-border payments from Russia before the ban. For instance, according to the bilateral remittance data from Knomad, while the average bank-intermediated remittance sent from Russia to the treatment group is $795 million, the maximum value is $4 billion. This could partially explain the insignificant coefficient on $POST_t*TREATED_i$ when the treatment effect is assumed to be *identical* for *all* treated countries. Therefore, this study uses a continuous variable, $RUSRBANKREMIT_i$, to capture the *intensity* of the treatment effect. $RUSBANKREMIT_i$ is the recipient country's share of bank-intermediated remittances from Russia in 2021. The higher the recipient country's share, the greater its reliance on bank remittances from Russia, and the greater the effect of the SWIFT ban.

Panel B of Table 4 reports the difference-in-differences results when the treatment effect is continuous. As noted in column 1, the slope coefficient on $RUSBANKREMIT_i$ is -0.035 and statistically insignificant, suggesting that the average Bitcoin outflow from cryptocurrency exchanges during the two-week window does *not* vary with the share of bank-intermediated remittances sent from Russia *before* the SWIFT ban. In contrast, the slope coefficient on $POST_t*RUSBANKREMIT_i$ is 0.043 and statistically significant with a $t(p)$-value of 2.385 (0.03). The positive coefficient on the interaction term suggests that, for every percentage

point increase in the share of bank-intermediated remittances sent from Russia in 2021, Bitcoin outflows from crypto exchanges to the country increase by 4.3% within the week *after* initiating the SWIFT ban, compared to the week before. As noted in column 2, with controlling for the effectiveness against money laundering and illicit activities ($AMLSCORE_i$), the slope coefficient on $POST_t$*$RUSBANKREMIT_i$ is 0.045 and statistically significant with a $t(p)$-value of 2.327 (0.03). As reported in column 3, the results are qualitatively similar when the sample excludes Russia and Ukraine.

In summary, the difference-in-differences results in Bitcoin outflows indicate that the SWIFT ban triggered more significant Bitcoin outflows from cryptocurrency exchanges to treated countries that received bank-intermediated remittances from Russia in the pre-shock period than control countries. The pattern is consistent with the interpretation that more Russians switched from banks to cryptocurrency for sending cross-border payments in response to the SWIFT ban. The substitution effect is more significant in treated countries that received a higher share of bank-intermediated remittances from Russia before the SWIFT ban. The higher cryptocurrency outflows from cryptocurrency exchanges to treated countries imply a substitution between banks and cryptocurrency in the cross-border payment market when the cross-border bank payment system is disrupted.

5. Cross-sectional Variation in the Effect of the SWIFT Ban

This section explores the bank-cryptocurrency interplay by examining whether the effect of the SWIFT ban varies with a country's banking access and the costs of sending bank-intermediated cross-border payments in the cross-section:

$$Ln(OUTFLOWFROMEXCHANGE)ipt = \alpha + \beta 1 * TREATED(RUSBANKREMIT)i + \beta 2 * POSTt + \beta 3 * TREATED(RUSBANKREMIT)i * POSTt + \beta 4 * BANKEDSHAREi + \beta 5 * POSTt * BANKEDSHAREi + \boldsymbol{\beta 6 * POSTt * TREATED\ (RUSBANKREMIT)i * BANKEDSHAREi} + \beta 7 * BANKCOSTi + \boldsymbol{\beta 8 * POSTt * TREATED(RUSBANKREMIT)i * BANKCOSTi} + \beta 9 * Ln(IMMIGRANTi) + \beta 10 * POSTt * Ln(IMMIGRANTi) + \beta 11 * POSTt * TREATED\ (RUSBANKREMIT)i * Ln(IMMIGRANTi) + Other\ control\ varaibles + \text{Platform fixed effects} + \varepsilon \qquad Equation\ (3)$$

In equation (3), the first variable of interest is $POST_t$*$TREATED(RUSBANKREMIT)_i$*$BANKEDSHARE_i$. Based on the conceptual framework outlined in section 2.2, the slope coefficient on

$POST_t$*$TREATED(RUSBANKREMIT)_i$*$BANKEDSHARE_i$ is expected to be positive if cryptocurrency and banks are perfect complements. The coefficient is expected to be negative if cryptocurrency and banks are perfect substitutes. The second variable of interest is $POST_t$*$TREATED(RUSBANKREMIT)_i$*$BANKCOST_i$. The slope coefficient on $POST_t$*$TREATED(RUSBANKEDREMIT)_i$*$BANKCOST_i$ is expected to be positive if the effect of the SWIFT ban on Bitcoin outflows from exchange platforms to country *i* is more pronounced when the cost of bank-intermediated cross-border payments is higher before the SWIFT ban. The slope coefficient on $POST_t$*$TREATED(RUSBANKEDREMIT)_i$*$BANKCOST_i$ is expected to be negative if the effect of the SWIFT ban on Bitcoin outflows from exchange platforms to country *i* is more pronounced when the pre-shock cost of bank-intermediated cross-border payments is lower.

5.1. Comparative statistic by access to the banking system

Panel A of Table 5 presents the results on whether the effect of the SWIFT ban varies with a country's banking access when the treatment effect is dichotomous. As noted in column 1, the slope coefficient on *POST*TREATED* is 1.028 and statistically significant, which indicates an overall greater number of Bitcoin outflows from cryptocurrency exchanges to treated countries than control countries after the SWIFT ban. The variable of interest, the slope coefficient on *POST*TREATED*BANKEDSHARE*, is -1.170 and statistically significant with a *t*(*p*)-value of -6.042 (0.001). The difference-in-differences results represent the combination of both the substitution and complementary effects between banks and cryptocurrency in cross-border payment markets. Therefore, the negative coefficient on *POST*TREATED*BANKEDSHARE* does *not* imply that the complementary effect between banks and cryptocurrencies is stronger than the substitution effect. Instead, this negative coefficient implies that such a complementary effect is more robust in countries with lower banked populations. In economic magnitude, the disparities in Bitcoin outflows from cryptocurrency exchanges to treated versus control countries decreased by 32.7% with a one-standard-deviation increase in the country's proportion of the banked population.

An alternative story is that Russian immigrants are more sensitive to crash/bankruptcy risk. Therefore, Russian immigrants are also worried about their savings in banks or security markets in their *residence* countries and thus purchase more cryptocurrencies (as assets). Anecdotally, an increased number

of people moved out of Russia after the outbreak of the war, who transferred cash physically to their residence countries. The physical cash transfers associated with emigration lowered the overall demand for cross-border payments from Russia via either banks or cryptocurrency *after* the SWIFT ban. Thus, it is essential to control for $POST_t$*$TREATED\ (RUSBANKREMIT)_i$*$Ln(IMMIGRANT_i)$ in equation (3). As reported in column 2, the slope coefficient on *POST*TREATED*Ln(IMMIGRANT)* is -0.043 and statistically significant, which implies that the disparities in Bitcoin outflows from cryptocurrency exchanges to treated versus control countries after the SWIFT ban are lower for countries with more immigrants from Russia after the outbreak of the war. In column 3, after controlling for *POST*TREATED*Ln(IMMIGRANT)*, the coefficient on *POST*TREATED*BANKEDSHARE* remains negative and statistically significant.

Panel B of Table 5 presents the results on whether the effect of the SWIFT ban varies with a country's banking access when the treatment effect is continuous. The continuous treatment effect is proxied by a country's share of bank-intermediated remittances from Russia in 2021 (the year before the ban). As noted in column 1, the slope coefficient on *POST*RUSBANKREMIT* is 0.452 and statistically significant. The variable of interest, the slope coefficient on *POST*RUSBANKREMIT*BANKEDSHARE*, is -0.577 and statistically significant with a t-value of -5.282. The negative coefficient on *POST*RUSBANKREMIT*BANKEDSHARE* indicates that the disparities in Bitcoin outflows from exchange platforms to treated versus control countries after the SWIFT ban are more significant for countries with lower banked populations. As reported in column 2, the slope coefficient on *POST*RUSBANKREMIT*Ln(IMMIGRANT)* remains negative and statistically significant. In column 3, the slope coefficient on *POST*RUSBANKREMIT*BANKEDSHARE* is -0.825 and statistically significant after controlling for *POST*RUSBANKREMIT*Ln(IMMIGRANT)*. In summary, the comparative statistic implies that the effect of the SWIFT ban on Bitcoin outflows from cryptocurrency exchanges is more pronounced for treated countries with lower banked populations in the cross-section.

5.2. Comparative statistic by costs of bank-intermediated cross-border payments

In theory, the cost of bank-intermediated cross-border payments could influence the use of cryptocurrency for cross-border payments *before* the SWIFT ban and thus induce variation in the effect of the SWIFT ban. $BANKCOST_i$ is the weighted average cost of receiving $200 across all bank-intermediated remittance corridors in recipient country *i* in 2021. The weight used in calculating the weighted average cost is the originating country's share of remittance inflows to the recipient country. The costs of receiving bank-intermediated cross-border payments are obtained from the World Bank Remittance Price Dataset.

Table 6 presents the results on whether and how the effect of the SWIFT ban varies with the cost of bank-intermediated cross-border payments in the cross-section. The number of observations declined to 5,824 because only 41% of countries in the sample are *recipient* countries of remittances. Thus, it is feasible to calculate the weighted average cost of receiving bank-intermediated remittances for those countries only. As reported in column 1, when the treatment effect is dichotomous, without controlling for the share of the banked population, the slope coefficient on *POST*TREATED*BANKCOST* is -0.671 and statistically significant. In column 2, after controlling for *BANKEDSHARE* and *POST*TREATED*BANKEDSHARE*, the slope coefficient on *POST*TREATED*BANKCOST* is -0.580, which is statistically significant. The negative coefficient on *POST*TREATED*BANKCOST* suggests that the effect of the SWIFT ban on Bitcoin outflows from cryptocurrency exchanges to country *i* is *less* pronounced when the cost of bank-intermediated cross-border payments is higher before the ban. It is worth noting that the coefficient on *POST*TREATED* remains positive and statistically significant, and the coefficient on *POST*TREATED*BANKEDSHARE* remains negative and statistically significant after controlling for the costs of bank-intermediated remittances. As column 3 reports, when the treatment effect is continuous, the coefficient on *POST*RUSBANKREMIT*BANKCOST* is -0.850 and statistically significant. As column 4 reports, after controlling for *BANKEDSHARE* and *POST*RUSBANKREMIT*BANKEDSHARE*, the slope coefficient on *POST*RUSBANKREMIT*BANKCOST* is -0.475, which is statistically significant.

In summary, the disparities in Bitcoin outflows from cryptocurrency exchanges to treated versus control countries after the shock are more pronounced in countries with lower banked populations and lower costs of bank-intermediated cross-border payments. The cross-sectional variation highlights the potential of

blockchain-powered cryptocurrency in providing a digital payment option and lowering costs in cross-border payment markets.

6. Supplementary Analyses

6.1. Geographical distribution of Stablecoins outflows from exchange platforms

Anecdotes suggest that sanctions against Russia have triggered increased trading between rubles and Tether (a Stablecoin) and requests to convert cryptocurrencies to rubles on cryptocurrency exchanges. The supplementary analysis first examines the geographical distribution of Stablecoin outflows from cryptocurrency exchanges to the destinations. Table 7 reports the difference-in-differences results on Stablecoins outflows from cryptocurrency exchanges. Panel A(B) presents the cross-sectional variation in the effect of the SWIFT ban when the treatment effect is dichotomous (continuous). As column 2 of Panel A reports, the slope coefficient on *POST*TREATED* is positive and statistically significant, and the coefficient on *POST*TREATED*BANKEDSHARE* is negative and statistically significant. As column 3 of Panel A reports, the slope coefficient on *POST*TREATED* is positive and statistically significant, and the coefficient on *POST*TREATED*Ln(IMMIGRANT)* is negative and statistically significant. As column 1 of Panel B reports, the slope coefficient on *POST*TREATED* *BANKEDSHARE* is negative and statistically significant. As column 2 of Panel B reports, the slope coefficient on *POST*TREATED*Ln(IMMIGRANT)* is negative and statistically significant. Thus, following the SWIFT ban on Russian banks, Stablecoin outflows from cryptocurrency exchanges to treated countries increased more than control countries. Comparatively, the disparities in Stablecoin outflows from cryptocurrency exchanges to treated versus control countries after the shock are more pronounced in countries with lower banked populations and fewer Russian immigrants after the outbreak of the war.

6.2. Longer effect of the SWIFT ban

In the primary analysis, this study focuses on the two-week window before and after initiating the SWIFT ban on February 26, 2022, to better identify the interplay between banks and cryptocurrency in response to the negative shock to the cross-border bank payment system. In the supplementary analysis,

this study extends the two-week window to a 30-day window and a 90-day window to capture the *relatively* longer effect of the SWIFT ban. In-untabulated results, this study documents a similar pattern in the geographical distribution of the destinations of Bitcoin and Stablecoin outflows from cryptocurrency changes after the SWIFT ban compared with the period before.

6.3. Calibrating the economic importance of cross-border remittances for on-chain flows

The difference-in-differences design in cryptocurrency inflows (outflows) to (from) cryptocurrency exchanges suggests that cryptocurrency provides a digital payment option to the *unbanked* population. Cryptocurrency inflows to exchange platforms are motivated by its use as a payment option or a vehicle for investment and speculation. This section calibrates the economic significance of cross-border remittances as *one* use case for cryptocurrency inflows (outflows) to (from) exchange platforms. Based on on-chain data, Bitcoin inflows from Russia to cryptocurrency exchanges during the week after the SWIFT ban were estimated at 6,973. The average Bitcoin price during the corresponding 7-day window is $41,390. Accordingly, the value of om-chain Bitcoin outflows from Russia to cryptocurrency exchanges is approximately 288.6 million during the week immediately after the SWIFT ban. Bitcoin inflows from Russia to all cryptocurrency exchanges were estimated at 431,631, and the average Bitcoin price was $28,293 in 2022. Thus, the total on-chain value of Bitcoin inflows from Russia to exchange platforms was estimated at $12.2 billion. According to Knomad, outward bank-intermediated remittances from Russia declined from 16.8 billion in 2021 to 5.8 billion in 2022. The decline in outward bank-intermediated remittances from Russia from 2021 to 2022 equals 90% of the value of on-chain Bitcoin outflows from Russia to cryptocurrency exchanges in 2022.

Applying a similar methodology, the cumulative Bitcoin outflow to treated countries during the week after the SWIFT ban was estimated to be 39,228, with an average Bitcoin price of $41,390. Accordingly, the value of Bitcoin outflows from cryptocurrency exchanges to treated countries is approximately 1.6 billion during the week immediately after the SWIFT ban. Bitcoin outflows from cryptocurrency exchanges to treated countries were estimated at 2,179,764, and the total on-chain value was estimated at 61.3 billion in 2022. The decline in outward bank-intermediated remittances from Russia from 2021 to 2022 equals

18% of the total value of on-chain Bitcoin inflows to treated countries in 2022. In summary, the economic magnitude of the estimated inflows from Russia and estimated outflows to treated countries imply that cross-border remittance is a significant use case for on-chain Bitcoin flows.

This study also estimates that the value of Stablecoins outflows from cryptocurrency exchanges to treated countries was approximately 4.6 billion in the week immediately after the SWIFT ban. In contrast, the corresponding value of Stablecoins outflows to all control countries was estimated at 3.5 billion during the same week. Stablecoin outflows from cryptocurrency exchanges collaborate with the conclusion that cross-border remittance is an economically significant use case for cryptocurrency flows on the blockchain.

6.4. Change specification to address the endogeneity of the banked population

Because the percentage of the banked population is not exogenous, this study uses a change specification (equivalent to including country-fixed effects) to alleviate the concern for time-invariant omitted correlated variables. The assumption underlying the change specification is that the *change* in the percentage of the banked population is *unlikely* caused by omitted correlated variables that are time-invariant within the relatively short window. The change specification effectively controls for time-invariant omitted variables and is equivalent to including country-fixed effects. Specifically, this study uses the following change specification to examine the bank-cryptocurrency interplay:

$$CHGONCHAINFLOWit = \alpha 1 + \boldsymbol{\sigma 1} * \boldsymbol{CHGBANKEDSHAREit} + \beta 2 * CHGINTERNETit + \beta 3 * CHGSMARTPHONEit + \beta 4 * CHGGDPit + \beta 5 * CHGINFLATIONit + \beta 6 * CHGFOREXit + \beta 7 * CHGEQUITYRETURNit + \beta 8 * CHGSTOCKMARKETSIZEit + \beta 9 * CHGCAPITALCONTROLit + \beta 10 * CHGMOBILEMONEYit + \beta 11 * CHGONCHAINCOSTt + \beta 12 * CHGPRICEt + \beta 13 * CHGAMLSCOREit + \beta 14 * CHGPOPit + \varepsilon 1 \qquad \textit{Equation (4)}$$

The dependent variable in equation (4) is the change in the estimated on-chain cryptocurrency inflow (normalized by GDP) to country *i* in year *t* relative to the previous period ($CHGONCHAINFLOW_{it}$). This study obtains and estimates on-chain cryptocurrency inflows for 154 countries during a 4-year window from 2019 to 2022. Accordingly, there are 462 country-year observations for the change in on-chain cryptocurrency inflows. However, information for explanatory variables is missing for 109 country-year observations. Accordingly, the sample includes 353 country-year observations for the change specification.

As the dependent variables are in the change forms, the variable of interest and control variables are all in the change form. Compared with equation (2), equation (4) includes three additional control variables (in change forms) to account for incentives to use cryptocurrency for purposes other than cross-border payments. For instance, users could hold cryptocurrencies as alternative investments, such as stablecoins, as safe assets (e.g., Makarov and Schoar, 2022). Therefore, adverse financial market shocks could affect the demand for cryptocurrencies as a vehicle for investment and speculation. To account for investment opportunities in conventional financial markets, equation (4) includes the return on equity ($EQUITYRETURN_{it}$), measured as the annualized return on equity investments, and the stock market size ($STOCKMARKETSIZE_{it}$), calculated as the total market capitalization of all listed companies as a percentage of GDP for country *i* in period *t* as control variables. According to Easley, O'Hara, and Basu (2019) and Hinzen, John, and Saleh (2022), Bitcoin users must pay proof-of-work fees to miners to confirm and record their transactions on the blockchain. This transaction fee fluctuates over time and is determined by the inflow rate of transactions and the user's waiting time. When the average cost of on-chain transactions is higher, holding other factors constant, users are less likely to adopt cryptocurrency. This study obtains the average fee for on-chain transactions from Sherlock Analytics at the time ($ONCHAINCOST_t$). Though the average cost of on-chain transactions fluctuates over time, it is *constant* for all on-chain transactions at a given time, regardless of the geographical location of the transaction. Therefore, $CHGONCHAINCOST_t$ is included to control for the time-series fluctuation in the costs of on-chain transactions in equation (4).

As reported in column 1 of Panel A of Table 8, when the dependent variable is *CHGONCHAINFLOW*, the slope coefficient on *CHGBANKEDSHARE* is -0.351 and statistically significant. The negative coefficient on *CHGBANKEDSHARE* suggests that, after controlling for contemporaneous changes in economic and technological factors, the on-chain cryptocurrency value received (deflated by GDP) decreases in the percentage of the banked population, implying a broader complementarity between banks and cryptocurrency for all use cases. As reported in column 2, the results are robust after controlling for

the change in remittances received by country *i* in period *t* as a percentage of the GDP relative to the previous period ($CHGREMITTANCE_{it}$).

Another possible scenario is that cryptocurrency and banks complement each other in that small value is transferred via cryptocurrency, whereas considerable value is transferred via banks. Makarov and Schoar (2021) find that large players dominate the Bitcoin ecosystem. For instance, one-third of Bitcoin's value is concentrated in 0.01% of accounts. To accommodate the scenario that users may prefer bank payments for large-value transfers and cryptocurrency for small-value transfers, this study examines whether the results are robust when the on-chain cryptocurrency inflow is limited to small-value transfers on the blockchain. A small-value transfer is a transaction under $10,000 worth of cryptocurrency. Specifically, this study uses the *retail* on-chain inflow ($RETAILONCHAINFLOW_{it}$) as the metric to capture small-value cryptocurrency transfers (deflated by GDP) by retail market participants. The results are similar. For instance, as reported in column 1 of Panel B of Table 8, the coefficient on *CHGBANKEDSHARE* is -0.179 and statistically significant. The negative coefficient on *CHGBANKEDSHARE* suggests that a decrease in the percentage of the banked population is associated with an increase in small-valued on-chain inflows. The results also ensure that large players and large values do not drive the interplay between banks and cryptocurrency. Not surprisingly, the comparison between the slope coefficients on variables of interest, as reported in Panel A versus Panel B, suggests that cross-border remittances play a more economically significant role in *retail* participation in cryptocurrency markets.

6.5. Lack of trust in financial institutions as a possible explanation

This section explores one possible explanation to substantiate the negative association between the change in the on-chain cryptocurrency inflow and the change in the percentage of the banked population. Conceptually, blockchain is a technology-based control system that can remove the need for a trusted third party. In a conventional bank payment system, users rely on a third-party intermediary to ensure funds are sent and received correctly; banks, credit card companies, and payment processors validate the transactions and minimize the risk of double spending. In contrast, the cryptocurrency payment system has no third-party intermediary—just the sender and the recipient. Parties trust the blockchain to do the things that banks

would do in a more conventional transaction: facilitate the transfer, ensure sender authenticity, and vouch for the validity of the exchange. Accordingly, when banks and third-party intermediaries become less trustworthy, market participants rely more on blockchain to mitigate counterparty risks, thus increasing blockchain-powered cryptocurrency transactions.

Panel A of Table 9 validates the lack of trust in financial institutions from the Global Findex Survey as a valid measure. As column 1 of Panel B of Table 9 reports, a lack of trust in financial institutions discourages financial account ownership but increases reliance on blockchain-powered control systems to mitigate counterparty risks, thereby increasing *on-chain* cryptocurrency flows. This relation is opposite to the *positive* effect of *generalized trust* on participating in conventional financial markets (e.g., Guiso, Sapienza, and Zingales 2008, 2009; Karolyi, 2016) and public interest in cryptocurrencies (Jalan et al. 2022). The finding of this study, however, is consistent with the negative association between the *level* of trust in banks and the adoption of Bitcoin infrastructure, as documented in Saiedi, Broström, and Ruiz (2021), the rise of Bitcoin prices after institutional failures, as reported in Tang, You, and Zhong (2023), and the increased probability of using FinTech with exposure to Wells Fargo scandal in the mortgage market, as documented in Yang (2023). This study and those studies mentioned above imply that a lack of trust in traditional financial institutions encourages participation in *nonconventional* financial markets. As a placebo test, column 2 finds that changes in trust in financial institutions *cannot* explain the changes in *off-chain* transactions, such as buying and selling cryptocurrencies on exchange platforms.

7. Conclusion

This study examines the interplay between cryptocurrency and banks in cross-border payment markets. Building upon a self-developed conceptual framework, this study analyzes the impact of a shock to the cross-border bank payment system on the geographic distribution of cryptocurrency flows on the blockchain. A difference-in-differences design reveals that, following the SWIFT ban on Russian banks, on-chain Bitcoin inflows to cryptocurrency exchanges from Russia increased more than those from other countries. Furthermore, Bitcoin outflows from cryptocurrency exchanges to treated countries increased

more than those to untreated countries. In the cross-section, the disparities in Bitcoin outflows from exchange platforms to treated versus control countries after the SWIFT ban are more pronounced in countries with lower banked populations and lower costs of bank-intermediated cross-border payments. In economic magnitude, cross-border remittance is a significant use case for cryptocurrency flows on the blockchain. Using a change specification to alleviate the concern for omitted correlated variables, this study finds a negative relation between the change in the percentage of the banked population and the change in on-chain cryptocurrency flows. Furthermore, a lack of trust in financial institutions partially explains the negative relation between the banked population and on-chain cryptocurrency flows. In contrast, it cannot explain the geography of off-chain cryptocurrency transactions, such as selling and buying Bitcoins on centralized cryptocurrency exchanges. In shedding light on the implications of cryptocurrencies on the global landscape, the evidence highlights the potential of blockchain-powered cryptocurrency in providing a digital cross-border payment option and lowering cross-border payment costs.

References

Angrist, J.D., and J.S. Pischke. Mostly harmless econometrics: An empiricist's companion. Princeton University Press, 2009.

Amiram, D., B. Jorgensen, and D. Rabetti. 2022. Coins for Bombs: The Predictive Ability of On-Chain Transfers for Terrorist Attacks. Journal of Accounting Research 60: 427-466.

Berg, T., V. Burg, A, Gombović, and M. Puri. 2020. On the rise of fintechs: Credit scoring using digital footprints. *Review of Financial Studies* 33 (7):2845–97. https://doi.org/10.1093/rfs/hhz099.

Blandin, A., G. Pieters, Y. Wu, T. Eisermann, A. Dek, S. Taylor, and D. Njoki. 2020. Third Global Cryptoasset Benchmarking Study. University of Cambridge, Judge Business School.

Bottazzi, L., M. Da Rin, and T. Hellmann. 2016. The importance of trust for investment: Evidence from venture capital. *Review of Financial Studies* 29:2283–2318.

Bratspies, R. 2018. Cryptocurrency and the myth of the trustless transaction. Michigan Technology Law Review 25 (1), 1–57. Available at: https://repository.law.umich.edu/mttlr/vol25/iss1/2/.

Buchak, G., G. Matvos, T. Piskorski, and A. Seru. 2018. Fintech, regulatory arbitrage, and the rise of shadow banks. *Journal of Financial Economics* 130 (3):453–83.

Bullock J., and D. Green DP. 2021. The Failings of Conventional Mediation Analysis and a Design-Based Alternative. *Advances in Methods and Practices in Psychological Science* 4(4). Doi:10.1177/25152459211047227

Bloomberg. 2024. China Banks Tighten Curbs on Russia After US Sanctions Order. Bloomberg News. January 16. https://www.bnnbloomberg.ca/china-banks-tighten-curbs-on-russia-after-us-sanctions-order-1.2022279.

Cameron, A.C., J. Gelbach, and D. Miller. 2008. Bootstrap-based improvements for inference with clustered errors. *The review of Economics and Statistics* 90: 414-427.

Cameron, A.C., and D. Miller. 2015. A practitioner's guide to cluster-robust inference. *Journal of Human Resources* 50: 317-372.

Chainalysis, 2021. The 2021 Geography of Cryptocurrency Report.

Chainalysis, 2022. The 2022 Geography of Cryptocurrency Report.

Cointelegraph. 2023. Crypto remittances offer cheaper alternatives but still face challenges to adoption Cointelegraph.com. November 2. https://cointelegraph.com/news/crypto-remittances-alternative-challenges-adoption

Cong, L., Z. He, and J. Li. 2020. Decentralized mining in centralized pools. *Review of Financial Studies*. https://doi.org/10.1093/rfs/hhaa040.

Congressional Research Service (CRS), May 26, 2022. Russia Sanctions and Cryptocurrencies: Policy Issues. IN11939. https://crsreports.congress.gov.

Demirgüç-Kunt, A., L. Klapper, D. Singer, S. Ansar, and J. Hess. 2018. *Global Findex Database 2017: Measuring Financial Inclusion and the Fintech Revolution.* Washington, DC: World Bank.

Demirgüç-Kunt, A., L. Klapper, D. Singer, and S. Ansar. 2022. *Global Findex Database 2021: Financial Inclusion, Digital Payments, and Resilience in the Age of COVID-19*. Washington, DC: World Bank.

Dupont, Q., and J. Karpoff. 2020. The trust triangle: Laws, reputation, and culture in empirical finance research. *Journal of Business Ethics* 163:217–38.

Easley, D., M. O'Hara, and S. Basu. 2019. From mining to markets: The evolution of bitcoin transaction fees. *Journal of Financial Economics* 134:91–109.

Financial Action Task Force, 2019. International standards on combating money laundering and the financing of terrorism and proliferation. http://www.fatf-gafi.org.

Foley, S., J. Karlsen, and T. Putniņš. 2019. Sex, drugs, and bitcoin: How much illegal activity is financed through cryptocurrencies? *Review of Financial Studies* 32:1798–1853. https://doi.org/10.1093/rfs/hhz015.

Fuster, A., M. Plosser, P. Schnabl, and J. Vickery. 2019. The role of technology in mortgage lending. *Review of Financial Studies* 32(5):1854–99.

Guardian. 2014. Kyrgyzstan Bitcoin experiment promises migrant workers big savings. Theguardian.com. July 06. https://www.theguardian.com/world/2014/jul/08/kyrgyzstan-bitcoin-experiment-migrant-savings.

Gelfand, M.J., J. Raver, L. Nishii, J. Lun, B.C. Lim, L. Duan, A. Almaliach, et al. 2011. Differences between tight and loose cultures: A 33-nation study. *Science* 332 (6033):1100-04.

Griffin, J.M., and A. Shams. 2020. Is Bitcoin really untethered? *Journal of Finance* 75(4):1913–64.

Guiso, L., P. Sapienza, and L. Zingales. 2008. Trusting the stock market. *Journal of Finance* 63:2557–2600.

Guiso, L., P. Sapienza, and L. Zingales. 2009. Cultural biases in economic exchanges? *Quarterly Journal of Economics* 124:1095–1131.

Hinzen, F., K. John, and F. Saleh. 2022. Bitcoin's limited adoption problem. *Journal of Financial Economics* 144: 347-369.

Hofstede. G. 1980. Culture and Organizations. *International Studies of Management & Organization* 10(4): 15–41.

Hofstede, G., 2001. Culture's consequences: Comparing values, behaviors, institutions, and organizations across nations. Sage publications.

Hu, Maggie, A. D. Lee, and T. J. Putninš. "Evading Capital Controls via Cryptocurrencies: Evidence from the Blockchain." Available at SSRN 3956933 (2021).

Huberman, G., J.D., Leshno, and C. Moallemi. 2021. Monopoly without a monopolist: an economic analysis of the Bitcoin payment system. *Review of Economic Studies* 88:3011-3040.

Jack, William, and Tavneet Suri. 2014. "Risk Sharing and Transactions Costs: Evidence from Kenya's Mobile Money Revolution." American Economic Review 104 (1): 183–223.

Jalan, A., R. Matkovskyy, A. Urquhart, and L. Yarovaya. 2022. The role of interpersonal trust in cryptocurrency adoption. Working paper. https://ssrn.com/abstract=4099518.

Karolyi, G. 2016. The gravity of culture for finance. *Journal of Corporate Finance* 41:610–25.

La Porta, R., F. Lopez-de-Silanes, A. Shleifer, and R. Vishny. 1998. Law and finance. *Journal of Political Economy* 106:1113–55.

Lyandres, E., B. Palazzo, and D. Rabetti. 2022. Initial Coin Offering (ICO) Success and Post-ICO Performance. *Management Science*. https://doi.org/10.1287/mnsc.2022.4312

Liu, Y., and A. Tsyvinski. 2021. Risks and returns of cryptocurrency. *Review of Financial Studies* 34:2689–2727.

Makarov. I., and A. Schoar. 2020. Trading and arbitrage in cryptocurrency markets. *J. Fin. Econ.* 135: 293–319.

Makarov, I., and A. Schoar. 2021, Blockchain analysis of the Bitcoin market. https://ssrn.com/abstract=3942181

Makarov, I. and A. Schoar. 2022, Cryptocurrencies and Decentralized Finance (DeFi), Technical Report, National Bureau of Economic Research.

Nahata, R., S. Hazarika, and K. Tandon. 2014. Success in global venture capital investing: Do institutional and cultural differences matter? *Journal of Financial and Quantitative Analysis* 49:1039–70.

Nakamoto, S. 2009. Bitcoin: Bitcoin is an open-source implementation of P2P currency. https://p2pfoundation.ning.com/forum/topics/bitcoin-open-source.

Parino, F., M. Beiro, and L. Gauvin. 2018. Analysis of the Bitcoin blockchain: Socio-economic factors behind the adoption. *EPJ Data Science.* https://doi.org/10.1140/epjds/s13688-018-0170-8.

Petersen, M., 2009. Estimating standard errors in finance panel data sets: Comparing approaches. *Review of Financial Studies* 22:435–80.

PYMNTS, 2021. The Digital Currency Shift: the Cross-border Remittances Report.

Reuters. 2021. Remittance firms slow to add bitcoin, despite El Salvador move. Reuters.com. June 14. https://www.reuters.com/business/remittance-firms-slow-add-bitcoin-despite-el-salvador-move-2021-06-11/

Saiedi, E., A. Broström, and F. Ruiz. 2021. Global drivers of cryptocurrency infrastructure adoption. *Small Business Economics* 57: 353–406.

Shams, A. 2020. The structure of cryptocurrency returns. Available at SSRN: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3604322.

Statista. December 12, 2023. Number of identity-verified cryptoasset users from 2016 to November 2023 (in millions). Retrieved January 05, 2024.

Russian Federal State Statistics Service. September 22, 2023. Total national and international migration in Russia from 1990 to 2022 by flow (in 1,000s). In Statista. Retrieved February 8, 2024.

Stulz, R., and R. Williamson. 2003. Culture, openness, and finance. *Journal of Financial Economics* 70:313–49.

Tang, H., 2019. Peer-to-Peer Lenders Versus Banks: Substitutes or Complements? *The Review of Financial Studies* 32:1900–1938.

Tang, B., Y. You, and Y. Zhong, Distrust and Cryptocurrency Price Deviations (December 30, 2023). Available at SSRN: https://ssrn.com/abstract=3981990 or http://dx.doi.org/10.2139/ssrn.3981990

Yang, Keer, Trust as an Entry Barrier: Evidence from FinTech Adoption (July 31, 2023). *Available at SSRN: https://ssrn.com/abstract=3761468 or http://dx.doi.org/10.2139/ssrn.3761468*

Figure 1

The Bank-intermediated Cross Border Money Transfer Flow with Banks and MTOs

This figure depicts the flow chart for the bank-intermediated cross-border remittances with banks and money transfer operators (MTOs). The source of this flow chart is available at https://www.linkedin.com/pulse/understanding-cross-border-remittances-venkat-nikhil-k.

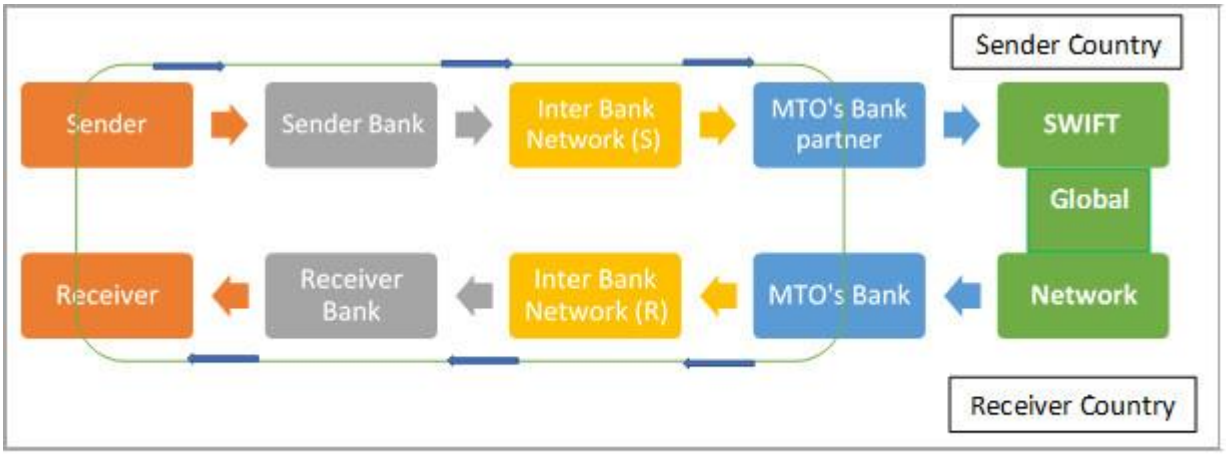
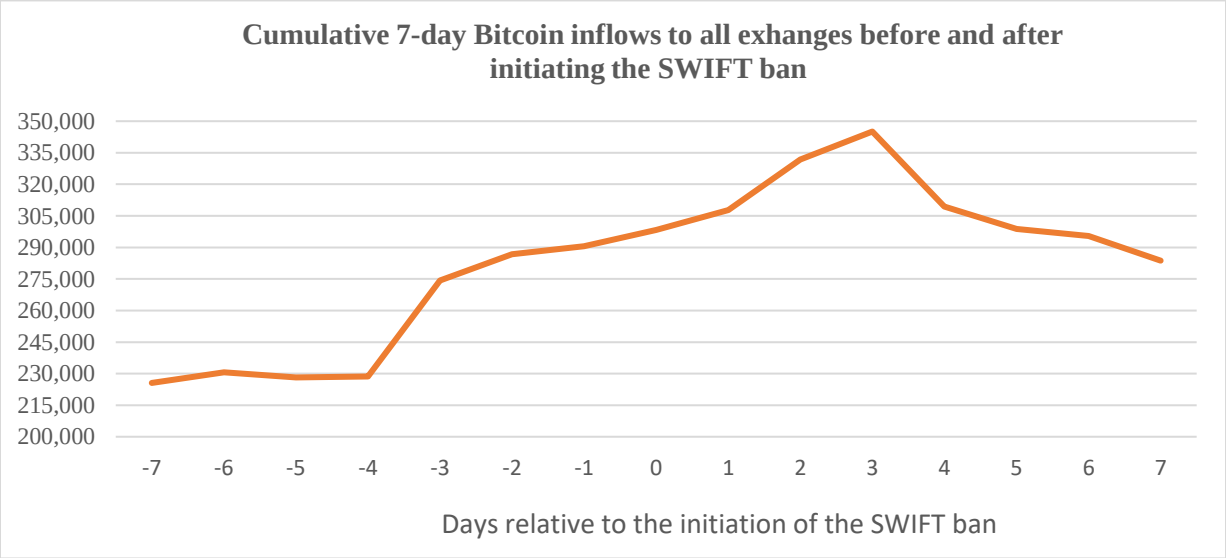


Figure 2

Overall Trend in Bitcoin Inflows and Outflows before and after the SWIFT Ban

Panels A, C, and E of this figure graph Bitcoin inflows to all cryptocurrency exchanges before and after three critical events associated with the SWIFT ban. Panels B, D, and F of this figure graph Bitcoin outflows from all cryptocurrency exchanges before and after three critical events associated with the SWIFT ban.

Panel A: Bitcoin inflows before and after initiating the SWIFT ban on Feb 26, 2022



Panel B: Bitcoin outflows before and after initiating the SWIFT ban on Feb 26, 2022

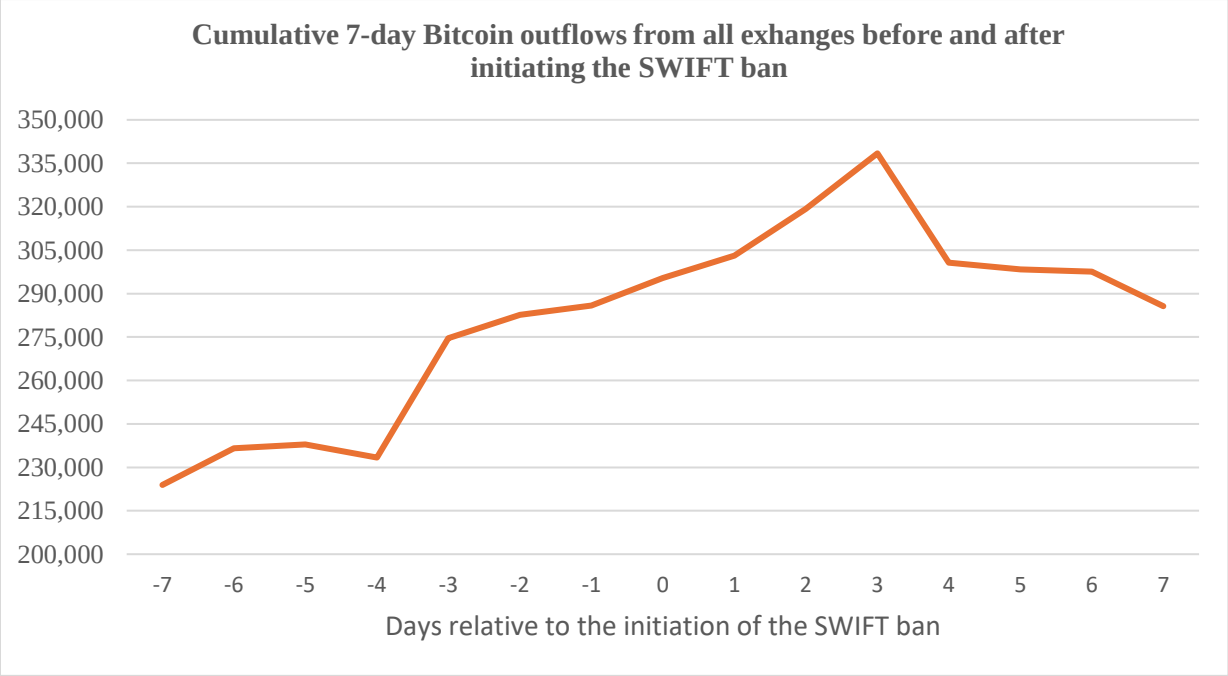
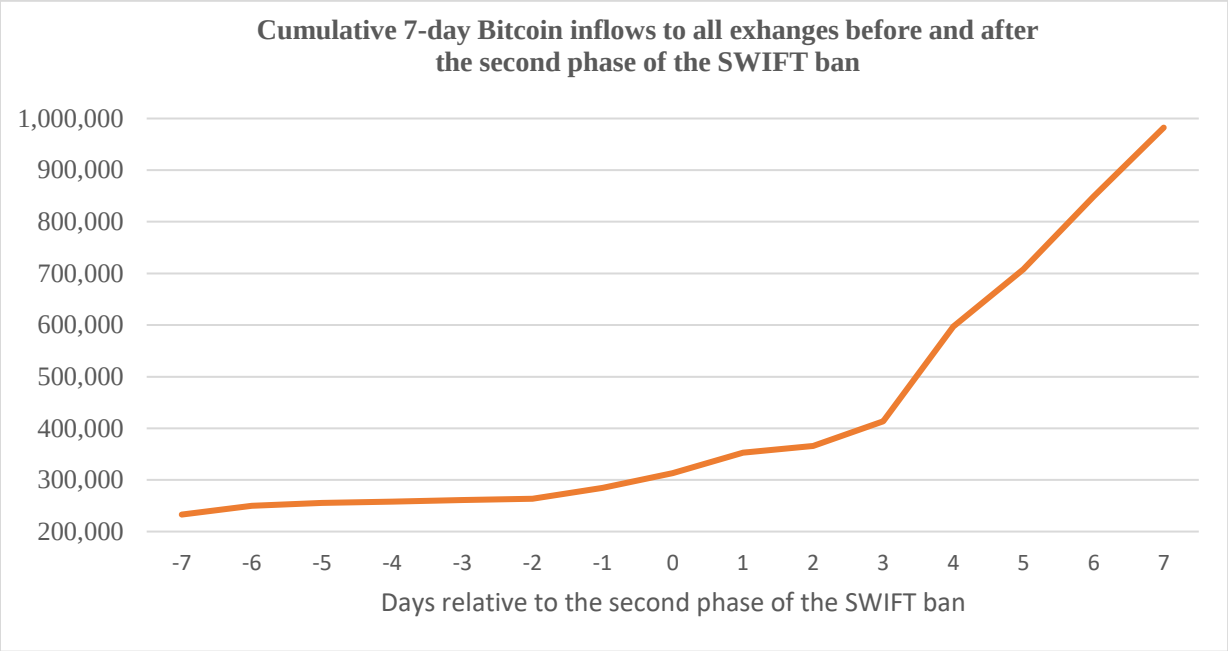


Table 2

(continued)

Panel C: Bitcoin inflows before and after the second phase of the SWIFT ban on May 4, 2022



Panel D: Bitcoin outflows before and after the second phase of the SWIFT ban on May 4, 2022

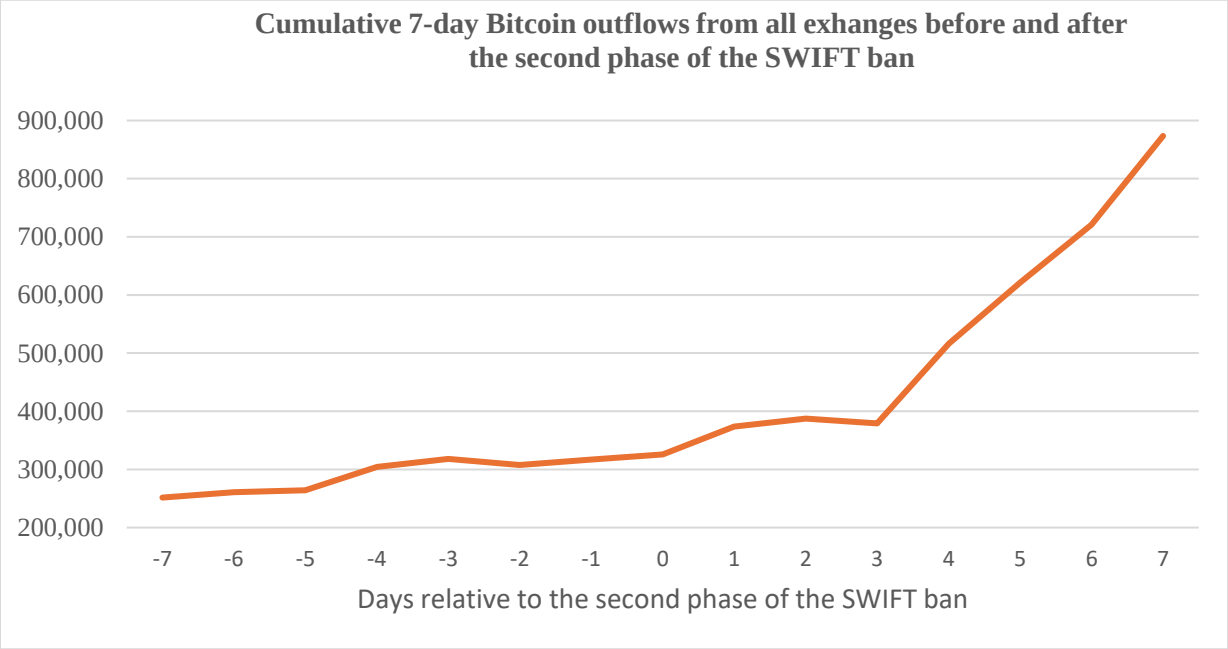
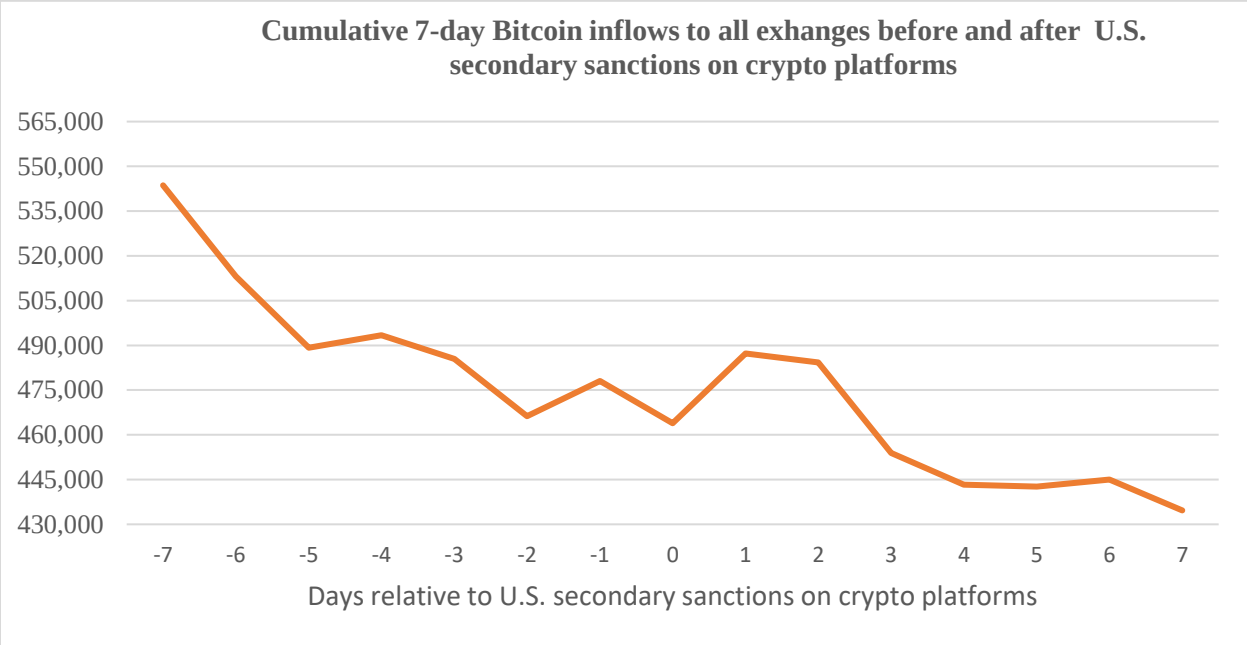


Figure 2

(Continued)

Panel E: Bitcoin inflows before and after secondary sanctions on platforms on March 25, 2024



Panel F: Bitcoin outflows before and after secondary sanctions on platforms on March 25, 2024

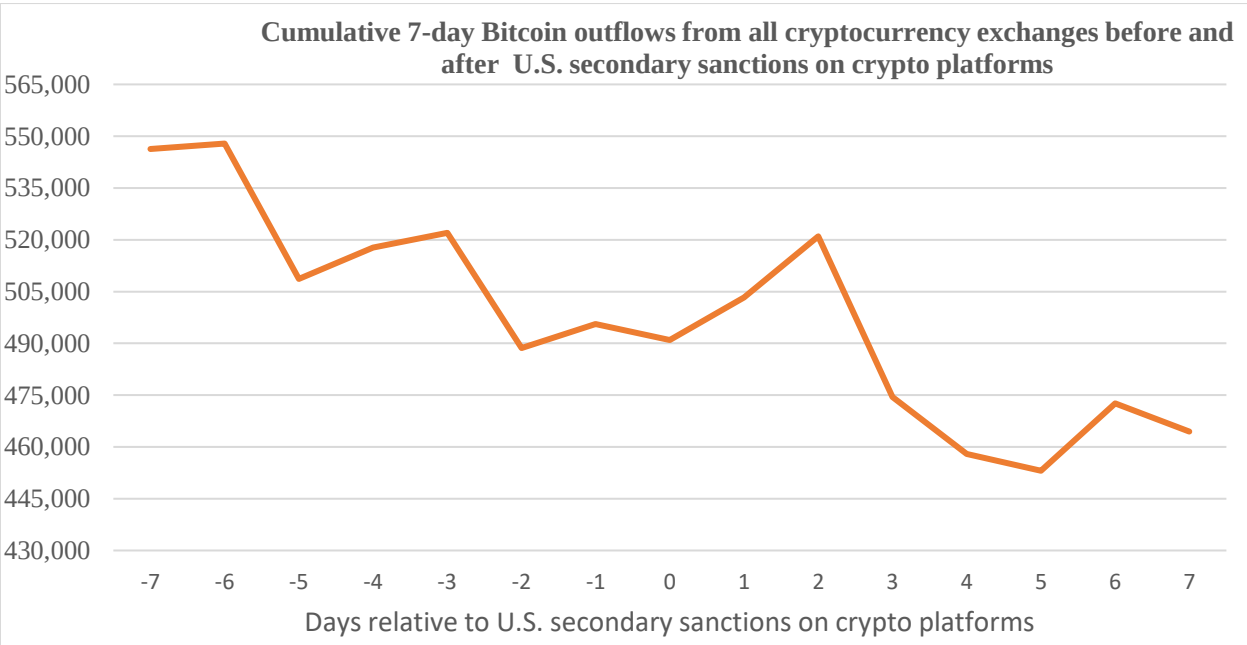


Figure 3

Bitcoin Inflows to Cryptocurrency Exchanges from Russia versus Other Countries

This figure graphs the rolling 7-day average Bitcoin inflows from Russia versus other countries to exchange platforms before and after the initiation of the SWIFT ban.

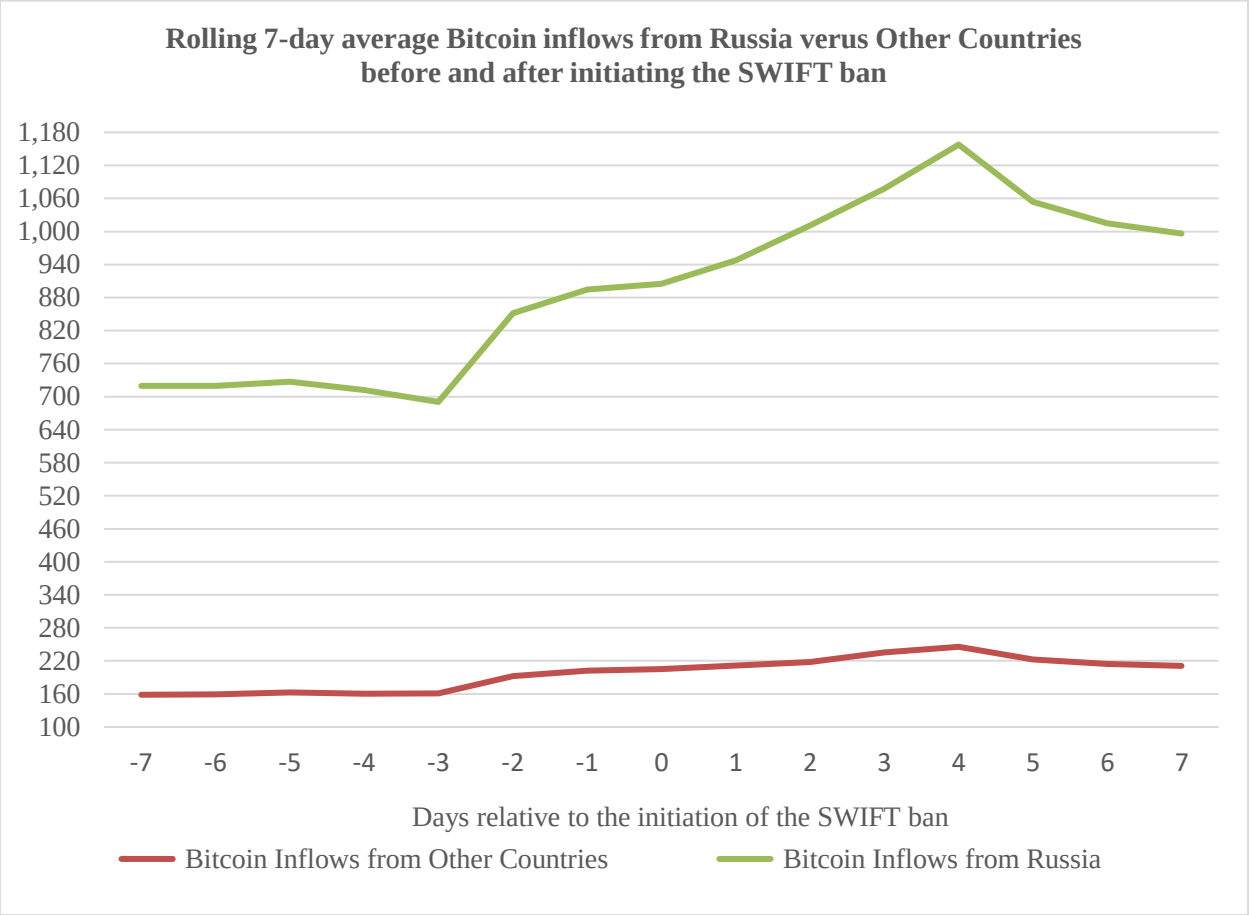
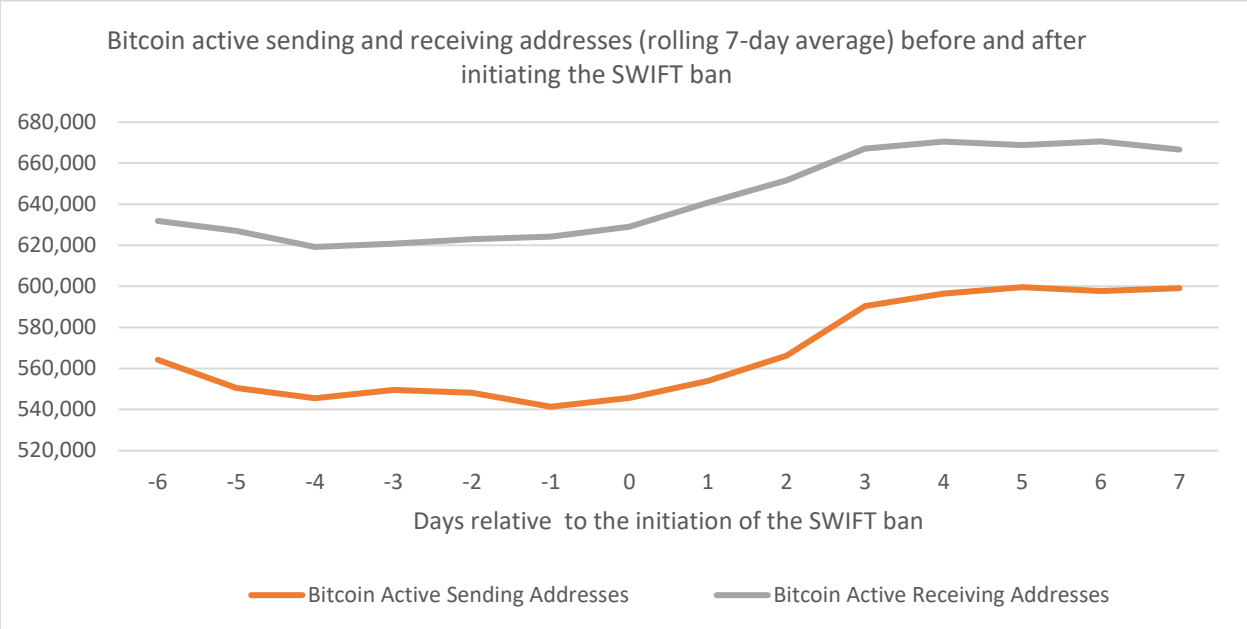


Figure 4

Overall Trend in Active Sending and Receiving Addresses Around the SWIFT Ban

Panel A graphs the number of active addresses that sent or received Bitcoin before and after the SWIFT ban on February 26, 2022. Panel B of this figure graphs the number of active addresses that sent or received Stablecoins before and after the SWIFT ban on February 26, 2022.

Panel A: Bitcoin active sending and receiving addresses around the SWIFT ban



Panel B: Stablecoins active sending and receiving addresses around the SWIFT ban

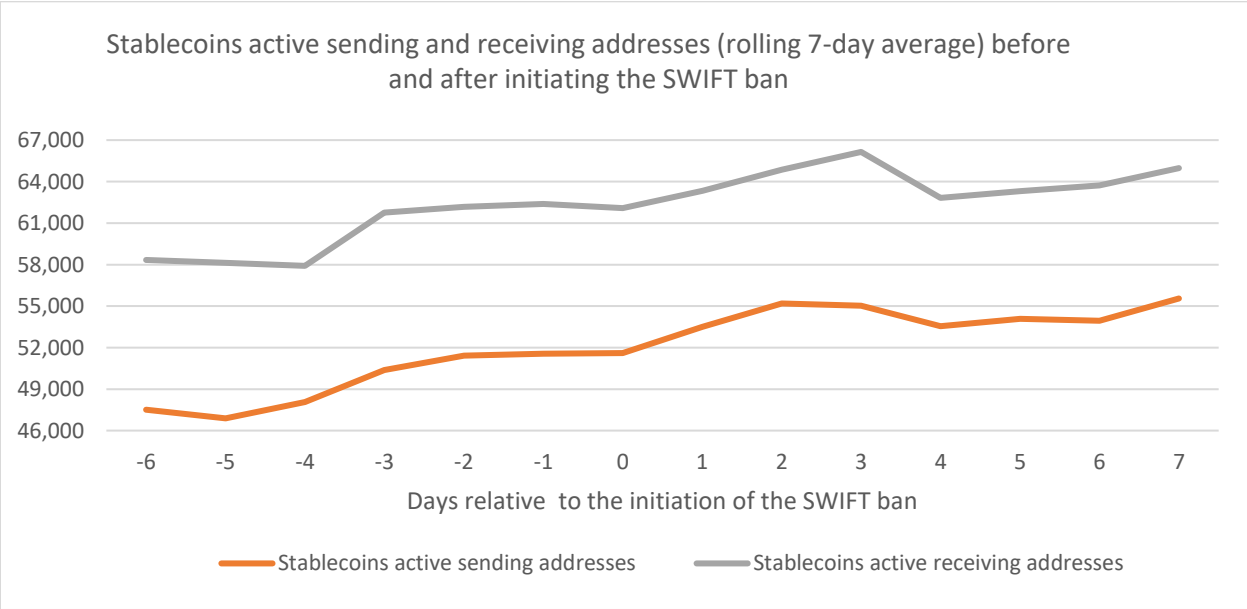


Figure 5

Bitcoin Outflows from Cryptocurrency Exchanges to Treated versus Control Countries

This figure graphs the rolling 7-day average Bitcoin outflows from cryptocurrency exchanges to treated versus control countries before and after the initiation of the SWIFT ban. This study classifies countries that received bank-intermediated remittances from Russia before the ban as treated countries and the remaining as control countries.

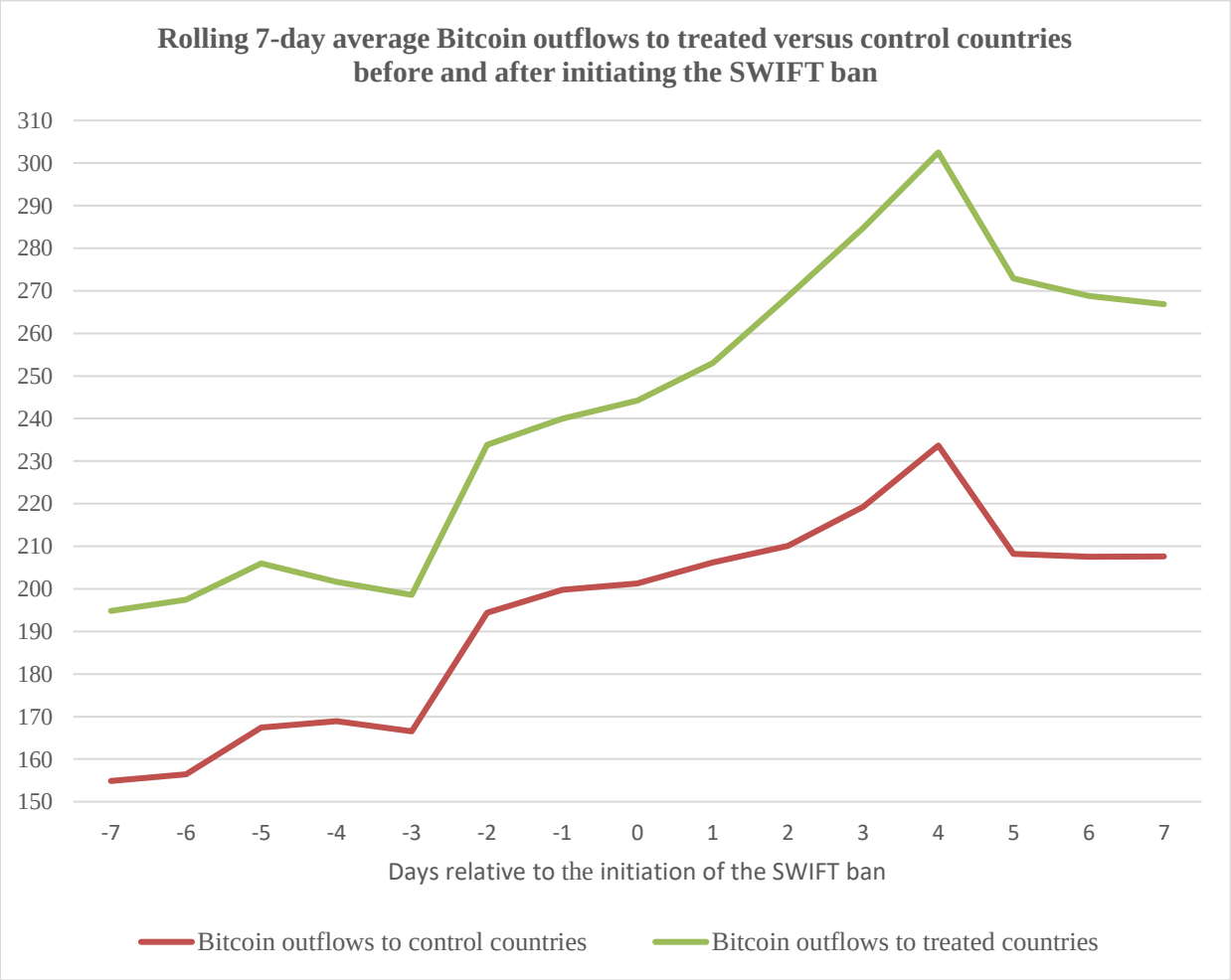


Table 1
Variable Definitions, Data Source, and Sample Formation

Panel A: Variable definitions and sources

VARIABLE	DEFINITION	SOURCE
$INFLOWTOEXCHANGE_{ipt}$	The estimated on-chain Bitcoin inflows from country *i* to exchange platform *p* in day *t*. The estimation is based on the total Bitcoin inflow to exchange platform *p* in day t and the web traffic share of country *i* on the exchange platform.	CryptoQuant and SimilarWeb
$OUTFLOWFROMEXCHANGE_{ipt}$	The estimated on-chain Bitcoin outflows from exchange platform *p* to country *i* in day *t*. The estimation is based on the total Bitcoin outflow from exchange platform *p* in day t and the web traffic share of country *i* on the platform.	CryptoQuant and SimilarWeb
$STABLECOINOUTFLOW_{ipt}$	The estimated on-chain Stablecoins outflows from exchange platform *p* to country *i* in day *t*. The estimation is based on the total Stablecoins outflow from platform *p* in day t and the web traffic share of country *i* on the platform.	CryptoQuant and SimilarWeb
$RUSSIA_i$	A dummy variable is set to 1 for Russia and 0 otherwise	
$UKRAINE_i$	A dummy variable is set to 1 for Ukraine and 0 otherwise	
TREATEDi	A dummy variable was set to 1 for countries that receive at least 0.1% of remittances sent by Russia and Belarus in 2021 (the year before the SWIFT ban) and 0 otherwise.	Knomad https://www.knomad.org/data/remittances
$RUSBANKREMIT_i$	The share of outward remittances sent from Russia to country *i* in 2021 (the last year before the SWIFT ban).	Knomad
$POST_t$	A dummy variable is set to 1 for periods after the SWIFT ban and 0 otherwise.	
$BANKEDSHARE_i$	The percentage of the population with at least one account in financial institutions for country *i*.	Global Findex Database https://www.worldbank.org/en/publication/globalfindex
$BANKCOST_{it}$	The weighted average cost of receiving $200 for recipients residing in country *i* via bank-intermediated remittance corridors.	World Bank Remittance Price Dataset
$IMMIGRANT_i$	The number of immigrants that move from Russia to country *i*	Knomad and Statista
$CAPITALCONTROL_i$	The restrictiveness of capital control measures adopted by country *i*	Fernández et al. (2016)
$AMLSCORE_i$	The effectiveness of laws and procedures against money laundering and illicit activities in country *i*	Basil Institute of Governance https://baselgovernance.org/basel-aml-index

$INTERNET_i$	The number of people with access to the Internet per 100 adults in country i	World Bank https://data.worldbank.org
$SMARTPHONE_i$	The number of mobile phones per 100 adults for country *i*	World Bank
$MOBILEMONEY_i$	The percentage of the population with mobile money accounts for country *i*	Global Findex Database
GDP_i	Gross domestic product (GDP) per capita converted into U.S. dollars using purchase power parity (PPP) for country *i*	World Bank
$INFLATION_i$	The official inflation rate for country *i*	World Bank
$FOREX_i$	The foreign exchange rate of country *i*'s fiat currency against U.S. dollars	World Bank
POP_i	The number of inhabitants in millions for country i	World Bank
$CHGPRICE_t$	The change in Bitcoin price on day *t* relative to the prior day	Sherlock Analytics
$ONCHAINCOST_t$	The average cost (in US dollars) of transactions on the Bitcoin blockchain in period *t*	Sherlock Analytics
$EQUITYRETURN_{it}$	The return on the stock market index for country *i* in period *t*. $CHGEQUITYRETURN_{it}$ is the change form of this variable.	World Bank
$STOCKMARKETSIZE_{it}$	The total market capitalization of all listed companies as a percentage of total GDP for country i in year *t*. $CHGSTOCKMARKETSIZE_{it}$ is the change of this variable.	World Bank
$ONCHAINFLOW_{it}$	The on-chain cryptocurrency inflow to country *i* in period *t*. $CHGONCHAINFLOW_{it}$ is the change form of this variable.	CryptoQuant and SimilarWeb
$RETAILONCHAINFLOW_{it}$	The small-valued on-chain cryptocurrency inflow to country *i* in period *t*. A small value is defined as a value less than $10,000. $CHGRETAILONCHAINFLOW_{it}$ is the change form of this variable.	CryptoQuant and SimilarWeb
$REMITTANCE_{it}$	Remittances received by country *i* in period t. $CHGREMITTANCE_{it}$ is the change form of this variable.	Knomad
$DISTRUST_{it}$	The percentage of respondents cite a lack of trust in financial accounts as a barrier to financial account ownership for country *i* in period *t*. $CHGLACKTRUST_{it}$ is the change form of this variable.	Global Findex Database
$WVSDISTRUSTBANK_i$	The percentage saying that "I have not much confidence in banks or none at all" in country *i* as reported by the World Value Survey Wave 7	World Value Survey https://www.worldvaluessurvey.org/WVSDocumentationWV7.jsp

Table 1
(Continued)

Panel B: Sample formation for the difference-in-differences design in on-chain inflows (outflows) to (from) exchange platform

	Total number of country-platform-day observations	***The number of unique exchange platforms***	***The number of unique countries***
On-chain Bitcoin Inflows and outflows to exchange platforms are available from CryptoQuant		21	
Web traffic analytics of exchange platforms available from SimilarWeb		31	
Both on-chain data and web traffic data are available to estimate Bitcoin inflows from country *i* to exchange platform *p* on day t (*INFLOWTOEXCHANGE*$_{ipt}$) as specified in equation (1)	19,656	18	78
Both on-chain data and web traffic data are available to estimate Bitcoin outflows from country *i* to exchange platform *p* on day *t* (*OUTFLOWTOEXCHANGE*$_{ipt}$) as specified in equation (2)	19,656	18	78
Country-platform-day observations with missing information on anti-money laundering score (*AMLSCORE*$_i$)	(5,544)	(0)	(22)
The final sample used in the difference-in-difference design as specified in equation (2) with AMLSCORE$_i$	***14,112***	***18***	***56***

Table 2

Descriptive Statistics for the difference-in-differences design in on-chain inflows (outflows) to (from) exchange platform

	Entire sample					
	N	***Mean***	***Median***	***Std***	***Min***	***Max***
INFLOWFROMEXCHANGE	14,112	22.16	0.55	256.60	0	15,104
OUTFLOWFROMEXCHANGE	14,112	22.11	0.46	268.48	0	16,150
STABLECOINOUTFLOW	14,112	916,327	25,377	31,264	0	260,640,309
TREATED	14,112	0.18	0.00	0.37	0.00	1.00
RUSBANKREMIT	14,112	0.70%	0%	2.42%	0%	65.00%
POST	14,112	0.50	0.50	0.50	0.00	1.00
BANKEDSHARE	14,112	0.71	0.84	0.28	0.09	1.00
IMMIGRANT	14,112	60,026	0	335,5155	0	3,537,271
INTERNET	14,112	70.71	78.12	23.12	9.80	100.00
SMARTPHONE	14,112	119.71	120.51	29.67	37.40	291.65
GDP	14,112	26,715	20,244	21,2051	1,230	116,518
INFLATION	14,112	6.87	2.58	35.35	-3.23	557.20
FOREX	14,112	686.71	8.85	3545.08	0.30	42,000
POP	14,112	65.55	11.83	202.36	0.37	1412.36
MOBILEMONEY	14,112	0.11	0.00	0.17	0.00	0.73
CAPITALCONTROL	14,112	0.35	0.25	0.26	0	0.89
AMLSCORE	14,112	5.31	5.20	1.17	3.06	8.49
BANKCOST	5,824	8.04%	6.13%	5.37%	1.97%	26.58%

** The difference between the treatment group and the control group is statistically significant with p-value < 0.05 & *** p-value < 0.01

Table 3
Difference-in-differences Design in Cryptocurrency Inflows

This table uses a difference-in-differences design as specified in equation (1) to identify the effect of the SWIFT ban on cryptocurrency inflows to exchange platforms from Russia versus other countries. The dependent variable is the natural log of $INFLOWTOEXCHANGE_{it}$, the number of coins flowing from country *i* to crypto exchange platform *p* on day *t*. This table reports the DID results on the inflow of three types of coins: Bitcoin, Ethereum, and Stablecoins. *RUSSIA* is a dummy variable set to 1 for Russia. *UKRAINE* is a dummy variable set to 1 for Ukraine. *POST* is a dummy variable set to 1 for the 7-day period after the SWIFT ban and 0 for the 7-day period up to the initiation of the SWIFT ban on February 26, 2022.

		Dependent Variable = $\boldsymbol{Ln(INFLOWTOEXCHANGE_{ipt})}$		
		Column 1	Column 2	Column 3
		Bitcoin inflows	Ethereum inflows	Stablecoins inflows
Explanatory variables	*Predicted sign*	Coefficient (*T*-value)	Coefficient (*T*-value)	Coefficient (*T*-value)
Intercept		0.042*** (5.599)	0.067*** (6.783)	0.044*** (3.936)
$POST_t$		0.001 (0.150)	-0.008 (-0.012)	-.081 (-0.498)
RUSSIAi		2.596 (10.496)	3.157*** (4.474)	8.985*** (5.785)
$\boldsymbol{POST_t*RUSSIA_i}$	***(+)***	***0.056****** ***(3.103)***	0.003 (0.025)	-.057 (-0.026)
UKRAINE		2.230*** (6.118)	1.349*** (7.642)	7.652*** (4.927)
$\boldsymbol{POST_t*UKRAINE_i}$		0.095** (2.033)	-0.033 (-0.304)	-.057 (-0.026)
Platform fixed effects		Included	Included	Included
Standard errors are cluster-adjusted by		country-platform pair	country-platform pair	country-platform pair
N		19,656	19,656	19,656
Adjusted R-squared		94.9%	60.3%	4.1%

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

Table 4

Bitcoin Outflows from Cryptocurrency Exchanges

This table uses a difference-in-differences design as specified in equation (2) to identify the interplay between banks and cryptocurrency in response to an exogenous shock to the cross-border bank payment system. The dependent variable is $OUTFLOWFROMEXCHANGE_{ipt}$, on-chain Bitcoin outflows from cryptocurrency exchange platform p to country *i* on day *t*. $POST_t$ is a dummy variable set to 1 for the 7-day window after the SWIFT ban and 0 for the 7-day window up to the initiation of the SWIFT ban on February 26, 2022. Panel A of this table reports the results when the treatment effect is dichotomous. $TREATED_i$ is a dummy variable set to 1 for countries that received at least 0.1% of bank-intermediated remittances from Russia and Belarus in 2021 (the last year before the SWIFT ban) and 0 otherwise. Panel B of this table reports the results when the treatment effect is continuous. $RUSBANKREMIT_i$ is a continuous variable that captures the *intensity* of the treatment effect. $RUSBANKREMIT_i$ is the recipient country's share of bank-intermediated remittances from Russia in 2021.

Panel A: Difference-in-differences in Bitcoin outflows when the treatment effect is dichotomous

		Dependent Variable = *Ln (**$OUTFLOWFROMEXCHANGE_{ipt}$**)*		
		Column 1	Column 2	Column 3
		All observations		Excluding Russia and Ukraine
Explanatory variables	*Predicted sign*	Coefficient (*T*-value)	Coefficient (*T*-value)	Coefficient (*T*-value)
$POST_t$		0.040 (1.151)	0.046 (1.082)	0.046 (1.097)
TREATEDi		-0.110*** (-4.326)	-0.145 (-4.797)	-0.251*** (-7.748)
$POST_t$*TREATED$_i$	***(+)***	***0.004*** ***(0.115)***	**0.008** **(0.201)**	**0.006** **(0.145)**
$BANKEDSHARE_i$		0.385*** (6.711)	0.280*** (3.721)	0.272*** (3.639)
*POST*BANKEDSHAREi*		-0.029 (-0.529)	-0.036 (-0.566)	-0.038 (-0.585)
$Ln(IMMIGRANT_i)$		0.018*** (6.049)	0.012*** (3.458)	0.023*** (6.215)
$POST_t$*$Ln(IMMIGRANT_i)$		-0.001 (-0.191)	-0.001 (-0.273)	-0.001 (-0.213)
$CAPITALCONTROL_i$		-0.099** (-2.430)	-0.155*** (-3.010)	-0.084* (-1.649)
$AMLSCORE_i$			-0.022* (-1.814)	-0.021* (-1.797)
Intercept		Included	Included	Included
Other control variables in equation (2)		Included	Included	Included
Platform fixed effects		Included	Included	Included
Standard errors are cluster-adjusted by		country-platform pair	country-platform pair	country-platform pair
N		19,656	14,112	13,888
Adjusted R-squared		69.3%	69.0%	69.1%

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

Table 4

(Continued)

Panel B: Difference-in-differences in Bitcoin outflows when the treatment effect is continuous

		Dependent Variable = *Ln(**OUTFLOWFROMEXCHANGE$_{ipt}$**)*		
		Column 1	Column 2	Column 3
		All observations		Excluding Russia and Ukraine
Explanatory variables	*Predicted sign*	Coefficient (*T*-value)	Coefficient (*T*-value)	Coefficient (*T*-value)
POST$_t$		0.036 (1.035)	0.036 (0.842)	0.045 (1.071)
RUSBANKREMIT$_i$		-0.035 (-0.027)	-0.082 (-0.555)	0.074 (0.490)
POST$_t$*RUSBANKREMIT$_i$	***(+)***	***0.043** (2.385)***	***0.045** (2.327)***	***0.024* (1.709)***
BANKEDSHARE$_i$		0.351*** (6.134)	0.198*** (2.658)	0.167** (2.238)
*POST$_t$*BANKEDSHARE$_i$*		-0.029 (-0.529)	-0.036 (-0.566)	-0.038 (-0.585)
Ln(IMMIGRANT$_i$)		0.013*** (4.419)	0.007** (2.061)	0.011*** (2.968)
*POST$_t$*Ln(IMMIGRANT$_i$)*		-0.001 (-0.191)	-0.001 (-0.273)	-0.001 (-0.213)
CAPITALCONTROL$_i$		-0.099** (-2.437)	-0.158*** (-3.064)	-0.123** (-2.392)
AMLSCORE$_i$			-0.032*** (-2.663)	-0.035*** (-2.961)
Intercept		Included	Included	Included
Other control variables in equation (2)		Included	Included	Included
Platform fixed effects		Included	Included	Included
Standard errors are cluster-adjusted by		country-platform pair	country-platform pair	country-platform pair
N		19,656	14,112	13,888
Adjusted R-squared		69.2%	69.0%	69.1%

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

Table 5
The Cross-sectional Variation in the Effect of the SWIFT Ban and Banking Access

This table uses a difference-in-differences design in equation (3) to explore whether the SWIFT ban's effect varies with the proportion of the banked population (*BANKEDSHAREi*). The dependent variable is $OUTFLOWFROMEXCHANGE_{ipt}$, on-chain Bitcoin outflows from cryptocurrency exchange platform p to country *i* on day *t*. $POST_t$ is a dummy variable set to 1 for the 7-day window after the SWIFT ban and 0 for the 7-day window up to the initiation of the SWIFT ban on February 26, 2022. Panel A of this table reports the results when the treatment effect is dichotomous. $TREATED_i$ is a dummy variable set to 1 for countries that received at least 0.1% of bank-intermediated remittances from Russia in 2021 (the last year before the SWIFT ban) and 0 otherwise. Panel B of this table reports the results when the treatment effect is continuous. $RUSBANKREMIT_i$ is the recipient country's share of bank-intermediated remittances from Russia in 2021.

Panel A: Bitcoin outflows from crypto exchanges when the treatment is dichotomous

		Dependent Variable = *Ln (**$OUTFLOWFROMEXCHANGE_{ipt}$**)*		
		Column 1	Column 2	Column 3
Explanatory variables	*Predicted sign*	Coefficient (*T*-value)	Coefficient (*T*-value)	Coefficient (*T*-value)
$POST_t$		0.021 (0.615)	0.048 (1.134)	0.014 (0.333)
TREATEDi		-0.110*** (-4.300)	-0.145*** (-4.806)	-0.147*** (-4.882)
$POST_t$*TREATED$_i$		***1.028****** ***(5.918)***	***0.399****** ***(4.547)***	***1.321****** ***(4.882)***
$BANKEDSHARE_i$		0.395*** (6.883)	0.282*** (3.748)	0.328*** (4.341)
$POST_t$*$BANKEDSHARE_i$		0.007 (0.122)	-0.089 (-1.388)	-0.020 (-0.308)
$POST_t$*TREATED$_i$*BANKEDSHARE$_i$	***(?)***	***-1.170****** ***(-6.042)***		***-1.099****** ***(-5.661)***
$Ln(IMMIGRANT_i)$		0.018*** (6.044)	0.012*** (3.443)	0.012*** (3.466)
$POST_t$* $Ln(IMMIGRANT_i)$		-0.002 (-0.417)	0.005 (1.224)	0.003 (0.571)
$POST_t$*TREATED$_i$* $Ln(IMMIGRANT_i)$	(?)		*-0.043****** *(-5.040)*	*-0.040****** *(-4.576)*
Intercept + all other control variables		Included	Included	Included
Platform fixed effects		Included	Included	Included
Standard errors are cluster-adjusted by		country-platform pair	country-platform pair	country-platform pair
N		14,112	14,112	14,112
Adjusted R-squared		69.1%	69.0%	69.1%

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

Table 5

(Continued)

Panel B: Bitcoin outflows from crypto exchanges when the treatment is continuous

		Dependent Variable = *Ln (**OUTFLOWFROMEXCHANGE$_{ipt}$**)*		
		Column 1	Column 2	Column 3
Explanatory variables	*Predicted sign*	Coefficient (*T*-value)	Coefficient (*T*-value)	Coefficient (*T*-value)
POST$_t$		0.021 (0.615)	0.048 (1.134)	0.014 (0.333)
RUSBANKREMITi		-0.017 (-1.169)	0.007 (0.510)	0.006 (0.402)
POST$_t$*RUSBANKREMIT$_i$		***0.452*** (5.692)***	***0.399*** (4.547)***	***0.894*** (8.260)***
BANKEDSHARE$_i$		0.250*** (3.322)	0.209*** (2.796)	0.290*** (3.844)
*POST$_t$*BANKEDSHARE$_i$*		0.047 (0.122)	-0.073 (-1.388)	-0.020 (-0.308)
POST$_t$*RUSBANKREMIT$_i$ *BANKEDSHARE$_i$	***(?)***	***-0.577*** (-5.282)***		***-0.825*** (-7.072)***
Ln(IMMIGRANT$_i$)		0.008** (2.185)	0.006* (1.753)	0.006* (1.718)
POST$_t$ Ln(IMMIGRANT$_i$)*		-0.005 (-0.417)	0.002 (1.224)	0.002 (0.171)
*POST$_t$*RUSBANKREMIT$_i$* Ln(IMMIGRANT$_i$)*	(?)		-0.018*** (-3.734)	-0.032*** (-6.003)
Intercept + all other control variables		Included	Included	Included
Platform fixed effects		Included	Included	Included
Standard errors are cluster-adjusted by		country-platform pair	country-platform pair	country-platform pair
N		14,112	14,112	14,112
Adjusted R-squared		69.0%	68.9%	69.0%

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

Table 6
The Cross-sectional Variation and Costs of Bank-intermediated Cross-border Payments

This table uses a difference-in-differences design in equation (3) to explore whether the SWIFT ban's effect varies with the costs of bank-intermediated cross-border payments. $BANKCOST_i$ is the *weighted* average cost of receiving $200 across all bank-intermediated remittance corridors in country *i* in 2021. The dependent variable is $OUTFLOWFROMEXCHANGE_{ipt}$, on-chain Bitcoin outflows from cryptocurrency exchange platform p to country *i* on day *t*. $POST_t$ is a dummy variable set to 1 for the 7-day window after the SWIFT ban and 0 for the 7-day window up to the initiation of the SWIFT ban on February 26, 2022. $TREATED_i$ is a dummy variable set to 1 for countries that received at least 0.1% of bank-intermediated remittances from Russia in 2021 and 0 otherwise. $RUSBANKREMIT_i$ is the recipient country's share of bank-intermediated remittances from Russia in 2021.

		Dependent Variable = $Ln(\boldsymbol{OUTFLOWFROMEXCHANGE_{ipt}})$			
		Dichotomous treatment effect		Continuous treatment effect	
		Column 1	Column 2	Column 3	Column 4
Explanatory variables	*Predicted sign*	Coefficient (*T*-value)	Coefficient (*T*-value)	Coefficient (*T*-value)	Coefficient (*T*-value)
$POST_t$		0.035 (0.701)	0.004 (0.077)	-0.021 (-0.432)	-.044 (-0.882)
$TREATED_i$		-0.231*** (-4.372)	-0.244*** (-4.605)		
$\boldsymbol{POST_t*TREATED_i}$		***3.301*** (7.283)***	***3.506*** (7.673)***		
RUSBANKREMITi				0.545 (0.217)	0.509 (0.203)
$\boldsymbol{POSTt*RUSBANKREMIT_i}$	***(+)***			***3.945*** (8.844)***	***2.874*** (3.842)***
$BANKCOST_{it}$		0.006 (0.997)	0.008 (1.241)	0.010 (1.534)	0.010 (1.483)
$\boldsymbol{POST_t*TREATED_i*BANKCOST_{it}}$		***-0.671*** (-7.429)***	***-0.580*** (6.159)***		
$\boldsymbol{POST_t*RUSBANKREMIT_i*}$ $\boldsymbol{BANKCOST_{it}}$	***(-)***			***-0.850*** (-8.870)***	***-0.475** (-2.049)***
$BANKEDSHARE_{it}$			0.304** (2.599)		0.106 (0.970)
$POST_t*BANKEDSHARE_{it}$			0.083 (0.885)		0.164 (1.711)
$POST_t*TREATED_i*BANKEDSHARE_{it}$			-0.860*** (-3.344)		
$POST_t*RUSBANKREMIT_i$ $*BANKEDSHARE_{it}$					-1.251* (-1.783)
Intercept and control variables in equation (3)		Included	Included	Included	Included
Standard errors are cluster-adjusted by country-platform pair		Yes	Yes	Yes	Yes
N		5,824	5,824	5,824	5,824
Adjusted R-squared		70.7%	70.8%	70.6%	70.6%

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

Table 7
The Effect of the SWIFT Ban on the Destinations of Stablecoins OutFlows

This table uses a difference-in-differences design in equation (3) to explore whether the SWIFT ban's effect varies with the proportion of the banked population (*BANKEDSHAREi*). The dependent variable is $STABLECOINOUTFLOW_{ipt}$, the on-chain Stablecoins outflow from exchange platform p to country *i* on day *t*. $POST_t$ is a dummy variable set to 1 for the 7-day window after the SWIFT ban and 0 for the 7-day window up to the initiation of the SWIFT ban on February 26, 2022. Panel A of this table reports the results when the treatment effect is dichotomous. $TREATED_i$ is a dummy variable set to 1 for countries that received at least 0.1% of bank-intermediated remittances from Russia in 2021 (the last year before the SWIFT ban) and 0 otherwise. Panel B of this table reports the results when the treatment effect is continuous. $RUSBANKREMIT_i$ is the recipient country's share of bank-intermediated remittances from Russia in 2021.

Panel A: Stablecoins outflows from crypto exchanges when the treatment is dichotomous

		Dependent Variable = Ln(***$STABLECOINOUTFLOW_{ipt}$***)		
		Column 1	Column 2	Column 3
Explanatory variables	*Predicted sign*	Coefficient (*T*-value)	Coefficient (*T*-value)	Coefficient (*T*-value)
$POST_t$		0.034 (0.696)	*-0.229** *(1.808)*	0.003 (0.023)
TREATEDi		-0.358*** (-3.955)	-0.373*** (-4.146)	-0.359*** (-3.966)
$POST_t$*TREATED$_i$		***0.008*** ***(0.061)***	***6.612****** ***(4.875)***	***1.341****** ***(5.110)***
$BANKEDSHARE_{it}$		-1.735*** (-7.702)	-1.415*** (-6.287)	-1.728*** (-7.682)
$POST_t$*$BANKEDSHARE_{it}$		0.008 (0.061)	0.406** (2.116)	-0.220 (-1.143)
$POST_t$*TREATED$_i$*BANKEDSHARE$_{it}$	***(?)***		***-7.578****** ***(-3.114)***	
Ln(IMMIGRANT)it		0.042*** (3.997)	0.042*** (4.064)	0.041*** (3.984)
POST Ln(IMMIGRANT)it*		-0.038 (-0.199)	-.016 (-1.030)	0.021 (1.531)
POST*TREATED* Ln(IMMIGRANT)it	**(?)**			***-0.148****** ***(-5.752)***
All other control variables		Included	Included	Included
Platform fixed effects and intercept		Included	Included	Included
Standard errors cluster-adjusted by		country-platform pair	country-platform pair	country-platform pair
N		13,230	13,230	13,230
Adjusted R-squared		71.6%	71.9%	71.6%

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

Table 7

(Continued)

Panel B: Stablecoins outflows from crypto exchanges when the treatment is continuous

		Dependent Variable = Ln(***STABLECOINOUTFLOW$_{ipt}$***)	
		Column 1	Column 2
Explanatory variables	*Predicted sign*	Coefficient (*T*-value)	Coefficient (*T*-value)
POST$_t$		0.032 (0.679)	0.041 (0.839)
RUSBANKREMITi		0.266*** (5.708)	0.261*** (5.681)
POST$_t$*RUSBANKREMIT$_i$	***(+)***	***3.716****** ***(4.053)***	***4.912****** ***(6.320)***
BANKEDSHARE$_{it}$		0.396 (2.881)	0.385*** (6.320)
*POST$_t$*BANKEDSHARE$_{it}$*		-0.006 (-0.080)	-0.026 (-0.135)
POST$_t$*RUSBANKREMIT$_i$*BANKEDSHARE$_{it}$	***(?)***	***-5.521****** ***(-4.472)***	
Ln(IMMIGRANTS)$_{it}$		-0.001 (-0.148)	0.008 (0.757)
POST Ln(IMMIGRANT)it*		0.004 (0.285)	0.003 (0.219)
POST$_t$*RUSBANKREMIT$_i$*Ln(IMMIGRANT)it	**(?)**		***-0.472****** ***(-6.342)***
All other control variables		Included	Included
Platform fixed effects and intercept		Included	Included
Standard errors cluster-adjusted		country-platform pair	country-platform pair
N		13,230	13,230
Adjusted R-squared		72.1%	71.7%

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

Table 8
Change specification to address the endogeneity of the percentage of the banked population

This table uses the change specification as specified in equation (4) to address the endogeneity of the percentage of the banked population. *CHGONCHAINFLOWit* is the change in the on-chain cryptocurrency inflow to country *i* in period *t*. $CHGRETAILONCHAINFLOW_{it}$ is the change in the on-chain small-valued cryptocurrency flow to country *i* in period *t*. $CHGBANKEDSHARE_{it}$ is the change in the percentage of the banked population for country *i* in period *t*. $CHGREMITTANCE_{it}$ is the change in inward remittances as a percentage of the GDP for country *i* in period *t*.

Panel A: On-chain cryptocurrency flows by all market participants

	Column 1 Equation (4)	Column 2 Equation (4)
	Dependent variable = ***$CHGONCHAINFLOW_{it}$***	Dependent variable = ***$CHGONCHAINFLOW_{it}$***
Explanatory variables	Coefficient (*T*-value)	Coefficient (*T*-value)
$CHGBANKEDSHARE_{it}$	***-0.351**** ***(-2.906)***	***-0.297**** ***(-2.430)***
$CHGREMITTANCE_{it}$		*3.608**** *(2.622)*
$CHGSMARTPHONE_{it}$	-0.111 (-0.979)	-0.552 (-1.425)
CHGMOBILEMONEYit	0.082* (2.500)	0.029 (0.659)
$CHGAMLSCORE_{it}$	0.014 (-1.476)	-0.021 (-0.962)
$CHGGDPpercapita_{it}$	-0.003 (-1.543)	-0.006** (-2.129)
$CHGFOREX_{it}$	0.224** (2.049)	0.236* (1.979)
$CHGINFLATION_{it}$	0.001* (1.901)	0.001** (2.050)
$CHGINTERNET_{it}$	0.001 (0.820)	0.001 (0.510)
$CHGPOP_{it}$	0.542 (0.798)	-0.211 (-0.268)
$CHGCAPITALCONTROL_{it}$	0.001 (0.747)	-0.229 (-1.608)
CHGSTOCKMARKETSIZEit	-0.001 (-0.460)	0.001 (0.121)
CHGEQUITYRETURNit	0.001 (0.924)	0.001 (1.372)
$CHGPRICE_t$	0.001 (0.162)	-0.029 (-1.058)
$CHGONCHAINCOST_t$	0.002 (1.641)	0.001 (0.511)
Intercept +year-fixed effects	Included	Included
Standard errors are cluster-adjusted by	Country	Country
N	353	353
Adjusted *R*-squared	5.7%	13.1%

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

Table 8
(Continued)

Panel B: On-chain cryptocurrency flows by all market participants

	Column 1 Equation (4)	Column 2 Equation (4)
	Dependent variable = ***CHGRETAIL ONCHAINFLOW$_{it}$***	Dependent variable = ***CHGRETAIL ONCHAINFLOW$_{it}$***
Explanatory variables	Coefficient (*T*-value)	Coefficient (*T*-value)
Intercept	Included	Included
CHGBANKEDSHARE$_{it}$	***-0.179***** ***(-3.307)***	***-0.134***** ***(-2.333)***
CHGREMITTANCE$_{it}$		3.032*** (5.486)
All control variables in equation (4)	Included	Included
Year-fixed effects	Included	Included
Standard errors are cluster-adjusted by	Country	Country
N	353	353
Adjusted R-squared	4.8%	12.5%

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

Table 9

Lack of Trust as an Explanation for the Interplay between Banks and Cryptocurrency

This table examines whether a lack of trust in financial institutions partially explains the interplay between banks and cryptocurrency. *CHGDISTRUST* replaces *CHGBANKEDSHARE* in equation (4). *CHGONCHAINFLOWit* is the change in the on-chain cryptocurrency inflow to country *i* in period *t*. $CHGOFFCHAINTRADE_{it}$ is the change in the volume of off-chain cryptocurrency trades for country *i* in year *t*. $CHGDISTRUST_{it}$ is the change in the percentage of adults citing a lack of trust in financial institutions as a barrier to financial account ownership from the 2021 survey relative to the 2017 survey.

Panel A: Validity of lack of trust in financial institutions from the Global Findex Survey

	Pearson correlation with *WVSDISTRUSTBANK* (% of the population saying that "I have not much confidence in banks or none at all" in the World Value Survey)	**Spearman** correlation with *WVSDISTRUSTBANK* (% of the population saying that "I have not much confidence in banks or none at all" in the World Value Survey)
DISTRUST (% of adults citing lack of trust in financial institutions as the reason for having no bank accounts from the Global Findex Survey)	0.842*** (N =33)	0.790*** (N =33)

Panel B: Lack of trust in financial institutions as an explanation

		Column 1	Column 2
		Dependent variable= ***$CHGONCHAINFLOW_{it}$***	Dependent variable = ***$CHGOFFCHAINTRADE_{it}$***
Explanatory variables	*Predicted sign*	Coefficient (*T*-value)	Coefficient (*T*-value)
Intercept		Included	Included
$CHGDISTRUST_{it}$	***(+)***	***0.511****** ***(3.262)***	***-0.059*** ***(-0.169)***
Control variables in equation (4)		Included	Included
Year fixed effects		Included	Included
Cluster-adjusted standard errors		By country	By country
N		353	353
Adjusted *R*-squared		24.6%	19.7%

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