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Global and local drivers of Bitcoin trading vis-à-vis fiat currencies

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Abstract

We analyse the drivers of Bitcoin transactions against 44 fiat currencies in the largest peer-to-peer crypto exchanges. Momentum and volatility in the cryptoasset market, as well as volatility and liquidity in global financial markets do matter for Bitcoin trading. There is suggestive evidence of a global *crypto* cycle driven by speculative motives. However, in emerging and developing economies (EMDEs), Bitcoin seems to offer also transactional benefits, since trading increases when the value of the domestic currency is unstable. Proxies of banking depth and digitalisation are negatively correlated with the currency loadings on the global factor, indicating that crypto-assets may offer a *speculative* alternative to traditional finance when this is not available, especially in EMDEs where the share of younger risk-prone population is higher. Our results clearly point to potential financial stability risks from cryptoisation in EMDEs with low levels of financial development and unstable fiat currencies.

JEL Classification: E42 F21 F24 F32 F38 G15 O33

Keywords: digital currencies, Bitcoin, peer-to-peer exchanges, financial development.

Non-technical summary

The popularity of Bitcoin and other cryptocurrencies has not been confined to few economies, but it has morphed into a global phenomenon, rapidly spreading to economies with disparate levels of economic development and financial literacy. Notably, Emerging and Developing Economies (EMDEs) are at the forefront of crypto adoption. There a number of potential reasons behind the growing popularity of Bitcoin and other cryptocurrencies in EMDEs. First, cryptocurrencies may be used as speculative assets, which may be particular attractive to investors from countries where the portfolio choice of investment assets is restricted by regulatory or institutional factors. Second, even though prices have been very volatile, these cryptocurrencies may represent a better store of value with respect to the domestic currency of countries where inflation is high and the exchange rate tends to depreciate. Third, residents from EMDEs may use cryptocurrencies as a means of payment in cross-border transactions to circumvent capital controls or to lower the cost of receiving remittances from abroad. How this range of explanations and drivers of crypto adoption maps into the cross-section of economies and their characteristics has so far received limited attention, largely due to data constraints and the inherent difficulty to track the final owners of cryptocurrencies.

In this study, we overcome the obstacle of limited country-by-country information by looking at *fiat currency* transactions against Bitcoin. The implied assumption is that those trading currencies that are not major international currencies, in particular currencies of EMDEs, are residents of the countries issuing that currency. We support this assumption for those transactions where data about the residence of the traders of Bitcoin are available. Compared to previous studies, we analyse transactions taking place in peer-to-peer (P2P) exchanges, outside the blockchain network (i.e. they are *off-chain*). These P2P exchanges have an important peculiarity: they target mainly small retail users. In these P2P exchanges, bid-ask spreads tend to be large so that these exchanges are usually not affected by the problem of market manipulation, such as *wash trading*, typical of centralized exchanges, thus making the transactions we analyse more reliable. The growth in cryptocurrency markets in recent years has taken place particularly through *off-chain* transactions and, in EMDEs, especially in P2P exchanges.[1] Specifically, we analyse trading volumes of Bitcoin versus the currencies of 14 Advanced Economies (AEs) – excluding the US dollar due to its

[1]While *on-chain* transactions occur on the blockchain network and need to be validated by miners, *off-chain* transactions are conducted outside the blockchain network, making them - in general - faster and cheaper. *Off-chain* transactions may take place in centralised exchanges that act as an intermediary, or peer-to-peer exchanges that only match offers from buyers and sellers but do not act as intermediaries.

special status – and the currencies of 30 EMDEs. Data are obtained from the largest P2P exchanges, namely LocalBitcoins and Paxful, over the period January 2018 - April 2022, on a weekly basis.

Our results, overall, reinforce the hypothesis, currently prevailing in the literature, that Bitcoin trading is driven by speculative motives. In this paper, we show that this is truly a global phenomenon. There is suggestive evidence of a global *crypto* cycle in Bitcoin trading against fiat currencies, with transactions across currencies and users around the world moving in tandem with fluctuations in the Bitcoin price. Similarly to other risky assets, momentum in the crypto-asset market, past Bitcoin price volatility as well as global financial market volatility do matter for Bitcoin trading against different fiat currencies.

However, Bitcoin seems to offer also specific transactional benefits, in particular in EMDEs. The depreciation of the domestic currency of EMDEs – notably *not* of the currency of AEs – induces more Bitcoin trading, in particular after the COVID-19 pandemic. This indeed suggests that Bitcoin, despite its wide price fluctuations, might have been appreciated also as a store of value or medium of exchange in countries which experienced a loss in the the purchasing power of their domestic currency. In turn, this implies that macroeconomic instability may potentially spur greater cryptoasset usage. This result is important for the asset pricing theory of cryptoassets, suggesting that the fundamental value of Bitcoin may be substantially different between AEs and EMDEs, since its transactional services are probably more elevated in less developed economies. Moreover, we find that proxies of banking depth and digitalisation are negatively correlated with the extent to which each currency loads on the global common factor in Bitcoin trading volumes, indicating that crypto-assets may offer a *speculative* alternative to traditional finance when this is not available, in particular in EMDEs where the share of younger risk-prone population is higher, another important finding of our analysis.

Our findings clearly point to potential financial stability risks in EMDEs with low levels of financial development and unstable fiat currencies. The intrinsic price volatility of Bitcoin may discourage its use as a store of value or means of payment; however, in the future, other crypto assets, such as stablecoins that pledge to ensure a parity to the US dollar or other reserve currencies, might become more widely used by individuals and firms in order to compensate for the lack of financial alternatives.

1 Introduction

To what extent is Bitcoin usage a global phenomenon driven by speculative demand? To what extent can country-specific factors explain the use of Bitcoin? What drives the adoption of an *unbacked* digital currency like Bitcoin? These are important questions that so far have received only partial answers, largely due to the difficulty to trace who owns and trades cryptocurrencies.

In this study, we overcome the obstacle of limited country-by-country information on cryptocurrency use by looking at *fiat currency* transactions against Bitcoin.[1] Compared to previous studies, we analyse transactions taking place in peer-to-peer (P2P) exchanges that perform transactions outside the blockchain network (i.e. they are *off-chain*) and in a decentralised manner (see Section 2). These P2P exchanges have an important peculiarity: they target mainly small retail users.[2] In these P2P exchanges, bid-ask spreads tend to be large so that these exchanges are usually not affected by the problem of market manipulation, such as *wash trading*, typical of centralised exchanges, thus making the transactions we analyse more reliable.[3] As shown in Figure 1, the growth in cryptocurrency markets in recent years has taken place particularly through *off-chain* transactions and in emerging and developing economies (EMDEs), especially in P2P exchanges (see Section 2).

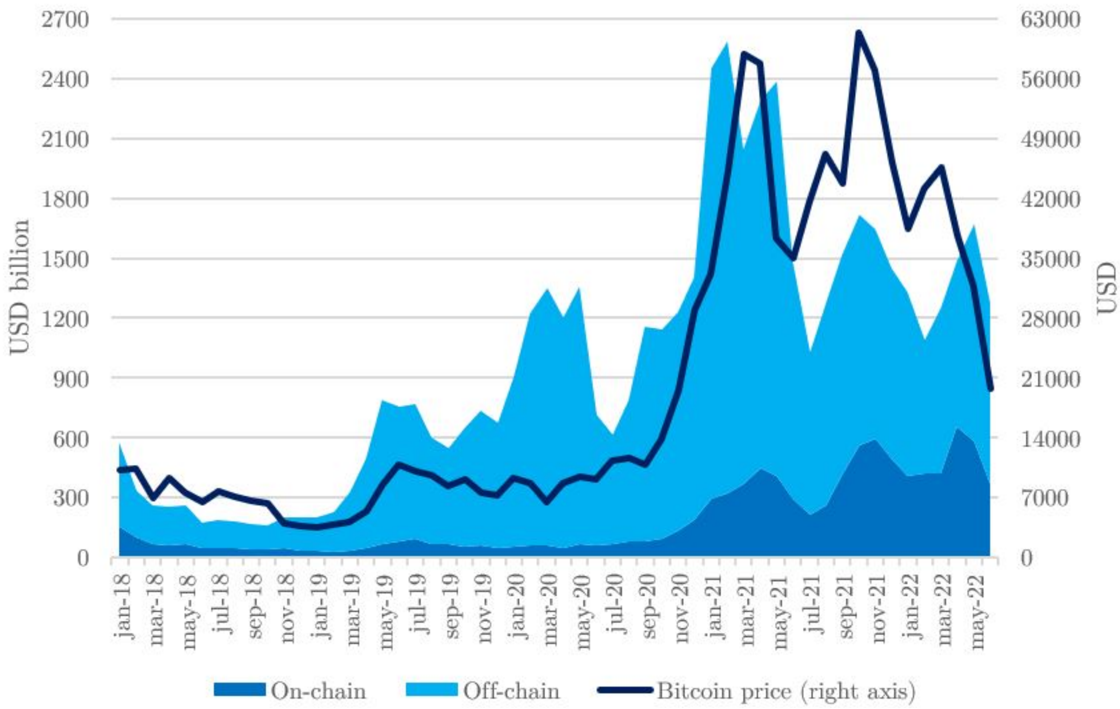
Specifically, we analyse trading volumes of Bitcoin versus the currencies of 14 advanced economies (AEs) – excluding the US dollar due to its special status – and the currencies of 30 EMDEs. Data are obtained from the largest P2P exchanges, namely LocalBitcoins and Paxful, over the period January 2018 - April 2022, on a weekly basis. First, we study the impact of a number of crypto-specific drivers, global drivers and local drivers on Bitcoin transactions in a fixed effect dynamic panel model in order to understand the motivations of Bitcoin trading. In particular, we investigate whether Bitcoin transactions have been driven by (i) trends that are specific to the crypto-market and may be ascribed to the demand factors highlighted by Biais et al. (2023); (ii) trends that are related to the traditional financial system, such as developments in global financial markets and liquidity, global macroeconomic

[1] The implicit assumption is that those trading currencies that are not major international currencies, in particular currencies of emerging and developing economies, are residents of the countries issuing that currency. We shall support this assumption for those transactions where data about the residence of the traders of Bitcoin are available.

[2] See Chainanalysis (2021), page 10. Graf von Luckner et al. (2023) calculate that the average trade size in one of the P2P platforms we study, Paxful, is around USD 150.

[3] Wash trading is the problem of having investors simultaneously selling and buying the same financial assets to create artificial activity in the marketplace, which is known to distort price, volume, and volatility, and reduce investors' confidence and participation in financial markets. According to Cong et al. (Forthcoming), analysing a sample of unregulated exchanges, wash trading is a serious problem, with the reported volumes inflated on average by over 70%.

Figure 1: Bitcoin price, on-chain and off-chain volumes.

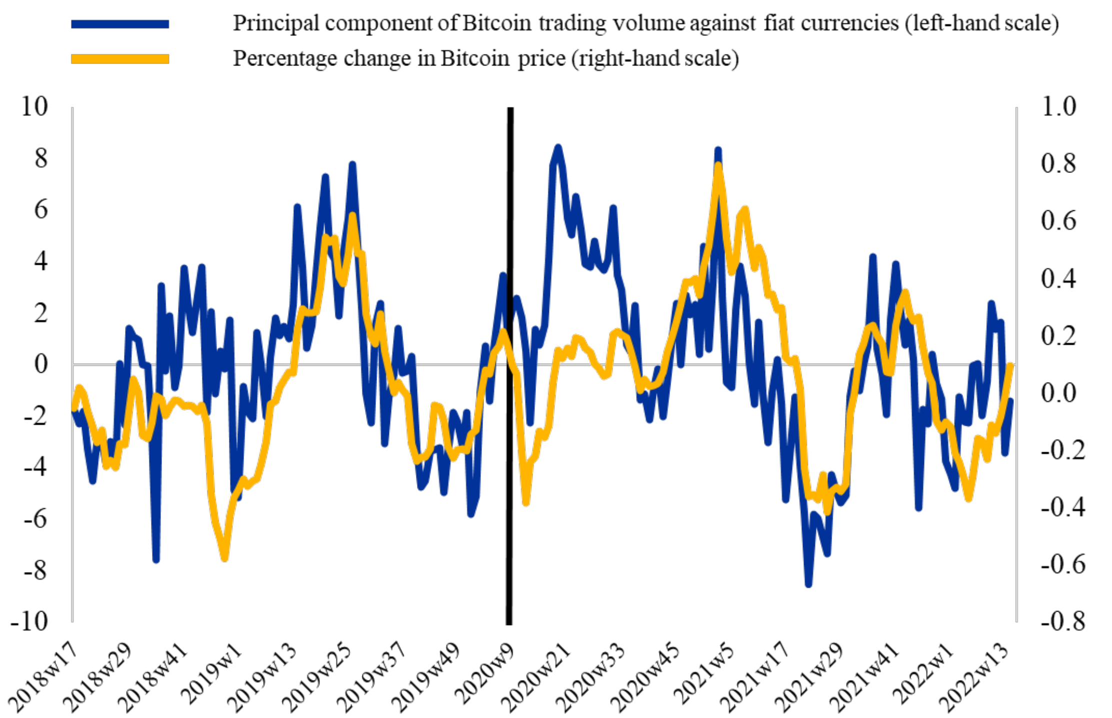


Source: CoinMetrics and CoinMarketCap.

conditions or geopolitical events, similarly to analyses of foreign exchange trading volumes (Cespa et al., 2022); and, finally, (iii) country-specific variables that reflect the weakness of the institutional and macroeconomic framework, which may influence the transactional services of Bitcoin and its fundamental value. Second, as the panel analysis finds that there is a large share of variation in Bitcoin transactions that is common across different currencies, we use a static factor model to identify common factors in Bitcoin trading against different fiat currencies and analyse their features. Finally, we turn our attention to EMDEs, including in our analysis a large number of economic and institutional variables that, according to the literature, might be associated with Bitcoin usage, studying which country features correlate with the currency loading on the main global component of Bitcoin trading.

We find that momentum and volatility in the crypto-asset market as well as global financial market volatility and liquidity do matter for Bitcoin trading against different fiat currencies. However, in a panel setting, a global component of Bitcoin trading still needs to be identified, since our crypto-assets and global drivers fail to capture the full extent of co-movement in Bitcoin trading across currencies and over time. Indeed, the factor analysis identifies a single global factor that on average explains up to around 40% of the variance of Bitcoin trading across different currencies in the COVID-19 period. There is therefore suggestive evidence of a global *crypto* cycle in Bitcoin transactions, echoing the findings of the global financial cycle literature for traditional asset markets (Miranda-Agrippino and Rey, 2022). This global factor, in turn, is correlated with the Bitcoin price, as shown in Figure 2. Trading across currencies and users around the world moves in tandem with fluctuations in the Bitcoin price, suggesting that Bitcoin is largely used as a speculative investment asset across advanced, emerging and developing economies.

Figure 2: A global factor in Bitcoin trading volumes against fiat currencies is correlated with the Bitcoin price



The figure shows the first factor extracted from the trading volume of Bitcoin transactions against fiat currencies (blue line) and the change in the Bitcoin price (yellow line). See section 4.2 for further details. Trading volumes and the Bitcoin price are detrended with the log difference with respect to the past 15-week moving average.

However, Bitcoin seems to offer also transactional benefits, in particular in EMDEs. The trading of Bitcoin against fiat currencies of EMDEs is somewhat different from that against currencies of AEs. The impact of momentum in the crypto-asset market is particularly strong in EMDEs in the period of the COVID-19 pandemic. Importantly, one local driver, the depreciation of the domestic currency versus the US dollar, plays a role in encouraging more Bitcoin trading against the currencies of EMDEs, again in particular since the start of the COVID-19 pandemic. This finding suggests that Bitcoin might be used as a store of value or medium of exchange in countries which experience a loss in the purchasing power of their domestic currency. Finally, the extent to which each currency of EMDEs loads on the global factor – the factor more closely associated with the Bitcoin price – is negatively correlated with the number of ATMs or the diffusion of digital payments in the countries issuing the respective currency and positively with a higher share of younger population. Possibly, the lack of a developed financial system, providing efficient payment rails and the ability to diversify the financial portfolio, encourages the youngest cohorts of the population in EMDEs to take the risk of a cryptoasset investment.

Our results point towards financial stability risks associated with cryptocurrency speculation. This is exacerbated by the limited consumer protection and high level of opaqueness in cryptomarkets, as suggested by evidence on price manipulation and insider trading (Gandal et al., 2018; Griffin and Shams, 2020). Moreover, the rather high price volatility of the cryptoasset markets has been punctuated by market crashes, while the link with the mainstream financial system has been increasing.[4] Notably, our results indicate that financial stability risks could be more pronounced in EMDEs with low levels of financial development and unstable fiat currencies. In these countries, Bitcoin – or, more likely, other crypto-assets like *stablecoins* in the future - might become widely used by individuals and firms for ordinary transactions or as a store of value, in order to compensate for the lack of financial alternatives.[5] These developments raise the risk of *cryptoisation* (IMF, 2021) – i.e. the substitution of the domestic currency with a cryptocurrency in the similar fashion as the US dollar is widely used in countries with high inflation – and represent a threat to the implementation of capital flow management policies in these countries (He et al., 2022). To a large extent, our results and policy implications concern EMDEs, as decentralised P2P exchanges found fertile ground in less developed economies, whereas residents of AEs tend to use *off-chain centralised* exchanges, which are beyond the scope of this study. However, financial stability risks stemming from cryptocurrencies, in general, are not confined to EMDEs, as US-based evidence points towards substantial spillover effects from cryptocurrencies on the real economy through consumption and investment into other asset classes (Aiello et al., 2023).

Our study contributes to a growing literature on the drivers of Bitcoin and other crypto assets usage. Bitcoin was created with the aim of providing an alternative payment system that would operate in a decentralised way, free of the control of a third party or an authority. Notably, like many other crypto-assets, Bitcoin is not backed by any real asset or any governmental claims (Halaburda et al., 2022).[6]

[4] For instance, the crash of the algorithmic stablecoin TerraUSD in May 2022, analysed in Uhlig (2022). Iyer (2022) provide evidence on the increased interconnection between cryptoasset and equity markets across economies over time, while Karau (2023) shows that Bitcoin prices respond to monetary policy shocks similarly to stock prices since the COVID-19 pandemic.

[5] Stablecoins are digital assets designed to minimise price volatility typically against a single fiat currency like the US dollar (or a basket of fiat currencies or reserve assets).

[6] According to the definition of the Financial Stability Board, crypto-assets like Bitcoin are a type of private sector digital asset that depend primarily on cryptography and distributed ledger or

Considering the apparent lack of a fundamental value, the exponential growth in the volume of transactions involving Bitcoin and in its price is certainly surprising (see Figure 1). This in turn has generated a lively and fast-growing debate among economists about the motivations behind the use of Bitcoin. After an initial usage by a small community of experts, the usage of Bitcoin has been subsequently driven by the black market of illegal goods and services and by gambling (Foley et al., 2019; Marmora, 2021). More recently, however, the soaring popularity of cryptocurrency exchange markets and Bitcoin might have also been driven by speculative motives (Baur et al., 2018) or, possibly, by its potential use for cross-border transactions and transfers (Graf von Luckner et al., 2023; Makarov and Schoar, 2021), although the high volatility of its price makes Bitcoin impractical as a medium of exchange (Baur and Dimpfl, 2021).[7]

The popularity of Bitcoin and other cryptocurrencies has not been confined to few economies, but it has morphed into a global phenomenon, rapidly spreading to economies with disparate levels of economic development and financial literacy. Notably, EMDEs are at the forefront of crypto adoption. According to Chainanalysis (2022), among the top 20 countries with the highest crypto adoption index, there are only two AEs, the United States and United Kingdom, whereas the remaining countries are all EMDEs from Asia, Africa, Europe or Latin America.[8]

There a number of potential reasons behind the growing popularity of Bitcoin and other cryptocurrencies in EMDEs. First, cryptocurrencies may be used as speculative assets, which may be particular attractive to investors from countries where the portfolio choice of investment assets is restricted by regulatory or institutional features. Second, even though prices have been very volatile, these cryptocurrencies may represent a better store of value or medium of exchange with respect to the domestic currency in countries where inflation is high and the exchange rate tends

similar technology (see https://www.fsb.org/work-of-the-fsb/financial-innovation-and-structural-change/crypto-assets-and-global-stablecoins/). Crypto-assets transactions that are recorded on a distributed ledger - the blockchain - are public and rely on consensus mechanisms instead of trusted parties. The transactions are not tied to real-world entities but rather crypto-addresses (i.e. account numbers) whose owners are not explicitly identified, thereby ensuring (pseudo) anonymity.

[7]Leveraging on a recent US survey of consumers, Auer and Tercero-Lucas (2022) show that cryptocurrency investors tend to be highly educated, young, male and digital natives, and that distrust in regular finance is not the key driver of investment in cryptocurrencies. Using data from a German online bank, Hackethal et al. (2021) find that cryptocurrency investors are active traders who are prone to investment biases and hold risky portfolios, tilting their portfolios toward even more risky securities after cryptocurrency usage. Weber et al. (2023) also rely on survey data on US households to report that cryptocurrency holders tend to be young, white, male and more libertarian relative to non-crypto holders.

[8]In September 2021, Bitcoin was even adopted as legal tender in El Salvador and Central African Republic. However, Alvarez et al. (2022) find that the use of Bitcoin for everyday transactions in El Salvador was low, based on a national survey conducted soon after the adoption of Bitcoin as legal tender.

to depreciate. Third, residents from EMDEs may use cryptocurrencies as a means of payment in cross-border transactions to circumvent capital controls or to lower the cost of receiving remittances from abroad (Graf von Luckner et al., 2023). Biais et al. (2023) offer a theoretical framework to explain the fundamental value of cryptocurrencies, which depends on their net transactional services. However, as these net benefits, in turn, depend on the price of the cryptocurrency, the equilibrium can reflect exogenous sunspots. Eventually, their calibration of the model shows that changes in fundamentals explain only a tiny fraction of variation in the Bitcoin price, while the remaining variation reflects *extrinsic volatility*. However, in countries where institutions are weak and the quality and efficiency of using the legal tender as a store of value or medium of exchange is impaired, the net transactional benefits of using cryptocurrencies are probably higher. In different terms, in the spirit of La Porta et al. (1997), the legal and institutional framework may affect the fundamental value of cryptocurrencies and their adoption. Unsurprisingly, studying deviations in Bitcoin prices in a sample of advanced and emerging economies, Makarov and Schoar (2020) find that the marginal Bitcoin investor operates from a country with poorly functioning financial institutions or tighter capital controls.

So far, with few exceptions such as Makarov and Schoar (2020), the ability to map cryptocurrency use into country features has been limited, largely due to data constraints and the inherent difficulty to track the final owners of cryptocurrencies. Scholars often relied on surveys. For instance, Alnasaa et al. (2022) argue that cryptocurrency usage is higher in countries with more corruption and stricter capital controls, based on an international survey of cryptocurrency users. Feyen et al. (2022) is one of the few studies that uses proprietary data on *on-chain* transactions *by country* to identify global and country-specific drivers of Bitcoin usage between 2019 and 2021.[9] The authors find an important role for global drivers, such as the gold price, and crypto-specific drivers, rather than country-level drivers to determine cross-country volumes across time.[10] However, the authors acknowledge that their *on-chain* data may not capture purchases and sales of crypto-assets for fiat currency. This may limit the potential to identify country-specific drivers of Bitcoin adoption and the role of small retail investors who have been enticed by the easiness to transact cryptocurrencies *off-chain* through dedicated applications.[11] Our study fills the gap

[9] Auer et al. (2022a) analyses data on retail downloads for crypto exchange apps across 95 countries and finds that a rising Bitcoin price is followed by the entry of new users.

[10] The prominent role of cryptocurrency prices for the investment choices in retail use is also confirmed by Kogan et al. (2023), using data from a centralised exchange.

[11] While *on-chain* transactions occur on the blockchain network and need to be validated by miners, *off-chain* transactions are conducted outside the blockchain network, making them - in general - faster and cheaper. *Off-chain* transactions may take place in centralised exchanges that act as an intermediary, or peer-to-peer exchanges that only match offers from buyers and sellers

in the literature on the role that specific institutional features may play in fostering crytpo adoption using actual data, not surveys. Specifically, we distinguish between *global drivers*, related to the demand for Bitcoin or to the spillover of shocks and liquidity in traditional financial markets, and *local drivers*, which may capture the presence of a weak institutional or macroeconomic environment that may foster the use of Bitcoin also as a store of value or medium of exchange.

The rest of paper is structured as follows. Section 2 describes the key distinctive features of P2P cryptoasset exchanges and Section 3 presents the data with their summary statistics. Section 4 discusses the empirical methodology and the key findings on the drivers of Bitcoin vis-à-vis fiat currency transactions, including robustness checks. Finally, Section 5 concludes.

2 P2P crypto exchanges

Our analysis is based on transaction data extracted from the two world's largest peer-to-peer (P2P) Bitcoin exchanges: LocalBitcoins and Paxful.[12] In this section we describe the specific features of these *off-chain decentralised* P2P exchanges in the crypto-assets ecosystem, differentiating them from *off-chain centralised* cryptocurrency exchanges and *on-chain decentralised* exchanges (see Table 1).

Table 1: Classification of exchange platforms

	Centralised (CEX)	Decentralised (DEX)
On-chain		DeFi (Uniswap, Sushiswap, Binance DEX, Bancor)
Off-chain	Centralised (Binance, Coinbase, Kraken, Gemini, Robinhood)	P2P (LocalBitcoin, Paxful, Remitano and Bisq)

The table reports a number of popular exchange platforms for illustrative purposes. The list is not exhaustive as the market is continuously evolving. For instance, Binance also introduced a P2P platform.

Centralised cryptocurrency exchanges (CEX) are online platforms that act as intermediaries and are used to buy and sell cryptocurrencies. CEX transactions are recorded on an exchange's internal database, being therefore *off-chain*. The main disadvantage of CEX is that traders have to give up the custody of the private keys to their accounts. An *on-chain* decentralised exchange (DEX) is a marketplace where

but do not act as intermediaries. See Section 2 for further details.

[12] From 2012 until 2021, LocalBitcoins was the largest off-chain P2P Bitcoin exchange. More recently, Paxful has overcome LocalBitcoins in terms of trading volumes. One peculiar strength of Paxful is the flexibility of its payment system, since it accepts over 300 payment methods. Both P2P exchanges allow Bitcoin to be traded against multiple different fiat currencies.

transactions occur directly between crypto traders and where crypto-assets are not held by an escrow service. In *on-chain* Decentralised Finance (DeFi) exchanges, transactions are carried out by algorithms known as smart contracts and atomic swaps, among others. These platforms exclusively trade cryptocurrency tokens for other cryptocurrency tokens and run directly on the blockchain network (*on-chain*), hence all the trades must be confirmed by a validator (Aspris et al., 2021).[13] P2P exchanges are online platforms that allow transactions between local currency and cryptocurrencies, typically Bitcoin. P2P exchanges only match buyers and sellers, but do not act as intermediaries. They offer an escrow service for traders but do not hold Bitcoin (or other crypto) or currency for the traders (hence they are non-custodial), with the result that they are exempt from regulation or lightly regulated. Trades are recorded on the exchange's internal database, being *off-chain* (Marmora, 2021).

P2P exchanges have gained popularity in particular in EMDEs, being more suitable for EMDE currencies that do not have a large trading pool to be easily used in centralised crypto exchanges (Aramonte et al., 2022). Figure 3a shows that Bitcoin is traded against the currencies of advanced economies mainly in centralised exchanges. In contrast, transactions involving currencies of EMDEs are concentrated in P2P exchanges. Note also that Bitcoin-US dollar transactions are predominantly executed in centralised exchanges (Figure 3a), as also shown in Auer et al. (2022b), but still represent a large fraction of total P2P transactions (Figure 3b). Once the US dollar is excluded, transactions of Bitcoin against the currencies of EMDEs – such as Nigeria, Russia, China or India – make up the most of P2P transactions (Figure 3b).

One of the main benefits of analysing transactions in P2P exchanges versus those in centralised exchanges is that P2P exchanges are utilised mainly by small retail users and are not affected by the problem of market manipulation, such as *wash trading*, thus minimising the possibility that our findings are affected by large trades of few individuals.[14]

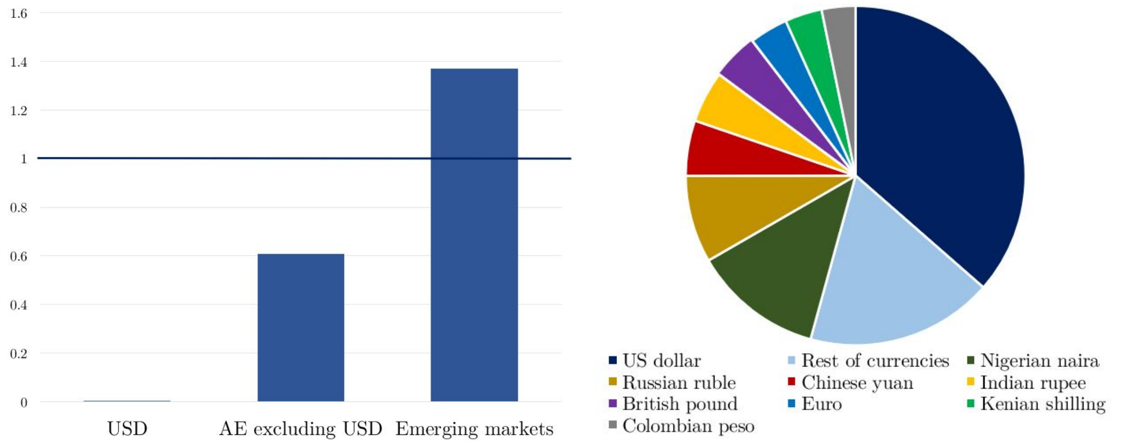
Our working assumption in this study is that, in the Bitcoin market, the currencies of EMDEs are mainly traded by residents of the countries that issue those currencies. Although it is not possible to have information on the location of the traders in LocalBitcoins, such information is available for Paxful. The available data from this source support our working assumption (see Figure 4). The ratio of local currency transactions where at least one of the traders is located in the domestic country over the total volume of transactions tends to be - on average - higher than 70%

[13] Makarov and Schoar (2022) offer an overview of decentralised finance.

[14] See discussion in Section 1.

Figure 3: P2P Bitcoin-fiat currency transactions. Average 2020-21

(a) P2P to CEX ratio (b) % currencies in P2P BTC-fiat transactions



Source: LocalBitcoins, Paxful and authors' calculations.

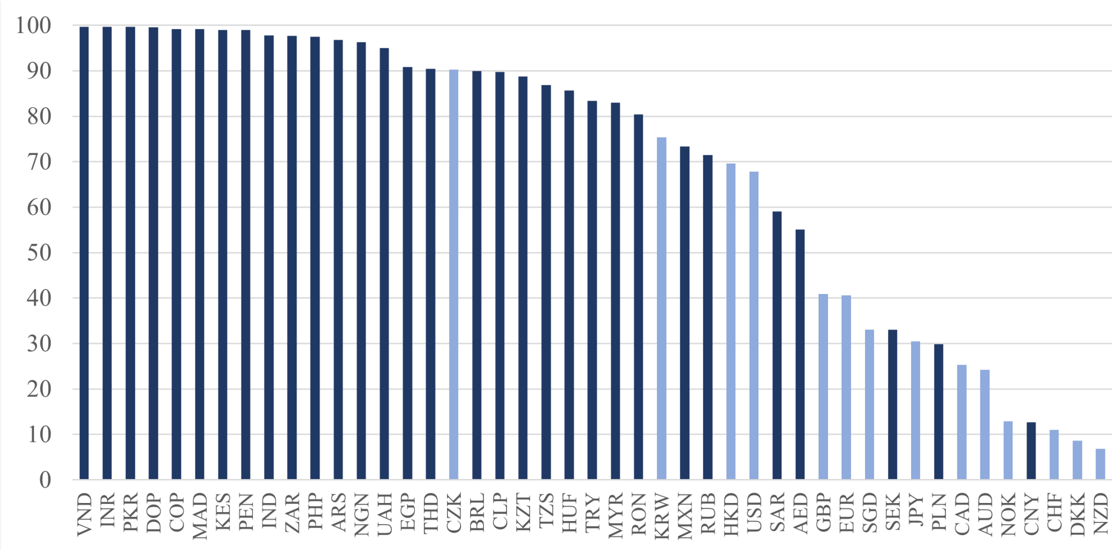
in EMDEs. There are two outliers in EMDEs where the association between the location of the trader and currency do not match closely: the Chinese renminbi, which is mainly traded by US residents, and the Polish zloty. In the case of AEs these ratios are instead lower than 50%. The close association between the currency and country of origin for the group of EMDEs provides support to the analysis presented in Section 4.3, where we introduce country specific institutional features to explain bilateral fiat currency-Bitcoin transactions.[15]

3 Data

Our variable of interest is the total trading volume of Bitcoin transactions in the two world's largest P2P Bitcoin exchanges, LocalBitcoins and Paxful, against 44 currencies (see Table A.3 in the Appendix for details), covering the period from the first week of 2018 to the fourteenth week of 2022. The US dollar has been excluded from the analysis because of its special status. Trading volumes denominated in the domestic currency of our sample of 44 economies have been downloaded from CryptoCompare and summed across the two P2P exchanges. Figure 5a shows the average size of weekly transactions since 2020, when Bitcoin transactions started to pick up significantly (see also Figure 1). In this section, in order to compare trading against different currencies, trading volumes have been converted in US dollar terms and then divided by the population to account for the relative size of various countries. The currencies of two African economies, Kenya and Nigeria, top

[15]Our results are robust to the exclusion the Chinese renminbi and the Polish zloty from our sample of currencies (see Section 4.4).

Figure 4: Ratio of transactions where at least one trader is local in Paxful. Average 2020-21 (percent)



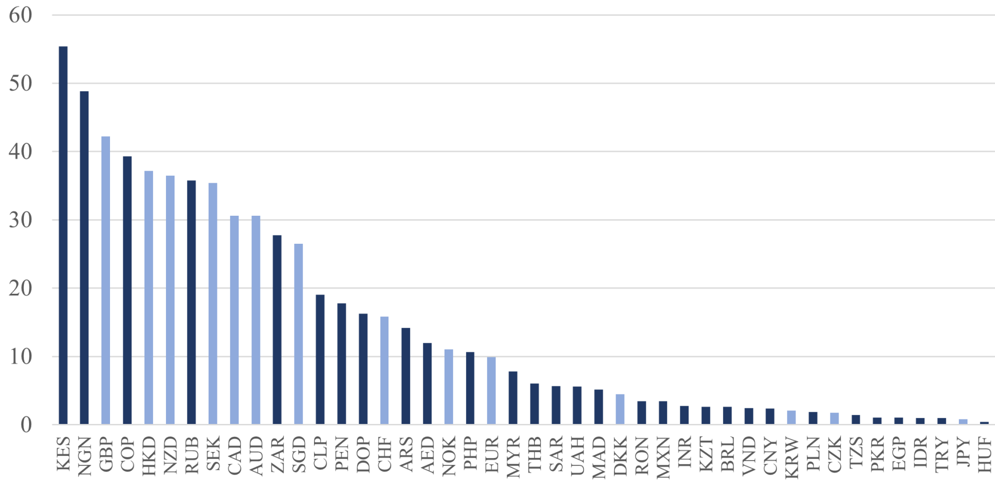
Source: Paxful and authors' calculations. Dark blue bars identify currencies of EMDEs, light blue bars currencies of AEs. See Table A.3 in the Appendix for the identification of currency codes.

the ranking of the most traded currencies in P2P exchanges, transacting each week their currency for an amount equivalent to around 50 US dollars per one thousand inhabitants. Note that according to Figure 4 domestic residents trade these two currencies. The British pound is the third most traded currencies and the first one among AEs, even though only about 40% of these transactions can be imputed to domestic residents. The Kenyan shilling and the Nigerian naira continue to top the ranking of the most traded currencies when scaling trading volumes by nominal GDP (see Figure 5b). As a ratio to GDP, inevitably, the trading volume of currencies of AEs tends to be smaller than according to the previous criterion. The British pound remains, though, the first most traded currency among AEs, but only the fifteenth in the whole sample.

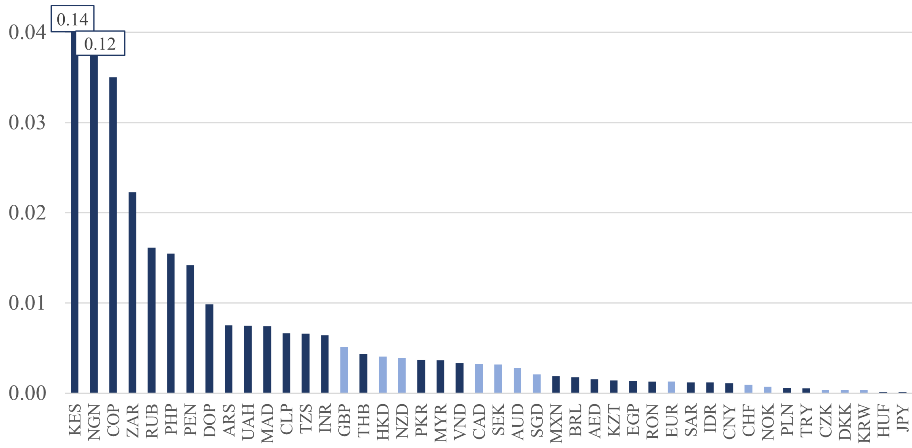
Our analysis relies on panel data with moderate N (44) and large T (222). Given the long time dimension of our series, the first step is to analyse the stationary properties of the data, in particular for our dependent variable, the trading volume of Bitcoin vis-à-vis currency transactions in local currency. We use the Im, Pesaran and Shin test (Im et al., 2003) to assess whether all panels have a unit root. The test suggests the rejection of the null hypothesis that all series include a unit root. Therefore, we control the stationarity of each trading volumes series by currency, finding that some series are trend-stationary, while others are not stationary. Eventually, in order to remove the trending behaviour of the variable, either stochastic or deterministic, we have detrended trading volumes, the Bitcoin price, the gold

Figure 5: Bitcoin transactions against fiat currencies since 2020

(a) Average weekly trading volume (USD per 1,000 inhabitants)



(b) Annual trading volume (percentage of GDP)



Source: LocalBitcoins, Paxful and authors' calculations. Bitcoin trading volumes in local currency converted in US dollar terms, using average nominal exchange rates from IMF/Haver. Dark blue bars identify currencies of EMDEs; light blue bars currencies of AEs. See Table A.3 in the Appendix for the identification of currency codes.

price and the exchange rate at time t with the moving average (MA) of the past 15 weeks, following a procedure that has been applied to trading volumes of stocks (Campbell et al., 1993; Llorente et al., 2002), foreign exchanges (Cespa et al., 2022) and cryptocurrency markets (Bianchi et al., 2022):

$$\tilde{Z}_t = \left(logZ_t - log \sum_{j=1}^{15} \frac{Z_{t-j}}{15} \right) * 100 \tag{1}$$

where $\tilde{Z}_t$ is the detrended measure of trading volumes or other non-stationary variables that will be used in the empirical analysis: the Bitcoin price, the gold price and the exchange rate. For robustness, in Section 4.4 we show that detrending with the first difference of these variables does not substantially alter the results.[16]

Table 2 provides an overview of the crypto-specific, global and local drivers that are available at a high-frequency and have been included in the empirical analysis as potential drivers of Bitcoin trading on a weekly basis. Additional details are available in Table A.1 in Appendix.

Table 2: Potential drivers of Bitcoin trading volumes

Variable	Source
Crypto-specific drivers	
Bitcoin price in USD, log-change 15-week MA (*BTC*)	CryptoCompare
Bitcoin price in USD, 7-day rolling standard deviation of daily percentage changes (*BTC VOL*)	CryptoCompare
Global drivers	
VIX index (*VIX*)	Haver
US Financial Stress Index (*FSI*)	St. Louis Fed/Haver
Geopolitical Risk Index (*GPRI*)	Iacoviello's website
Gold price in USD, log-change 15-week MA (*GOLD*)	Refinitiv
Global factor of bid-ask spread (*BIDASK*)	WMR and authors' calculations
US Weekly Economic Indicator, Index (*WEI*)	New York Fed
Emerging Markets Economic Surprise Index (*EME ESI*)	Citigroup/Haver
Local drivers	
Exchange rate local currency vs USD, log-change 15-week MA (FX_i)	Haver
Bid-ask spread in the currency quote vs USD ($BIDASK_i$)	WM/Refinitiv
Bitcoin searches in Google of word "Bitcoin", log ($GT\ BTC_i$)	Google Trends
Bitcoin searches in Google of word "inflation", log ($GT\ INFL_i$)	Google Trends

Crypto-specific drivers. These are variables that capture demand for Bitcoin, potentially as a speculative investment (Baur et al., 2018).[17] As a proxy of *momentum* in the Bitcoin market, we include the log-change in the Bitcoin price in US dollar, detrended with the 15-week moving average (BTC). The Bitcoin price is sourced from CryptoCompare, which aggregates transaction data from more than 250 exchanges, using a 24-hour volume-weighted average. Moreover, we control for past Bitcoin return volatility, calculated as the annualised 7-day rolling standard deviation of daily changes of the Bitcoin price ($BTC\ VOL$), also sourced from CryptoCompare. These variables can help us to assess whether Bitcoin is used for speculative investment.

Global drivers. These are variables that capture any potential linkage between traditional financial markets – in particular the risk and liquidity factors that drive these markets – and crypto markets. We include the Chicago Board Options Exchange's CBOE Volatility Index (VIX), retrieved from Haver and calculated as the 30-day expected volatility of the S&P500 stock index, as a proxy of global financial

[16] Technically, the use of the moving average for detrending is superior with respect to first differences because it avoids the generation of autocorrelation in the residuals of the dependent variable for those series that are trend-stationary.

[17] The link between Bitcoin usage and Bitcoin price is supported by evidence in Auer et al. (2022a) and Kogan et al. (2023).

risk, in order to check whether Bitcoin transactions are related to shifts in global risk aversion. As an alternative to the VIX index, we use the US Financial Stress Index (FSI), also obtained from Haver, that is in any case highly positively correlated with the VIX. We also consider the Geopolitical Risk Index ($GPRI$) at global level computed by Caldara and Iacoviello (2022) to control if Bitcoin trading volumes tend to increase in combination with major geopolitical events. We include a global factor that has been extracted from the bid-ask spread of our sample of currencies ($BIDASK$) as a global proxy for FX liquidity (see below for data source). The log change in the gold price in US dollar ($GOLD$), detrended with the 15-week moving average, downloaded from Refinitiv, accounts for the recurring reference to Bitcoin as "digital gold" (Baur and Hoang, 2021).[18] Finally, we include two macroeconomic indexes: the Weekly Economic Indicator (WEI) of the US economy from the New York Fed and the Emerging Market Economic Surprise Index ($EME\ ESI$) computed by Citigroup. In Table B.1 in Appendix we report the cross-correlation among global and crypto-specific drivers. Except for the case of VIX and FSI, the cross-correlations among these country-invariant drivers are low.

Local drivers. These are variables that may capture transactional benefits stemming from the use of Bitcoin that are specific to certain currencies and economies. Domestic macroeconomic instability might prompt investors to find refuge in the Bitcoin. While investors from AEs with open capital accounts and developed financial markets may potentially find alternative assets to hedge against exchange rate and inflation risk, investors from emerging markets may be restricted by capital controls or domestic regulation. The availability of high frequency proxies of macroeconomic instability for a large cross-section of economies including EMDEs is limited. For this reason, we include the log change in the exchange rate of the local currencies versus the US dollar (FX_i), detrended with the 15-week moving average, obtained from Haver as a main high-frequency proxy of domestic macro-instability.[19] In addition, we calculated the relative bid-ask spread for each currency ($BIDASK_i$), taking the quotes of the exchange rate against the US dollar from WM/Refinitiv, so that we may control if liquidity in traditional foreign exchange markets spills over to the

[18]The association with gold is made because also Bitcoin is characterised by limited supply (21 million) and is independent of any authority.

[19]An increase (decrease) in the exchange rate implies a depreciation (appreciation) of the local currency versus the US dollar. Our sample includes a small number of economies that peg their currencies to the US dollar. Instead of relying on popular *off-the-shelf* exchange rate classification, which generally do not cover our sample period from 2018 to early 2022, we control directly for nominal exchange rate volatility in our sample. In particular, in our sample period, the currencies of the United Arab Emirates, Saudi Arabia, Tanzania, Vietnam and Hong Kong were *de facto* pegged to the US dollar (see Figure C.4). We shall run specific controls to account for these currencies in the empirical analysis.

crypto market.

We have also collected Google trends data for the term "inflation" in each country ($GT\ INFL_i$) as a proxy for *inflation attention* and macroeconomic instability.[20] Google trends data searching for the term "Bitcoin" ($GT\ BTC_i$) are used as an indicator of *crypto attention*, similarly to Liu and Tsyvinski (2021). Finally, for the sample of advanced economies, we have included also their stock market indices in our analysis, obtained from Haver.

Table 3 provides summary statistics for the variables included in the benchmark specification. We can notice that the kurtosis is higher for EMDEs than AEs, implying larger tails for their distributions. This is particularly relevant for the exchange rate, where we notice that the distribution features not only fatter tails but, unsurprisingly, also larger depreciation in EMDEs than in AEs.

Table 3: Summary statistics

LOCAL VARIABLES AE	N	mean	sd	min	max	skewness	kurtosis	p1	p99
P2P VOL$_i$ (%)	3,090	-7.09	35.23	-230.9	153.9	-0.55	6.62	-118.3	85.7
GT BTC$_i$ (log)	3,330	2.90	0.63	1.61	4.62	0.60	2.55	1.95	4.50
GT INFL$_i$ (log)	3,330	3.36	0.52	1.39	4.62	-0.21	3.08	2.08	4.53
BIDASK$_i$ (%)	3,108	0.06	0.06	0.01	0.72	4.09	23.28	0.01	0.36
FX$_i$ (%)	3,079	0.24	2.38	-13.02	18.02	0.51	7.32	-5.75	7.79
Number of groups	14	14	14	14	14	14	14	14	14
LOCAL VARIABLES EMDE	**N**	**mean**	**sd**	**min**	**max**	**skewness**	**kurtosis**	**p1**	**p99**
P2P VOL$_i$ (%)	6,180	-3.85	38.60	-388.7	298.6	-1.46	15.63	-134.9	80.8
GT BTC$_i$ (log index)	6,660	3.09	0.68	0.69	4.62	-0.50	3.82	1.10	4.52
GT INFL$_i$ (log index)	6,660	3.37	0.67	0.00	4.62	-1.24	6.37	1.61	4.48
BIDASK$_i$ (%)	6,660	0.13	0.19	0.00	2.28	3.20	17.07	0.01	0.98
FX$_i$ (%)	6,169	1.09	3.71	-12.79	39.61	2.70	18.90	-6.08	16.0
Number of groups	30	30	30	30	30	30	30	30	30
CRYPTO/GLOBAL VARIABLES	**N**	**mean**	**sd**	**min**	**max**	**skewness**	**kurtosis**	**p1**	**p99**
BTC (%)	206	4.53	26.64	-57.60	79.91	0.31	2.67	-45.17	64.66
BTC VOL (%)	222	0.68	0.32	0.13	2.41	1.41	6.81	0.17	1.70
VIX (index)	222	20.54	8.56	9.34	74.62	2.60	13.62	11.25	57.79
GOLD (%)	206	1.33	4.07	-7.39	14.01	0.36	2.80	-6.77	11.65
BIDASK (%)	222	0.00	2.86	-3.92	17.91	2.83	14.52	-3.34	14.04
EME ESI (index)	222	9.55	29.88	-39.52	82.04	0.66	2.26	-35.12	76.16
WEI (index change)	221	0.01	0.70	-3.03	3.05	-0.17	8.20	-2.28	2.24

See Table 2 for the definition of variables.

Institutional features and country characteristics. These are again variables that may capture country-specific transactional benefits from the use of Bitcoin, but are available at a lower frequency and will be used in a second step of our analysis. We focused on EMDEs and have selected a large number of low-frequency institutional features that may correlate with Bitcoin trading activity against specific

[20] As an alternative measure to capture inflation at a higher frequency, we have also tried the consumer price index at monthly (or quarterly) frequency, transformed into weekly data using a cubic spline interpolation.

fiat currencies (see Table 4). For these low-frequency country-specific institutional variables or characteristics, we take the average value between 2018 and 2021 or the latest available data at annual frequency. Data are not always available for all the 30 countries of interest, the smallest set being 26 in case of the measure of dollarisation. Additional details on their measurement is provided in Table A.2 in Appendix.

Table 4: Additional institutional features of EMDEs

Variable	Source
Remittance costs (REM)	World Bank
Remittances over GDP (REM_GDP)	World Bank
Share of population with bank account ($BANK$)	World Bank
Index of strength of capital controls (CC)	Fernández et al. (2016)
Size of shadow economy over GDP ($SHADOW$)	Medina and Schneider (2019)
Index of financial institutions depth (FID)	Svirydzenka (2016)
Average annual CPI inflation, 2018-2021 ($INFL$)	Haver
Dollarisation ($DOLL$)	Levy Yeyati (2006)
Share of surveyed individuals making digital payments ($DIGITAL$)	World Bank
Political Risk Rating (PRR)	ICRG
Number of ATMs per 100,000 adults (ATM)	IMF
Median age (AGE)	UN
Rule of law ($RULE\_LAW$)	World Bank

Following the list of potential demand drivers for digital money in EMDEs in Feyen et al. (2021), we use data on the share of remittances over GDP (REM_GDP), available for the year 2021 from World Bank, and data on remittance costs (REM), provided by the World Bank at quarterly frequency. These drivers can shed light on whether the need to send remittances could motivate the use of cryptocurrencies in some EMDEs. We include the index of capital controls (CC), compiled by Fernández et al. (2016), to account for easiness of cross-border transfers in order to check if Bitcoin usage is stronger in countries where investment abroad is more restricted. The average annual CPI inflation over the 2018-2021 period ($INFL$) and a measure of dollarisation, the share of dollar deposits in local deposit money banks ($DOLL$) (Levy Yeyati, 2006), account for weak macroeconomic fundamentals. Financial inclusion is another important driver mentioned in Feyen et al. (2021). In order to test whether a country's financial development matters for the use of cryptocurrencies, we use different proxies of financial development. We employ the index of financial institutions depth (FID) computed by Svirydzenka (2016), which captures the importance of the financial sector relative to the economy. We consider the share of banked people, i.e. the share of population with a bank account ($BANK$), provided by the World Bank and the number of ATMs per 100,000 adults (ATM), provided by the IMF through the Financial Access Survey. In addition, the share of digital payments carried out according to country-based surveys ($DIGITAL$) from the World Bank Global Findex database has been included in the dataset. We use also different measures related to the political institutions and the governance of countries, such as the size of the shadow economy ($SHADOW$), computed by Medina and Schneider (2019) and the strength of the rule of law ($RULE\_LAW$), extracted from the World Bank Worldwide Governance Indicators database. We consider also the Political Risk Rating (PRR), computed by the International Country Risk Guide, which provides a synthetic index of political and institutional stability. Finally, we use the median age of the population (AGE), retrieved from UN data. The motivation for the inclusion of this variable comes from the findings of Auer and Tercero-Lucas (2022) and Auer et al. (2022a) who identify young age as an important driver of retail cryptocurrency use.

4 Empirical analysis

In this section, we shall apply standard dynamic panel models and factor models to study the drivers of Bitcoin transactions against a number of currencies of AEs and EMDEs. First, we include a number of crypto-specific drivers, global drivers and local drivers in a fixed-effect dynamic panel model in order to understand the motivations of Bitcoin trading, i.e. whether transactions have been dominated by trends that are specific to the crypto-asset market, possibly linked to speculative motives, whether conditions in global financial markets influence Bitcoin trading and, finally, whether Bitcoin trading activity may react to country specific macroeconomic conditions in an attempt to hedge domestic shocks. Second, a static factor model is used to identify common factors in Bitcoin trading against different fiat currencies. Finally, focusing on EMDEs, we include in our analysis a large number of economic and institutional variables that might be associated with Bitcoin usage, according to the literature, studying which features correlate with the currency loading on the common factor that has been identified in the previous step.

As a preview of our main results, we find that momentum and volatility in the crypto market, as well as proxies of global financial market volatility and liquidity do matter for Bitcoin trading against different fiat currencies. Among local drivers, the nominal exchange rate is important in spurring more Bitcoin trading, in particular among emerging markets during the COVID-19 pandemic, suggesting that the loss of purchasing power of the domestic currency may be a driver of crypto usage and that Bitcoin might be valued for its transactional benefits as suggested by Biais et al. (2023). Importantly, we find that there is a significant degree of comovement in Bitcoin trading against different fiat currencies. One common factor on average explains up to 40% of the variance of the data in the COVID-19 period, across both

AEs and EMDEs. In other words, when Bitcoin trading against the euro or the British pound, for instance, tends to raise, Bitcoin trading against the Pakistani or Indian rupee also tends to increase. We show that this global component in Bitcoin trading, in turn, is correlated with the Bitcoin price, suggesting that speculative motives entice residents in different parts of the world to trade Bitcoin versus their own currency. Finally, the extent to which each currency loads on this common component in Bitcoin trading volumes is negatively correlated with the number of ATMs or the diffusion of digital payments in the countries issuing the respective currency and positively with economies with a higher share of younger population. Overall, taken together, these results suggest that Bitcoin is largely used as a speculative investment asset across advanced, emerging and developing economies, but for EMDEs transactional services may be important. In EMDEs, the attractiveness of Bitcoin as speculative investment and, possibly, also as means of payments is further fostered by exchange rate instability, the limited development of digital and payment rails and a younger population.

4.1 Determinants of P2P Bitcoin trading volumes

We study Bitcoin trading volumes against local currencies in a dynamic panel model, including fixed effects to account for country-specific time-invariant features. The relatively large time dimension (T=222) justifies the adoption of this empirical set-up. As mentioned in the previous section, all variables are stationary or detrended to ensure stationarity. The model is the following:

$$Y_{i,t} = \alpha_i + \sum_{j=1}^{p} \rho_j Y_{i,t-j} + \boldsymbol{\beta G_{t,t-1}} + \boldsymbol{\gamma L_{i,t-1}} + \eta EY_t + u_{i,t} \tag{2}$$

where $Y_{i,t}$, the dependent variable, represents our detrended measure of Bitcoin trading volumes in P2P platforms against the currency of country i at time t (see Section 3). The subscript p is the number of lags of the dependent variable included. $\boldsymbol{G_{t,t-1}}$ is a vector of global drivers (e.g. global risk or a common component in the bid-ask spread of various currencies, all at time t) and crypto-specific drivers (e.g. momentum in Bitcoin prices or volatility in cryptocurrency markets, all at time $t-1$) which may influence Bitcoin trading volumes along the whole cross section of currencies. $\boldsymbol{L_{i,t-1}}$, instead, is a vector of local drivers that may influence trading volumes of Bitcoin against specific currencies (e.g. inflation, exchange rate movements and the liquidity in the specific foreign exchange market). The parameters of interest to be estimated are $\boldsymbol{\beta}$ and $\boldsymbol{\gamma}$. EY_t is a dummy which is equal to 1 in the last week and first week of each year to control for the visible reduction in trading volumes during this period of the year. Finally, α_i is the unobserved country-specific driver and $u_{i,t}$ the idiosyncratic residual term.

With the exception of variables capturing global risk and global foreign exchange liquidity, the regressors enter the model with a lag, in order to reduce any potential simultaneity or endogeneity bias. We estimate a fixed-effects model and use Driscoll-Kraay standard errors to account for any remaining cross-sectional and temporal dependence of the residuals.

Table 5 reports the results of the benchmark model represented in Equation 2 for the whole cross-section of AEs and EMDEs. Our detrended measure of Bitcoin trading volumes still presents some persistence, requiring us to introduce 3 lags of the dependent variable in the regressions (see column 1). Then, progressively we add crypto drivers (column 2) and global drivers (column 3), which are country invariant, and local drivers (column 4). Finally, we specify the best model (see column 5) and compare the results to the model including time fixed effects and excluding country-invariant drivers (column 6).

Starting from the crypto-specific drivers (see column 2) most closely related to demand factors, *momentum* in the cryptocurrency market (BTC) is a statistically significant driver of Bitcoin transactions, echoing the findings of Liu and Tsyvinski (2021) and Liu et al. (2022) on the returns of cryptocurrencies and Feyen et al. (2022) on cross-country onchain Bitcoin transactions. Indeed, the coefficient associated with the lagged Bitcoin price growth is positive and statistically significant. A positive association between returns and trading volumes is also consistent with Jermann (2021) who finds a particularly large money demand sensitivity to expected price changes for Bitcoin. Past Bitcoin price volatility (BTC_VOL) also seems to matter. An increase in Bitcoin price volatility leads to retrenchment in transactions the following period, suggesting that transactions are most likely motivated by speculative motives that are in turn discouraged by the volatility of the cryptocurrency market. These dynamics are partly similar to stocks (Llorente et al., 2002), further confirming that Bitcoin trades around the world as a speculative asset. The end of the year dummy is also negative and statistically significant, capturing the decline in transactions in this holiday period.

Turning to the global macroeconomic or financial variables (see column 3) proxying for potential linkages with traditional financial markets, we find that Bitcoin trading volumes against local currencies are not linked to macroeconomic drivers, such as global (WEI) or emerging market macronews (EME_ESI), reflecting similar results by Liu and Tsyvinski (2021) on returns. Bitcoin trading against different currencies increases when global risk – as proxied by the VIX – is on the rise. This result chimes with the finding of Cespa et al. (2022) for foreign exchange volumes, despite the fact that probably the agents in these two markets are different, since small retail investors operate in P2P exchanges, whereas professional investors such as institutional investors and hedge funds operate in the foreign exchange market.[21] Interestingly, there seems to be a connection between global liquidity in FX markets and Bitcoin trading volumes against fiat currencies. When a global component of bid-ask spreads in the FX market ($BIDASK$) widens, i.e. when FX markets become less liquid, Bitcoin trading volumes against different fiat currencies tend to rise. Since Karnaukh et al. (2015) show that there is a positive relationship between global risk and illiquidity in the FX market, this variable is probably capturing the positive impact on Bitcoin trading volumes of traditional financial market tensions. Taken together, the statistical significance of the proxies of global risk and global FX liquidity suggests that global financial shocks in traditional asset markets tend to spill over to cryptomarkets. Geopolitical risk ($GPRI$), differently from global financial risk, does not seem to matter. The relationship between gold prices ($GOLD$) and Bitcoin trading volumes is not statistically significant (see columns 3 and 4). This result is in line with the near-zero correlation between the Bitcoin price and the gold price found in Baur and Hoang (2021).

Our list of local drivers that are available at a relatively high - weekly - frequency is somewhat limited, in particular for EMDEs. Google searches for the word "Bitcoin" ($GT\ BTC_i$) – our proxy of investor attention in the Bitcoin market – or for the word "inflation" ($GT\ INFL_i$) – controlling if the popularity of Bitcoin transactions is linked to a presumed ability of this cryptocurrency to hedge against inflation risk – are both not statistically significant. For the subset of advanced economies, we have also included the stock market returns as local drivers, but they were not significant (not shown). There is, however, an important result among the local drivers, as Bitcoin trading is connected with the value of the domestic currency. Bitcoin transactions against local currencies tend to increase after a fall in the value of the latter against the US dollar. The coefficient associated with the nominal depreciation of the local currency against the US dollar (FX_i) is positive and statistically significant. Theoretically, this result is consistent with the use of the Bitcoin as a store of value or means of payment, e.g. to transfer money cross border (Graf von Luckner et al., 2023), in a similar way as the US dollar replaces the domestic currency in economies where the purchasing power of the latter is unstable. Our findings on

[21]Replacing the VIX with the St. Louis Fed Financial Stress index, which is positively correlated with the VIX, we obtain similar results, although less robust across specifications.

the importance of the exchange rate highlights the difference between our analysis of P2P cryptocurrency exchanges with respect to the analysis of onchain Bitcoin volumes carried out in Feyen et al. (2022), where local drivers are found not to be significant drivers. Finally, the currency-specific component of foreign exchange liquidity ($BIDASK(i)$) is positively associated with Bitcoin trading; however the coefficient is not statistically significant.

Eventually, our baseline model includes crypto drivers, such as Bitcoin price growth and volatility, proxies of volatility in traditional financial markets, such as the VIX, global liquidity in FX markets and the gold price, and local drivers, such as the nominal exchange rate against the US dollar, and currency-specific liquidity (see column 5). The R-squared of the model including only the autoregresssive terms in column 1 (0.30) and that of the the baseline model in column 5 (0.33) are not too different, indicating that the ability of our global and local drivers in explaining the volatility of Bitcoin transactions is somewhat limited. Interestingly, if we exclude all country-invariant crypto and global local drivers and we include a time fixed-effect in the model, the R-squared increases considerably to 0.39 (see column 6), suggesting that there is a large share of variation in Bitcoin transactions that is common across different currencies but it is not captured by our set of crypto and global drivers. This motivates a further deepening of the analysis of the global component of Bitcoin trading against fiat currencies in the next subsection 4.2.

One may wonder whether the drivers of Bitcoin transactions differ across AEs and EMDEs. Moreover, the exposure of the crypto-markets to global macro drivers is still an open question. In particular, Iyer (2022) stresses that the exposure of cryptocurrencies to macro drivers has increased significantly since the COVID-19 crisis in March 2020. We tackle these two issues in Table 6, which presents the baseline model after distinguishing currencies of AEs from currencies of EMDEs and splitting the sample before and after the onset of the COVID-19 pandemic. The first three columns of Table 6 show that, over the whole sample, our baseline model works equally well in explaining Bitcoin trading in both AEs and EMDEs. However, there are qualitative differences between these two groups of countries that emerge in particular when splitting the sample around the onset of the COVID-19 pandemic (see columns 4 to 10). First, the global component of FX liquidity is more relevant for Bitcoin trading against the currencies of AEs than currencies of EMDEs (see columns 2 and 3, but also 5, 6, 8 and 10). This result echoes the finding of Karnaukh et al. (2015), who show that the liquidity of currencies of more developed economies is more adversely affected by an increase in FX volatility than that of currencies of less-developed economies, as the financial systems of the former group of economies

Table 5: Key drivers of Bitcoin trading volumes against fiat currencies

	(1) incl. lags	(2) incl. crypto	(3) incl. global	(4) incl. local	(5) baseline	(6) time FE
P2P volume (t-1)	0.42***	0.41***	0.40***	0.40***	0.41***	0.40***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.06)
P2P volume (t-2)	0.10***	0.10***	0.10***	0.10***	0.10***	0.11***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.02)
P2P volume (t-3)	0.09***	0.09***	0.08***	0.08***	0.08***	0.08***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)
BTC (t-1)		0.07**	0.10***	0.10***	0.09***	
		(0.03)	(0.03)	(0.03)	(0.03)	
BTC VOL (t-1)		-6.65***	-9.71***	-8.34***	-8.84***	
		(2.14)	(2.35)	(1.98)	(1.90)	
VIX (t)			0.21**	0.21**	0.23**	
			(0.09)	(0.08)	(0.09)	
GOLD (t)			0.21	0.27		
			(0.18)	(0.18)		
BIDASK (t)			0.50***	0.47***	0.57***	
			(0.17)	(0.17)	(0.16)	
GPRI (t)			-0.00			
			(0.01)			
EME ESI (t)			-0.01			
			(0.03)			
WEI (t)			-1.79			
			(1.09)			
FX (i,t-1)				0.49***	0.46***	0.39***
				(0.14)	(0.15)	(0.10)
GT BTC (i,t-1)				-0.72		
				(1.61)		
GT INFL (i,t-1)				0.64		
				(0.90)		
BIDASK (i,t-1)				6.34		
				(3.89)		
EY (t)	-11.56**	-10.20***	-9.72***	-9.30***	-8.99***	
	(4.49)	(3.35)	(3.21)	(3.38)	(3.19)	
Observations	8,932	8,932	8,932	8,911	8,911	8,911
Number of groups	44	44	44	44	44	44
Country FE	YES	YES	YES	YES	YES	YES
Time FE	NO	NO	NO	NO	NO	YES
R2	0.30	0.31	0.32	0.33	0.33	0.39

The table reports the results of the estimation of the dynamic panel fixed-effect model in equation 2. The dependent variable is the log-change in the volume of Bitcoin transactions against local currencies in P2P platforms, detrended with the moving average of the past 15 weeks (P2P volume). See Table 2 for the definition of variables. Dryscoll-Kray standard errors are reported in parentheses. The asterisks ***, ** and * indicate statistical significance at the 1%, 5% and 10% level, respectively. The models include also a constant and a time dummy for the first week of 2022, not reported for brevity.

are more internationally integrated. Second, the impact of the exchange rate on Bitcoin trading is well identified for the currencies of EMDEs, whereas the statistical significance of the coefficient associated with currencies of AEs is weaker. Indeed, this is not surprising as the exchange rate volatility of EMDEs currencies is larger than that of AEs (see Table 3). Splitting the sample between the period before the COVID-19 pandemic (columns 4 to 6) and the subsequent period (columns 6 to 10), we find that the coefficient associated with the exchange rate becomes larger and statistically significant in the second part of the sample (see column 7). This suggests that in the last few years Bitcoin might have offered transactional benefits in economies where the purchasing power of the domestic currency was not stable.[22] Quite strikingly, since the beginning of the COVID-19 pandemic, the coefficient associated with the exchange rate impact of AEs currencies (column 8) is larger than that of EMDEs (column 10). This rather surprising result prompts us to further dissect this issue. We re-run the panel regressions excluding each currency one by one from the sample of AEs. The full set of results is reported in Table B.3 in the Appendix. It shows that, indeed, the exchange rate does *not* matter for Bitcoin trading against the currencies of AEs and the result in column 8 of Table 6 is entirely driven by an outlier, the Czech koruna. Excluding this currency, the coefficient associated with the exchange rate for AEs is not statistically significant anymore (see column 9 of Table 6).[23] Finally, focussing on the period of the COVID-19 pandemic, note that the statistical significance of the coefficient associated with Bitcoin momentum is driven by EMDEs currencies, which is consistent with the narrative of the progressive extension of the Bitcoin adoption as speculative alternative in EMDEs in the most recent years.

Whether the COVID-19 pandemic played a specific role in fostering Bitcoin transactions is an issue that goes beyond the scope of this study. In this respect, Divakaruni and Zimmerman (2023) show that the release of governments' one-off stimulus payments to households in three large economies, during the COVID-19 crisis, constituted a positive demand shock for Bitcoin. For the purpose of this study, it is interesting to note that drivers such as Bitcoin momentum and the exchange rate become more important in EMDEs as Bitcoin trading increases (see Figure 1). A number of robustness tests to validate these results are discussed in Section 4.4.

[22] Since several currencies, in particular those of EMDEs, depreciated sharply during the most acute phase of the pandemic in the spring of 2020, in order to exclude the possibility that the impact of this variable on Bitcoin trading is driven by this specific episode, we re-run the panel regressions excluding this period, but we find no significant difference in the results. Results are available upon request to the authors.

[23] The results for EMDEs are instead fully robust to the exclusion of each currency from the sample one at a time (see Table B.4 in the Appendix).

Table 6: Key drivers of Bitcoin trading volumes: comparing AEs with EMDEs, before and during the COVID-19 pandemic

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Full sample			Pre COVID			COVID			
	All	AE	EMDE	All	AE	EMDE	All	AE	AE ex. CZK	EMDE
BTC (t-1)	0.09***	0.09*	0.09***	0.11**	0.17**	0.10**	0.10***	0.06	0.06	0.12***
	(0.03)	(0.05)	(0.03)	(0.05)	(0.08)	(0.05)	(0.03)	(0.05)	(0.05)	(0.04)
BTC VOL (t-1)	-8.84***	-7.86**	-9.15***	-7.79**	-4.28	-8.80***	-10.57***	-10.85***	-7.95**	-10.42***
	(1.90)	(3.12)	(1.78)	(2.97)	(4.77)	(2.91)	(2.65)	(3.56)	(3.59)	(2.76)
VIX (t)	0.23**	0.19**	0.24**	0.46**	0.80**	0.40*	0.30**	0.25**	0.16	0.33**
	(0.09)	(0.09)	(0.10)	(0.22)	(0.34)	(0.21)	(0.12)	(0.12)	(0.12)	(0.14)
BIDASK (t)	0.57***	0.83***	0.44**	0.41***	0.56**	0.32*	0.76*	1.33**	1.23**	0.52
	(0.16)	(0.23)	(0.17)	(0.12)	(0.22)	(0.17)	(0.43)	(0.64)	(0.55)	(0.43)
FX (i,t-1)	0.46***	0.57*	0.42***	0.17	-0.62	0.25	0.65***	0.84**	0.39	0.60***
	(0.15)	(0.31)	(0.15)	(0.28)	(0.42)	(0.31)	(0.17)	(0.32)	(0.28)	(0.18)
Observations	8,911	2,832	6,079	4,126	1,313	2,813	4,785	1,519	1,410	3,266
Number of groups	44	14	30	44	14	30	44	14	13	30
Country FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
R2	0.33	0.25	0.36	0.32	0.26	0.35	0.31	0.26	0.28	0.35

The table reports the results of the estimation of the dynamic panel fixed-effect model in equation 2. The dependent variable is the log-change in the volume of Bitcoin transactions against local currencies in P2P platforms, detrended with the moving average of the past 15 weeks. See Table 2 for the definition of variables. Coefficients of lags of the dependent variable, constant and dummies not reported here. "Full sample" refers to the whole sample period from week 1 of 2018 until week 14 of 2022. The "Pre COVID" sample period runs from week 1 of 2018 until week 8 of 2020. The "COVID" sample period runs from week 9 of 2020 until week 14 of 2022. In Column (10) the Czech koruna is excluded from the sample of fiat currencies. Dryscoll-Kray Standard errors in parentheses. The asterisks ***, ** and * indicate statistical significance at the 1%, 5% and 10% level, respectively.

4.2 Factor analysis

The panel analysis in the previous section has shown that a number of global variables, related to the crypto market and to traditional financial markets' volatility and liquidity, do matter for Bitcoin trading volumes against different fiat currencies. Moreover, we found that these global drivers fail to capture the full extent of co-movement in Bitcoin trading across currencies and over time. In this section, we tackle this issue from a different angle, following the literature on the global financial cycle (Miranda-Agrippino and Rey, 2022) and specifying a Static Factor Model for our panel of Bitcoin transactions against fiat currencies.

$$Y_{i,t} = \boldsymbol{F}_t \boldsymbol{\lambda_{i,t}} + \epsilon_{i,t}, \tag{3}$$

where $\boldsymbol{\lambda_{i,t}}$ is a k×1 vector of factor loadings and $\boldsymbol{F}_t$ is a 1×k vector of global factors. The loadings are currency-specific and capture the correlation between the common factor and the volume of transactions of each currency.

There are different criteria to select the optimal number of factors to approximate the information in a large set of panel data. Table 7 reports the Info Criteria (IC) developed by Bai and Ng (2002), the Eigenvalue Ratio (ER) and Growth Rate (GR) estimators proposed by Ahn and Horenstein (2013), the Edge Distribution (ED) estimator developed by Onatski (2010) and the estimator proposed by Gagliardini et al. (2019). Overall, the criteria suggest to select one or two factors.

Table 7: Criteria for determining the number of factors

Criterion	N. factors selected
IC_{p1}	2
IC_{p1}	2
IC_{p1}	2
ER	1
GR	1
GOL	1
ED	1

The table reports the Info Criteria (IC) by Bai and Ng (2002), the Eigenvalue Ratio (ER) and Growth Rate (GR) by Ahn and Horenstein (2013), the Edge Distribution (ED) estimator by Onatski (2010) and the estimator by Gagliardini et al. (2019) to determine the number of factors in the volume of Bitcoin transactions against fiat currencies, detrended with a 15-week moving average. IC_{p1}, IC_{p2} and IC_{p3} refer to different penalty functions utilised.

Despite the heterogeneity of the currencies considered, we find that the first global factor accounts for around 30% of the variation in Bitcoin trading volumes against different fiat currencies, while the second factor accounts for less than 10% of variation of the series (see columns 1 to 3 in Table 8). Since the onset of the COVID-19 pandemic, the momentum behind the adoption of Bitcoin becomes increasingly global. If we extract the factor for the sample period of the COVID-19 crisis, the share of variance explained by the first main factor increases by ten percentage points, explaining up to around 40% of variation in Bitcoin trading across both AEs and EMDEs and up to 50% if we include a second factor (see columns 7 to 9).[24] These are large shares that are comparable to those for traditional asset markets from the literature on the global financial cycle. For instance, Miranda-Agrippino and Rey (2022) show that one factor explains up to around 24% of the variance in asset prices or 21% (or 35% including a second factor) of the variance in capital flows, using quarterly data. Davis et al. (2021) manage to explain up to 40% to 50% of the variation in gross capital flows with two global factors, but with annual data that are considerably less volatile. The results are even more striking if we zoom in on specific currencies. Figure 6 shows this detail. Since the beginning of the COVID-19 pandemic, one global factor explains between 50% to almost 70% of the variation in Bitcoin trading against the Canadian dollar, the euro or the British pound (see darker blue bars in Figure 6a). Among EMDEs, there are ten currencies for which one global factor explains around 50% or more of the variation in trading volumes. The global factor explains almost 60% of the variation in Bitcoin trading volumes against the Kenyan shilling and up to 70% of the variation against the Indian or the Pakistani rupee (see darker blue bars in Figure 6b). In a nutshell, as there is evidence of a global financial cycle in asset prices and capital flows, there is also evidence of a global cycle in Bitcoin trading against fiat currencies.

Table 8: Variance in Bitcoin trading volumes explained by main factors

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Full sample			Pre COVID			COVID		
	All	AE	EMDE	All	AE	EMDE	All	AE	EMDE
First factor	0.29	0.34	0.31	0.27	0.33	0.28	0.37	0.40	0.40
Second factor	0.07	0.09	0.09	0.07	0.13	0.08	0.10	0.09	0.11
Residual	0.64	0.57	0.60	0.66	0.54	0.64	0.53	0.51	0.49

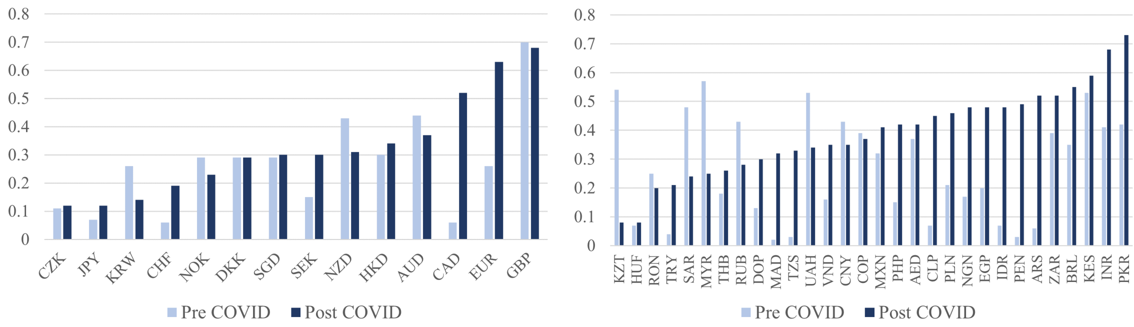
The table reports the share of variance in the volume of Bitcoin transactions against fiat currencies, detrended with a 15-week moving average, that is explained by the factors estimated in equation 3. "Full sample" refers to the whole sample period from week 1 of 2018 until week 14 of 2022. The "Pre COVID" sample period runs from week 1 of 2018 until week 8 of 2020. The "COVID" sample period runs from week 9 of 2020 until week 14 of 2022.

In the next step of the analysis, we try to identify what may be behind this global *crypto* cycle. Table 9 reports the correlation of the main global factor with a number of potential global drivers of Bitcoin trading. The main global factor in Bitcoin trading volumes is highly correlated with the Bitcoin price (0.52), suggesting that the speculative motive may be behind the global crypto cycle (see also Figure 2 in Section

[24] The criteria mentioned above provide similar results if we split the sample period before and after the start of COVID-19 and if we select only AE currencies or EMDE currencies.

Figure 6: Variance in Bitcoin trading volumes explained by the main global factor tends to increase in the COVID-19 period

(a) Advanced economies (b) Emerging and developing economies



The figures report the share of variance in the volume of Bitcoin transactions against fiat currencies, detrended with a 15-week moving average, that is explained by the first common factor estimated in equation 3. The "Pre COVID" sample period runs from week 1 of 2018 until week 8 of 2020. The "COVID" sample period runs from week 9 of 2020 until week 14 of 2022.

1). Notably, this correlation with the Bitcoin price is higher if we extract a factor from EMDE currencies (0.53) than for a factor extracted from AE currencies (0.42), a result that confirms the finding in the panel analysis for the variable associated with the *momentum* in the Bitcoin price in Section 4.1. Apart from the Bitcoin price, the other potential global drivers are also positively correlated with the global factor in Bitcoin transactions, but less tightly than for the correlation with the former variable. Interestingly, the correlation of the VIX with the global component in Bitcoin trading increases significantly to around 30% in the COVID-19 period, which reflects the finding in the panel analysis in the previous section and the results of other studies that have found a stronger linkage between the Bitcoin price and risky assets since 2020 (Iyer, 2022). It is instead more difficult to interpret which global variable may be associated with the second factor in Bitcoin trading. Table B.2 in the appendix reports the correlations of this second factor with our global variables and shows that also this second factor may be correlated with the Bitcoin price, but only in the COVID-19 period.

To conclude, there is evidence of a global *crypto* cycle in Bitcoin trading against fiat currencies. The trading of Bitcoin against different fiat currencies, involving traders around the world, moves in tandem with fluctuations in the Bitcoin price. This is particularly the case for the currencies of EMDEs in the COVID-19 period. Considering the greater popularity of decentralised P2P platforms in EMDEs compared to AEs and that only for this group of countries it is possible to associate more clearly Bitcoin-fiat currency transactions with local traders, we turn our attention to EMDEs to study whether country-specific institutional features may foster Bitcoin trading.

Table 9: Correlations of the first factor in Bitcoin trading against fiat currencies with global variables

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Full sample			Pre COVID			COVID		
	All	AE	EMDE	All	AE	EMDE	All	AE	EMDE
BTC	0.52*	0.42*	0.53*	0.63*	0.54*	0.62*	0.46*	0.33*	0.49*
BTC VOL	0.00	0.06*	-0.03	0.13*	0.20*	0.10*	-0.07*	-0.02	-0.09*
VIX	0.23*	0.19*	0.22*	0.08*	0.11*	0.06*	0.30*	0.22*	0.32*
GOLD	0.15*	0.16*	0.13*	0.11*	0.22*	0.04*	0.17*	0.09*	0.20*
BIDASK	0.11*	0.16*	0.08*	0.08*	0.16*	0.03	0.13*	0.14*	0.12*

The table reports the correlation between global variables (see Table 2 for the definition) and the first factor extracted from the model in equation 3 for the volume of Bitcoin transactions against local currencies, detrended with the moving average of the past 15 weeks. The asterisk * indicates statistical significance at 5 percent level.

4.3 The role of institutional features

In this section, we make a further step in our understanding of the potential motivations behind Bitcoin trading, studying the relationship between a large number of country-specific institutional features, which have been described in Section 3 (see Table 4), and the loadings of the global factor on each currency that have been identified in the previous section. In particular, we restrict this analysis to EMDEs, the group of countries where particular characteristics – such as macroeconomic and political instability, the lack of developed financial markets and investment opportunities, the presence of capital controls, the importance of remittances, a higher share of risk-prone younger population compared to advanced economies – are expected to foster the usage of Bitcoin as a store of value, speculative investment asset or means of payment to circumvent local restrictions. Moreover, as discussed in Section 2 and shown in Figure 4, Bitcoin transactions against currencies of EMDEs generally involve local traders so that we may associate these country features to the trading of fiat currencies. The measurement of these institutional features is generally available at a very low frequency and unlikely to change significantly over the relatively short time frame of our analysis. Therefore, as a general rule, we shall use the information included in the cross-section of the country characteristics in our empirical analysis. We shall relate these country-specific features to the currency loadings on the main global factor that has been identified in the previous section. These loadings indicate the extent to which the global factor, in turn correlated with the Bitcoin price, does matter for Bitcoin trading against each currency. We run simple pooled cross section regressions of the currency loadings on the global factor for EMDEs against institutional features or other country characteristics that may be relevant for crypto usage. As we have a limited number of observations in the cross-section, the various country-specific features are included one by one.

Table 10 reports the result for the regression of these factor loadings by currency on different country-specific features. Interestingly, the coefficients of most regressors enter with the expected sign, even though only few variables are statistically significant. Notably, countries where the share of digital payments ($DIGITAL$) is lower tend to have a higher currency loading on the global factor, suggesting that crypto usage may be a substitute for the lack of an efficient payment system. Moreover, the number of ATMs, a proxy of the domestic development of the banking system is negatively associated with the currency loadings on the global factor, suggesting that indeed cryptocurrencies could cater for the absence of a developed banking system. Finally, the coefficient associated with AGE is negative and statistically significant. A larger presence of a younger population is associated with a larger factor loading of each currency, echoing a recent finding by Auer et al. (2022a) and Weber et al. (2023). The role of these country-specific features is also reported in Figures C.1 - C.3 in Appendix. Our proxies of macroeconomic instability, such as inflation and dollarisation, instead, do not appear to be positively associated with factor loadings.

In a robustness test, reported in the Appendix, we check whether these results are driven by particular outliers, finding that the results are generally robust to this control (see Table B.5). Finally, as a further robustness test, we replace the dependent variable. Instead of the currency loading, we use the volume of Bitcoin transactions against local currencies in P2P platforms over the country's GDP in 2021 and calculate its growth rate versus the level of this variable in the pre COVID-19 period (2018-19). The results are qualitatively similar (see Table B.6 in the Appendix).

Table 10: Currency loadings on the global factor in Bitcoin trading volumes and country features

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
PRR	-0.12 (0.09)												
RULE_LAW		-1.48 (1.32)											
SHADOW			-0.02 (0.07)										
DIGITAL				-0.06** (0.03)									
ATM					-0.03* (0.02)								
BANK						-1.42 (1.29)							
FID							0.31 (3.02)						
AGE								-0.22** (0.08)					
REM_GDP									0.17 (0.20)				
REM										0.02 (0.41)			
CC											2.26 (2.12)		
INFL												0.35 (0.98)	
DOLL													-3.20 (3.53)
Observations	30	30	28	28	29	30	30	30	29	28	30	30	26
R2	0.07	0.04	0.00	0.16	0.11	0.04	0.00	0.20	0.03	0.00	0.04	0.00	0.03

The table reports the results of cross-section regressions. The dependent variable is the currency loading on the first common factor for Bitcoin trading volumes against currencies of EMDEs in the COVID period, multiplied by 100. See Table 4 for the definition of variables. Coefficients of constant not reported here. Standard errors in parentheses. The asterisks ***, ** and * indicate statistical significance at the 1%, 5% and 10% level, respectively.

4.4 Robustness

This section presents a number of additional robustness tests that have been performed to validate the results of our empirical analysis in Section 4.1.

First, as mentioned in Section 3, our baseline model relies on a detrended measure of our dependent variable, Bitcoin trading volumes against fiat currencies, and other non-stationary regressors, namely the Bitcoin price, the gold price and the exchange rate versus the US dollar, which takes the log difference of this variables with respect to 15-week moving average. One may wonder whether this choice affects the results. Thus, we rerun our baseline model with the first difference of those variables, without detrending them with their average value over the previous 15 weeks. Comparing Table 6 with Table B.7 shows that our key results are robust to the use of this alternative detrending method.

Second, we control for potential non-linearities in the impact of the variables that have been identified as significant drivers of Bitcoin trading volumes. The baseline empirical model in equation 2 is extended with the inclusion of the squared value of the determinants. Table B.8 in Appendix reports the results of this robustness exercise. Generally, we do not find evidence of non-linearities in our model.

Third, some currencies in our sample are *de facto* pegged to the US dollar and characterised by extremely low volatility in the nominal exchange rate, which could potentially impact our estimate of the sensitivity of Bitcoin trade to this variable (see Figure C.4 in Appendix). We identify five currencies with very limited volatility – Hong Kong dollar, Saudi Arabian riyal, Tanzanian schilling, United Arab Emirates dirham, Vietnamese dong – and re-run our main regression models excluding these currencies. Comparing the results of this robustness test (see Table B.9 in Appendix) with those in Table 6, we conclude that these fixed exchange rate regimes do not affect the results of our analysis.

Fourth, one of our underlying assumptions was that the country of issuance of the currency against which Bitcoin is traded largely coincides with the residence of the trader. We have repeated the analysis with country-specific interactions terms excluding the currencies of EMDEs where the share of transactions from local traders in Paxful was lower-than-average, i.e. the Polish zloty and the Chinese renminbi. Results are overall robust to the exclusion of these two currencies.

Finally, we control if the sensitivity of Bitcoin trading to high-frequency drivers – such as momentum, Bitcoin volatility, global risk and FX liquidity or the nominal exchange rate – does change according to specific country characteristics. To do so, we rank countries according to a specific institutional feature and create dummies that indicate if one country belongs to the group of countries with the highest or lowest value of that feature, experimenting with different thresholds of the distribution.[25] Then, we estimate the model described in Equation 4 with country-specific interaction dummies.

$$Y_{i,t} = \alpha_i + \sum_{j=1}^{p} \rho_j Y_{i,t-j} + \boldsymbol{\beta}_1 \boldsymbol{K_{(i)t,t-1}} + \boldsymbol{\beta}_2 \boldsymbol{K_{(i)t,t-1}} D^F_{(i)t} + \delta D^F_{(i)t} + \eta EY_t + u_{i,t} \tag{4}$$

where the notation is similar to equation 2; in this case, though, $\boldsymbol{K_{(i)t,t-1}}$ is a vector containing both local and global drivers and $D^F_{(i)t}$ is a dummy taking value equal to one when a country belongs to a specific group. We have tested all the country-specific features. For reasons of space, we focus on the results for the country characteristics that were highlighted as most relevant in the cross-section analysis in Section 4.3, i.e. the models with the dummies identifying countries in the 25th or 10th percentile of the distribution for (i) the number of ATMs over 100,000 adults, (ii) the share of digital payments and (iii) the median age of the population.

Table B.10 reports the results of this exercise. Overall, it does not seem that institutional features alter in a systematic way the the transmission of the global and local drivers that we have identified in Section 4.1. Interestingly, there is some suggestive evidence that the importance of the local currency depreciation is higher in countries with relatively low level of financial development and a younger population. In the case of the exchange rate, we further tested its interaction with proxies of macroeconomic instability like dollarisation or inflation and with capital controls, but we did not find any divergence in its impact on Bitcoin trading.[26]

5 Conclusion

Despite an extremely volatile price and various crashes in the cryptoasset market, Bitcoin remains very popular, trading across different currencies and constituencies. In this paper, in order to understand the potential motivations of Bitcoin trading, we have taken the cross-currency dimension to the forefront of our analysis, a novel angle so far neglected by the fast growing literature on this topic.

Our results, overall, reinforce the hypothesis, currently prevailing in the literature, that Bitcoin trading is driven by speculative motives. In this paper we show that

[25]Specifically, we control if countries are above (below) the 75th (25th) or the 90th (10th) percentile of the distribution of a specific country feature. We look at the upper or lower end of the distribution, depending on the potential economic significance of each feature for Bitcoin transactions.

[26]The latter results are omitted for reasons of space and available upon request to the authors.

this is truly a global phenomenon. There is evidence of a global *crypto* cycle in Bitcoin trading against fiat currencies, with transactions across currencies and users around the world moving in tandem with fluctuations in the Bitcoin price. Similarly to other risky assets, momentum and volatility in the crypto-asset market, as well as global financial market volatility and liquidity do matter for Bitcoin trading against different fiat currencies.

However, Bitcoin seems to offer also specific transactional benefits, in particular in EMDEs. The depreciation of the domestic currency of EMDEs – notably *not* of the currencies of AEs – induces more Bitcoin trading, in particular since the onset of the COVID-19 pandemic. This indeed suggests that Bitcoin, despite its wide price fluctuations, might have been appreciated also as a store of value or medium of exchange in countries which experienced a loss in the the purchasing power of their domestic currency. In turn, this implies that macroeconomic instability may potentially spur greater cryptoasset usage. This result is important for the asset pricing theory of cryptoassets, suggesting that the fundamental value of Bitcoin may be substantially different between AEs and EMDEs, since its transactional services are probably more elevated in the latter group of countries. Moreover, we find that proxies of banking depth and digitalisation are negatively correlated with the extent to which each currency loads on the global common factor in Bitcoin trading volumes, indicating that crypto-assets may offer a *speculative* alternative to traditional finance when this is not available, in particular in EMDEs where the share of younger risk-prone population is higher, another important finding of our analysis.

Our findings clearly point to potential financial stability risks in EMDEs with low levels of financial development and unstable fiat currencies. The intrinsic price volatility of Bitcoin may discourage its use as a store of value or means of payment. However, in the future, other crypto-assets, such as stablecoins that pledge to ensure a parity to the US dollar or other reserve currencies, might become more widely used by individuals and firms in order to compensate for the lack of financial alternatives. Evidently, the relationship between financial development, macroeconomic instability and the risk of *cryptoisation* deserves further investigation. This paper has moved a step in that direction.

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Appendix A Data

Table A.1: Global and local drivers of Bitcoin trading volumes - detailed description

Variable	Description	Frequency	Coverage	Source
Bitcoin price	Bitcoin price in centralised market	D	Global/Crypto	CryptoCompare
Bitcoin volatility	Annualised 7-day rolling standard deviation of daily percentage changes of prices in centralised market	D	Global/Crypto	CryptoCompare
VIX	30-day expected volatility of the U.S. stock market	D	Global	Haver
Gold price	Gold price in USD	D	Global	Refinitiv
Geopolitical Risk index	US newspapers-based measure of adverse geopolitical events and associated risks	D	Global	Matteo Iacoviello's website
Financial Stress Index	Degree of financial stress in the markets, constructed by St. Luis Fed	W	Global	Haver
Weekly Economic Indicator	Index of ten indicators of real economic activity, constructed by New York Fed	W	Global	New York Fed
Emerging Markets Economic Surprise Index	Weighted historical standard deviations of data surprises (actual releases vs Bloomberg survey median) for Emerging Market Economies, computed by Citigroup. With a sum over 0, its economic performance generally beats market expectations. With a sum below 0, its economic conditions are generally worse than expected	D	Global	Haver
Exchange rate	Exchange rate versus USD	D	Country-specific	Haver
Bitcoin searches	Index of searches of word "Bitcoin" in google	W	Country-specific	Google Trends
Inflation searches	Index of searches of word "inflation" in google	W	Country-specific	Google Trends
Stock market	Stock market indexes for Advanced Economies	D	Country-specific	Haver
Bid-ask spread	Biad-ask spread of a currency trading	D	Country-specific	WM/Refinitiv

Table A.2: Country features - detailed description

Variable	Description	Frequency	Source
Remittance costs	Total cost in percentage of sending 200 USD to a specific country on average across all the remittance corridors	Q	World Bank, Remittance Prices Worldwide
Remittances over GDP	Share of remittances over GDP	Y	World Bank
Share of population with bank account	Percentage of respondents who report having an account at a bank or another type of financial institution or report personally using a mobile money service in the past 12 months	Y	World Bank, Global Findex database
Index of capital controls	Index of strength of controls on inflows and outlows	Y	Fernández et al. (2016)
Shadow economy	Size of productive economic activities that would normally be included in national accounts, but which remain underground due to tax or regulatory burdens	Y	Medina and Schneider (2019)
Index of financial institutions depth	Index based on data from bank credit to the private sector, assets of the mutual fund and pension fund industries and the size of life and non-life insurance premiums.	Y	Svirydzenka (2016)
Inflation	Average annual growth of the Consumer Price Index over the period 2018-21	Y	Haver
Dollarisation	Share of dollar deposits over total deposits in local deposit money banks	Y	Updated dataset from Levy Yeyati (2006)
Share of digital payments	Percentage of respondents who report using mobile money, a debit or credit card, or a mobile phone to make a payment from an account–or report using the internet to pay bills or to buy something online or in a store–in the past year	Y	World Bank, Global Findex database
Political Risk Rating	Rating of political risk calculated as weighted average of various indices related to government stability, socioeconomic conditions, investment profile, internal conflict, external conflict, corruption, military in politics, religious tensions, law and order, ethnic tensions, democratic accountability, bureaucracy quality	Y	International Country Risk Guide
Number of ATMs per 100,000 adults	Number of ATMs per 100,000 adults	Y	IMF, Financial Access Survey
Median age	Median age of the population	Y	United Nations
Rule of Law	Rule of Law captures perceptions of the extent to which agents have confidence in and abide by the rules of society, and in particular the quality of contract enforcement, property rights, the police, and the courts, as well as the likelihood of crime and violence	Y	World Bank, Worldwide Governance Indicators

Table A.3: Sample of currencies

Advanced economies (14):
Australian dollar (AUD); Canadian dollar (CAD); Swiss franc (CHF); Czech koruna (CZK); Danish krone (DKK); euro (EUR); British pound (GBP); Hong Kong dollar (HKD); Japanese yen (JPY); South Korean won (KRW); Norwegian krone (NOK); New Zealand dollar (NZD); Swedish krona (SEK); Singapore dollar (SGD).
Emerging and developing economies (30)
United Arab Emirates dirham (AED); Argentinian peso (ARS); Brazilian real (BRL); Chilean peso (CLP); Chinese yuan (CNY); Colombian peso (COP); Dominican peso (DOP); Egyptian pound (EGP); Hungarian forint (HUF); Indonesian rupiah (IND); Indian rupee (INR); Kenyan schilling (KES); Kazakhstani tenge (KZT); Moroccan dirham (MAD); Mexican peso (MXN); Malaysian ringgit (MYR); Nigerian naira (NGN); Peruvian sol (PEN); Philippine peso (PHP); Pakistani rupee (PKR); Polish zloty (PLN); Romanian leu (RON); Russian rouble (RUB); Saudi Arabian riyal (SAR); Thai baht (THD); Turkish lira (TRY); Tanzanian schilling (TZS); Ukrainian hryvnia (UAH); Vietnamese dong (VND); South African rand (ZAR).

Appendix B Additional tables

Table B.1: Correlation matrix of global drivers of Bitcoin trading

	VIX	FSI	GPRI	GOLD	WEI	EME ESI	BTC	BTC VOL	BIDASK
VIX	1.00								
FSI	0.77	1.00							
GPRI	0.02	-0.13	1.00						
GOLD	0.21	0.25	0.16	1.00					
WEI	-0.26	-0.33	-0.06	-0.03	1.00				
EME ESI	0.13	-0.27	0.04	-0.08	0.11	1.00			
BTC	-0.07	-0.11	-0.17	-0.10	0.24	0.18	1.00		
BTC VOL	0.35	0.38	0.05	0.00	-0.20	0.10	0.03	1.00	
BIDASK	0.21	0.17	0.04	0.21	-0.06	0.09	0.05	-0.02	1.00

Table B.2: Correlation of second factor in Bitcoin trading with global drivers

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Full sample			Pre COVID			COVID		
	All	AE	EMDE	All	AE	EMDE	All	AE	EMDE
BTC	0.14*	-0.05*	0.00	-0.12*	0.05*	0.26*	0.42*	0.49*	0.38*
BTC VOL	-0.14*	0.03	0.14*	0.05*	0.08*	-0.06*	-0.13*	-0.08*	-0.12*
VIX	0.00	0.13*	0.05*	0.41*	-0.28*	-0.53*	0.13*	0.10*	0.08*
GOLD	-0.07*	0.28*	0.06*	0.53*	-0.29*	-0.32*	0.07*	-0.02	-0.00
BIDASK	-0.04*	0.02	0.01	0.02	-0.03	0.10*	0.08*	-0.08*	0.13*

The table reports the correlation between global variables (see Table 2 for the definition) and the second factor extracted from the model in equation 3 for the volume of Bitcoin transactions against local currencies, detrended with the moving average of the past 15 weeks. The asterisk * indicates statistical significance at 5 percent level.

Table B.3: Advanced economies in the COVID-19 period, excluding currencies one at a time

VARIABLES	(1) NOK	(2) CAD	(3) GBP	(4) HKD	(5) DKK	(6) EUR	(7) AUD	(8) KRW	(9) NZD	(10) CZK	(11) JPY	(12) CHF	(13) SGD	(14) SEK
BTC (t-1)	0.07	0.07	0.06	0.05	0.06	0.06	0.09*	0.07	0.05	0.06	0.08	0.05	0.05	0.06
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
BTC VOL (t-1)	-10.09***	-11.66***	-10.84***	-9.55***	-10.45***	-10.91***	-12.03***	-11.58***	-11.63***	-7.95**	-12.53***	-11.15***	-10.16***	-11.51***
	(3.68)	(3.79)	(3.61)	(3.41)	(3.31)	(3.68)	(3.64)	(3.63)	(3.52)	(3.59)	(3.53)	(3.78)	(3.51)	(3.76)
VIX (t)	0.21	0.28**	0.23*	0.24*	0.22*	0.27**	0.26**	0.23*	0.27**	0.16	0.33***	0.26**	0.23*	0.25*
	(0.13)	(0.13)	(0.12)	(0.12)	(0.12)	(0.12)	(0.12)	(0.12)	(0.13)	(0.12)	(0.12)	(0.12)	(0.13)	(0.13)
BIDASK (t)	1.29*	1.32**	1.38**	1.61**	1.30**	1.30*	1.25*	1.39**	1.36**	1.23**	1.08*	1.31*	1.44**	1.40**
	(0.68)	(0.63)	(0.64)	(0.63)	(0.58)	(0.66)	(0.66)	(0.68)	(0.65)	(0.55)	(0.63)	(0.66)	(0.66)	(0.70)
FX (i,t-1)	0.92**	0.87**	0.86**	0.75**	0.86***	0.90**	1.17***	0.88***	0.93***	0.39	0.80**	0.79**	0.81**	0.94**
	(0.35)	(0.34)	(0.33)	(0.33)	(0.29)	(0.35)	(0.40)	(0.31)	(0.35)	(0.28)	(0.33)	(0.33)	(0.32)	(0.36)
Observations	1,410	1,410	1,410	1,410	1,410	1,410	1,410	1,410	1,410	1,410	1,417	1,410	1,410	1,410
Number of groups	13	13	13	13	13	13	13	13	13	13	13	13	13	13
R2	0.25	0.26	0.25	0.26	0.28	0.26	0.25	0.27	0.26	0.28	0.25	0.27	0.26	0.26

The table reports the results of the estimation of the dynamic panel fixed-effect model in equation 2. The dependent variable is the volume of Bitcoin transactions against local currencies in P2P platforms detrended with the moving average of the past 15 weeks. The heading of each column indicates the currency that has been excluded from the sample. See Table 2 for the definition of variables. Coefficients of lags of the dependent variable, constant and dummies not reported here. The COVID-19 sample period runs from week 9 of 2020 until week 14 of 2022. Dryscoll-Kray Standard errors in parentheses. The asterisks ***, ** and * indicate statistical significance at the 1%, 5% and 10% level, respectively. The models include also a time dummy for week 1 of 2022.

Table B.4: Emerging and developing economies in the COVID-19 period, excluding currencies one at a time

VARIABLES	(1) NGN	(2) DOP	(3) TZS	(4) KES	(5) EGP	(6) INR	(7) CLP	(8) ARS	(9) UAH	(10) ZAR	(11) KZT	(12) SAR	(13) VND	(14) MYR	(15) PKR
BTC (t-1)	0.12***	0.11***	0.12***	0.12***	0.11***	0.12***	0.12***	0.12***	0.12***	0.13***	0.12***	0.11***	0.14***	0.12***	0.12***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.03)	(0.03)	(0.04)	(0.04)	(0.03)
BTC VOL (t-1)	-11.00***	-10.21***	-10.23***	-10.69***	-10.57***	-10.45***	-10.30***	-10.18***	-10.55***	-10.80***	-10.22***	-9.50***	-10.99***	-10.23***	-10.47***
	(2.68)	(2.82)	(2.70)	(2.71)	(2.71)	(2.75)	(2.89)	(2.66)	(2.76)	(2.73)	(2.90)	(2.69)	(2.90)	(2.78)	(2.80)
VIX (t)	0.35**	0.33**	0.33**	0.34**	0.33**	0.34**	0.32**	0.32**	0.33**	0.34**	0.31**	0.31**	0.34**	0.33**	0.33**
	(0.14)	(0.14)	(0.14)	(0.14)	(0.14)	(0.14)	(0.14)	(0.14)	(0.14)	(0.14)	(0.13)	(0.14)	(0.14)	(0.14)	(0.14)
BIDASK (t)	0.49	0.52	0.53	0.48	0.48	0.52	0.52	0.49	0.52	0.53	0.71	0.58	0.50	0.55	0.53
	(0.42)	(0.44)	(0.44)	(0.42)	(0.42)	(0.42)	(0.43)	(0.42)	(0.44)	(0.44)	(0.46)	(0.43)	(0.42)	(0.43)	(0.42)
FX (i,t-1)	0.57***	0.58***	0.59***	0.60***	0.58***	0.60***	0.61***	0.61***	0.59***	0.59***	0.54***	0.57***	0.64***	0.60***	0.60***
	(0.18)	(0.18)	(0.18)	(0.18)	(0.18)	(0.18)	(0.18)	(0.19)	(0.18)	(0.18)	(0.17)	(0.18)	(0.19)	(0.18)	(0.18)
Observations	3,157	3,157	3,157	3,157	3,157	3,157	3,157	3,157	3,157	3,157	3,157	3,157	3,158	3,157	3,157
Number of groups	29	29	29	29	29	29	29	29	29	29	29	29	29	29	29
R2	0.34	0.34	0.34	0.34	0.34	0.34	0.34	0.34	0.34	0.34	0.35	0.35	0.34	0.35	0.34

VARIABLES	(16) PLN	(17) MXN	(18) PEN	(19) PHP	(20) RON	(21) THB	(22) BRL	(23) CNY	(24) RUB	(25) TRY	(26) IDR	(27) HUF	(28) AED	(29) MAD	(30) COP
BTC (t-1)	0.12***	0.12***	0.12***	0.12***	0.12***	0.12***	0.12***	0.12***	0.12***	0.12***	0.12***	0.10***	0.11***	0.11***	0.12***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.03)	(0.03)	(0.04)	(0.04)
BTC VOL (t-1)	-10.14***	-10.38***	-10.10***	-10.81***	-10.30***	-10.46***	-10.28***	-10.37***	-10.54***	-10.69***	-10.01***	-11.14***	-10.33***	-10.33***	-10.42***
	(2.77)	(2.71)	(2.81)	(2.74)	(2.84)	(2.78)	(2.75)	(2.84)	(2.81)	(2.67)	(2.89)	(2.70)	(2.68)	(2.74)	(2.85)
VIX (t)	0.32**	0.33**	0.33**	0.34**	0.33**	0.32**	0.33**	0.33**	0.32**	0.32**	0.32**	0.30**	0.32**	0.32**	0.32**
	(0.14)	(0.14)	(0.14)	(0.14)	(0.14)	(0.14)	(0.14)	(0.14)	(0.14)	(0.14)	(0.13)	(0.13)	(0.13)	(0.14)	(0.14)
BIDASK (t)	0.49	0.49	0.46	0.42	0.51	0.48	0.50	0.52	0.55	0.52	0.52	0.51	0.55	0.51	0.50
	(0.42)	(0.43)	(0.43)	(0.40)	(0.43)	(0.43)	(0.42)	(0.43)	(0.43)	(0.44)	(0.43)	(0.45)	(0.41)	(0.44)	(0.43)
FX (i,t-1)	0.60***	0.64***	0.60***	0.62***	0.58***	0.62***	0.57***	0.60***	0.59***	0.67***	0.58***	0.60***	0.58***	0.58***	0.58***
	(0.18)	(0.19)	(0.19)	(0.19)	(0.18)	(0.18)	(0.19)	(0.18)	(0.19)	(0.19)	(0.18)	(0.15)	(0.18)	(0.18)	(0.18)
Observations	3,157	3,157	3,157	3,157	3,157	3,157	3,157	3,157	3,157	3,157	3,157	3,157	3,158	3,157	3,157
Number of groups	29	29	29	29	29	29	29	29	29	29	29	29	29	29	29
R2	0.35	0.34	0.34	0.33	0.35	0.35	0.34	0.34	0.34	0.35	0.34	0.40	0.35	0.34	0.34

The table reports the results of the estimation of the dynamic panel fixed-effect model in equation 2. The dependent variable is the volume of Bitcoin transactions against local currencies in P2P platforms detrended with the moving average of the past 15 weeks. The heading of each column indicates the currency that has been excluded from the sample. See Table 2 for the definition of variables. Coefficients of lags of the dependent variable, constant and dummies not reported here. The COVID sample period runs from week 9 of 2020 until week 14 of 2022. Dryscoll-Kray Standard errors in parentheses. The asterisks ***, ** and * indicate statistical significance at the 1%, 5% and 10% level, respectively. The models include also a time dummy for week 1 of 2022.

Table B.5: Currency loadings on the global factor and country features. Robustness

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
PRR	-0.10												
	(0.09)												
RULE_LAW		-1.22											
		(1.34)											
SHADOW			-0.04										
			(0.07)										
DIGITAL				-0.06*									
				(0.03)									
ATM					-0.03*								
					(0.02)								
BANK						-0.94							
						(1.31)							
FID							0.07						
							(2.99)						
AGE								-0.21**					
								(0.09)					
REM_GDP									0.14				
									(0.20)				
REM										-0.47			
										(0.44)			
CC											0.85		
											(2.19)		
INFL												-1.11	
												(1.46)	
DOLL													-2.92
													(3.57)
Observations	30	30	28	28	29	30	30	30	29	27	30	29	26
R2	0.04	0.03	0.01	0.12	0.10	0.02	0.00	0.17	0.02	0.04	0.01	0.02	0.03

The table reports the results of robust cross-section regressions accounting for the presence of outliers. The dependent variable is the currency loading on the first common factor for Bitcoin trading volumes against currencies of EMDEs in the COVID-19 period, multiplied by 100. See Table 4 for the definition of variables. Coefficients of constant not reported here. Standard errors in parentheses. The asterisks ***, ** and * indicate statistical significance at the 1%, 5% and 10% level, respectively.

Table B.6: Bitcoin volume (as ratio to GDP) growth between 2021 and 2018-19 and country features

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
PRR	-0.01												
	(0.02)												
RULE_LAW		-0.18											
		(0.38)											
SHADOW			-0.02										
			(0.02)										
DIGITAL				-0.02**									
				(0.01)									
ATM					-0.01**								
					(0.00)								
BANK						-0.51							
						(0.35)							
FID							0.38						
							(0.84)						
AGE								-0.05*					
								(0.02)					
REM_GDP									0.06				
									(0.06)				
REM										0.06			
										(0.13)			
CC											0.19		
											(0.60)		
INFL												0.38	
												(0.26)	
DOLL													-1.01
													(1.12)
Observations	30	30	28	28	29	30	30	30	29	28	30	30	26
R2	0.00	0.01	0.04	0.20	0.16	0.07	0.01	0.13	0.03	0.01	0.00	0.07	0.03

The table reports the results of robust cross-section regressions, accounting for the presence of outliers. The dependent variable is the growth rate in the volume of Bitcoin transactions against local currencies in P2P platforms over the country's GDP in 2021 versus the preCovid period (2018-19). Coefficients of constant not reported here. Standard errors in parentheses. The asterisks ***, ** and * indicate statistical significance at the 1%, 5% and 10% level, respectively.

Table B.7: Baseline model in log difference

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Full sample			Pre COVID			COVID			
	All	AE	EMDE	All	AE	EMDE	All	AE	AE ex. CZK	EMDE
BTC (t-1)	0.28***	0.32**	0.25***	0.24**	0.21	0.26**	0.35***	0.45***	0.33**	0.30***
	(0.08)	(0.13)	(0.08)	(0.12)	(0.21)	(0.11)	(0.10)	(0.15)	(0.14)	(0.10)
BTC VOL (t-1)	-8.72***	-9.01***	-8.56***	-8.33***	-8.12*	-8.27***	-9.19***	-9.26***	-7.61**	-9.25***
	(1.76)	(3.10)	(1.79)	(2.35)	(4.59)	(2.35)	(2.59)	(3.42)	(3.28)	(2.98)
VIX (t)	0.16*	0.13	0.18*	0.25	0.36	0.24	0.20*	0.16	0.08	0.22*
	(0.08)	(0.08)	(0.09)	(0.20)	(0.29)	(0.19)	(0.10)	(0.12)	(0.11)	(0.12)
BIDASK (t)	0.45**	0.74***	0.31	0.35***	0.67***	0.21	0.69	1.13	1.08	0.50
	(0.19)	(0.24)	(0.20)	(0.13)	(0.18)	(0.18)	(0.55)	(0.81)	(0.70)	(0.50)
FX (i,t-1)	1.16***	1.36**	1.08**	0.64	0.94	0.55	1.50***	1.64*	0.97	1.45***
	(0.40)	(0.66)	(0.43)	(0.72)	(1.11)	(0.75)	(0.43)	(0.84)	(0.58)	(0.48)
Observations	9,425	2,997	6,428	4,644	1,478	3,166	4,781	1,519	1,410	3,262
Number of groups	44	14	30	44	14	30	44	14	13	30
Country FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
R2	0.26	0.31	0.24	0.22	0.28	0.20	0.32	0.35	0.39	0.30

The table reports the results of the estimation of the dynamic panel fixed-effect model in equation 2. The dependent variable is the volume of Bitcoin transactions against local currencies in P2P platforms detrended with the log difference. See Table 2 for the definition of variables. Other non-stationary series are also detrended taking the log difference. Coefficients of lags of the dependent variable, constant and dummies not reported here. "Full sample" stands for whole sample period from week 1 of 2018 until week 14 of 2022. The "Pre COVID" sample period runs from week 1 of 2018 until week 8 of 2020. The "COVID" sample period runs from week 9 of 2020 until week 14 of 2022. In Column (9) the Czech koruna is excluded from the sample of fiat currencies. Dryscoll-Kray Standard errors in parentheses. The asterisks ***, ** and * indicate statistical significance at the 1%, 5% and 10% level, respectively. The models include also a time dummy for week 1 of 2022.

Table B.8: Emerging and developing economies: non linearities

VARIABLES squared	(1) BTC	(2) BTC VOL	(3) VIX	(4) BIDASK	(5) FX
BTC (t-1)	0.08***	0.08***	0.08**	0.09***	0.09***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
BTC squared (t-1)	0.00				
	(0.00)				
BTC VOL (t-1)	-9.27***	-4.40	-7.92***	-8.74***	-8.84***
	(2.16)	(5.36)	(2.06)	(1.89)	(1.89)
BTC VOL squared (t-1)		-2.57			
		(2.49)			
VIX (t)	0.23***	0.24***	0.56**	0.21**	0.23**
	(0.09)	(0.09)	(0.23)	(0.09)	(0.09)
VIX squared (t)			-0.01*		
			(0.00)		
BIDASK (t)	0.58***	0.56***	0.56***	0.73**	0.57***
	(0.16)	(0.16)	(0.15)	(0.36)	(0.16)
BIDASK squared (t)				-0.02	
				(0.03)	
FX (i,t-1)	0.47***	0.46***	0.49***	0.46***	0.48***
	(0.15)	(0.15)	(0.14)	(0.15)	(0.18)
FX squared (i,t-1)					-0.00
					(0.01)
Observations	8,911	8,911	8,911	8,911	8,911
Number of groups	44	44	44	44	44
Country FE	YES	YES	YES	YES	YES
R2	0.33	0.33	0.33	0.33	0.33

The table reports the results of the estimation of the dynamic panel fixed-effect model in equation 2, augmented with the squared-terms of the selected regressors. The dependent variable is the volume of Bitcoin transactions against local currencies in P2P platforms detrended with the moving average of the past 15 weeks. See Table 2 for the definition of variables. Coefficients of lags of the dependent variable, constant and dummies not reported here. Dryscoll-Kray Standard errors in parentheses. The asterisks ***, ** and * indicate statistical significance at the 1%, 5% and 10% level, respectively.

Table B.9: Excluding currencies with very low exchange rate volatility

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
		Full sample			Pre COVID				COVID	
	All	AE	EMDE	All	AE	EMDE	All	AE	AE ex. CZK	EMDE
BTC (t-1)	0.07**	0.08	0.07**	0.09*	0.16**	0.07	0.10***	0.05	0.05	0.11***
	(0.03)	(0.05)	(0.03)	(0.05)	(0.07)	(0.04)	(0.03)	(0.05)	(0.05)	(0.03)
BTC VOL (t-1)	-7.92***	-6.12*	-8.61***	-6.73**	-1.95	-8.37***	-9.67***	-9.55***	-6.22*	-9.70***
	(1.89)	(3.14)	(1.78)	(2.78)	(4.70)	(2.85)	(2.51)	(3.41)	(3.35)	(2.68)
VIX (t)	0.22**	0.19**	0.23**	0.48**	0.79**	0.42**	0.30**	0.24*	0.15	0.32**
	(0.09)	(0.09)	(0.09)	(0.22)	(0.34)	(0.20)	(0.12)	(0.12)	(0.11)	(0.13)
BIDASK (t)	0.62***	0.90***	0.47***	0.43***	0.58***	0.32*	0.93**	1.61**	1.52***	0.62
	(0.17)	(0.24)	(0.18)	(0.14)	(0.22)	(0.17)	(0.44)	(0.63)	(0.52)	(0.42)
FX (i,t-1)	0.40***	0.52*	0.36**	0.05	-0.62	0.10	0.62***	0.75**	0.29	0.59***
	(0.15)	(0.31)	(0.15)	(0.27)	(0.41)	(0.29)	(0.17)	(0.33)	(0.28)	(0.19)
Observations	7,898	2,629	5,269	3,657	1,219	2,438	4,241	1,410	1,301	2,831
Number of groups	39	13	26	39	13	26	39	13	12	26
Country FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
R2	0.32	0.25	0.36	0.33	0.26	0.36	0.30	0.26	0.28	0.34

The table reports the results of the estimation of the dynamic panel fixed-effect model in equation 2. The dependent variable is the volume of Bitcoin transactions against local currencies in P2P platforms detrended with the moving average of the past 15 weeks. We have excluded Hong Kong dollar, Saudi Arabian riyal, Tanzanian schilling, United Arab Emirates dirham, Vietnamese dong. Coefficients of lags of the dependent variable, constant and dummies not reported here. "Full sample" stands for whole sample period from week 1 of 2018 until week 14 of 2022. "Pre COVID" stands for the sample period from week 1 of 2018 until week 8 of 2020. "COVID" stands for the sample period from week 9 of 2020 until week 14 of 2022. Dryscoll-Kray Standard errors in parentheses. The asterisks ***, ** and * indicate statistical significance at the 1%, 5% and 10% level, respectively.

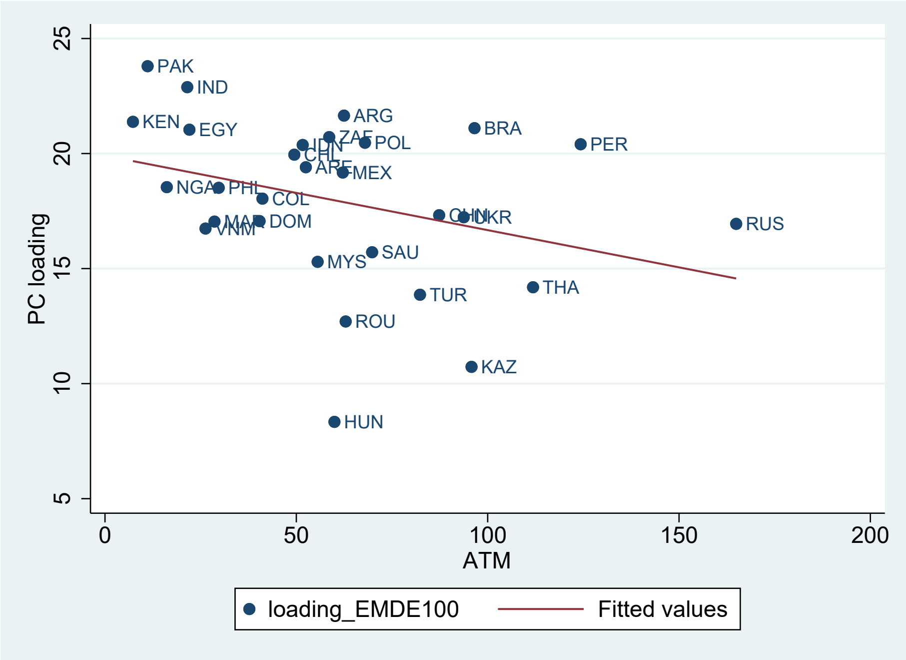
Table B.10: Sensitivity of key drivers in Bitcoin trading volumes against fiat currencies to country-specific features

VARIABLES	(1) ATM<25pct	(2) ATM<10pct	(3) Digital<25pct	(4) Digital<10pct	(5) Age<25pct	(6) Age<10pct
BTC (t-1)	0.08***	0.10***	0.12***	0.10***	0.09***	0.10***
	(0.04)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
BTC VOL (t-1)	-10.50***	-10.04***	-10.44***	-9.80***	-10.05***	-10.01***
	(2.17)	(1.83)	(1.94)	(1.88)	(1.97)	(1.80)
VIX	0.29***	0.27***	0.24***	0.26***	0.28***	0.28***
	(0.10)	(0.10)	(0.09)	(0.10)	(0.10)	(0.10)
BIDASK (t)	0.38**	0.47**	0.36**	0.41***	0.40***	0.44**
	(0.17)	(0.16)	(0.16)	(0.16)	(0.15)	(0.17)
FX (i,t-1)	0.32**	0.41***	0.45***	0.40**	0.37**	0.40***
	(0.16)	(0.15)	(0.13)	(0.16)	(0.16)	(0.15)
BTC (t-1) * D_ATM	0.05	-0.03				
	(0.04)	(0.03)				
BTC VOL (t-1) * D_ATM	4.33	7.55***				
	(3.54)	(1.94)				
VIX (t) * D_ATM	-0.06	-0.02				
	(0.10)	(0.07)				
BIDASK (t-1) * D_ATM	0.25	-0.22				
	(0.38)	(0.43)				
FX (t-1) * D_ATM	1.04***	0.20				
	(0.38)	(0.32)				
BTC (t-1) * D_DIGITAL			-0.08**	0.01		
			(0.03)	(0.03)		
BTC VOL (t-1) * D_DIGITAL			2.99	1.44		
			(3.25)	(3.74)		
VIX (t) * D_DIGITAL			0.09	-0.01		
			(0.09)	(0.10)		
BIDASK (t-1) * D_DIGITAL			0.16	-0.16		
			(0.32)	(0.38)		
FX (t-1) * D_DIGITAL			-0.33	-0.10		
			(0.62)	(0.31)		
BTC (t-1) * D_AGE					0.07	0.01
					(0.04)	(0.04)
BTC VOL (t-1) * D_AGE					3.95	7.83**
					(3.43)	(3.16)
VIX (t) * D_AGE					-0.08	-0.21**
					(0.11)	(0.10)
BIDASK (t-1) * D_AGE					0.06	-0.30
					(0.36)	(0.28)
FX (t-1) * D_AGE					0.81**	1.14***
					(0.39)	(0.38)
Observations	5,905	5,905	5,703	5,703	6,109	6,109
Number of groups	29	29	28	28	30	30
Country FE	YES	YES	YES	YES	YES	YES
R2	0.35	0.35	0.35	0.35	0.36	0.36

The table reports the results of the estimation of the dynamic panel fixed-effect model in equation 4. The dependent variable is the volume of Bitcoin transactions against local currencies in P2P platforms detrended with the moving average of the past 15 weeks. See Table 2 and 4 for the definition of variables. ATM<25pct (10pct) is a dummy variable equal to 1 when the number of ATMs per 100,000 adults is below the 25th (10th) percentile of its distribution. DIGITAL<25pct (10pct) is a dummy variable equal to 1 when the value of the share of digital payments is below the 25th (10th) percentile of its distribution. AGE<25pct (10pct) is a dummy variable equal to 1 when the median age is below the 25th (10th) percentile of its distribution. Coefficients of lags of the dependent variable, constant and dummies not reported here. Dryscoll-Kray Standard errors in parentheses. The asterisks ***, ** and * indicate statistical significance at the 1%, 5% and 10% level, respectively.

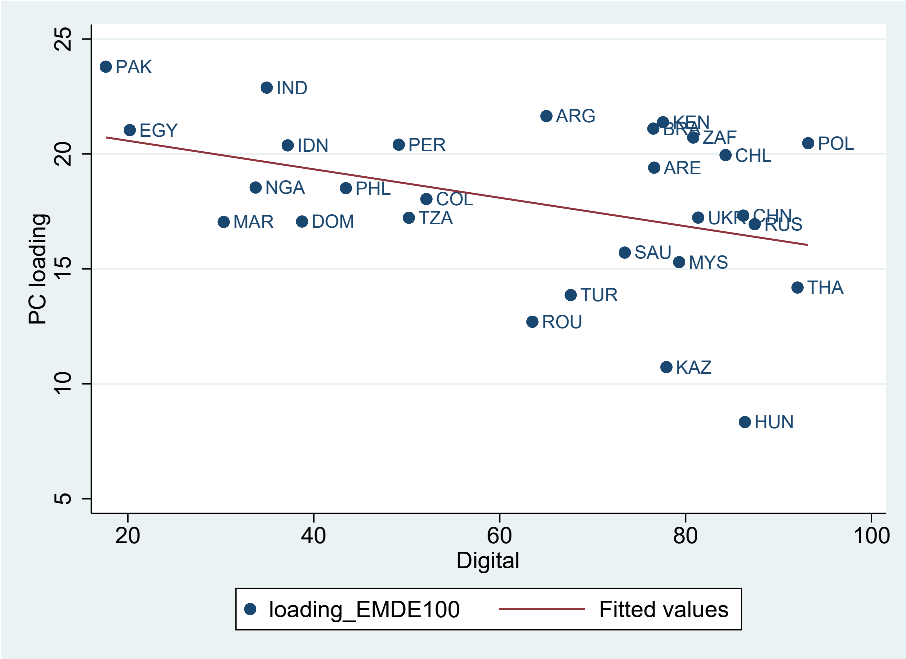
Appendix C Additional figures

Figure C.1: Factor loadings versus ATM



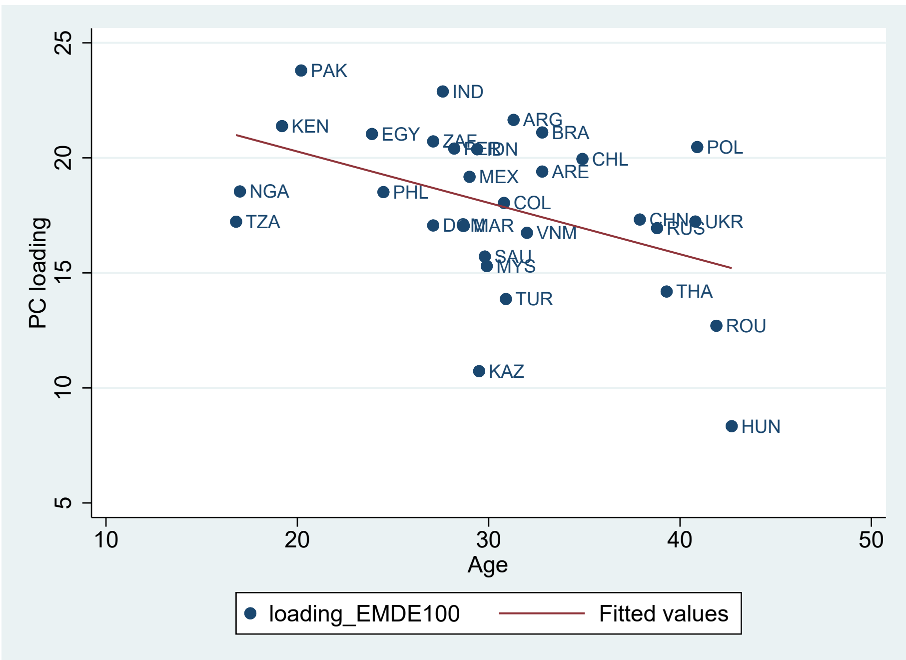
The figure shows on the vertical axis the currency loadings – multiplied by 100 – on the first factor extracted from the model in equation 3 for the volume of Bitcoin transactions against the currencies of EMDEs in the COVID-19 period. The figure refers to the regression in Table 10.

Figure C.2: Factor loadings versus digital payment



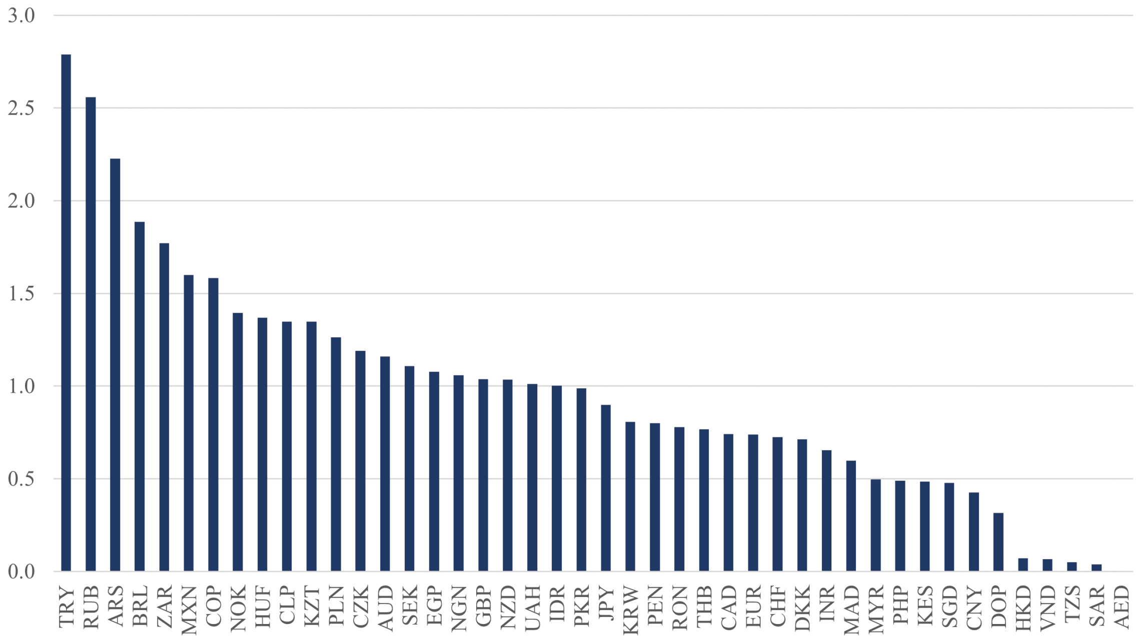
The figure shows on the vertical axis the currency loadings – multiplied by 100 – on the first factor extracted from the model in equation 3 for the volume of Bitcoin transactions against the currencies of EMDEs in the COVID-19 period. The figure refers to the regression in Table 10.

Figure C.3: Factor loadings versus median age



The figure shows on the vertical axis the currency loadings – multiplied by 100 – on the first factor extracted from the model in equation 3 for the volume of Bitcoin transactions against the currencies of EMDEs in the COVID-19 period. The figure refers to the regression in Table 10.

Figure C.4: Exchange rate volatility (percent)



The figure reports the standard deviation of weekly changes in the nominal exchange rate against the US dollar. Source: IMF/Haver and authors' calculations.

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