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

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Abstract

We analyse global and local drivers of Bitcoin transactions against 45 fiat currencies in the largest peer-to-peer crypto exchanges. Global factors, such as momentum in the crypto-asset market or financial market volatility, do matter for Bitcoin trading. There is evidence of a global *crypto* cycle driven by speculative motives. Trading across currencies and users around the world moves in tandem with fluctuations in the Bitcoin price. Crypto shocks and global risk shocks are behind this cyclical comovement. Crucially, Bitcoin seems to offer also utility benefits in emerging and developing economies, since trading increases after idiosyncratic, currency-specific shocks that depreciate the currency. Local projections analysis and case studies confirm this important link between exchange rate instability and Bitcoin transactions.

JEL Classification: E42 F21 F24 F32 F38 G15 O33

Keywords: digital currencies, Bitcoin, peer-to-peer exchanges, exchange rates, emerging markets.

1 Introduction

The rising popularity of Bitcoin and other cryptocurrencies that are not backed by any asset and, generally, do not offer cash flows is intriguing many economists, who are trying to figure out the reasons behind the soaring demand for these cryptocurrencies. Two broad classes of explanation of the *crypto-frenzy* emerge from the fast growing body of literature on this topic: first, demand driven by *users* who value the *transactional or utility benefits* from holding the cryptocurrency (e.g. to do payments without being traced, but also to send remittances or find an alternative to a domestic currency whose value is unstable); and, second, demand driven by (speculative) *investors* who try to guess the peak in the demand for transactional reasons or, irrespective of transactional motives, anticipate a future inflow of investors' funds in a typical *rational bubble equilibria* (van Oordt, 2024).

In this study, we provide indirect support to these potential explanations of crypto-assets demand, studying the factors driving Bitcoin transactions across a number of advanced and emerging economies, distinguishing between those *global* and *crypto* factors that might be associated with investment motives, and unrelated to transactional or utility benefits, from *local* factors, stemming from the utility of holding a currency that is not denominated in the local fiat currency. Our main contribution is to show that there are factors common to *all* countries/currencies, either advanced or emerging, that are important drivers of Bitcoin trading and give rise to a *global crypto cycle* co-moving with the Bitcoin price; but at the same time there is an important local factor, the exchange rate, that helps to explain greater use of Bitcoin in a subset of countries/currencies, namely in emerging and developing economies. To our knowledge, there is no study so far that has been able to isolate these two distinct potential drivers of crypto trading, which in turn echo the two main potential theoretical explanations of crypto usage.

To run our analysis, 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. P2P platforms gained popularity during the period around the COVID-19 crisis to exchange Bitcoin *off-chain*, in particular in emerging and developing economies (EMDEs) (Chainalysis, 2023), before being replaced by the growth of *off-chain centralised* exchanges. Even

[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 transactions where data about the residence of the traders of Bitcoin are available.

though *decentralised* P2P platforms are not the main exchanges to trade Bitcoin worldwide, they have two important peculiarities. First, in the sample period of this study, P2P exchanges were the main platforms to trade Bitcoin against EMDEs currencies (see Section 3). Second, 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.[3]

Specifically, we analyse trading volumes of Bitcoin versus the currencies of 15 advanced economies (AEs) and the currencies of 30 EMDEs. Data are obtained from the largest P2P exchanges in our sample period, namely LocalBitcoins and Paxful, between January 2018 and 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-effects 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 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 conditions, or geopolitical events, similarly to analyses of foreign exchange trading volumes (Cespa et al., 2022); and, finally, (iii) country-specific factors that reflect the weakness of the institutional and macroeconomic framework, which may influence the transactional or utility services of Bitcoin and its fundamental value. We use local projection analysis to deepen our understanding of these local factors. 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 drivers with VAR analysis.

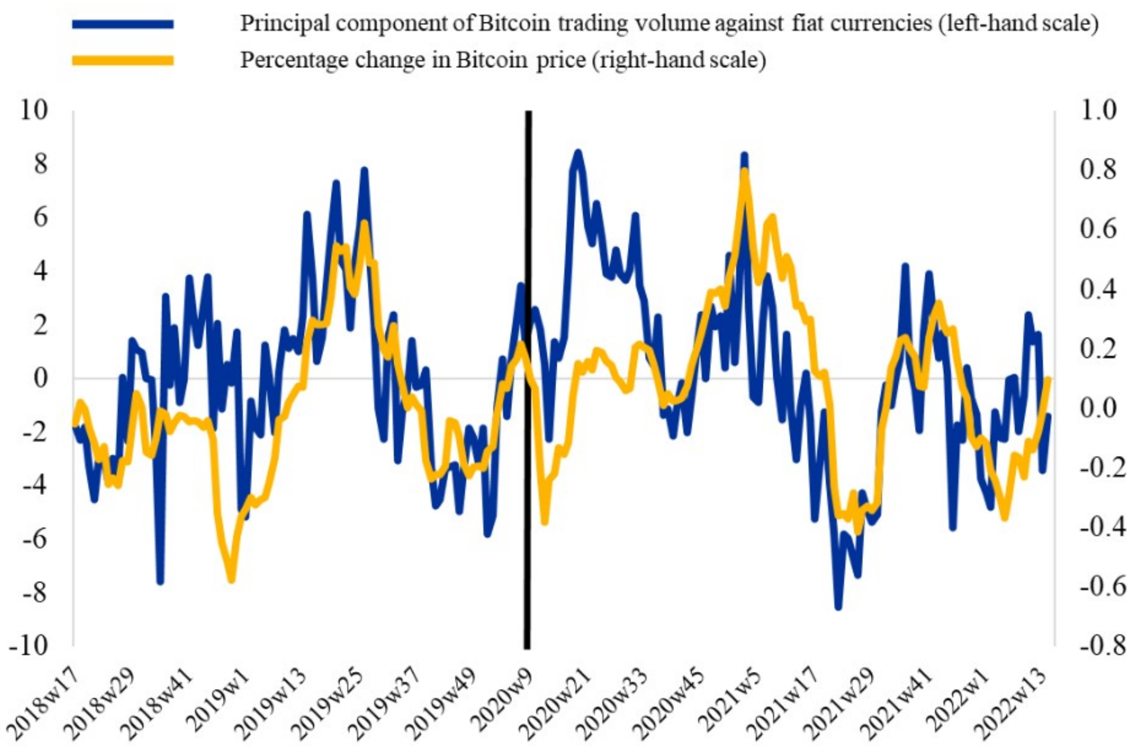
Two main results emerge from our analysis. First, global factors are important for Bitcoin trading. In the panel analysis, we find that momentum and volatility in the crypto-asset market as well as global financial market volatility and liquidity do matter for Bitcoin trading against different fiat currencies. In factor analysis, we

[2]See Chainalysis (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. (2023) who analysed a sample of unregulated exchanges, wash trading is a serious problem, with the reported volumes inflated on average by more than 70%.

identify a single global factor that on average explains up to about 40% of the variance of Bitcoin trading between different currencies in the COVID-19 period. There is 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 1. Trading across currencies and users around the world moves in tandem with fluctuations in the Bitcoin price, indicating that Bitcoin is largely used as a speculative investment asset across advanced, emerging and developing economies. Our analysis finds that this *global crypto cycle* is driven by crypto specific shocks and global risk shocks.

Figure 1: 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 6 for further details. Trading volumes and the Bitcoin price are detrended with the log difference with respect to the past 15-week moving average.

Second, turning to country-specific factors, one local driver, the depreciation of the domestic currency versus the US dollar due to idiosyncratic shocks plays a role in encouraging more Bitcoin trading against the currencies of EMDEs. Therefore, Bitcoin seems to offer utility benefits, in particular in EMDEs where there is exchange rate instability. Local projections analysis with instrumental variables and specific episodes, such as the realignment of a fixed exchange rate peg in Nigeria or the impact of the Russian invasion of Ukraine in 2022 on Bitcoin trading against the hryvnia, support this finding. This clearly indicates that Bitcoin might be used as an alternative investment asset in countries that experience a loss in the purchasing power of their domestic currency.

Our results point towards financial stability risks associated with cryptocurrency speculation, in particular in EMDEs. This is exacerbated by the limited consumer protection and the 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 crypto-asset markets has been punctuated by market crashes, while the link to 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 (Le et al., 2023) - 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; IMF, 2023b), calling for a coherent policy framework to tackle macrofinancial risks stemming from crypto assets (IMF, 2023a). To a large extent, our results and policy implications concern EMDEs, as decentralised P2P exchanges found fertile ground in less developed economies, while residents of AE tend to use *off-chain centralised* exchanges, which are beyond the scope of this study. However, financial stability risks arising from cryptocurrencies, in general, are not limited to EMDEs, as US-based evidence points to substantial spillover effects of cryptocurrencies on the real economy through consumption and investment in other asset classes (Aiello et al., 2023).

The remainder of the paper is structured as follows. Section 2 anchors our empirical model to the theoretical literature on the competition between fiat currencies and digital currencies and reviews the existing literature. Section 3 describes the key distinctive features of P2P crypto-asset exchanges, and Section 4 presents the data with their summary statistics. Section 5 discusses the empirical methodology and

[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 crypto-asset 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).

the key findings on the drivers of Bitcoin vis-à-vis fiat currency transactions. Section 6 studies the comovement of Bitcoin transactions against different fiat currencies and the underlying drivers from a different angle, applying factor analysis. Finally, Section 7 concludes.

2 Conceptual framework and review of the literature

Our empirical investigation can be framed in the theoretical literature which analyses the competition between different fiat currencies and digital currencies in open economy models, such as Benigno et al. (2022), Ferrari Minesso et al. (2022) or Murakami and Viswanath-Natraj (2025). However, to a large extent, these models abstract from the demand for digital currencies of investors who expect future price increases, instead focussing on the arbitrage opportunities offered by the potential remuneration of digital currencies, either private or public, vis-à-vis fiat currencies. Therefore, these models generally speak to the potential competition between fiat currencies, central bank digital currencies, and stablecoins, and do not embed the role of *investors* demanding unbacked cryptocurrencies based on the expectation that their price will continue to increase. For this reason, we amend the model of Benigno et al. (2022), in particular the case of *money-in-the-utility-function*, and adapt it to our problem, assuming that the price of a global crypto currency is *not* fixed in terms of foreign (US dollar) currency units and can vary over time, as in the case of Bitcoin. Furthermore, we simplify their model assuming that there is only one alternative foreign currency, the US dollar, as this is a realistic assumption for many emerging markets and, in general, as most investors follow the price of Bitcoin in US dollar terms. The simple extension of this model is detailed in the Appendix A. By solving the first-order conditions of the model for global crypto currency holdings G, it is possible to obtain its demand function:

$$G_t = \left\{ \beta E_t \left[\frac{\lambda_{t+1}}{\lambda_t}(1+\sigma_{t+1})(1+\pi^G_{t+1}) \right] + \frac{V'_{G,t}}{\lambda_t S_t P^G_t} - 1 \right\} \frac{1}{\phi^G} \tag{1}$$

where E_t is the expectation operator, λ_t is the Lagrange multiplier, $V'_{G,t}$ is the derivative of the utility function for G and defines the convenience yield of holding crypto-assets that derives, for example, from their potential use in payments or as store of value, S_t is the level of the exchange rate against the US dollar; σ_{t+1} is the rate of depreciation of the domestic currency with respect to the US dollar, P^G_t is the price of the crypto currency in terms of US dollar and π^G_{t+1} is the relative change in the price of the crypto asset in US dollar terms. This equation shows that the demand for the global crypto asset increases if households *expect* capital gains from crypto-asset holdings originating from:

1. an *expected* increase in the dollar price of the global crypto currency (π^G_{t+1}), or
2. an *expected* depreciation of the domestic currency against the US dollar (σ_{t+1})

These are the two main propositions that the empirical model of the paper will try to validate. In addition, the equation shows that the demand for the global crypto asset:

- increases in the convenience yield on the crypto-asset ($V'_{G,t}$), or[6]
- decreases in the transaction costs (ϕ^G).

A number of control variables, such as bid-ask spreads in the currency market or proxies of inflation expectations, shall try to control for these additional factors in the empirical model.

Our study contributes to a growing literature on the drivers of Bitcoin and other crypto-assets usage. Like many other crypto-assets, Bitcoin is not backed by any real asset or any governmental claim (Halaburda et al., 2022). 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. This in turn has generated a lively and fast-growing debate among economists about the motivations behind the use of Bitcoin. Initially, the usage of Bitcoin has been associated with the black market of illegal goods and services and gambling activities (Foley et al., 2019; Marmora, 2021). These factors alone cannot explain the soaring popularity of cryptocurrency exchange markets and Bitcoin, which 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 Chainalysis (2024), among the top 20 countries with the highest crypto adoption index, there are only three AEs, the United States, the United Kingdom, and Canada, while the remaining countries are all EMDEs from Asia, Africa, Europe or Latin America. Therefore, scholars turned to speculative motives as the main factor behind Bitcoin adoption (Baur et al., 2018). Studies based on survey data indicate that cryptocurrency investors tend to be highly educated, young, male, and digital natives (Auer and Tercero-Lucas, 2022; Weber et al., 2023) and hold risky portfolios (Hackethal et al., 2021). The use of Bitcoin as a speculative

[6]Notice that, as shown by Benigno et al. (2022), these results are robust to assuming no convenience yields on G, i.e. $V'_{G,t} = 0 \;\forall\; t$.

investment may be particularly attractive to investors based in EMDEs, where the portfolio choice of investment assets is restricted by regulatory or institutional features. Cryptocurrencies have been argued to represent a better store of value when inflation is elevated, so that Bitcoin may be used as a hedge against inflation (Blau et al., 2021), although evidence of a causal link has been limited to date to the COVID-19 period (Conlon et al., 2021) or an emerging market such as India (Cong et al., 2024). In addition, despite the high volatility of its price that makes Bitcoin impractical as a medium of exchange (Baur and Dimpfl, 2021), there is solid evidence that EMDE residents can use cryptocurrencies as a means of payment in cross-border transactions to bypass capital controls or reduce the cost of receiving remittances from abroad (Cerutti et al., 2024; Graf von Luckner et al., 2023, 2024).

Biais et al. (2023) offer a theoretical framework to explain the fundamental value of cryptocurrencies, which depends on their net transactional services. However, since 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 the 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.

A second strand of theoretical literature has tried to incorporate the demand by forward-looking investors to explain the dynamics of cryptocurrency prices. In this second strand of literature, the demand for cryptocurrencies is driven by (speculative) investors who try to guess the peak demand for transactional reasons (Bolt and Van Oordt, 2020) or, irrespective of transactional and utility motives, anticipate a future inflow of investors' funds that allows rational bubble equilibria (Canidio, 2023; van Oordt, 2024; Wei and Dukes, 2021).

So far, with few exceptions such as Makarov and Schoar (2020), the ability to map cryptocurrency use to country features has been limited, mainly due to data constraints and the inherent difficulty in tracking 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.[7] 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.[8] 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.[9] Our study fills the gap 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 can capture the presence of a weak institutional or macroeconomic environment that may encourage the use of Bitcoin also as a store of value or a medium of exchange.

3 P2P crypto exchanges

Our analysis is based on transaction data extracted from the world's two largest peer-to-peer (P2P) Bitcoin exchanges: LocalBitcoins and Paxful.[10] In this section, we describe the specific features of these *off-chain decentralised* P2P exchanges in the crypto-asset ecosystem, differentiating them from *off-chain centralised* cryptocurrency exchanges and *on-chain decentralised* exchanges (see Table 1).

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

[7] Auer et al. (2022) 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.

[8] The prominent role of cryptocurrency prices for the investment choices in retail use is also confirmed by Kogan et al. (2024), using data from a centralised exchange.

[9] 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. See Section 3 for further details.

[10] 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.

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.

keys to their accounts. An *on-chain* decentralised exchange (DEX) is a marketplace where 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).[11] 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 on centralised crypto exchanges (Aramonte et al., 2022). The Appendix B explains the functioning and peculiarities of these P2P exchanges and quantifies their relative importance compared to centralised exchanges. In particular, Figure B.3a shows that, over our sample period, transactions involving currencies of EMDEs are mainly taking place in P2P exchanges, whereas Bitcoin is traded against the currencies of advanced economies mainly on centralised exchanges. Therefore, our results, eventually, are particularly relevant for Bitcoin usage in EMDEs

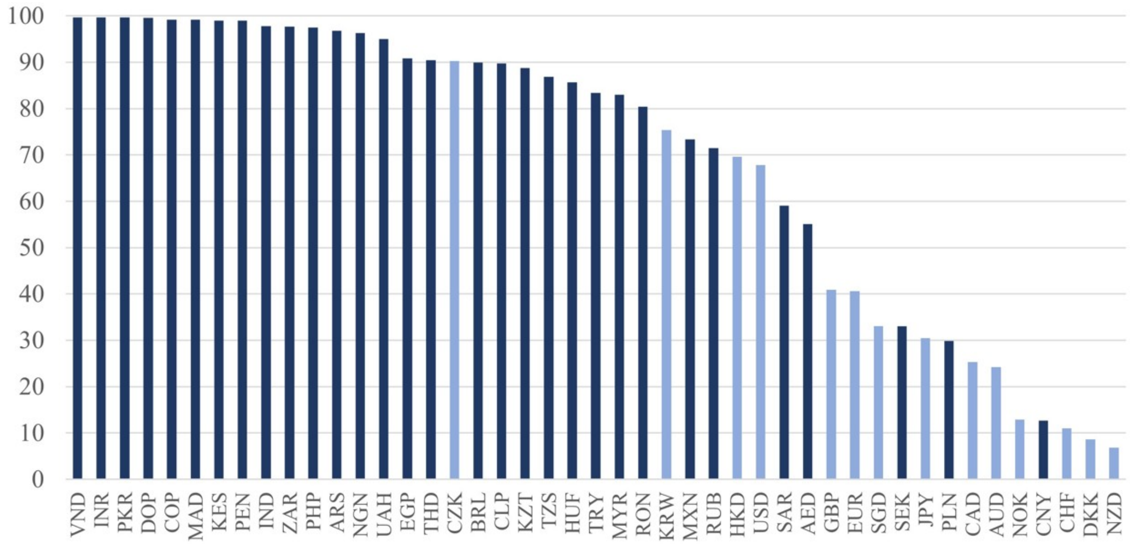
One of the main benefits of analysing transactions in P2P exchanges versus those in centralised exchanges is that P2P exchanges are used mainly by small retail users and are not affected by the problem of market manipulation, such as *wash trading*, thus minimising the possibility that our findings are affected by large trades of few individuals.[12]

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

[12] See discussion in Section 1.

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 2). The ratio of local currency transactions where at least one of the traders is located in the domestic country to the total volume of transactions tends to be - on average - higher than 70% in EMDEs. There are two outliers in EMDEs where the association between the location of the trader and currency does not match closely: the Chinese renminbi, which is mainly traded by US residents, and the Polish zloty.[13] In the case of AEs these ratios are, instead, lower than 50%.

Figure 2: 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 C.2 in the Appendix for the identification of currency codes.

4 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 45 currencies (see Table C.2 in the Appendix for details). Daily data were converted into weekly data by averaging. The final dataset covers the period from the first week of 2018 to the fourteenth week of 2022. Trading volumes denominated in the domestic

[13]Our results are robust to the exclusion the Chinese renminbi and the Polish zloty from our sample of currencies (see Section 5.2).

currency of our sample of 45 economies have been downloaded from CryptoCompare and summed across the two P2P exchanges.[14]

Our analysis relies on panel data with moderate N (45) 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, to remove the trending behaviour of the variable, either stochastic or deterministic, we have detrended trading volumes, the Bitcoin price, the gold 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):

$$\tilde{Z}_t = \left(log Z_t - log \sum_{j=1}^{15} \frac{Z_{t-j}}{15} \right) * 100 \tag{2}$$

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 5.2 we show that the detrending with the first difference of these variables does not substantially alter the results.[15]

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 C.1 in the Appendix.

Crypto-specific drivers. These are variables that capture demand for Bitcoin, potentially as a speculative investment (Baur et al., 2018).[16] As a proxy of *momentum* in the Bitcoin market, we include the log-change in the Bitcoin price in US dollar,

[14]The currencies of two African economies, Kenya and Nigeria, top 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 1,000 inhabitants (see Figure E.1a in the Appendix). These two currencies continue to top the ranking of the most traded currencies when scaling trading volumes by nominal GDP (see Figure E.1b).

[15]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.

[16]The link between Bitcoin usage and Bitcoin price is supported by evidence in Auer et al. (2022) and Kogan et al. (2024).

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
Flows of equity funds ($FUNDS_i$)	EPFR
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

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 the volatility of the past Bitcoin return, calculated as the annualised 7-day rolling standard deviation of daily changes in the Bitcoin price ($BTC\ VOL$), also sourced from CryptoCompare. These variables can help us assess whether Bitcoin is used for speculative investments.

Global drivers. These are variables that capture any potential link 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 risk, 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, which is in any case highly positively correlated with the VIX. We also consider the Geopolitical Risk Index ($GPRI$) at the global level computed by Caldara and Iacoviello (2022) to control whether 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).[17] 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 D.1 in the 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 and utility benefits stemming from the use of Bitcoin that are specific to certain currencies and economies. Domestic macroeconomic instability might prompt investors to seek refuge in Bitcoin. Although investors in AEs with open capital accounts and developed financial markets may potentially find alternative assets to hedge against exchange rate and inflation risk, investors in 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.[18] In addition, we calculated the relative bid-ask spread for each currency ($BIDASK_i$), taking the exchange rate quotes against the US dollar from WM/Refinitiv, so that we may control if liquidity in traditional foreign exchange markets spills over to the crypto market. Finally, as an additional control for a limited number of emerging markets, we replace the official exchange rates with the *shadow* exchange rates of Graf von Luckner et al. (2024), which are derived from crypto markets. Among the local factors, we control also for portfolio equity flows towards each country, proxied by weekly equity fund flows, measured as percentage of assets under management (AuM), downloaded from EPFR.

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.[19] Google Trends data searching for the term "Bitcoin" ($GT\ BTC_i$) are

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

[18] An increase (decrease) in the exchange rate implies a depreciation (appreciation) of the local currency versus the US dollar. For the case of USD transactions we use the change in the USD nominal effective exchange rate. 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 classifications, 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 E.3). We shall run specific controls to account for these currencies in the empirical analysis.

[19] As an alternative measure to capture inflation at a higher frequency, we have also tried the

used as an indicator of *crypto attention*, similar to Liu and Tsyvinski (2021). Finally, for the sample of advanced economies, we have also included their stock market indices, obtained from Haver, in our analysis.

Table 3 provides summary statistics for the variables included in the benchmark specification. We can notice that the kurtosis is higher for EMDEs than for 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. Finally, note that the volatility of our series, detrended with the 15-week moving average – such as Bitcoin trading volumes, their returns, and exchange rate returns – is relatively elevated due to the specific detrending transformation.

Table 3: Summary statistics

LOCAL VARIABLES AE	N	mean	sd	min	max	skewness	kurtosis	p1	p99
P2P VOL$_i$ (%)	3,330	-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
FUNDS$_i$ (%)	3,330	0.04	0.20	-1.95	1.48	-0.62	11.85	-0.54	0.57
FX$_i$ (%)	3,079	0.23	2.22	-8.47	18.02	0.17	7.37	-6.15	5.87
Number of groups	15	15	15	15	15	15	15	15	15
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
FUNDS$_i$ (% of AuM)	6,660	0.04	0.60	-15.10	23.79	9.33	576.24	-0.81	0.75
FX$_i$ (%)	6,180	0.92	3.58	-12.79	39.61	2.95	21.71	-6.17	15.90
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.

5 The determinants of P2P Bitcoin trading volumes

In this section, we shall apply standard dynamic panel models to study the drivers of Bitcoin transactions against a number of AE and EMDEs currencies. First, we

consumer price index at monthly (or quarterly) frequency, transformed into weekly data using a cubic spline interpolation.

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.

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.[20] Among local drivers, the nominal exchange rate is important in spurring more Bitcoin trading, in particular among emerging markets during the COVID-19 pandemic. Therefore, the loss of purchasing power of the domestic currency may be a driver of crypto usage, and Bitcoin could be valued for its utility benefits as suggested by the theoretical literature (van Oordt, 2024).

5.1 Dynamic panel model of 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:

$$Y_{i,t} = \alpha_i + \sum_{j=1}^{p} \rho_j Y_{i,t-j} + \boldsymbol{\beta} \boldsymbol{G_{t,t-1}} + \boldsymbol{\gamma} \boldsymbol{L_{i,t-1}} + \eta EY_t + u_{i,t} \tag{3}$$

where $Y_{i,t}$, the dependent variable, represents our detrended measure of Bitcoin trading volumes on P2P platforms against the currency of country i at time t (see Section 4). The subscript p is the number of lags in the dependent variable. $\boldsymbol{G_{t,t-1}}$ 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 Bitcoin trading volumes against specific currencies (e.g. inflation, exchange rate movements, and liquidity

[20]Results are robust to excluding transactions in the US dollar.

in the specific foreign exchange market). The parameters of interest are $\boldsymbol{\beta}$ and $\boldsymbol{\gamma}$. EY_t is a dummy, which is equal to 1 in the last week and the 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 4 reports the results of the benchmark model represented in Equation 3 for the entire 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. In fact, the coefficient associated with the lagged growth of the Bitcoin price is positive and statistically significant. An increase in the returns of Bitcoin by one standard deviation (26%) leads to an increase in the trading volumes by around 2.5 percentage points. 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 volatility in Bitcoin price (BTC_VOL) also seems to matter. An increase in the volatility of the Bitcoin price leads to retrenchment in transactions in the following period, implying 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 from 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 echoes 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 on P2P exchanges, whereas professional investors such as institutional investors and hedge funds operate in the foreign exchange market.[21] Interestingly, there is 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, that is, 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 frequency - weekly - 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. On the one hand, the absence of the impact of our proxy for inflation is in line with the results of Conlon et al. (2021). On the other hand, it may be that a better proxy of inflation expectations, not available at the high frequency of our data, is needed to identify the impact of inflation on crypto usage (Cong et al., 2023). For the subset of advanced economies, we have also included stock market returns as local drivers, but they were not significant (not shown). However, there is an important result among local drivers, as Bitcoin trading is

[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.

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 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 the importance of the exchange rate highlight 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 to be not 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 autoregressive terms in column 1 (0.31) and that of the baseline model in column 5 (0.32) are not too different, indicating that the ability of our global and local drivers to explain the volatility of Bitcoin transactions is somewhat limited. Interestingly, if we exclude all country-invariant crypto and global local drivers and include a time fixed-effect in the model, the R-squared increases considerably to 0.39 (see column 6). Therefore, there is a large share of variation in Bitcoin transactions that is common across different currencies but is not captured by our set of crypto and global drivers, which motivates the factor analysis of the global component of Bitcoin trading against fiat currencies in Section 6.

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 5, 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 5 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

Table 4: 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)	(0.05)
P2P volume (t-2)	0.10***	0.10***	0.10***	0.09***	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***	0.09***	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)		-6.53***	-9.56***	-8.35***	-8.90***	
		(2.10)	(2.35)	(1.99)	(1.90)	
VIX (t)			0.21**	0.21**	0.23**	
			(0.10)	(0.08)	(0.09)	
GOLD (t)			0.19	0.28		
			(0.18)	(0.18)		
BIDASK (t)			0.50***	0.46***	0.56***	
			(0.17)	(0.17)	(0.16)	
GPRI (t)			0.00			
			(0.01)			
EME ESI (t)			-0.01			
			(0.03)			
WEI (t)			-1.81*			
			(1.09)			
FX (i,t-1)				0.49***	0.45***	0.42***
				(0.15)	(0.16)	(0.11)
GT BTC (i,t-1)				-0.83		
				(1.61)		
GT INFL (i,t-1)				0.74		
				(0.93)		
BIDASK (i,t-1)				6.52*		
				(3.93)		
FUNDS (i,t-1)				0.74		
				(0.55)		
Observations	9,135	9,135	9,135	9,135	9,135	9,135
Number of groups	45	45	45	45	45	45
Country FE	YES	YES	YES	YES	YES	YES
Time FE	NO	NO	NO	NO	NO	YES
R2	0.31	0.32	0.32	0.32	0.32	0.39

The table reports the results of the estimation of the dynamic panel fixed-effect model in equation 3. 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). Coefficients of end-of-year dummy not reported here. 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.

in particular when splitting the sample around the onset of the COVID-19 pandemic, in particular as regards the impact of FX liquidity and FX depreciation (see columns 4 to 9). 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 9). 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 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 7 to 9), we find that the coefficient associated with the exchange rate is actually negative for AEs (column 5) or not statistically significant (see columns 4 and 6) and it becomes positive since the onset of the COVID-19 pandemic, when the US dollar appreciated across the board on the back of global risk aversion. In this context, Bitcoin might have offered utility benefits in economies where the purchasing power of the domestic currency was not stable.[22] Somewhat puzzling, the coefficient associated with the impact of depreciation of AEs currencies on Bitcoin trading (column 8) is larger than that of EMDEs (column 9). This rather surprising result prompted us to further dissect this issue, finding that that, indeed, the impact of the exchange rate on Bitcoin trading in AEs economies is not robust. Specifically, we re-run the panel regressions excluding currencies that are strictly pegged to the US dollar — where exchange rate stability is not an issue – and then excluding each currency one by one from the sample of AEs to evaluate whether our results are driven by one specific country or set of countries during the COVID-19 period. Overall, most of the results are robust to the exclusion of fixed pegs and one country at a time, but the significance of the exchange rate coefficient in AEs is not. This is entirely driven by an outlier, the Czech koruna. Excluding this currency, the exchange rate depreciation is not a significant driver of P2P transactions in advanced economies in the COVID period. The full set of results is reported in

[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.

Table D.2 in the Appendix. Therefore, the exchange rate does *not* matter for Bitcoin trading against the currencies of AEs. The results for EMDEs are instead fully robust to the exclusion of strict pegs and each currency from the sample one at a time (see Table D.3 in the Appendix).[23]

A number of additional robustness tests have been performed to validate the results of our empirical analysis. First, as mentioned in Section 4, 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 these variables, without detrending them with their average value over the previous 15 weeks. Comparison of Table 5 with Table D.4 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 3 is extended with the inclusion of the squared value of the determinants. Table D.5 in the Appendix reports the results of this robustness exercise. Generally, we do not find evidence of non-linearities in our model.

Third, 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 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. The results are overall robust to the exclusion of these two currencies.

[23] 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 (2024) 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.

Table 5: 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)
	Full sample			Pre COVID			COVID		
	All	AE	EMDE	All	AE	EMDE	All	AE	EMDE
BTC (t-1)	0.09***	0.09*	0.09***	0.12**	0.15**	0.11**	0.11***	0.08	0.12***
	(0.03)	(0.05)	(0.03)	(0.05)	(0.07)	(0.05)	(0.03)	(0.05)	(0.04)
BTC VOL (t-1)	-8.90***	-7.86**	-9.39***	-8.06***	-4.14	-9.54***	-10.76***	-11.64***	-10.50***
	(1.90)	(3.05)	(1.78)	(2.93)	(4.57)	(2.86)	(2.69)	(3.43)	(2.79)
VIX (t)	0.23**	0.18**	0.26***	0.47**	0.77**	0.42**	0.31**	0.26**	0.33**
	(0.09)	(0.09)	(0.10)	(0.22)	(0.31)	(0.21)	(0.12)	(0.12)	(0.14)
BIDASK (t)	0.56***	0.80***	0.43**	0.37***	0.43**	0.29*	0.73*	1.19*	0.51
	(0.16)	(0.23)	(0.17)	(0.12)	(0.21)	(0.16)	(0.45)	(0.67)	(0.43)
FX (i,t-1)	0.45***	0.73*	0.36**	-0.19	-1.31**	-0.07	0.75***	1.20***	0.62***
	(0.16)	(0.39)	(0.15)	(0.24)	(0.61)	(0.24)	(0.19)	(0.41)	(0.19)
Observations	9,135	3,045	6,090	4,230	1,410	2,820	4,905	1,635	3,270
Number of groups	45	15	30	45	15	30	45	15	30
Country FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
R2	0.32	0.26	0.36	0.32	0.26	0.34	0.31	0.27	0.35

The table reports the results of the estimation of the dynamic panel fixed-effect model in equation 3. 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. Dryscoll-Kray Standard errors in parentheses. The asterisks ***, ** and * indicate statistical significance at the 1%, 5% and 10% level, respectively.

5.2 The impact of exchange rate instability on Bitcoin trading in EMDEs

The result that connects exchange rate instability to greater trading in Bitcoin in EMDEs is an important finding that deserves further scrutiny. In this section, first, we run a set of robustness tests specific to EMDEs to validate the impact of the exchange rate coefficient on trading since the onset of the COVID crisis; second, we analyse the dynamic response to exchange rate shocks using local projections and delve into two interesting country cases, Nigeria and Ukraine.

5.2.1 Robustness of the exchange rate coefficient for EMDEs

Table 6 reports the results of a number of robustness tests that are particularly relevant for the impact of exchange rate instability on Bitcoin trading. First, some currencies in our sample, in particular EMDE currencies, are *de facto pegged* to the US dollar and are characterised by low volatility in the nominal exchange rate, which could potentially impact our estimate of the sensitivity of Bitcoin trade to this variable. Therefore, we rerun our main regression models for the COVID-19 period excluding these currencies. Specifically, we distinguish between currencies that are strictly pegged, when the standard deviation of weekly exchange rate returns is less than 0.1%, and those *loosely pegged*, with a standard deviation lower than 0.5% in our sample period.[24] Excluding these currencies from the sample (see columns 2 and 3 of Table 6, the coefficient associated with the exchange rate is virtually identical to the one in the baseline results reported in the first column of Table 6.

Second, one may be concerned that the exchange rate is endogenously determined together with Bitcoin trading volumes, thus making the coefficient biased. For this reason, we have run a version of our regression models by instrumenting the exchange rate changes, in order to make sure that we capture exogenous developments in exchange rates. In order to identify these exogenous exchange rate movements, we follow Arndt and Enders (2024) and use spikes in the detrended exchange rate series to create a dummy variable in the following way:

$$Z_{t,i} = \begin{cases} 1 & \text{if} \quad \text{spike}_{t,i} > 0 \\ -1 & \text{if} \quad \text{spike}_{t,i} < 0 \\ 0 & \text{else} \end{cases} \tag{4}$$

[24] Strictly pegged currencies include: Saudi Arabian riyal (SAR), Tanzanian schilling (TZS), United Arab Emirates dirham (AED), Vietnamese dong (VND), Hong Kong dollar (HKD). Loose pegs include: Malaysian ringgit (MYR), Philippine peso (PHP), Kenyan shilling (KES), Chinese yuan (CNY), Dominican peso (DOP), Singapore dollar (SGD). See Figure E.3 in the Appendix.

The spikes (or outliers) in the series are identified as movements above the 90th (below the 10th) percentile. The idea behind this identification strategy is that outliers in exchange rate movements are often due to rare and unforeseen events, and thus should be correlated with the exogenous shocks that we wish to identify. These instruments are highly relevant for the exchange rate movements.[25] What makes them good instruments is also that it is plausible to assume that they are related to Bitcoin volumes only through exchange rate movements (exclusion restriction). The results of this robustness exercise are shown in column (4) of Table 6. The coefficient associated with the exchange rate is positive and statistically significant. Not surprisingly, the estimated impact, with a coefficient close to one, is even larger than in the baseline regressions. This implies that a large shock of around two standard deviations in the detrended series of exchange rates produces an increase in P2P bitcoin trading volumes by 7.5 percentage points.

Third, in some instances, the official exchange rates of EMDEs may deviate from market rates and provide a distorted picture of exchange rate instability in these countries. For this reason, we have rerun our model replacing the market exchange rates of EMDEs with the estimates of *shadow exchange rates* which are derived by Graf von Luckner et al. (2024) from crypto exchanges.[26] As expected, the impact of exchange rates that are closer to market rates, reported in column (5) of Table 6, is larger than the impact of official exchange rates in the baseline model (column 1).

Finally, in some of the countries in our sample (China, Egypt and Morocco) transactions in cryptocurrencies are deemed illegal. Nevertheless, citizens have managed to use P2P platforms to purchase or sell cryptocurrencies. To ascertain if these bans of crypto influence the impact of global, crypto or local factors, we split the sample between countries with and countries without the crypto ban. Table D.6 reports these results. Interestingly, the impact of global and crypto factors do not change, while we find a larger impact of the exchange rate on Bitcoin transactions in the countries with a crypto ban. Even though large, this difference is not statistically significant so that this remains only suggestive evidence of the potential role of bans in amplifying the impact of local factors on Bitcoin trading.[27]

[25] The identification of exogenous exchange rate shocks in a panel of different countries is not a trivial task. A natural candidate are U.S. monetary policy shocks, which may lead to sudden changes in the exchange rates of EMDEs currencies. We have tried to include the shocks identified according to the recent literature with surprises in the future rates around Fed monetary policy meetings. However, the absence of large monetary policy shocks in our relatively short sample period resulted in a very weak instrument for the exchange rates of the EMDEs. In any case, the instruments are largely uncorrelated with U.S. monetary policy shocks and the other global factors we include in the analysis. Thus, the exchange rate shocks we identify are indeed local.

[26] Data on crypto shadow exchange rates are available at monthly frequency, we have transformed them into weekly frequency with cubic spline.

[27] We test the statistical significance of this difference introducing a dummy for the countries

Table 6: Robustness of exchange rate impact in EMDEs (COVID period)

	(1) baseline	(2) no strict pegs	(3) no pegs	(4) IV ER spike	(5) shadow
BTC (t-1)	0.12***	0.12***	0.13***	0.12***	0.14***
	(0.04)	(0.03)	(0.04)	(0.03)	(0.05)
BTC VOL (t-1)	-10.50***	-9.72***	-9.88***	-10.61***	-12.39***
	(2.79)	(2.71)	(2.81)	(1.72)	(3.09)
VIX (t)	0.33**	0.33**	0.37**	0.28***	0.41**
	(0.14)	(0.13)	(0.15)	(0.05)	(0.16)
BIDASK (t)	0.51	0.62	0.52	0.43	1.12
	(0.43)	(0.42)	(0.45)	(0.28)	(0.79)
FX (i,t-1)	0.62***	0.61***	0.62***	1.03***	0.84**
	(0.19)	(0.19)	(0.21)	(0.30)	(0.34)
Observations	3,270	2,834	2,289	3,270	1,026
Number of groups	30	26	21	30	14
R2	0.26	0.34	0.31	0.36	0.32

The table reports the results of the estimation of the dynamic panel fixed-effect model in equation 3 for the sample of EMDEs. 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. The sample period is the "COVID" sample period, from week 9 of 2020 until week 14 of 2022. In Column (2) strict pegs (AED, SAR, TZS and VND) are excluded, in Column (3) strict and looser (CNY, DOP, KES, MYR and PHP) pegs are excluded. In Column (4) exchange rate movements are instrumented with spike dummies identified as the movements above the 90th (below the 10th) percentile of the exchange rate series. In Column (5) we use the shadow crypto exchange rates of Graf von Luckner et al. (2024). Dryscoll-Kray Standard errors in parentheses. The asterisks ***, ** and * indicate statistical significance at the 1%, 5% and 10% level, respectively.

5.2.2 Dynamic responses to exchange rate shocks

We expand the robustness analysis carried out in the previous section to assess the dynamic impact of exogenous changes in the exchange rates of EMDEs on Bitcoin trading volumes on P2P platforms since March 2020. To do so, we use local projections instrumental variables (LP IV) methods. Following Jordà and Taylor (Forthcoming), the two-stage regressions are as follows:

$$y_{t+h,i} - y_{t,i} = \alpha_{1,h,i} + \beta_{IV,h}\hat{x}_{t,i} + \gamma_h' \boldsymbol{W_{t,i}} + \epsilon_{t,h,i} \tag{5}$$

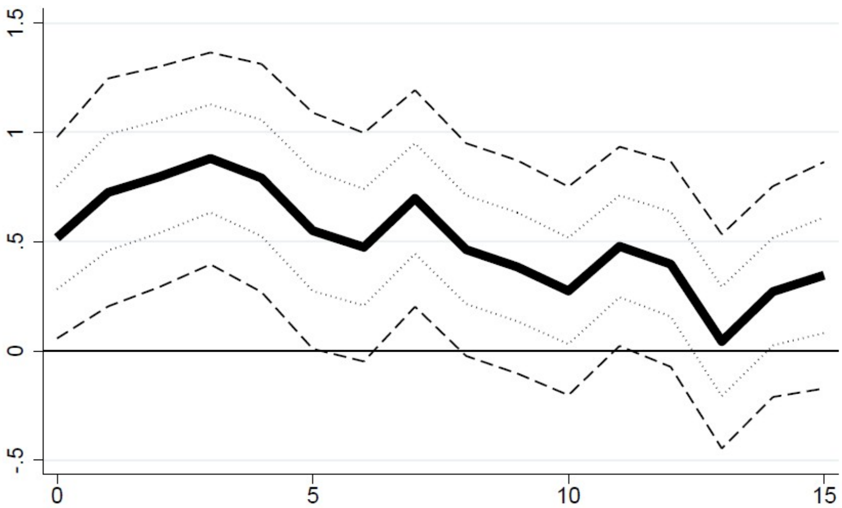
$$x_{t,i} = \alpha_{2,i} + \beta_2 Z_{t,i} + \delta' \boldsymbol{W_{t,i}} + u_{t,i} \tag{6}$$

where $y_{t,i}$ is the detrended measure of Bitcoin trading volumes used in the previous sections, $x_{t,i}$ is the detrended measure of exchange rate movements and

with a crypto ban interacted with the exchange rate and find that this dummy is not statistically significant. Results of this test are available upon request to the authors.

$Z_{t,i}$ is its instrument, $W_{t,i}$ is a vector of control variables, h is the horizon of the local projections (equal to 15 weeks in our case) and i is each currency of EMDEs, excluding strict pegs.

Figure 3: Impulse response of Bitcoin trading volumes to exchange rate shock in the COVID-19 period



The figure reports the impulse response of the volume of Bitcoin transactions against fiat currencies, detrended with a 15-week moving average, to the exchange rate shock estimated with panel local projection IV method, over the period from week 9 of 2020 until week 14 of 2022. The panel excludes the EMDE currencies strictly pegged to the US dollar (SAR. Dotted (dashed) lines denote 68% (95%) confidence interval.

As in the previous section, exogenous exchange rate movements are identified through spikes in the detrended exchange rate series and dummy variables which are used as instruments, following Arndt and Enders (2024). In order to make sure that the assumption of exogeneity holds, we add control variables ($W_{t,i}$), i.e. (lagged) momentum in Bitcoin prices, (lagged) volatility in crypto currency markets and global risk (VIX). Furthermore, we add 3 lags of the dependent variable, as done in the panel data analysis, and use robust standard errors.

Figure 3 shows the impulse response of Bitcoin trading volumes against the panel of EMDEs currencies to exchange rate shocks identified through this procedure. The dynamic impact peaks after three weeks and is still statistically significant after seven weeks. The size of the coefficient, reassuringly, is similar to those reported in Table 6 in the previous section. In the following, we zoom in on specific country cases of particular interest for the economic significance of their results, Nigeria and Ukraine, to confirm our results that idiosyncratic exogenous events that lead to currency instability are associated with a rise in Bitcoin transactions.

The realignment of the Nigerian naira in Spring 2021. In May 2021, the official exchange rate of the Nigerian naira against the US dollar central bank, which had been pegged at 380 naira per dollar since August 2020, was devalued by 8 percent to 410 naira per dollar, amid a scarcity of foreign exchange in Nigeria and a widening gap between the official rate and parallel unofficial exchange rates (see panel b of Figure 4).[28] Indeed, tensions in the *unofficial* foreign exchange market had already appeared towards the end of 2020 and intensified in February 2021. The *unofficial* market rate provided by the Financial Times recorded a depreciation by 3 percentage points in the exchange rate of the naira in the last two weeks of 2020 and further devaluation by 4.3 percentage points in mid-February.[29]

In terms of Bitcoin trading, in our estimates, a shock of 8 percentage points in the exchange rate triggers an increase in Bitcoin trading volumes against the Nigerian naira of approximately 25 percentage points after four weeks (see panel a of Figure 4). In the data, the first months of 2021 are characterised by an intensification of Bitcoin transactions against the Nigerian naira, particularly in the weeks following pressures in the parallel *unofficial* market in early 2021, but also after the step devaluation of the *official* rate of the naira in May. In February 2021, Bitcoin trading volumes were growing at an average weekly rate (detrended) of more than 20 percentage points. In mid-March 2021, four weeks after the steepest depreciation of the unofficial rate by almost 5 percentage points, the (detrended) growth rate of Bitcoin trading volumes peaked at 28 percentage points. This is a relatively high growth rate in Bitcoin trading volumes, corresponding to one and half standard deviations of the series for Nigeria, a level seen only in the spring of 2020, in the most acute phase of the COVID crisis, which was associated with a global diffusion of Bitcoin. At the end of June 2021, one month after the *official* devaluation of the naira, (detrended) Bitcoin trading volumes were growing at a rate of almost 20 percentage points. In contrast, in the last three months of 2020, Bitcoin-naira trading volumes had posted a dramatic decline, by around 16 percentage points, on average (see panel b of Figure 4).[30]

[28]See "Nigeria lets naira weaken in possible move to unify exchange rates", Reuters, 14 May 2021.

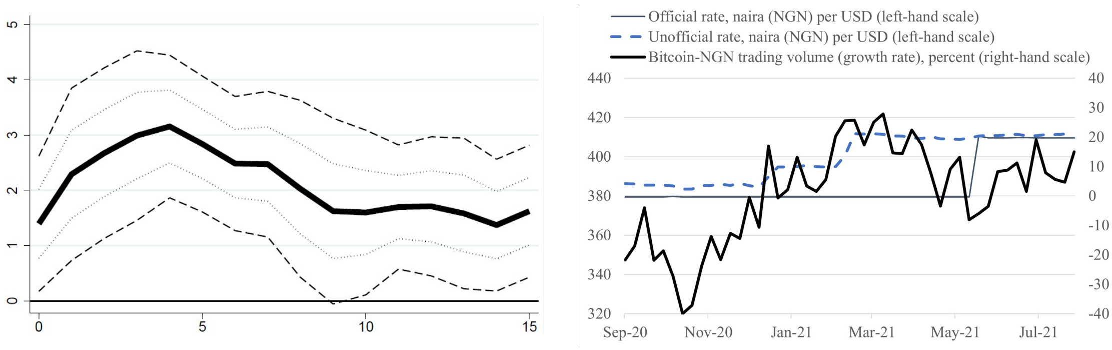
[29]Eventually, by the 19th of February 2021, the naira was trading at around 410 naira against the US dollar in the *unofficial* market, whereas the *official* rate was still quoted at 380 naira per dollar.

[30]The growth in Bitcoin transactions in the first months of 2021, probably, was also driven by a global run on Bitcoin, whose price spiked to more than USD 60,000 in April 2021. However, by the end of May 2021, the Bitcoin price had crashed to USD 35,000 following Tesla's decision to suspend payments from the Bitcoin network and China's crackdown on cryptocurrencies. In contrast, between June and July 2021, Bitcoin trading volumes against the naira continued to grow at a robust pace of almost 10 percentage points on a weekly basis. This confirms that the country-specific instability situation was contributing to larger Bitcoin transactions, regardless of global conditions in cryptocurrency markets.

Figure 4: The Nigerian naira (NGN) and Bitcoin trading volumes

(a) Impulse response of Bitcoin trading volumes to NGN shocks

(b) The realignment of the naira in May 2021 and Bitcoin trading volumes



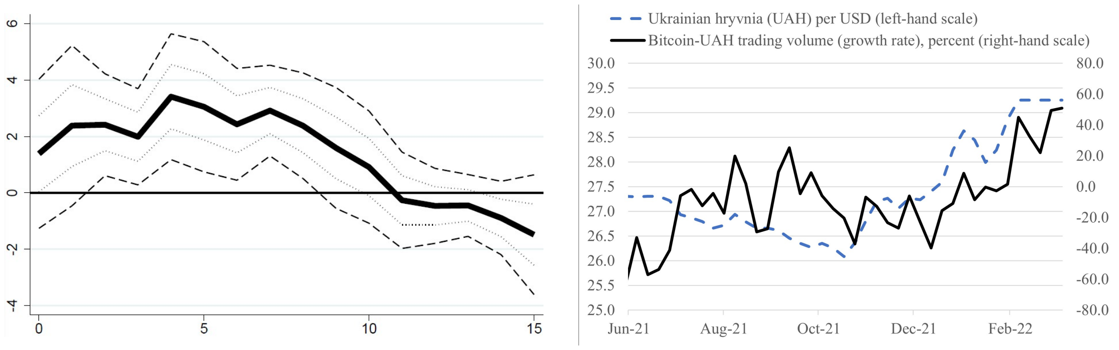
Source: Haver, Financial Times, CryptoCompare and authors' calculations. Notes: in panel a) dotted (dashed) lines denote 68% (95%) confidence interval; the solid black line is the local projection response. In panel b) the growth rate of Bitcoin trading volume is the log change with respect to the 15-week moving average.

The devaluation of the hryvnia in the run-up to the Russian invasion of Ukraine in early 2022. The Ukrainian hryvnia offers another telling example of the link between currency instability and Bitcoin transactions. The impulse response function indicates that the impact of the exchange rate depreciation on Bitcoin trading is large, the coefficient peaks at a value of 3.4 after four weeks and is statistically significant (see panel a of Figure 5). A large two-standard deviation foreign exchange shock (around 6 percentage points) therefore translates into an increase by 20 percentage points in Bitcoin trading (approximately one standard deviation). Apart from the COVID crisis in 2020, the largest shock to the hryvnia is driven by the Russian invasion of Ukraine in early 2022, an episode which is still included in our sample period. As rumours of a potential invasion of Ukraine by Russia began circulating in January 2022, the hryvnia started depreciating. Our detrended measure of exchange rate changes peaks at around 6% in the last week of January. Bitcoin transactions against the hryvnia, which were on a declining trend in the previous three months, suddenly spiked in the last week of January 2022 and accelerated abruptly towards the end of February, when the invasion actually began, averaging more than 40% in the month of March, as Ukrainians rushed to find refuge in cryptocurrencies, including those transacted in P2P markets (see panel b of Figure 5).

Figure 5: The Ukrainian hryvnia (UAH) and Bitcoin trading volumes

(a) Impulse response of BTC trading volumes to UAH shocks

(b) The Russian invasion in 2022, hryvnia devaluation and Bitcoin trading volumes



Source: Haver, CryptoCompare and authors' calculations. Notes: in panel a) dotted (dashed) lines denote 68% (95%) confidence interval; the solid black line is the local projection response. In panel b) the growth rate of Bitcoin trading volume is the log change with respect to the 15-week moving average.

6 Factor analysis and the drivers of cyclical comovement in Bitcoin trading against different fiat currencies

In this section, we apply factor analysis to study the extent of comovement among Bitcoin transactions against different fiat currencies, identifying the main factors behind this comovement through VAR analysis. To preview the main results, we find that there is a significant degree of comovement in Bitcoin trading against different fiat currencies. On average, a common factor 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 rise, 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. VAR analysis confirms that crypto-specific shocks drive the common factor, but also global risk shocks play a role.

6.1 Factor analysis

The panel analysis in the previous section has shown that several global variables, related to the crypto market and the volatility and liquidity of traditional financial markets, do matter for Bitcoin trading volumes against different fiat currencies. Moreover, we found that these global drivers fail to capture the full extent of comovement 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.[31]

$$Y_{i,t} = \boldsymbol{F}_t \boldsymbol{\lambda_{i,t}} + \epsilon_{i,t}, \tag{7}$$

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 D.7 in Annex 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). In general, the criteria suggest the selection of one or two factors.

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 the variation of the series (see columns 1 to 3 in Table 7). 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).[32] 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 E.2 in the Appendix shows this detail. Since the beginning of the COVID-19 pandemic, one global factor explains between 50% and

[31] In order not to capture a global factor due to the global financial cycle, we conduct the factor analysis on all the transactions of Bitcoin and fiat currencies, excluding the ones with US dollar.

[32] 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.

almost 70% of the variation in Bitcoin trading against the Canadian dollar, the euro, or the British pound (see darker blue bars in Figure E.2a). Among EMDEs, there are ten currencies for which one global factor explains around 50% or more of the variation in trading volumes. (see the darker blue bars in Figure E.2b). 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 7: 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 7. "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 8 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 1 in Section 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 5.1. Apart from the Bitcoin price, the other potential global drivers are barely correlated with the global factor in Bitcoin transactions, including the nominal effective exchange rate of the US dollar. Interestingly, the correlation of the VIX with the global component in Bitcoin trading increases significantly to around 30% in the COVID-19 period, in line with the finding of the panel analysis in the previous section and the results of other studies that have found a stronger link between the Bitcoin price and risky assets since 2020 (Iyer, 2022). Instead, it is more difficult to interpret which global variable may be associated with the second factor in Bitcoin trading.[33]

Table 8: 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*
USDNEER	-0.07*	-0.06*	-0.07*	0.00	-0.20*	0.11*	-0.09*	0.02	-0.13*

The table reports the correlation between global variables (see Table 2 for the definition) and the first factor extracted from the model in equation 7 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.

6.2 Drivers of cyclical comovement

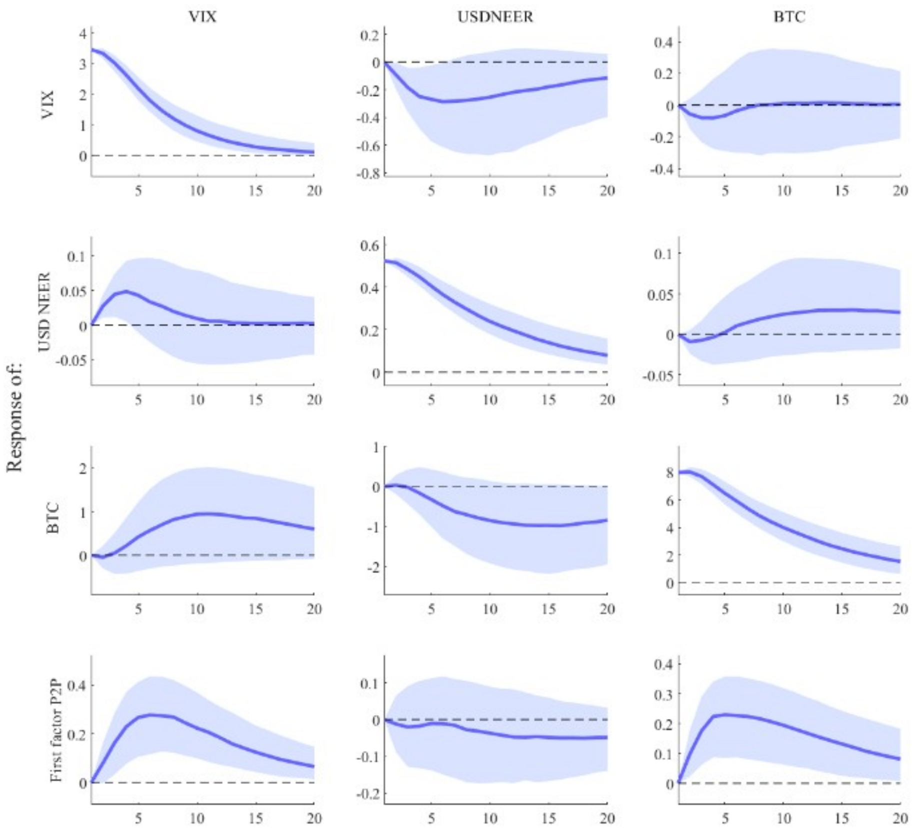
In order to disentangle the drivers of the global crypto-cycle identified in the previous section, we perform a structural BVAR analysis. We use a four-variable system with the VIX index, the US dollar, the Bitcoin price, and the P2P volume factor. The VIX index is intended to capture shocks to global risk aversion that may influence the global crypto-cycle. The US dollar is included for its role as a key barometer of risk taking capacity in global capital markets (Avdjiev et al., 2019) and in the transmission of global risk to the world economy (Georgiadis et al., 2024). In our case, the inclusion of the US dollar is particularly important as a potential indicator of a global debasement of EMDEs currencies. Finally, the Bitcoin price is used to derive a crypto-specific shock. We rely on Choleski identification, ordering the variables as just mentioned and assuming that VIX and US dollar are block exogenous, i.e. shocks to Bitcoin price and the P2P volume factors cannot affect VIX and the US dollar.

Our simple identification strategy delivers results in line with the international finance literature; in fact, we find that a positive global risk shock delivers an appreciation of the US dollar (Figure 6). More importantly, we find that both the VIX shock and the crypto shock generate a significantly positive comovement between Bitcoin prices and the P2P volumes factor.[34] Looking at the magnitude of the responses, a one standard deviation shock to VIX and the Bitcoin price deliver a similar response of the P2P factor, suggesting that shocks are equally important. Instead, the shock identified through the US dollar does not have significant effects

[33] Table D.8 in the Appendix reports the correlations of this second factor with our global variables and shows that this second factor may also be correlated with the Bitcoin price, but only in the COVID-19 period.

[34] Results are similar if we use only the factor extracted from AE currencies or EMDE currencies.

Figure 6: Impulse responses to global and crypto shocks



The figures report the impulse response functions of a 4-variable BVAR estimated from week 1 of 2018 until week 14 of 2022, using Choleski identification, with the following variables in this order: VIX, detrended US dollar effective exchange rate, detrended Bitcoin price, first factor extracted from P2P volumes. We include also a Covid dummy. We report only the first 3 shocks of interest.

on the factor of P2P volumes. Matching this result with the findings of the previous section on the impact of exchange rate instability on Bitcoin trading in EMDEs, we can conclude that it is the idiosyncratic, currency-specific nature of the shock that really matters for Bitcoin trading, not the broader role of the US dollar exchange rate in dictating global risk sentiment or EMDEs currency instability.

To conclude, there is evidence of a global *crypto* cycle in Bitcoin trading against fiat currencies. The trading of Bitcoin against different fiat currencies, which involve 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. This crypto cycle is driven by global risk shocks, as captured by the VIX, and crypto specific shocks, e.g. events that influence the global sentiment towards crypto currencies and are unrelated to developments in global traditional financial markets. The absence of a US dollar factor driving global Bitcoin transactions suggests that only the idiosyncratic, country-specific, component of the exchange rate matters for

Bitcoin transactions.

7 Conclusion

Despite an extremely volatile price and various crashes in the crypto-asset market, Bitcoin remains very popular, trading in different currencies and across diverse 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 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 Bitcoin price. This global crypto cycle is *driven by crypto-specific shocks, as well as by global risk shocks*. 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 also seems to offer specific utility benefits, in particular in EMDEs. The depreciation of the domestic currency of EMDEs - notably not of the currencies of AEs - due to idiosyncratic, country-specific shocks induces more Bitcoin trading, in particular since the onset of the COVID-19 pandemic. Specific episodes, such as the realignment of a fixed exchange rate peg in Nigeria in 2021 or the impact of the Russian invasion of Ukraine in 2022 on Bitcoin trading against the hryvnia support this important finding. This in fact suggests that Bitcoin, despite its wide price fluctuations, might also have been appreciated as an alternative investment asset in countries that experienced a loss in the purchasing power of their domestic currency. In turn, this implies that macroeconomic instability can potentially spur increased use of crypto-assets. This result is important for the asset pricing theory of crypto-assets, suggesting that the fundamental value of Bitcoin may be substantially different between AEs and EMDEs, since its utility services are probably more elevated in the latter group of countries.

Our findings clearly point to potential financial stability risks in EMDEs. The intrinsic price volatility of Bitcoin may discourage its use as a store of value or a 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 taken a step in that direction.

References

Ahn, Seung C. and Alex R. Horenstein, "Eigenvalue Ratio Test for the Number of Factors," *Econometrica*, 2013, *81* (3), 1203–1227.

Aiello, Darren, Scott R Baker, Tetyana Balyuk, Marco Di Maggio, Mark J Johnson, and Jason D Kotter, "The Effects of Cryptocurrency Wealth on Household Consumption and Investment," *NBER Working Paper*, 2023, (31445).

Alnasaa, Marwa, Nikolay Gueorguiev, Jiro Honda, Eslem Imamoglu, Paolo Mauro, Keyra Primus, and Dmitriy Rozhkov, "Crypto-assets, Corruption, and Capital Controls: Cross-country Correlations," *Economics Letters*, 2022, *215*, 110492.

Aramonte, Sirio, Huang Wenqian, and Andreas Schrimpf, "Tracing the Footprint of Cryptoization in Emerging Market Economies," *BIS Quarterly Review*, 2022, (March).

Arndt, Sarah and Zeno Enders, "The Transmission of Supply Shocks in Different Inflation Regimes," *Banque de France Working Paper*, 2024, (938).

Aspris, Angelo, Sean Foley, Jiri Svec, and Leqi Wang, "Decentralized Exchanges: The "wild west" of Cryptocurrency Trading," *International Review of Financial Analysis*, 2021, *77*, 101845.

Auer, Raphael and David Tercero-Lucas, "Distrust or Speculation? The Socioeconomic Drivers of U.S. Cryptocurrency Investments," *Journal of Financial Stability*, 2022, (101066).

_ , Giulio Cornelli, Sebastian Doerr, Jon Frost, and Leonardo Gambacorta, "Crypto Trading and Bitcoin Prices: Evidence from a New Database of Retail Adoption," *BIS Working Paper*, 2022, (1049).

Avdjiev, Stefan, Wenxin Du, Catherine Koch, and Hyun Song Shin, "The dollar, bank leverage, and deviations from covered interest parity," *American Economic Review: Insights*, 2019, *1* (2), 193–208.

Bai, Jushan and Serena Ng, "Determining the Number of Factors in Approximate Factor Models," *Econometrica*, 2002, *70* (1), 191–221.

Baur, Dirk G and Lai Hoang, "The Bitcoin Gold Correlation Puzzle," *Journal of Behavioral and Experimental Finance*, 2021, *32*, 100561.

_ **and Thomas Dimpfl**, "The Volatility of Bitcoin and its Role as a Medium of Exchange and a Store of Value," *Empirical Economics*, 2021, *61* (5), 2663–2683.

Baur, Dirk G., KiHoon Hong, and Adrian D. Lee, "Bitcoin: Medium of Exchange or Speculative Assets?," *Journal of International Financial Markets, Institutions and Money*, 2018, *54*, 177–189.

Benigno, Pierpaolo, Linda M. Schilling, and Harald Uhlig, "Cryptocurrencies, currency competition, and the impossible trinity," *Journal of International Economics*, 2022, *136*, 103601. NBER International Seminar on Macroeconomics 2021.

Biais, Bruno, Christophe Bisiere, Matthieu Bouvard, Catherine Casamatta, and Albert J Menkveld, "Equilibrium Bitcoin Pricing," *The Journal of Finance*, 2023, *78* (2), 967–1014.

Bianchi, Daniele, Mykola Babiak, and Alexander Dickerson, "Trading Volume and Liquidity Provision in Cryptocurrency Markets," *Journal of Banking & Finance*, 2022, *142* (106547).

Blau, Benjamin M, Todd G Griffith, and Ryan J Whitby, "Inflation and Bitcoin: A descriptive time-series analysis," *Economics Letters*, 2021, *203*, 109848.

Bolt, Wilko and Maarten RC Van Oordt, "On the value of virtual currencies," *Journal of Money, Credit and Banking*, 2020, *52* (4), 835–862.

Caldara, Dario and Matteo Iacoviello, "Measuring Geopolitical Risk," *American Economic Review*, April 2022, *112* (4), 1194–1225.

Campbell, John Y, Sanford J Grossman, and Jiang Wang, "Trading Volume and Serial Correlation in Stock Returns," *The Quarterly Journal of Economics*, 1993, *108* (4), 905–939.

Canidio, Andrea, "Financial bubbles in infinitely repeated auctions with tokens," in "AEA Papers and Proceedings," Vol. 113 American Economic Association 2014 Broadway, Suite 305, Nashville, TN 37203 2023, pp. 263–267.

Cerutti, Eugenio, Jiaqian Chen, and Martina Hengge, "A Primer on Bitcoin Cross-Border Flows: Measurement and Drivers," *IMF Working Paper*, 2024, (85).

Cespa, Giovanni, Antonio Gargano, Steven J Riddiough, and Lucio Sarno, "Foreign Exchange Volume," *The Review of Financial Studies*, 2022, *35* (5), 2386–2427.

Chainalysis, "The 2021 Geography of Cryptocurrency Report," Report 2021.

_ , "The 2023 Geography of Cryptocurrency Report," Report 2023.

_ , "The 2024 Geography of Cryptocurrency Report," Report 2024.

Cong, Lin William, Pulak Ghosh, Jiasun Li, and Qihong Ruan, "Inflation Expectation and Cryptocurrency Investment," NBER Working Papers 32945, National Bureau of Economic Research, Inc September 2024.

_ , Xi Li, Ke Tang, and Yang Yang, "Crypto Wash Trading," *Management Science*, 2023, *69* (11), 6427–6454.

Conlon, Thomas, Shaen Corbet, and Richard J McGee, "Inflation and cryptocurrencies revisited: A time-scale analysis," *Economics Letters*, 2021, *206*, 109996.

Davis, J. Scott, Giorgio Valente, and Eric van Wincoop, "Global Drivers of Gross and Net Capital Flows," *Journal of International Economics*, 2021, *128*, 103397.

Divakaruni, Anantha and Peter Zimmerman, "Uncovering Retail Trading in Bitcoin: The Impact of COVID-19 Stimulus Checks," *Management Science*, 2024, *70* (4), 2066–2085.

Eichenbaum, M S, B K Johannsen, and S T Rebelo, "Monetary Policy and the Predictability of Nominal Exchange Rates," *The Review of Economic Studies*, 05 2020, *88* (1), 192–228.

Ferrari Minesso, Massimo, Arnaud Mehl, and Livio Stracca, "Central bank digital currency in an open economy," *Journal of Monetary Economics*, 2022, *127*, 54–68.

Feyen, Erik H.B., Yusaku Kawashima, and Raunak Mittal, "Crypto-Assets Activity around the World : Evolution and Macro-Financial Drivers," *The World Bank Working Paper*, 2022, (9962).

Foley, Sean, Jonathan R Karlsen, and Tālis J Putniņš, "Sex, Drugs, and Bitcoin: How Much Illegal Activity is Financed Through Cryptocurrencies?," *The Review of Financial Studies*, 2019, *32* (5), 1798–1853.

Gagliardini, Patrick, Elisa Ossola, and Olivier Scaillet, "A Diagnostic Criterion for Approximate Factor Structure," *Journal of Econometrics*, 2019, *212* (2), 503–521.

Gandal, Neil, JT Hamrick, Tyler Moore, and Tali Oberman, "Price Manipulation in the Bitcoin Ecosystem," *Journal of Monetary Economics*, 2018, *95*, 86–96.

Georgiadis, Georgios, Gernot J Müller, and Ben Schumann, "Global risk and the dollar," *Journal of Monetary Economics*, 2024, *144*, 103549.

Graf von Luckner, Clemens, Carmen M Reinhart, and Kenneth S Rogoff, "Decrypting New Age International Capital Flows," *Journal of Monetary Economics*, 2023, *138*, 104–122.

_ , Robin Koepke, and Silvia Sgherri, "Crypto as a Marketplace for Capital Flight," *IMF Working Paper*, 2024, (133).

Griffin, John M and Amin Shams, "Is Bitcoin Really Untethered?," *The Journal of Finance*, 2020, *75* (4), 1913–1964.

Hackethal, Andreas, Tobin Hanspal, Dominique M Lammer, and Kevin Rink, "The Characteristics and Portfolio Behavior of Bitcoin Investors: Evidence from Indirect Cryptocurrency Investments," *Review of Finance*, 12 2021, *26* (4), 855–898.

Halaburda, Hanna, Guillaume Haeringer, Joshua Gans, and Neil Gandal, "The Microeconomics of Cryptocurrencies," *Journal of Economic Literature*, 2022, *60* (3), 971–1013.

He, Dong, Annamaria Kokenyne, Xavier Lavayssière, Inutu Lukonga, Nadine Schwarz, Nobuyasu Sugimoto, and Jeanne Verrier, "Capital Flow Management Measures in the Digital Age: Challenges of Crypto Assets," *IMF Fintech Notes*, 2022, (5).

Im, Kyung So, M Hashem Pesaran, and Yongcheol Shin, "Testing for Unit Roots in Heterogeneous Panels," *Journal of Econometrics*, 2003, *115* (1), 53–74.

IMF, "Global Financial Stability Report," Technical Report, IMF October 2021.

_ , "Elements of Effective Policies for Crypto Assets," Policy Paper No. 2023/004, IMF February 2023.

_ , "G20 Note on the Macrofinancial Implications of Crypto Assets," Technical Report, IMF February 2023.

Iyer, Tara, "Cryptic Connections: Spillovers between Crypto and Equity Markets," *IMF Global Financial Stability Notes*, 2022.

Jermann, Urban J., "Cryptocurrencies and Cagan's Model of Hyperinflation," *Journal of Macroeconomics*, 2021, *69* (103340).

Jordà, Òscar and Alan M Taylor, "Local Projections," *Journal of Economic Literature*, Forthcoming.

Karau, Sören, "Monetary Policy and Bitcoin," *Journal of International Money and Finance*, 2023, *137.*

Karnaukh, Nina, Angelo Ranaldo, and Paul Söderlind, "Understanding FX Liquidity," *The Review of Financial Studies*, 2015, *28* (11), 3073–3108.

Kogan, Shimon, Igor Makarov, Marina Niessner, and Antoinette Schoar, "Are Cryptos different? Evidence from Retail Trading," *Journal of Financial Economics*, 2024, *159*, 103897.

Le, Anh, Alexander Copestake, Brandon Tan, Mr Shanaka J Peiris, and Umang Rawat, "Macro-Financial Impacts of Foreign Digital Money," Working Paper n.2023/249 2023.

Liu, Yukun, Aleh Tsyvinski, and Xi Wu, "Common Risk Factors in Cryptocurrency," *The Journal of Finance*, 2022, *77* (2), 1133–1177.

_ **and** _ , "Risks and Returns of Cryptocurrency," *The Review of Financial Studies*, 2021, *34* (6), 2689–2727.

Llorente, Guillermo, Roni Michaely, Gideon Saar, and Jiang Wang, "Dynamic Volume-return Relation of Individual Stocks," *The Review of Financial Studies*, 2002, *15* (4), 1005–1047.

Makarov, Igor and Antoinette Schoar, "Trading and Arbitrage in Cryptocurrency Markets," *Journal of Financial Economics*, 2020, *135* (2), 293–319.

_ **and** _ , "Cryptocurrencies and Decentralized Finance (DeFi)," *NBER Working Papers*, 2022, (30006).

Marmora, Paul, "Currency Substitution in the Shadow Economy: International Panel Evidence using Local Bitcoin Trade Volume," *Economics Letters*, 2021, *205*, 109926.

Miranda-Agrippino, Silvia and Hélène Rey, "The Global Financial Cycle," in Gita Gopinath, Elhanan Helpman, and Kenneth Rogoff, eds., *Handbook of International Economics: International Macroeconomics*, Vol. 6, Elsevier, 2022, pp. 1–43.

Murakami, David and Ganesh Viswanath-Natraj, "Cryptocurrencies in emerging markets: a stablecoin solution?," *Journal of International Money and Finance*, 2025, p. 103344.

Onatski, Alexei, "Determining the Number of Factors from Empirical Distribution of Eigenvalues," *The Review of Economics and Statistics*, 11 2010, *92* (4), 1004–1016.

Porta, Rafael La, Florencio Lopez de Silanes, Andrei Shleifer, and Robert W Vishny, "Legal Determinants of External Finance," *The Journal of Finance*, 1997, *52* (3), 1131–1150.

Schmitt-Grohé, Stephanie and Martın Uribe, "Closing small open economy models," *Journal of International Economics*, 2003, *61* (1), 163–185.

Uhlig, Harald, "A Luna-tic Stablecoin Crash," *NBER Working Paper*, 2022, (30256).

van Oordt, Maarten RC, "On bubbles in cryptocurrency prices," Technical Report, Tinbergen Institute Discussion Paper 2024.

Weber, Michael, Bernardo Candia, Olivier Coibion, and Yuriy Gorodnichenko, "Do You Even Crypto, Bro? Cryptocurrencies in Household Finance," *NBER Working Paper*, 2023, (31284).

Wei, Yanhao and Anthony Dukes, "Cryptocurrency adoption with speculative price bubbles," *Marketing Science*, 2021, *40* (2), 241–260.

Appendix A Theoretical framework

We consider the model of competition between fiat currencies and a global crypto currency by Benigno et al. (2022), in particular the case of *money-in-the-utility-function*, and adapt it to our problem, assuming that the price of a global crypto currency is *not* fixed in terms of foreign (US dollar) currency units and can vary over time, as in the case of Bitcoin. Domestic households can allocate savings between local and foreign fiat currencies and a global crypto currency. Although fiat currencies can be used for transactions only in their countries of origin, the global crypto currency can be used in both countries. Households maximise the sum of future expected utility:

$$\mathcal{W}_0 = E_{t_0} \sum_{t=t_0}^{\infty} \beta^{t-t_0} \left[U(C_t) + V(M_t, M_t^*, G_t) \right] \tag{8}$$

where E is the expectation operator, $U(.)$ is a concave function that strictly increases in consumption, $V(.)$ is a function weakly increasing in money balances but may exhibit a satiation point at a finite level of real money balances and β is a discount factor. Households derive utility in each period from consumption (C) and from holding monetary balances: domestic currency (M), foreign currency (M^*), and global crypto-currency (G), in our case Bitcoin. We simplify the model of Benigno et al. (2022) assuming that there is only one foreign currency, the US dollar, which is also the currency in which the global crypto currency (e.g. Bitcoin) is priced. Money balances may give utility for different reasons: they facilitate transactions, can be used as collateral for credit, or reduce risks of income shocks. Benigno et al. (2022) provides a discussion on how different assumptions on why households hold money balances change the results at the margin. The budget constraint is:

$$\begin{aligned} C_t + S_t M_t^* + P_t^G S_t G_t + M_t \leq \\ Y_t + M_{t-1} + S_t M_{t-1}^* + P_t^G S_t G_{t-1} - \frac{\phi^G}{2 P_t^G S_t} \left(P_t^G S_t G_t \right)^2 - \frac{\phi^M}{2 S_t} \left(S_t M_t^* \right)^2 + T_t \end{aligned} \tag{9}$$

where Y is the endowment for the period, S is the exchange rate of the domestic currency against the US dollar, expressed as units of domestic currency per unit of US dollar. P^G is price of the global crypto currency in US dollar terms, and T represents lump sum taxes and transfers. As is standard in international finance models with multiple assets (Eichenbaum et al. (2020) and Schmitt-Grohé and Uribe (2003)), we assume that markets have frictions and imperfect risk sharing. This is captured by introducing transaction costs for accessing foreign assets, ϕ^G and ϕ^M.

All variables are expressed in real terms.

First-order conditions for the global crypto currency holdings are:

$$-\lambda_t S_t P_t^G + \beta E_t\left[\lambda_{t+1} S_{t+1} P_{t+1}^G\right] - \lambda_t \phi^G S_t P_t^G G_t + V'_{G,t} = 0 \quad (10)$$

where $V'_{G,t}$ is the derivative of the utility function for G and defines the convenience yield of holding crypto-assets that derives, for example, from their potential use in payments or as store of value and λ_t is the Lagrange multiplier. Ruling out the equilibria where the price of Bitcoin or/and the USD exchange rate are equal to zero, we simplify the formula to:

$$-\lambda_t + \beta E_t\left[\lambda_{t+1}\frac{S_{t+1}P_{t+1}^G}{S_t P_t^G}\right] - \lambda_t \phi^G G_t + \frac{V'_{G,t}}{S_t P_t^G} = 0 \quad (11)$$

Solving for G yields the following:

$$G_t = \left\{\beta E_t\left[\frac{\lambda_{t+1}}{\lambda_t}(1+\sigma_{t+1})(1+\pi_{t+1}^G)\right] + \frac{V'_{G,t}}{\lambda_t S_t P_t^G} - 1\right\}\frac{1}{\phi^G} \quad (12)$$

where σ_{t+1} is the rate of depreciation of the domestic currency with respect to the US dollar and π_{t+1}^G is the relative change in the price of the crypto asset in US dollar terms. This equation shows that the demand for the global crypto asset increases if households *expect* capital gains from cryptoasset holdings originating from:

1. an *expected* increase in the dollar price of the global crypto currency (π_{t+1}^G), or
2. an *expected* depreciation of the domestic currency against the US dollar (σ_{t+1})

These are the two main propositions that the empirical model of the paper will try to validate. In addition, the equation shows that the demand for the global crypto asset:

- increases in the convenience yield on the crypto-asset ($V'_{G,t}$), or[35]
- decreases in the transaction costs (ϕ^G).

[35] Notice that, as shown by Benigno et al. (2022), these results are robust to assuming no convenience yields on G, i.e. $V'_{G,t} = 0 \ \forall \ t$.

Appendix B Peer-to-peer decentralized exchanges

Decentralised P2P cryptocurrency exchanges are online platforms that facilitate direct transactions between local fiat currencies and various cryptocurrencies. These exchanges enable users to engage in peer-to-peer transactions, eliminating the need for intermediaries or centralised control. Specifically, their decentralised nature allows these exchanges to operate without requiring any central authority to oversee or authorise transactions within the exchange.

In these platforms, peer-to-peer trading is facilitated by matching buyers and sellers. Peers interface with the advertisements of other peers offering to trade for cryptocurrencies using different payment methods (online wallets like PayPal, gift cards, domestic bank transfers, and others). Cryptocurrencies are held by an escrow service and the exchanges only offer matching of traders, not intermediation, and are therefore noncustodial. The escrow wallet is under the control of the exchange. Trades are recorded in the exchange's internal database, i.e. *off-chain*.

Our analysis is based on transaction data extracted from the two world's largest peer-to-peer (P2P) Bitcoin exchanges up to 2022: LocalBitcoins and Paxful. In order to better understand how these exchanges work, let us assume that there are two agents, Alice and Bob, that want to sell and buy Bitcoins, respectively. These are the steps that occur when the Bitcoin exchange is happening:

1. Alice initiates the sale of bitcoins on the LocalBitcoins platform, setting the quantity and terms for potential buyers.

2. The platform matches Alice's offer with interested buyers like Bob.

3. Alice securely deposits the bitcoins for sale into an escrow account facilitated by the exchange, ensuring the funds are reserved for the transaction.

4. Bob, the buyer, sends the agreed-upon fiat currency directly to Alice's external account, completing the payment outside of the LocalBitcoins platform.

5. Alice confirms the receipt of Bob's payment, verifying that the fiat currency has been transferred successfully.

6. Upon Alice's confirmation, the bitcoins held in escrow are released and transferred from Alice's escrow account to Bob's wallet.

7. Bob receives the purchased bitcoins in his wallet.

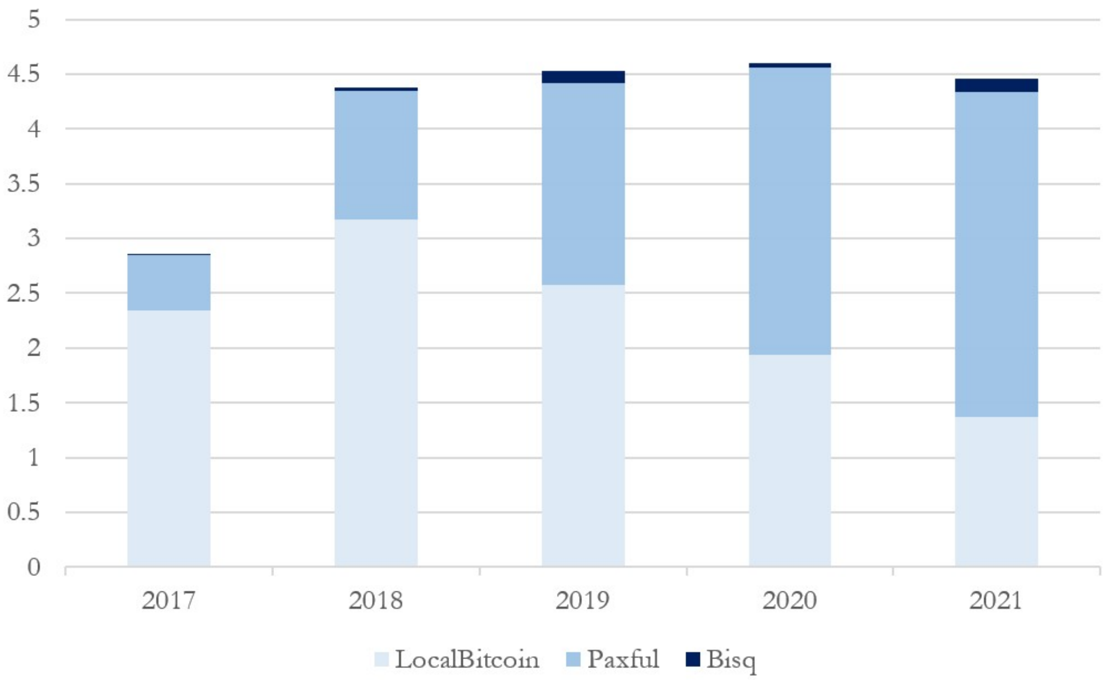
8. The transaction is completed and both parties, Alice and Bob, have fulfilled their roles in the sale and purchase of bitcoins.

As these decentralised exchanges operate in a noncustodial manner, allowing users to maintain control and ownership of their private keys, they are preferred for high privacy and anonymous transactions. Although details about individuals holding accounts can potentially be obtained through off-chain centralised trading platforms, P2P is an easier way to escape oversight because transactions often involve traders from different countries.

P2P decentralised exchanges in Figures

P2P off-chain exchanges have grown in importance during the 2018-2021 period, particularly in emerging and developing economies. Among the notable platforms in this domain are LocalBitcoins, Paxful, and Bisq, with LocalBitcoins and Paxful holding a notably higher transaction volume compared to Bisq.

Figure B.1: Peer-to-peer off-chain exchanges in Bitcoin (billions of US$)



Source: CoinDance, CoinMarketCap and Paxful.

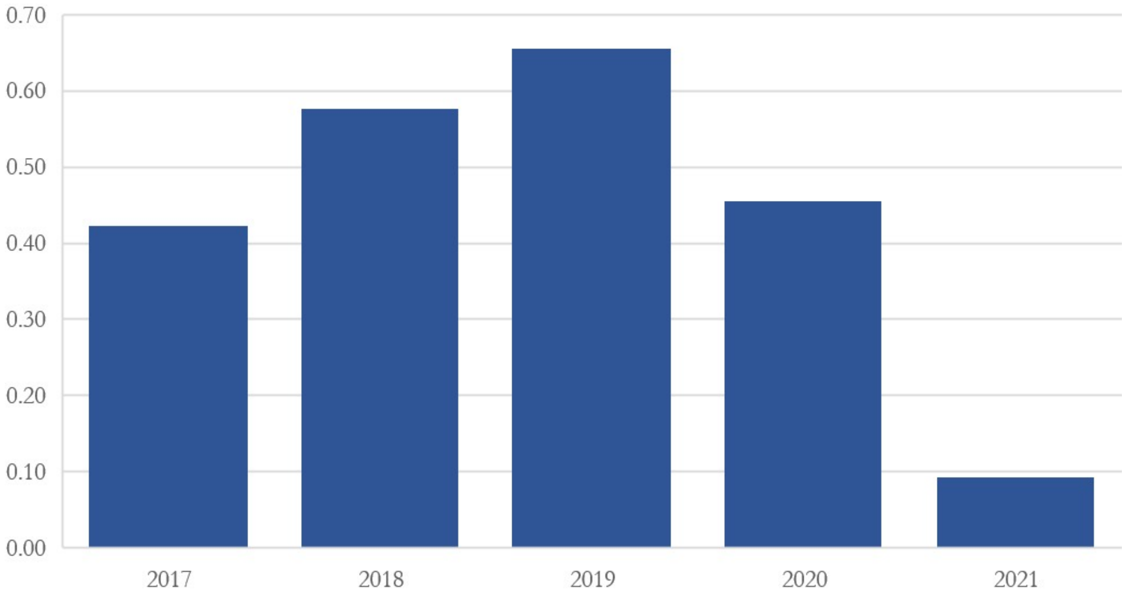
Figure B.1 shows aggregated yearly BTC trading volumes in the three main P2P exchanges until 2021. Volume data from P2P exchanges is obtained by aggregating all transactions from fiat currency to Bitcoin and vice versa. The importance of Bisq varies from a minimum of 0.2% in 2017 to a maximum of 2.9% in 2021 among these exchanges.[36] Among the P2P exchanges we explored in our analysis, Paxful became the most important P2P off-chain exchange since 2020 surpassing LocalBitcoins in

[36] We were not able to obtain disaggregated data by fiat currency in Bisq so we exclude it from our analysis.

terms of transaction volume. Importantly, Paxful stands out for its provision of trader-specific transaction data, encompassing both the trader's (reported) country and the payment method.

Nevertheless, the volume of transactions conducted on P2P exchanges is marginal in contrast to the volume of *off-chain* transactions occurring within *centralized* exchanges. Specifically, as Figure B.2 shows, the aggregate volume represented by the sum of LocalBitcoins and Paxful - P2P exchanges - accounts for less than 1% of the overall transaction activity observed in centralised exchanges.

Figure B.2: Share of P2P off-chain exchanges vs. off-chain CEX (in %)



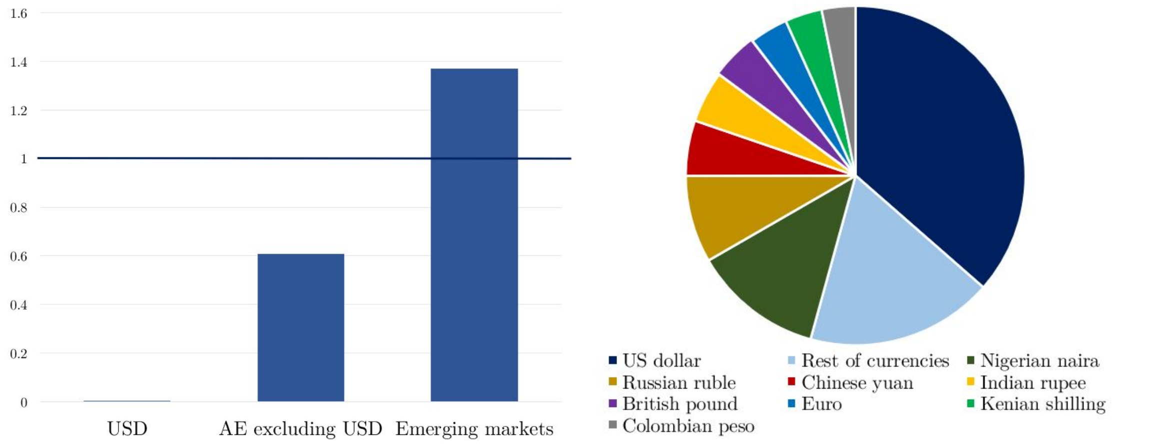
Source: CoinDance, Cryptocompare and Paxful. CEX data is obtained from Cryptocompare that aggregates the most relevant CEX platforms (for more information about their methodology, see https://ccdata.io/indices/index-documentation).

Most of BTC trading occurs on centralised exchanges (more than 99% compared to P2P exchanges). In Figure B.3a, we disaggregate the ratio of the P2P trading volume to the CEX trading volume into three different categories: USD, advanced economies excluding the USD and currencies of emerging economies. An unweighted average is used across the 2020-2021 is taken. Note that once the US dollar is excluded, Bitcoin transactions against EMDEs currencies – such as Nigeria, Russia, China, or India – make up the most of P2P transactions (Figure B.3b).

Table B.1 shows the ratio between the volume in P2P exchanges (sum of LocalBitcoins and Paxful) and CEX for all the fiat currencies analyzed in this paper for the 2020-2021 period. Transactions involving Bitcoin and currencies from developed economies predominantly occur within centralized exchanges. For example, the ratio of transactions involving Bitcoin and the USD in P2P exchanges with respect to CEX is less than 0.7%. Ratios are lower for the euro, Korean won

Figure B.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.

and Japanese yen. Nonetheless, the ratio is higher in P2P exchanges than in CEX for the Danish krone and the Norwegian krone, among others. This happens because trading volumes in these fiat currencies are low in both P2P and CEX exchanges, but especially in the last ones. In contrast, exchanges involving currencies from EMDEs are often higher in P2P platforms with respect to CEX, such as in the case of the Kenyan shilling, Indian Rupee, Philippine peso, and Pakistani Rupee, among others.

Table B.1: Ratio between the volume in P2P exchanges (LocalBitcoins and Paxful) and CEX for selected fiat currencies (2020-2021, in %).

Currencies of developed economies							
USD	EUR	GBP	AUD	JPY	KRW	CHF	NZD
0.45	0.20	1.30	1.55	0.00	0.00	3.30	34.05

Currencies in other EU countries and Norway							
CZK	DKK	HRK	HUF	NOK	PLN	RON	SEK
0.65	226.10	80.85	114.6	138.9	0.00	105.90	114.95

Turkey, Russia, Ukraine, Middle Eastern countries, and Pakistan							
TRY	RUB	UAH	AED	KZT	IRR*	PKT	SAR
0.1	53.30	7.20	140.60	85.45	101.75	782.20	119.90

Currencies of Latin-American countries						
ARS	BRL	CLP	COP	MXN	DOP	PEN
19.20	1.75	NA	1.85	84.85	108.30	57.95

Asian currencies						
CNY	IDR	INR	PHP	MYR	THB	VND
290.9	11.75	333.2	1109.7	4.7	1.9	NA

African currencies						Hong Kong and Singapore	
NGN	KES	MAD	EGP	TZS	ZAR	HKD	SGD
21.00	351.85	140.95	141.10	112.40	2.85	317.25	6.20

Sources: Cryptocompare, Coindance and Paxful. ECB calculations.
Note. *The Iranian Rial (IRR) data is not available in Paxful.

Appendix C Data

Table C.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
Equity funds	Flows of equity funds	D	Country-specific	EPFR
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 C.2: 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), US dollar (USD).
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 shilling (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 (THB); Turkish lira (TRY); Tanzanian schilling (TZS); Ukrainian hryvnia (UAH); Vietnamese dong (VND); South African rand (ZAR).

Appendix D Additional tables

Table D.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 D.2: Advanced economies in the COVID-19 period, excluding currencies one at a time

VARIABLES	(1) USD	(2) NOK	(3) CAD	(4) GBP	(5) DKK	(6) EUR	(7) AUD	(8) KRW	(9) NZD	(10) CZK	(11) JPY	(12) CHF	(13) SGD	(14) SEK
BTC (t-1)	0.08	0.09*	0.09	0.08	0.08	0.08	0.09*	0.09*	0.07	0.07	0.10*	0.07	0.07	0.08
	(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)	-12.12***	-11.12***	-12.50***	-11.68***	-11.31***	-11.52***	-12.02***	-12.40***	-12.49***	-8.62**	-13.21***	-11.95***	-10.95***	-12.37***
	(3.45)	(3.51)	(3.62)	(3.46)	(3.05)	(3.57)	(3.50)	(3.54)	(3.40)	(3.61)	(3.47)	(3.65)	(3.34)	(3.62)
VIX (t)	0.27**	0.23*	0.29**	0.25*	0.23*	0.27**	0.28**	0.24*	0.28**	0.18	0.33**	0.27**	0.24*	0.25*
	(0.12)	(0.13)	(0.13)	(0.13)	(0.12)	(0.13)	(0.13)	(0.12)	(0.13)	(0.12)	(0.13)	(0.13)	(0.13)	(0.13)
BIDASK (t)	1.20*	1.12	1.16*	1.22*	1.16*	1.18*	1.15*	1.23*	1.19*	1.11*	0.97	1.17*	1.28*	1.23*
	(0.65)	(0.70)	(0.67)	(0.67)	(0.61)	(0.69)	(0.68)	(0.71)	(0.69)	(0.59)	(0.66)	(0.69)	(0.69)	(0.73)
FX (i,t-1)	1.21***	1.37***	1.25***	1.22***	1.22***	1.22***	1.31***	1.26***	1.31***	0.73*	1.21***	1.16***	1.13***	1.28***
	(0.40)	(0.45)	(0.43)	(0.41)	(0.37)	(0.41)	(0.45)	(0.40)	(0.43)	(0.38)	(0.43)	(0.42)	(0.39)	(0.42)
Observations	1,526	1,526	1,526	1,526	1,526	1,526	1,526	1,526	1,526	1,526	1,526	1,526	1,526	1,526
Number of groups	14	14	14	14	14	14	14	14	14	14	14	14	14	14
R2	0.26	0.26	0.27	0.26	0.29	0.27	0.26	0.28	0.27	0.29	0.26	0.28	0.27	0.27

The table reports the results of the estimation of the dynamic panel fixed-effect model in equation 3. 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 D.3: Emerging and developing economies in the COVID-19 period, excluding currencies one at a time

VARIABLES	(1) NGN	(2) DOP	(3) KES	(4) EGP	(5) INR	(6) CLP	(7) ARS	(8) UAH	(9) ZAR	(10) KZT	(11) COP	(12) MYR	(13) PKR
BTC (t-1)	0.12***	0.11***	0.12***	0.11***	0.12***	0.12***	0.12***	0.12***	0.12***	0.12***	0.12***	0.11***	0.12***
	(0.04)	(0.04)	(0.04)	(0.03)	(0.04)	(0.03)	(0.04)	(0.03)	(0.04)	(0.03)	(0.03)	(0.03)	(0.03)
BTC VOL (t-1)	-10.37***	-9.43***	-10.01***	-9.85***	-9.72***	-9.55***	-9.40***	-9.84***	-10.14***	-9.46***	-9.69***	-9.46***	-9.74***
	(2.62)	(2.79)	(2.65)	(2.70)	(2.70)	(2.85)	(2.63)	(2.69)	(2.69)	(2.83)	(2.80)	(2.72)	(2.75)
VIX (t)	0.35**	0.33**	0.34**	0.33**	0.34**	0.32**	0.32**	0.33**	0.34**	0.30**	0.32**	0.33**	0.32**
	(0.13)	(0.14)	(0.13)	(0.14)	(0.14)	(0.13)	(0.13)	(0.14)	(0.13)	(0.12)	(0.14)	(0.13)	(0.13)
BIDASK (t)	0.59	0.62	0.58	0.58	0.62	0.63	0.59	0.63	0.64	0.84*	0.60	0.66	0.64
	(0.41)	(0.45)	(0.41)	(0.42)	(0.41)	(0.43)	(0.42)	(0.45)	(0.43)	(0.47)	(0.43)	(0.43)	(0.41)
FX (i,t-1)	0.58***	0.59***	0.61***	0.59***	0.61***	0.62***	0.62***	0.60***	0.61***	0.55***	0.60***	0.61***	0.61***
	(0.19)	(0.19)	(0.19)	(0.19)	(0.19)	(0.19)	(0.20)	(0.19)	(0.19)	(0.18)	(0.19)	(0.19)	(0.19)
Observations	2,725	2,725	2,725	2,725	2,725	2,725	2,725	2,725	2,725	2,725	2,725	2,725	2,725
Number of groups	25	25	25	25	25	25	25	25	25	25	25	25	25
R2	0.33	0.34	0.33	0.34	0.34	0.34	0.34	0.34	0.34	0.35	0.33	0.34	0.34

VARIABLES	(14) PLN	(15) MXN	(16) PEN	(17) PHP	(18) RON	(19) THB	(20) BRL	(21) CNY	(22) RUB	(23) TRY	(24) IDR	(25) HUF	(26) MAD
BTC (t-1)	0.11***	0.12***	0.11***	0.12***	0.11***	0.11***	0.11***	0.12***	0.12***	0.12***	0.11***	0.09***	0.11***
	(0.04)	(0.04)	(0.03)	(0.04)	(0.04)	(0.03)	(0.04)	(0.04)	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)
BTC VOL (t-1)	-9.35***	-9.63***	-9.31***	-10.18***	-9.54***	-9.73***	-9.51***	-9.64***	-9.79***	-10.02***	-9.20***	-10.45***	-9.57***
	(2.74)	(2.65)	(2.76)	(2.69)	(2.77)	(2.72)	(2.70)	(2.79)	(2.74)	(2.63)	(2.83)	(2.62)	(2.70)
VIX (t)	0.31**	0.32**	0.33**	0.35**	0.32**	0.32**	0.33**	0.33**	0.32**	0.32**	0.31**	0.30**	0.32**
	(0.14)	(0.13)	(0.14)	(0.13)	(0.14)	(0.13)	(0.13)	(0.14)	(0.13)	(0.14)	(0.13)	(0.12)	(0.14)
BIDASK (t)	0.59	0.59	0.56	0.51	0.61	0.58	0.60	0.62	0.67	0.62	0.63	0.60	0.62
	(0.41)	(0.43)	(0.42)	(0.40)	(0.41)	(0.43)	(0.41)	(0.43)	(0.43)	(0.43)	(0.42)	(0.45)	(0.45)
FX (i,t-1)	0.61***	0.65***	0.61***	0.63***	0.59***	0.63***	0.58***	0.61***	0.58***	0.69***	0.59***	0.61***	0.59***
	(0.19)	(0.20)	(0.20)	(0.21)	(0.19)	(0.19)	(0.20)	(0.19)	(0.21)	(0.20)	(0.19)	(0.15)	(0.19)
Observations	2,725	2,725	2,725	2,725	2,725	2,725	2,725	2,725	2,725	2,725	2,725	2,725	2,725
Number of groups	25	25	25	25	25	25	25	25	25	25	25	25	25
R2	0.34	0.34	0.34	0.32	0.35	0.34	0.34	0.33	0.33	0.35	0.33	0.41	0.34

The table reports the results of the estimation of the dynamic panel fixed-effect model in equation 3. 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 D.4: 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)	0.27***	0.28**	0.26***	0.24**	0.20	0.27**	0.34***	0.35**	0.23	0.32***
	(0.08)	(0.13)	(0.08)	(0.10)	(0.20)	(0.11)	(0.10)	(0.15)	(0.14)	(0.11)
BTC VOL (t-1)	-7.76***	-6.86**	-8.20***	-7.31***	-5.05	-8.28***	-8.40***	-8.57**	-6.50*	-8.48***
	(1.71)	(3.02)	(1.76)	(2.21)	(4.27)	(2.38)	(2.54)	(3.64)	(3.40)	(2.85)
VIX (t)	0.16**	0.11	0.18**	0.31	0.33	0.34*	0.19*	0.13	0.06	0.23**
	(0.08)	(0.09)	(0.09)	(0.19)	(0.27)	(0.19)	(0.10)	(0.12)	(0.11)	(0.11)
BIDASK (t)	0.50**	0.81***	0.32	0.36***	0.69***	0.20	0.86	1.40*	1.35*	0.57
	(0.20)	(0.25)	(0.21)	(0.12)	(0.16)	(0.17)	(0.58)	(0.84)	(0.72)	(0.51)
FX (i,t-1)	1.13***	1.30*	1.06**	0.45	0.25	0.46	1.55***	1.93**	1.18	1.45***
	(0.41)	(0.75)	(0.43)	(0.73)	(1.38)	(0.72)	(0.43)	(0.96)	(0.73)	(0.47)
Observations	8,600	3,010	5,590	4,240	1,484	2,756	4,360	1,526	1,417	2,834
Number of groups	40	14	26	40	14	26	40	14	13	26
Country FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
R2	0.27	0.31	0.24	0.23	0.28	0.21	0.33	0.37	0.41	0.31

The table reports the results of the estimation of the dynamic panel fixed-effect model in equation 3, excluding currencies that have a strict peg. 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 D.5: Non linearities

VARIABLES squared	(1) BTC	(2) BTC VOL	(3) VIX	(4) BIDASK	(5) FX
BTC (t-1)	0.06**	0.07**	0.07**	0.07**	0.07**
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
BTC squared (t-1)	0.00				
	(0.00)				
BTC VOL (t-1)	-9.06***	-5.11	-7.25***	-8.04***	-8.15***
	(2.09)	(5.21)	(2.08)	(1.90)	(1.89)
BTC VOL squared (t-1)		-1.76			
		(2.41)			
VIX (t)	0.23***	0.24***	0.56**	0.21**	0.22**
	(0.08)	(0.09)	(0.23)	(0.09)	(0.09)
VIX squared (t)			-0.01*		
			(0.00)		
BIDASK (t)	0.64***	0.61***	0.61***	0.78**	0.62***
	(0.17)	(0.17)	(0.16)	(0.38)	(0.17)
BIDASK squared (t)				-0.02	
				(0.03)	
FX (i,t-1)	0.43***	0.41***	0.45***	0.41***	0.42**
	(0.15)	(0.15)	(0.14)	(0.15)	(0.18)
FX squared (i,t-1)					-0.00
					(0.01)
Observations	7,917	7,917	7,917	7,917	7,917
Number of groups	39	39	39	39	39
Country FE	YES	YES	YES	YES	YES
R2	0.32	0.32	0.32	0.32	0.32

The table reports the results of the estimation of the dynamic panel fixed-effect model in equation 3, augmented with the squared-terms of the selected regressors, excluding strict pegs and US dollar. 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 D.6: Role of crypto bans

	(1) EMDE crypto ban	(2) EMDE no ban
BTC (t-1)	0.12***	0.09***
	(0.04)	(0.03)
BTC VOL (t-1)	-12.72***	-9.15***
	(3.97)	(1.82)
VIX (t)	0.36***	0.25**
	(0.10)	(0.10)
BIDASK (t)	0.31	0.45**
	(0.28)	(0.18)
FX (i,t-1)	1.33**	0.33**
	(0.54)	(0.15)
Observations	609	5,481
Number of groups	3	27
Country FE	YES	YES
R2	0.33	0.36

The table reports the results of the estimation of the dynamic panel fixed-effect model in equation 3, differentiating the currencies depending on whether the country has banned transactions in cryptocurrencies. 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 are not reported here. The sample period runs from week 1 of 2018 until week 14 of 2022. The asterisks ***, ** and * indicate statistical significance at the 1%, 5% and 10% level, respectively.

Table D.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.

Table D.8: Correlation of second factor in Bitcoin trading with global drivers

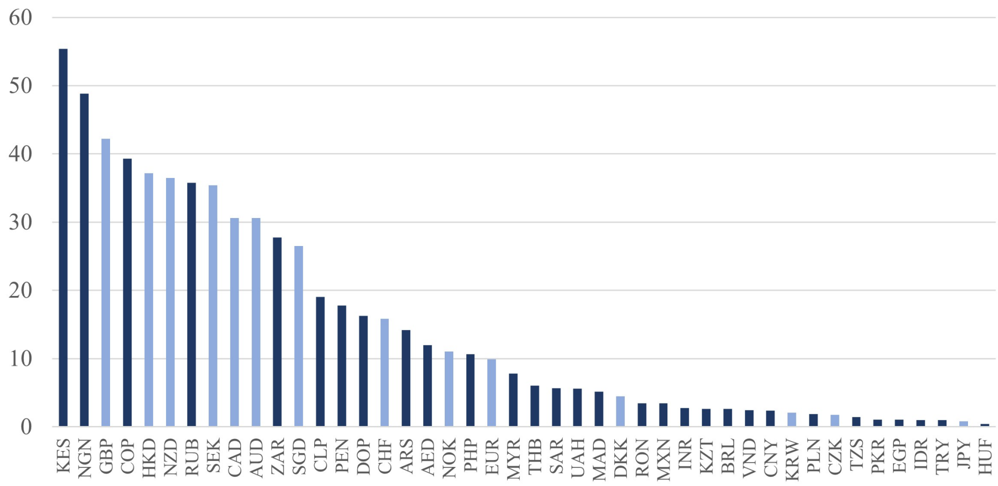
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Full sample			Pre COVID			COVID		
	All	AE	EMDE	All	AE	EMDE	All	AE	EMDE
BTC	0.14*	-0.05*	0.00	-0.12*	0.05*	0.26*	0.42*	0.49*	0.38*
BTC VOL	-0.14*	0.03	0.14*	0.05*	0.08*	-0.06*	-0.13*	-0.08*	-0.12*
VIX	0.00	0.13*	0.05*	0.41*	-0.28*	-0.53*	0.13*	0.10*	0.08*
GOLD	-0.07*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

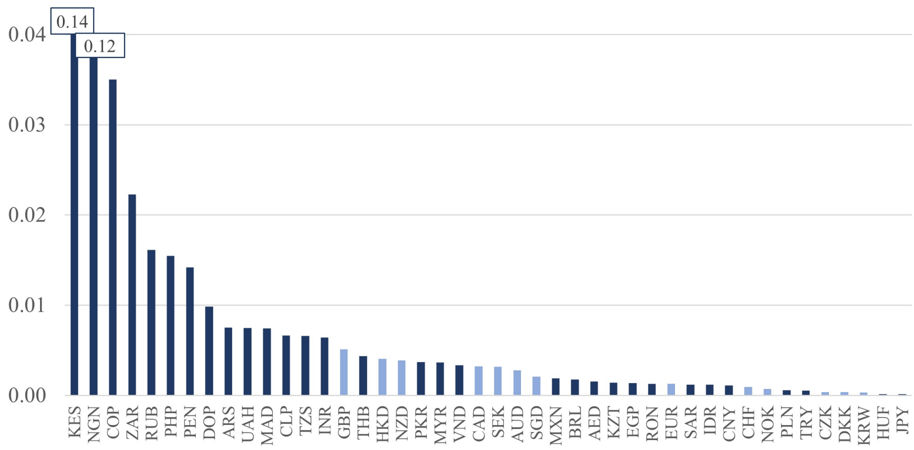
Appendix E Additional figures

Figure E.1: Bitcoin transactions against fiat currencies since 2020

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



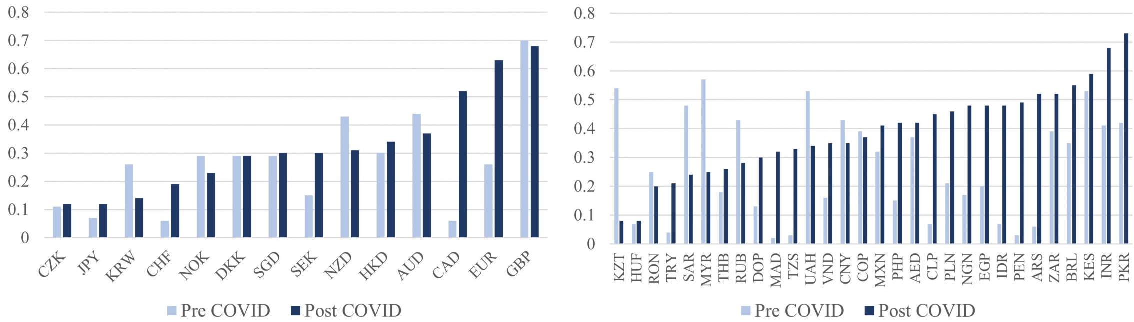
(b) Annual trading volume (percentage of GDP)



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 C.2 in the Appendix for the identification of currency codes.

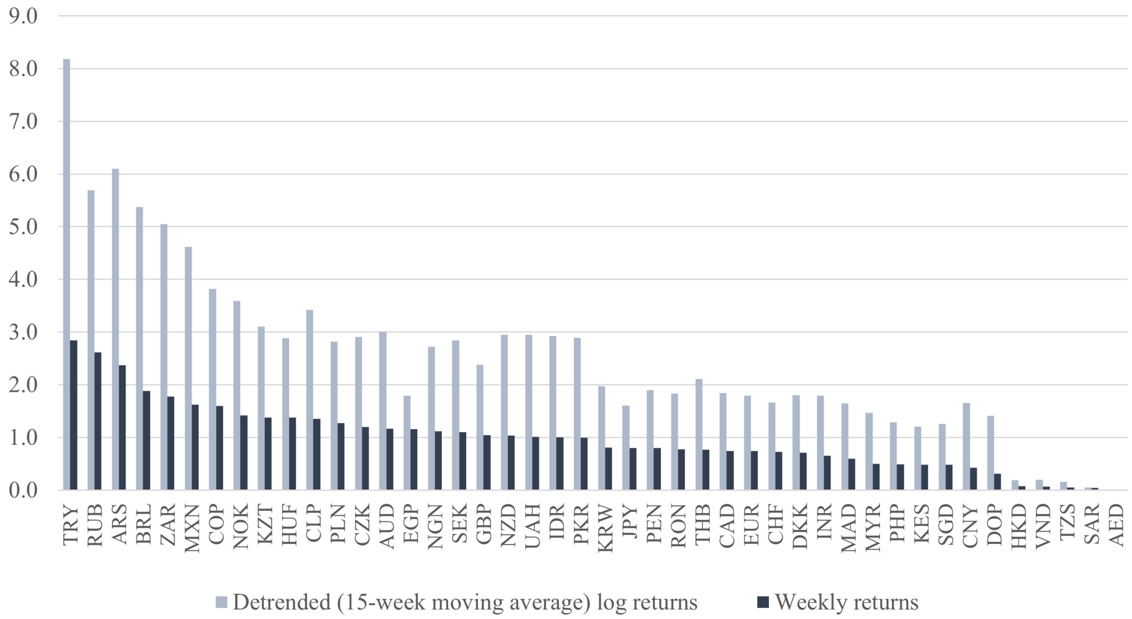
Figure E.2: Variance in Bitcoin trading volumes explained by the main global factor tends to increase in the COVID-19 period

(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 7. 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.

Figure E.3: Exchange rate volatility (percent)



The figure reports the standard deviation of weekly returns in the nominal exchange rate against the US dollar (dark blue bars) and of the log returns detrended with the 15-week moving average (light blue bars). Source: IMF/Haver and authors' calculations.