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Decrypting new age international capital flows ☆

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A B S T R A C T

This paper employs high frequency transactions data on the world's two oldest and most extensive centralized peer-to-peer Bitcoin markets, enabling trade in the currencies of more than 160 countries. We develop an algorithm that allows us, with high probability, to detect "crypto vehicle transactions" in which crypto currency is used to move capital across borders, and/or to exchange one fiat currency for another. The data suggest that the use of Bitcoin has become an increasingly important channel to receive remittances and evade capital controls in emerging markets. Two event studies on Venezuela and Argentina provide supporting evidence.

1. Introduction

The claim that Bitcoin has no actual transactions use underpins the oft-stated view that it is a purely speculative asset with no real underlying value. Nevertheless, theoretical models that attempt to rationalize a positive value invariably invoke Bitcoin's possible use in transactions (Athey et al., 2016; Fernandez-Villaverde and Sanches, 2019; Schilling and Uhlig, 2019; Bolt and van Oordt, 2020; Biais et al., 2023). Yet direct empirical evidence on transactions use remains largely anecdotal.

This paper develops a novel method for detecting and demonstrating transactions use of Bitcoin (or more generally cryptocurrencies) in thinly regulated off-chain markets with global reach. Although the markets we study only constitute a fraction of the Bitcoin universe, the results are nevertheless suggestive that transactions use of crypto – more as a new-age alternative to paper currency and to Western Union (rather than to banks) – is already far greater than generally recognized.

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With the proof of concept, we show that in the current global regulatory environment, and possibly long into the future, Bitcoin can be and is being used to circumvent taxes and regulations, i.e., to evade restrictions on international capital flows and foreign exchange transactions, including on remittances.[1] Such use appears most prominent in emerging markets and developing economies.

Our methodology employs high-frequency data from the world's two oldest centralized peer-to-peer exchanges covering 163 fiat currencies, the large majority of which are not served by any other crypto-currency exchange.[2] The data cover all trades, including currency used (data that does not exist for on-chain transactions), the quantity of Bitcoins purchased, and a precise time stamp to the second. For the data from one of the two exchanges, we further have information about the geolocation of the trading parties. By matching identical-size (to eight digits, since trade sizes are expressed in Satoshi – one hundred millionths of a Bitcoin) transactions that take place within a short window, we are able to identify with high probability trades that involve using Bitcoin as a transactions vehicle. Very often this involves moving fiat currency across borders and/or for converting one fiat currency into another.[3] To the best of our knowledge, we are the first to present concrete quantitative evidence of such transactions use.[4]

As a very conservative probabilistic lower bound, we estimate that at least 11% of all trades in our data are crypto vehicle transactions, which is sufficient to establish that transactions use is significant. The dollar equivalent of Bitcoin trades involved in these transactions amounts to USD 1.2 Bn (or USD 0.51 Bn sent through Bitcoin as a transaction). The actual share and amount involving transactions use is very likely much higher. A natural experiment involving a power outage in Venezuela strongly confirms this conjecture.

In nearly 90% of the (high probability) transactions, the parties involved are located in different countries; a small but significant share involve two different fiat currencies. Not surprisingly, countries with substantial restrictions on international capital flows are heavily overrepresented in the data. Descriptive statistics from an event study in Argentina support the hypothesis that use of crypto currencies increases with the tightening of capital controls.

The first part of the paper describes our novel data set, with further details provided in the Data Appendix. We emphasize that although many other Bitcoin exchanges exist, very few offer their services globally, the way P2P exchanges such as Localbitcoins and Paxful do. The second section describes our probabilistic matching methodology. In a large fraction of cases, the individual trades we pair are like matching snowflakes that occur nowhere else (or almost nowhere else) in the data. The third section presents the main results, which we interpret as compelling evidence that Bitcoin are being used for the international transmission of funds (including the large global pool of international remittances).

Finally, we briefly sketch other possible implications and applications of our cryptocurrency vehicle transaction detection algorithm. The insight that cryptocurrencies are indeed being used as cross-border transactions vehicle in developing economies (and emerging markets) with thin, highly regulated capital markets implies that these trades indeed constitute a parallel (black-) market for hard currency. Thus, one can examine whether the crypto price data tracks the parallel exchange rate where comparable data exist; showing that in effect, the crypto market can provide an indication of parallel market pressure. When an indicator of parallel rates movements, crypto prices can hence serve as a real-time, high-frequency indicator of macroeconomic imbalances for developing-country policymakers and investors alike. Further, we discuss extensions including how our identification methodology might be applied by regulators who can command otherwise confidential exchange data. The final section concludes and draws some analogies between detecting transactional use of Bitcoin and transactional use of large-denomination paper currency.

Literature: The fast-growing literature on the economics of Bitcoin has been mainly concerned with one question: What can explain the price of Bitcoin? In a first attempt to answer this question, a wide range of studies have empirically investigated Bitcoin pricing and its drivers (Liu and Tsyvinski, 2021; Kaminski, 2014; Garcia et al., 2014; Glaser et al., 2014; Kristoufek, 2015; Mai et al., 2015; Wang and Vergne, 2017), as well as cross-country and cross-exchange price differences (Makarov and Schoar, 2020; Borri and Shakhnov, 2022; Hautsch et al., 2018).

To gain further insights into the underlying mechanisms, a theoretical branch of this literature arose, extending models of money to Bitcoin. That literature found the use case, especially transactional use, to be crucial to giving Bitcoin value. In the model by Schilling and Uhlig (2019), Bitcoin prices in the long run follow a martingale, where the fundamental price is derived from the transactional use of Bitcoin as a medium of exchange. Transactional use is of similar importance in the framework introduced by Athey et al. (2016), with the difference that their model explicitly assumes transactional use for remittances, rather than payments – though until today there has been only anecdotal evidence of such use. In the general equilibrium analysis of cryptocurrency pricing by Biais et al. (2023), the fundamental value of Bitcoin again relies on

[1] Although there has been some previous quantitative research providing some insight into the use of Bitcoin in facilitating illegal activities, this work typically concentrates on the analysis of the users, not the type of use, classifying users into legal and illegal agents, rather than distinguishing between investment purchases and transactions use. Furthermore, these analyses have only been applied to on-chain transactions; See Chung (2019), Foley et al. (2019), Framewala et al. (2020), Ron and Shamir (2013), Yang et al. (2019) and Zhao and Guan (2015).

[2] Though arriving at a precise estimate is difficult, as not all exchanges provide data on trade volumes, while others might have incentives to provide inaccurate data, the off-chain transaction volume involving Bitcoin (exchange trades) appears to have been at least 10 times the volume recorded on the Bitcoin blockchain (Sources: CryptoCompare.com API, Blockchain.com API).

[3] Although it has been shown that arbitrage opportunities across Bitcoin markets exist (Makarov and Schoar, 2020; Borri and Shakhnov, 2022), the 1% transaction fee (2% to both buy and sell) makes LocalBitcoins.com a relatively unattractive vehicle for arbitrageurs.

[4] Indeed, in its recent survey of evidence on transactions use, the IMF (October 2021) considers survey data and chain analysis and concludes "the interpretation of the data poses significant challenges."

a transactional value proposition, since "transactional benefits are to cryptocurrencies what dividends are to stocks" (Biais et al., 2023). In their model, Bitcoin retrieves its value from providing transactional benefits fiat money cannot provide, e.g., for citizens in countries with capital controls or dysfunctional currencies/banking systems seeking to make cross-border transfers. While they find that fundamentals only explain a relatively small share of return variations on bitcoins, the importance of fundamentals, relative to speculative use, is expected to increase over time (Bolt and van Oordt, 2020). Finally, even in theoretical models where self-fulfilling beliefs are the main drivers of the value, transactional use still remains a fundamental assumption (Garrat and Wallace, 2018; Fernandez-Villaverde and Sanches, 2019).

Systematic evidence on the transactions use of Bitcoin – as opposed to store of value and speculation – remains extremely thin, given the anonymity constraints specific to Bitcoin data. The earliest empirical attempts to answer the questions of what Bitcoin is used for relied on survey data from Canada and the US respectively (Henry et al., 2017; Schuh and Shy, 2016). However, given that part of the uptake of Bitcoin is likely driven by a desire for secrecy, the insights gained were limited. So as not to rely on people's willingness to disclose information, an alternative approach, namely the analysis of publicly available blockchain data, has also been employed (Athey et al., 2016; Bolt and van Oordt, 2020; Tasca et al., 2018; Foley et al., 2019). These studies typically rely on the fact that some identities behind addresses on the blockchain are known and leverage this knowledge to classify transactions into subcategories (e.g., gambling, speculation, black market purchases). Though insightful, the share of directly or indirectly identifiable addresses (combining network analysis tools and publicly revealed addresses) remains constrained, at less than 50%, making up less than 25% of transferred value (see Halaburda et al. 2022 for a detailed discussion).

Our analysis is in a similar spirit to this literature, contributing in at least two ways: First, we are able to shift the focus from users to actual transactions; moreover, we link these to fiat currencies and geographic locations. This is crucial in that it allows us to show that the cross-border use assumed in the theoretical literature may indeed be an important factor. As we do not rely on the same on-chain data as most of the literature, our off-chain dataset can be understood as a new and unique window into the broader crypto world. Our off-chain data is structurally similar in that the exchanges we retrieve our data from, just like the blockchain itself, are global and designed to facilitate P2P transactions, in a way that is extremely expensive and impractical for authorities in most countries to detect. It differs only in that the exchanges are centralized and that the fees are variable rather than fixed. This, in turn, makes these off-chain exchanges vastly more attractive for small transactions (where the off-chain variable fee is far smaller than the fixed on-chain fees) and thus for the type of retail use case the literature has posited in theory, but not previously demonstrated quantitatively in practice. Indeed, we also debunk the assumption typically made in the extant empirical literature, that the use of off-chain exchanges – which in total account for vastly more trade than on-chain exchanges –can entirely be classified as speculation (Glaser et al., 2014; Tasca et al., 2018; Athey et al., 2016; Hayes, and Liu, 2018).

Our paper also relates to the work of Benigno et al. (2022) who show that the existence of a global (crypto) currency has direct impact on monetary policy in countries where it is being used. And it represents a tangent to the literature on the vehicle currencies, and the rise and perseverance there of (see Rey 2001 and the literature cited therein). Finally, our work relates to yet another literature, spearheaded by Auer and Claessens (2018), on regulating cryptocurrencies. However, whereas their paper analyses the effect of crypto regulation, our study provides insights into how regulation of other sectors (capital control restrictions) indirectly impacts the use of Bitcoin.

2. LocalBitcoins, Paxful, and off-chain exchange

The core data set, described in detail in the Data Appendix (Appendix A.6), makes use of data from LocalBitcoins.com and Paxful.com, the world's two largest peer-to-peer (P2P) Bitcoin exchanges during the time covered by our dataset.[5] The data encompass more than 128 million trades over the period March 15, 2017–May 3rd, 2022.[6] To contextualize, the universe of trades that occurred on-chain over the same period, encompasses 513 million transactions.[7] P2P exchanges like the ones we retrieve our data from are able to operate in a large number of countries simultaneously because these exchanges only offer deposit services for members' Bitcoins, but do not offer deposits in national fiat currencies, thereby side-stepping the national banking regulations that impact most crypto exchanges.[8]

[5] Localbitcoins.com has discontinued its services in February 2023, after Paxful.com and notably Binance's more recently launched P2P exchange undercut Localbitcoins' more expensive fee structure. However, Binance, at least as of May 2023, does not share trade-level data from its P2P exchange.

[6] LocalBitcoins was operating between 2012 and 2023; Paxful has existed since 2015. However, we limit our analysis to the period since March 2017, when LocalBitcoins revamped the exchange's back-end, guaranteeing consistency in the format of the data.

[7] One transaction recorded on the Blockchain can include the transfer from one sender to many recipients, thus, when instead counting these as individual transfers, the cumulative number of on-chain transactions from the inception of Bitcoin in 2009 through May 2021 amounts to 977 million (Source: Blockchain.com API, Authors' Calculations).

[8] That is, LocalBitcoins.com and Paxful.com intermediate trades only to the extent that the exchanges wait to clear the internal transfer of claims on the exchange to Bitcoin only after payment has been confirmed. The fact the exchange is only matching parties and not intermediating the fiat money payments is what allows them to operate outside the financial regulatory framework in most countries, answering only to its home base regulator, e.g., in Finland for LocalBitcoins. Although several competitors have tried to clone LocalBitcoins, or improve on it, none have been terribly successful. Notable is Ripple's XRP, which – because of its centrally owned and regulated structure – remains much smaller than the Bitcoin in both emerging and developing economy markets.

Table 1
Descriptive statistics.

Number of Trades	128,493,700
USD Trade Volume	USD 19.0 billion
Average Trade Size (USD)	148
Average Trade Size (BTC)	0.0185150 Bitcoin
Largest Trade Size Recorded	USD 2.3 million
Number of Fiat Currencies	163

Source: LocalBitcoins.com API, Paxful.com API, authors' calculations.

P2P Bitcoin exchanges, such as Localbitcoins.com and Paxful.com, enable peer-to-peer transfers of Bitcoin between accounts on the respective platform, by offering an escrow service that holds up Bitcoin part of an ongoing transaction until both parties confirm that the agreed fiat payment has been successful.[9] Note that the payment in fiat currency does not occur on the platforms. The transfer of bitcoin thereby is "off-chain" in that individuals buy and sell only their claims on bitcoins that the intermediary houses, without any bitcoin being transferred between addresses on the blockchain.[10] Using either website, it is possible to buy Bitcoin from an account holder in country A using A's currency and sell to a third account holder in country B in exchange for B's currency.[11] (Intra-country payments and transfers are similarly straightforward.) In Section 2 we provide an example of how this can be used to evade capital controls.

In principle, off-chain exchanges can be required to collect information on account holders, albeit cross-country standards vary greatly. This means that a determined and well-resourced regulator can track individual activity related to Bitcoin much more easily for an off-chain exchange transaction than for a pure "peer-to-peer" on-chain transaction involving no intermediary. However, particularly in the case of an exchange that allows citizens from more than a hundred countries to trade, such as LocalBitcoins or Paxful, the international dimension makes regulation of transactions use much more difficult. LocalBitcoins for instance, was incorporated in Finland and governed by Finish regulators, and thus not obliged to share private information with developing country authorities. Although surely, they would offer information access in egregious cases of crime or terrorism, it is unlikely to be granted on a routine basis, say if Bitcoin is used to evade capital controls. Nevertheless, we highlight that publicly available data alone are sufficient to establish that the market is being used in a significant way as a "crypto vehicle currency" to make fiat currency payments (at home or abroad) or to send capital abroad.

Of course, there is already substantial anecdotal evidence on the use of crypto for transactions purposes; it is well known that Bitcoin is the medium of choice on the Dark Web, not to mention ransomware.[12] But systematic analysis has been lacking. Our methodology allows us to identify such use conceptually, and further establish a lower bound on the use of Bitcoin as a medium for transactions use within the exchanges we assess. It is quantitative, rather than anecdotal. In principle, the same algorithm, or a variant, can be applied to data from any exchange, should the researcher or regulator obtain (or demand) similar data to ours.

Table 1 provides some descriptive statistics of the core data set.

For each trade, the data include the timestamp, trade-size, fiat currency used, and the price paid in fiat currency. (As already noted, on-chain transactions do not record currency or price, nor is an exact time stamp possible because trades clear in blocks.) For the data from Paxful, representing more than half of the trades we analyze, we also have information on the geolocation of traders. We note that the average trade size is relatively small, in part because agents – who must communicate anyway to make the P2P exchange – have an incentive to shift modalities for large trades after matching.[13] This allows them to engage in a more efficient non-intermediated peer-to-peer exchange, which might involve trading paper currency for crypto in person, thereby avoiding the 1% fee charged by the platform.[14] However, even within the limited trade one can observe publicly, a significant proportion turns out to be transactional, and often cross-border.

[9] In case a conflict arises, because the parties disagree as to whether a fiat payment was made, the exchanges investigate and attempt to provide a solution before releasing the bitcoin from the escrow account.

[10] Despite their many account holders, LocalBitcoins and Paxful each represent only a few addresses on the blockchain. Addresses are often also referred to as *wallets*. However, a *keychain* might be the better analogy, given that one such address prefix can have an infinite number of address suffixes its users can use to send Bitcoin *via* the blockchain to their account with LocalBitcoins or Paxful. Because LocalBitcoins and Paxful each represent only one node on the Bitcoin blockchain, the only transfers visible on the public blockchain are thus transfers of Bitcoin to, and withdrawal of Bitcoin from, the exchanges.

[11] Note that fintech solutions (e.g., Wise or Revolut) have made opening accounts in foreign currencies relatively easy. Alternatively, bitcoin-sellers can ask the counterparty to transfer the funds to a third part, e.g., a relative or to a provider of goods/services the bitcoin-seller wants to purchase. Finally, payment methods include the transfer of coupons that can be used to make purchases, such as Amazon/Google or Apple Store value. Hence even individuals without offshore accounts, can leverage crypto-vehicle-trades to evade capital controls.

[12] For an example of such anecdotal evidence, see "Cryptocurrencies: developing countries provide fertile ground", *Financial Times*, September 2021.

[13] There also exists an incentive to split larger trades into smaller ones to minimize exposure to sudden price volatility.

[14] We have already distinguished P2P matching services such as LocalBitcoins and Paxful from decentralized peer-to-peer trades which go through the blockchain; these involve paying miners a fee to verify the transaction, with the fees endogenously depending on congestion. However, there is no centralized authority of any sort.

3. Algorithm for detecting international crypto vehicle transactions

In this section, we discuss our algorithm for (probabilistic) identification of cases where Bitcoin trades are likely being used for cross-border wealth transfers and payments. The mechanics are simple. Suppose an Argentine citizen wants to convert pesos in her Buenos Aires account to dollars in her Miami account but evade Argentine capital controls. Or alternatively, she might want to buy a painting from a New York gallery to give to her sister who lives in New Jersey. Traditional interbank markets are expensive and subject to capital controls, and whereas there are other ways to avoid capital controls, most of them have significant barriers to entry (e.g. trade mis-invoicing).[15] With the rise of crypto markets all around the globe, there now exists an easy and widely accessible alternative: An Argentine citizen can simply trade pesos for Bitcoin through an exchange or P2P platform (presumably from an Argentine resident), and then turn around and sell the same amount in exchange for dollars, presumably from an American resident. The dollars can then be used to make payments or be deposited in an American bank. The reverse process (from New York to Buenos Aires or elsewhere) encompasses the vast transactions associated with remittances. (For the rest of this paper, we use "crypto vehicle trades" and "crypto vehicle transactions" interchangeably.)

Given that Bitcoin prices are volatile, and that the fiat currency amounts being traded are highly varied, there is a very low probability of observing two identical-size matching trades (to eight digits), in and out of Bitcoin, within a relatively brief time window (say five hours) unless it is a vehicle trade. Observing the same identical amount of bitcoin being traded twice within a short period of time, during which a countable number of trades take place, is thus akin to a probabilistic event, such as a die landing on the same side twice within a set number of throws – only that the Bitcoin *die* is not balanced, and has over 100 million sides.[16] We verify that a significant share of the 8-digit trades we document appear only twice in the data set, and often within a very short time window. Because our data set contains quantity (in Satoshi), time stamp, price and fiat currency used, we can then infer the flow of funds across countries and currencies, as well as use in domestic transactions.[17] Table 2 illustrates with an example from the data.

Table 2
Extract from the data.

Timestamp	Trade Size	Price (Local Currency/Bitcoin)	Fiat Currency
2021–03–15 14:42:22	0.00098037	1.02E+11	Venezuelan Bolivar
2021–03–15 14:42:24	0.01157996	60,449.26	US Dollar
2021–03–15 14:42:27	0.00022173	4,509,989.50	Indonesian Rial
2021–03–15 14:42:27	0.00047619	42,000.04	British Pound
2021–03–15 14:42:28	0.00093023	6,450,017.50	Kenyan Shilling
2021–03–15 14:42:29	0.00063638	4,321,317.50	Russian Ruble
2021–03–15 14:42:33	0.00039107	1,554,708.87	Ukrainian Hryvnia
…	…	…	
2021–03–15 15:28:53	0.01157996	1.04E+11	Venezuelan Bolivar

Source: LocalBitcoins.com API[18].

Both P2P platforms charge a commission (averaging 1%) on both buy and sell trades, but this is generally paid directly by the market maker and does not affect the Bitcoin trade quantity or price reported, and therefore does not interfere with our matching algorithm.

With this preamble, we now turn to the algorithm we use to identify crypto vehicle trades. Considering the large size of the data set, even with trade sizes documented out to eight digits, there is still a possibility of two identical-sized trades randomly appearing close together, especially as some trade sizes appear somewhat more frequently than others. The goal of our identification methodology is to arrive at an algorithm that identifies crypto vehicle transactions with a 95% confidence level. And an aggregate that sums over the identified trades, whilst controlling for the multiple hypothesis testing framework. We aim to estimate the probability that two matching trades represent a crypto-currency vehicle trade, if they occur within, say, a five-hour window. The choice of window gives rise to the usual Type I and Type II errors trade-off. The shorter the window, the more matches we miss, the longer the window the more likely we are counting a random reoccurrence of an eight-digit match as and "in and out" vehicle trade. Our main results will turn out to be quite robust to the window choice; this is in part because the probabilistic approach directly controls for changes in the time window.

Our algorithm is constructed to generate an unbiased estimate of the share of trades on LocalBitcoins and Paxful that are clearly identifiable as Crypto Vehicle Trades, while controlling for potential false discoveries.

[15] Haibo (2008), Aizenman (2008), Coppola et al. (2020) and Schneider (2003).

[16] More precisely, when considering that a Bitcoin trade-size can indeed be greater than 1 Bitcoin, the "dice" theoretically has 21 quadrillion sides - 21 million Bitcoins that can be mined, times 100 million Satoshi or decimal places.

[17] As noted earlier, "on-chain" trades contain only the addresses involved, Bitcoin size and time, but not the fiat currency used, or the price paid.

[18] Paxful's data has the same format except that the data also includes the fields *user_cc* and *advertiser_cc*, as well as information on payment methods.

3.1. Identifying crypto vehicle trades individually

For each of the two datasets separately,[19] let S be the set of all I individual trades in the dataset, i, each of which has a trade-size, x_i. With the subscript t we denote subsets that have occurred prior to timestamp t of trade i. Distinct trade sizes that arrived prior to i, denoted by x_k, are assumed be an element of

$$X_t = \{x_1, \ \ldots, \ x_K\}, \tag{1}$$

which at time t is fixed and known.[20] To simplify notation we drop the subscript t in x_K. Our null hypothesis (H_0) corresponds to a model of what one would expect if there were no vehicle trades, and any exact matching transactions were solely random.

Assumption 1 (Null Model). *Assume that under the model implied by the null hypothesis, trades of any given size appear as independent Poisson processes. The number of times any unique trade size, x_k occurs from time 0 to time t is thus defined as $PP(\vartheta\, p_k)$, where $\vartheta > 0$ and $p_k \geq 0$. The Poisson process' intensity, $\vartheta\, p_k$, is the product of p_k, the probability of any new trade having the size x_k, such that $\sum_{k=1}^{K} p_k = 1$; and ϑ, the number of arrivals of trades over the time period of interest.*

For any trade, i, we will estimate p_i (i.e. the probability of trade i's trade size x_i having the observed size $x_i = x_k$) based on our data, specifically X_t, making use of the frequency of the trade size x_i prior to timestamp t, $\hat{p}_i = \hat{p}_{k,t} = \frac{\sum_{i=1}^{I_t} 1\{x_i = x_k\}}{I_t}$ (Table A.1).

We denote this $\hat{p}_i$ to stress it being unique to each trade i. The probability of a trade size that has never occurred in the data set, thus has a probability, $\hat{p}_i$, equal to zero.[21,22]

Consider the benchmark case of a 5 h period prior to any given trade i, where N_i total trades happen and let n_i denote the number of times trade size x_i occurs. Under the null hypothesis, n_i follows a single multinomial draw,

$$n_i \mid N_i \ \sim \ MultiN(N_i; \, p_i) \tag{2}$$

This is because conditioning on N_i removes ϑ from the conditional probability distribution.[23]

Rejections of the null implies the presence of vehicle trades in the data. To assess whether the null hypothesis holds or not, define

$$\theta_i \ = \ P\,((n_i > 0) \mid N_i) \in [0, 1] \tag{3}$$

Note that without imposing any underlying structure to the data, θ_i can only be observed as a categorical variable, taking on the values $\{0, 1\}$. Meanwhile, under the null model, the multinomial structure implies that $P\,((n_i > 0) \mid N_i)$ would equal

$$\hat{\theta}_i^* = 1 - \ (1 - \hat{p}_i)^{N_i} \tag{4}$$

To detect vehicle trades, we test for departures from the model under the null hypothesis of purely random pairings.

If $\hat{p}_i$ is not very small (as we shall see later, in Fig. 2 below, certain size trades are common), then $n_i > 0$ becomes much more likely under the null. That is, $n_i > 0$ is more likely to have occurred by chance.[24] We formalize disregarding such random discoveries in the following way.

Definition 2. *Let $\Theta_\theta \in [0; 1]$* be some preset number (i.e., a threshold). The trade i is not a candidate for a statistical vehicle trade of size x_i, if

$$H_{0,i} : \ \hat{\theta}_i^* \ \geq \ \Theta_\theta, \ i = 1, \ \ldots, \ I, \tag{5}$$

Otherwise, i is potentially a statistical vehicle trade of size x_i.

We set Θ_θ to 0.05 to remove trades which are relatively common across the entire data set, so that finding a match (i.e., $n_i = 1$) provides little evidence of a vehicle trade. For each i, the discovery algorithm is a single hypothesis test with a size (under the null hypothesis) of $\hat{\theta}_i^*$ and significance level Θ_θ.

Definition 3. We declare a "discovery" of a vehicle trade of size x_i, if

$$n_i > 0 \ and \ \hat{\theta}_i^* < \Theta_\theta \tag{7}$$

This is recorded by $d_i = \alpha_i\, \phi_i$ *with* $\phi_i = \begin{cases} 1 \ if \ n_i > 0 \\ 0 \ otherwise \end{cases}$ *and* $\alpha_i = \begin{cases} 1 \ if \ \hat{\theta}_i^* < \Theta_\theta \\ 0 \ otherwise \end{cases}$.

[19] The two datasets from Paxful.com and LocalBitcoins.com are treated separately, as moving Bitcoin between them, on-chain, would be costly and have no obvious benefit, making cross-exchange crypto vehicle transactions unlikely.

[20] We denote trade sizes by subscript k, as certain trade sizes occur more than once in the data so that $K_t \leq I_t$.

[21] In contrast, when applying an alternative Bayesian approach, one might instead attach positive probabilities even to trades that did not occur. We do not think a Bayesian approach would significantly affect our core results, although of course it could certainly affect how individual matches are assessed.

[22] Note that Bitcoin being denoted with eight decimal places typically leads to a very low $\hat{p}_i$. The algorithm leverages this particularity of Bitcoin to identify vehicle trades. When instead using the algorithm on a dataset with less specific trade sizes, values of $\hat{p}_i$ would be inflated, making it impossible to identify statistically significant departures from the null.

[23] For every trade i, we are interested in the number of times the corresponding trade size x_i occurs in the five-hour window prior to the time of trade i. We denote this n_i.The effects of applying overlapping five-hour windows rather than distinct time-windows in our application are discussed further in Appendix A.1.

[24] Note that we declare the rare case, where $n_i > 1$ and $\hat{\theta}_i^* < \Theta_\theta$ a false discovery and drop these cases from the sample.

3.2. Estimating the share of vehicle trades in the sample

Recalling that I is the total number of trades in the entire data set, the "vehicle trade share estimand" under the null assumption is

$$\varphi = \frac{2\sum_{i=1}^{I} \alpha_i \left(\theta_i - \hat{\theta}_i^*\right)}{I}, \text{ with } \alpha_i = \begin{cases} 1 \text{ if } \hat{\theta}_i^* < \Theta_\theta \\ 0 \text{ if } \hat{\theta}_i^* \geq \Theta_\theta \end{cases} \tag{6}$$

Under the null hypothesis $\varphi = 0$, since φ captures the excess clustering of trades at particular trade sizes, that is, in excess of what one would expect under H_0.

Given that I is large, it is important to recognize there are I hypotheses, relating our approach to the multiple hypotheses testing literature (Efron, 2007; Wakefield, 2007), which has been extensively applied to genomic sequencing and chromosome segmentation. However, in this literature, because of technological/economic constraints, one normally does not have the full population of the underlying data. By contrast, in this exercise we have access to the full distribution of trades (the full trade data set for LocalBitcoins and Paxful respectively). This allows us to control for "false positives" due to the assessment of multiple hypothesis tests by estimating the expected share misidentified as vehicle trades by our algorithm.

To control for false "discoveries" due to the multiple hypothesis testing – context; and to establish our estimate of the share of crypto vehicle trades, $\hat{\varphi}$, we introduce a measure of the number of trades one would expect to falsely discover as vehicle trades, c_i.

$$\hat{\varphi} = \frac{2\sum_{i=1}^{I} (d_i - c_i)}{I}, \tag{8}$$

where, $c_i = \alpha_i \hat{\theta}_i^*$. Over i, c_i describes the probabilities of a trade seeing a random match within the five hours prior under the null model. Summing c_i over i thus represents a measure of the expected number of matches under the null assumption.

Theorem *Under an arbitrary data generating process for* $(n_1, \ldots, n_I)$,

$$E[\hat{\varphi} \mid N_{i,\ldots,I}] = \varphi \tag{9}$$

Proof of Theorem 4:

$$E[\hat{\varphi} \mid N_{i,\ldots,I}] = \frac{2\sum_{i=1}^{I} (E[d_i \mid N_i] - c_i)}{I} \tag{10}$$

$$= \frac{2}{I}\sum_{i=1}^{I} \boldsymbol{\alpha_i} \left(E[\boldsymbol{\phi_i} \mid N_i] - \hat{\theta}_i^*\right) \tag{11}$$

$$= \varphi \tag{12}$$

Above, we make use of the fact that for any single i, $E[\boldsymbol{\phi}_i \mid N_i] = 1 * P((n_i > 0) \mid N_i)$.

The algorithm's capacity to identify transactions thus relies on two conditions: First, for trades to be matched with a degree of confidence, individual crypto trade sizes must be sufficiently unique. If the majority of the trades had the exact same nominal size, the matching algorithm would be of limited use. This feature does not, however, characterize our data, where there exist 12.7 million different trade sizes (more precisely 12,670,887).[25] Around two-thirds of these occur twice or less. The distribution of trade sizes for the data set is illustrated in Fig. 1.

The figure includes trades with sizes between 0.00000001 Bitcoin and 10 Bitcoin. We apply this distribution to derive the applied probability density function that is used to estimate the probability of a trade size occurring under the null model, and thus to control for the probability of false discovery. Source: LocalBitcoins.com API, Paxful.com API, Authors' calculations

The second condition the algorithm relies on is that market participants who are aiming to use Bitcoin as a vehicle for making fiat currency transactions, will have strong incentives to minimize their holding times. The main constraint is that the requisite fiat money transfers on both ends, buying and selling, can take time, which is especially an issue for some less liquid developing-economy currencies. Indeed, for many trades, the time between the legs of a vehicle trade is typically only a few hours or less (see Appendix A.1). This is likely driven by the high volatility of Bitcoin prices. Since significant delays between the purchase and the execution of trades would risk leading to losses on the buyer or seller side, depending on whether Bitcoin prices rise or fall; recent studies find Bitcoin-fiat volatility to exceed the volatility of major currency pairs by a factor of ten (Baur and Dimpfl, 2021).[26] The annualized standard deviation of USD/BTC since 2014 is 93%, compared, for example, to 8% and 12% for USD/EUR and USD/MXN exchange rates. Our key assumption is that market participants not

[25] The value which occurs most often in the dataset is 0.0010000 BTC, with 107,505 trades having that nominal value.

[26] Of course, especially in the post-pandemic context, there exist some developing economy currencies which are quite volatile, but not on the order of Bitcoin, certainly not for any extended period.

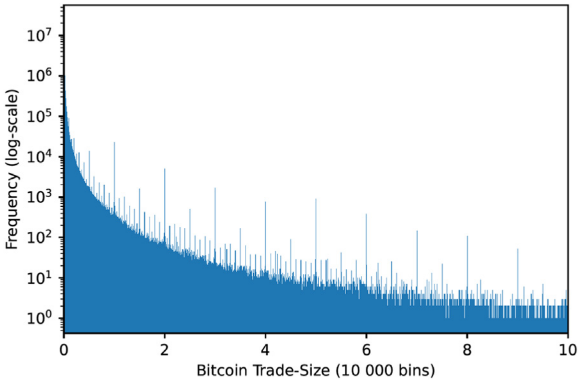

Fig. 1. The historical distribution of trade-sizes.

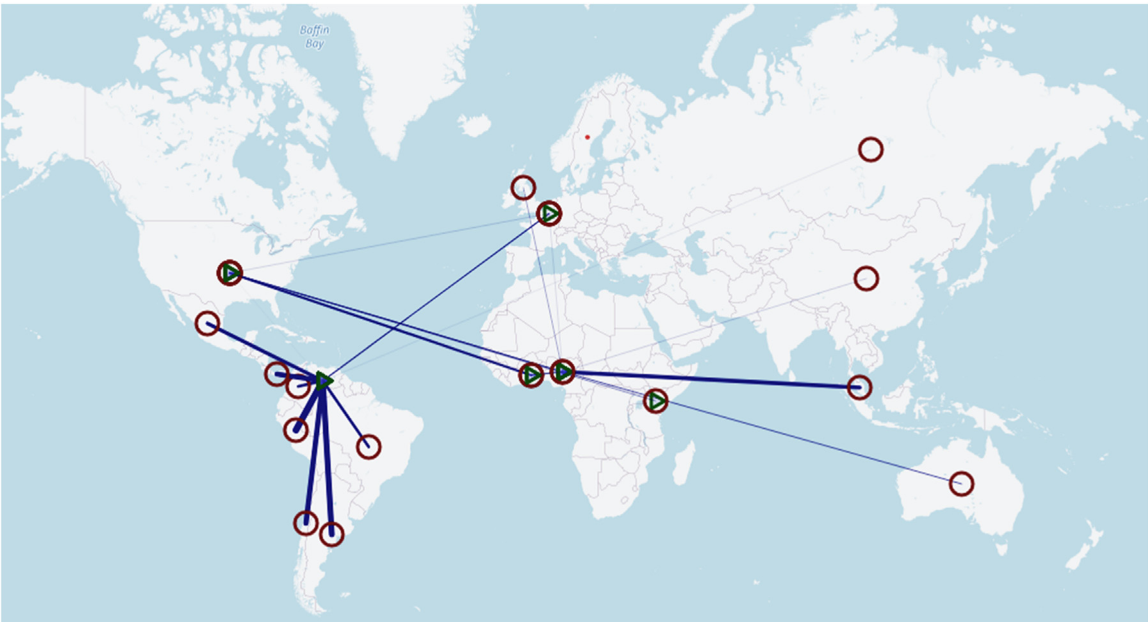

Fig. 2. The World's 25 biggest Crypto Vehicle Channels. Circles: Origin, Triangles: Destination. Line-width: Channel volume as share identified trade volume in Origin Currency Sources: LocalBitcoins.com API, Paxful.com API, Authors' Calculations.

interested in exposure to Bitcoin per se, will try to trade in and out of the digital currency as quickly as possible, are thus likely to minimize holding time in most cases.[27]

However, even though participants engaged in crypto vehicle trades have a strong incentive to get in and out quickly, in practice there can be speed limits imposed by domestic financial systems. Within the two P2P platforms, trades typically clear very quickly; the time between an order being made and the escrow being released is typically very short. However, when crypto vehicle trades involve one or two inefficient developing-economy fiat payment platforms, there can potentially be a much longer delay.[28] The five-hour time window we employ in our baseline estimates (results applying for shorter and longer windows are reported in the appendix) reflects the findings from the analysis of trade delays, as well as the trade-off described above.

[27] It is certainly possible that some percentage of agents using Bitcoin mainly as transfer vehicle do not mind – or possibly even prefer – some exposure to price volatility. To the extent we are too conservative in picking a relatively short time window, this constitutes another reason our estimates are a lower bound on crypto vehicle trades.

[28] For example, when in a given market there exist no fintech alternatives to the interbank market for making domestic transactions, transactions would usually take at least one working day to clear, meaning the Bitcoin would remain in the escrow for that long, meaning in turn that the time between two trades must exceed the five-hour window we consider.

Table 3
Crypto vehicle trades.

Total Number of trades	128,493,700
Number of trades with one match	17,936,236
Number of trades identified as vehicle trades ((P(Match is Random) < 0.05), d_i	16,568,776
Expected "False Discoveries" in a data set without vehicle trades, c_i	1,142,482
Share of total trades identified as crypto vehicle trades, φ	**11.1%**

Source: LocalBitcoins.com API, Paxful.com API, Authors' Calculations.

4. Results

Table 3 gives results for our matching algorithm using a five-hour window to identify crypto vehicle trades. Of the 128 million trades, just under 18 million trades (or 14%) are part of an exact match in terms of Satoshi size and occur within the five-hour time window. However, running our algorithm conservatively excludes 1.4 million of these trades because the trade size is sufficiently common (for example 0.1 Bitcoin) that the algorithm cannot attach a 95% confidence interval to a matched pair of being a crypto vehicle trade. Further, we deduct the number of trades one would expect to match with a 95% confidence interval even in a data set without any real vehicle trades (i.e., the False Discovery Rate). This brings the percentage of crypto vehicle trades in the data set down to a conservative lower bound of 11.1%.

In Appendix A.2, we consider an alternative approach, performing a Monte Carlo simulation where we draw random samples of trades from the data set (Figs. A.3 and A.4).[29] Applying the algorithm on these randomly constructed data sets, only about 1% are individually identified as vehicle trades, leading to virtually identical results to Table 3. And, as predicted by the null model, 0% remain identified as vehicle trades after deducting the false discovery control discussed in Section 2.

Appendix Table A.2 looks at the robustness of our results to the time window, using two-hour, five-hour and ten-hour windows. As can be seen in the table, as the time-window increases, the number of candidate vehicle trades increases. However, because the number of trades encompassed also increases as N_i increases, ceteris paribus, P increases, so that the number of trades that we identify as matched vehicle trades with at least a 95% confidence level decreases (Appendix A.1, Fig. A.2)

Most of the vehicle trades we identify appear to involve moving money internationally. In the 13% of trades identified as crypto vehicle trades, where the two trades matched involve different fiat currencies, the international dimension is obvious. Yet the share that is used for cross border transfers is likely much higher: Just over half of crypto vehicle trades use US dollars as the fiat currency of both trade legs. However, interpretating this result as meaning that 50% of all trades are domestic transactions within the United States (where the crypto vehicle trade mechanism must compete with highly efficient payment providers/methods, such as *Venmo*, *Zelle*, or the *ACH* network) would be ignoring the US dollar's role as de-facto (and at times de-jure) secondary, or even primary currency in many emerging markets. More to the point, the data from one of our two exchanges, Paxful, includes the trading parties' geolocation. Indeed, the largest country-pair for USD-to-USD vehicle trades, involves one party from the United States and one from Nigeria (35% of all USD-USD vehicle trades) – in line with the finding when only analyzing cross-country-flows on the basis of currencies involved. Based on the additional geolocation indicator for Paxful trades (and assuming the same would hold if we had geolocation data for LocalBitcoins), *90% of crypto vehicle trades are cross-border capital transfers.*

Fig. 3 below represent these world's 25 biggest channels graphically.[30] The fact the countries that feature prominently as both senders and receivers (e.g. Nigeria, Ghana, Venezuela, Argentina) are also countries known to have strong capital and exchange controls, strongly suggests that circumvention of such controls (both for outflows and inflows, i.e. remittances) is likely a major incentive for using crypto vehicle transactions.[31]

Fig. 4 lists the twenty highest volume crypto vehicle trade currencies, breaking them down into the share where the two matched transactions are in the same currency versus the share where the second currency differs. It is again notable that the currencies with the highest share of cross-currency transactions align well with countries that have had significant capital controls throughout the period, for example, Ghana, Argentina and Nigeria**.**

We reiterate that what we present are estimates of the identifiable share of trades that are crypto vehicle trades, with the true share – including trades not identifiable by our methodology – likely being much higher for several reasons, summarized in Table 4 below.

[29] For details see Appendix A2.

[30] These statistics are based on the identified trades using a five-hour window. Whenever we present ratios or shares of vehicle trades, we moreover consider any trade whose individual hypothesis test leads to a rejection of the match not being a vehicle trade with a 95% confidence level. Under the assumption that false-discoveries are homogenously distributed across our sample, the false-discoveries and numerators and denominators cancel out, so that the false-discovery-control is not required.

[31] We note that the Paxful geo data confirms that virtually all crypto vehicle transactions involving two different currencies involve accounts located in the two corresponding countries.

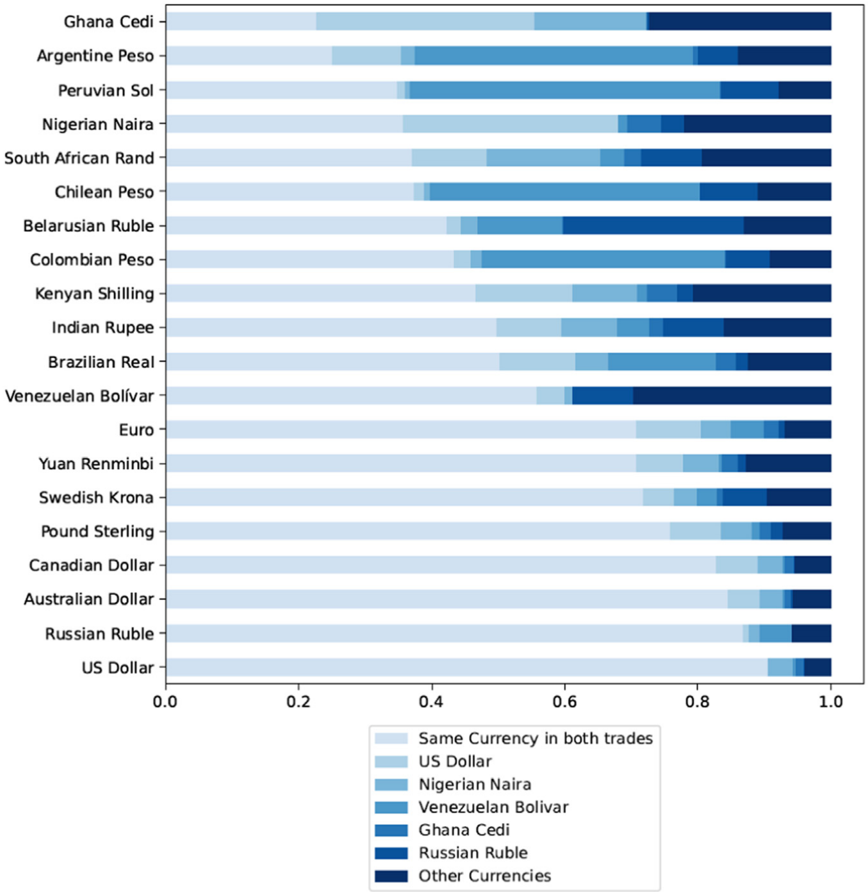

Fig. 3. 20 currencies with largest CVT volume and their most prevalent counterparty currencies. Source: LocalBitcoins.com API, Paxful.com API, Authors' Calculations.

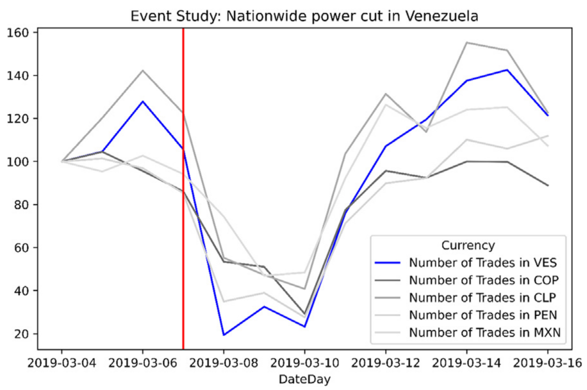

Fig. 4. Event Study: Nationwide Power Cut in Venezuela, March 2019.

5. Event study: República Bolivariana de Venezuela

In the prior section we have outlined reasons why the true share of crypto vehicle trades that is used to move money across borders is likely far higher than the share we can identify in the data. To underscore this point, it is interesting to consider the spillover effects of a massive unanticipated three-day power outage that took place in the Venezuela, starting March 7th, 2019.

Table 4
Factors leading to algorithm understating the share of trades being crypto vehicle trades.

Factor leading to algorithm understating	Explanation
The P2P platform is used only for one of the two legs	Imagine a remittance sending agent, working and living in a country with centralized exchanges and sending his remittances to a developing country, where the only platform available for Bitcoin trades is the P2P exchange. It might be cost efficient to purchase Bitcoin on the lower cost centralized exchange of the sending country, transfer it to the e-wallet of the P2P platform, and then sell it on the P2P platform in the destination country. Our algorithm would not detect this vehicle trade, as only one of two trades is recorded in our P2P data.
The amount in Bitcoin of the two legs might differ.	The algorithm only identifies a vehicle trade where the amount of Bitcoin for both legs is identical. Yet, some cases might exist, where an agent uses his wallet both for vehicle trades and speculative purposes, so the two amounts might differ. The same can happen when the best P2P price offer of the second leg is limited to a trade-size $Z < X$, when the agent to might split the second trade into two. The same could happen, when traders split trades in order to reduce caption risk, if our methodology became applied by regulators.
The two trades lie farther apart than our time window (five hours in the baseline case) allows.	Our algorithm does not match any two trades when the time difference between them exceeds 300 min (for a five-hour window). If the trader has access to a perpetual futures contract, that allows her to wait for better terms of trade on the destination country P2P market, this can allow her to accept much longer periods of exposure to Bitcoin price volatility.
The payment techno-logy in (at least) one country involved is slow.	Because the clearing time of the two trades is highly dependent on transfer technologies in the countries involved, our methodology might not capture trades from countries where the prevalent money transaction technology has a clearance time that exceeds the chosen window.
The trade is matched but wrongfully disregarded, because of the probability of it being matched by chance	The algorithm applies a conservative methodology in identifying trades, skewed towards reducing Type 1 errors (False-Identification as vehicle trades) at the cost of larger Type 2 Errors (disregarding a trade that indeed was a vehicle trade).
The parties involved in a planned trade cancel the transaction to complete it in cash and avoid the escrow fees	Whereas a 1% fee for the transaction amount of 100 USD hardly creates an incentive to face the potential risk and nuisance of a arranging an in-person transaction, anecdotal evidence suggests that agents seeking to make larger trades often seek to circumvent the fees by cancelling trades on the P2P platform and instead use the messenger function on to organize an exchange of the crypto currency for cash and in person. Offers by sellers - who as market makers pay the 1% fees, proposing to share the amount saved by avoiding the fees are indeed common on the platform.
The sending party is a market maker in one of the two trade-legs	Because the transactions' nominal trade size sold by a market maker would incorporate the exchange's 1% fee, the offsetting trade would no longer match, and our algorithm would not include the pair. As discussed, this point likely applies to most arbitrageurs' trades as well.

If a significant share of the trades indeed involve cross-border transfers, an exogenous shock that constrains the ability to trade Bitcoins in one currency should impact Bitcoin trade in other currencies that are a major destination for/origin for cross-border-flows from the affected country.

A major power-cut in the Venezuela that began on March 7, 2019, provides an interesting natural experiment.[32] The power-cut, caused by an incident at the country's major hydro-electric power plant at Guri Dam, left more than 30 million Venezuelans without electricity for more than 72 h. Many Bitcoin trades were obviously halted. A question worth asking is how this affected Venezuela's main trading partners' (as identified by our algorithm) Bitcoin trade volume.

The number of trades is normalized to 100 on March 4th, three days before the power cut. See Fig. A1 in the Appendix for the same graph, including a control group of countries not identified as engaged in Vehicle Trades with Venezuela. Source: LocalBitcoins.com API, Paxful.com API, Authors' Calculations.

Fig. 5 shows the results of the event study, comparing P2P trade volumes in Venezuela around the time of the power cut with the number of trades effectuated in four other currencies: the Mexican peso, the Peruvian sol, the Chilean peso and the Colombian peso—these have been important destinations in the Venezuelan diaspora.[33] The event study highlights (a) the importance of cross-border crypto vehicle trades in the Bitcoin market and (b) that the share we identify as crypto vehicle trades likely only represents a lower bound of the true volume of crypto vehicle trades.

Indeed, the results from this natural experiment suggest that for the Venezuela and its main cash transfer partners, crypto vehicle trades seem to constitute a very large share of total trades made, over 50% for Mexico, Peru, Chile and Colombia. It is instructive to compare Figs. 4 and 5. Fig. 4 shows at the share of cross-currency trade pairs (within the five hour window) out of all trades identified as transactions related, including for countries such as Peru, Chile and Colombia for each of which the share of identified vehicle trades that is cross-border amounts to around 60%, But in Fig. 5, the drop in these same countries' trade represents a fall as a share of *all* P2P trades, which is an order of magnitude larger.[34]

Consider the case of Peru, where the algorithm finds that at least 6.3% of all trades involving the Peruvian sol are crypto vehicle transactions. Of the 6.3%, 38% represent trades where the other fiat currency involved is the Venezuelan bolivar. If this estimate captured most of the action, then we would expect the collapse of the Venezuelan market due to the

[32] See *The Guardian*, "Venezuela: huge power outage leaves much of country in the dark", from March 8th, 2019

[33] See also Matt Ahlborg's medium post from March 24, 2020 for a related discussion (https://medium.com/open-money-initiative/latin-american-Bitcoin-trading-follows-the-heartbeat-ofvenezuela-71a28cb86ba0).

[34] Importantly, we have not found any evidence that these countries were affected by the power-cut directly.

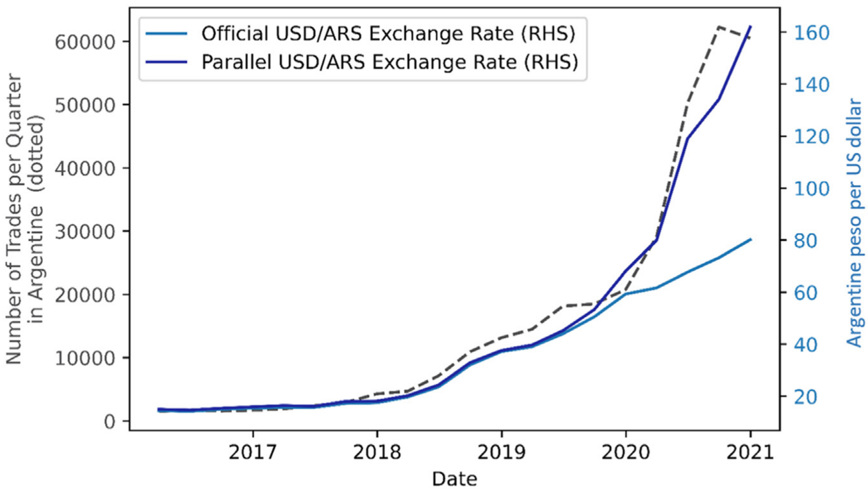

Fig. 5. Example of Bitcoin market expansion coinciding with capital controls in Argentina Source: LocalBitcoins.com API, BlueDollar.net, Authors' Calculations.

electricity shutoff to lead to an approximately 2.3% reduction in trades in Peruvian sol during the blackout (0.38 times 6.1%). Instead, as Fig. 5 shows, the actual drop in trades was around 60%. Of course, this does not suffice to arrive at a more precise estimate of the crypto vehicle trade-share in Peru, since secondary non-linear effects were likely at play (such as less liquidity driving up prices and pushing many out of the market). Yet it provides strong evidence that the estimates we provide are only minima of the real underlying share of trades that are used for crypto vehicle transactions.[35]

6. Extensions and applications

6.1. Crypto trades as a window into the parallel exchange rate market

Because multicurrency crypto exchanges create a mechanism for converting one fiat currency into another (*via* trading quickly in and out of crypto), they provide, in effect, a parallel exchange market.[36] To illustrate, Fig. 6 presents the results of another case study, the case of Argentina in 2019 when substantial capital controls were imposed, giving rise to parallel markets for dollars and other hard currency. The figure presents the number of LocalBitcoins trades in our data set where the Argentine peso is involved in a trade.[37] The rapid expansion of the Bitcoin market in Argentina, occurring in lockstep with the rise of the parallel market premium, is consistent with crypto vehicle trades having become an important parallel exchange market and thus the 21st century's novel channel for capital control evasion.

Although generally of little consequence for 21st century advanced economies, the parallel market exchange rate can be an extremely important piece of information for investors and policymakers in developing economies where the official exchange rate is supported, in part, through restrictions and rationing.[38]

Why are parallel rates of such great interest to policymakers? First, as a number of studies have shown, significant premia in the parallel market can be a signal of deep economic distress and often constitute strong predictors of future official exchange rate changes (where the distorted official rate "concedes" to the market-based parallel rate).[39] The parallel market exchange rate tends to be a much better barometer of price inflation, in general, than the official rate. For a macroeconomist working on a developing country, knowing the parallel premium is one of the most valuable pieces of information on the economy. But availability is a major problem. Much like finding street price data on illegal drugs, collecting parallel market exchange rate data can be highly problematic. Whereas there can be exceptions, most of the time, this valuable data is very sparse. Crypto market data, by contrast, are quite transparent and readily available. And, as we show by means of four

[35] We note, however, that the gap between our algorithm's estimate and the true measure of crypto cross-country vehicle trades might be particularly large for transactions involving Venezuela's currency, where lags in fiat money payments are likely to take much longer than for most other countries, given the country's economic dysfunction during this period. Thus, our maximum 5 h window (and even the 10 h window results included in the appendix) is likely to miss the majority of crypto-vehicle transactions involving Venezuela – a hypothesis supported by the event study.

[36] The idea that crypto markets might be used to infer parallel exchange rates has been made previously in an important early contribution by Pieters (2016). Their paper, however, has data for only a handful of emerging markets, which does not allow the application of our algorithm to discriminate market frictions from premia of economic significance. The issue of whether the parallel market is actually used for transactions is also not addressed.

[37] As is discussed by Ilzetzki, Reinhart and Rogoff (2019), inter alia, the rise of a parallel market for hard currency is the best market-based indicator for the existence of capital controls.

[38] This graph does not use Paxful data since the exchange had no or close to no trading activity in Argentina for most of the period concerned.

[39] Reinhart and Rogoff (2004) and more recently Gray (2021) and Farah Yacoub et al. (2022), among others, show that the parallel premia is strong predictor of future exchange rate changes.

examples in Graf von Luckner et al. (2022), when parallel rates exist, the relative price of Bitcoin on exchanges such as Paxful and LocalBitcoins appears to move in lockstep with the estimates of the parallel rate. Yet not every relative price premium in Bitcoin presents proof of a parallel market. Bitcoin markets are often shallow and subject to volatile regulatory regimes, so there remain factors other than capital controls that can give rise to premia in the bitcoin market. Thus, while Bitcoin prices are already an important real time indicator today, it remains important to consider factors such as market depth before making conclusions about the existence of a parallel (black) market for hard currency.

6.2. Applying the methodology to other exchanges and for other purposes

We have explored comprehensive off-chain transactions data from the world's largest peer-to-peer crypto exchange platforms over the past five years. The analysis provides evidence that strongly suggests that Bitcoin is used actively as a vehicle currency in international transactions; in most countries it is also used extensively as vehicle for domestic currency transactions. This evidence runs counter to the oft-expressed view of crypto currencies as a purely speculative asset class; this is not the case in emerging markets and low-income developing economies. Off-chain Bitcoin is used for transactional purposes, including for cross-border flows and the exchange of one fiat currency into another. As we have emphasized, the nature of the data and, in particular, our approach to tracing transactions price and currency is completely different than in any previous research, virtually all of which has focused on analyzing on-chain transactions.

In principle, our methodology can be applied to any more targeted investigation of a particular country/region, as well as to data from any exchange that identifies trades in terms of the fiat currency used to purchase crypto. Of course, when applying our methodology to data from other exchanges, one must account of their individual structure and features, including the fee structure and the average speed of clearing fiat money payments; note that our methodology can also be applied to assess the probability of a single pair of trades constituting a crypto vehicle transaction for any time window (which could be one minute or one week) and for any probability threshold (which could be, say 80% instead of 95%); in some exchanges high-frequency trades might be arbitrage although due to the fee structure, this is highly unlikely in the two P2P exchanges we analyze.[40]

Although data from many exchanges is private, regulators can typically access data from centralized exchanges in their own local jurisdiction, or potentially beyond that given sufficient international cooperation. Regulators might, for example, use this algorithm to identify suspicious cases for which they can make targeted requests for IP addresses from exchanges. Our approach also allows researchers to show how cryptocurrencies are used for off-chain capital flows and transactions, without requiring knowledge of private data.

7. Conclusions

The results of this paper challenge the dominant view that Bitcoin is little used for transactions purposes (other than buying other cryptocurrencies), and that its value is almost entirely based on speculation. In fact, there is already a growing market for using crypto as vehicle currency for transactions in developing economies and emerging markets, especially for international capital flight and evading exchange controls. Given that the global underground economy (including tax and regulatory evasion) is quite substantial, perhaps as much as 20% of global GDP,[41] the value to an innovation that helps facilitate these "illegitimate" transactions could be very substantial, particularly if regulators cannot, or choose not, to curtail it.

Although the results here cover only two of the many off-chain Bitcoin markets – albeit historically important ones – it is precisely these two that have the global reach and publish the necessary data to give a window into transactions use in the larger universe of Bitcoin. Such insights are scarce precisely since most exchanges are, by design, opaque; that is how users prefer it. By way of loose analogy, outside of occasional publicity surrounding law and tax enforcement, there is very little hard evidence on the transactions use of large denomination notes worldwide (e.g., $100 bills); yet these notes account for more than 80% of the global paper currency supply (Rogoff, 2016). The extremely limited number of small-scale central bank surveys on paper currency modest as they are, have proven quite useful benchmarks for analysis. Here, similarly, having hard quantitative evidence that Bitcoin is indeed being used for international transactions, especially in lower-income economies, is also potentially valuable. Moreover, our approach offers a road map to encompass other markets if and when the requisite detailed data becomes available.

Already, there exist off-chain markets – and couple of which already have vast global reach – that can be used to develop new ways of estimating parallel exchange rate premia that are extremely valuable to policymakers and investors. Even if transactions use of cryptocurrencies were taking place almost exclusively in middle- and low-income countries, this could form part of the basis for valuation of crypto in advanced economy portfolios.[42]

We do not comment here on the future of Bitcoin regulation, but one can certainly infer from these results that any country aiming to institute or maintain capital controls will also need to find a way to prevent these from being circum-

[40] Similarly wash trades, a common and unregulated phenomenon in crypto markets (Cong et al., 2022; Le Pennec et al., 2021), can also be controlled, by assessing international capital flows exclusively.

[41] See Medina and Schneider (2018) and Rogoff (2016).

[42] For a discussion of the impact of regulation on cryptocurrency prices, transactions and user bases, see Auer and Claessens (2018).

vented *via* crypto (in addition to the plethora of "traditional" methods), and that regulation will be much more effective if there is widespread international cooperation.[43] Transactions use may not yet significant in advanced economies, but already appears to having significant macroeconomic impact elsewhere.

Data availability

Data will be made available on request.

Appendix

A.1 Robustness Check - Applying different Time Windows

As Table A.2 and Fig. A.2 show, our main result, that Bitcoin is used for crypto vehicle trades is robust to the selection of the time-window. However, the two illustrations also show that whereas the number of matched trades increases with longer time-windows considered to identify matching trades, the number of trades that happen within the time window considered, N_i, must increase also, meaning that ceteris paribus, θ_i^* increases, so that the number of trades that we identify as matched vehicle trades with at least a 95% confidence level eventually decreases. To choose a time window from the selection of time-windows applied, we applied a decision rule that imposed moving to the next longer time-window whenever the impact of matching new trades that were missed using the shorter time window is greater than the number of trades that are no longer considered in a longer time-window, because of the greater number of trades, N_i.

Table A.1
Algorithm output example.

Timestamp 1st trade	Currency 1st trade	Trade size x_i (1st and 2nd trade)	Timestamp 2nd trade	Currency 2nd trade	p_i	N_i
2020–11–01 01:12:43	USD	0.00202160	2020–11–01 02:03:431	VES	0.0000763	4083

Note: The matched trade presented in this table would not be considered a Crypto Vehicle trade, as the probability of the amount of 0.0020216 Bitcoin occurring, p_i in conjunction with the number of trades that occurred within five hours after the first trade, N_i, leads to a probability of this match being random that is greater than the 0.05 threshold.

Table A.2
Robustness check: time windows compared.

	(1) 2h Window	(2) 5h Window	(3) 10h Window	(3) 24h Window
Number of trades with one match	17,076,838	17,936,236	18,802,132	20,244,038
Number trades identified as vehicle-trade with (P(Match is Random) $<$ 0.05), d_i	16,25,962	16,568,776	16,178,522	11,454,968
Number trades identified as vehicle-trade with (P(Match is Random) $<$ 0.05), d_i net of False Discoveries from multiple hypothesis test, c_i	13,920,178	14,283,813	12,854,589	8,335,910
Share of trades identified as vehicle-trades, φ	10.8%	11.1%	10.0%	6.5%

Formally, let $y(t)$ be the number of trades identified with a 95% confidence interval, as a function of the time-window, t, and define $z(t)$ as the number of trades that are disregarded, (although they are matched), because the individual test's $\theta_i^* > 0.05$. Then, our decision rule chooses the next longer time window as long as:

$$\frac{dy}{dt} > \left|\frac{dz}{dt}\right|$$

Finally, note that regardless the length of the time window, applying overlapping time-windows, meaning a single time window for each trade, allows us to update the information for every trade, however it also means a departure from the strict independence between individual hypothesis tests, because a matching trade in the previous five-hour window would de facto reduce the trades of the following window by one. Although the large number of trades in each window renders

[43] Controls on crypto also need to be included in any "new age" measure of controls on international capital movements. For example, the International Monetary Fund has recently argued for explicitly incorporating controls into fully defining a country's exchange rate regime (see also Ilzetzki et al. 2019, Erten et al. 2021 and Basu et al. 2020). If so, then transfers *via* cryptocurrencies increasingly need to be accounted for.

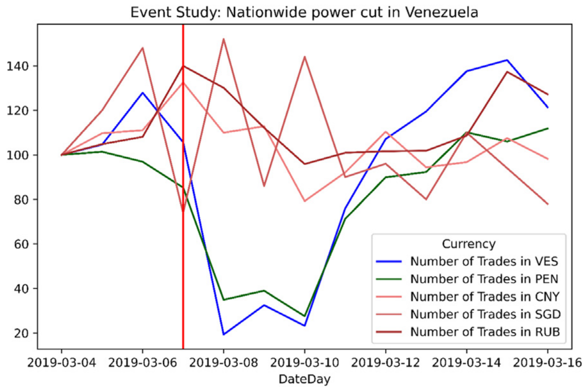

Fig. A.1. Crypto trades in currencies without significant vehicle trade volume to/from Venezuela around the power cut in Venezuela, compared to one currency (PEN) with significant vehicle trade volume with Venezuela. Sources: LocalBitcoins.com API, Paxful.com API, Authors' Calculations.

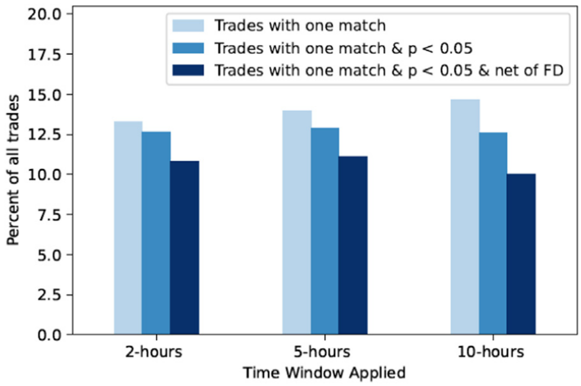

Fig. A.2. Time windows compared.

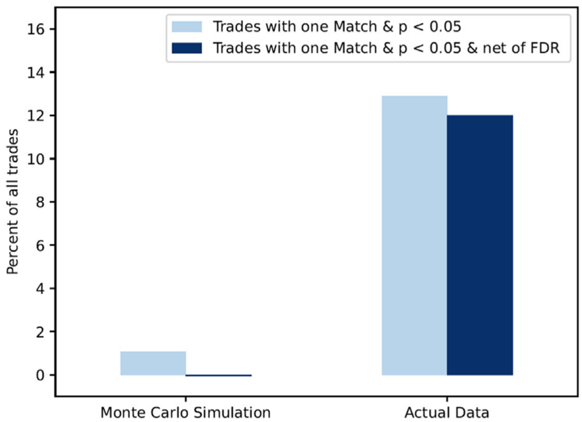

Fig. A.3. Monte Carlo simulation result compared to real results.

the impact of the departure negligible, as a robustness check, we applied an alternative approach, where we apply distinct and non-overlapping time-windows, thus guaranteeing the independence between distinct hypothesis tests.[44] The results are available upon request. The alternative algorithm differs from the original approach, in that we concentrate on separate, non-overlapping five-hour windows, and analyze the number of times each trade size occurs in these five-hour windows. However, the results suggest that the impact (of the overlapping windows), if any, is negligible.

[44] The authors are extremely grateful for Neil Shephard for suggesting this robustness test and suggesting the proof of unbiasedness.

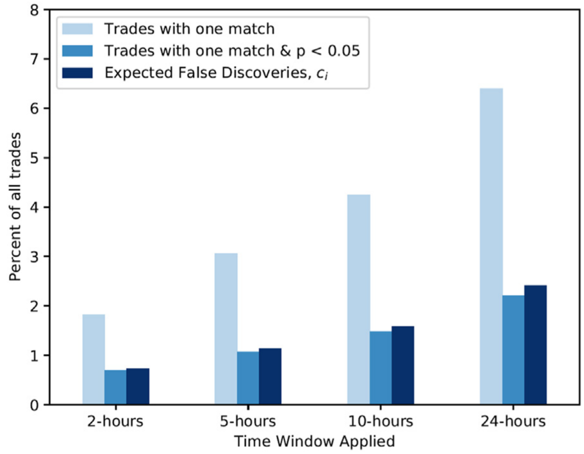

Fig. A.4. Monte Carlo Simulation using different time windows.

A.2. Monte Carlo Simulation of trade matching in randomly drawn samples

Our vehicle trade identification algorithm relies on the assumption that identifying the same trade size twice within a short time window is unlikely to happen purely by chance, given the fact that trade sizes are specified to the 8th decimal place and given the historical distribution of different trade sizes being sufficiently widely spread (i.e., the algorithm would not prove efficient in a world, where all trades were to be of the same trade-size, regardless how many decimal places that number has). We support this assumption by running a Monte Carlo simulation, using a pair of randomly matched trade size and number of trades within five hours before and including the time of the trade and equally as many trades randomly drawn from the real historical distribution, to analyze how many vehicle trades are identified as such purely by chance. This simulation proceeds as follows:

1. Based on the data since 2017 we record in our sample; we derive two quasi-random variables for the trade-size and number of trades occurring within five hours. We therefore define the trade-size

$$x_i \sim X()$$

and the number of trades within five hours,

$$N_i \sim \Theta(\,)$$

where, $X()$ and $\Theta()$ are probability distribution functions based on the historical distribution of trade sizes and number of trades occurring within five hours, respectively.

2. We then draw 1000,000 random pairs of xi and Ni from X() and Θ().[45]
3. For each pair (xi, Ni), we further draw a random multiset, Si with Ni elements from X().
4. We count the number of instances, where xi occurs in Si,

$$\sum_{s \in S} 1_{s=x} \geq 1$$

and the probability

$$P\left(\sum_{s \in S} 1_{s=x} \geq 1\right) = 1 - (1 - p_i)^{N_i} < 0.05$$

where, p_i is the unconditional probability of x_i being drawn from X().

In short, we replicate the trade vehicle identification algorithm on randomly drawn subsets of the data, whereby the trade-sizes have been shuffled and randomly matched with numbers of trades within five hours. If it were true that rather than true instances of vehicle trades, our algorithm identified trades that randomly happen to have the same trade size, the share of trades identified as vehicle trades should be approximately the same in the Monte Carlo simulation and our algorithm's output. Instead, in the Monte Carlo simulation 1.1% of trades that find a match are whose individual hypothesis

[45] The exercise yields similar results even for much a much smaller number of draws, e.g., 10,000 draws.

test leads to the conclusion that they are indeed crypto vehicle trades. This number is significantly lower than the share of trades identified with the same methodology applied to the real data.

Of course, because the sample is randomly drawn, all of the vehicle trades identified within such a data set must be false positives. Applying the False-Discovery control we introduced in Section 2 should thus control for these false-positives and lead to a share of crypto-vehicle trades identified close to or equal to zero. And indeed, when deducting the share of expected false positives given the data structure in the Monte Carlo simulations, we arrive at an estimate of crypto vehicle trades equal to 0%.[46] Again, this result stands in stark contrast to the 11.1% of trades being identified as crypto vehicle trade (net of False Discoveries) found in the real data.

A.3. Crypto vehicle trade volume estimate

For the largest part of the paper, we ask what share of trades in our dataset are likely to be Crypto Vehicle Trades. An equally important question, especially for the capital flow related literature, would be the size of the transfer volume that is associated with crypto-vehicle-trading. The following extension of the methodology allows us to arrive at unbiased estimate of measurable crypto vehicle trade volume, γ, while controlling for false discoveries.

Whereas Assumption 1 and Definitions 2 and 3 remain the same as in the original methodology, the “vehicle trades volume estimand” is now equal to

$$\gamma = \sum_{i=1}^{I} x_i\, \alpha_i \left(\theta_i - \theta_i^*\right) with\ \alpha_i = \begin{cases} 1\ if\ \theta_i^* < \Theta_\theta \\ 0\ if\ \theta_i^* \geq \Theta_\theta \end{cases}$$

We thus arrive at what can be thought of as a thresholding device, with the estimated volume of vehicle trades discovered being equal to:

$$\hat{\gamma} = \sum_{i=1}^{I} x_i\,(d_i - c_i)$$

Theorem 4 still holds, because both the estimator and the estimand were adjusted in the same fashion:

Theorem 4b.

$$\mathrm{E}[\hat{\gamma} \mid N_{i,\,\ldots,\,I}] = \varphi$$

Proof.

$$\mathrm{E}[\hat{\gamma} \mid N_{i,\,\ldots,\,I}\Big] = \sum_{i=1}^{I} x_i\,(E\,[d_i \mid N_i\Big] - c_i)$$

$$= \sum_{i=1}^{I} x_i\,\alpha_i\,(E\,[\phi_i \mid N_i] - \theta_i^*)$$

$$= \gamma$$

A.4. Data appendix

The core data set makes use of data from the Application Programming Interface (API) published by LocalBitcoins.com and Paxful.com respectively. In principle, the data, made available in JSON format, goes back to the year 2013 (Paxful’s first data become available after 2015). However, the standards have seen some changes over the period prior to March 2017. Which is why, for our analyses, we concentrate on the trades that occurred between March 15, 2017 and May 3rd, 2022. The trades are grouped and thus retrieved by fiat currency. For each of the observations we retrieve, there exists a unique trade id, the timestamp (converted to a UTC ISO format), the trade size, expressed in Bitcoin, and the price paid (expressed as the price of one Bitcoin in the given fiat currency). Paxful.com further provides data on payment methods and the geolocation of the user and advertiser involved in the trade. Though not described in the Paxful’s API documentation, for both market-makers and counterparties, the API provides information on both parties’ “country”.[47] The data does not

[46] More precisely, -0.06% of trades are identified as vehicle trades in the randomly shuffled data set. The estimate being negative stems from the fact that the Monte Carlo simulation only considers instances with exactly one match, whereas the False-Discovery-Control per se also considers instances where there is more than one match, meaning the latter is slightly greater than the former, meaning subtracting the latter from the former results in a number smaller than 0. Because under the null hypothesis it is extremely rare for trades to find two matches within a five-hour-time window, the impact of this difference on the results is negligible.

[47] Because the documentation does not mention these variables as part of the documentation on what the access-point is supposed to provide to the requesting party, it is unclear, whether these countries are the country of origin, residence or IP location at the time of the trade. It is possible that this data provision itself is a bug.

include identifiers of the trading partners. Because the trades are retrieved by fiat currency, we add that information to each observation. The fiat currencies included in the data from LocalBitcoins are:

UAE Dirham, Afghani, Albanian Lek, Armenian Dram, Netherlands Antillean Guilder, Kenyan Kwanza, Argentine Peso, Australian Dollar, Aruban Florin, Azerbaijan Manat, Bosnia & Herzegovina's Convertible Mark, Barbados Dollar, Bangladeshi Taka, Bulgarian Lev, Bahraini Dinar, Burundi Franc, Bermudian Dollar, Brunei Dollar, Boliviano, Brazilian Real, Bahamian Dollar, Botswana Pula, Belarusian Ruble, Belize Dollar, Canadian Dollar, Congolese Franc, Swiss Franc, Chilean Peso Chinese Offshore Renminbi, Chinese Yuan Renminbi, Colombian Peso, Costa Rican Colon, Peso Convertible, Czech Koruna, Danish Krone, Dominican Peso, Algerian Dinar, Egyptian Pound, Eritrea Nakfa, Ethiopian Birr, Euro, Fiji Dollar, Pound Sterling, Georgian Lari, Ghana Cedi, Gambian Dalasi, Guinean Franc, Guatemala Quetzal, Guyana Dollar, Hong Kong Dollar, Honduras Lempira, Croatian Kuna, Haiti Gourde, Hungarian Forint, Indian Rupiah, New Israeli Sheqel, Indonesian Rial, Iraqi Dinar, Iranian Rial, Iceland Krona, Jamaican Dollar, Jordanian Dinar, Japanese Yen, Kenyan Shilling, Kyrgyz Som, Cambodian Riel, Korean Won, Kuwaiti Dinar, Cayman Islands Dollar, Kazakhstan Tenge, Lebanese Pound, Sri Lanka Rupee, Liberian Dollar, Lesotho Loti, Moroccan Dirham, Moldovan Leu, Malagasy Ariary, North Macedonian Denar, Myanmar Kyat, Macao Pataca, Mauritius Rupee, Maldives Rufiyaa, Malawi Kwacha, Mexican Peso, Malaysian Ringgit, Mozambique Metical, Namibia Dollar, Nigerian Naira, Cordoba Oro, Norwegian Krone, Nepalese Rupee, New Zealand Dollar, Rial Omani, Panama Balboa, Peruvian Sol, Papua New Guinea Kina, Philippine Peso, Pakistan Rupee, Polish Zloty, Paraguayan Guarani, Qatari Rial, Romanian Leu, Serbian Dinar, Russian Ruble, Rwanda Franc, Saudi Riyal, Seychelles Rupee, Sudanese Pound, Swedish Krona, Singapore Dollar, Saint Helena Pound, Surinam Dollar, South Sudanese Pound, Syrian Pound, Eswatini Lilangeni, Thai Baht, Tunisian Dinar, Turkish Lira, Trinidad and Tobago Dollar, New Taiwan Dollar, Tanzanian Shilling, Ukrainian Hryvnia, Uganda Shilling, US Dollar, Peso Uruguayo, Uzbekistan Sum, Venezuelan Bolívar Soberano, Vietnamese Dong, CFA Franc BEAC, East Caribbean Dollar, CFA Franc BCEAO, Yemeni Rial, South African Rand, Zambian Kwacha, Zimbabwe Dollar.[48]

Further, Paxful.com's data includes the following currencies:

Guinean Franc, Malawi Kwacha, Lebanese Pound, Tanzanian Shilling, Vietnamese Dong, Ethiopian Birr, Danish Krone, Iceland Krona, Uganda Shilling, Cabo Verde Escudo, Tala, Ghana Cedi, Peruvian Sol, Pound Sterling, Georgian Lari, Guernsey Pound, Unidad de Fomento, Czech Koruna, Iraqi Dinar, South African Rand, Australian Dollar, Korean Won, Moldovan Leu, Indian Rupee, Denar (N. Macedonia), Ngultrum (Bhutan), Hong Kong Dollar, Malaysian Ringgit, Swedish Krona, Kina (Pappua New Guinea), Indonesian Rial, Forint (Hungary), Tenge (Kazakhstan), Tugrik (Mongolia), Argentine Peso, Ouguiya (Mauritius), Rwanda Franc, CFA Franc BEAC, Yemeni Rial, Dobra, Polish Zloty, Boliviano, Vatu, Romanian Leu, Singapore Dollar, Kyat (Myanmar), Dominican Peso, Bangladeshi Taka, Belarusian Ruble, Brazilian Real, Namibia Dollar, Bahamian Dollar, Lao Kip, Lempira (Honduras), Mauritanian Ouguiya (discontinued), São Tomé And Príncipe Dobra (pre-2018), New Zealand Dollar, Mexican Peso, Kuna (Croatia), Turkish Lira, Pataca (Macao), Tunisian Dinar, Afghani, Trinidad and Tobago Dollar, Moroccan Dirham, Belize Dollar, Fiji Dollar, Sri Lanka Rupee, Thai Baht, Qatari Rial, Bahraini Dinar, Mozambique Metical, Isle of Man Pound, Cambodian Riel, Somali Shilling, Colombian Peso, UAE Dirham, Serbian Dinar, Kuwaiti Dinar, Peso Uruguayo, Venezuelan Bolívar (VEF, VES and VED), Leone (Sierra Leone), US Dollar, Canadian Dollar, Zambian Kwacha, Comorian Franc, Rial Omani, Hryvnia, Nepalese Rupee, Yuan Renminbi, Russian Ruble, Pakistan Rupee, Malagasy Ariary, Surinam Dollar, Netherlands Antillean Guilder, North Korean Won, Albanian Lek, El Salvador Colon, Cayman Islands Dollar, Paanga, Azerbaijan Manat, Guyana Dollar, Saint Helena Pound, Saudi Riyal, Falkland Islands Pound, Euro, Bulgarian Lev, CFA Franc BCEAO, Jersey Pound, CFP Franc, Uzbekistan Sum, Gourde (Haiti),Guatemalan Quetzal, Kwanza (Angola), Djibouti Franc, Balboa, Congolese Franc, Yen, Cordoba Oro (Nicaragua), Barbados Dollar, Armenian Dram, Solomon Islands Dollar, Pula (Botswana), Norwegian Krone, Bermudian Dollar, Chilean Peso, Gibraltar Pound, Jamaican Dollar, Rufiyaa (Maldives), New Taiwan Dollar, Aruban Florin, Liberian Dollar, Loti (Lesotho), Algerian Dinar, Jordanian Dinar, Kenyan Shilling, New Israeli Sheqel, Som (Kyrgyzstan), East Caribbean Dollar, Seychelles Rupee, Eritrean Nakfa, Somoni, Swiss Franc, Guarani (Paraguay), Mauritius Rupee, Dalasi (The Gambia), Burundi Franc, Costa Rican Colon, Turkmenistan New Manat, Philippine Peso, Egyptian Pound, Lilangeni (Eswatini), Zimbabwe Dollar, Convertible Mark (Bosnia-Herzegovina), Brunei Dollar, Nigerian Naira

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[48] Additional to the 163 fiat currencies, the dataset includes three further non-traditional-fiat-currency means of payments: silver, gold, and Ethereum (9127 trades), but as these represent less than 0.1% of all trades, we disregard in them in the further analysis. It is important to note that the transaction volume in each of these currencies can differ widely, with some currencies seeing only a small number of trades over the period we study.

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