Decrypting New Age International Capital Flows

Graf von Luckner, Reinhart and Rogoff

March 28, 2023
Motivation

1. Lack of legitimate transactions use underpins the view of Bitcoin as purely speculative asset without real value.

2. Models which rationalize a positive inherent value invariably base it on transactions use (Athey et al., 2016; Fernandez-Villaverde and Sanches, 2019; Schilling and Uhlig, 2019; Bolt and van Oordt, 2020; Biais et al., 2022 etc.)

3. Where and when Bitcoin markets thrive, seems to be anything but random:
We develop an algorithm that provides first evidence on Bitcoin being used to move capital across borders, and/or exchange one fiat currency for another.

- Within the off-chain dataset we analyse, at least 11% of trades are used for such transfers.
- Bitcoin appear to be used to circumvent taxes and regulations, i.e. to evade restrictions on international capital flows and foreign exchange transactions, including on remittances.
- The use case we find is most prominent emerging markets.
Content

- Conceptually: How to move capital through crypto vehicles?
- The algorithm: Identifying crypto vehicle trades in off-chain data
- Findings
- Additional evidence: event study (and some anecdotal evidence)
Moving capital through cryptocurrencies in theory
Moving capital through cryptocurrencies in theory
Moving capital through cryptocurrencies in theory

P2P Exchange

$\rightarrow$ Bitcoin

A's Offshore Investment/Bank Account

Outside Country of A

Inside Country of A

A

P2P Exchange
How to identify Crypto Vehicle trades in Bitcoin Data
The data

- **Novel dataset of 128 million off-chain P2P trades** via LocalBitcoins.com and Paxful.com, the world’s biggest P2P Exchange Platforms

<p>| | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of Trades</td>
<td>128 493 700</td>
</tr>
<tr>
<td>USD Trade Volume</td>
<td>USD 19 billion</td>
</tr>
<tr>
<td>Average Trade Size (USD)</td>
<td>148</td>
</tr>
<tr>
<td>Largest Trade Size</td>
<td>USD 2.3 million</td>
</tr>
<tr>
<td>Number of Fiat Currencies</td>
<td>163</td>
</tr>
</tbody>
</table>

- **Differs from Blockchain data in that:**
  - It includes information on fiat currencies used and prices paid for the crypto currency
  - The timestamp is an accurate reflection of time of execution (not affected by potential queuing)

For details on the difference between on-chain and off-chain data
Can one identify Crypto Vehicle trades in the data?

- **Given:** trade-size, fiat-currency used, price in fiat-currency and timestamps of about 128 million individual trades since 2017.
  - Every Bitcoin has 100 million Satoshi, so every Bitcoin trade size has 8 decimal points
  - 66% of all trade sizes occur only once or twice within our sample.

- **Key Assumption:** Bitcoin vehicle traders aim to minimize exposure to the volatile Bitcoin prices and thus sell all the purchased Bitcoin as quickly as possible.

- **Evidence in support of this Assumption**

- **Idea:** Matching Snowflakes: Identify equal trade sizes reoccurring within short time windows.
The Identification Algorithm

In two parts:

1. Identification of individual crypto vehicle trade

2. Estimation of the share of trades that are crypto vehicle trades.
The Identification Algorithm - for individual trades

1. Each trade in sample, \( i \), has a trade-size \( x_i \).

2. Define \( n_i \) as the number of times that the trade size \( x_i \) occurs within five hours prior to trade \( i \).

3. We are interested in times when \( n_i > 0 \).
   - But this could happen just by chance, when many trades happen in five hours, or when the trade size \( x_i \) is common, exempli gratia 1.00000000 Bitcoin.

4. To evaluate the random-match-hypothesis, we require a null hypothesis: Matches being random.

**Assumption 1 - The null model:** Assume trades of any size \( x_k \) appear as independent Poisson processes. The Poisson process intensity being the product of \( p_k \) (the probability of any new trade having the size \( x_k \)), and the number of arrivals of trades over the time period of interest.
The Identification Algorithm - for individual trades

Under the null, the probability of a trade finding a match is like that in a multinomial draw:

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

For a detailed discussion

Where we will estimate $p_i$ based on data prior to $t$:

$$\hat{p}_i = \frac{\sum_{i=1}^{I_t} 1\{x_i = x_k\}}{I_t}$$

**Definition 1 - Discovery** We declare a discovery, when we find $n_i > 0$, and can reject

$$H_{(0,i)} : \hat{\theta}_i^* \geq \Theta_{\theta}$$

Example
The Identification Algorithm - trade share estimand

- Sum of individual hypothesis tests would create an inflated share of trades. Biased equal to Θ at most.
- Multiple hypothesis tests ⇒ need to net false discovery rate.
- False discovery rate derived from Null model
  \[ \sum_{i=1}^{l} \hat{\theta}_i^* \] serves as an estimate of the number of matches to expect in a data set without vehicle trades.
- Allows us to control for the expected False Discovery Rate, and thus arrive at an unbiased estimate of the share of trades that are crypto vehicle trades.

For a detailed discussion and proof of unbiasedness
## Findings

### Table: Crypto Vehicle Trades

<table>
<thead>
<tr>
<th>Description</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total Number of trades</td>
<td>128,493,700</td>
</tr>
<tr>
<td>Number of trades with one match</td>
<td>17,936,236</td>
</tr>
<tr>
<td>Number of trades identified as vehicle trades</td>
<td>16,568,776</td>
</tr>
<tr>
<td>Net of expected False Discoveries</td>
<td>14,283,812</td>
</tr>
<tr>
<td>Share of total trades identified as vehicle trades</td>
<td>11.1%</td>
</tr>
</tbody>
</table>

For structural reasons why 11.1% is likely a lower bound.
Findings

**Figure**: The World’s 25 biggest Crypto Vehicle Channels. **Circles**: Origin, **Triangles**: Destination. **Line-width**: Channel volume as share identified trade volume in Origin Currency.
Robustness Checks & Additional Evidence
Robustness Checks & Additional Evidence

- Applying different time-windows See Appendix
- Apply algorithm to randomly shuffled dataset $p_i$ See Appendix
**Figure:** Event Study: Guri-Dam Power-cut in Venezuela between March 7th and March 9th 2019

<table>
<thead>
<tr>
<th>Currency</th>
<th>COP</th>
<th>MXN</th>
<th>PEN</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Share of Total Trade Identified</td>
<td>6.5% (42%)</td>
<td>6.6% (30%)</td>
</tr>
<tr>
<td></td>
<td>(Share of id. trade volume in base currency with VES as origin or destination)</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
**Figure:** Bitcoin Trades as parallel market is born (once again) in Argentina in 2019.
“The plural of anecdote is data”

— Raymond Wolfinger
Anecdotal Evidence from Lebanon - Crypto Vehicle Trades used to evade Capital Controls during the Lebanese Conglomerate Crisis 2021

OTC Exchange in Beirut - Estimated On-Chain Bitcoin transactions between 2019 - 2021:

> US$ 35 million.
Anecdotal Evidence

Anecdotal Evidence from Lebanon - Crypto Vehicle Trades used to evade Capital Controls during the Lebanese Financial Crisis 2021

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Cryptocurrencies serve as a channel for transactions between fiat currencies, especially when capital controls aim at impeding such transfers.

This use cases for Bitcoin challenges the view of Bitcoin as a purely speculative bubble.

International capital flows through Crypto Vehicle Trades remain off the radar of any stock taking agency (similar to transactions with large denomination cash (Rogoff, 2016)).

Possible Policy Implications: Capital controls = Crypto Controls

Outlook: Rise of stable coins - accelerator of crypto vehicle trades or beginning of the end of Bitcoin?
Appendix
(1) Bitcoin price puzzle: staggering evaluation without an evident use case.

Source: Yahoo Finance
On Chain vs Off-Chain
Around 99% of all trades occur off-chain.
The estimate of $p_i$ - the probability of a randomly drawn trade size having size $x_i$ is based on:
Appendix: The Identification Algorithm

- Because we can condition on the discrete number of trades occurring within the 5-hour time window after trade $i$
  
  \[ n_i, \quad |N_i| \sim \text{MultiN}(N_i; p_i) \]

- Under this model, the probability of a trade occurring at least once in the five hours prior to a trade is thus:
  \[ \hat{\theta}_i^* = 1 - (1 - \hat{p}_i)^{N_i}, \quad i = 1, \ldots, I. \]

- $\hat{\theta}_i^*$ allows us to
  (A) estimate the probability of any trade finding a match randomly; and thus
  (B) set a threshold below which we consider a trade likely to be vehicle trade.
<table>
<thead>
<tr>
<th>Timestamp 1st trade</th>
<th>Currency 1st trade</th>
<th>Trade size ( x_i ) (1st &amp; 2nd trade)</th>
<th>Timestamp 2nd trade</th>
<th>Currency 2nd trade</th>
<th>( p_i )</th>
<th>( N_i )</th>
</tr>
</thead>
<tbody>
<tr>
<td>2020-11-01 01:12:43</td>
<td>USD</td>
<td>0.0020216</td>
<td>2020-11-01 02:03:31</td>
<td>VES</td>
<td>0.0000763</td>
<td>4086</td>
</tr>
</tbody>
</table>

\[
\theta_i^* = 1 - (1 - 0.0000763)^{4086} \approx 0.26785
\]
Appendix: The Identification Algorithm

- Let $\Theta_\theta \in [0; 1]$ be some preset number, in our case we set it to 0.05. The trade $i$ is not a candidate for a statistical vehicle trade of size $x_i$, if $H_{0,i}: \hat{\theta}_i^* \geq \Theta_\theta$, $i = 1, \ldots, I$.

- The vehicle trade share estimand is thus

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

- To arrive at an estimate of the estimand, we define a discovery as

$$d_i = \alpha_i \phi_i \text{ with } \phi_i = \begin{cases} 
1 & \text{if } n_i > 1 \\
0 & \text{otherwise}
\end{cases}$$

- And control for false discoveries, with the expected matches in a random sample: $c_i = \alpha_i \theta_i^*$.
Appendix: The Identification Algorithm

The share of trades that are crypto vehicle trades thus becomes:

\[ \hat{\phi} = \frac{2 \sum_{i=1}^{I} (d_i - c_i)}{I} \]

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

\[ E[ \hat{\phi} | N_i, \ldots, I ] = \phi \]

**Proof of Theorem:**

\[ E[ \hat{\phi} | N_i, \ldots, I ] = \frac{2 \sum_{i=1}^{I} (E[d_i | N_i] - c_i)}{I} \]  \hspace{1cm} (1)

\[ E[ \hat{\phi} | N_i, \ldots, I ] = \frac{2}{I} \sum_{i=1}^{I} \alpha_i (E[ \phi_i | N_i] - \hat{\theta}_i^*) \]  \hspace{1cm} (2)

\[ E[ \hat{\phi} | N_i, \ldots, I ] = \phi \]  \hspace{1cm} (3)

Where we make use of the fact that for any single \(i\):  \( E[\phi_i | N_i] = 1 \times P((n_i > 1) | N_i) \).
Empirical Evidence in Support of Key Assumption

Figure: Daily Maximum Drawdown. Sources: Bloomberg and CryptoCompare

<table>
<thead>
<tr>
<th></th>
<th>USD/BTC</th>
<th>USD/EUR</th>
<th>USD/MXN</th>
</tr>
</thead>
<tbody>
<tr>
<td>Annualized Standard Deviation</td>
<td>93 %</td>
<td>8 %</td>
<td>12 %</td>
</tr>
</tbody>
</table>
Limitations of the Algorithm: Vehicle trades structurally missed:

- Different vehicle-trade-legs’ trade sizes
- Very large trades likely circumvent the high P2P platform fees
- One vehicle-trade-leg uses centralized exchange or OTC transfer
- Delays of more than 5 hours
  - Slow payment mechanism at on-ramp or off-ramp lead to delays of more than 5 hours
  - Hedged Bitcoin price exposure
Applying alternative Time Windows

<table>
<thead>
<tr>
<th>Time Window Applied</th>
<th>Percent of all trades</th>
</tr>
</thead>
<tbody>
<tr>
<td>2-hours</td>
<td>Trades with one match</td>
</tr>
<tr>
<td>5-hours</td>
<td>Trades with one match &amp; p &lt; 0.05</td>
</tr>
<tr>
<td>10-hours</td>
<td>Trades with one match &amp; p &lt; 0.05 &amp; net of FD</td>
</tr>
</tbody>
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Applying algorithm to shuffled dataset

Monte Carlo Simulation vs. Actual Data

- Trades with one Match & p < 0.05
- Trades with one Match & p < 0.05 & net of FDR

Percent of all trades

- Monte Carlo Simulation
- Actual Data
Figure: Event Study: Guri-Dam Power-cut in Venezuela between March 7th and March 9th 2019