Decrypting New Age International Capital Flows

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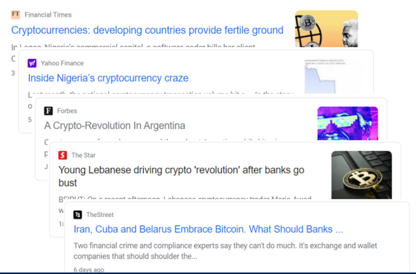
March 28, 2023

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:



Summary: Decrypting Capital Flight through Cryptocurrencies

We develop an algorithm that provides first evidence on Bitcoin being used to move capital 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

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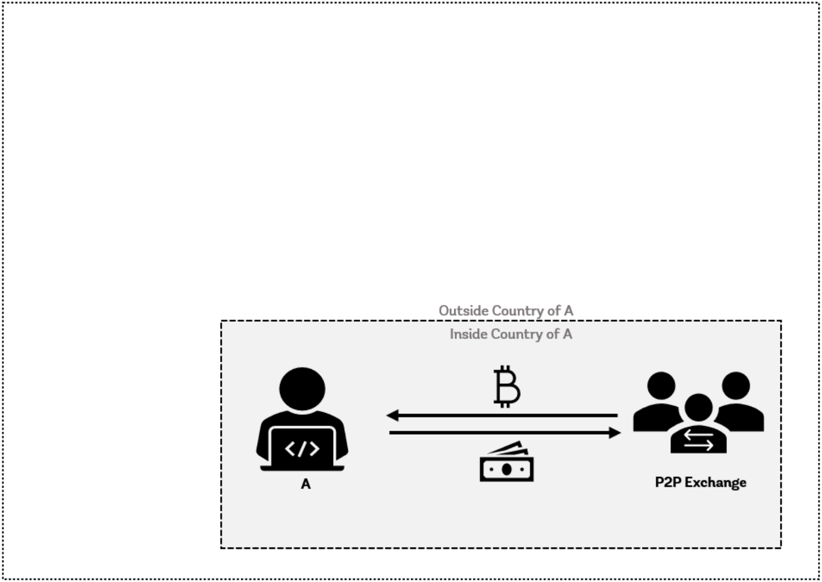
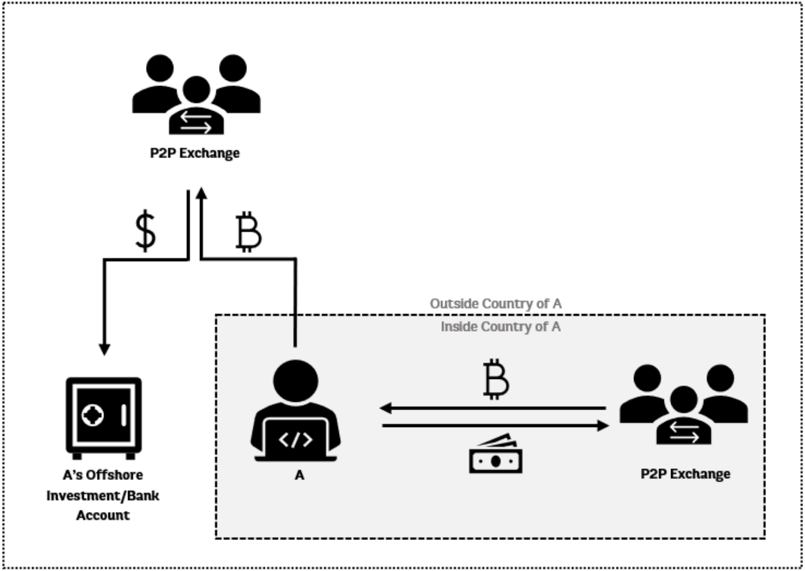


Moving capital through cryptocurrencies in theory



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

Number of Trades	128 493 700
USD Trade Volume	USD 19 billion
Average Trade Size (USD)	148
Largest Trade Size Recorded	USD 2.3 million
Number of Fiat Currencies	163

- Differs from Blockchain data in that:
  - It includes information on fiat currencies used and prices paid for the crypto currency
  - The timestamp is 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. For an illustration of trade size distribution

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
- $\sum_{i=1}^{I} \hat{\theta}_i^*$ 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

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)	16 568 776
Net of expected False Discoveries	14 283 812
Share of total trades identified as vehicle trades	**11.1%**

For structural reasons why 11.1% is likely a lower bound

Findings

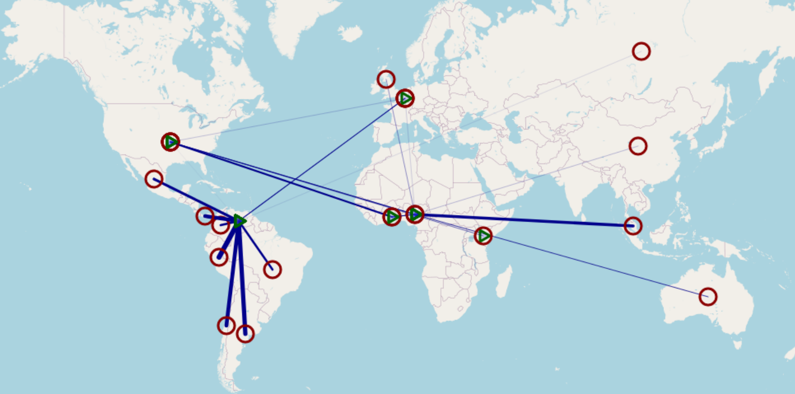
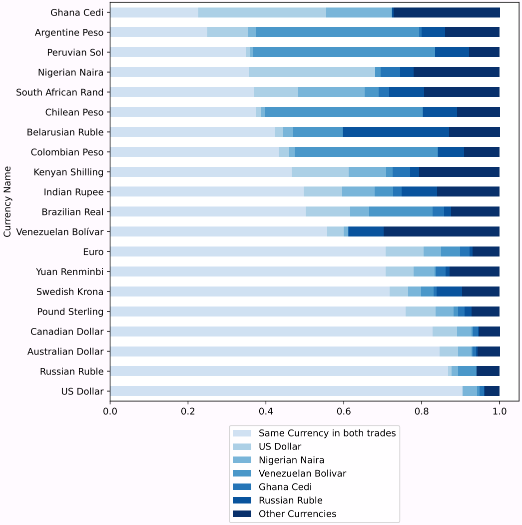


Figure: The World's 25 biggest Crypto Vehicle Channels. Circles: Origin, Triangles: Destination. Line-width: Channel volume as share identified trade volume in Origin Currency

Findings



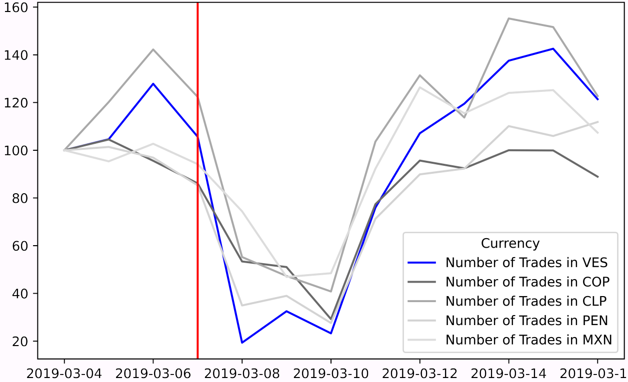
Ghana Cedi
Argentine Peso
Peruvian Sol
Nigerian Naira
South African Rand
Chilean Peso
Belarusian Ruble
Colombian Peso
Kenyan Shilling
Indian Rupee
Brazilian Real
Venezuelan Bolívar
Euro
Yuan Renminbi
Swedish Krona
Pound Sterling
Canadian Dollar
Australian Dollar
Russian Ruble
US Dollar
Currency Name
0.0
0.2
0.4
0.6
0.8
1.0
Same Currency in both trades
US Dollar
Nigerian Naira
Venezuelan Bolivar
Ghana Cedi
Russian Ruble
Other Currencies

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

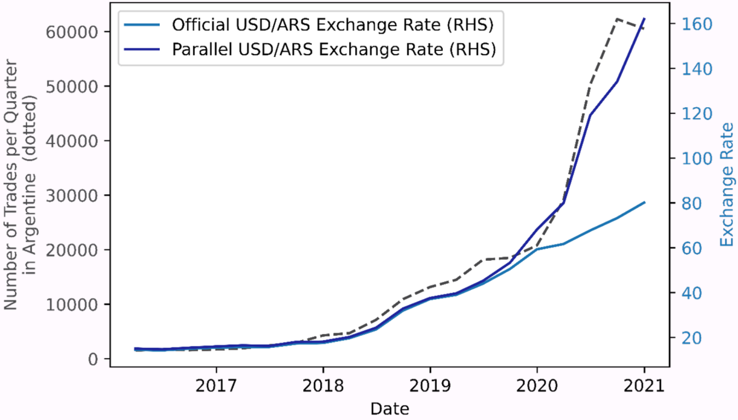


	COP	MXN	PEN
Share of Total Trade Identified (Share of id. trade volume in base currency with VES as origin or destination)	6.5% (42%)	6.6% (30%)	7.5% (38%)

Diff-in-Diff Graph Counterfactual

Robustness Checks & Additional Evidence

Figure: Bitcoin Trades as parallel market is born (once again) in Argentina in 2019.

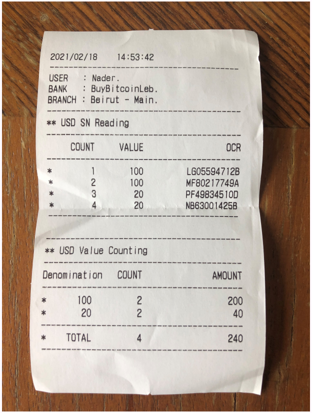


Anecdotal Evidence

"*The plural of anecdote is data*"
— Raymond Wolfinger

Anecdotal Evidence

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



2021/02/18 14:53:42

USER : Nader.
BANK : BuyBitcoinLeb.
BRANCH : Beirut - Main.

** USD SN Reading

	COUNT	VALUE	OCR
*	1	100	LG05594712B
*	2	100	MF80217749A
*	3	20	PF49834510D
*	4	20	NB63001425B

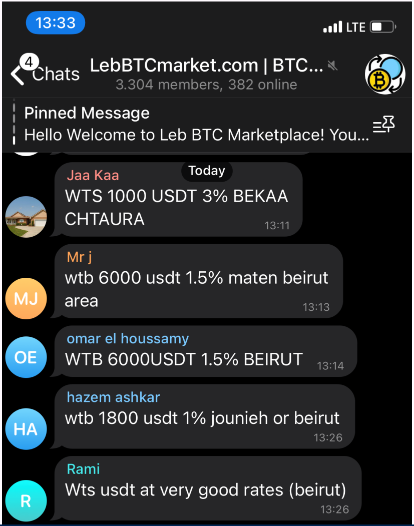
** USD Value Counting

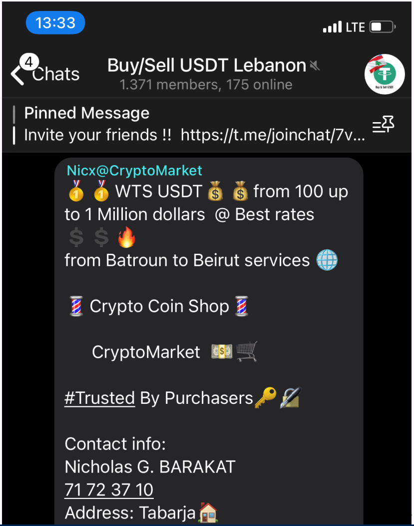
	Denomination	COUNT	AMOUNT
*	100	2	200
*	20	2	40
*	TOTAL	4	240

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





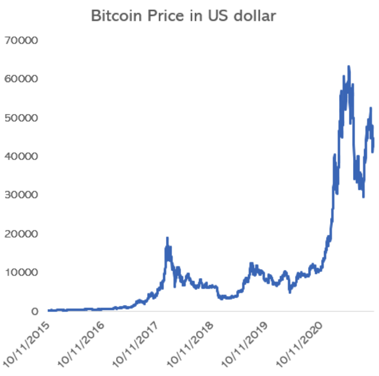
Conclusion

- 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

Motivation

(1) Bitcoin price puzzle: staggering evaluation without an evident use case.



Source: Yahoo Finance

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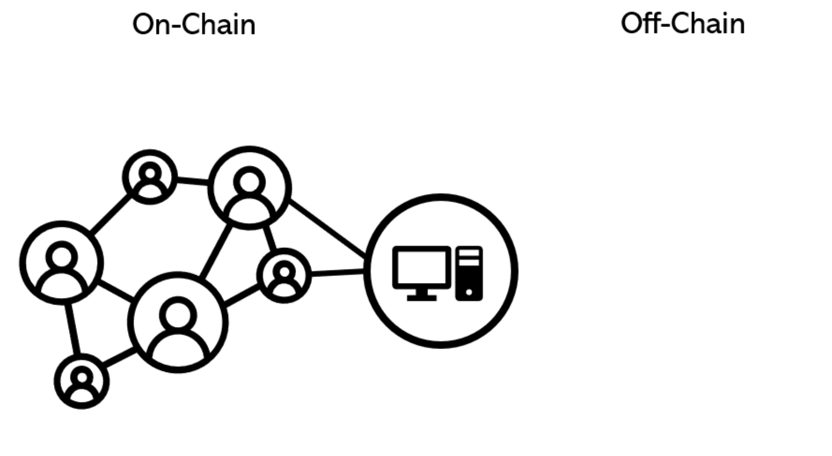
On Chain vs Off-Chain



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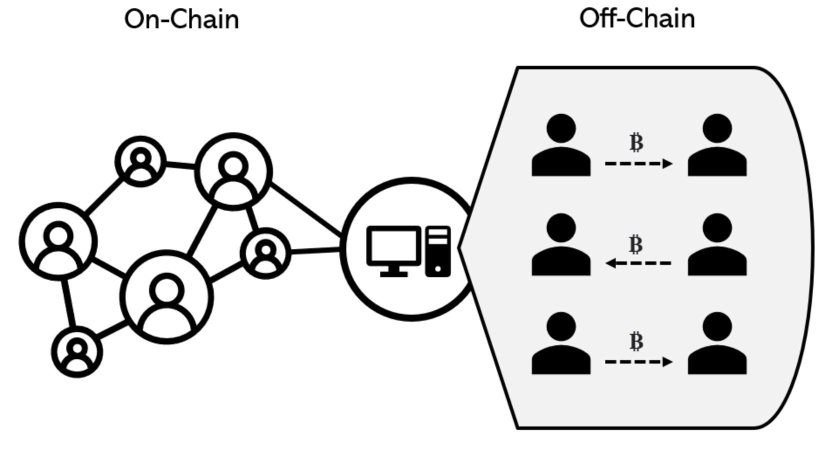
On Chain vs Off-Chain



Around 99% of all trades occur off-chain.

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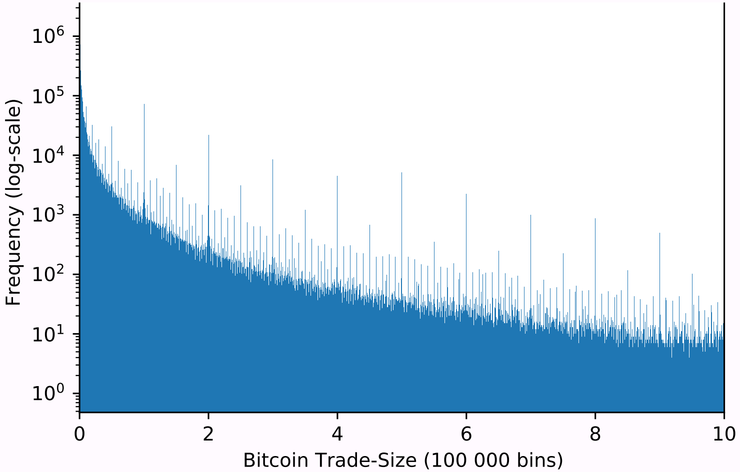
The estimate of p_i - the probability of a randomly drawn trade size having size x_i is based on:



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Appendix: The Identification Algorithm

- Because we can condition on the discrete number of trades occurring within the 5-hour time window after trade i

$$n_i, \mid N_i \sim \; MultiN(N_i; p_i)$$

- Under this model, the probability of a trade occurring at least once in the five hours prior to a trade is thus:

$$\hat{\theta}_i^* = 1 - (1 - \hat{p}_i)^{N_i}, \qquad i = 1, ..., I.$$

- $\hat{\theta}_i^*$ 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.

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Timestamp 1st trade	Currency 1st trade	Trade size x_i (1st & 2nd trade)	Timestamp 2nd trade	Currency 2nd trade	p_i	N_i
2020-11-01 01:12:43	USD	0.0020216	2020-11-01 02:03:31	VES	0.0000763	4086

$$\theta_i^* = 1 - (1 - 0.0000763)^{4086} \approx 0.26785$$

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

- The vehicle trade share estimand is thus

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

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

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

- And control for false discoveries, with the expected matches in a random sample: $c_i = \alpha_i \, \theta^*_i$

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Appendix: The Identification Algorithm

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

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

Theorem: Under an arbitrary data generating process for $(n_1, \ \ldots, \ n_{\ I})$,

$$E[\ \hat{\varphi} \mid \ N_i, \ \ \ldots\ , \ I\ ] = \varphi$$

Proof of Theorem:

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

$$E[\ \hat{\varphi} \mid \ N_i, \ \ \ldots\ , \ I\ ] \ = \frac{2}{I}\sum_{i=1}^{I}\ \alpha_i\ \ (E\ [\ \phi_i \mid N_i] - \hat{\theta}_i^*) \tag{2}$$

$$E[\ \hat{\varphi} \mid \ N_i, \ \ \ldots\ , \ I\ ] \ = \varphi \tag{3}$$

Where we make use of the fact that for any single i: $E[\phi_i \mid N_i\ ] = 1 * P((n_i > 1)|N_i)$.

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Empirical Evidence in Support of Key Assumption

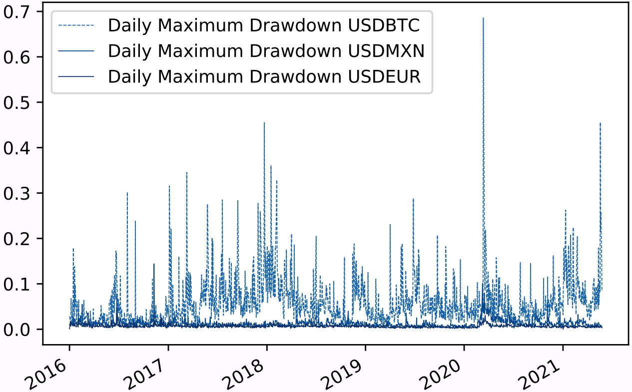

Figure: Daily Maximum Drawdown. Sources: Bloomberg and CryptoCompare

	USD/BTC	USD/EUR	USD/MXN
Annualized Standard Deviation	93 %	8 %	12 %

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The Identification Algorithm

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

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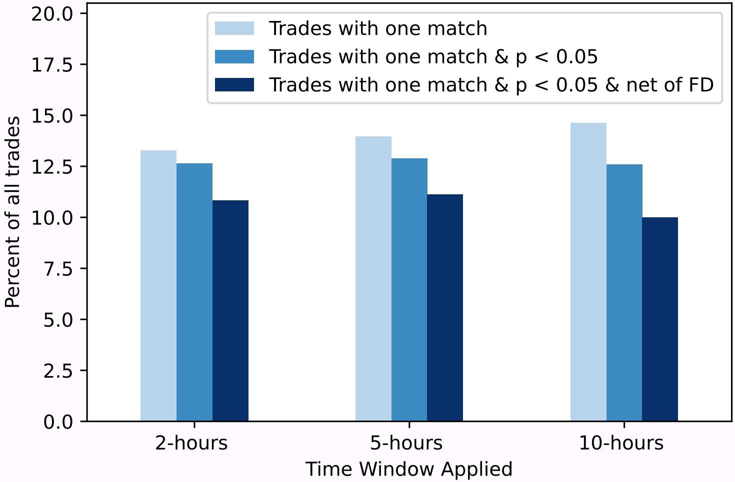
Applying alternative Time Windows



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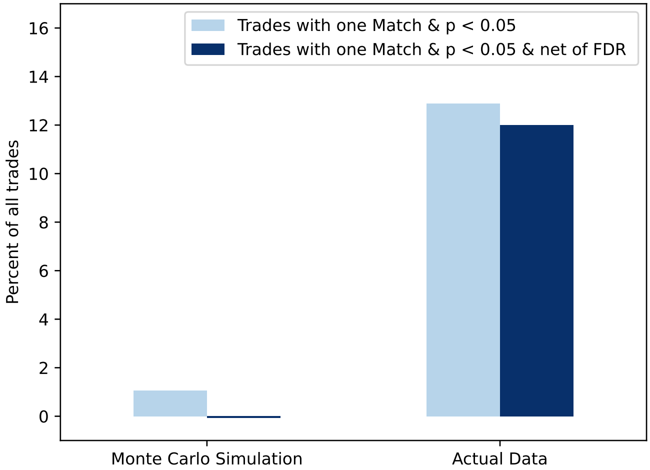
Applying algorithm to shuffled dataset



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Robustness Checks & Additional Evidence (appendix)

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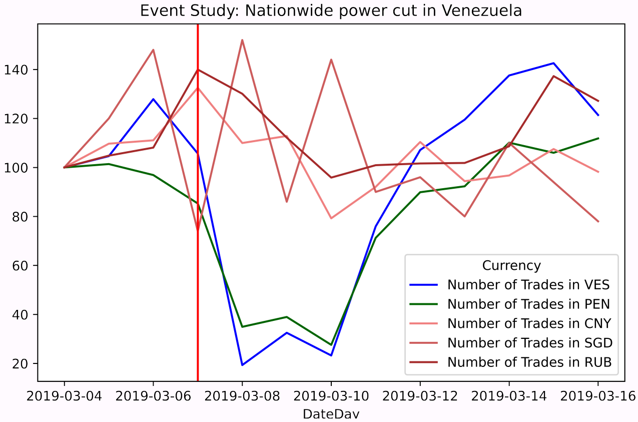
Figure: Event Study: Guri-Dam Power-cut in Venezuela between March 7th and March 9th 2019



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For a full list of references see the WP at NBER, CEPR or WBWP