Binance and Tether

Brazilian Finance Meeting

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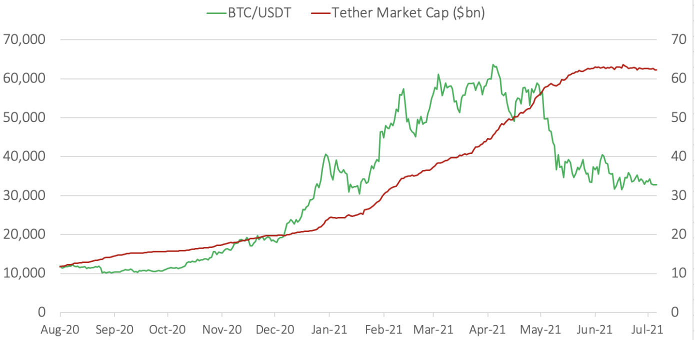
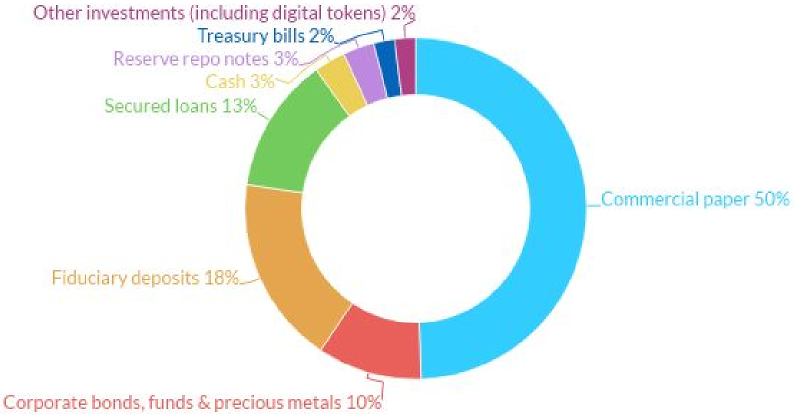
Bitcoin Price and Tether Market Cap



1 Aug 2020 to 14 July 2021

Tether Reserves Breakdown, 31 March 2021



Source: Fitch Ratings, Tether

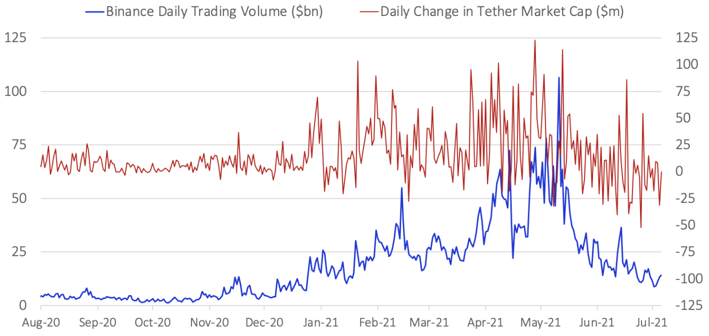
FitchRatings

Binance Exchange

Binance Trading View

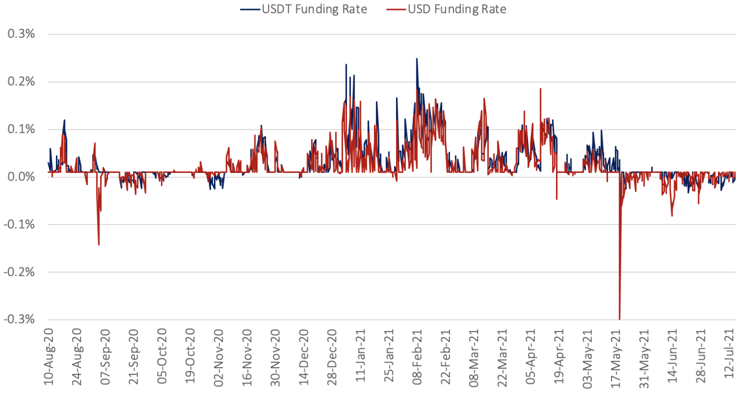
- Unregulated, not domiciled in any jurisdiction
- Centralised, crypto only
- Regulatory push-back on subsidiaries
- Class actions esp. 19 May 2021 (Lexia)

Growth in Binance Volume and Change in Tether Cap



- Growth in tether corresponds to growth in Binance trading volumes
- Binance top of tether rich list – around $17 billion in hot wallet

Perpetual Contracts



Prices of perpetual and spot tied via funding payments between long and short counterparties

Perpetual Contract Specifications

	USD Contracts		USDT Contracts	
	Binance	Bybit	Binance	Bybit
Type	Inverse	Inverse	Direct	Direct
Contract Size	100 USD	1 USD	0.001 BTC	1 BTC
Initial Margin Rate	$>$ 0.8%*	1%	$>$ 0.8%*	1%
Settlement Currency	BTC	BTC	USDT	USDT
Trading Days	24/7	24/7	24/7	24/7
Funding Frequency	8 hrs	8 hrs	8 hrs	8 hrs
Fees (maker/taker) bps	1/5	-2.5/7.5	2/4	-2.5/7.5
Tick Size	0.1 USD	0.5 USD	0.01 USDT	0.5 USDT

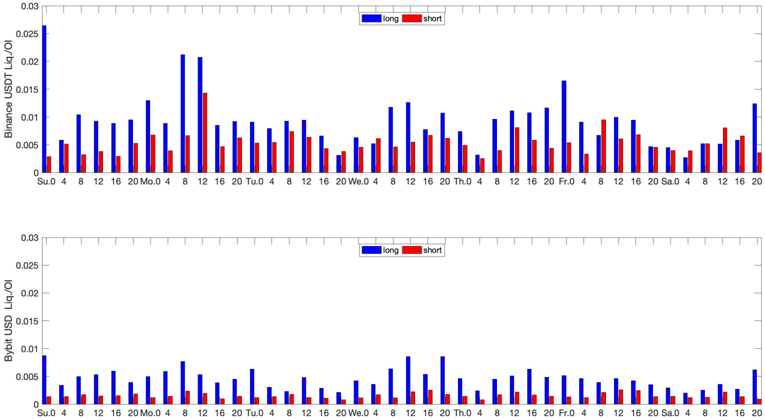
* Margin rates on Binance increase with notional value of position

Margin Mechanisms

- Suppose Alice opens a long position of 250,000 USDT with 100X leverage
- Alice's initial margin is just 2,500 USDT – i.e. initial margin rate is 1%
- Maintenance margin rate is 0.5%, i.e. margin level is 1,250 USDT
- A BTC price fall $> 0.5\% \Rightarrow$ zero collateral in Alice's margin account
- Binance issues *no margin calls*
- Auto-liquidations start if marked loss exceeds collateral in margin account
- Binance also takes a auto-liquidation fee to finance the insurance fund
- Insurance fund cover counterparty Bob's gains when Alice is auto-liquidated
- For instance, suppose the BTC price falls much more than 0.5%, say 10%
- Alice owes Bob 25,000 USDT but she only put 2,500 USDT on the platform
- The other 22,500 USDT *should* come from the insurance fund
- Insurance fund illiquidity? Bob's position is auto-deleveraged

Time Pattern of Auto-Liquidations?

Auto-liquidations as % OI on Binance and Bybit in 4hr time buckets



4-hourly data from coinanalyse.net

Binance Leads Bitcoin Price Discovery

Let $\mathbf{p}_t$ be the $n \times 1$ vector of cointegrated log prices at time t and let $z_t = \boldsymbol{\beta}^T \mathbf{p}_t$ denote their deviations from long-run equilibrium. Then the VECM is:

$$\Delta \mathbf{p}_t = \boldsymbol{\alpha} + \sum_{i=1}^{q-1} \boldsymbol{\Gamma}_i \Delta \mathbf{p}_{t-i} + \boldsymbol{\delta} z_{t-1} + \mathbf{e}_t,$$

where $\mathbf{e}_t$ are serially uncorrelated innovations with zero mean and covariance matrix $\boldsymbol{\Omega}$ and $\boldsymbol{\delta}$ captures reactions to transitory equilibrium deviations. Inverting and integrating gives:

$$\mathbf{p}_t = \mathbf{p}_0 + \boldsymbol{\Psi}(1) \sum_{j=1}^{t} \mathbf{e}_j + \boldsymbol{\Psi}^{\star}(L) \mathbf{e}_t$$

where $\boldsymbol{\Psi}(1)$ i.e. the sum of the MA coefficients in the inversion of the AR, has identical rows which we denote $\boldsymbol{\psi}$. Then the scalar $\boldsymbol{\psi} \mathbf{e}_t$ is the long-term common efficient price which has variance $\boldsymbol{\psi} \boldsymbol{\Omega} \boldsymbol{\psi}^T$ and $\boldsymbol{\Psi}^{\star}(L) \mathbf{e}_t$ captures the transitory components

Price Discovery Metrics

Estimated VECM allows one to compute the component share of Gonzalo and Granger (1995) which *assigns shares of the permanent, long-memory components of the common efficient price*. This measures the impact of each product on long-term price formation.

Also, the Hasbrouck (1995) information share asks *When new information enters the network, what proportion of the total price innovation originates on each product*? It is measured by its relative contribution to the variance of the common efficient price, i.e.:

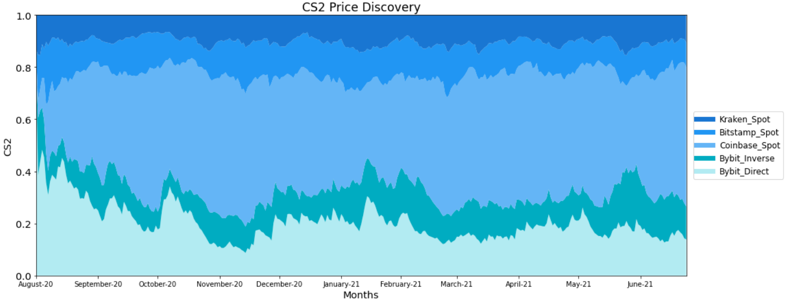
$$\mathsf{IS}_i = \frac{([\boldsymbol{\psi}\mathbf{M}]_i)^2}{\boldsymbol{\psi}\boldsymbol{\Omega}\boldsymbol{\psi}^T} \quad \text{for } i = 1, \ldots, N,$$

where $\mathbf{M}$ is the lower triangular matrix of the Cholesky decomposition of $\boldsymbol{\Omega}$ and $[\boldsymbol{\psi}\mathbf{M}]_i$ is the i-th entry of $\boldsymbol{\psi}\mathbf{M}$

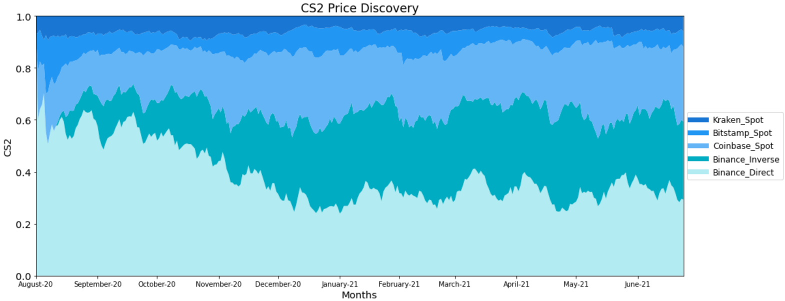
Results for Bybit

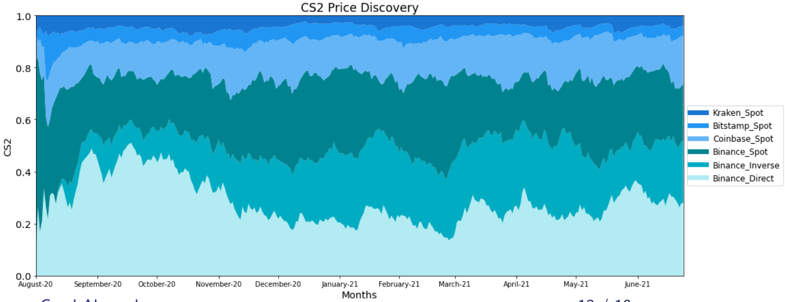
Alexander, Carnaghan and Heck “The Role of Binance in Bitcoin Price Discovery”

Minute-level data $\rightarrow$ day by day VECM estimation



Results for Binance





Binance leads High-Frequency Volatility Spillover

Alexander, Heck and Kaeck (2021) The Role of Binance in Bitcoin Volatility Transmission

Exchanges

Spot	Perpetuals
Bitstamp$^{\$}$	Binance$^{\$}$
Coinbase$^{\$}$	Bybit$^{\$}$
Kraken$^{\$}$	Binance^{T}
Binance^{T}	
Huobi^{T}	

Research Questions

- Do volatility flows change over the course of the day?
- Where does bitcoin volatility emerge?
- To which exchanges does volatility transmit?

Intra-day Realised Volatility Patterns (UTC)

Note: The figure shows the intraday pattern of 5-minute realised volatility (in million USD) for USD spot pairs (upper graph) as well as USDT spot pairs and perpetuals (lower graph), measured as the average five-minute realised volatility over the period from 1 January to 31 March 2021. All times are in UTC.

Vector Logarithmic Multiplicative Error Model

Basic specification for 5-min realised volatilities of 6 exchanges, $\boldsymbol{x}_t$:

$$\begin{aligned} \boldsymbol{x}_t &= \boldsymbol{\mu}_t \odot \boldsymbol{\varepsilon}_t \\ \log \boldsymbol{\mu}_t &= \mathbf{w} + \mathbf{A} \log \boldsymbol{x}_{t-1} + \mathbf{B} \log \boldsymbol{\mu}_{t-1} \end{aligned}$$

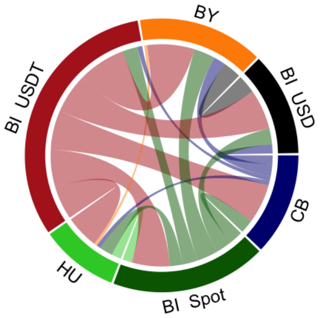
- Implicitly guarantees non-negativity of realised volatilities
- Decomposes realised volatility into Hadamard product of conditional mean and error term with unit mean and a distribution with non-negative support
- Log conditional mean is autoregressive $\Rightarrow$ long-term effects **B**
- Dependence on lagged observations $\log \boldsymbol{x}_{t-1} \rightarrow$ short-term spillovers, **A**
- Add asymmetric response component to capture leverage effect
- Also use an extension to capture zeros in high-frequency time series
- Also use dummies to investigate time-zone effects

Results – Main Instruments

	Coinbase	Binance^S	Huobi	Binance^T	Bybit	Binance$^\$$
CB	0.2108	-0.0895	0.0352^{ns}	0.2548	0.0088^{ns}	-0.0173^{ns}
BI^S	-0.0164^{ns}	0.0742	0.0626	0.2439	0.0105^{ns}	0.0223^{ns}
HU	-0.0282	-0.0851	0.2720	0.2177	0.0198	-0.0108^{ns}
BI^T	-0.0307	-0.0995	0.0247^{ns}	0.4702	0.0149^{ns}	0.0132^{ns}
BY	-0.0761	-0.1373	0.0441^{ns}	0.3085	0.1450	0.1200
BI$^\$$	-0.0594	-0.1039	0.0110^{ns}	0.2606	0.0134^{ns}	0.2742

- Parameter estimates for matrix **A** of the multivariate LogMEM$(1{,}1)_1$, fitted to 5-min realised volatility on Coinbase (CB), Binance Spot (BI^S), Huobi (HU), Binance USDT-perpetual (BI^T), Bybit (BY) and Binance USD-perpetual (BI$^\$$)
- Column denotes emitting exchange, row denotes receiving exchange
- Diagonals in red capture flows back into exchange
- Superscript ^{ns} indicates estimate is not significant at 1%
- Data period 1 January to 31 March 2021.

Answers to Research Questions



- Do volatility flows change over the course of the day?
  Yes, they increase at time of funding payments on perpetuals
- Where does bitcoin volatility emerge?
  Almost all from Binance Asia, mostly from the tether perpetual
- To which exchanges does volatility transmit?
  Bybit and the spot exchanges Coinbase and Binance US

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