le cnam

Liquidity connectedness between decentralised cryptocurrency exchanges and their centralised counterparts during US banking crisis

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Background & problem

BINANCE

UNISWAP

US banking turmoil

SIGNATURE BANK®

svb Silicon Valley Bank

Silvergate

Regulation

Securities and Exchange Commission

Commodity Futures Trading Commission

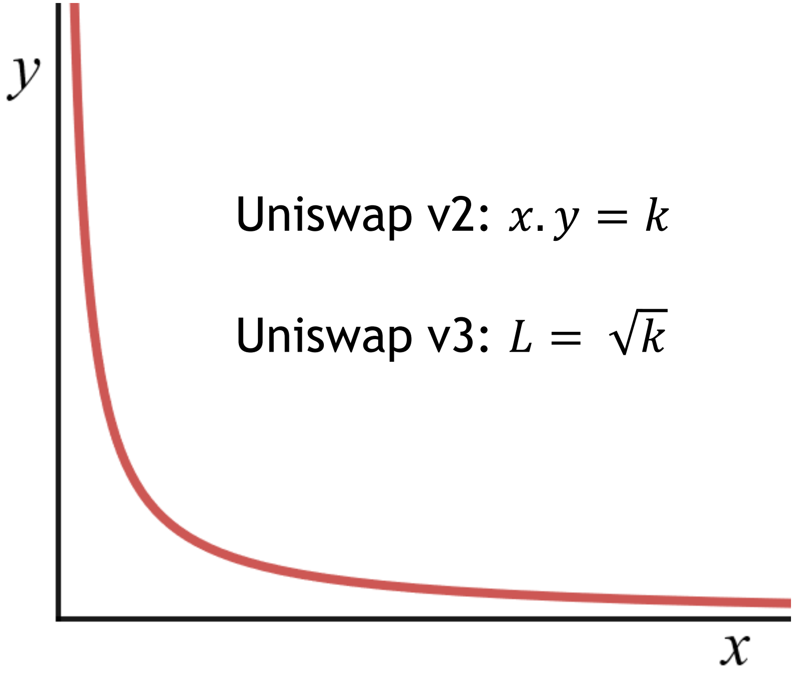
US National Futures Association

US House of Representations draft bill on crypto stablecoins

EU regulation for crypto assets

Uniswap

Decentralised exchange based on constant function market maker



Uniswap v2: $x.y = k$

Uniswap v3: $L = \sqrt{k}$

Transparency

Operates on blockchain

Custody of wallet

Connection with banking system

Binance

Centralised exchange with double auction limit order book

Asks

Price(USDT)	Amount(BTC)	Total
27120	0.00100	27.12
26830	0.00100	26.82
26820	0.00142	38.08
26740	3.84177	102,728.93
26650	0.07011	1,868.08
26640	0.00202	53.79
26630	0.49719	13,237.20
26620	1.78567	47,525.44
26610	4.54944	121,044.19
26600	27.36380	727,757.08
26590	0.79853	21,229.31
26580	16.88039	448,649.21
26570	20.33074	540,108.02
26560	32.83246	871,880.47
26550	15.39932	408,778.47
26540	34.17318	906,778.23
26530	22.17797	588,304.09
26,522.09↑	€24,877.72	More
26520	33.49050	888,179.72
26510	20.02593	530,990.05
26500	27.67782	733,608.33
26490	18.27181	484,093.41
26480	33.47616	886,554.51
26470	22.91668	606,676.15
26460	15.26679	403,991.26
26450	19.37585	512,531.05
26440	10.35221	273,781.65
26430	0.32072	8,479.48
26420	0.02124	561.24
26410	0.00679	179.37
26390	0.00883	233.07
26380	0.50000	13,194.05
26350	5.84314	153,966.74

Bids

Hypothesis

Uniswap acts as a satellite or proxy to Binance

Liquidity on Binance drives Uniswap?

Shocks to Binance reverberate in Uniswap

Uniswap is insulated from connection to traditional financial system?

Methodology

1
- Collect appropriate data
- Find comparable & representative token pairs

2
- Identify and construct relevant variables
- Examine data & transform if necessary

3
- Use a suitable model to explore relationship between DEX and CEX

Data collection & processing

Uniswap: choice of token pairs

Criteria: cumulative volume

JavaScript and GraphQL queries for TheGraph subgraph

Dates: All time

Dates: 27 Feb – 2 May

Binance order book

Criteria: 8 token pairs, 5,000 order book depth, every 20 minutes

Python calls to Binance API, scheduled using Cron job

Total 2% depth
Total 1% depth
Quoted spread

Binance trades

Criteria: 8 token pairs, historical trade data

Python scripts provided by Binance

Number of trades
Volume of tokens
Size of trades
Amihud illiquidity ratio

Uniswap liquidity pools

Criteria: 8 token pairs, historical liquidity pool data for v2 & v3

JavaScript and GraphQL queries for TheGraph subgraph

$\sqrt{k}$

Pandas dataframe

Using Pickle file format and Dask

Sample code

Python script merging order book, trades and Uniswap liquidity variables together in a Pandas dataframe

R script creating combinations of regressors to determine optimum lag length using Akaike information criterion

```python
for timestamp in df.index:
    print(f'Looking for timestamp: {timestamp}')
    # Need an hour behind and make milliseconds
    start_timestamp = (int(timestamp)-hour)*1000
    end_timestamp = (int(timestamp)-1)*1000
    file_name = f'{token_pair["binance"]}_{start_timestamp}_{end_timestamp}.pkl'
    file_path = f'{trades_dir}{token_pair["binance"]}/{file_name}'
    if os.path.exists(file_path) == True:
        with open(file_path, 'rb') as file:
            trade_indicators = pickle.load(file)
        df.loc[timestamp, 'num_txs'] = trade_indicators['num_txs']
        df.loc[timestamp, 'vol'] = trade_indicators['vol']
        df.loc[timestamp, 'trade_size'] = trade_indicators['trade_size']
        df.loc[timestamp, 'amihud'] = trade_indicators['amihud']
    else:
        print('File does not exist.')
        quit()
    # Merge with Uniswap v3 liquidity snapshots
    uniswap_v3_file = token_pair['uniswap']
    with open(f'{uniswap_v3_dir}{uniswap_v3_file}.pkl', 'rb') as liquidity_file:
        liquidity_snapshots = pickle.load(liquidity_file)
```

```r
# All possible regressors
regressors <- c('total2', 'total1', 'QS', 'num_txs', 'vol', 'trade_size', 'amihud')
# *** Combinations of model ***
combos <- combn(regressors, 3, simplify = FALSE)
lowest_AIC <- 1000000000
for(i in 1:length(combos)) {
  ind_vars <- unlist(combos[i], use.names = FALSE)
  dep_var <- "uniswap_root_k"
  formula_concat <- as.formula(paste(dep_var, paste(ind_vars, collapse=" + "), sep=" ~ "))
  max_lag <- 3
  USDT_DAI_panel_a_lags <- auto_ardl(formula_concat, data = USDT_DAI_panel_a,  max_order = max_lag)
  USDT_DAI_panel_b_lags <- auto_ardl(formula_concat, data = USDT_DAI_panel_b,  max_order = max_lag)
  USDT_DAI_panel_c_lags <- auto_ardl(formula_concat, data = USDT_DAI_panel_c,  max_order = max_lag)
  # Best model
  current_AIC_a <- USDT_DAI_panel_a_lags$top_orders[1,]$AIC
  current_AIC_b <- USDT_DAI_panel_b_lags$top_orders[1,]$AIC
  current_AIC_c <- USDT_DAI_panel_c_lags$top_orders[1,]$AIC
  total_AIC <- current_AIC_a + current_AIC_b + current_AIC_c
  if(total_AIC < lowest_AIC)
  {
    lowest_AIC <- total_AIC
    best_order_total_a <- USDT_DAI_panel_a_lags$best_order
    best_order_total_b <- USDT_DAI_panel_b_lags$best_order
    best_order_total_c <- USDT_DAI_panel_c_lags$best_order
  }
}
```

Sample data

BTC/USDT order book with 3 bids and 3 asks of depth, via Binance API

lastUpdateId	bids		asks	
	price	quantity	price	quantity
32857738668	24,250.09	0.04123	24,634.80	0.04000
	24,250.00	11.37131	24,634.86	0.00070
	24,249.95	0.00042	24,634.88	0.01056

ETH/BTC trade data for 5 trades, via Binance

id	price	qty	quoteQty	time	isBuyerMaker	isBestMatch
155601310	0.017954	0.22	0.00394988	1577836801725	TRUE	TRUE
155601311	0.017953	0.313	0.00561928	1577836801725	TRUE	TRUE
155601312	0.01795	3.189	0.05724255	1577836801725	TRUE	TRUE
155601313	0.017948	1.956	0.03510628	1577836801725	TRUE	TRUE
155601314	0.017951	0.272	0.00488267	1577836802641	TRUE	TRUE

WBTC/WETH liquidity pool on 5 May 2021 15:59:58, Uniswap v3, via subgraph hosted on TheGraph

id		0xcbcdf9626bc03e24f779434178a73a0b4bad62ed			**volumeToken0**	0.00186388
feeTier		3000			**volumeToken1**	0.03
liquidity		38565229780743			**feePercent**	0.003
token0	**symbol**	WBTC	**__typename**	Token	**tvlAdjust0**	0.00000279582
token1	**symbol**	WETH	**__typename**	Token	**tvlAdjust1**	0.00004499999999999996
totalValueLockedToken0		0.24085025			**tvlToken0**	0.24084745417999998
totalValueLockedToken1		2.942327559186704555			**tvlToken1**	2.9422825591867046

Econometrics

- Construction of liquidity measures
  - Total 2% depth (*total2*)
  - Total 1% depth (*total1*)
  - Quoted spread (*QS*)
  - Number of trades (*num_txs*)
  - Volume of tokens (*vol*)
  - Size of trades (*trade_size*)
  - Amihud illiquidity ratio (*amihud*)
  - Uniswap ($\sqrt{k}$)

- Descriptive statistics
  - Skewness and kurtosis
- Line plots
- Temporal patterns
- Autocorrelation
- Structural breaks (Chow test)
- Unit root tests (Augmented Dickey Fuller)
- Order of integration

- Lag selection using (AIC)
- Pesaran et al. 2001 approach:
  - Residual autocorrelation
  - Residual heteroscedasticity
- F-bounds test
- T-bounds test

- Autoregressive Distributed Lag Model

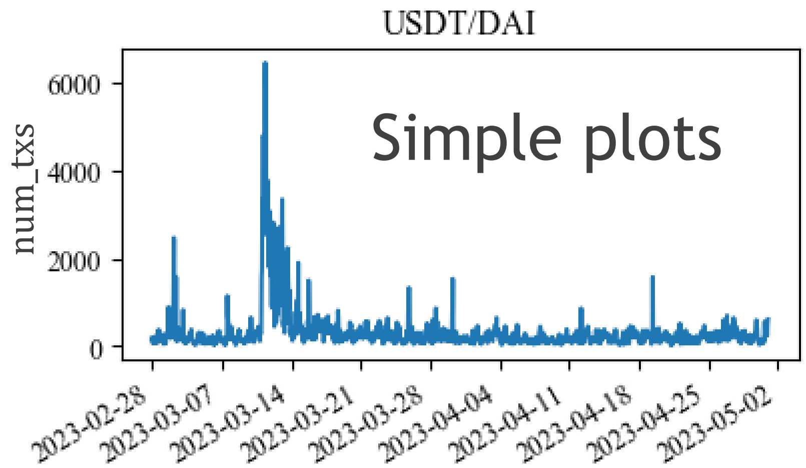
$$Y_t = \beta_0 + \beta_1 Y_{t-1} + \beta_2 Y_{t-2} + \ldots + \beta_p Y_{t-p} + \delta_1 X_{t-1} + \delta_2 X_{t-2} + \ldots + \delta_q X_{t-q} + u_t$$

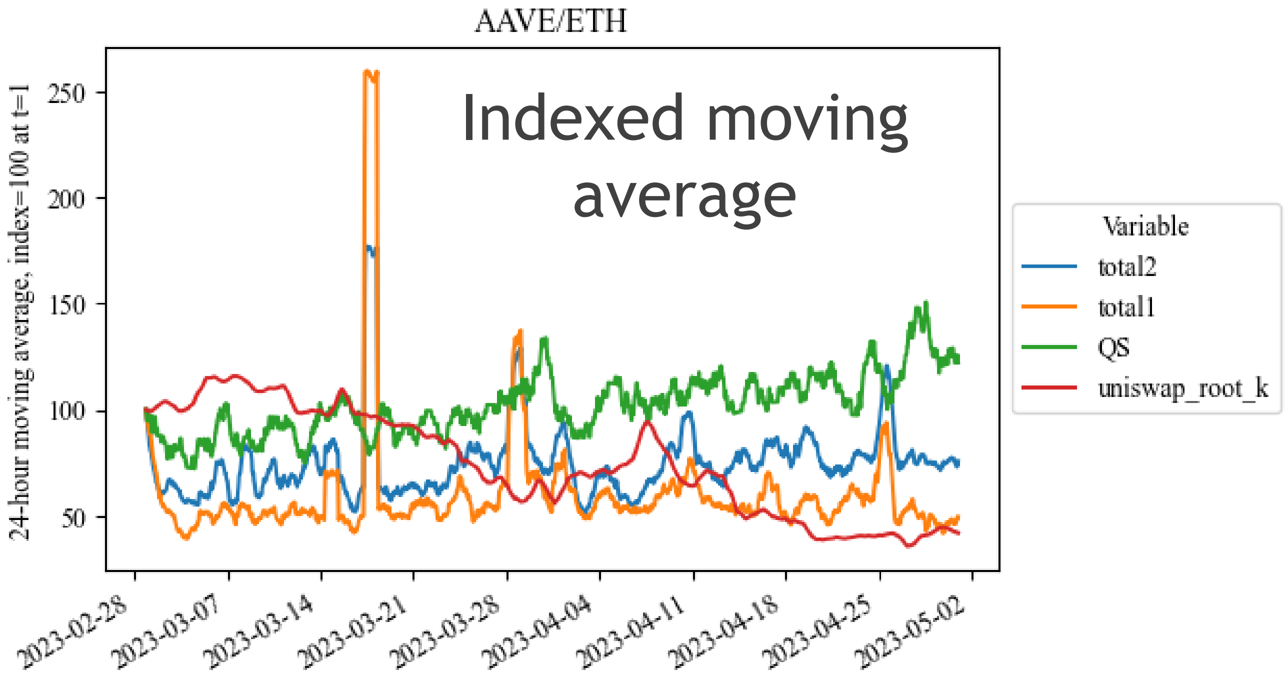
- Our variables, e.g.

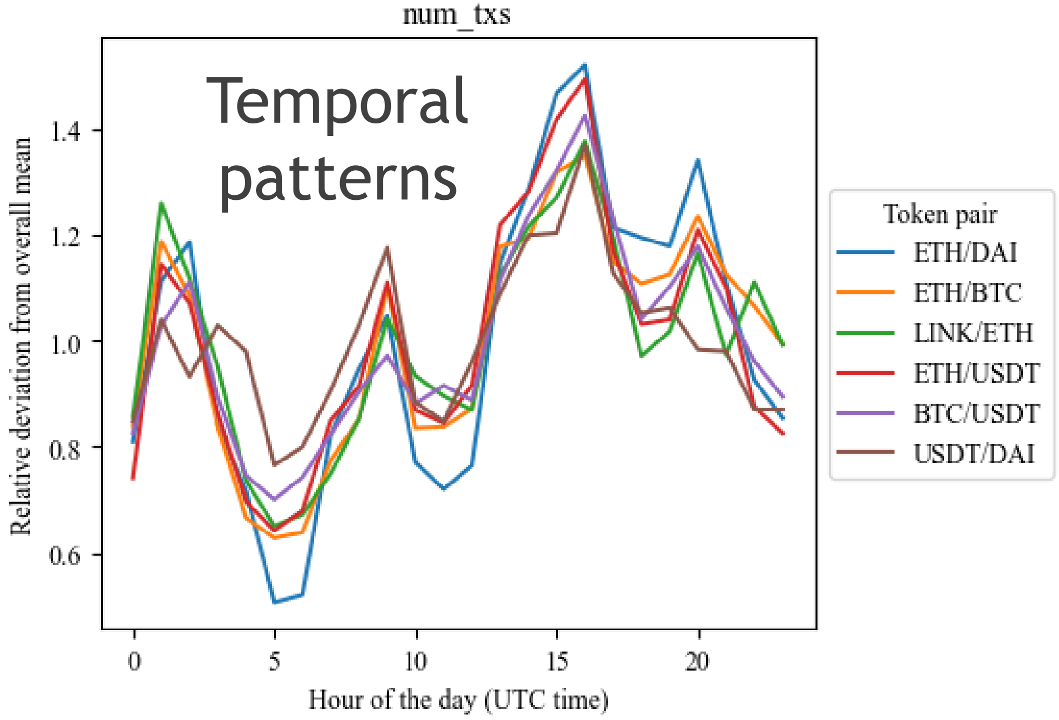
$$\sqrt{k}_t = \beta_0 + \beta_1 \sqrt{k}_{t-1} + \beta_2 \sqrt{k}_{t-2} + \ldots + \beta_p \sqrt{k}_{t-p} + \delta_1 total2_{t-1} + \delta_2 total2_{t-2} + \ldots + \delta_q total2_{t-q} + u_t$$

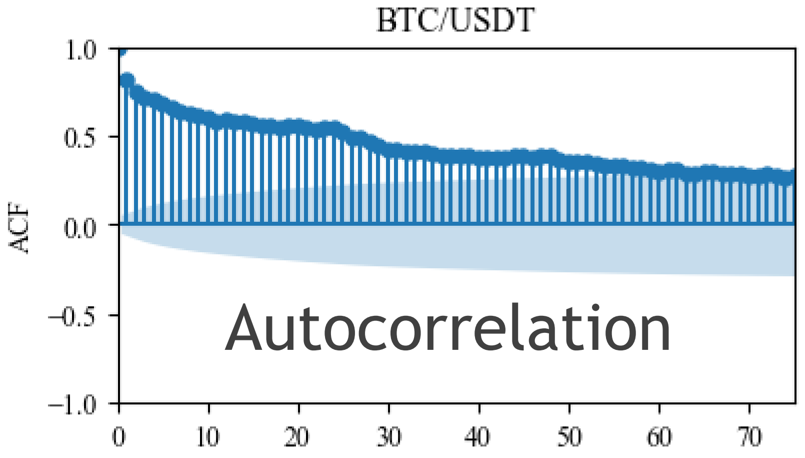
- Error Correction Model (ECM)

Results of preliminary analysis









ARDL results

Unrestricted ECM for USDT/DAI with Heteroscedasticity-consistent standard errors

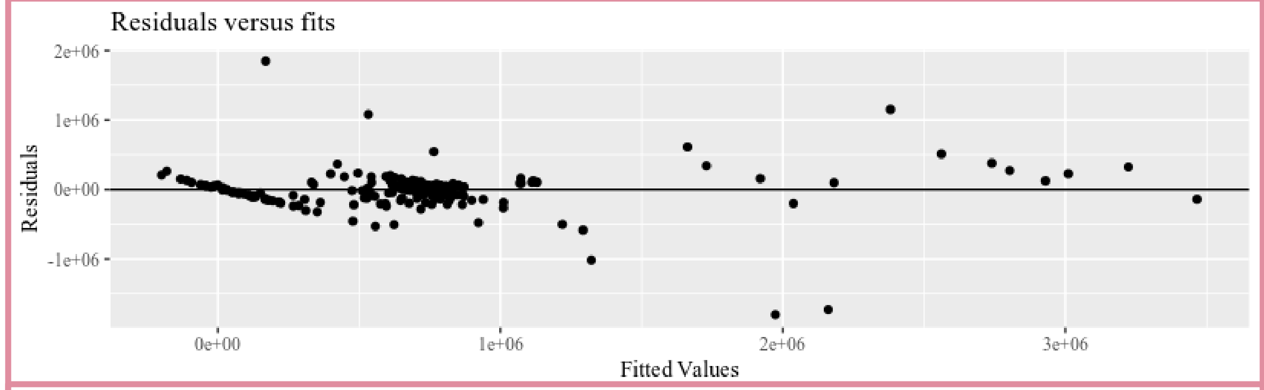
	Dependent variable $\Delta uniswap\_root\_k$			
Characteristic	**Beta**[1]	**SE**[2]	**95% CI**[2]	**p-value**
Intercept	124,560.21	65,927	-4,654.33, 253,774.74	0.059
$uniswap\_root\_k_{t-1}$	-0.19**	0.070	-0.33, -0.06	0.005
$total2_{t-1}$	0.02	0.009	0.00, 0.04	0.056
$total1_{t-1}$	-0.02	0.015	-0.04, 0.01	0.28
num_txs_{t-1}	-31.59	19.8	-70.49, 7.31	0.11
$\Delta total2$	0.09*	0.044	0.00, 0.17	0.042
$\Delta total2_{t-1}$	0.03	0.028	-0.02, 0.09	0.23
$\Delta total2_{t-2}$	0.03	0.019	-0.01, 0.07	0.10
$\Delta total1$	-0.03	0.022	-0.07, 0.02	0.21
$\Delta total1_{t-1}$	0.03	0.027	-0.02, 0.09	0.21
$\Delta total1_{t-2}$	0.03	0.017	0.00, 0.06	0.059
Δnum_txs	-8.35	44.9	-96.34, 79.64	0.85
Δnum_txs_{t-1}	115.40	63.1	-8.30, 239.09	0.067

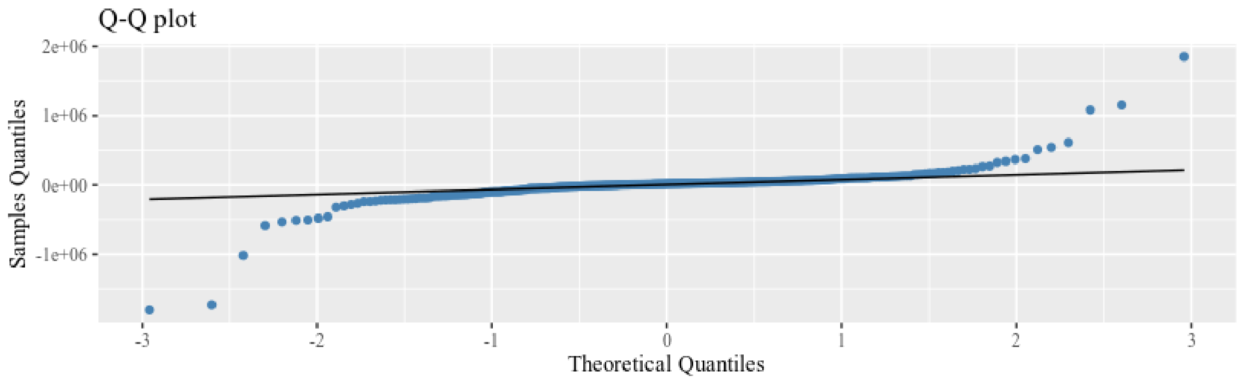
[1] *p<0.05; **p<0.01; ***p<0.001

[2] SE = Standard Error, CI = Confidence Interval

- Restricted (ECM) using Case 3: Unrestricted intercept and no trend.
- Robustness
- Long-run relationship USDT/DAI $ARDL(1,3,3,2)$

$$\begin{array}{llllll} uniswap\,\sqrt{k} = & 640{,}249.9 & + 0.09 total2 & - 0.08 total1 & - 162.39 num\_txs & - 0.19 \\ & (204{,}929.4) & (0.05) & (0.07) & (76.53) & (0.07) \\ & [0.002] & [0.07] & [0.28] & [0.03] & [0.006] \end{array}$$





Conclusion

- Binance shows clear temporal patterns in the number of transactions and volume
- 71% of our variables across 8 token pairs support 2 structural breaks
- Mix of stationary and non-stationary variables
- Evidence for 3 cointegrating relationships with USDT/DAI, ETH/DAI & ETH/USDT
- ETH/DAI and USDT/DAI show evidence (at least 10% level) for significance of Binance liquidity measures on Uniswap in the long-run relationship
- USDT/DAI shows total depth at 1% and 2% are both significant at < 1% level in short run dynamics

Discussion, limitations & future research

- Lack of evidence for Panel A & Panel C restricts ability to make inferences
- All cointegrating relationships involve stablecoins
- Investigate non-cointegrating relationships
- Questions over specification of model: Uniswap $\sqrt{k}$, liquidity indicators
- Problems with Uniswap v2 data
- Econometric technique: analysis of variance, e.g. ARCH or GARCH
- Flows of liquidity on Binance might be better examined through public wallets
- Flows of liquidity on Uniswap could be explored through “mints” or “burns”

References

- **Images** Binance order book for BTC/USDT via Binance web app.
- **Code** All code hosted on https://github.com/daniel-finnan/memoire/ with access available on request.
- **Data presented in samples** via Binance API, Binance historical trades & TheGraph subgraph.
- **Autoregressive Distributed Lag Model** Stock, J. H., & Watson, M. W. (2018). *Introduction to Econometrics*. Pearson.
- Pesaran, M. H., Shin, Y., & Smith, R. J. (2001). Bounds Testing Approaches to the Analysis of Level Relationships. *Journal of Applied Econometrics*, 289-326.