The Information Content of Blockchain Fees

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Outline

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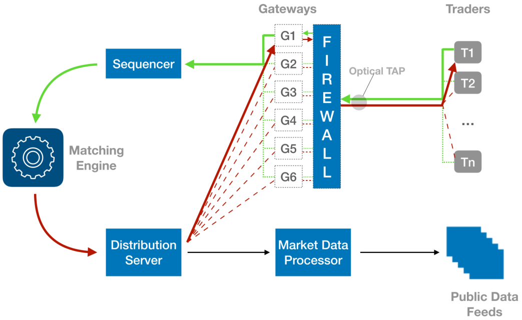
Centralized exchanges (CEXs)

- A CEX typically runs a central limit order book (CLOB) and executes orders continuously.
- Market orders are not visible ex ante.
- HFT traders compete on speed.

Figure 1: Exchange schematic. Source: Aquilina, Budish, and O'Neill (2021)



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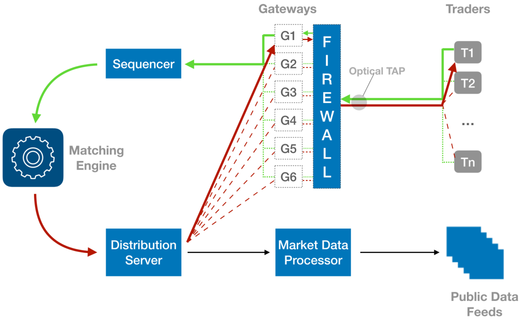

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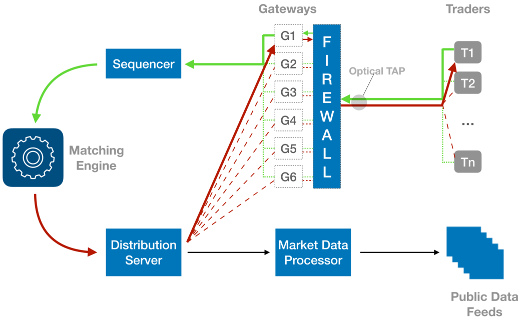
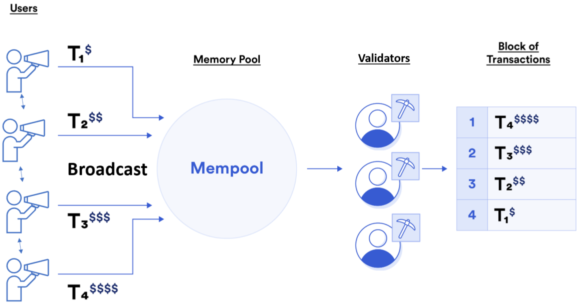


Decentralized exchanges (DEXs)

- A DEX (e.g., Uniswap) typically runs an automated market maker (AMM) and processes orders discretely in block time (e.g., every 13 seconds for Ethereum blockchain).
- Traders on DEXs compete on **blockchain fees** to prioritize their orders.
- DEX orders pending in the mempools are visible to all.



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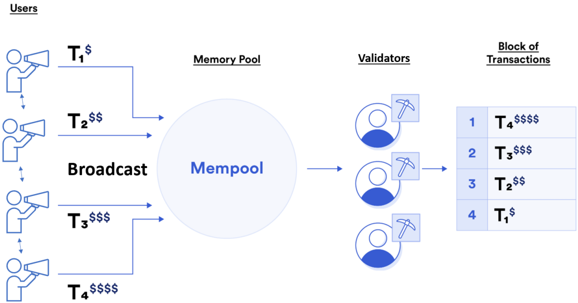

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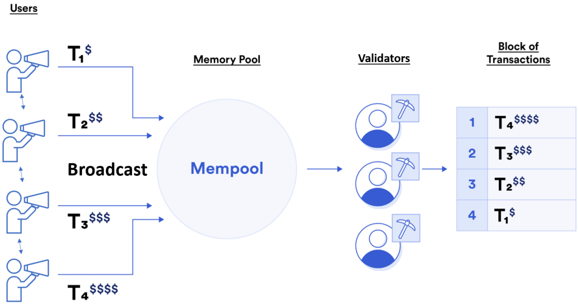
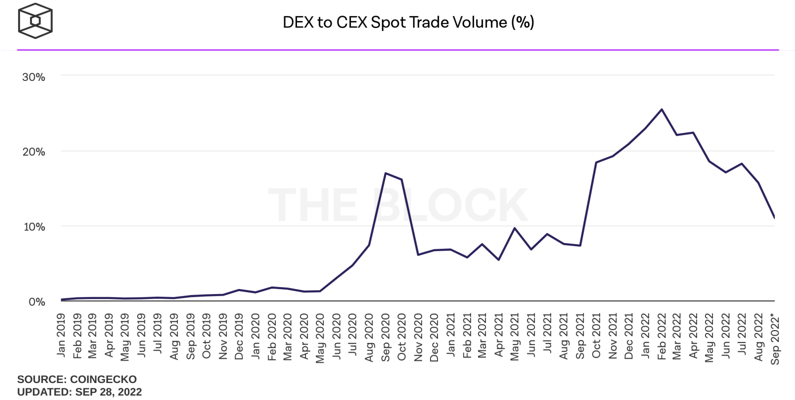


Decentralized exchanges (DEXs)

- Starting from May 2020, trading volume on DEXs took off, hovering between 50 billion USD and 200 billion USD, which correspond to about 10% and 25% to that on CEXs.



Paper in a nutshell

- Research questions:
  - Do blockchain fees convey any information?
  - If so, do high-fee trades reveal private information or simply respond to released public information?
  - What are the plausible economic channels?
- Main results:
  - The higher the fee, the more the private information in DEX trades
  - The higher the fee, the larger the sensitivity of DEX trades to changes in CEX prices
  - High fees are not the result of competition among traders on private or public information.

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Literature

- How do public characteristics of trades (e.g., size) reveal their private information content?
  - block trades versus non-block trades (Easley and O'Hara, 1987)
  - odd-lot trades versus round-lot trades (O'Hara, Yao, and Ye, 2014)
  - trades executed on ECNs versus the NASDAQ exchange (Barclay, Hendershott, and McCormick, 2003)
  - **Contribution**: we study private information content revealed through blockchain fees, a featuring characteristic of trades executed on DEXs and a new public signal observed by all traders.

Literature (Cont.)

- How do arbitrageurs respond to public information, and what are the implications on liquidity and price efficiency?
  - Biais, Foucault, and Moinas (2015), Budish, Cramton, and Shim (2015), Foucault, Hombert, and Roşu (2016), Hoffmann (2014), and Jovanovic and Menkveld (2016)
  - **Contribution**: Trading on DEXs runs in discrete time and traders compete by bidding blockchain fees, not on speed. Analyze impact of this trading mechanism on price efficiency on DEXs.
- Decentralized exchanges, and role of fees for provision of trading and liquidity incentives
  - Park (2021), Capponi and Jia (2021), Barbon and Ranaldo (2021), Parlour and Lehar (2021), Aoyagi and Ito (2021)
  - **Contribution**: highlight how blockchain fees convey both private and public information.

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Executed trades data

- **Trades** executed on the largest CEX (**Binance**) and the largest DEX (**Uniswap**) for **eight token pairs** in the period of **November 1, 2020 through March 24, 2021**.
  - Both Binance and Uniswap: timestamp, trade size, execution price.
  - Uniswap only: block number, trader address, transaction nonce, gas price, and gas used
- Token pairs: Summary statistics: daily trading volume
  - Stable-Stable pairs: USDC-USDT, DAI-USDT
  - Nonstable-Stable pairs: ETH-USDT, ETH-USDC, ETH-DAI
  - Nonstable-Nonstable pairs: WBTC-ETH, LINK-ETH, AAVE-ETH

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Mempool orders data

- Mempool orders broadcast for the above eight token pairs in the period Feb 7, 2021 through March 24, 2021
  - Timestamp, trader address, transaction nonce, gas price and gas used
- About transaction nonce:
  - Each nonce for each trader can only be used once and in an increasing order.
  - An order with a larger nonce can not be executed before ones with a smaller nonce are executed first.
  - So when a trader wants to speed up his pending order, she broadcasts a new order with the same nonce and a higher gas fee.

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Methodology: structural VAR Model

- A general structural VAR model can be specified as follows:

$$Ay_t = \quad ¸ \quad {}_1 y_{t \; 1} \; ¸ \qquad ¸ \quad {}_p y_{t \; p} \; ¸ \quad {}_t$$

  - ${}_1 \cdots {}_p$: system matrices of the VAR model
  - y_t: endogenous variable vector
  - A: structural matrix capturing the *contemporaneous* correlations between the endogenous variables
  - ${}_t$: the vector of structural innovations and satisfies the following conditions: E¹ ${}_t$º = 0; E¹ ${}_t \; {}_t^{0}$º = ; E¹ ${}_t \; {}_s^{0}$º = 0 for $s < t$.

Baseline specification

- Our endogenous variable vector:

$$y_t = \begin{pmatrix} r_t^{\text{CEX}} & x_t^{\text{LowFee-DEX}} & x_t^{\text{MidFee-DEX}} & x_t^{\text{HighFee-DEX}} \end{pmatrix}'$$

  - t: indexes block time
  - r_t^{CEX}: Binance return from block time $t-1$ to t
  - $x_t^{\text{LowFee-DEX}}$, $x_t^{\text{MidFee-DEX}}$ and $x_t^{\text{HighFee-DEX}}$: Uniswap trade flows in block t, respectively with low, mid and high gas fee levels:

$$x_t^i = \sum_k d_k^i s_k^i,$$

    where d_k is the trade direction indicator (+1 for buys and -1 for sells), and s_k is the trade size

Baseline specification (Cont.)

Implementation details

- Our contemporaneous correlation matrix:

$$A = \begin{bmatrix} 1 & a_{12} & a_{13} & a_{14} \\ 0 & 1 & 0 & 0 \\ 0 & a_{32} & 1 & 0 \\ 0 & a_{42} & a_{43} & 1 \end{bmatrix}$$

- Assumptions on the contemporaneous correlations:
  - All three DEX trade flow variables cause CEX return but not vice versa
  - Low-fee DEX trade flow causes mid-fee and high-fee DEX trade flow
  - Mid-fee DEX trade flow causes high-fee DEX trade flow
  - Such a recursive structure gives a lower bound on the price impact of high-fee DEX trade flow

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Gas fee level classification

To classify trades in the current block t

1. First sort them together with all trades within the last 20 non-empty blocks, i.e., block t 20 to block t 1 based on their gas fee in descending order.

2. Then trades in block t are classified into three groups: Summary statistics of DEX trade characteristics by fee level

   I Trades in the top quartile (775% quantile): high-fee-price trades, $x_t^{\text{HighFee-DEX}}$

   I Trades in the bottom quartile (525% quantile): low-fee-price trades, $x_t^{\text{LowFee-DEX}}$

   I Other trades (between 25% and 75% quantile): mid-fee-price trades, $x_t^{\text{MidFee-DEX}}$

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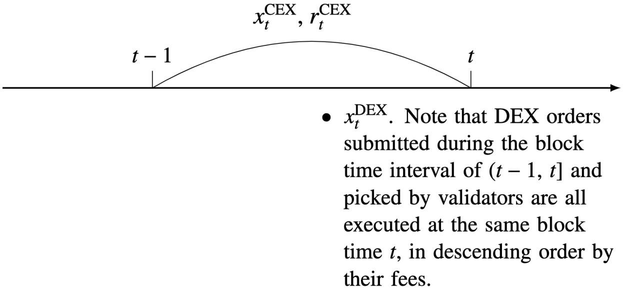
Timestamp convention

- r_t^{CEX}: the log difference between the price of the last Binance trade before block time t 1 and that of the last Binance trade before block time t.
- Uniswap trade flows, $x_t^{\text{LowFee-DEX}}$, $x_t^{\text{MidFee-DEX}}$ and $x_t^{\text{HighFee-DEX}}$, are computed based on trades executed at the same block time t.

Figure 2: Timestamp convention. This figure illustrates our time convention. t indexes block times.



Permanent price impact and information share

- Permanent price impact (PPI) of a DEX trade flow variable k: cumulative impulse responses of CEX return to a unit shock to that variable (Hasbrouck, 1991)

$$\mathrm{PPI}_k = \frac{\sum_{j=0}^{\infty} \partial r^{\mathrm{CEX}}_{t+j}}{\partial \ \ _{k,t}} = [\ (1)]_{1,k}$$

where $[\ (1)]_{1,k}$ denotes the $(1,k)$-*th* entry of $\ (1)$, which is sum of vector moving average (VMA) parameters.

- Information share (IS) of the CEX return or a DEX trade flow variable: PPI weighted by its innovation variance

$$\mathrm{IS}_k = \frac{\mathrm{PPI}_k^2 \ \ _k^2}{\sum_k \mathrm{PPI}_k^2 \ \ _k^2}$$

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$$\mathrm{IS}_k = \frac{\mathrm{PPI}_k^2\,\sigma_k^2}{\sum_k \mathrm{PPI}_k^2\,\sigma_k^2}$$

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Summary statistics of return and trade flow variables

(a) Stable-Stable token pairs. All trade flow variables are denominated in thousand USD. N is the number of blocks in our sample period.

		N	Mean	SD	Min	50%	Max
USDC-USDT	r_t^{CEX}	109436	0.00	0.97	-93.50	0.00	78.48
	x_t^{CEX}	109436	-1.61	146.78	-4994.91	0.00	7305.06
	x_t^{DEX}	109436	0.01	10.93	-403.21	-0.01	500.00
	$x_t^{LowFee\text{-}DEX}$	109436	0.03	3.97	-145.13	0.00	430.50
	$x_t^{MidFee\text{-}DEX}$	109436	0.06	6.88	-206.70	0.00	500.00
	$x_t^{HighFee\text{-}DEX}$	109436	-0.08	7.51	-403.21	0.00	348.85
DAI-USDT	r_t^{CEX}	63442	0.00	2.53	-89.16	0.00	93.20
	x_t^{CEX}	63442	0.21	46.93	-1162.58	0.00	1009.53
	x_t^{DEX}	63442	0.01	5.78	-142.20	-0.00	141.16
	$x_t^{LowFee\text{-}DEX}$	63442	0.01	2.23	-61.21	0.00	58.82
	$x_t^{MidFee\text{-}DEX}$	63442	0.01	3.60	-81.14	0.00	68.87
	$x_t^{HighFee\text{-}DEX}$	63442	-0.02	3.87	-142.20	0.00	94.93

Summary statistics of return and trade flow variables (Cont.)

(b) NonStable-Stable token pairs. All trade flow variables are denominated in ETH. N is the number of blocks in our sample period.

		N	Mean	SD	Min	50%	Max
ETH-USDT	r_t^{CEX}	636959	0.02	9.52	-551.79	0.00	362.82
	x_t^{CEX}	636959	-0.57	201.40	-7800.81	0.04	13897.08
	x_t^{DEX}	636959	0.17	45.18	-4304.51	0.02	5398.51
	$x_t^{LowFee\text{-}DEX}$	636959	-0.03	10.23	-2935.73	0.00	1241.70
	$x_t^{MidFee\text{-}DEX}$	636959	-0.08	23.93	-2579.05	0.00	2147.57
	$x_t^{HighFee\text{-}DEX}$	636959	0.28	36.87	-4304.51	0.00	5398.51
ETH-USDC	r_t^{CEX}	593951	0.02	10.42	-456.54	0.00	353.11
	x_t^{CEX}	593951	-0.08	23.98	-3693.72	0.00	2345.59
	x_t^{DEX}	593951	0.20	49.79	-7426.57	-0.08	8305.92
	$x_t^{LowFee\text{-}DEX}$	593951	-0.12	10.45	-1558.00	0.00	1086.42
	$x_t^{MidFee\text{-}DEX}$	593951	-0.14	27.15	-2612.99	0.00	3005.27
	$x_t^{HighFee\text{-}DEX}$	593951	0.46	39.81	-7426.57	0.00	8305.92
ETH-DAI	r_t^{CEX}	381166	0.04	11.98	-529.28	0.00	949.91
	x_t^{CEX}	381166	-0.03	7.10	-850.26	0.00	679.90
	x_t^{DEX}	381166	0.25	51.99	-9281.89	-0.00	3300.12
	$x_t^{LowFee\text{-}DEX}$	381166	-0.02	15.78	-6140.64	0.00	2165.82
	$x_t^{MidFee\text{-}DEX}$	381166	0.21	28.50	-1718.83	0.00	2841.28
	$x_t^{HighFee\text{-}DEX}$	381166	0.06	42.20	-11038.04	0.00	3196.28

Summary statistics of return and trade flow variables (Cont.)

(c) NonStable-NonStable token pairs. All trade flow variables are denominated in ETH. N is the number of blocks in our sample period.

		N	Mean	SD	Min	50%	Max
WBTC-ETH	r_t^{CEX}	156096	0.00	12.89	-360.42	0.00	300.74
	x_t^{CEX}	156096	0.07	8.90	-502.95	0.00	1991.97
	x_t^{DEX}	156096	0.02	77.20	-3465.19	0.18	4369.22
	$x_t^{LowFee\text{-}DEX}$	156096	0.05	18.64	-1690.72	0.00	1250.70
	$x_t^{MidFee\text{-}DEX}$	156096	0.23	48.26	-2954.34	0.00	4369.22
	$x_t^{HighFee\text{-}DEX}$	156096	-0.27	56.60	-3465.19	0.00	2344.65
LINK-ETH	r_t^{CEX}	113044	-0.04	22.72	-639.83	0.00	828.08
	x_t^{CEX}	113044	-0.46	17.64	-2047.56	0.00	603.75
	x_t^{DEX}	113044	-0.04	22.19	-1187.08	-0.06	661.38
	$x_t^{LowFee\text{-}DEX}$	113044	-0.04	5.44	-202.07	0.00	255.32
	$x_t^{MidFee\text{-}DEX}$	113044	-0.10	14.54	-1187.08	0.00	652.36
	$x_t^{HighFee\text{-}DEX}$	113044	0.09	15.63	-432.35	0.00	661.38
AAVE-ETH	r_t^{CEX}	66875	0.17	38.81	-429.98	0.00	420.53
	x_t^{CEX}	66875	-0.28	10.68	-676.27	0.00	493.72
	x_t^{DEX}	66875	0.12	18.88	-417.79	0.04	509.38
	$x_t^{LowFee\text{-}DEX}$	66875	0.05	5.43	-150.28	0.00	329.71
	$x_t^{MidFee\text{-}DEX}$	66875	0.03	12.84	-417.79	0.00	509.38
	$x_t^{HighFee\text{-}DEX}$	66875	0.05	12.84	-221.06	0.00	374.95

SVAR results: Permanent price impact of DEX trade flows

- Key results:
  - Stable-Stable: DEX trade flows of all fee levels contain no private information
  - NonStable-Stable and NonStable-NonStable: **High-fee DEX trade flow has a much larger permanent price impact than low-fee DEX trade flow.**

Table 2: Cumulative impulse responses of CEX return to DEX trade flows with di�erent gas price levels.

PairType	Variable	r_t^{CEX}	$x_t^{LowFee\text{-}DEX}$	$x_t^{MidFee\text{-}DEX}$	$x_t^{HighFee\text{-}DEX}$
Stable-Stable	r_t^{CEX}	0.63***	0.0	0.0	−0.01
		(0.02)	(0.01)	(0.01)	(0.01)
NonStable-Stable	r_t^{CEX}	0.97***	0.0	0.47***	3.41***
		(0.01)	(0.04)	(0.08)	(0.19)
NonStable-NonStable	r_t^{CEX}	0.81***	1.74***	3.47***	6.5***
		(0.01)	(0.31)	(0.37)	(0.54)

SVAR results: Information share of high-fee DEX trades

- Key result:
  - CEX return innovation itself, a measure of public information, contributes the lion's share of total information.
  - NonStable-Stable and NonStable-NonStable token pairs: **high-fee DEX trade flow has an information share about 10%, which is much larger than low-fee DEX trade flow.**

PairType Variable	Stable-Stable	NonStable-Stable	NonStable-NonStable
r_t^{CEX}	97.98	89.07	84.17
	(0.27)	(0.48)	(0.96)
$x_t^{LowFee\text{-}DEX}$	0.6	0.21	1.84
	(0.14)	(0.03)	(0.35)
$x_t^{MidFee\text{-}DEX}$	0.76	0.49	3.66
	(0.16)	(0.07)	(0.49)
$x_t^{HighFee\text{-}DEX}$	0.66	10.23	10.32
	(0.14)	(0.46)	(0.73)

SVAR results: DEX trade flows' responses to public information

- Keys results:
  - Stable-Stable: DEX trade flows do not respond to CEX return innovations
  - NonStable-Stable and NonStable-NonStable: **High-fee DEX trade flow has a larger impulse response to CEX return innovations, i.e., they respond more to public information**

Table 3: Cumulative impulse responses of DEX trade flows to CEX return shocks.

	Stable-Stable r_t^{CEX}	NonStable-Stable r_t^{CEX}	NonStable-NonStable r_t^{CEX}
r_t^{CEX}	0.63***	0.97***	0.81***
	(0.02)	(0.01)	(0.01)
$x_t^{LowFee\text{-}DEX}$	0.01	0.0***	0.0***
	(0.01)	(0.0)	(0.0)
$x_t^{MidFee\text{-}DEX}$	−0.01	0.01***	0.01***
	(0.02)	(0.0)	(0.0)
$x_t^{HighFee\text{-}DEX}$	0.01	0.04***	0.02***
	(0.01)	(0.0)	(0.0)

Dynamics of impulse responses between CEX return and DEX trade flows

- **CEX return responds quickly to high-fee DEX trade flow**, indicating that traders learn the private information contained in the high-fee DEX trade flow quickly, and thus update the market price to the **efficient** price faster.
  - Return IRFs are positive and significant in the contemporaneous ($t = 0$) and the next block ($t = 1$) They become insignificant from the second block ($t = 2$) onwards.
- **Response of DEX trade flows to public information is more sticky.**
  - The IRFs of high-fee and mid-fee trade flows to CEX returns are statistically significant for about five blocks ($t = 1$ to $t = 5$). Slow adjustment of DEX prices to the efficient CEX price

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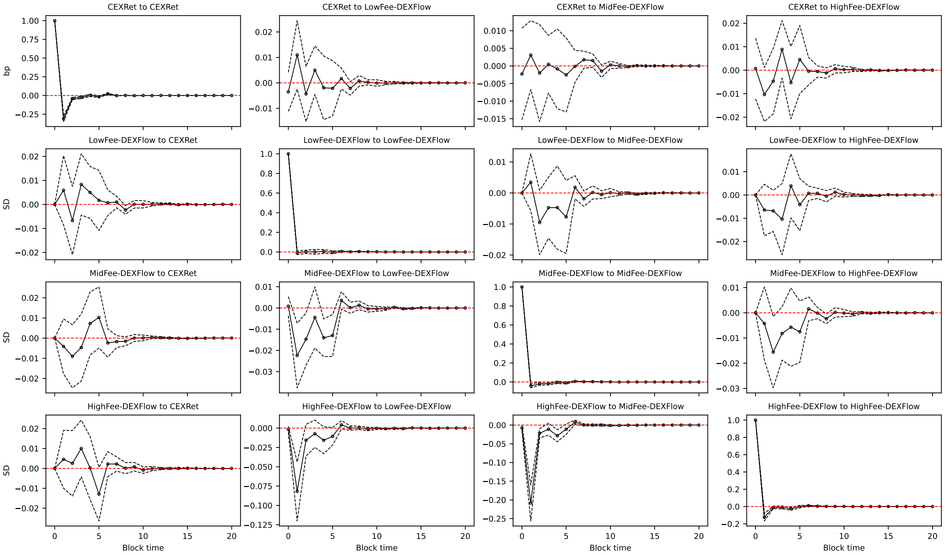
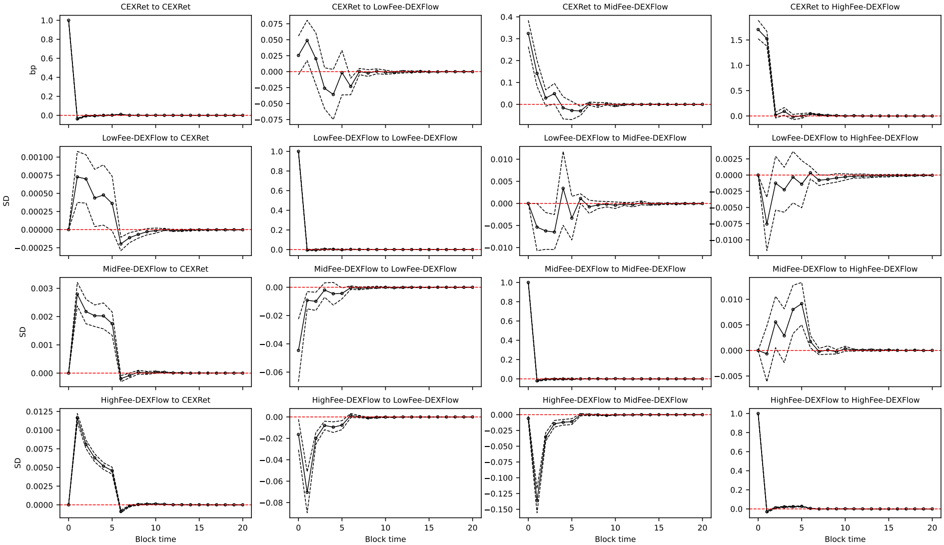
  - The IRFs of high-fee and mid-fee trade flows to CEX returns are statistically significant for about five blocks ($t = 1$ to $t = 5$). Slow adjustment of DEX prices to the efficient CEX price

Dynamics of IRFs (Stable-Stable)



Dynamics of IRFs (NonStable-Stable.)



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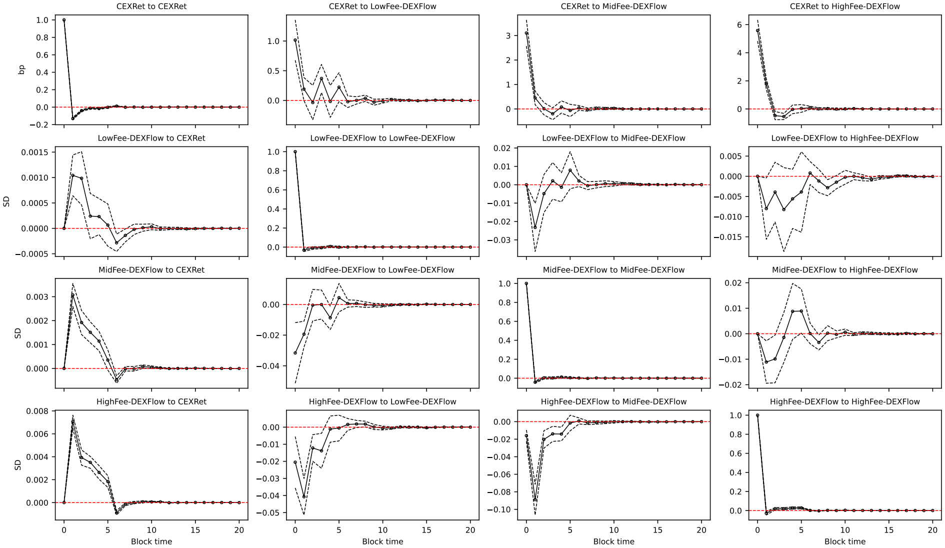

Plausible explanations:

Why do informed traders pay higher fees? Three plausible explanations:

- **Explicit competition**: traders participate in multiple-round fee auction.
- **Implicit competition**: anticipating competition, traders bid high fees ex-ante.
- **Blockchain congestion**: traders bid high fees to lower execution risk due to blockchain congestion (e.g, NFT auctions).

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Mempool order revision	Yes	No	No
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Identify trades in explicit competition

- We identify "explicit competition trades" by matching executed trades with their previous mempool orders, if they exist, based on the following criteria:
  1. Matched orders must have the same submission address and nonce as the executed trade.
  2. The gas price of the executed trade must be higher than that of its matched order(s).
  3. Matched orders for the executed trade in block t must arrive at the mempool between $t - 1$ and t.

- Matching results: only around 1% of executed trades are "explicit competition trades"

	Blocks	0	1	2	3-5	6-10	10+	All-Matched	Unmatched
Stable -Stable	USDC-USDT	0.64	0.26	0.15	0.34	0.34	1.13	2.86	97.14
	DAI-USDT	0.63	0.35	0.19	0.33	0.42	1.46	3.39	96.61
NonStable -Stable	ETH-USDT	0.78	0.34	0.19	0.33	0.30	1.19	3.13	96.87
	ETH-USDC	0.92	0.35	0.19	0.33	0.29	1.19	3.27	96.73
	ETH-DAI	1.08	0.39	0.22	0.38	0.35	1.51	3.94	96.06
NonStable -NonStable	WBTC-ETH	0.99	0.31	0.15	0.33	0.28	1.15	3.20	96.80
	LINK-ETH	1.32	0.51	0.27	0.37	0.35	1.56	4.37	95.63
	AAVE-ETH	1.59	0.50	0.27	0.24	0.34	1.69	4.64	95.36

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Do "explicit competition trades" drive SVAR results?

- Although the fraction of "explicit competition trades" is low, they might drive our SVAR results.
- Approach: We exclude "explicit competition trades" and re-implement the structural VAR.
  Second approach
- Cumulative impulse responses of CEX return to DEX trade flows barely changes.
  Baseline PPI results

Table 5: Cumulative impulse responses of CEX return to DEX trade flow shocks: Excluding "competition trades".

PairType	Variable	r_t^{CEX}	$x_t^{LowFee\text{-}DEX}$	$x_t^{MidFee\text{-}DEX}$	$x_t^{HighFee\text{-}DEX}$
Stable-Stable	r_t^{CEX}	0.59***	0.46	0.05	0.01
		(0.01)	(0.42)	(0.16)	(0.05)
NonStable-Stable	r_t^{CEX}	0.96***	0.0	0.41***	3.25***
		(0.01)	(0.04)	(0.08)	(0.18)
NonStable-NonStable	r_t^{CEX}	0.81***	1.84***	3.16***	6.47***
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Do "explicit competition trades" drive SVAR results? (Cont.)

- The cumulative impulse responses of DEX trade flows to CEX return barely change as well when excluding "explicit competition trades". Baseline public information results

- Thus, we can rule out the "explicit competition" channel.

Table 6: Cumulative impulse responses of DEX trade flows to CEX return shocks : Excluding "explicit competition trades".

	Stable-Stable	NonStable-Stable	NonStable-NonStable
	r_t^{CEX}	r_t^{CEX}	r_t^{CEX}
r_t^{CEX}	0.59***	0.96***	0.81***
	(0.02)	(0.01)	(0.01)
$x_t^{LowFee\text{-}DEX}$	0.01	0.0***	0.0***
	(0.01)	(0.0)	(0.0)
$x_t^{MidFee\text{-}DEX}$	−0.01	0.01***	0.01***
	(0.02)	(0.0)	(0.0)
$x_t^{HighFee\text{-}DEX}$	0.01	0.03***	0.02***
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Are high-fee trades more profitable?

- Simple revenue metric:

$$\text{Revenue} = \overbrace{\text{RPI}}^{\text{Price gain}} - \overbrace{\text{RES}}^{\text{Immediate price impact cost}} - \overbrace{\text{BlockchainFee}}^{\text{Blockchain fee cost}}$$

where RPI is relative price impact. RES is relative effective spread. BlockchainFee is the relative blockchain fee defined as the dollar blockchain fee divided by the dollar size of the trade.

- RPI and RES of a trade t are defined below:

$$\text{RPI}_t = \frac{d_i\,(\text{Mid}_{t+\Delta t} - \text{Mid}_t)}{\text{Mid}_t}, \quad \text{RES}_t = \frac{d_i\,(p_t - \text{Mid}_t)}{\text{Mid}_t}, \tag{1}$$

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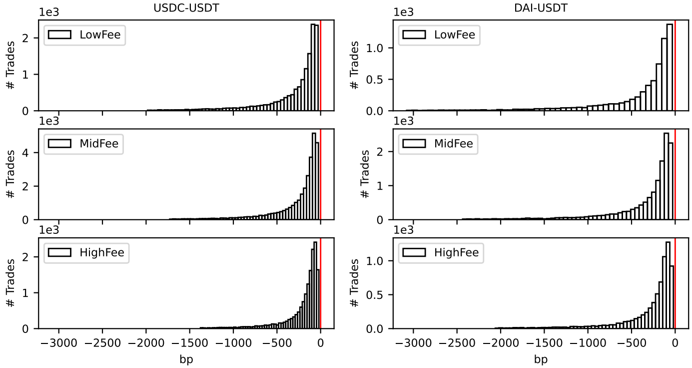
Revenue distribution of DEX trades by gas fee level

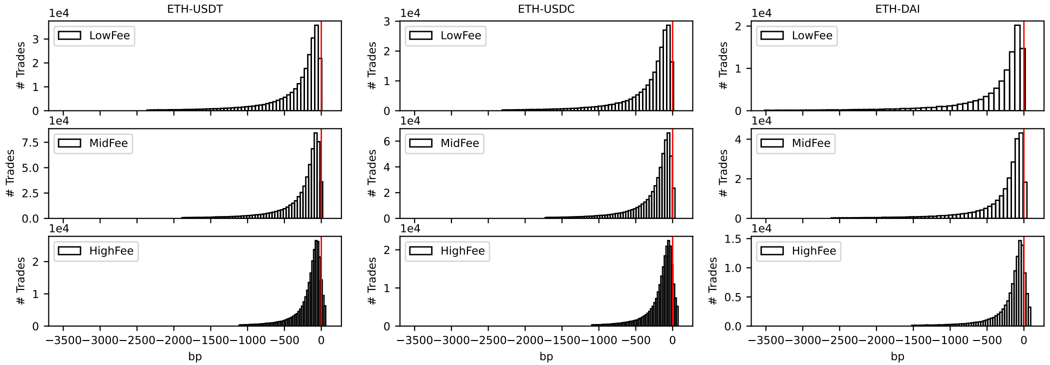
- Key result: A larger fraction of high-fee DEX trades have positive revenue compared to low-fee DEX trades.
- It lends support to "blockchain congestion" channel, versus "implicit competition" channel.

(a) Stable-Stable token pairs.



Revenue distribution (Cont.)

(b) NonStable-Stable token pairs.



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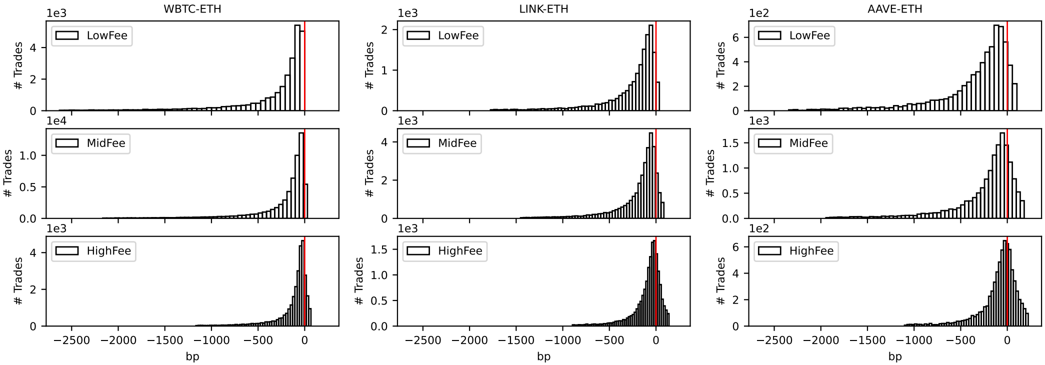

(c) NonStable-NonStable token pairs.

Outline

Conclusion

- We have shown that, compared with low-fee DEX trade flow, high-fee DEX trade flow
  - is more privately informed
  - responds more to public price innovations on CEXs, i.e., public information
- We test possible economic channels using a unique data set of Ethereum mempool orders.
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Thank You!

Outline

Robustness: SVAR specification with CEX trade flow

- Potential problem with the baseline specification: ◂ Baseline SVAR specification
  - Informed traders might split their trades between CEX and DEX. Thus CEX trade flow and DEX trade flow might be correlated.
- An alternative specification controlling for CEX trade flow:

$$y_t = \begin{pmatrix} r_t^{CEX} & x_t^{CEX} & x_t^{LowFee\text{-}DEX} & x_t^{MidFee\text{-}DEX} & x_t^{HighFee\text{-}DEX} \end{pmatrix} \tag{2}$$

$$A = \begin{pmatrix} 1 & a_{12} & a_{13} & a_{14} & a_{15} \\ 0 & 1 & 0 & 0 & 0 \\ 0 & a_{32} & 1 & 0 & 0 \\ 0 & a_{42} & a_{43} & 1 & 0 \\ 0 & a_{52} & a_{53} & a_{54} & 1 \end{pmatrix} \tag{3}$$

- So CEX trade flow contemporaneously affect DEX trade flows, but not vice versa.

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Robustness: Permanent price impacts of DEX trade ows

- Results are qualitatively the same as the baseline. Baseline PPI results

Table 7: Cumulative impulse responses of CEX return to CEX and DEX trade ows with di erent fee levels.

PairType	Variable	r_t^{CEX}	x_t^{CEX}	$x_t^{LowFee\text{-}DEX}$	$x_t^{MidFee\text{-}DEX}$	$x_t^{HighFee\text{-}DEX}$
Stable -Stable	r_t^{CEX}	0.55*** (0.01)	0.32*** (0.03)	0.01 (0.01)	0.0 (0.01)	=0.01 (0.01)
NonStable-Stable	r_t^{CEX}	0.97*** (0.01)	3.73*** (0.28)	=0.01 (0.04)	0.4*** (0.08)	3.06*** (0.17)
NonStable-NonStable	r_t^{CEX}	0.8*** (0.01)	5.07*** (0.44)	1.76*** (0.32)	3.18*** (0.37)	6.09*** (0.55)

Robustness: DEX trade ows' responses to public information

- Results are qualitatively the same as the baseline. Baseline public information results

Table 8: Cumulative impulse responses of DEX trade ows to CEX return shocks.

	Stable-Stable r_t^{CEX}	NonStable-Stable r_t^{CEX}	NonStable-NonStable r_t^{CEX}
r_t^{CEX}	0.55***	0.97***	0.8***
	(0.01)	(0.01)	(0.01)
x_t^{CEX}	=0.2***	0.0***	0.0***
	(0.03)	(0.0)	(0.0)
$x_t^{LowFee-DEX}$	0.01	0.0***	0.0***
	(0.02)	(0.0)	(0.0)
$x_t^{MidFee-DEX}$	0.0	0.01***	0.01***
	(0.02)	(0.0)	(0.0)
$x_t^{HighFee-DEX}$	0.0	0.03***	0.02***
	(0.01)	(0.0)	(0.0)

Daily trading summary statistics on Uniswap and Binance

Data description

(a) Stable-Stable token pairs. Trading volume is denominated in thousand USDT. N refers to the number of days in our sample period.

Pair		N	Mean	SD	Min	Med	Max
USDC-USDT	TradingVolume-Uniswap	145	3804	2257	364	3885	11641
	TradeCount-Uniswap	145	869	351	415	773	3085
	TradingVolume-Binance	145	107896	69910	16396	102837	398522
	TradeCount-Binance	145	50266	21949	14182	47198	135409
DAI-USDT	TradingVolume-Uniswap	145	1258	1152	54	960	5830
	TradeCount-Uniswap	145	494	368	161	352	2068
	TradingVolume-Binance	145	12086	10135	694	9946	77831
	TradeCount-Binance	145	8279	6782	1211	7071	58558

Daily trading summary statistics on Uniswap and Binance (Cont.)

Data description

(b) NonStable-Stable token pairs. Trading volume is denominated in ETH. N refers to the number of days in our sample period.

Pair		N	Mean	SD	Min	Med	Max
ETH-USDT	TradingVolume-Uniswap	145	72574	38805	36596	61494	263356
	TradeCount-Uniswap	145	8601	1452	6311	8308	16419
	TradingVolume-Binance	145	1243663	635988	438952	1052452	4245010
	TradeCount-Binance	145	948849	479112	181369	915584	2577496
ETH-USDC	TradingVolume-Uniswap	145	79559	39893	32878	70621	302051
	TradeCount-Uniswap	145	7595	1405	4681	7549	13851
	TradingVolume-Binance	145	27927	20587	5808	21350	142110
	TradeCount-Binance	145	19292	13222	3158	16554	80061
ETH-DAI	TradingVolume-Uniswap	145	54327	69493	9992	39382	746637
	TradeCount-Uniswap	145	3834	1353	1591	3547	7786
	TradingVolume-Binance	145	8737	8823	245	6529	51489
	TradeCount-Binance	145	17390	17435	285	14180	103522

Daily trading summary statistics on Uniswap and Binance (Cont.)

Data description

(c) NonStable-NonStable token pairs. Trading volume is denominated in ETH. N refers to the number of days in our sample period.

Pair		N	Mean	SD	Min	Med	Max
WBTC-ETH	TradingVolume-Uniswap	145	31604	21973	6278	26293	139189
	TradeCount-Uniswap	145	1304	531	646	1141	3338
	TradingVolume-Binance	145	1684	1688	18	1261	9984
	TradeCount-Binance	145	6260	6397	92	4503	35191
LINK-ETH	TradingVolume-Uniswap	145	9348	5870	1949	7958	42520
	TradeCount-Uniswap	145	920	366	367	873	2682
	TradingVolume-Binance	145	4463	2489	1071	3975	13598
	TradeCount-Binance	145	11630	7337	2200	11226	43491
AAVE-ETH	TradingVolume-Uniswap	145	6442	4418	819	5595	29936
	TradeCount-Uniswap	145	536	277	136	502	1514
	TradingVolume-Binance	145	1876	1381	348	1546	10143
	TradeCount-Binance	145	6272	4708	1075	5322	36964

Summary statistics of trade characteristics by fee level

Gas fee classi cation

(a) Stable-Stable token pairs. Transaction size is in USDT. N refers to the number of trades for each token pair during our sample period.

Pair	Variable	GasLevel	N	Mean	SD	Median
USDC-USDT	GasPrice	LowGas	29932	82.00	57.73	68.00
		MidGas	60522	96.14	68.66	80.00
		HighGas	32632	143.29	139.21	117.00
	TxSize	LowGas	29932	3.00	8.12	0.98
		MidGas	60522	3.95	11.05	1.14
		HighGas	32632	6.37	14.57	2.20
DAI-USDT	GasPrice	LowGas	17056	73.57	50.70	61.00
		MidGas	32797	90.15	63.40	76.00
		HighGas	18773	130.72	196.34	104.00
	TxSize	LowGas	17056	1.90	4.28	0.55
		MidGas	32797	2.31	5.06	0.78
		HighGas	18773	3.52	6.90	1.19

Summary statistics of trade characteristics by gas fee level

Gas fee classi cation

(b) NonStable-Stable token pairs. Transaction size is in ETH. N refers to the number of trades for each token pair during our sample period.

Pair	Variable	GasLevel	N	Mean	SD	Median
ETH-USDT	GasPrice	LowGas	266642	88.21	67.25	74.00
		MidGas	676442	100.95	76.10	85.00
		HighGas	299408	170.99	350.67	128.00
	TxSize	LowGas	266642	3.54	19.04	0.83
		MidGas	676442	6.22	135.13	1.24
		HighGas	299408	17.72	71.87	3.22
ETH-USDC	GasPrice	LowGas	235734	92.43	70.59	80.00
		MidGas	594722	106.48	80.76	91.00
		HighGas	266117	179.85	410.45	135.00
	TxSize	LowGas	235734	4.30	18.83	0.94
		MidGas	594722	7.89	32.35	1.54
		HighGas	266117	21.59	57.04	4.19
ETH-DAI	GasPrice	LowGas	123305	82.09	68.38	65.00
		MidGas	292993	96.50	83.46	76.00
		HighGas	135614	172.27	603.48	115.23
	TxSize	LowGas	123305	5.36	38.55	0.75
		MidGas	292993	10.42	45.81	1.20
		HighGas	135614	25.14	206.29	4.48

Summary statistics of trade characteristics by gas fee level

Gas fee classi cation

(c) NonStable-NonStable token pairs. Transaction size is in ETH. N refers to the number of trades for each token pair during our sample period.

Pair	Variable	GasLevel	N	Mean	SD	Median
WBTC-ETH	GasPrice	LowGas	43947	93.62	73.42	81.00
		MidGas	94110	113.76	89.82	97.00
		HighGas	47870	200.66	920.11	144.00
	TxSize	LowGas	43947	10.86	42.08	1.58
		MidGas	94110	21.21	71.58	3.15
		HighGas	47870	42.14	92.33	14.72
LINK-ETH	GasPrice	LowGas	31427	81.82	68.14	64.64
		MidGas	65276	100.83	86.63	80.00
		HighGas	33554	199.03	478.83	130.00
	TxSize	LowGas	31427	4.44	10.98	1.18
		MidGas	65276	9.38	26.37	2.22
		HighGas	33554	16.91	26.12	10.39
AAVE-ETH	GasPrice	LowGas	18186	75.26	59.33	59.00
		MidGas	37196	97.12	78.39	78.00
		HighGas	19205	190.04	322.35	127.86
	TxSize	LowGas	18186	5.58	13.14	1.40
		MidGas	37196	11.74	21.37	4.27
		HighGas	19205	18.49	19.95	16.91

Implementation details

◂ Baseline speci cation

- Model estimated at block-by-block frequency
- We set the number of lags in the structural VAR model to 5. In Appendix, we change the number of lags included in the structural VAR model to 10 and 20, and show that estimation results remain qualitatively the same.
- As the base currency varies across token pairs, to ease comparison and aggregation across token pairs, we standardize all trade ow variables such that they have zero mean and unit variance.
- Hence, the impulse responses reported below should be interpreted as permanent price impacts in basis points per standard deviation increase in the trade ow.

Private information content of explicit competition trades (Approach #2)

First approach

- Approach #2: We separate competition trades from non-competition trades and include both in the structural VAR analysis.
- DEX trade ow consisting of competition trades has a smaller permanent price impact than that consisting of non-competition trades .

Table 11: Cumulative impulse responses between CEX return and DEX trade ows: Excluding competition trades .

PairType	Variable	r_t^{CEX}	$x_t^{LF\text{-}NC\text{-}DEX}$	$x_t^{LF\text{-}C\text{-}DEX}$	$x_t^{HF\text{-}NC\text{-}DEX}$	$x_t^{HF\text{-}C\text{-}DEX}$
Stable-Stable	r_t^{CEX}	0.61*** (0.03)	0.02 (0.02)	0.01 (0.02)	0.0 (0.02)	0.0 (0.01)
NonStable-Stable	r_t^{CEX}	0.97*** (0.01)	0.11 (0.07)	0.09 (0.07)	3.06*** (0.2)	1.16*** (0.16)
NonStable-NonStable	r_t^{CEX}	0.83*** (0.02)	2.45*** (0.5)	1.37*** (0.46)	7.03*** (0.78)	1.34*** (0.47)

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Stable-Stable	r_t^{CEX}	0.61*** (0.03)	0.02 (0.02)	0.01 (0.02)	0.0 (0.02)	0.0 (0.01)
NonStable-Stable	r_t^{CEX}	0.97*** (0.01)	0.11 (0.07)	0.09 (0.07)	3.06*** (0.2)	1.16*** (0.16)
NonStable-NonStable	r_t^{CEX}	0.83*** (0.02)	2.45*** (0.5)	1.37*** (0.46)	7.03*** (0.78)	1.34*** (0.47)

Response of explicit competition trades to public information (Approach #2)

- Competition trades respond less to CEX return innovations than non-competition trades .

Table 12: Cumulative impulse responses of DEX trade ows to CEX return shocks : Separating competition trades .

	Stable-Stable r_t^{CEX}	NonStable-Stable r_t^{CEX}	NonStable-NonStable r_t^{CEX}
r_t^{CEX}	0.61***	0.97***	0.83***
	(0.03)	(0.01)	(0.01)
$x_t^{LF\text{-}NC\text{-}DEX}$	0.0	0.0***	0.0***
	(0.02)	(0.0)	(0.0)
$x_t^{LF\text{-}C\text{-}DEX}$	0.04	0.00	0.0***
	(0.03)	(0.0)	(0.0)
$x_t^{HF\text{-}NC\text{-}DEX}$	=0.01	0.04***	0.02***
	(0.02)	(0.0)	(0.0)
$x_t^{HF\text{-}C\text{-}DEX}$	0.02	0.01***	0.0***
	(0.02)	(0.0)	(0.0)

Are profitable trades result from competition?

- Only a very small fraction of profitable trades are “explicit-competition trades”

PairType	Pair	Revenue	Competition trades	Non-competition trades
Stable-Stable	USDC-USDT	% Negative	0.38	99.62
		% Positive	2.98	97.02
	DAI-USDT	% Negative	0.33	99.67
		% Positive	0.00	100.00
NonStable-Stable	ETH-USDT	% Negative	0.42	99.58
		% Positive	1.60	98.40
	ETH-USDC	% Negative	0.45	99.55
		% Positive	1.81	98.19
	ETH-DAI	% Negative	0.50	99.50
		% Positive	2.39	97.61
NonStable-NonStable	WBTC-ETH	% Negative	0.44	99.56
		% Positive	2.06	97.94
	LINK-ETH	% Negative	0.83	99.17
		% Positive	1.92	98.08
	AAVE-ETH	% Negative	0.89	99.11
		% Positive	1.34	98.66