Market Quality of Automated Market Makers

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Stage 3 Presentation

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Why do we trade?

Trading makes us better off (Gains from trade)

- Transfer resources through space and time, transfer risk
- Pool resources to most productive use, generate information

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- Electronic markets
- **Decentralized markets and AMMs***

Market Quality of Automated Market Makers

Are AMMs the next evolution in markets?

- Facilitate the exchange of tokenized assets
- Low cost
- Passive liquidity

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Market quality

- Liquidity (Chapter 2)
  - ◇ Can AMM liquidity provision improve modern markets?
- Price discovery (Chapter 3)
  - ◇ Can AMMs provide price discovery?
- Market Integrity (Chapters 4 and 5)
  - ◇ How much misconduct occurs in DEXs?
  - ◇ Is there insider trading on crypto listing announcements?

Liquidity That Lasts: Learning from AMMs for Market Liquidity

Liquidity that lasts

Limit orders provide temporary liquidity

- Once matched the order is removed from the book
- Market makers often replenish orders once traded
- Avoid adverse selection, constant monitoring to stay active

Trades in AMMs do not deplete liquidity

- Orders are automatically managed by the pricing function
- Passive liquidity provision

Is AMMs liquidity more stable?

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Is AMMs liquidity more stable?

Can AMM liquidity improve modern markets?

- Resilience of liquidity

Automated Market Makers

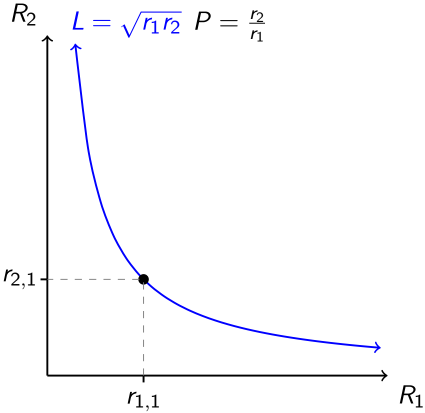
Passive liquidity

- Liquidity providers (LPs) pool assets
- Mathematical function determines trade amounts
- Traders pay a small fee to the LPs
- Enforced by smart contracts on blockchains

Popular AMM designs

- Constant Product Market Maker ($xy = k$, $\sqrt{r_1 r_2} = L$)
- Concentrated liquidity
- Stableswap

Constant Product Market Maker (CPMM)



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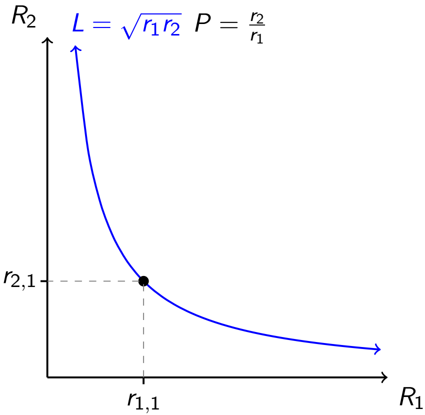
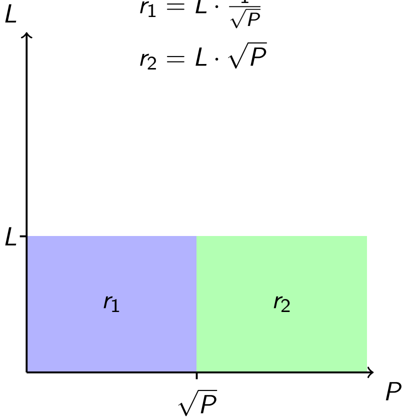
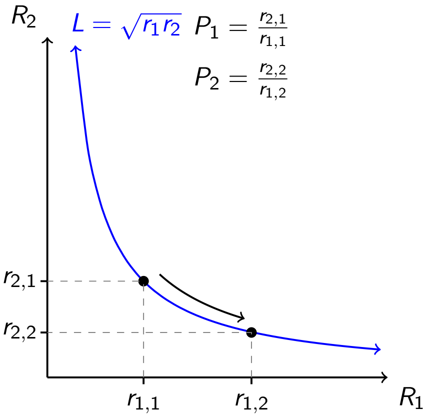


$$r_1 = L \cdot \frac{1}{\sqrt{P}}$$

$$r_2 = L \cdot \sqrt{P}$$

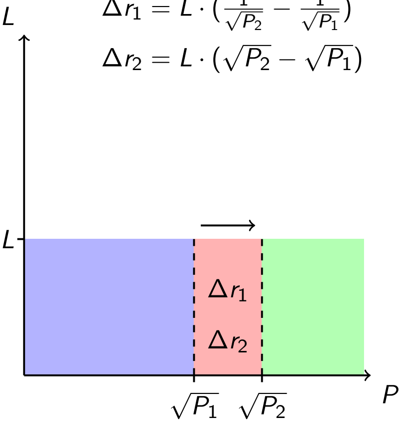


Swapping in a CPMM

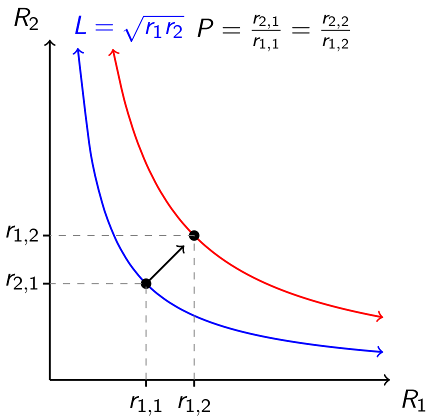


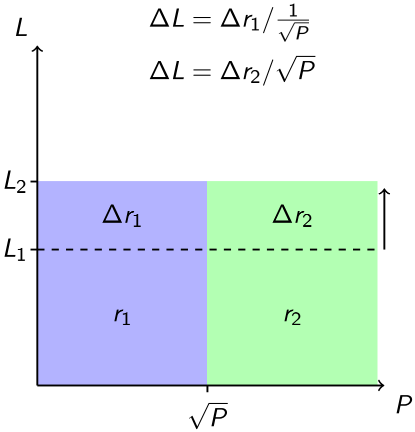
$$\Delta r_1 = L \cdot \left(\frac{1}{\sqrt{P_2}} - \frac{1}{\sqrt{P_1}}\right)$$

$$\Delta r_2 = L \cdot \left(\sqrt{P_2} - \sqrt{P_1}\right)$$



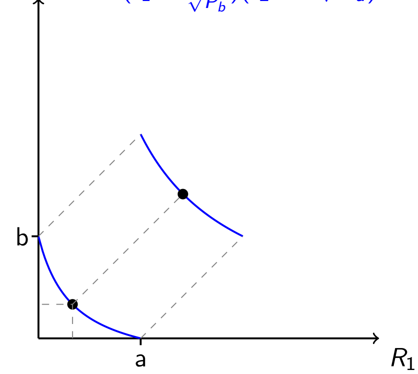
Changing liquidity in a CPMM





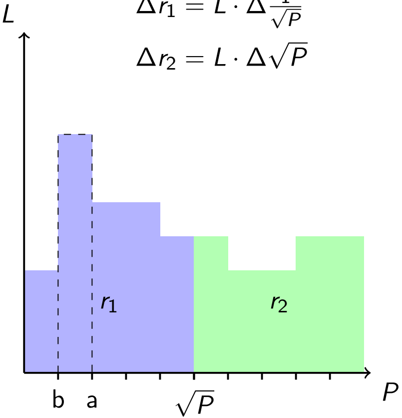
Concentrated liquidity

$$L^2 = \left(r_1 + \frac{L}{\sqrt{P_b}}\right)\left(r_2 + L\sqrt{P_a}\right)$$

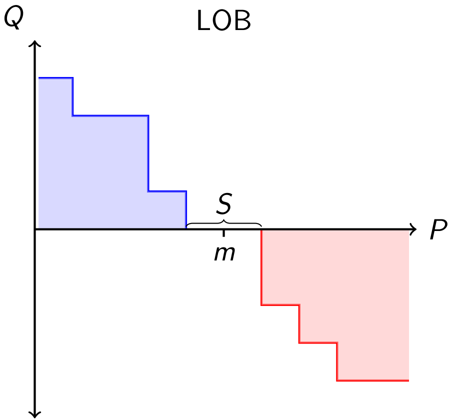


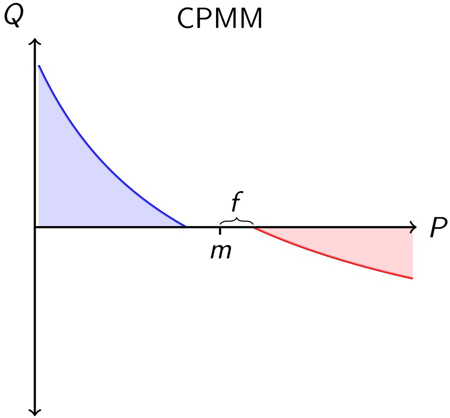
$$\Delta r_1 = L \cdot \Delta \frac{1}{\sqrt{P}}$$

$$\Delta r_2 = L \cdot \Delta \sqrt{P}$$



AMMs and LOBs





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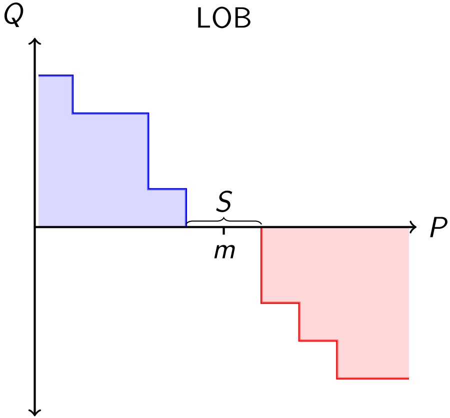
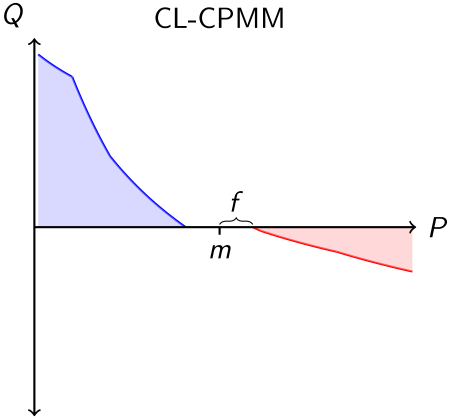




Comparable liquidity

AMMs and LOBs both have

- Mid-price
- Spread
- Depth

but differ in

- AMMs have continuous prices
- LOB orders are cleared after trading

Comparable measures of liquidity

- Quoted spread $\rightarrow 2 \cdot \mathit{fee}$
- Depth $\rightarrow \Delta r_1(1 + \mathit{fee})$

Is AMM liquidity more stable?

Compare hourly measures of liquidity across Binance (LOB) and Uniswap v2, v3 and Quickswap v2, v3 (AMM)

- Ethereum, Polygon, Arbitrum, and Optimism

Daily measure of liquidity variance by taking log difference of the min and max hourly liquidity.

- Effective spread, 1% Depth , Amihud ILLIQ

$$LiquiditySpread_{i,t} = \alpha + AMMDummy_{i,t} + Controls_{i,t} + \epsilon_{i,t},$$

Regressions to assess AMM liquidity stability

	(1)	(2)	(3)
Dependent variable:	$\Delta_{max}^{min} ES$	$\Delta_{max}^{min} Depth_{1\%}$	$\Delta_{max}^{min} ILLIQ$
CPMM	0.028***	−4.175***	−1.008***
	(3.16)	(-376.53)	(-43.40)
CL-CPMM	0.195***	−3.327***	0.014
	(21.53)	(-295.73)	(0.55)
Volume	0.168***	0.107***	0.379***
	(76.69)	(39.43)	(65.81)
Volatility	−0.003***	0.040***	−0.027***
	(-2.90)	(28.63)	(-9.35)
$Depth_{1\%}$	−0.238***	−0.119***	−0.319***
	(-106.83)	(-43.37)	(-51.37)
HalfQuotedSpread	−0.278***	0.248***	0.224***
	(-92.78)	(66.96)	(28.73)
Intercept	−0.137***	5.880***	3.540***
	(-4.65)	(161.43)	(41.19)
Pair Effects	Y	Y	Y
Observations	84,225	83,881	54,446
Adjusted R^2	36.4%	71.0%	16.8%

Significance: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Implications

Blockchain fees and network characteristics influence stability of liquidity in AMMs

- Gas $\uparrow$ Liquidity variance
- Ethereum $\downarrow$ Liquidity variance

AMM liquidity is more **stable** and could improve modern markets

Propose various models to incorporate AMMs in to modern markets

- Automate trading in LOB to replicate an AMM
- Limit orders into AMM through hooks
- Introducing AMM like orders into an orderbook market
    - similar to Bullish crypto exchange

Can Automated Market Makers Provide Price Discovery?

Motivation

Price discovery is a key function of financial markets

- LPs in AMMs let traders set price through a mathematical formula
- In LOB markets quotes provide the bulk of price discovery (Brogaard, Hendershott, and Riordan 2019)
- LPs face increased adverse selection which theory suggests to be a driver of illiquidity (Kyle 1985; Glosten and Milgrom 1985)
    - ◇ AMMs should be illiquid and inefficient

Price discovery: Information $\rightarrow$ Prices

- When AMMs are the only market can they provide price discovery?
- Can AMMs lead price discovery?

Can AMMs provide price discovery?

Compare sample of assets that trade only on AMM and pairs that trade on AMM and LOB

- Matched sample based on market, year, month and nearest neighbor by volume up to 20% threshold

Variance Decomposition (Brogaard et al. 2022)

- Innovations in price that can be explained by sources of market, private or public information. Asset returns: $r_t = \mu + \theta_{r_m}\varepsilon_{r_m,t} + \theta_x\varepsilon_{x,t} + \theta_r\varepsilon_{r,t} + \Delta s_t$
- Structural VAR with market returns (r_m), signed dollar volume (x) and returns (r) 12 lags hourly frequency
  - θ's from cumulative impulse response function
  - ε's from the VAR residuals
  - *MarktInfoShare*, *PrivateInfoShare*, *PublicInfoShare*, and *NoiseShare*

Variance decomposition shares

Panel A. AMM and LOB Summary Statistics	Mean	Standard Deviation	p10	Median	p90
MarketInfoShare (%)	7.44	14.86	0.04	2.24	17.58
PrivateInfoShare (%)	42.35	25.03	4.99	45.22	73.88
PublicInfoShare (%)	5.45	9.37	0.21	2.14	11.72
NoiseShare (%)	44.76	25.11	17.59	39.67	88.37
Panel B. AMM Only Summary Statistics					
MarketInfoShare (%)	5.64	11.67	0.05	1.23	14.77
PrivateInfoShare (%)	45.02	21.87	11.47	48.85	71.57
PublicInfoShare (%)	4.80	5.73	0.21	2.99	12.47
NoiseShare (%)	44.53	19.82	20.07	43.34	72.32

Testing if AMMs can provide price discovery?

To test if AMMs can provide price discovery we use the following regression model:

$$VarShare_{i,t} = \alpha_{i,t} + \beta_1 AMMOnly_{i,t} + \beta_2 Liquidity_{i,t} + \beta Controls_{i,t} + \epsilon_{i,t}$$

Where *VarShare* is a measure of variance shares such as the *NoiseShare*, *MarketInfoShare*, *PrivateInfoShare*, or the *PublicInfoShare*.

Focus on the *NoiseShare*

- If an AMM on its own cant provide price discovery the noise share should be higher (less information in price)

Variance shares regressions

Dependent variable:	*NoiseShare*	*MarketInfoShare*	*PrivateInfoShare*	*PublicInfoShare*
AMM Only	−0.036**	−0.004	0.039**	0.002
	(−2.26)	(−0.42)	(2.09)	(0.31)
EffectiveSpread	0.092***	0.002	−0.103***	0.009
	(5.51)	(0.27)	(−6.74)	(0.95)
$Depth_{[1.5\%]}$	0.004	0.014*	−0.020**	0.002
	(0.76)	(1.84)	(−2.22)	(0.56)
Volume	−0.035***	0.014**	0.026**	−0.006
	(−4.59)	(2.14)	(2.50)	(−1.53)
RealizedVolatility	0.052***	−0.024***	−0.017	−0.012*
	(4.61)	(−3.52)	(−1.35)	(−1.95)
CL	0.121***	0.027	−0.123***	−0.025***
	(4.76)	(1.53)	(−4.07)	(−2.64)
Controls	Y	Y	Y	Y
Observations	522	522	522	522
Adjusted R^2	39.3%	20.3%	20.8%	6.4%

Significance: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Can AMMs provide price discovery?

Yes

- Significantly less (<5%) *NoiseShare* in AMM only pairs
  - Not economically significant 3% less noise
- Listings are not random, However this work against our findings
  - List tokens that contain information
  - Sample matching based on volume

AMMs can provide price discovery when they are the only market

- Support low cost trading

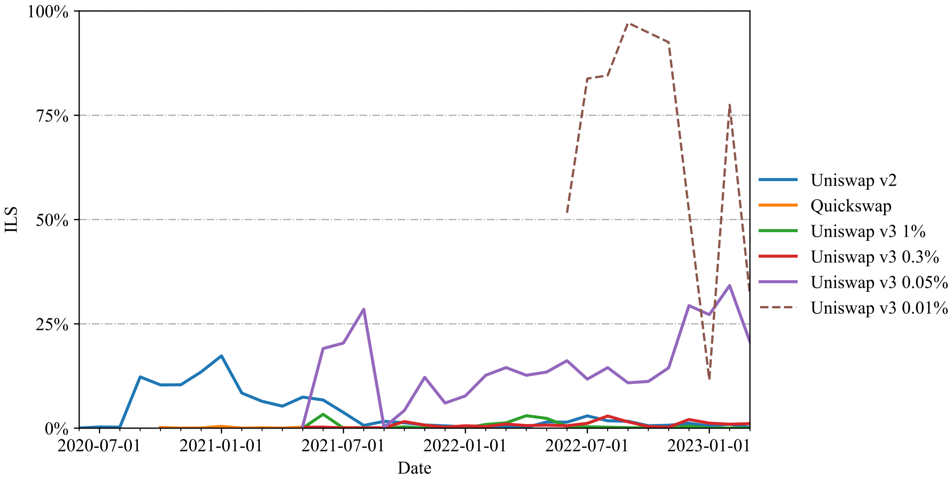
Can AMMs lead price discovery?

Compare trading pairs that trade on both the AMM and the LOB

Extend Yan-Zivot-Putnins Information Leadership Share (*ILS*) to *n* markets (Putniņš 2013)

- Significant difference in volatility between markets
  - ◇ Information Share (IS) and Component Share (CS) both measure a relative avoidance of noise
- VECM with 300 lags ($\sim$1 hour)
  - ◇ Mid-quote prices for all Uniswap markets and Binance
  - ◇ Ethereum blocktime (12 seconds*)

Information Leadership Share



Informed traders

Informed traders face a venue selection choice

- Profit maximisation: Implicit cost and explicit costs
- More liquid AMM (LOB) have lower implicit costs
- Informed traders are sensitive to gas fees on Ethereum (Capponi, Jia, and Yu 2023)
- Information is revealed to block builder in AMM

What AMM determines price leadership?

Average ILS for AMM pool is 4.3%

- Uniswap v3 0.05% has an ILS of 13.6%
- Uniswap v3 0.01% has an ILS of 67.5% (FUNToken)

From regressions we find:

- AMM price leadership $\uparrow$ with AMM liquidity
- AMM price leadership $\downarrow$ with LOB liquidity
- AMM price leadership $\downarrow$ with gas fees
- Venue selection choice for informed traders impacted by both implicit and explicit costs

Misconduct in Decentralized Exchanges

Cryptocurrencies and Crime

- $180 billion in total value linked to illicit addresses between 2020 and 2024 (Chainalysis, 2025)
- Features of blockchains are attractive to bad actors
    - ◇ Pseudonymous (no Know-Your-Customer (KYC))
    - ◇ Permissionless
    - ◇ Lack of clear regulation

What happens when markets inherit these features?

- Decentralised Exchanges (DEXs)

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- Decentralised Exchanges (DEXs)
- **Market Misconduct?**

Regulatory concerns

DEXs are becoming a popular way to trade cryptocurrencies

- Regulators concerned with manipulation in these markets (ESMA 2023a, 2023b)
    - Blockchain based markets introduce new forms of manipulation
    - AMMs unclear pre-trade reporting requirements
    - Policing challenges

Little is known about the extent and impact of market misconduct on DEXs

- Handful of papers look at specific aspects of misconduct on DEXs

Misconduct in DEXs

Quantify the amount of market misconduct in DEXs

- Sandwich attacks
- Wash trading
- Rug pulls
- Money laundering

Build an index to track the amount of market misconduct across DEXs from June 2020 to December 2024

- Uniswap v2 (Ethereum, BSC)
- Uniswap v3 (Ethereum, Polygon)
- Pancakeswap v2 (BSC)
- Pancakeswap v3 (BSC)
- Sushiswap (Ethereum, BSC)
- Sushiswap v3 (Ethereum)
- Quickswap (Polygon)
- Quickswap v3 (Polygon)

Sandwich Attack

Front running then back running a trade on AMM to profit from the increased price impact faced by the trader

- Use position privilege as a block builder to profit from AMM trades
- Attacker Buy (Sell) $\rightarrow$ Victim Buy (Sell) $\rightarrow$ Attacker Sell (Buy)
  - ◇ Single block, similar volume on attacker trades (1%)

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- Attacker Buy (Sell) → Victim Buy (Sell) → Attacker Sell (Buy)
    - ◇ Single block, similar volume on attacker trades (1%)

Identify **$149 billion** in sandwich attacker volume

- Consistent with share of volume across exchanges
- BSC $6.7 billion, Polygon $0.6 billion

Wash Trading

Buy and sell the same asset to create the illusion of volume

- Inflate volumes, more liquidity in the market
- Hinders decision making
- Circular trading flow in an hour from single address
  - Net volume $<$ 5% total volume in hour
  - Removing sandwich attacks

Wash Trading

Buy and sell the same asset to create the illusion of volume

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  - Removing sandwich attacks

Identify **$73 billion** in wash trading volume

- Uniswap v2 on Ethereum, $41 billion
- Pancakeswap v2 on BSC, $11 billion

Rug pulls

A developer creates and promote a token, attract liquidity from investors, and then abruptly withdraw funds, leaving the token worthless.

- Mislead investors with the intention to profit from the created token
- Classify rug pulls following Aliyev, Allahverdiyeva, and Putniņš (2023)
    - Price pattern (Run-up and reversal)
    - Profit pattern (Token creator profit)
    - Activity pattern (Pool is inactive)

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Identify **$184 billion** in volume from rug pull pools

- Uniswap v3 on Ethereum, $133 billion, Smaller run-ups and reversals
- 294k rug pulls, Pancakeswap v2 on BSC
- 76k rug pulls, Uniswap v2 on Ethereum

Money Laundering

Concealing the source of funds gained from illegal activity

- Hides the source of illicit funds
- Calculate the swap volume of addresses related with “money laundering”
    - ◇ Rekt DB (Known hack addresses)
    - ◇ Tornado Cash (Mixer)

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Identify **$35 billion** in volume from money laundering addresses

- No money laundering on either Quickswap exchange
- Uniswap v2 on Ethereum, $25 billion

Market Integrity Index

We create indexes to track the proportion of volume associated with each form of misconduct:

$$SAI_{i,t} = \frac{SandwichAttackerVolume_{i,t}}{TotalVolume_{i,t}} \tag{1}$$

$$WTI_{i,t} = \frac{WashtradingVolume_{i,t}}{TotalVolume_{i,t}} \tag{2}$$

$$RPI_{i,t} = \frac{RugPullVolume_{i,t}}{TotalVolume_{i,t}} \tag{3}$$

$$MLI_{i,t} = \frac{MoneyLaunderingVolume_{i,t}}{TotalVolume_{i,t}} \tag{4}$$

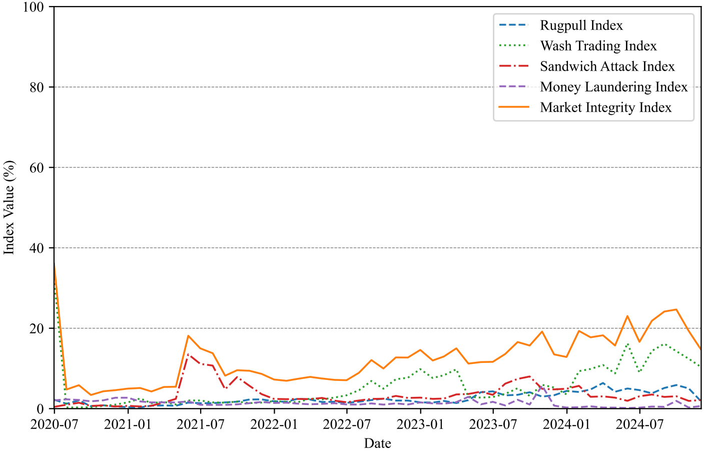
$$MII_{i,t} = SAI_{i,t} + WTI_{i,t} + RPI_{i,t} + MLI_{i,t} \tag{5}$$

Market integrity indexes

Identify **$413 billion** in volume from market misconduct

Exchange	Chain	*WTI*	*SAI*	*RPI*	*MLI*	*MII*
Uniswap v2	Ethereum	8.59	9.18	4.82	3.86	24.67
Uniswap v2	BSC	33.33	2.12	4.16	0.32	37.52
Uniswap v3	Ethereum	0.68	5.22	10.99	0.03	16.21
Uniswap v3	Polygon	0.84	0.24	0.57	0.00	1.62
Pancakeswap v2	BSC	4.74	1.03	8.92	0.53	14.25
Pancakeswap v3	BSC	0.85	3.21	0.06	0.83	4.92
Sushiswap	Ethereum	10.75	3.91	0.17	3.30	17.17
Sushiswap	BSC	16.51	1.08	0.04	0.18	17.79
Sushiswap v3	Ethereum	4.59	14.75	0.00	2.87	22.03
Quickswap	Polygon	1.09	2.08	0.03	0.00	3.20
Quickswap v3	Polygon	0.78	0.12	0.03	0.00	0.92

Aggregate Index



Does misconduct matter?

Do other market participants care about the levels of misconduct in DEXs?

$$\Delta Activity_{i,t} = \alpha + \Delta Integrity_{i,t} + \Delta Integrity_{i,t-1} + ExchangeEffects_i \qquad (6)$$

Volume as activity

- Some positive contemporaneous effects (Significant at 10%)
- Lagged *SAI* positive significant at 5%

TVL as activity

- No significant laged effects

Integrity issues do not impact DEXs

Market integrity of DEXs

DEXs lack regulatory oversight

- Enforcement is challenging
- Widespread misconduct (12% or $413 billion of volume)

Traders are unaffected by increases in market integrity

- Can be selective of pool
- Are not exploited by the AMM pricing

LPs want trading and fees, regardless of the misconduct

Insider Trading in Cryptocurrency Markets

Do DEXs have a wider impact on market integrity

Misconduct is widespread in DEXs, does this spill over to other markets?

First prosecuted case of insider trading in crypto markets around token listing announcements

- Coinbase employee, his brother and a friend
- Tip-off on twitter
- Guilty plea
- Blockchain data allows for direct analysis

How do bad actors respond to regulation?

Identifying insider trading

Identify wallets that trade around the listing announcements

- Buy token 7 days before listing
- Sell token 7 days after listing
- Exclude “known” wallets from public labels

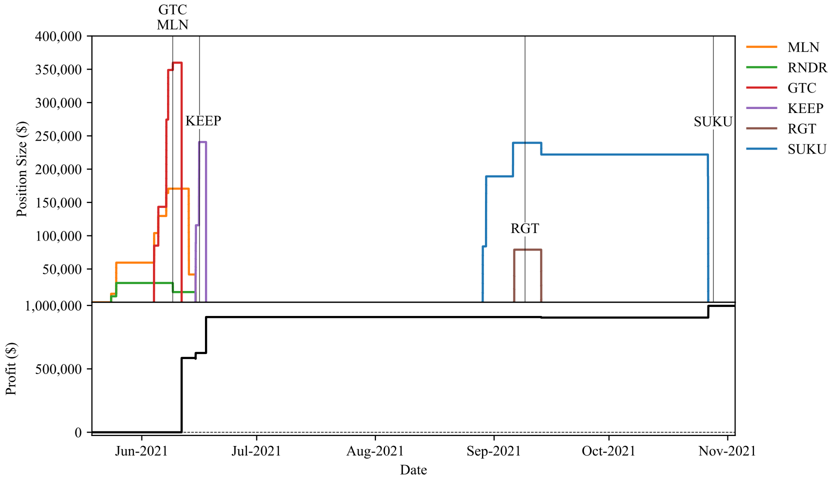
Blatant insider traders

- Wallet trade on 3 or more announcements
- $25k value traded

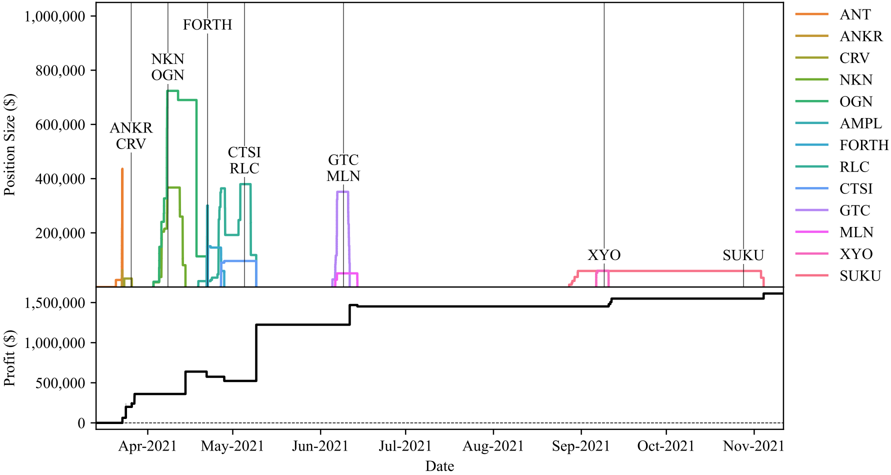
Semi-concealed insider traders

- Cluster wallets on strongly connected components of graph
- Cluster trade on 3 or more announcements
- $25k value traded

Blatant insider trading example



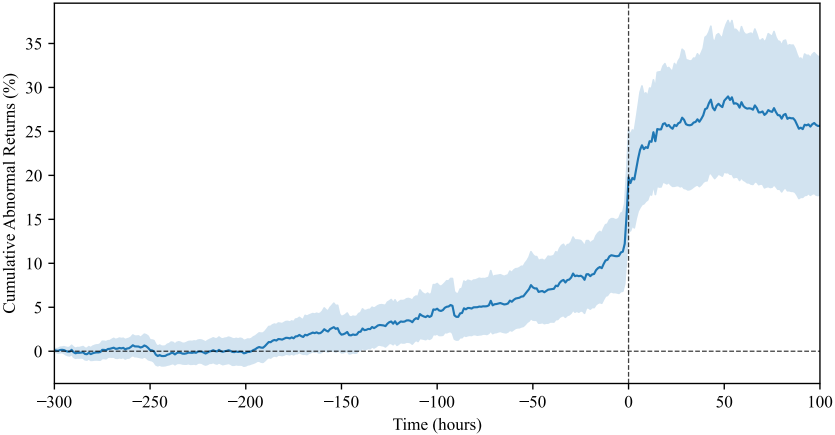
Semi-concealed insider trading example



Insider trading wallet summary statistics

Panel A. Total trading activity of insider trading wallets			
	Blatant insider traders	Semi-concealed insider traders	Total insider traders
Announcements	71	118	122
Wallets	49	1,161	1,210
Clusters		7	26
Total Position Size ($M)	31.1	175.4	206.5
Total Estimated Profit ($M)	5.7	24.6	30.3

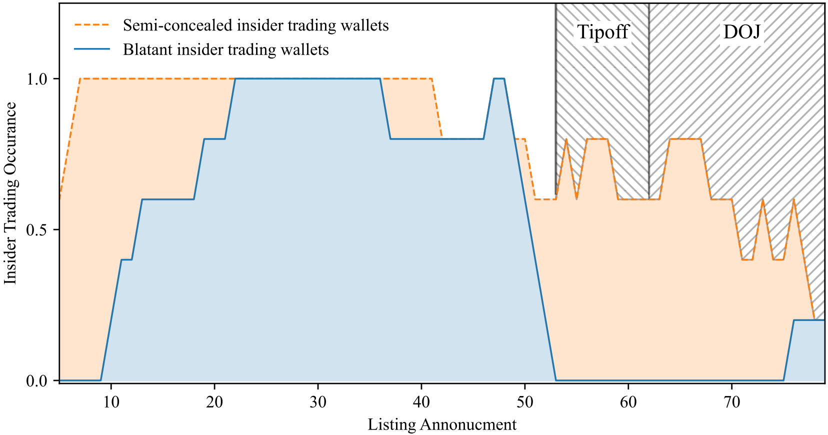
Market evidence of insider trading



Where do insiders trade?

- Insiders are active compared to a matched sample
- 96% (93%) of blatant (semi-concealed) insiders trade on DEXs
- 98% (85%) of blatant (semi-concealed) insiders trade on CEXs
- 2.6% of semi-concealed insiders use tornado cash

How do insiders respond to regulatory scrutiny?



Implications

Insider trading occurs ahead of 28-48% of cryptocurrency listings.

- $30.3 million in profit

Regulation and enforcement do not stop insider trading

- Insiders instead trade through methods of concealment
- Challenges for policing misconduct in crypto markets
- Pseudo-anonymity and lack geographical border

Conclusion

Conclusion

Thesis shows that AMMs are a viable market structure

- Can provide price discovery
- More stable liquidity

However DEXs introduce challenges for market integrity

- Widespread misconduct in DEXs
- Blockchain based markets are difficult to police

But AMMs do not need DEXs

Appendix

Exchange summary statistics

Panel A. Limit Order Book Summary Statistics					
	Mean	Standard Deviation	p10	Median	p90
Volume ($)	278	1,003	0	1	534
Trades	241.3	928.1	0.4	4.1	560.1
Volatility (%)	0.26	1.28	0.00	0.05	0.53
Mean Trade ($)	549	555	88	330	1,511
Half Quoted Spread (%)	0.12	0.12	0.00	0.08	0.28
Effective Spread (%)	0.11	0.12	0.01	0.08	0.26
Realized Spread (%)	0.15	0.15	0.02	0.11	0.35
$\text{Depth}_{[1\%]}$ ($)	1.27	3.69	0.00	0.04	3.42
Amihud ILLIQ	2.08	4.75	0.00	0.17	6.15

Exchange summary statistics

Panel B. Automated Market Maker Summary Statistics					
	Mean	Standard Deviation	p10	Median	p90
Volume ($)	15	70	0	1	28
Trades	1.1	3.2	0.0	0.1	2.7
Volatility (%)	0.25	1.67	0.00	0.04	0.47
Mean Trade ($)	15,067	39,940	319	2,644	33,131
Half Quoted Spread (%)	0.34	0.26	0.05	0.30	1.00
Effective Spread (%)	0.74	11.91	0.15	0.44	1.21
Realized Spread (%)	0.55	13.10	0.11	0.44	1.21
$\text{Depth}_{[1\%]}$ ($)	8.86	36.50	0.00	0.06	6.77
Amihud ILLIQ	2.67	202.73	0.00	0.15	4.04

Liquidity variance summary statistics

Panel A. Limit Order Book Summary Statistics					
	Mean	Standard Deviation	p10	Median	p90
Δ_{max}^{min}Half Quoted Spread	0.75	0.52	0.27	0.64	1.32
Δ_{max}^{min}Effective Spread	1.76	0.84	0.94	1.64	2.71
Δ_{max}^{min}Depth$_{[1\%]}$	3.77	1.76	1.63	3.61	6.12
Δ_{max}^{min}ILLIQ	4.67	1.60	3.08	4.45	6.46

Panel B. Automated Market Maker Summary Statistics					
	Mean	Standard Deviation	p10	Median	p90
Δ_{max}^{min}Half Quoted Spread	0.01	0.11	0.00	0.00	0.00
Δ_{max}^{min}Effective Spread	1.09	0.93	0.24	0.84	2.19
Δ_{max}^{min}Depth$_{[1\%]}$	0.43	0.72	0.02	0.10	1.20
Δ_{max}^{min}ILLIQ	3.93	1.70	1.93	3.85	6.01

Determinants of liquidity stability in AMMs

	(1)	(2)	(3)
Dependent variable:	$\Delta_{max}^{min} ES$	$\Delta_{max}^{min} Depth_{1\%}$	$\Delta_{max}^{min} ILLIQ$
CPMM	−0.145***	−0.778***	−0.545***
	(-20.94)	(-124.16)	(-21.62)
Volume	0.210***	0.112***	0.491***
	(88.40)	(52.20)	(76.10)
Volatility	−0.002*	0.022***	−0.025***
	(-1.86)	(21.02)	(-8.05)
$Depth_{1\%}$	−0.261***	−0.120***	−0.379***
	(-112.14)	(-57.12)	(-55.57)
HalfQuotedSpread	−0.457***	−0.003	−0.179***
	(-114.22)	(-0.70)	(-13.39)
Intercept	−1.230***	0.891***	0.039
	(-42.20)	(33.89)	(0.35)
Pair Effects	Y	Y	Y
Observations	65,056	65,496	40,823
Adjusted R^2	44.3%	24.1%	25.5%

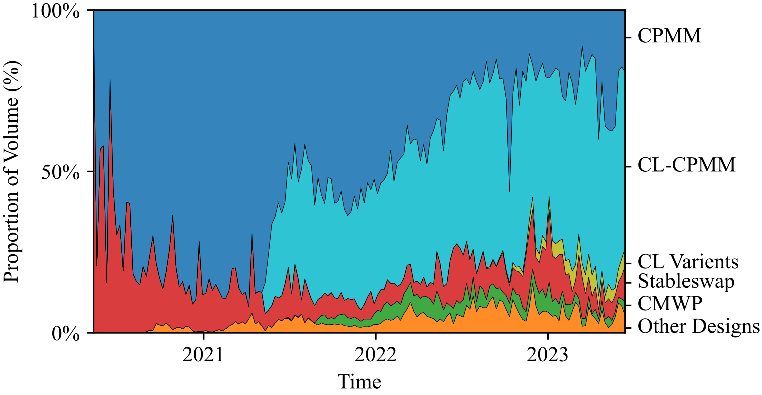
Significance: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Blockchain determinants of liquidity stability in AMMs

	(1)	(2)	(3)
Dependent variable:	$\Delta^{min}_{max} ES$	$\Delta^{min}_{max} Depth_{1\%}$	$\Delta^{min}_{max} ILLIQ$
Arbitrum	0.126***	0.293***	0.811***
	(9.16)	(26.54)	(23.46)
Optimism	0.062**	0.800***	0.359***
	(2.08)	(33.20)	(5.05)
Polygon	−0.194***	0.284***	0.012
	(-10.02)	(18.35)	(0.26)
GasPrice	0.010***	0.041***	−0.050***
	(4.23)	(21.72)	(-8.71)
Volume	0.045***	0.018***	0.243***
	(31.23)	(15.43)	(66.14)
Volatility	0.024***	0.028***	0.014***
	(17.74)	(25.65)	(4.54)
Intercept	0.976***	0.884***	−0.311***
	(25.87)	(29.17)	(-3.24)
Pair Effects	Y	Y	Y
Observations	65,060	65,496	40,827
Adjusted R^2	14.5%	7.8%	19.7%

Significance: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

AMM design dominance



Descriptive Statistics

Panel A. Limit Order Book Summary Statistics					
	Mean	Standard Deviation	p10	Median	p90
Volume ($)	4,583	20,104	3	24	4,319
Trades	4,052.5	19,592.6	16.1	87.3	5,109.0
Mean Trade ($)	482	486	113	298	1,230
Median Trade ($)	147	161	30	91	372
Realized Volatility (%)	1.48	2.04	0.24	0.85	3.42
Half Quoted Spread (%)	0.21	0.17	0.04	0.18	0.40
Effective Spread (%)	0.25	0.30	0.03	0.18	0.51
$\text{Depth}_{[1.5\%]}$ ($)	1.81	6.12	0.01	0.07	3.27
$\text{Depth Variance}_{[1.5\%]}$ (%)	45.31	24.48	23.78	40.04	70.98

Descriptive Statistics

Panel B. Automated Market Maker Summary Statistics

	Mean	Standard Deviation	p10	Median	p90
Volume ($)	314	1,281	2	15	785
Trades	48.1	149.0	0.5	3.1	107.6
Mean Trade ($)	12,663	31,560	867	4,118	24,477
Median Trade ($)	6,058	17,715	164	1,823	10,499
Realized Volatility (%)	21.44	261.69	0.07	0.72	5.48
Half Quoted Spread (%)	0.31	0.21	0.05	0.30	0.30
Effective Spread (%)	4.95	20.47	0.17	0.88	4.30
$\text{Depth}_{[1.5\%]}$ ($)	4.88	44.74	0.00	0.03	2.98
$\text{Depth Variance}_{[1.5\%]}$ (%)	81.66	127.54	7.45	38.96	174.93

Variance decomposition estimation

Two key inputs are needed to construct the components of variance which we can get by estimating a reduced form structural VAR model: the variance of the innovations in each variable, $\sigma^2_{\epsilon_{r_m}}$, $\sigma^2_{\epsilon_x}$, $\sigma^2_{\epsilon_r}$ and the long-run cumulative responses to these shocks θ_{r_m}, θ_x, θ_r.

$$r_{m,t} = a_0^* + \sum_{l=1}^{12} a_{1,l}^* r_{m,t-l} + \sum_{l=1}^{12} a_{2,l}^* x_{t-l} + \sum_{l=1}^{12} a_{3,l}^* r_{t-l} + e_{r_m,t}$$

$$x_t = b_0^* + \sum_{l=1}^{12} b_{1,l}^* r_{m,t-l} + \sum_{l=1}^{12} b_{2,l}^* x_{t-l} + \sum_{l=1}^{12} b_{3,l}^* r_{t-l} + e_{x,t}$$

$$r_t = c_0^* + \sum_{l=1}^{12} c_{1,l}^* r_{m,t-l} + \sum_{l=1}^{12} c_{2,l}^* x_{t-l} + \sum_{l=1}^{12} c_{3,l}^* r_{t-l} + e_{r,t}$$

Variance decomposition estimation

The reduced form residuals can be written as linear models of the structural-model residuals:

$$\begin{aligned} e_{r_m,t} &= \epsilon_{r_m,t} \\ e_{x,t} &= \epsilon_{x,t} + b_{1,0}\epsilon_{r_m,t} = b_{1,0}e_{r_m,t} + \epsilon_{x,t} \\ e_{r,t} &= \epsilon_{r,t} + (c_{1,0} + c_{2,0}b_{1,0})\epsilon_{r_m,t} + c_{2,0}\epsilon_{x,t} = c_{1,0}e_{r_m,t} + c_{2,0}e_{x,t} + \epsilon_{r,t} \end{aligned}$$

Although the structural-model residuals are uncorrelated contemporaneously by design, the Equation shows that the reduced-form residuals exhibit contemporaneous correlation. This correlation allows for inference about the structural-model residuals. We use linear regressions to estimate the parameters $b_{1,0}$, $c_{1,0}$ and $c_{2,0}$

Variance decomposition estimation

Using the estimated parameters $b_{1,0}$, $c_{1,0}$ and $c_{2,0}$, along with the estimated variances of the reduced-form residuals $\sigma^2_{e_{rm}}$, $\sigma^2_{e_x}$, and $\sigma^2_{e_r}$ we derive estimates for the variances of the structural model shocks by rearranging the variance expression of the Equation.

$$
\begin{aligned}
\sigma_{\epsilon_{rm}} &= \sigma_{e_{rm}} \\
\sigma_{\epsilon_x} &= \sigma_{e_x} - b^2_{1,0}\sigma^2_{e_{rm}} \\
\sigma_{\epsilon_r} &= \sigma_{e_r} - (c^2_{1,0} + 2c_{1,0}c_{2,0}b_{1,0})\sigma^2_{e_{rm}} - c^2_{2,0}\sigma^2_{e_x}
\end{aligned}
$$

Variance decomposition estimation

To estimate the long-run cumulative impulse response functions of the structural model, we compute the equivalent reduced-form shocks and feed them through the reduced-form model. Specifically:

1. A structural shock to market returns $[\epsilon_{r_m,t}, \epsilon_{x,t} \epsilon_{r,t}]' = [1, 0, 0]'$ has a reduced-form equivalent $[e_{r_m,t}, e_{x,t} e_{r,t}]' = [1, b_{1,0}, (c_{1,0} + c_{2,0} b_{1,0})]'$
2. A structural shock to market returns $[\epsilon_{r_m,t}, \epsilon_{x,t} \epsilon_{r,t}]' = [0, 1, 0]'$ has a reduced-form equivalent $[e_{r_m,t}, e_{x,t} e_{r,t}]' = [0, 1, c_{2,0}]'$
3. A structural shock to market returns $[\epsilon_{r_m,t}, \epsilon_{x,t} \epsilon_{r,t}]' = [0, 0, 1]'$ has a reduced-form equivalent $[e_{r_m,t}, e_{x,t} e_{r,t}]' = [0, 0, 1]'$

The cumulative return response to each of these shocks, evaluated at $t = 36$ (the point where the responses stabilize), provides estimates for θ_{r_m}, θ_x, and θ_r respectively.

Variance decomposition estimation

Taking the variance of the innovations in the efficient price we get $\sigma_w^2 = \theta_{r_m}^2 \sigma_{\epsilon_{r_m}}^2 + \theta_x^2 \sigma_{\epsilon_x}^2 + \theta_r^2 \sigma_{\epsilon_r}^2$. The errors in the structural model are contemporaneously uncorrelated by construction and therefore the covariance terms are all zero. The contribution to the variation in the efficient price from each of the information components is $\theta_{r_m}^2 \sigma_{\epsilon_{r_m}}^2$ (market-wide information), $\theta_x^2 \sigma_{\epsilon_x}^2$ (private firm-specific information), and $\theta_r^2 \sigma_{\epsilon_r}^2$ (public firm-specific information). The estimated components of variance are therefore

$$MarketInfo = \theta_{r_m}^2 \sigma_{\varepsilon_{r_m}}^2$$
$$PrivateInfo = \theta_x^2 \sigma_{\varepsilon_x}^2$$
$$PrivateInfo = \theta_r^2 \sigma_{\varepsilon_r}^2$$
$$Noise = \sigma_s^2$$

Variance decomposition estimation

Normalizing these variance components to sum to 100% gives variance shares:

$$MarketInfoShare = \theta_{r_m}^2 \sigma_{\varepsilon_{r_m}}^2 / (\sigma_w^2 + \sigma_s^2)$$
$$PrivateInfoShare = \theta_x^2 \sigma_{\varepsilon_x}^2 / (\sigma_w^2 + \sigma_s^2)$$
$$PrivateInfoShare = \theta_r^2 \sigma_{\varepsilon_r}^2 / (\sigma_w^2 + \sigma_s^2)$$
$$NoiseShare = \sigma_s^2 / (\sigma_w^2 + \sigma_s^2)$$

Price discovery estimation

For each pair-month, we estimate a reduced form VECM of the log price series ($p_{1,t}$ to $p_{n,t}$) with 300 lags (prices are sampled based on the Ethereum block time where trading is continuous in the AMM and the LOB).

$$\Delta p_t = aZ_{t-1} + \sum_{i=1}^{300} b_i \Delta p_{t-i} + \epsilon_t \tag{7}$$

where Δp_t is the $n \times 1$ midquote return vector, α is the $n \times (n-1)$ matrix of error correction coefficients, Z_{t-1} is the $n \times 1$ co-integrating vector, b_i is the $n \times n$ coefficient matrix for lag i and ϵ_t is the $n \times 1$ vector of residuals.

Price discovery estimation

From the reduced form VECM estimates in 7 we derive the corresponding infinite lag VMA representation in structural form assuming recursive contemporaneous causality running from the first through to the last price series.

$$
\begin{aligned}
\Delta p_{1,t} &= \sum_{l=0}^{\infty} A_{1,l}\varepsilon_{1,t-1} + \sum_{l=0}^{\infty} A_{2,l}\varepsilon_{2,t-1} + \cdots + \sum_{l=0}^{\infty} A_{n,l}\varepsilon_{n,t-1} \\
\Delta p_{2,t} &= \sum_{l=0}^{\infty} B_{1,l}\varepsilon_{1,t-1} + \sum_{l=0}^{\infty} B_{2,l}\varepsilon_{2,t-1} + \cdots + \sum_{l=0}^{\infty} B_{n,l}\varepsilon_{n,t-1} \\
&\vdots \qquad\qquad\qquad\qquad \vdots \qquad\qquad\qquad\qquad \vdots \\
\Delta p_{n,t} &= \sum_{l=0}^{\infty} N_{1,l}\varepsilon_{1,t-1} + \sum_{l=0}^{\infty} N_{2,l}\varepsilon_{2,t-1} + \cdots + \sum_{l=0}^{\infty} N_{n,l}\varepsilon_{n,t-1}
\end{aligned}
$$

Price discovery estimation

We obtain the structural VMA coefficients by computing the orthogonalized impulse response functions and the (contemporaneously uncorrelated) structural VMA errors ($\varepsilon_{1,t}$ to $\varepsilon_{n,t}$) by mapping their relation to the reduced form errors. Innovations in the permanent component (the efficient price, m_t) are given by

$$\Delta m_t = \theta_{\varepsilon 1}\varepsilon_{1,t} + \theta_{\varepsilon 2}\varepsilon_{2,t} + \cdots + \theta_{\varepsilon n}\varepsilon_{n,t}$$

The variance of the innovations in the efficient price is therefore:

$$\begin{aligned} Var(\Delta m_t) &= Var(\theta_{\varepsilon 1}\varepsilon_{1,t} + \theta_{\varepsilon 2}\varepsilon_{2,t} + \cdots + \theta_{\varepsilon n}\varepsilon_{n,t}) \\ &= \theta_{\varepsilon 1}^2 Var(\varepsilon_{1,t}) + \theta_{\varepsilon 2}^2 Var(\varepsilon_{2,t}) + \cdots + \theta_{\varepsilon n}^2 Var(\varepsilon_{n,t}) \end{aligned}$$

Price discovery estimation

Information shares (IS) are obtained as each price's contribution to the variance of the efficient price innovations

$$IS_n = \frac{\theta_{\varepsilon n}^2 Var(\varepsilon_{n,t})}{Var(\Delta m_t)}$$

Component shares (CS) are obtained by normalizing the permanent price impacts of each price series in the reduced form model.

$$CS_n = \frac{\theta_{\epsilon n}}{\sum_{i=1}^{n} \theta_{\epsilon i}}$$

Price discovery estimation

Finally, we calculate the information leadership share (ILS). In the two-price case, market's propensity to reflect new information (how much market is price responds to an innovation in the efficient price) can be obtained from the ratio $\beta_i = \frac{IS_i}{CS_i}$, which when normalized gives the information leadership share

$$ILS_n = \frac{\beta_n^2}{\sum_{i=1}^{n} \beta_i^2}$$

Determinants of AMM price discovery

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable:	*ILS*	*ILS*	*ILS*	*ILS*	*ILS*	*ILS*	*ILS*	*ILS*
QuotedSpread	−0.079***			−0.078***	−0.068***			−0.069***
	(−7.20)			(−7.08)	(−6.86)			(−7.17)
EffectiveSpread		0.007		0.012**		0.011**		0.014***
		(1.27)		(2.46)		(2.15)		(2.79)
$Depth_{[1.5\%]}$			−0.011***	−0.007***			−0.005**	0.000
			(−4.89)	(−3.91)			(−2.43)	(0.09)
$DepthVariance_{[1.5\%]}$			−0.025***	−0.017***			−0.001	0.006
			(−5.87)	(−4.52)			(−0.26)	(1.64)
Volume	0.004	0.017***	0.028***	0.016***	0.007***	0.023***	0.025***	0.010***
	(1.49)	(5.22)	(7.80)	(4.36)	(2.58)	(6.66)	(6.75)	(3.05)
RealizedVolatility	0.015***	0.003	−0.007	0.003				
	(4.12)	(0.78)	(−1.62)	(0.88)				
Gas	0.000	0.000	0.000	0.000				
	(0.19)	(−0.04)	(0.15)	(0.04)				
Intercept	−0.346***	−0.186***	−0.419***	−0.561***	−0.434***	−0.302***	−0.307***	−0.426***
	(−5.53)	(−3.59)	(−6.12)	(−7.12)	(−5.22)	(−3.97)	(−3.91)	(−5.03)
Pair Effects	N	N	N	N	Y	Y	Y	Y
Month Effects	N	N	N	N	Y	Y	Y	Y
Observations	1,709	1,709	1,709	1,709	1,709	1,709	1,709	1,709
Adjusted R^2	15.7%	4.6%	9.4%	19.3%	37.4%	31.9%	31.9%	37.9%

Significance: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

LOB determinants of AMM price discovery

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable:	*ILS*	*ILS*	*ILS*	*ILS*	*ILS*	*ILS*	*ILS*	*ILS*
LOBQuotedSpread	0.011***			0.016***	0.004			0.000
	(3.73)			(3.78)	(1.31)			(−0.11)
LOBEffectiveSpread		−0.004		−0.022***		0.016**		0.012
		(−0.39)		(−2.89)		(2.08)		(1.49)
$LOBDepth_{[1.5\%]}$			−0.020**	−0.013**			−0.033***	−0.031***
			(−2.00)	(−2.05)			(−3.86)	(−3.54)
$LOBDepthVariance_{[1.5\%]}$			−0.005	−0.010			−0.012	−0.013
			(−0.57)	(−1.08)			(−1.27)	(−1.34)
LOBVolume	0.000	−0.004	0.011*	0.003	−0.019***	−0.017***	−0.006	−0.006
	(0.03)	(−1.48)	(1.72)	(0.94)	(−3.38)	(−3.14)	(−1.00)	(−0.90)
RealizedVolatility		0.002	−0.010					
		(0.24)	(−1.39)					
Intercept	0.117***	0.095**	−0.019	0.088***	0.368***	0.416***	0.478***	0.514***
	(6.04)	(2.16)	(−0.30)	(4.13)	(3.20)	(3.32)	(3.90)	(4.00)
Pair Effects	N	N	N	N	Y	Y	Y	Y
Month Effects	N	N	N	N	Y	Y	Y	Y
Observations	1,709	1,709	1,709	1,709	1,709	1,709	1,709	1,709
Adjusted R^2	0.6%	0.0%	0.4%	1.1%	28.2%	28.3%	28.6%	28.6%

Significance: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Relative determinants of AMM price discovery

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable:	*ILS*	*ILS*	*ILS*	*ILS*	*ILS*	*ILS*	*ILS*	*ILS*
QuotedSpreadRatio	−0.030***			−0.037***	−0.032***			−0.036***
	(−6.84)			(−6.74)	(−6.17)			(−6.36)
EffectiveSpreadRatio		0.008		0.024***		0.009		0.018***
		(1.17)		(3.58)		(1.53)		(2.82)
$Depth_{[1.5\%]}Ratio$			−0.007***	−0.003*			−0.005**	−0.002
			(−3.18)	(−1.69)			(−2.13)	(−0.82)
$DepthVarience_{[1.5\%]}Ratio$			−0.010***	0.000			0.001	0.006*
			(−2.88)	(−0.11)			(0.23)	(1.68)
VolumeRatio	0.008***	0.016***	0.018***	0.014***	0.016***	0.025***	0.026***	0.021***
	(5.30)	(6.35)	(7.61)	(5.28)	(6.00)	(6.73)	(7.20)	(5.70)
Intercept	0.080***	0.047***	0.055***	0.041***	0.058	−0.011	0.014	0.036
	(10.76)	(3.94)	(10.10)	(3.75)	(1.03)	(−0.19)	(0.26)	(0.60)
Pair Effects	N	N	N	N	Y	Y	Y	Y
Month Effects	N	N	N	N	Y	Y	Y	Y
Observations	1,709	1,709	1,709	1,709	1,709	1,709	1,709	1,709
Adjusted R^2	10.8%	5.7%	6.9%	13.2%	35.4%	32.8%	32.9%	36.3%

Significance: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Determinants of AMM price discovery by share of volume

	(1)	(2)	(3)	(4)	(5)
Dependent variable: ILS	($Q1$)	($Q2$)	($Q3$)	($Q4$)	($Q5$)
QuotedSpread	−0.020	−0.001*	−0.052**	−0.126***	−0.120***
	(−1.37)	(−1.90)	(−2.28)	(−4.68)	(−5.46)
EffectiveSpread	0.004	0.000	−0.007***	0.012	0.041***
	(0.72)	(−1.25)	(−2.60)	(1.21)	(2.85)
$Depth_{[1.5\%]}$	0.000	0.000	0.003***	−0.003	−0.009**
	(0.25)	(0.41)	(2.71)	(−1.13)	(−2.34)
$DepthVariance_{[1.5\%]}$	0.005	0.000	−0.009**	−0.010	−0.069***
	(1.00)	(−0.03)	(−2.49)	(−0.99)	(−4.34)
Volume	−0.001	0.001	−0.011**	0.019**	0.045***
	(−0.55)	(1.14)	(−2.31)	(2.06)	(3.65)
RealizedVolatility	0.000	0.003*	0.007**	0.014	0.022
	(0.07)	(1.76)	(2.22)	(1.45)	(1.17)
Gas	0.000	0.000	0.000	0.002	−0.001
	(0.44)	(−1.07)	(0.38)	(1.30)	(−0.23)
Intercept	−0.065	0.014	−0.111	−0.775***	−1.004***
	(−1.48)	(0.94)	(−1.22)	(−3.44)	(−3.83)
Observations	342	342	341	341	343
Adjusted R^2	4.6%	2.6%	17.4%	30.0%	30.0%

Significance: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Determinants of AMM price discovery by blockchain

	(1)	(2)	(3)	(4)
Dependent variable:	*ILS*	*ILS*	*ILS*	*ILS*
Polygon	−0.070***			−0.083***
	(−5.21)			(−5.13)
Optimism		−0.005		−0.059***
		(−0.42)		(−3.09)
Arbitrum			−0.029	−0.022
			(−1.38)	(−1.08)
Gas	−0.003***	0.000	0.001	−0.003***
	(−3.66)	(−0.04)	(1.26)	(−2.93)
Intercept	−0.603***	−0.561***	−0.558***	−0.610***
	(−7.32)	(−7.12)	(−7.14)	(−7.36)
Controls	Y	Y	Y	Y
Observations	1,709	1,709	1,709	1,709
Adjusted R^2	20.2%	19.3%	19.4%	20.4%

Significance: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Exchange summary statistics

Exchange	Chain	Daily Volume ($M)	Daily TVL ($M)	Pairs	Volume Share (%)
Uniswap v2	Ethereum	359.2	2,438.8	391,308	21.03
Uniswap v2	BSC	0.3	0.5	1,049	0.00
Uniswap v3	Ethereum	1,103.7	2,602.9	29,184	49.72
Uniswap v3	Polygon	61.3	104.8	25,710	2.35
Pancakeswap v2	BSC	287.6	2,767.5	1,294,265	13.50
Pancakeswap v3	BSC	177.3	309.1	39,203	3.85
Sushiswap	Ethereum	131.6	1,308.5	4,138	7.26
Sushiswap	BSC	0.2	1.8	1,632	0.01
Sushiswap v3	Ethereum	0.4	2.0	288	0.01
Quickswap	Polygon	24.6	278.0	57,303	1.33
Quickswap v3	Polygon	33.8	38.1	4,535	0.95

Sandwich attack summary statistics

Exchange	Chain	Mean Victim Trade ($)	Total Victim Volume($M)	Mean Attacker Trade ($)	Total Attacker Volume($M)
Uniswap v2	Ethereum	5,081	18,707.2	13,413	49,565.2
Uniswap v2	BSC	373	0.4	1,425	1.6
Uniswap v3	Ethereum	37,769	20,079.7	158,479	84,251.8
Uniswap v3	Polygon	829	178.5	884	190.7
Pancakeswap v2	BSC	1,086	1,254.5	1,837	2,126.2
Pancakeswap v3	BSC	1,578	889.3	8,053	4,544.9
Sushiswap	Ethereum	32,501	5,361.4	45,548	7,517.9
Sushiswap	BSC	486	1.1	863	2.0
Sushiswap v3	Ethereum	5,465	4.8	56,778	50.0
Quickswap	Polygon	706	407.7	564	327.6
Quickswap v3	Polygon	778	31.5	1,052	42.6

Wash trading summary statistics

Exchange	Chain	Mean Wash Trade ($)	Median Wash Trade ($)	Total Value Wash Traded ($M)
Uniswap v2	Ethereum	68,141	956	40,609
Uniswap v2	BSC	29,131	17	20
Uniswap v3	Ethereum	91,016	7,553	11,149
Uniswap v3	Polygon	1,468	101	526
Pancakeswap v2	BSC	9,223	109	11,189
Pancakeswap v3	BSC	3,451	336	944
Sushiswap	Ethereum	127,428	6,537	8,431
Sushiswap	BSC	3,279	24	34
Sushiswap v3	Ethereum	24,781	2,028	11
Quickswap	Polygon	540	40	167
Quickswap v3	Polygon	2,261	377	223

Rug pull summary statistics

Exchange	Chain	Price Runup (%)	Price Reversal (%)	Rugpulls	Total Rugpull Volume ($M)
Uniswap v2	Ethereum	237.99	−99.92	75,809	22,350.1
Uniswap v2	BSC	38.07	−98.74	57	3.0
Uniswap v3	Ethereum	68.08	−74.28	11,788	133,618.5
Uniswap v3	Polygon	50.76	−64.65	4,026	275.4
Pancakeswap v2	BSC	261.08	−100.00	293,722	27,594.3
Pancakeswap v3	BSC	654.60	−98.57	253	75.9
Sushiswap	Ethereum	937.30	−99.98	341	303.0
Sushiswap	BSC	266.11	−99.79	52	0.1
Sushiswap v3	Ethereum			0	
Quickswap	Polygon	1,524.98	−100.00	39	4.6
Quickswap v3	Polygon	33.75	−75.80	380	5.9

Money laundering summary statistics

Exchange	Chain	Mean Launder Trade ($)	Total Launder Volume($M)	Money Launderers
Uniswap v2	Ethereum	25,596	25,262.4	15,472
Uniswap v2	BSC	85	0.1	20
Uniswap v3	Ethereum	77,150	671.3	51
Uniswap v3	Polygon	267,268	0.5	1
Pancakeswap v2	BSC	2,215	1,715.1	14,466
Pancakeswap v3	BSC	5,220	599.3	3,616
Sushiswap	Ethereum	28,746	7,372.9	8,119
Sushiswap	BSC	187	0.9	352
Sushiswap v3	Ethereum	2,882	2.3	103
Quickswap	Polygon			0
Quickswap v3	Polygon			0

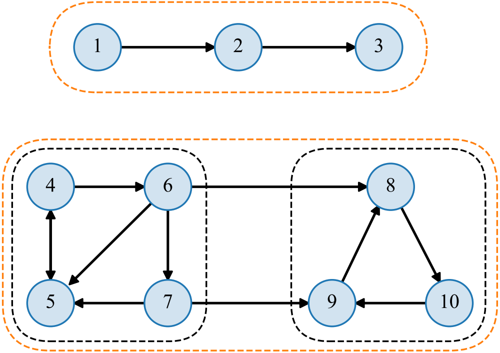
Listing announcement statistics

Panel A. Breakdown of listing announcements	
Number of listings	293
Listed before September 25, 2018	4
Stablecoins	10
Wrapped/Staked Tokens	10
Forks/Migrations	3
First announced by Coinbase	23
Final sample	252
ERC20 announcements	203

Listing announcement statistics

Panel B. Summary Statistics	Mean	Standard Deviation	p10	Median	p90
Market Cap ($ Millions)	679	1,928	10	123	1,349
Trade Volume ($ Millions)	1,085	4,340	0	22	2,071
Previous Listings	7	5	1	5	15
ERC20 Transfers	4,929	12,447	76	989	11,443
ERC20 Transfer Addresses	2,177	7,261	49	397	4,339
ERC20 Transfer Volume ($ Millions)	206	794	0	13	260
$CAR_{[-300,+100]}$	0.25	0.62	−0.20	0.07	0.95
$CAR_{[-168,-1]}$	0.14	0.31	−0.10	0.06	0.44
$CAR_{[-72,-1]}$	0.10	0.21	−0.08	0.06	0.37
$CAR_{[-24,-1]}$	0.07	0.16	−0.06	0.04	0.21

Strongly (weakly) connected components of a graph



Interactions of insider trading wallets

	Blatant insider traders		Semi-concealed insider traders		Total insider traders		Matched sample	
	#	%	#	%	#	%	#	%
Coinbase	18	36.7%***	272	23.2%***	290	23.8%***	1,332	13.3%
Binance	38	77.6%***	759	64.9%***	797	65.4%***	5,797	58.0%
FTX	19	38.8%***	241	20.6%***	260	21.3%***	780	7.8%
Top Tier CEX	7	14.3%	250	21.4%***	257	21.1%***	1,014	10.1%
Low Tier CEX	32	65.3%	689	58.9%	721	59.1%	5,780	57.8%
Total CEX	48	98.0%**	997	85.2%	1,045	85.7%	8,525	85.2%
Uniswap	47	95.9%***	1,032	88.2%***	1,079	88.5%***	6,267	62.7%
Sushiswap	32	65.3%***	721	61.6%***	753	61.8%***	1,887	18.9%
1inch	37	75.5%***	627	53.6%***	664	54.5%***	1,371	13.7%
Other DEX	27	55.1%**	889	76.0%***	916	75.1%***	3,760	37.6%
Total DEX	47	95.9%***	1,083	92.6%***	1,130	92.7%***	6,862	68.6%
NFT Exchanges	12	24.5%	617	52.7%***	629	51.6%***	2,192	21.9%
DeFi Protocols	13	26.5%	683	58.4%***	696	57.1%***	2,663	26.6%
Tornado Cash	0	0.0%	31	2.6%***	31	2.5%***	40	0.4%
Total Wallets	49		1,170		1,219		10,000	

Significance: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Impact of regulatory shocks on the prevalence of insider trading

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:	*Blatant*		*SemiConcealed*		*Total*	
Tipoff	−0.381***	−0.088	−0.074	0.264**	−0.107	0.237*
	(−3.30)	(−0.65)	(−0.54)	(2.10)	(−0.75)	(1.69)
DOJ	0.168**	0.465***	0.120	0.449***	0.127	0.466***
	(2.02)	(3.99)	(0.83)	(3.14)	(0.89)	(3.27)
PreviousListings	−0.051	−0.069	0.044	0.020	0.043	0.020
	(−0.91)	(−1.43)	(0.75)	(0.40)	(0.73)	(0.39)
MarketCap	−0.043	−0.025	−0.032	−0.008	−0.032	−0.009
	(−1.33)	(−1.14)	(−1.02)	(−0.43)	(−1.06)	(−0.50)
TradeVolume	0.004	0.001	−0.003	−0.007	−0.004	−0.007
	(0.43)	(0.06)	(−0.30)	(−0.65)	(−0.32)	(−0.67)
Transfers	0.034	−0.008	0.055	0.004	0.048	−0.004
	(1.03)	(−0.34)	(1.38)	(0.12)	(1.12)	(−0.10)
TransferVolume	0.032**	0.036***	0.032**	0.038**	0.036**	0.041**
	(2.39)	(2.75)	(2.09)	(2.36)	(2.22)	(2.49)
time		0.002***		0.002***		0.002***
		(4.02)		(3.62)		(3.78)
time^2		−1.297***		−1.401***		−1.458***
		(−4.00)		(−4.81)		(−4.82)
Intercept	0.440	0.143	0.238	−0.069	0.280	−0.045
	(0.73)	(0.36)	(0.44)	(−0.20)	(0.51)	(−0.13)
Observations	203	203	203	203	203	203
Adjusted R^2	15.7%	27.3%	15.8%	29.3%	15.6%	29.8%

Significance: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$