The Viability of Blockchain Markets under Discrete Clearing and Paid Priority

Agostino Capponi* Álvaro Cartea† Fayçal Drissi‡

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ABSTRACT

We develop a model to evaluate the viability of blockchain markets as the sole venue for price formation. Blockchains clear at discrete intervals called *block time*, and transactions are executed sequentially according to *priority fees* paid by traders who compete for queue position. We show that these features undermine the viability of markets. Paid-priority ordering induces endogenous selection, where only traders with sufficiently high valuations participate. The participation cutoff rises with competition, which intensifies when information costs fall or uninformed demand increases. This hinders price discovery. Competition on blockchains also reduce liquidity because liquidity suppliers absorb aggregate adverse selection risk in a single clearing round. Although longer block times enhance consensus security, beyond a critical block time, markets shut down.

*A. Capponi is with the Industrial Engineering and Operations Research, Columbia University.
†Á. Cartea is with the Oxford-Man Institute and the Mathematical Institute, University of Oxford.
‡F. Drissi is with the Oxford-Man Institute, University of Oxford.
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A central ambition of blockchain technology is to provide a decentralized infrastructure to organize economic activity at scale. The viability of financial markets within this infrastructure is therefore a fundamental test of that ambition. This paper develops a theoretical framework that models the blockchain as the sole venue for price formation to assess its viability as an infrastructure to support markets. The model endogenizes entry into trading, liquidity supply, trading volumes, and the amount of information revealed in equilibrium. It incorporates three defining features of blockchain infrastructure: clearing occurs discretely in a single round within each block; block time determines the length of the round and is necessary to conduct security consensus and preserve decentralization; transactions are ordered through paid-priority discriminatory pricing.

Specifically, blockchains operate in discrete time, and information is revealed through an auction with discriminatory pricing. Orders are recorded into *blocks* built at regular intervals, called *slots*, and the duration of a slot is referred to as *block time*. At the end of each slot, a *builder* selects transactions and sequences them according to *priority fees* paid by traders who compete for queue position, and then sequentially clears the market. Consequently, traders engage in *priority gas auctions* (PGAs) to optimize their queue positions in the block. This structure contrasts with traditional markets with continuous trading, where transactions that would be aggregated within a single clearing round corresponding to a blockchain slot instead unfold over multiple short clearing rounds.

We model the strategic interaction between liquidity supplier and liquidity takers for a risky asset on a blockchain in three stages. In stage zero, traders decide whether to enter and acquire information at a cost. In stage one, a liquidity supplier sets the depth of an automated market maker (AMM) operating as a smart contract under the blockchain protocol.[1] In stage two, informed traders with noisy valuations compete in the PGA to buy

[1]AMMs are the most widely used type of blockchain market and employ algorithms to price and trade digital assets. In 2025, AMMs support monthly trading volumes of approximately $420 billion. A growing literature studies their microstructure (Lehar and Parlour (2025); Capponi and Jia (2021); Barbon and Ranaldo (2021); John, Kogan, and Saleh (2023); Klein, Kozhan, Viswanath-Natraj, and Wang (2023)) and compares them with traditional exchanges; see Barbon and Ranaldo (2021); Aoyagi and Ito (2021). The blockchain protocol defines the rules governing how transactions are recorded and determines the lifecycle

or sell the asset. They bid for block priority to mitigate the adverse price impact generated by preceding trades within the block.

We show that the defining features of blockchains fundamentally reshape market outcomes. Our main findings are threefold. First, competition in paid-priority contests generates endogenous selection, where only traders with sufficiently high valuations participate, which hinders price discovery by truncating information and biasing prices. Second, this selection mechanism raises adverse selection costs and decreases liquidity, potentially leading to market shutdown. Third, the very feature that supports decentralization, namely block time for consensus, undermines market viability by amplifying these distortions and by tightening the constraint for viable markets. We elaborate on each of these findings below.

Our first two findings indicate that increased competition between informed traders in blockchains generates adverse effects for both liquidity and price efficiency. First, we show that there exists a cutoff for private valuations below which traders choose not to participate in the PGA, so only aggressive traders with high valuations transact in the blockchain. The intuition is as follows. Low valuations correspond to low desired volumes and less aggressiveness in priority fee bidding. This results in worse queue positions within the block and, consequently, higher adverse price impact from traders with better positions in the block. For traders with sufficiently low valuations, the adverse price impact associated with high-valuation traders will discourage participation because expected wealth from trading is negative. Hence, only a small fraction of traders in the blockchain with high enough valuations participate in the PGA.

Two factors exacerbate these negative effects on markets. First, as the number of competitors grows, the participation cutoff rises, so increasingly higher valuations are required for participation. Thus, competition narrows the range of private valuations revealed to the market, and limits the amount of information that is disseminated. Second, although the portion of private valuations generating transactions becomes smaller as competition

of orders.

intensifies, the adverse selection losses of liquidity suppliers do not decrease.

This finding contrasts with market outcomes in traditional markets where trading unfolds over multiple short clearing rounds. There, greater competition among informed traders accelerates the incorporation of information in the early rounds, and market depth typically improves thereafter; see Holden and Subrahmanyam (1992). The mechanism behind our result is fundamentally different. In blockchains, trades are executed in a single round and priced according to priority fees. Traders pay both the cost of market impact and the bid required to secure queue position. Thus, the liquidity supplier on a blockchain must absorb the full adverse selection risk from aggregate trading volume in a single decision, rather than adjusting liquidity across successive rounds. As a result, competition decreases liquidity instead of deepening it.

Due to this mechanism, even though our model shows that a larger mass of uninformed demand and lower information costs increase the equilibrium number of informed traders who enter the blockchain, which would improve price efficiency in standard markets, the effect is reversed under paid-priority pricing. In blockchains, greater entry raises the participation cutoff, so that only increasingly high valuations are revealed. Information becomes more truncated, and price efficiency deteriorates.

Our third main finding is that block time creates a security–efficiency tradeoff. Longer blocks increase the dispersion of private valuations and intensify adverse selection, while simultaneously reducing the effective mass of uninformed demand. As a result, liquidity contracts, market viability constraints tighten, and beyond a critical block time the market collapses.

Our model implies several stylized facts that we take to the data. First, because only high-valuation traders participate in equilibrium, trading volumes on blockchains should be larger on average than in traditional markets. This prediction is consistent with empirical evidence showing that per-transaction volumes in blockchain markets are significantly higher than those in electronic limit order books; see Cartea, Drissi, and Monga (2025). Second, the model predicts that both trading volumes and priority fees increase with private valuations, so earlier positions in the block correspond to larger trades. Using historical data from the most liquid AMM on Ethereum (Uniswap v3), we document that transaction volumes decrease with queue position, providing empirical support for this prediction.

Our main theoretical contribution is to propose and solve a multi-prize auction model for the PGA which describes the economic forces behind transaction ordering and priority fees. In stage two, informed traders compete for block priority to avoid potentially worse execution prices resulting from the adverse price impact of preceding orders in the block. We model the PGA among traders as a special form of multi-prize auction in which each trader's payoff depends on the rank of their bid relative to that of others. Specifically, the surplus from bidding a priority fee represents the expected price impact that a trader avoids by improving her queue position. In the perfect Bayesian equilibrium of the PGA, traders determine both their priority fees and their trading volumes.

Informed traders determine their priority fees by balancing profits from better execution prices against the costs of paying the fee to the builder. To determine trading volumes, informed traders balance increased expected profits from trading larger positions against the costs and priority fees, which increase with order size. In stage one, the liquidity supplier sets the AMM's reserves by balancing revenue from elastic and uninformed demand against expected losses to informed traders.

The trade-off faced by informed traders in PGAs is analogous to that faced by political contestants or researchers in R&D races; see Lazear and Rosen (1981); Hillman and Riley (1989); Barut and Kovenock (1998). In such contests, the cost of the effort exerted by contestants corresponds to the priority fee paid by traders, and the payoff linked to achieving a particular rank in the race corresponds to the surplus in the PGA; see also Klose and Kovenock (2015).

Multi-prize contests are typically modeled as independent private cost contests, where the cost of effort is private but the prize vector is known ex ante; see Moldovanu and Sela

(2001). In contrast, in the PGA, the *prize* from attaining a given position is not fixed but depends on the private valuations and trading volumes of competitors. In the PGA, the value of a given position corresponds to the adverse price impact that a trader avoids by securing that position within the block. Specifically, it is determined by the price impact generated by the trading volumes of traders in the AMM who obtain worse ranks in the block. As in contests, the equilibrium total effort, or the sum of equilibrium priority fees in the case of the PGA, is inefficiently high: the all-pay structure implies that aggregate effort dissipates the total expected trading profits.

The model of this paper is related to the literature that studies the properties of price and liquidity in traditional exchanges. Our model is information based, however, it shares features of the multi-stage inventory-based models in Biais (1993); De Frutos and Manzano (2002). We extend and adapt these models to account for information dissemination, and for the blockchain protocol, whereby traders compete for queue position instead of speed (O'Hara (1998)). Moreover, blockchain-based liquidity supply accumulates in a common pool, and the AMM sets the price of liquidity algorithmically. Our model is also related to the theory on the costs of information processing such as that in Grossman and Stiglitz (1980), Verrecchia (1982), Kyle (1989), and Baldauf and Mollner (2020).

Some studies examine periodic uniform price auctions for market clearing (Madhavan (1992); Budish, Cramton, and Shim (2015)), and they show that these auctions enhance price efficiency but impose higher information costs on traders. Instead, our model considers discretionary, public auctions in which liquidity suppliers do not participate. Moreover, much of the microstructure literature assumes an information monopolist (Kyle (1985a)). In blockchains, monopolistic information would drive priority fees to zero in equilibrium, which contradicts empirical evidence showing that priority fees increase with the informational content of transactions; see Capponi, Jia, and Yu (2024). Competition among multiple informed traders, as in Holden and Subrahmanyam (1992) and Foster and Viswanathan (1996), leads to an instantly revealing equilibrium where prices fully reflect private information. Our model mirrors this result, because traders submit fully revealing priority fees. However, blockchains operate with periodic clearing, so the revealing equilibrium is delayed until the end of block time.

The study of trader behavior throughout slots in DEXs operating on blockchains resembles the study of trader behavior during preopening sessions of traditional electronic exchanges. In both settings, markets do not clear until some given time. At the end of preopening and closing sessions, all orders are executed at a uniform clearing price that maximizes trading volume. In contrast, orders in the memory pool are sequenced and executed based on their priority fees, and trading volume is not necessarily maximized. While there are fundamental differences in the purpose and mechanics of preopening sessions and blockchain slots, similarities exist. Like memory pools, markets clear only at the end of preopening sessions. However, unlike memory pools, traders in preopening sessions of traditional electronic markets observe only partial information about the market state, such as liquidity supply at the best prices or a virtual clearing price; see Van Bommel and Hoffmann (2011) for further details. Biais, Hillion, and Spatt (1999) propose several hypotheses regarding the informativeness of preopening prices, and our empirical results on trader behavior in memory pools supports the *pure-noise hypothesis*, which posits that trading activity before the end of the slot contains no new information and that strategies may delay price discovery; see details in Appendix A. Similarly, Medrano and Vives (2001) find that trading volumes and information revelation accelerate toward the end of preopening sessions, which provides further empirical support for our results.

Our work is also related to the literature on the microstructure of AMMs.[2] In contrast

[2] See Hasbrouck, Rivera, and Saleh (2022); Angeris, Evans, and Chitra (2021); Capponi, Iyengar, Sethuraman, et al. (2023a); Milionis, Moallemi, Roughgarden, and Zhang (2022); Cartea, Drissi, and Monga (2023, 2024a) who show that AMMs cause losses to liquidity suppliers. Lehar and Parlour (2025) describe competition between AMMs and order books. Klein et al. (2023) study the role of informed liquidity supply in price discovery. Park (2023) studies the different types of cost when trading in AMMs. Hasbrouck, Rivera, and Saleh (2023) study concentrated liquidity AMMs. Malinova and Park (2024) examine the potential of AMMs to organize trading for equity. Capponi et al. (2024) studies the influence of gas fees on the informativeness of trades in AMMs. Cartea, Drissi, Sánchez-Betancourt, Siska, and Szpruch (2024b) propose AMM designs to mitigate losses of liquidity suppliers.

to this literature, we study DEXs as the interplay of AMMs and the blockchain on which they operate. The economic trade-offs for liquidity supply in AMMs are similar to those in market making within limit order books and dealer markets, and insights from classical models apply (e.g., Ho and Stoll (1983), Glosten and Milgrom (1985)). In particular, the trading function of an AMM can be viewed as a parameterized price schedule in electronic exchanges; see Glosten (1994); Biais, Martimort, and Rochet (2000). As a consequence, while our model assumes trading occurs within an AMM, similar conclusions apply if the blockchain runs other market infrastructures. He, Yang, and Zhou (2025) study the role of priority fees when arbitrageurs trade between a blockchain and a competing venue where prices are formed. In contrast, this paper studies theoretically whether the blockchain itself can serve as the primary venue for price formation.

Finally, blockchain technology is profoundly reshaping the financial landscape (Harvey (2016); Cong and He (2019)), and blockchain economics are a growing topic in the literature (Biais, Capponi, Cong, Gaur, and Giesecke (2023b); Petryk, Müller-Bloch, Hahn, Halaburda, Henfridsson, Obermeier, and Yoo (2025)). John, Rivera, and Saleh (2020) study the equilibrium security of blockchains. Cong, Li, and Wang (2021) analyze the adoption of digital platforms. Biais, Bisiere, Bouvard, Casamatta, and Menkveld (2023a) study the drivers of cryptocurrency prices and risks. Cong, Hui, Tucker, and Zhou (2023); Harvey, Saleh, and Sverchkov (2025) study the economic implications of *layer-2* blockchains. Harvey and Rabetti (2024) explore how investors and regulators engage effectively with blockchains. Finally, the applications of decentralized finance extend beyond DEXs. They include central bank digital currencies (Fung and Halaburda (2016); Auer, Frost, Gambacorta, Monnet, Rice, and Shin (2022)), cross-border settlement (Harvey (2021); Hub (2023); Cardozo, Fernández, Jiang, and Rojas (2024)), and asset tokenization (Heines, Dick, Pohle, and Jung (2021)).

The remainder of this paper proceeds as follows. In Section I, we present notation, assumptions, and structure of the model. In Section II, we study the priority fee bidding strategies and trading volumes of informed traders. In Section III, we analyze the liquidity supply. In Section IV, we study incentives to acquire information at a cost. In Section V, we study the economic effects of block time. In Appendix A, we describe the features of blockchains that underpin our model. Finally, Appendix B outlines the key features of AMMs which motivate our model assumptions and Appendix C collects the proofs.

I. General features of the model

In this section, we introduce the features of our model for the strategic interactions of market participants in blockchain-based markets.

The liquidity pool of an automated market maker (AMM) supplies liquidity in a reference asset X (e.g., dollar) and in a risky asset Y.[3] There are three types of agent, a representative liquidity supplier (he), informed traders (she), and noise traders (they) with price-sensitive demand.

Informed traders hold private incomplete information about the future liquidation value of the asset, and they submit transactions with priority fees to compete for queue priority in the next block. In contrast, noise traders do not submit priority fees.[4] The entry to blockchain trading, liquidity supply in the AMM, and the subsequent trading process are modeled as a game which proceeds as follows.

- *Stage zero*: M traders decide whether to pay a fixed information cost C to enter the blockchain and to observe private information. This choice depends on whether informed trading yields an expected future payoff higher than C.
- *Stage one*: the liquidity supplier sets the reserves in the AMM by balancing expected

[3]See Appendix B and Capponi and Jia (2021); Cartea et al. (2024a); Lehar and Parlour (2025) for more details on the mechanics of AMMs.

[4]Builders are paid *gas fees* by agents to include their transactions in a block. Gas fees consist of two components: the *base fee* and the *priority fee*. The base fee is mandatory for inclusion and is paid by all users. We therefore assume that noise traders pay only the base fee, which we normalize to zero without loss of generality, as it does not affect strategic ordering within the block. See Appendix A for further institutional details on the blockchain protocol.

losses to informed traders and fee revenue from noise traders. The level of reserves determines the cost of liquidity.

- *Stage two*: informed traders observe private information, referred to as *valuations*, about the liquidation value V of the asset at the end of the next block. Based on these private valuations, traders determine their bids and trading volumes by balancing expected profits against execution costs, infrastructure costs, and the adverse price impact generated by traders with better positions in the block.

Noise traders submit transactions to the memory pool with zero priority fees. After the three stages, a builder constructs the block by sorting transactions according to their priority fees. Specifically, the block executes the transactions of informed traders first, followed by those from noise traders who only pay the base fee. The final liquidation value of the asset is then realized, resolving any remaining uncertainty.[5]

After the liquidity supplier sets the AMM's reserves in stage one, we assume for simplicity that he remains passive and does not compete with traders for queue priority in the subsequent block. Although the liquidity supplier does not compete directly, his strategy depends indirectly on the behavior of informed traders: he chooses the cost of liquidity in the AMM based on rational expectations about their best response in the next stage.

At the start of the PGA in stage two, each informed trader observes a private valuation, which is a noisy signal of the liquidation value V, drawn from a common and known distribution. A key assumption of the model is that all informed traders know whether the fundamental price innovation is positive or negative. This determines the sign of all valuations and whether traders are buyers or sellers.[6]

We motivate this assumption as follows. We assume that informed traders submit their

[5] Our model mirrors the structure of microstructure models for traditional electronic exchanges, where rounds of trading occur with sequential decisions from different types of market participants.

[6] More precisely, the conditional information structure is as follows. At the beginning of the PGA, a public indicator reveals the direction of the fundamental price innovation, after which each informed trader observes a private and independent valuation regarding the magnitude of the innovation. As detailed below, positive valuations are drawn from a distribution with positive support, while negative valuations follow a symmetric distribution with negative support.

transactions near the end of the blockchain slot and rely on private information observed at that time.[7] Blockchains operate with slots of 12 seconds or longer. Thus, substantial price movements can occur during this period and cause most private valuations to take a definite sign. Our focus is on price discovery and liquidity in such settings, where the fundamental value of the asset is likely to diverge, so most informed traders are either buyers or sellers, and the PGA serves as the primary mechanism through which information is incorporated into prices.[8]

We solve for a perfect Bayesian equilibrium of this game by backward induction. At stage two (Section II), given a known level of liquidity supply κ and a known number M of competing informed traders, the bidding strategies and trading volumes are determined. At stage one (Section III), given a known number M of competing informed traders, the liquidity supply κ is determined based on the supplier's rational expectations of future trading volumes and noise trading activity. At stage zero (Section IV), the number M of informed traders who pay the cost of information is determined. The sequence of events is described in more detail in the next sections and is illustrated in Figure 1.

II. Stage two: priority fees and trading volumes

This section studies the priority fee bidding strategies and trading volumes of informed traders (hereafter, traders) who compete for queue priority in stage two. Traders take as given the liquidity supply in the AMM and the number M of competitors. Assume that informed traders know the liquidation value V is positive, so they wish to buy the asset.

[7] Specifically, we assume that informed traders either transact through private memory pools or wait until the end of block time in public memory pools, consistent with the empirical evidence reported in Appendix A.A and Appendix A.B.

[8] In contrast, when the future value of the asset is close to the initial value, private valuations are more dispersed in direction. In such situations, if an informed buyer and an informed seller both submit transactions within the same block, each has an incentive for the other's trade to be executed first, because this improves their own execution price. Consequently, the expected value of queue priority becomes non-positive for both traders, leading to zero equilibrium bids and limited informational content in the auction outcome.

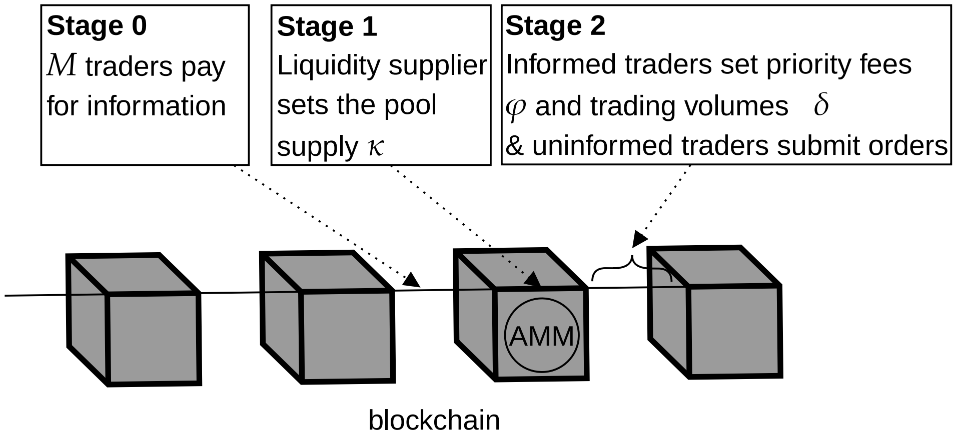

Figure 1. Sequence of events.

The case in which informed traders are sellers is symmetric and yields identical equilibrium priority fee bidding strategies, and trading volumes of opposite sign.

A. Assumptions

Let κ denote the depth of liquidity in the AMM determined in stage one.[9] We normalize the AMM's initial price at the start of the blockchain slot to zero, without loss of generality. In stage two, M risk-neutral informed traders compete for queue priority in the next block.

Traders compete for block priority to avoid potentially worse execution prices resulting from the adverse price impact of preceding orders in the block. The supply κ determines execution prices and the magnitude of price impact. For instance, consider two traders, 1 and 2, who sequentially buy quantities $\delta_1 > 0$ and $\delta_2 > 0$ of asset Y. The execution price for trader 1, assuming she has queue priority, is δ_1/κ, after which the AMM price updates to $2\,\delta_1/\kappa$. Consequently, the execution price for trader 2, who trades second in the block, is $\delta_2/\kappa + 2\,\delta_1/\kappa$.[10]

The PGA among traders is a multi-prize contest in which each competitor's payoff depends on the rank of her priority fee relative to others. As discussed in Appendix A, the PGA is *blind* because traders either compete in the private memory pool or submit their

[9]See Appendix B for the exact definition of AMM depth of liquidity.
[10]See Appendix B for more details on execution prices and price impact in AMMs.

transactions to the public memory pool immediately before block creation. Moreover, the PGA is *all-pay* because traders' transactions are all executed, so builders collect priority fees regardless of relative ranks within the block.

Before submitting their transactions at the end of the blockchain slot, traders simultaneously observe private valuations $\{v_1, \ldots, v_M\}$ of the risky asset, and they know whether they are all buyers or all sellers. Each valuation is an independent and noisy signal of the liquidation value and it is used by traders to assess the asset's worth. More precisely, the expected liquidation value from the perspective of trader i is

$$\mathbb{E}_i[V] = \mathbb{E}[V \mid v_i] = v_i \,. \tag{1}$$

In the perfect Bayesian equilibrium of the PGA, the M risk-neutral traders determine their priority fees $\{\varphi_1, \cdots, \varphi_M\}$ and their trading volumes $\{\delta_1, \cdots, \delta_M\}$.

B. *The priority gas auction*

This section derives the expected utility of competing traders in the PGA. The contest is symmetric, and we describe it from the perspective of trader $i \in \{1, \ldots, M\}$. Trader i competes with $M-1$ other traders in the PGA. From her perspective, the $M-1$ valuations of her competitors are i.i.d. draws from the same distribution; likewise, the $M-1$ trading volumes of her competitors are i.i.d. draws from the same distribution. We denote by $\varphi_{(j)}$, for $j \in \{1, \ldots, M-1\}$, the j-th largest bid among the $M-1$ competitors, so that $\varphi_{(j)} < \varphi_{(j+1)}$ and $\varphi_{(M-1)}$ is the largest competing priority fee. We denote by $v_{(j)}$ and $\delta_{(j)}$ the valuation and trading volume, respectively, of the competitor submitting the j-th largest priority fee.

If trader i wins priority in the block, i.e., if $\varphi_i > \varphi_{(M-1)}$, her buy order is executed first in the next block at the price $\delta_i/\kappa + \pi$ per unit of the asset; see (B2). In this case, the trader's terminal wealth consists of the priority fee paid to the builder, the cash paid to the AMM to purchase δ_i units of the asset, the proportional AMM fee π, the information cost C incurred in stage zero, and the terminal value of her holdings:

$$W_{i,(M-1)} = \underbrace{-\varphi_i}_{\text{priority fee}} - \underbrace{\delta_i\left(\frac{\delta_i}{\kappa} + \pi\right)}_{\text{cash paid to AMM}} + \underbrace{\delta_i V}_{\text{terminal value of holdings}} - \underbrace{C}_{\text{information cost}} . \tag{2}$$

If trader i's priority fee φ_i lies between the j-th and $(j+1)$-th largest priority fees among her competitors, i.e.,

$$\varphi_{(j)} < \varphi_i < \varphi_{(j+1)} \,,$$

then exactly $M-1-j$ traders, with trading volumes $\{\delta_{(j+1)}, \ldots, \delta_{(M-1)}\}$, are executed in the block before trader i's buy order. The price impact in the AMM when trading a volume δ is $2\delta/\kappa$. Hence, trader i's execution price per unit of the risky asset is

$$\underbrace{\frac{\delta_i}{\kappa}}_{\text{execution cost}} + \underbrace{\frac{2}{\kappa}\sum_{\ell=j+1}^{M-1}\delta_{(\ell)}}_{\text{impact of traders with higher priority fees}} + \underbrace{\pi}_{\text{AMM fee}} .$$

Accordingly, trader i's terminal wealth in this case is

$$W_{i,(j)} = \underbrace{-\varphi_i}_{\text{priority fee}} - \underbrace{\delta_i\left(\frac{\delta_i}{\kappa} + \frac{2}{\kappa}\Delta_{(j+1:M-1)} + \pi\right)}_{\text{cash paid to AMM}} + \underbrace{\delta_i V}_{\text{terminal value of holdings}} - \underbrace{C}_{\text{information cost}} , \tag{3}$$

where, for convenience, we define

$$\Delta_{(l:L)} = \sum_{\ell=l}^{L}\delta_{(\ell)}, \qquad l \in \{2, \ldots, M-2\}, \quad L > l.$$

Finally, if trader i's priority fee is lower than the lowest competing fee, i.e.,

$$\varphi_i < \varphi_{(1)} \,,$$

then her terminal wealth is

$$W_{i,(0)} = -\varphi_i - \delta_i\left(\frac{\delta_i}{\kappa} + \frac{2}{\kappa}\,\Delta_{(1:M-1)} + \pi\right) + \delta_i V - C\,.$$

Using the cases above, the expected utility of trader i can be written as

$$\begin{aligned}\mathbb{E}_i[W_i] &= \sum_{j=0}^{M-1} \mathbb{E}_i\left[W_{i,(j)}\right] \\ &= \sum_{j=0}^{M-1} \mathbb{E}_i\left[\mathbb{1}_{\varphi_{(j)}<\varphi_i<\varphi_{(j+1)}}\left(-\varphi_i - \delta_i\left(\frac{\delta_i}{\kappa} + \frac{2}{\kappa}\,\Delta_{(j+1:M-1)} + \pi\right) + \delta_i V - C\right)\right],\end{aligned}$$

with the conventions

$$\Delta_{(M:M-1)} = 0, \qquad \varphi_{(M)} = \infty, \qquad \varphi_{(0)} = -\infty.$$

At stage two, trader i's valuation of the asset is v_i, and she knows the AMM supply κ, the number of competing traders M, her trading volume δ_i, and her priority fee φ_i. She understands that her queue position depends on the rank of φ_i relative to her competitors. Hence the expected wealth of trader i can be written as

$$\mathbb{E}_i\big[W_i\big] = -\varphi_i + \delta_i\left(v_i - \pi - \frac{\delta_i}{\kappa}\right) - C - \frac{2\,\delta_i}{\kappa}\sum_{j=0}^{M-1} \mathbb{E}_i\left[\mathbb{1}_{\{\varphi_{(j)}<\varphi_i<\varphi_{(j+1)}\}}\,\Delta_{(j+1:M-1)}\right]. \tag{4}$$

The expected wealth (4) consists of (i) the expected profit $\delta_i\, v_i$ and (ii) several trading costs. These costs include the priority fee paid to builders, the AMM fee, the information cost, the expected adverse price impact generated by trader i's competitors, and the execution price paid to the AMM.

When submitting a transaction, trader i determines both the priority fee and the volume, thus she solves the problem

$$\sup_{\delta_i}\sup_{\varphi_i} \mathbb{E}_i\left[W_i\right]\,. \tag{5}$$

The objective function in (5) is a bounded real-valued function, allowing the interchange of the order in which one computes the suprema with respect to δ_i and φ_i.

Intuitively, traders buy and sell volumes proportional to their private valuations of the asset. In the optimization problem (5), the trading volume δ_i for trader i depends on v_i. Similarly, the priority fee φ_i depends on the trading volume δ_i. Thus, in equilibrium, both the volume δ_i and the priority fee φ_i are functions of the private valuation v_i.[11] Section II.C derives the equilibrium priority fees for a fixed distribution of trading volumes, and Section II.D then derives the equilibrium trading volumes given these priority fees.

C. *Priority fees*

Here, we solve for the equilibrium priority fee under an arbitrary distribution of trading volumes. Let δ denote the random variable representing the trading volume of each trader, drawn from the interval $[0, \overline{\delta}]$ according to a density function g with finite first and second moments, which may include an atom $p = G(\{0\})$ at zero volume. We denote by G the cumulative distribution function of volumes. At zero volume, traders submit the minimum zero priority fee. Equivalently, they do not participate in the PGA, and their expected wealth equals $-C$.[12] The equilibrium distribution of trading volumes is derived in Section II.D.

When solving for the equilibrium at stage two, informed traders take the depth κ as fixed and independent of the priority fee φ_i. Although the priority fee does not directly affect liquidity supply, it exerts an indirect influence. As shown in Section III, the liquidity supplier anticipates the priority fees and trading volumes of informed traders when determining the depth of the AMM's pool.

To better characterize the economic object of competition in the PGA, we rewrite

[11] Specifically, note that $\partial_{\delta_i}\mathbb{E}_i\left[W_i\right]$ is a function v_i, i.e., $\partial_{\delta_i v_i}\mathbb{E}_i\left[W_i\right] \neq 0$. Thus, the optimal trading volume $\arg\max_{\delta_i} \mathbb{E}_i\left[W_i\right]$ is a function of the valuation v_i. Similarly, $\partial_{\varphi_i v_i}\mathbb{E}_i\left[W_i\right] \neq 0$, so the priority fee also depends on the private valuation.

[12] In particular, no tie-breaking rule is required for zero volumes. Note also that a zero trading volume generates no adverse price impact on subsequent transactions within the block.

trader i's expected wealth in (4) as

$$\mathbb{E}_i[W_i] = \mathbb{E}_i[W_{i,0}] + \frac{2\,\delta_i}{\kappa} \sum_{j=0}^{M-1} \mathbb{E}_i\left[\mathbb{1}_{\{\varphi_{(j)}<\varphi_i<\varphi_{(j+1)}\}}\,\Delta_{(1:j)}\right], \tag{6}$$

which has the following economic interpretation. The term $\mathbb{E}_i[W_{i,0}]$ represents trader i's expected wealth if she is executed last in the block. By submitting a positive priority fee φ_i, she obtains, with positive probability, an additional surplus. This surplus,

$$\frac{2\,\delta_i}{\kappa} \sum_{j=0}^{M-1} \mathbb{E}_i\left[\mathbb{1}_{\{\varphi_{(j)}<\varphi_i<\varphi_{(j+1)}\}}\,\Delta_{(1:j)}\right], \tag{7}$$

represents the expected price impact that trader i avoids by improving her queue position. The magnitude of this surplus increases with the rank of φ_i among competitors and with the quantity demanded by the trader.

Trader i expects her competitors to employ the increasing priority fee bidding strategy $\varphi(\cdot)$. Therefore, the probability of submitting the $j+1$-th largest priority fee is

$$\mathbb{P}_i\left[\varphi_{(j)} < \varphi_i < \varphi_{(j+1)}\right] = \mathbb{P}_i\left[\delta_{(j)} < \varphi^{-1}\left(\varphi_i\right) < \delta_{(j+1)}\right] .$$

To determine her optimal priority fee, trader i solves the optimization problem

$$\sup_{\varphi_i} \mathbb{E}_i\left[W_i\right] , \tag{8}$$

which is equivalent to solving

$$\sup_{\varphi_i} \left\{ -\varphi_i + \frac{2\,\delta_i}{\kappa} \sum_{j=0}^{M-1} \mathbb{E}_i\left[\mathbb{1}_{\varphi_{(j)}<\varphi_i<\varphi_{(j+1)}}\Delta_{(1:j)}\right] \right\} . \tag{9}$$

That is, trader i chooses her priority fee to maximize the sum of (i) the loss from paying the priority fee to the builder and (ii) the gain from the surplus. Trader i therefore faces a trade-off: lowering the priority fee increases expected wealth but decreases the probability of attaining a higher position in the queue.

To further analyze the optimization problem, the following lemma is useful, because it simplifies trader i's estimation of the expected surplus from the PGA.

LEMMA 1: *Assume $M > 2$. The surplus* (7) *is given by*

$$\frac{2}{\kappa} \sum_{j=0}^{M-1} \mathbb{E}_i \left[\mathbb{1}_{\{\varphi_{(j)} < \varphi_i < \varphi_{(j+1)}\}} \Delta_{(1:j)} \right] = \frac{2}{\kappa} \, (M-1) \int_0^{\varphi^{-1}(\varphi_i)} x \, dG\,(x) \; . \tag{10}$$

Lemma 1 shows that the expected surplus is obtained by averaging the price impact of transactions with volumes lower than trader i's inverse bid. This result follows from the structure of the PGA. First, it arises from the additive and linear price impact in the AMM. In practice, nonlinearities exist in the aggregate impact of consecutive trades; see Cartea et al. (2023). However, we model competition within a block whose duration is short enough for our linear approximation (B3) to be accurate in practice. Second, the result of Lemma 1 also relies on the strict ordering of transactions by priority fee within the block. In practice, while builders have reputational incentives to maintain strict ordering, they are not required to do so by the blockchain protocol. Such strategic interactions are beyond the scope of this work.

In a Bayesian-Nash equilibrium, trader i finds it optimal to adopt the same differentiable and increasing strategy φ, which pins down the equilibrium strategy. The solution is characterized in the following result.

PROPOSITION 1: *The equilibrium priority fee is*

$$\varphi\,(\delta_i) = \frac{2}{\kappa}\,(M-1) \int_0^{\delta_i} x^2 \, dG\,(x) \; . \tag{11}$$

The priority fee is increasing in the trading volume δ_i, increasing in the number of informed *traders M, and decreasing in the liquidity depth κ. Finally, trader i's objective* (9) *is*

$$\frac{2}{\kappa}\,(M-1)\int_0^{\delta_i} x\,(\delta_i - x)\;dG\,(x)\;, \tag{12}$$

Trader i uses the reservation priority fee

$$\frac{2\,\delta_i}{\kappa}\,(M-1)\int_0^{\delta_i} x\,dG(x)$$

as a baseline when computing her optimal fee. This reservation priority fee is the level that makes trader i indifferent between participating in the PGA and abstaining, that is, it sets her objective (12) equal to zero. Trader i then applies a discount to this baseline in order to capture a surplus. In particular, as trader i's trading volume δ_i increases, the likelihood that her reservation fee exceeds those of other traders also rises. Consequently, trader i applies a larger discount as the value of her private volume increases.

For a fixed arbitrary distribution of trading volumes, equilibrium priority fees increase with the number of competitors. Specifically, as the number of informed traders rises, the expected adverse price impact becomes larger, incentivizing each trader to raise her priority fee. Conversely, equilibrium priority fees decrease with liquidity supply. Specifically, when κ is large, price impact is low and the cost of losing queue priority becomes less significant.

As we show below, however, these relationships do not necessarily hold (i) when informed traders choose their trading volumes strategically as a function of anticipated priority fees, and (ii) when liquidity suppliers set their supply strategically as a function of anticipated trading volumes.

D. Trading volumes

The section above derived the equilibrium priority fees of informed traders for an arbitrary distribution g of trading volumes with support $\left[0, \overline{\delta}\right]$. We now endogenize this distribution by determining the volumes that maximize the informed traders' objective. Substituting the optimal priority fee φ_i from (11) into the objective function (5), we express trader i's optimization problem as

$$\sup_{\delta_i} \left\{ -\frac{2}{\kappa}(M-1)\left(\int_0^{\delta_i} x^2\, dG(x) + \delta_i \int_{\delta_i}^{\overline{\delta}} x\, dG(x)\right) + \delta_i\left(v_i - \pi - \frac{\delta_i}{\kappa}\right)\right\}. \tag{13}$$

The programme (13) can be interpreted as follows. In equilibrium, all traders employ the same priority fee bidding strategy, allowing them to estimate, on average, the expected costs of the PGA in the form of expected adverse price impact and priority fees. Additional trading costs incurred by trader i include (i) the execution cost $-\delta_i^2/\kappa$, (ii) the AMM's fee $\pi\,\delta_i$, and (iii) the cost of information. Both trading and infrastructure costs increase with trading volume, creating an incentive for trader i to reduce her trading volume δ_i. However, trader i expected trading profits at the end of blockchain slot are $\delta_i\, v_i$. This provides an incentive for trader i to increase her holdings in the asset.

We assume that trading volumes are a weakly monotone function of private valuations and we write $\delta_i = \delta(v_i)$ for $v_i \in [0, \overline{v}]$. In particular, the minimum and maximum trading volumes satisfy

$$\delta(0) = 0 \qquad \text{and} \qquad \overline{\delta} = \delta(\overline{v})\,.$$

We later verify that our assumption holds in equilibrium. The distribution of trading volumes, expressed as a function of the cumulative distribution function F of valuations, is given by

$$G(x) = F\big(\delta^{-1}(x)\big)\,, \tag{14}$$

where δ^{-1} denotes the generalized inverse of the function δ. In what follows, we assume that F is continuous on its support $[0, \overline{v}]$ and has no atom at $\overline{v}$. Moreover, we assume that the largest valuation satisfies $\pi < \overline{v} < \infty$.

The adverse price impact of competing traders depends on trader i's private valuation of the asset. Lower valuations correspond to lower volumes and to worse queue positions within the block, and consequently, to higher adverse price impact from traders with better positions. For sufficiently low valuations, the adverse price impact associated with high-valuation traders may discourage trader i from submitting a transaction if doing so results in a negative objective (13). In what follows, we show that there indeed exists a participation cutoff $\underline{v}_M$, which increases with the number M of competitors, below which trader i optimally chooses not to submit a transaction.

Using (14), the first-order condition (FOC) derived from the optimization problem (13) yields the following implicit integral equation for the optimal trading volume

$$(v_i - \pi)\,\kappa - 2\,\delta(v_i) - 2\,(M-1)\int_{v_i}^{\overline{v}} x\, dF(x) = 0\,. \tag{15}$$

Next, Lemma 2 characterizes the participation cutoff, and Proposition 2 derives the equilibrium trading volumes and their distribution.

LEMMA 2: *There exists a unique nonnegative* $\underline{v}_M > \underline{v}$ *which satisfies*

$$\underline{v}_M - \pi - \int_{\underline{v}_M}^{\overline{v}} \left(e^{(1-F(u))(M-1)} - 1\right) du = 0\,. \tag{16}$$

Moreover, $\underline{v}_M$ *is increasing in* M *and* $\lim_{M\to\infty} \underline{v}_M = \overline{v}$.

PROPOSITION 2: *Fix* $M > 2$*. If* $v_i < \underline{v}_M$*, where* $\underline{v}_M$ *is defined in* (16)*, then the equilibrium trading volume is* $\delta(v_i) = 0$*. If* $v_i \geq \underline{v}_M$*, then the equilibrium trading volume is linear in the liquidity supply* κ*,*

$$\delta(v_i) = \kappa\,\tilde{\delta}(v_i)\,, \tag{17}$$

where

$$\tilde{\delta}(v_i) = \frac{1}{2}\left((\overline{v} - \pi)\, e^{-(M-1)(1-F(v_i))} - \int_{v_i}^{\overline{v}} e^{-(M-1)(F(u)-F(v_i))}\, du \right). \tag{18}$$

Moreover,

$$\delta(\underline{v}_M) = 0 \qquad \text{and} \qquad \overline{\delta} = \delta(\overline{v}) = \kappa\frac{\overline{v} - \pi}{2}.$$

The equilibrium trading volume $\delta(v_i)$ *is increasing in the private valuation* v_i*, decreasing in* *the number of informed traders M with limit* $\lim_{M\to\infty} \delta(v_i) = 0$.

Proposition 2 implies that the equilibrium distribution of trading volumes is a transformation of the truncated distribution of valuations on $[\underline{v}_M, \overline{v}]$:

$$G(\{0\}) = F(\underline{v}_M) \qquad \text{and} \qquad G\big(\delta(v)\big) = F(v) \quad \text{for } v \in [\underline{v}_M, \overline{v}]\,. \tag{19}$$

Hence, on average, for a given number M of competing traders, the expected number of active traders is $M\big(1 - F(\underline{v}_M)\big)$ (those with sufficiently high valuations for the asset—participate in the PGA). We refer to traders whose valuations are high enough to participate as *active traders*. Next, we examine the implications of our result for blockchain-based markets.

D.1. Equilibrium priority fees

When a trader's valuation exceeds the participation cutoff $\underline{v}_M$, Proposition 2 shows that her trading volume is proportional to the liquidity supply κ, with proportionality *factor* $\tilde{\delta}(v_i)$. This is intuitive, because deeper liquidity reserves allow traders to extract greater profits from private information. In contrast, trading volumes decrease with the number of traders in anticipation of higher expected PGA costs.

Moreover, the factor $\tilde{\delta}(v_i)$ increases with the private valuation v_i. This occurs for two reasons. One, a higher valuation strengthens the incentive to trade, and two, it increases the expected surplus from the PGA. Thus, higher private valuations correspond to larger trading volumes, and as shown in Proposition 1, they are also associated with better queue positions. Figure 2 shows the average trading volume across multiple AMM pools on Ethereum as a function of their queue position within the block. The figure shows that the volume of transactions decreases with queue position, and lends empirical support to the findings of our model.

For a fixed arbitrary distribution of trading volumes, Proposition 1 showed that higher competition in the PGA increase priority fees and that higher supply decrease them. How-

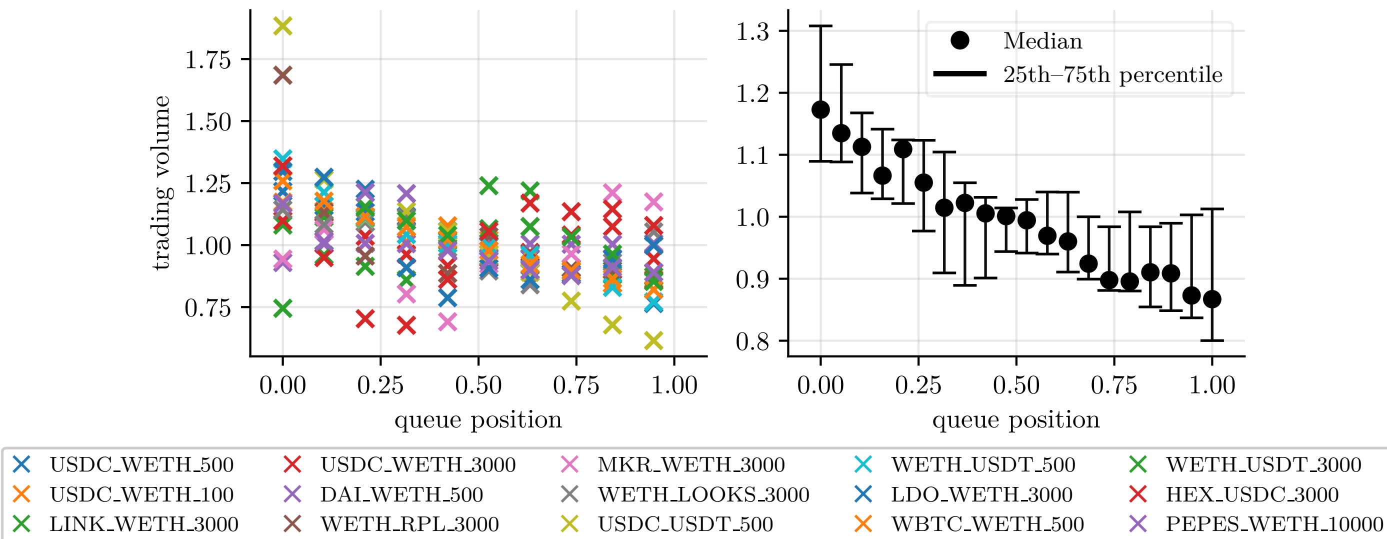

Figure 2. Left panel: Average absolute trading volume as a function of queue position in the block for transactions in multiple Uniswap v3 pools; 0 corresponds to first position and 1 to last position. The transactions are between 1 January 2023 and 31 December 2023 in 15 different Uniswap v3 pools with multiple transactions in at least 10 different blocks. For each pool, the trading volumes are normalized by the standard deviation of trading volumes. Right panel: average and inter-quartile trading volumes across the 15 pools.

ever, trading volumes are part of the traders' equilibrium strategy and they adjust to expected profits and trading costs, including valuations and priority fees. The next result derives the equilibrium priority fee accounting for strategic trading volumes.

PROPOSITION 3: *The equilibrium priority fee is zero if* $v_i \leq \underline{v}_M$. *Otherwise, when* $v_i > \underline{v}_M$ *, the equilibrium priority fee accounting for strategically adjusted trading volumes, is*

$$\varphi\left(v_i\right) = 2\,\kappa\left(M-1\right)\int_{\underline{v}_M}^{v_i} \tilde{\delta}\left(x\right)^2\, dF\left(x\right)\,. \tag{20}$$

The equilibrium priority fee is increasing in the liquidity depth κ, *and tends to zero when the number of traders on the blockchain tends to infinity:*

$$\lim_{M\to\infty} \varphi(v_i) = 0\,.$$

Proposition 3 shows that the equilibrium priority fees $\varphi(\delta(v))$, accounting for strategically adjusted volumes, converge monotonically to zero with the number of informed traders in the memory pool. The intuition is that increased competition raises anticipated PGA costs and expected adverse price impact, which induces an exponential down scaling in equilibrium trading volumes. As $M \to \infty$, both trading volumes and priority fees converge to zero.

Similar arguments to those above show that the equilibrium priority fees and trading volumes derived earlier also apply when traders wish to sell the asset. As a consequence, traders are symmetrically aggressive in equilibrium, i.e., they buy and sell the same volumes for valuations of equal absolute value and opposite signs.

D.2. Participation cutoff and trading volumes

Proposition 2 shows that the participation cutoff $\underline{v}_M$ for profitable informed trading increases with M. Therefore, as the number of competitors grows, increasingly higher valuations are required to participate. Because only high-valuation traders ultimately submit transactions in blockchains, higher trading volumes, associated with higher valuations, should be more frequently observed on blockchains. This prediction is consistent with empirical evidence showing that per-transaction trading volume in blockchain markets are significantly larger than those in traditional electronic limit order books. For instance, Cartea et al. (2025) report that between 1 July 2021 and 31 December 2023, the average size of liquidity-taking trades in the most active AMM on Ethereum was approximately \$70,000, compared with about \$1,200 for the same pair of assets on Binance.

The next result characterizes the behavior of price and volume in blockchain markets as competition intensifies.

PROPOSITION 4: *The expected number of active traders $M\,(1 - F(\underline{v}_M))$ tends to infinity as $M \to \infty$. The expected aggregate trading volume of active informed traders admits the limit*

$$\lim_{M\to\infty} \kappa\, M \int_{\underline{v}_M}^{\overline{v}} \tilde{\delta}(x)\, dF(x) = \kappa\, \frac{\overline{v} - \pi}{2} = \kappa\, \tilde{\delta}(\overline{v})\,.$$

Moreover, the expected price at the end of the block converges to $\overline{v} - \pi$*.*

Proposition 4 shows that, as competition intensifies, a growing mass of informed traders with increasingly high valuations participate in the PGA. In the limit, aggregate volume converges to the volume $\kappa\,\tilde{\delta}(\overline{v})$ associated with an informed trader holding the maximal valuation $\overline{v}$. Moreover, the expected price at the end of the block converges to $\overline{v} - \pi$, which corresponds to the upper bound of the valuation support net of fees.

The economic mechanism is endogenous selection. As M increases, participation requires progressively more aggressive bidding in order to remain competitive. Traders anticipate both higher expected priority fees and the adverse price impact generated by participants with larger valuations. This raises the cutoff $\underline{v}_M$ and excludes traders with moderate valuations from the market. In equilibrium, only the most aggressive traders remain active. Their aggregate trading volume therefore reflects valuations arbitrarily close to $\overline{v}$, pushing the execution price toward its maximal feasible level net of fees.

These results have direct implications for price efficiency on a blockchain that serves as the venue for price formation. From the perspective of an uninformed observer, only non-zero priority fees and executed volumes reveal private information. As competition increases, the fraction of the valuation distribution that generates transactions shrinks (Lemma 2). Price formation is thus driven by an increasingly thin upper tail of the distribution. Thus, the transaction price becomes systematically biased upward relative to its fundamental value, irrespective of the shape of the distribution F.

As we discuss below, an increase in block time, that is, the time required for a block to be created and markets to clear, may raise the upper bound of possible valuations $\overline{v}$ and amplify the upward price bias. These effects play a role in shaping the equilibrium supply of liquidity, which we characterize in the next section.

III. Stage one: liquidity supply

A. Assumptions

The level of reserves deposited in the AMM determines the execution costs and the price impact of liquidity taking trades. At stage one, a risk-neutral representative liquidity supplier sets the AMM reserves by balancing losses to informed traders with fee revenue from noise traders.[13]

For simplicity, we assume that noise traders transact a net volume that sums to zero in expectation, but an absolute expected volume which is price-sensitive. Specifically, the liquidity demanded by buyers is decreasing in the price $1/\kappa$ and its expected volume is

$$\frac{N}{2} \times \frac{1}{1+\theta/\kappa},$$

and the expected liquidity demanded by sellers is symmetric.

Demand on each side is therefore characterized by two parameters: $N/2$, the aggregate positive (resp. negative) liquidity needs over the blockchain slot, and θ, which governs the sensitivity of realized demand to liquidity depth κ. When $\kappa \ll \theta$, demand responds approximately linearly to liquidity, with slope proportional to $1/\theta$. As κ increases, marginal gains from additional liquidity diminish. Smaller values of θ imply that most of the available demand is captured at relatively modest depth, whereas larger values imply that demand is more elastic and requires substantial liquidity to materialize. Our specification is bounded, so realized demand does not exceed the available mass N. Liquidity demand follows, in spirit, the reduced-form models of demand in Garman (1976); Ho and Stoll (1981); Hendershott

[13] Unlike traditional venues such as limit order books or dealer markets, the permissionless nature of blockchains facilitates entry to liquidity provision, particularly by less sophisticated participants. As a result, strategic liquidity suppliers cannot freely set the price of liquidity because of *noise liquidity suppliers*. This feature of blockchains may explain the losses observed in practice; see Cartea et al. (2024a).

and Menkveld (2014). The liquidity supplier's expected fee revenue is therefore

$$\pi N \frac{\kappa}{\kappa+\theta}. \tag{21}$$

The liquidity supplier does not hold the same information about the future liquidation value V of the asset as that of informed traders. At stage one, he assumes that with probability 1/2, the liquidation value V of the asset is positive, in which case the informed traders buy the asset and their private valuations are drawn from the interval $[0, \overline{v}]$ according to the continuous and differentiable density f. Similarly, with probability 1/2, the liquidation value of the asset is negative, in which case the informed traders sell the asset and their valuations are drawn from the interval $[-\overline{v}, 0]$, according to the symmetric density $f(-x)$.

Recall that only traders who value the asset above the cutoff (16) submit transactions with volumes (17). We denote the total trading volume of informed traders by

$$\Delta_M = \sum_{k=1}^{M} \delta(v_k)\,. \tag{22}$$

From the perspective of the supplier, Δ_M is a random variable, whose expected value is zero, and which is assumed to be independent of the noise liquidity demand.

The liquidity supplier balances fee revenue with expected losses to informed traders. According to the analysis in Milionis et al. (2022) and Appendix B, the adverse selection cost for the liquidity supplier is[14]

$$-\Delta_M^2\,/\kappa\,. \tag{23}$$

Thus, at stage one, the expected loss of the liquidity supplier to informed traders in stage two is

$$-\frac{1}{\kappa}\,\mathbb{E}\left[\Delta_M^2\right] = -\frac{1}{\kappa}\,\mathbb{V}[\Delta_M] = -\frac{M}{\kappa}\,\mathbb{E}\left[\delta(v)^2\right] = -\kappa\,M\,S_M\,,\,. \tag{24}$$

[14]This loss is commonly referred to as *impermanent loss*, and it is nonpositive because liquidity suppliers hold more reserves of the asset whose price has decreased and less reserves of the asset whose price has increased, see Appendix B for more details.

where

$$S_M = \int_{\underline{v}_M}^{\overline{v}} \tilde{\delta}(u)^2 \, dF(u) \,, \tag{25}$$

the volume function $\tilde{\delta}$ is defined in (17).

B. *Equilibrium liquidity supply*

The risk-neutral liquidity supplier balances expected adverse selection losses to informed traders with expected fee revenue from noise traders. The optimization problem, which is solved in the next proposition, is

$$\sup_{\kappa} \left\{ \pi \, N \, \frac{\kappa}{\kappa + \theta} - \kappa \, M \, S_M \right\} \,. \tag{26}$$

PROPOSITION 5: *In equilibrium, the supply of liquidity is*

$$\kappa^{\star} = \sqrt{\frac{\pi \, N \, \theta}{M \, S_M}} - \theta \,, \tag{27}$$

where S_M is defined in (25). *The supply increases in the profitability of noise trading flow, and admits the limit*

$$\lim_{M \to \infty} \kappa^{\star} = \frac{\sqrt{8 \, \pi \, N \, \theta}}{\overline{v} - \pi} - \theta \,. \tag{28}$$

The condition for markets to remain open is

$$M \, S_M \leq \frac{\pi \, N}{\theta} \,. \tag{29}$$

Trading volumes in stage two are strategically set by informed traders to be proportional to the liquidity depth κ. Thus, greater liquidity provision in stage one amplifies, on average, the dollar value of informed trading profits and, consequently, the expected losses (24) of the liquidity supplier. The liquidity supplier anticipates that the dispersion S_M of aggregate trading volumes determines these losses and decreases supply accordingly. Conversely, he anticipates that noise demand is profitable and increases supply in response.

We now discuss how liquidity supply depends on the degree of competition in the PGA. There are two opposing forces. As the number of competitors M increases, each individual active trader's expected volume (17) decreases and tends to zero. However, as shown in Proposition 4, a larger M also expands (i) the pool of active participants in the PGA and (ii) the participation cutoff (16), so that only high-valuation traders remain active. In the limit as $M \to \infty$, the variance of aggregate active trading volume, $M\,S_M$, converges to $\frac{(\overline{v}-\pi)^2}{8}$. Liquidity supply therefore converges to (28), and only an arbitrarily small portion of private information is revealed.[15]

Our results stand in sharp contrast to the effect of competition among informed traders in traditional markets with continuous trading and multiple clearing rounds. In such markets, as the number of informed traders tends to infinity, prices become fully revealing in early rounds and adverse selection premia vanish later; see Holden and Subrahmanyam (1992). Market depth increases as private information is incorporated through successive rounds of trading.

The mechanism behind our result is fundamentally different. In blockchains, trades are executed in a single discrete clearing and priced according to priority fees. Traders pay both the cost of market impact and the priority bid required to secure queue position. Because clearing occurs in one round, the liquidity supplier must absorb the full adverse selection risk from aggregate trading volume in a single decision, rather than adjusting liquidity across successive rounds. As a result, competition decreases liquidity instead of deepening it.

C. *Market viability*

The liquidity supplier's expected payoff is

$$\pi\,N\,\frac{\kappa^{\star}}{\kappa^{\star}+\theta} - \kappa^{\star}\,M\,S_M\,, \tag{30}$$

[15] It can be shown that for a broad class of distributions, liquidity supply decreases monotonically toward its limit.

which establishes the condition (29) for the viability of blockchain markets. Condition (29) is standard, it states that if the fee revenue from liquidity demand is less than the expected losses to informed traders, the supplier's profits become negative, making liquidity provision unsustainable. The degree to which this condition must hold depends on the price-sensitivity parameter θ. All else being equal, as demand becomes more elastic, the viability of liquidity provision requires either greater liquidity demand N, higher fee rates π, or reduced variance in trading volumes. This condition mirrors that in Glosten and Milgrom (1985) where markets shut down due to liquidity freeze if the valuation of informed traders is too precise relative to the price-sensitivity of liquidity demand.

When the variance of trading volumes is maximal, i.e., when

$$S_M = \frac{\pi\, N}{M\, \theta}\,, \tag{31}$$

then the liquidity depth is $\kappa^\star = 0$.

Our analysis in this section treats the number M of informed traders as exogenous. In the next section, we endogenize entry into blockchains. The equilibrium number of competing traders in the PGA is constrained by the cost of acquiring information and by the limited profitability induced by defensive liquidity supply.

IV. Stage zero: information acquisition

Our results in Section III show that, upon observing their private valuations, traders with low valuations submit zero trading volumes, while traders with high valuations participate in the PGA. At stage zero, however, traders must decide whether to incur the information cost C to acquire private information before observing their valuations. These costs include expenditures on proprietary blockchain data, centralized exchange data, searcher contract deployment, and blockchain monitoring tools.

Assume that the total number of traders eligible to acquire information is arbitrarily large, and let M denote the subset that chooses to do so. In equilibrium, entry into informed trading is determined by the comparison between the expected profitability of informed trading and the information cost C. At stage zero, the equilibrium number of informed traders M is the largest integer value such that the marginal trader does not gain from entering the blockchain. We characterize this equilibrium number in the following result.

PROPOSITION 6: *The equilibrium number of informed traders is the largest integer M such that*

$$C = \underbrace{\kappa^\star \int_{\underline{v}_M}^{\overline{v}} \left[\tilde{\delta}(v)\big(v - \pi - \tilde{\delta}(v)\big) - 2\,(M-1) \left((1 - F(v))\tilde{\delta}(v)^2 + \int_{v}^{\overline{v}} \tilde{\delta}(v)\tilde{\delta}(u)\, dF(u) \right) \right] dF(v)}_{H(M) = \text{ex-ante trading profits net of execution costs and priority fees}}, \tag{32}$$

where $\underline{v}_M$ and $\tilde{\delta}$ are defined in (16) *and* (18)*, respectively. The function $H(M)$ converges to a nonpositive limit as $M \to \infty$. If $H(2) > C$, then an equilibrium number $M^\star \geq 2$ of informed traders exists and is given by the largest integer M satisfying* (32)*. Moreover, $M^\star$ increases with the size N and the price-sensitivity parameter θ of uninformed demand, and decreases with the information cost C.*

In the equilibrium condition (32), the integrand on the right-hand side represents the expected profit from participating in the PGA when a trader observes a valuation $v > \underline{v}_M$ and liquidity supply is set at its equilibrium level (27). These expected profits are weighted by the likelihood $dF(v)$ of observing valuation v in stage two. Proposition 6 also shows that the mass of informed traders decreases with the cost of information and increases with the size of uninformed demand.

In markets, price efficiency is directly related to the number of traders who incur the cost of acquiring information. Each revealed valuation reduces the conditional variance of the fundamental price from the perspective of an uninformed observer. Thus, lower information costs C and greater noise trading improve price efficiency. However, under paid-priority discriminatory pricing of blockchains, price efficiency is also related to the participation cutoff (16) below which traders abstain from the PGA. An increase in entry raises the participation cutoff, so that only increasingly high valuations are revealed. Information becomes more truncated, and price efficiency deteriorates.

V. Block time

Our model endogenizes trading volumes, entry into the blockchain, participation in the PGA, liquidity supply, and the amount of information in the market. The primitives are the price-sensitivity and total mass of noise trading flow, the distribution of private valuations, and the cost of acquiring information.

An additional primitive specific to blockchains is the length of the slot, i.e., block time. Block time directly affects both the distribution of private valuations and the intensity of uninformed trading. As block time increases, the likelihood of large innovations in fundamentals increases. There are two immediate consequences. The dispersion of private valuations increases, and uninformed traders face greater execution risk within the block. We now incorporate these features into our model and discuss the effect of block time.

Let T denote block time, which is common knowledge to all competitive agents. To perform comparative statics with respect to T, we assume that the distribution F of private valuations depends on block time. Specifically, the upper bound of the support satisfies $\overline{v} = \overline{v}(T)$, where $\overline{v}(T)$ is positive and strictly increasing in T. Moreover, if $T' > T$, then the distribution $F(\cdot; T')$ first-order stochastically dominates $F(\cdot; T)$ on $[0, \overline{v}(T)]$, that is,

$$F(v; T') < F(v; T) \quad \text{for all } v \in [0, \overline{v}(T)].$$

Longer block times therefore generate more extreme valuations.

Block time also affects uninformed demand. In Section III, uninformed demand depended mainly on the depth κ. In practice, execution quality for noise traders deteriorates not only because of limited depth, but also because of ordering within the block after informed traders. Longer block times increase this execution risk.

We capture this effect in reduced form by assuming that expected fee revenue from noise traders is

$$\pi\, N(T)\, \frac{\kappa}{\kappa + \theta}, \tag{33}$$

where $N(T) \geq 0$ and $N(T)$ is decreasing in T. Thus, longer block times reduce the effective mass of uninformed flow.

Fix the number M of competing informed traders. The participation cutoff (16) is strictly increasing in T.[16] Longer block times therefore discourage entry: only traders with increasingly higher signals participate.

In the regime with many informed traders, Proposition 4 shows that the end-of-block price on the blockchain converges to the upper bound $\overline{v}(T) - \pi$. Since $\overline{v}(T)$ increases with T, longer block times push prices to more extreme levels.

Moreover, adverse selection becomes more severe as block time increases. In the regime with many informed traders, equilibrium liquidity converges to the upper bound

$$\frac{\sqrt{8\, \pi\, N(T)\, \theta}}{\overline{v}(T) - \pi} - \theta,$$

given in (28). This bound is inversely proportional to the dispersion term $\overline{v}(T) - \pi$, which expands with block time, and it also scales with the volume of uninformed demand $N(T)$, which decreases in T. Longer blocks therefore decrease the maximum sustainable liquidity, and for sufficiently large T, liquidity collapses.

Even away from the high-M limit, block time reduces equilibrium liquidity through the channel of less profitable uninformed demand. From (27),

$$\kappa^{\star} = \sqrt{\frac{\pi\, N(T)\, \theta}{M\, S_M(T)}} - \theta.$$

Longer blocks reduce fee revenue and induce defensive liquidity withdrawal. In particular,

[16] This follows by differentiating (16) with respect to T.

the blockchain viability condition becomes

$$M \int_{\underline{v}_M}^{\overline{v}(T)} \tilde{\delta}(u;T)^2 \, dF(u;T) \leq \frac{\pi\, N(T)}{\theta}.$$

Block time therefore tightens this constraint.

Block time also affects the equilibrium number $M^\star$. As $N(T)$ decreases with T, liquidity falls, reducing informed traders' expected profits and lowering the number $M^\star$ willing to pay the information cost.

Blockchain design. In traditional markets with continuous trading, transactions that would be aggregated within a single blockchain slot instead unfold over multiple short clearing rounds. Greater competition among informed traders accelerates the incorporation of information in the early rounds, and market depth typically improves thereafter; see Holden and Subrahmanyam (1992).

In contrast, blockchain trading is discrete and transactions are ordered through a paid-priority queue. These features discourage broad participation in informed trading. As a result, only traders with sufficiently high valuations, who also generate the largest adverse selection losses for liquidity suppliers, trade in meaningful size.

The stated ambition of blockchains is to provide a decentralized alternative to intermediaries and to organize economic activity at scale. Financial markets are a central component of that ambition. Yet our analysis shows that the very features that secure decentralization, most notably block time to conduct consensus, can undermine market viability: while longer block times enhance consensus security, they also decrease liquidity, deter entry, and impair price efficiency.

If blockchains are to become a credible infrastructure for price discovery, protocol design must carefully address how transactions are organized and prioritized within each block.

VI. Conclusions

We proposed the first theoretical model of price formation and liquidity in a blockchain market with discriminatory pricing based on paid-priority queues and discrete clearing. The model endogenizes trading volumes, entry into informed trading, participation in the priority gas auction, liquidity supply, and payment for information. We showed that market outcomes are governed by three key primitives: the distribution of private valuations, the mass of uninformed trading flow, and the length of the blockchain slot. Our analysis highlights a structural tension. Priority-based ordering, discrete clearing, and block time decrease liquidity and impair price discovery. In general, under these design features, blockchains are not viable for price discovery. If blockchains are to host markets, modifications to clearing mechanisms are necessary.

Appendix A. Institutional details

The microstructure of DEXs differs fundamentally from that of traditional financial markets due to the unique blockchain infrastructure on which they operate. In this section, we outline the defining institutional features of blockchains and AMMs that underpin the framework of our model. Further details on AMMs are provided in Appendix B.

Appendix A. Ethereum blockchain

A blockchain is a distributed digital ledger stored by participants, referred to as nodes, within a public network. All blockchain activity is publicly visible. When an agent submits a transaction, it is pending and not immediately included in a block. Instead, the pending transaction is stored in a *memory pool*. For a pending transaction to be executed on the blockchain, it must be included in a block created by a *builder*. Blocks are sequentially added to the ledger at regular intervals called *slots*, the duration of which is referred to as *block time*.[17]

The block builder selects pending transactions from the memory pool to create the next block. Builders are paid *gas fees* by agents to include their transactions in the block. Gas fees consist of two components: the *base fee* and the *priority fee*. The base fee is paid to all nodes and it is mandatory for inclusion in a block.[18] The base fee is used by the blockchain to regulate network traffic. In contrast, the priority fee is optional, paid exclusively to the builder, and incentivizes transaction inclusion and queue priority in the block. Builders order transactions by priority fee within the block they construct.[19] Thus, users compete for

[17]Block time must be long enough to allow for secure confirmation of blocks. This process requires aggregating a large number of cryptographic signatures in multiple rounds of network communications. Shortening block time excludes slower participants and concentrates rewards among those with superior connectivity, undermining decentralization. Thus, block time is a buffer that balances asset and decentralization.

[18]More precisely, the base fee is *burned*, meaning it is removed from circulation, thereby reducing the supply of the blockchain's native currency. This increases the value of each unit of the native currency.

[19]We make the simplifying assumption that builders strictly sort transactions in the block by priority fee. In practice, they are not required by the blockchain protocol to do so. However, failing to do so reduces builder reputation and weakens the incentive to pay priority fees in the future. Future work will explore the long-term effects of multiple rounds of interaction between agents and builders.

priority within a block to secure better execution prices or to exploit arbitrage opportunities. This competition is referred to as *priority gas auctions* (PGAs).

Block time on the Ethereum blockchain is deterministic, with time divided into fixed 12-second slots, each producing a new block. Accordingly, there are three stages in the lifecycle of a transaction: (i) *submission*, where an agent specifies the transaction details and sets a gas fee (base and priority fee); (ii) *storage in the memory pool*, where the pending transaction awaits selection by a builder; and (iii) *inclusion in a block*, which corresponds to the execution of the transaction. Transaction submission may occur at any time within the 12-second slot, and it is executed provided the transaction reaches the builder's memory pool before block creation.[20]

There are two types of memory pools: public and private. Pending transactions in the public memory pool are visible prior to execution, so agents operating on the Ethereum blockchain are exposed to arbitrage and predatory attacks. Private memory pools have recently emerged in the blockchain ecosystem as a means of protecting users; see Capponi (2024); Wang, Huang, Zhang, Huang, Wang, and Tang (2025).[21] Users using these private channels send their transactions directly to builders to conceal transaction details and avoid targeted attacks. At present, the vast majority of trading flow in Ethereum DEXs passes through private memory pools.[22] For additional details on blockchain protocols, see John, Monnot, Mueller, Saleh, and Schwarz-Schilling (2025).

Appendix B. Priority gas auctions

PGAs are key in the microstructure of blockchain. They differ across public and private memory pools. In private memory pools, traders do not observe each other's bids before block creation, so the PGA effectively operates as a sealed-bid static auction. In contrast, in public memory pools, bids are visible prior to execution, and traders compete in an online auction

[20]In practice, if there are too many transactions in the memory pool, only a fraction of all transactions is executed.

[21]www.flashbots.net

[22]See www.dune.com/queries/5184076/8532375.

throughout the blockchain slot.[23] In public memory pools, users benefit from waiting until the end of block time to submit their transactions for three reasons. First, early bids reveal information to competitors, second, early bids set a minimum fee due to the *account nonce*;[24] and third, late bidding allows users to incorporate the most up-to-date information available. As a result, late bidding has emerged as the dominant strategy as shown in Figure 3. As a result, PGAs in public memory pools can also be modeled as sealed-bid auctions, and our model below can therefore be used to describe the microstructure of blockchains in both private and public memory pools.

At present, PGAs are mainly between specialized users (searchers or bots) who exploit the discrete-time structure of blockchains to extract *maximal extractable value* (MEV) through two types of strategies. First, attacks on visible transactions in public memory pools,[25] and second, by closing arbitrage opportunities across different DEXs or between a DEX and a competing trading venue with continuous trading such as Binance; see Heimbach, Pahari, and Schertenleib (2024). These opportunities are public, and users compete for such opportunities in PGAs by submitting transactions that are *reverted* if the arbitrage opportunity no longer exists.[26] In public memory pools, all priority fee bids are paid to the builder, even when the corresponding transaction is not executed. In contrast, in private memory pools, priority fee bids are private and only the transaction of the highest bidder is executed and paid. This latter PGA effectively functions as a first-price sealed-bid auction in which the value of the item is public and known to all competitors. As predicted by

[23] Moreover, in public memory pools, failed transactions still pay the gas fees attached to them.

[24] A *nonce* tracks the number of transactions and it is assigned to each user to prevent replay and double-spending attacks; see Vujičić, Jagodić, and Ranđić (2018). Let n denote a user's current nonce. When submitting a transaction, users specify a nonce which determines its eligibility: (i) a nonce strictly smaller than n is rejected by the network, (ii) a nonce $n+1$ are eligible for inclusion in the next block, and (iii) a nonce strictly greater than $n+1$ is placed in a queue until all lower-nonce transactions are executed. Transactions confirmed by the network cannot be canceled, however, users can modify pending transactions before they are included in a block by submitting a new one with the same nonce and a higher gas fee. Builders, who maximize revenue, will select the transaction with the highest gas fee. Consequently, users can only revise gas fees upward.

[25] These include frontrunning, backrunning, and sandwich attacks.

[26] In blockchains, transactions are reverted, or cancelled, if the smart contract code refuses the transaction. This can happen for instance when a transaction has a cap on slippage or execution prices.

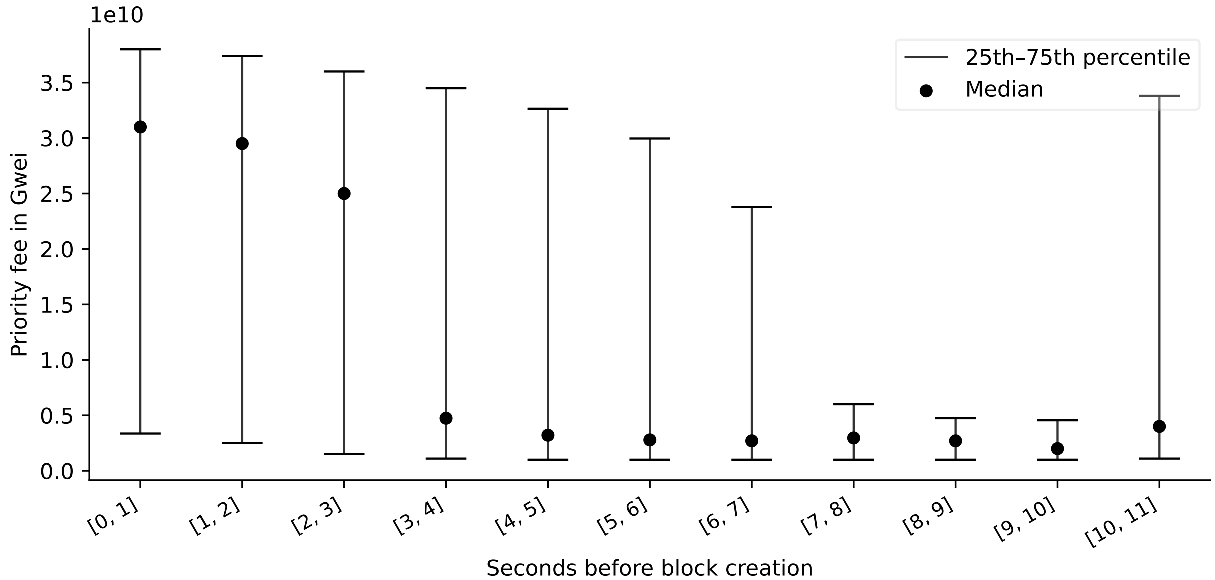

Figure 3. Distribution of priority fees as a function of timing within the blockchain slot. Informed traders are typically associated with higher priority fees, as shown empirically in Capponi et al. (2023b) and theoretically in our model below. The figure shows that they tend to submit their transactions very close to the end of the blockchain slot. The data is from *EthPandaOps* and it includes 10^7 transactions observed in the public memory pool of Ethereum between 20 March 2024, 00:00, and 21 March 2024, 17:08. This data corresponds to a period when the public memory pool accounted for approximately 60% of DEX trading volumes. At present (November 2025), this share is about 16%. The SQL data tables and other details are here. See Liu et al. (2022); Mizrach and Yoshida (2025) for a more detailed empirical analysis.

standard auction theory and as observed empirically, the majority of the revenue from such competitions is ultimately paid back to builders

Understanding how blockchains sustain price formation is crucial for assessing the long-term viability and design of existing blockchain protocols. Thus, the objective of this paper is not to study the PGAs mechanism for capturing public MEV opportunities. Instead, we focus on the fundamental question of market properties when the blockchain infrastructure supports price formation. To this end, akin to classical models that analyze the properties of traditional markets based on their mechanisms (Kyle (1985b); Huddart, Hughes, and Levine (2001); Biais (1993)), we study the blockchains under the assumption that they serve as the main trading venue, with no CEX against which users can arbitrage AMMs.

Specifically, in our model, the true fundamental value of the asset is unknown to all traders, who compete to buy or to sell based on noisy valuations of this true value. In this setting, traders do not compete for the same public arbitrage opportunity, and their transactions are non-conflicting. We endogenize the number of competing traders who choose to execute trades on the blockchain, where participation occurs only if their expected wealth exceeds the cost of entering. As a result, it is always profitable for traders to submit transactions, and transactions are not reverted.

Appendix B. Automated market makers

Blockchain determine the lifecycle of transactions and introduce specific infrastrcuture costs. The second key determinant of DEX microstructure is the AMM. In this section, we outline market frictions and wealth considerations for liquidity takers and suppliers, which are relevant to our model. In AMMs, rules specify how liquidity supply, in the form of aggregated reserves in a liquidity pool, determines execution prices and price impact; see Lehar and Parlour (2025), Capponi and Jia (2021), and Cartea et al. (2025).

Liquidity takers in DEXs. Assume trading is conducted in an AMM that supplies liquidity x_0 in the reference asset X and y_0 in the risky asset Y. A trading function Φ, known to all market participants, defines the combinations of reserves $\{x = \Phi(y), y\}$ that make liquidity suppliers indifferent, i.e., an iso-liquidity curve. This has the following implications for liquidity takers. Let $\delta > 0$ denote a quantity of asset Y that a trader wishes to buy (resp. sell), for which the trader pays (resp. receives) the amount $\Phi(y_0 - \delta) - \Phi(y_0)$ (resp. $\Phi(y_0 + \delta) - \Phi(y_0)$) in asset X. Thus, the execution prices per unit of the risky asset are

$$\text{price to sell } \delta : \quad \frac{\Phi(y_0) - \Phi(y_0 + \delta)}{\delta}, \qquad \text{price to buy } \delta : \quad \frac{\Phi(y_0 - \delta) - \Phi(y_0)}{\delta}, \tag{B1}$$

so the execution prices for an infinitesimal volume $\delta \to 0$ converge to $V_0 = -\Phi'(y_0)$, which we refer to as the *marginal price* of asset Y in terms of X, or simply the price of asset Y.

The marginal price is a reference price, and the difference between execution prices and marginal prices represent execution costs. This is similar to the difference between the mid-price in a limit order book and the execution price obtained from matching resting limit orders, or the difference between the fundamental price in an over-the-counter market and the bid/ask prices quoted by dealers; see Kyle (1985b); Biais (1993) for more details. In AMMs, the reserves y_0 in the pool determine execution costs, which we define as the difference between the price V_0 and the execution prices in (B1). The reserves also determine the impact of a liquidity taking trade on the price. In our model, the buy and sell prices, per unit of asset traded, are

$$\begin{aligned}
\text{price to sell } \delta: \quad & \frac{\Phi(y_0) - \Phi(y_0 + \delta)}{\delta} \approx V_0 - \frac{1}{2}\,\delta\,\Phi''(y_0)\,, \\
\text{price to buy } \delta: \quad & \frac{\Phi(y_0 - \delta) - \Phi(y_0)}{\delta} \approx V_0 + \frac{1}{2}\,\delta\,\Phi''(y_0)\,.
\end{aligned} \tag{B2}$$

Similarly, the impact on the price following a trade of volume δ is

$$\begin{aligned}
\text{impact after the sell order}: \quad & -\Phi'(y_0 + \delta) - V_0 \approx -\delta\,\Phi''(y_0)\,, \\
\text{impact after the buy order}: \quad & -\Phi'(y_0 - \delta) - V_0 \approx \delta\,\Phi''(y_0)\,.
\end{aligned} \tag{B3}$$

Equations (B2) and (B3) consider a second and first-order approximation of execution costs and price impact. The term $\frac{1}{2}\,\delta\,\Phi''(y_0)$ in the execution prices in (B2) is akin to the difference between (i) the volume-weighted average price received by a trader and (ii) the mid-price in a limit order book. Figure 4 uses DEX data from the Ethereum blockchain to show that our approximations are accurate in practice.

The convexity Φ'' of the trading function is key to determine trading frictions, i.e., execution costs and price impact, when the supply of liquidity is limited. In AMMs, the convexity

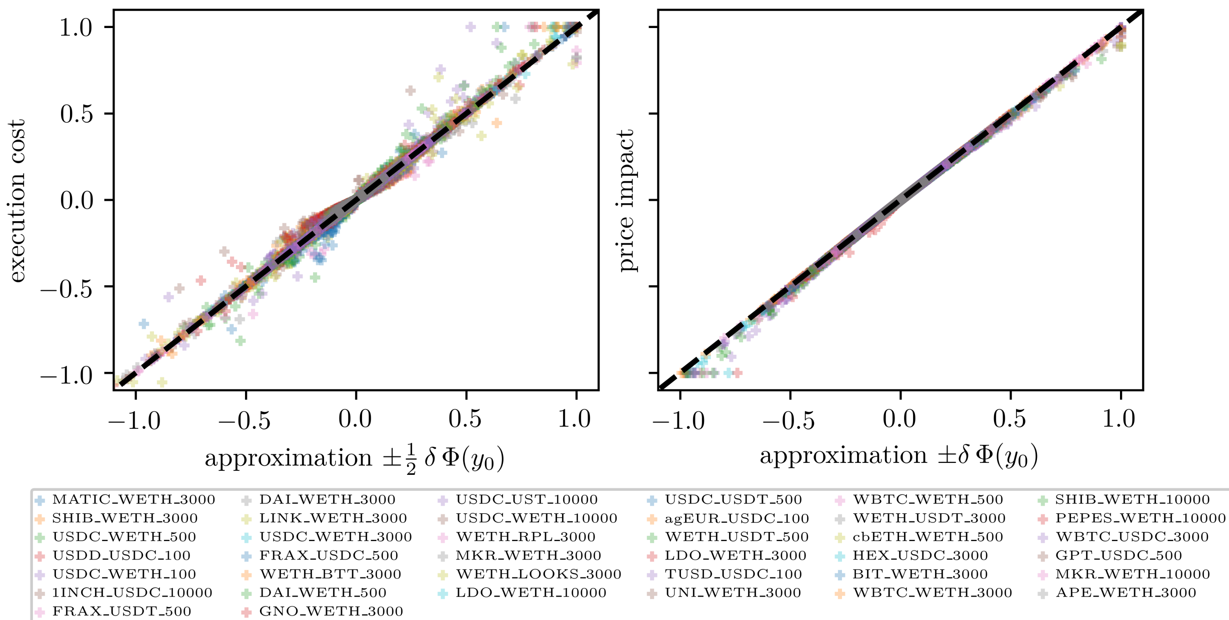

Figure 4. Scatter plots of the execution cost and the price impact of 2.622 million LT transactions against the approximations (B2) and (B3). The transactions are between 1 January 2023 and 31 December 2023 in 38 different Uniswap v3 pools. For each pool, the execution costs and price impacts are scaled between $[0, 1]$ for buy orders and $[-1, 0]$ for sell orders.

is inversely proportional to the size of the pool, and we refer to

$$\kappa = 2/\Phi''(y_0) \tag{B4}$$

as the *depth of liquidity*.[27] Thus, execution costs in (B2) are given by δ/κ. Akin to traditional electronic markets, execution costs and price impact, defined in (B2) and (B3), increase with the traded volume δ and decrease with the depth of liquidity κ.

The depth of liquidity κ influences the execution prices of subsequent trades in the pool. In PGAs within memory pools, informed traders compete for block priority to avoid potentially worse execution prices caused by the price impact of preceding orders in the block. For instance, assume that two traders consecutively buy an amount δ_1 and δ_2 of asset Y. Using the formula for execution costs in (B2) and price impact in (B3), the execution

[27] For example, the trading function for constant product markets like Uniswap, which are the most popular DEXs, is $\Phi(y) = \kappa^2/y$ so $k = 2\,V_0^{3/2}/\kappa \implies \kappa = 2/k = y_0$.

price for the trader with queue priority in the block is $V_0 + \delta_1/\kappa$, after which the new price updates to $V_1 = V_0 + 2\,\delta_1/\kappa$. Consequently, the execution price for the trader without queue priority, when is $V_1 + \delta_2/\kappa = V_0 + 2\,\delta_1/\kappa + \delta_2/\kappa$.

Liquidity suppliers in DEXs. This section studies the adverse selection losses of liquidity suppliers. Assume that a representative liquidity supplier sets a pool with depth κ, that the initial marginal price is V_0, and that informed traders transact the quantity δ in the pool. Use (B3) and (B4) to obtain the new marginal price $V_1 = -\Phi'(y_0 + \delta) = V_0 + 2\,\delta/\kappa$ in the DEX.

Next, assume the future liquidation value of asset Y is V. Let $y = y_0 + \delta$ denote the AMM's reserves when the price of the asset is V.

LEMMA 3: *The trading function of the AMM is convex to guarantee no profitable roundtrip arbitrage. Additionally, the change in the wealth W_L of the liquidity supplier is given by*

$$y_0\,(V - V_0) - (\Phi(y_0) - \Phi(y_0 + \delta) - \delta\,V)\,. \tag{B5}$$

When $V_1 = -\Phi'(y_0 + \delta) = V$, the term $-(\Phi(y_0) - \Phi(y_0 + \delta) - \delta\,V)$ in (B5) *is always nonpositive.*

Proof. Consider the prices to buy and sell a quantity δ in (B2). To guarantee no profitable roundtrip arbitrage, we require for all $y > 0$ and for all $0 < \delta < y$ that

$$\underbrace{\frac{\Phi(y) - \Phi(y + \delta)}{\delta}}_{\text{price sell } \delta} \leq -\Phi'(y) \leq \underbrace{\frac{\Phi(y - \delta) - \Phi(y)}{\delta}}_{\text{price buy } \delta},$$

which implies that Φ must be convex.

Next, assume that the initial reserves in an AMM are $\{\Phi(y_0), y_0\}$ so the initial wealth of the liquidity supplier is

$$\Phi(y_0) + y_0\,V_0\,.$$

Following a trading volume δ, the new AMM price is V_1, the liquidation value is V, and the reserves are $y_0 + \delta$. Thus, the change in the wealth of the liquidity supplier is

$$\begin{aligned}(\Phi(y_0+\delta)+(y_0+\delta)\,V)-(\Phi(y_0)+y_0\,V_0) &= \Phi(y_0+\delta)-\Phi(y_0)+(y_0+\delta)\,V-y_0V_0\\ &= y_0\,(V-V_0)+\Phi(y_0+\delta)-\Phi(y_0)+\delta\,V\,.\end{aligned}$$

which corresponds to (B5). When $V = -\Phi'(y_0+\delta)$, the term $\Phi(y_0+\delta)-\Phi(y_0)-\delta\,\Phi'(y_0+\delta)$ is negative because Φ is convex. $\square$

The change in the wealth of the liquidity supplier can be interpreted as follows. The first term on the right-hand side of (B5) represents the change in wealth had the initial reserves y_0 been held outside the pool. The second term in (B5) is an adjustment due to the change in value of reserves when traders transact volume δ. This term, commonly referred to as *impermanent loss*, reflects the adverse selection loss to informed traders. The last term on the right-hand side of (B5) represents the fee revenue.

In our model, we approximate the adverse selection loss from supplying liquidity with

$$\Phi(y_0+\delta)-\Phi(y_0)+\delta\,V \approx \delta\,\Phi'\,(y_0+\delta)-\frac{1}{2}\,\Phi''(y)\,(y-y_0)^2+\delta\,V = \delta\,\left(V-V_1\right)-\delta^2\,/\kappa\,,$$

where κ is the depth of the AMM's liquidity. Using $V_1 = -\Phi'(y_0+\delta) = V_0 + 2\,\delta/\kappa$ in (B3), we obtain

$$\Phi(y_0+\delta)-\Phi(y_0)+\delta\,V \approx \delta\,\left(V-V_0\right)-3\,\delta^2\,/\kappa\,, \tag{B6}$$

Intuitively, when $V_1 = V$, i.e., when the liquidity taking trade δ aligns the AMM marginal price to the fundamental price, the impermanent loss (B6) is nonpositive because liquidity providers hold more reserves of the asset whose price has decreased and less reserves of the asset whose price has increased. More precisely, after a liquidity-taking trade of size δ, the LP earns revenue δ/κ due to execution costs in (B2), while incurring adverse selection costs $-2\,\delta/\kappa$ due to price impact in (B3). This effect is akin to traditional markets.

Appendix C. Proofs

Appendix A. Proof of Lemma 1

First, by definition of the conditional expectation write

$$\begin{aligned}
&\sum_{j=0}^{M-1} \mathbb{E}_i \left[\mathbb{1}_{\varphi_{(j)}<\varphi_i<\varphi_{(j+1)}} \Delta_{(j+1:M-1)} \right] \\
&= \sum_{j=0}^{M-1} \mathbb{P}_i \left[\delta_{(j)} < \varphi^{-1}(\varphi_i) < \delta_{(j+1)} \right] \mathbb{E}_i \left[\Delta_{(j+1:M-1)} \mid \delta_{(j)} < \varphi^{-1}(\varphi_i) < \delta_{(j+1)} \right] .
\end{aligned}$$

For $j = 0$, the term writes

$$\mathbb{P}_i \left[\varphi^{-1}(\varphi_i) < \delta_{(1)} \right] \mathbb{E}_i \left[\Delta_{(1:M-1)} \mid \varphi^{-1}(\varphi_i) < \delta_{(1)} \right] ,$$

and for $j = M-1$, use $\Delta_{(M:M-1)} = 0$, so the term is zero. Thus,

$$\sum_{j=0}^{M-1} \mathbb{E}_i \left[\mathbb{1}_{\varphi_{(j)}<\varphi_i<\varphi_{(j+1)}} \Delta_{(j+1:M-1)} \right] \tag{C1}$$

$$= \sum_{j=1}^{M-1} \mathbb{P}_i \left[\delta_{(j)} < \varphi^{-1}(\varphi_i) < \delta_{(j+1)} \right] \mathbb{E}_i \left[\Delta_{(j+1:M-1)} \mid \delta_{(j)} < \varphi^{-1}(\varphi_i) < \delta_{(j+1)} \right] \tag{C2}$$

$$+ \mathbb{P}_i \left[\varphi^{-1}(\varphi_i) < \delta_{(1)} \right] \mathbb{E}_i \left[\Delta_{(1:M-1)} \mid \varphi^{-1}(\varphi_i) < \delta_{(1)} \right] . \tag{C3}$$

First, we study the term

$$\sum_{j=1}^{M-1} \mathbb{P}_i \left[\delta_{(j)} < \varphi^{-1}(\varphi_i) < \delta_{(j+1)} \right] \mathbb{E}_i \left[\Delta_{(j+1:M-1)} \mid \delta_{(j)} < \varphi^{-1}(\varphi_i) < \delta_{(j+1)} \right] ,$$

in (C1). First, for $j \in \{1, \ldots, M-1\}$,

$$\mathbb{E}_i \left[\Delta_{(j+1:M-1)} \mid \delta_{(j)} < \varphi^{-1}(\varphi_i) < \delta_{(j+1)} \right] = (M-1-j)\, \mathbb{E}_i \left[\delta \mid \delta > \varphi^{-1}(\varphi_i) \right] . \tag{C4}$$

Thus, we obtain

$$\begin{aligned}
&\sum_{j=1}^{M-1}(M-1-j)\,\mathbb{P}_i\left[\delta_{(j)}<\varphi^{-1}(\varphi_i)<\delta_{(j+1)}\right]\mathbb{E}_i\left[\delta\mid\delta>\varphi^{-1}(\varphi_i)\right]\\
=&\mathbb{E}_i\left[\delta\mid\delta>\varphi^{-1}(\varphi_i)\right]\sum_{j=1}^{M-1}(M-1-j)\int_0^{\bar{\delta}}\int_0^{\bar{\delta}}1_{x<\varphi^{-1}(\varphi_i)}1_{\varphi^{-1}(\varphi_i)<y}g_{\delta_{(j)},\delta_{(j+1)}}(x,y)\,dxdy\\
=&\mathbb{E}_i\left[\delta\mid\delta>\varphi^{-1}(\varphi_i)\right]\sum_{j=1}^{M-1}(M-1-j)\int_{\varphi^{-1}(\varphi_i)}^{\bar{\delta}}\int_0^{\varphi^{-1}(\varphi_i)}g_{\delta_{(j)},\delta_{(j+1)}}(x,y)\,dxdy\,,
\end{aligned}$$

where

$$g_{\delta_{(j)},\delta_{(j+1)}}(x,y)=\frac{(M-1)!}{(j-1)!\,(M-j-2)!}G(x)^{j-1}(1-G(y))^{M-2-j}\,g(x)\,g(y)\ ,$$

is the joint distribution of the j-th and $j+1$-th order statistics of the continuous distribution with PDF g. Thus, with some algebra we obtain

$$\begin{aligned}
&\sum_{j=1}^{M-1}(M-1-j)\,\mathbb{P}_i\left[\delta_{(j)}<\varphi^{-1}(\varphi_i)<\delta_{(j+1)}\right]\\
=&\sum_{j=1}^{M-1}\frac{(M-1-j)(M-1)!}{(j-1)!\,(M-j-2)!}\int_{\varphi^{-1}(\varphi_i)}^{\bar{\delta}}\left(\int_0^{\varphi^{-1}(\varphi_i)}G(x)^{j-1}g(x)\,dx\right)(1-G(y))^{M-2-j}\ g(y)\,dy\\
=&\sum_{j=1}^{M-1}\frac{(M-1-j)(M-1)!}{j\,(j-1)!\,(M-j-2)!}G\left(\varphi^{-1}(\varphi_i)\right)^j\int_{\varphi^{-1}(\varphi_i)}^{\bar{\delta}}(1-G(y))^{M-2-j}\ g(y)\,dy\\
=&\sum_{j=1}^{M-1}\frac{(M-1)!}{j!\,(M-j-2)!}G\left(\varphi^{-1}(\varphi_i)\right)^j\left(1-G\left(\varphi^{-1}(\varphi_i)\right)\right)^{M-1-j}\\
=&\sum_{j=1}^{M-1}(M-j-1)\begin{pmatrix}M-1\\ j\end{pmatrix}G\left(\varphi^{-1}(\varphi_i)\right)^j\left(1-G\left(\varphi^{-1}(\varphi_i)\right)\right)^{M-1-j}\ .
\end{aligned}$$

Next, to study the term

$$\mathbb{P}_i\left[\varphi^{-1}(\varphi_i)<\delta_{(1)}\right]\ \mathbb{E}_i\left[\Delta_{(1:M-1)}\mid\varphi^{-1}(\varphi_i)<\delta_{(1)}\right]\ ,$$

in (C1), use the order statistics' distribution and the identity above to obtain

$$
\begin{aligned}
&\mathbb{P}_i\left[\varphi^{-1}(\varphi_i)<\delta_{(1)}\right]\,\mathbb{E}_i\left[\Delta_{(1:M-1)}\mid\varphi^{-1}(\varphi_i)<\delta_{(1)}\right]\\
=&\left(1-G_{\delta_{(1)}}\left(\varphi^{-1}(\varphi_i)\right)\right)\,\mathbb{E}_i\left[\Delta_{(1:M-1)}\mid\varphi^{-1}(\varphi_i)<\delta_{(1)}\right]\\
=&\left(1-\sum_{j=1}^{M-1}\begin{pmatrix}M-1\\ j\end{pmatrix}G\left(\varphi^{-1}(\varphi_i)\right)^j\left(1-G\left(\varphi^{-1}(\varphi_i)\right)\right)^{M-1-j}\right)\,\mathbb{E}_i\left[\Delta_{(1:M-1)}\mid\varphi^{-1}(\varphi_i)<\delta_{(1)}\right]\\
=&\mathbb{E}_i\left[\delta\mid\delta>\varphi^{-1}(\varphi_i)\right]\left((M-1)-\sum_{j=1}^{M-1}(M-1)\begin{pmatrix}M-1\\ j\end{pmatrix}G\left(\varphi^{-1}(\varphi_i)\right)^j\left(1-G\left(\varphi^{-1}(\varphi_i)\right)\right)^{M-1-j}\right)\\
=&\mathbb{E}_i\left[\delta\mid\delta>\varphi^{-1}(\varphi_i)\right](M-1)\left(1-\sum_{j=1}^{M-1}\begin{pmatrix}M-2\\ j-1\end{pmatrix}G\left(\varphi^{-1}(\varphi_i)\right)^j\left(1-G\left(\varphi^{-1}(\varphi_i)\right)\right)^{M-1-j}\right)\,.
\end{aligned}
$$

Summing the two terms, we find

$$
\begin{aligned}
&\sum_{j=0}^{M-1}\mathbb{E}_i\left[\mathbb{1}_{\varphi_{(j)}<\varphi_i<\varphi_{(j+1)}}\Delta_{(j+1:M-1)}\right]\\
=&\mathbb{E}_i\left[\delta\mid\delta>\varphi^{-1}(\varphi_i)\right]\sum_{j=1}^{M-1}(M-j-1)\begin{pmatrix}M-1\\ j\end{pmatrix}G\left(\varphi^{-1}(\varphi_i)\right)^j\left(1-G\left(\varphi^{-1}(\varphi_i)\right)\right)^{M-1-j}\\
&+\mathbb{E}_i\left[\delta\mid\delta>\varphi^{-1}(\varphi_i)\right]\left((M-1)-\sum_{j=1}^{M-1}(M-1)\begin{pmatrix}M-1\\ j\end{pmatrix}G\left(\varphi^{-1}(\varphi_i)\right)^j\left(1-G\left(\varphi^{-1}(\varphi_i)\right)\right)^{M-1-j}\right)\\
=&\mathbb{E}_i\left[\delta\mid\delta>\varphi^{-1}(\varphi_i)\right](M-1)\\
&\quad\left(1-G\left(\varphi^{-1}(\varphi_i)\right)\sum_{j=1}^{M-1}\begin{pmatrix}M-2\\ j-1\end{pmatrix}G\left(\varphi^{-1}(\varphi_i)\right)^{j-1}\left(1-G\left(\varphi^{-1}(\varphi_i)\right)\right)^{M-1-j}\right)\,.
\end{aligned}
$$

Finally, by the binomial theorem, we find

$$
\sum_{j=0}^{M-2}\begin{pmatrix}M-2\\ j\end{pmatrix}G\left(\varphi^{-1}(\varphi_i)\right)^j\left(1-G\left(\varphi^{-1}(\varphi_i)\right)\right)^{M-2-j}=1\,,
$$

and we obtain the desired result. $\square$

Appendix B. Proof of Proposition 1:

First, consider the function

$$\mathbb{E}\left[\delta \mid \delta > x\right] = \tau\left(x\right) \ ,$$

for the random variable δ with continuous distribution g. Write

$$\tau\left(x\right) = \frac{\int_x^{\overline{\delta}} u\, g\left(u\right)\, du}{1 - G\left(x\right)} \ ,$$

to obtain

$$\begin{aligned}
\tau'\left(x\right) =& \frac{-x\, g\left(x\right)}{1 - G\left(x\right)} + g\left(x\right) \frac{\int_x^{\overline{\delta}} u\, g\left(u\right)\, dx}{\left(1 - G\left(x\right)\right)^2} \\
=& \frac{g\left(x\right)}{1 - G\left(x\right)} \left(\tau\left(x\right) - x\right) \ .
\end{aligned}$$

Thus, the FOC derived from the optimization problem in (9) is

$$\begin{aligned}
\varphi^{'}\left(\varphi^{-1}\left(\varphi_i\right)\right) =& \left(2\,\delta_i \big/ \kappa\right)\ \left(M-1\right) g\left(\varphi^{-1}\left(\varphi_i\right)\right) \tau\left(\varphi^{-1}\left(\varphi_i\right)\right) \\
& - \left(2\,\delta_i \big/ \kappa\right)\ \left(M-1\right) \left(1 - G\left(\varphi^{-1}\left(\varphi_i\right)\right)\right) \tau'\left(\varphi^{-1}\left(\varphi_i\right)\right) \\
=& \frac{2\,\varphi^{-1}\left(\varphi_i\right)}{\kappa}\ \left(M-1\right) g\left(\varphi^{-1}\left(\varphi_i\right)\right) \mathbb{E}\left[\delta \mid \delta > \varphi^{-1}\left(\varphi_i\right)\right] \\
& - \frac{2\,\varphi^{-1}\left(\varphi_i\right)}{\kappa}\ \left(M-1\right) g\left(\varphi^{-1}\left(\varphi_i\right)\right) \left(\mathbb{E}\left[\delta \mid \delta > \varphi^{-1}\left(\varphi_i\right)\right] - \varphi^{-1}\left(\varphi_i\right)\right) \\
=& \frac{2}{\kappa}\left(M-1\right)\ \varphi^{-1}\left(\varphi_i\right)^2\ g\left(\varphi^{-1}\left(\varphi_i\right)\right) \ .
\end{aligned}$$

In equilibrium, trader i finds it optimal to adopt the same strategy φ, so $\varphi^{-1}\left(\varphi_i\right) = \delta_i$, so the FOC becomes

$$\varphi^{'}\left(\delta_i\right) = \frac{2}{\kappa}\left(M-1\right)\ \delta_i^2\, g\left(\delta_i\right)),$$

with boundary condition $\varphi(\underline{\delta}) = 0$, proving the result. $\square$

Appendix C. Proof of Lemma 2

For $M \geq 1$ and $v \in [0, \overline{v}]$, define the function

$$h_M(v) = v - \pi - \int_v^{\overline{v}} \left(e^{(1-F(u))(M-1)} - 1\right) du, \qquad v \in [0, \overline{v}]. \tag{C5}$$

First, we show that the function h_M is increasing in v. Note that the integrand $e^{(1-F(u))(M-1)} - 1$ is continuous and nonnegative. Thus, h_M is continuous and differentiable on $(\underline{v}, \overline{v})$ with derivative

$$h_M'(v) = e^{(1-F(v))(M-1)} > 1.$$

Thus h_M is strictly increasing.

Next we show the existence and uniqueness of the root. Because h_M is strictly increasing, it can have at most one root. Use the endpoint conditions

$$h_M(0) < 0 \qquad \text{and} \qquad h_M(\overline{v}) = \overline{v} - \pi > 0\,.$$

By continuity of h_M, we obtain existence of a unique $\underline{v}_M \in (0, \overline{v})$ satisfying $h_M(\underline{v}_M) = 0$. Since $h_M(\overline{v}) > 0$, the root cannot equal $\overline{v}$ and thus $\underline{v}_M < \overline{v}$.

Next, we show that the root, i.e., the valuation cutoff, is increasing in the number of informed traders M that paid the cost of acquiring information in stage zero. For fixed v, differentiate $h_M(v)$ with respect to M to obtain:

$$\partial_M h_M(v) = -\int_v^{\overline{v}} (1 - F(u))\, e^{(1-F(u))(M-1)}\, du < 0.$$

Thus for every v, the function $M \mapsto h_M(v)$ is strictly decreasing. Use the identity $h_M(\underline{v}_M) = 0$ and the implicit function theorem to write

$$\partial_M \underline{v}_M = -\frac{\partial_M h_M(\underline{v}_M)}{\partial_v h_M(\underline{v}_M)} > 0,$$

because $\partial_M h_M(\underline{v}_M) < 0$ and $\partial_v h'_M(\underline{v}_M) > 0$. Therefore, the cutoff $\underline{v}_M$ is strictly increasing in M.

Finally, we show that $\lim_{M\to\infty} \underline{v}_M = \overline{v}$. First, we use (C5) to obtain that for all $v < \overline{v}$, $\lim_{M\to\infty} h_M(v) = -\infty$. Thus, for each $\epsilon > 0$, there exists a large enough $M(\epsilon)$ such that for all $M > M(\epsilon)$, $h_M(\overline{v} - \epsilon) < 0$. Use that (i) $h_M(\cdot)$ is increasing, (ii) $h_M(\overline{v} - \epsilon) < 0$, and (iii) the definition of the cutoff $h(\underline{v}_M) = 0$, to obtain that for all $\epsilon > 0$ and $M > M(\epsilon)$, $\overline{v} - \epsilon \leq \underline{v}_M$. Next, we showed earlier that for all M, $\underline{v}_M \leq \overline{v}$. Thus, for all $M > M(\epsilon)$,

$$\overline{v} - \epsilon \leq \underline{v}_M \leq \overline{v},$$

and we conclude that $\lim_{M\to\infty} \underline{v}_M = \overline{v}$.

□

Appendix D. Proof of Proposition 2:

Use the optimal priority fee (11) in the objective (5) to write the expected wealth of trader i as

$$\mathbb{E}_i\left[W_i\right] = -\frac{2}{\kappa}\left(M-1\right)\left(\int_{\underline{\delta}}^{\delta_i} x^2\, dG\left(x\right) + \delta_i \int_{\delta_i}^{\overline{\delta}} x\, dG\left(x\right)\right) + \delta_i\, \left(v_i - \pi - \frac{\delta_i}{\kappa}\right) - C\,.$$

The optimal trading volume is the solution of $\partial_{\delta_i}\mathbb{E}\left[W_i\right] = 0$ or

$$0 = \left(v_i - \pi\right)\kappa - 2\,\delta_i - 2\,\left(M-1\right)\int_{\delta_i}^{\overline{\delta}} x\, dG\left(x\right)\,. \tag{C6}$$

Recall that, in equilibrium, G is the distribution of trading volumes pinned down by the equilibrium increasing trading volume function δ, so

$$G\left(\delta_i\right) = F\left(v_i\right)\,.$$

Rearranging (C6) one obtains the boundary condition

$$\overline{\delta} = \kappa \frac{\overline{v} - \pi}{2}$$

and differentiating we find that the trading volumes solve the ODE

$$\delta'(v_i) = \frac{\kappa}{2} + (M-1)\,\delta(v_i)\ f(v_i)\ ,$$

whose solution is in the statement of the result. The solution is increasing in v, and trader i's optimization problem is over nonnegative volumes. Thus the boundary condition is at the lowest valuation $\underline{v}_M$ for which the trader optimally chooses a nonnegative volume. This cutoff is characterized in Lemma 2 and corresponds to when the FOC (C6) is satisfied at $\underline{v}_M$ with $\delta(\underline{v}_M) = 0$. Note that to obtain the form in Lemma 2, we replace δ by the optimal trading volume in (17). □

Appendix E. Proof of Proposition 3

Trader i uses the priority fee (11) for an arbitrary distribution of volumes with cumulative distribution function G:

$$\varphi(\delta_i) = \frac{2}{\kappa}(M-1)\int_0^{\delta_i} u^2\, dG(u)\ . \tag{C7}$$

The optimal volumes of PGA competitors are distributed according to the distribution G described in (19):

$$G(\{0\}) = F(\underline{v}_M) \qquad \text{and} \qquad G\big(\delta(v)\big) = F(v) \quad \text{for } v \in [\underline{v}_M, \overline{v}]\,, \tag{C8}$$

The priority fee is trivially zero for $\delta_i = 0$, i.e., when $v_i \leq \underline{v}_M$. Next, fix $v_i \in [\underline{v}_M, \overline{v}]$. Note that the atom at zero causes no problem because the integrand u^2 evaluated at zero is zero.

Thus, the mass $G(\{0\})$ contributes zero to the Stieltjes integral, and we write

$$\int_0^{\delta_i} u^2\, dG(u) = 0\, G(\{0\}) + \int_{(0,\delta_i]} u^2\, dG(u) = \int_{\underline{v}_M}^{\overline{v}} \delta(x)^2\, dF(x)\,. \tag{C9}$$

where we used that $\delta : [\underline{v}_M, \overline{v}] \mapsto [0, \delta(\overline{v})]$, defined in (17), is increasing and continuous, hence it is invertible on its image and $G(\delta(v)) = F(v)$ for $v \geq \underline{v}_M$. Use the definition of $\tilde{\delta}$ in (18) to obtain the result.

Next, we show that for all $v_i < \overline{v}$, the priority fee tends to zero when the number of competitors M tends to infinity. Consider the strategic volumes (18):

$$\tilde{\delta}(x) = \frac{1}{2}\Big((\overline{v} - \pi)e^{-(M-1)(1-F(x))} - \int_x^{\overline{v}} e^{-(M-1)(F(u)-F(x))}\, du\Big) \quad \text{if } x \geq \underline{v}_M,$$

and zero otherwise. The second term in $\tilde{\delta}(x)$ is nonnegative so

$$0 \leq \tilde{\delta}(x) \leq \frac{\overline{v} - \pi}{2}\, e^{-(M-1)(1-F(x))} \implies \tilde{\delta}(x)^2 \leq \frac{(\overline{v} - \pi)^2}{4} e^{-2(M-1)(1-F(x))}.$$

Fix $v_i < \overline{v}$. Since F is nondecreasing, for all $x \leq v_i$ we have $F(x) \leq F(v_i)$ and therefore

$$1 - F(x) \geq 1 - F(v_i) > 0.$$

Thus,

$$\tilde{\delta}(x)^2 \leq \frac{(\overline{v} - \pi)^2}{4} e^{-2(M-1)(1-F(v_i))} \quad \text{for all } x \in [\underline{v}_M, v_i].$$

It follows from the definition of the equilibrium priority fee in (20), accounting for strategic volumes, that

$$\varphi(v_i) = 2\kappa(M-1)\int_{\underline{v}_M}^{v_i} \tilde{\delta}(x)^2\, dF(x) \leq 2\kappa(M-1)(F(v_i) - F(\underline{v}_M))\frac{(\overline{v} - \pi)^2}{4} e^{-2(M-1)(1-F(v_i))}. \tag{C10}$$

Since $F(v_i) - F(\underline{v}_M) \leq 1$, we obtain

$$0 \leq \varphi(v_i) \leq \frac{\kappa(\overline{v} - \pi)^2}{2}(M-1)e^{-2(M-1)(1-F(v_i))}.$$

Because $1 - F(v_i) > 0$ for all $v_i < \overline{v}$, we conclude that, for all $v_i < \overline{v}$,

$$\lim_{M\to\infty} \varphi(v_i) = 0.$$

$\square$

Appendix F. Proof of Proposition 4

Recall that for $v_i \geq \underline{v}_M$,

$$\tilde{\delta}(v_i) = \frac{1}{2}\left((\overline{v} - \pi)e^{-(M-1)(1-F(v_i))} - \int_{v_i}^{\overline{v}} e^{-(M-1)(F(u)-F(v_i))}\,du\right).$$

Factoring out $e^{-(M-1)(1-F(v_i))}$ yields

$$\tilde{\delta}(v_i) = \frac{1}{2}e^{-(M-1)(1-F(v_i))}\left(\overline{v} - \pi - \int_{v_i}^{\overline{v}} e^{(M-1)(1-F(u))}\,du\right).$$

Hence, the expected total trading volume of informed traders is

$$M\int_{\underline{v}_M}^{\overline{v}} \tilde{\delta}(x)\,dF(x) = \frac{M(\overline{v}-\pi)}{2}\int_{\underline{v}_M}^{\overline{v}} e^{-(M-1)(1-F(x))}\,dF(x) \tag{C11}$$

$$- \frac{M}{2}\int_{\underline{v}_M}^{\overline{v}} e^{-(M-1)(1-F(x))}\left[\int_{x}^{\overline{v}} e^{(M-1)(1-F(u))}\,du\right]dF(x). \tag{C12}$$

We first evaluate (C11). Using the change of variable $z = 1 - F(x)$,

$$\frac{M(\overline{v}-\pi)}{2}\int_{\underline{v}_M}^{\overline{v}} e^{-(M-1)(1-F(x))}\,dF(x) = \frac{M(\overline{v}-\pi)}{2}\int_0^{1-F(\underline{v}_M)} e^{-(M-1)z}\,dz$$
$$= \frac{M(\overline{v}-\pi)}{2(M-1)}\left(1 - e^{-(M-1)(1-F(\underline{v}_M))}\right). \tag{C13}$$

We now show that

$$\lim_{M\to\infty}(M-1)\big(1-F(\underline{v}_M)\big) = \infty.$$

Suppose instead that this sequence is bounded. Then there exists $C > 0$ such that

$$(M-1)\big(1-F(\underline{v}_M)\big) < C \qquad \text{for all } M.$$

Using the definition of $\underline{v}_M$ in (16),

$$\underline{v}_M - \pi = \int_{\underline{v}_M}^{\overline{v}} \left(e^{(M-1)(1-F(u))} - 1\right) du,$$

and the bound $1 - F(u) \leq 1 - F(\underline{v}_M)$, we obtain

$$0 \leq \underline{v}_M - \pi \leq \left(e^{(M-1)(1-F(\underline{v}_M))} - 1\right)(\overline{v} - \underline{v}_M) \leq \left(e^C - 1\right)(\overline{v} - \underline{v}_M).$$

By Lemma 2, $\underline{v}_M \to \overline{v}$ as $M \to \infty$. The inequality above would then imply $\underline{v}_M \to \pi$, which contradicts Lemma 2. Hence,

$$(M-1)\big(1-F(\underline{v}_M)\big) \to \infty.$$

Combining this result with (C13) gives

$$\lim_{M\to\infty}\frac{M(\overline{v}-\pi)}{2}\int_{\underline{v}_M}^{\overline{v}} e^{-(M-1)(1-F(x))}\,dF(x) = \frac{\overline{v}-\pi}{2}.$$

We now turn to (C12). Define

$$I_2 = \frac{M}{2} \int_{\underline{v}_M}^{\overline{v}} e^{-(M-1)(1-F(x))} \left[\int_x^{\overline{v}} e^{(M-1)(1-F(u))} \, du \right] dF(x).$$

Reversing the order of integration,

$$I_2 = \frac{M}{2} \int_{\underline{v}_M}^{\overline{v}} e^{(M-1)(1-F(u))} \left[\int_{\underline{v}_M}^{u} e^{-(M-1)(1-F(x))} \, dF(x) \right] du.$$

With the change of variable $z = 1 - F(x)$,

$$\begin{aligned}
\int_{\underline{v}_M}^{u} e^{-(M-1)(1-F(x))} \, dF(x) &= \int_{1-F(u)}^{1-F(\underline{v}_M)} e^{-(M-1)z} \, dz \\
&= \frac{1}{M-1} \left(e^{-(M-1)(1-F(u))} - e^{-(M-1)(1-F(\underline{v}_M))} \right).
\end{aligned}$$

Substituting back,

$$I_2 = \frac{M}{2(M-1)} \int_{\underline{v}_M}^{\overline{v}} \left(1 - e^{-(M-1)(1-F(\underline{v}_M))} e^{(M-1)(1-F(u))} \right) du.$$

Hence,

$$I_2 = \frac{M}{2(M-1)} \left[(\overline{v} - \underline{v}_M) - e^{-(M-1)(1-F(\underline{v}_M))} \int_{\underline{v}_M}^{\overline{v}} e^{(M-1)(1-F(u))} \, du \right].$$

Using the definition of $\underline{v}_M$ and the fact that $\underline{v}_M \to \overline{v}$, we obtain

$$\int_{\underline{v}_M}^{\overline{v}} e^{(M-1)(1-F(u))} \, du \longrightarrow \overline{v} - \pi, \qquad \text{as } M \to \infty.$$

Since $(M-1)(1-F(\underline{v}_M)) \to \infty$, the exponential term vanishes, and therefore $I_2 \to 0$ as $M \to \infty$.

Combining the limits of (C11) and (C12), we conclude that

$$\lim_{M\to\infty} M \int_{\underline{v}_M}^{\overline{v}} \tilde{\delta}(u)\, dF(u) = \frac{\overline{v} - \pi}{2}.$$

$\square$

Appendix G. Proof of Proposition 5

The expression for the optimal liquidity supply in (27) follows directly from the first-order condition associated with the liquidity provider's optimization problem (26). The condition (29) for the viability of the blockchain as a trading venue is obtained by imposing non-negativity of the supplier's equilibrium payoff when liquidity is chosen optimally according to (27).

Finally, the asymptotic behavior as $M \to \infty$ follows from the fact that, from the perspective of the liquidity supplier, the variance of total trading volume generated by active traders admits the limit

$$\lim_{M\to\infty} \kappa^2\, M \int_{\underline{v}_M}^{\overline{v}} \tilde{\delta}(x)^2\, dF(x) = \kappa^2\, \frac{(\overline{v} - \pi)^2}{8}.$$

This limit is obtained using arguments analogous to those employed in the proof of Proposition 4.

Appendix H. Proof of Proposition 6

Use the expected wealth of trader i, conditional on observing a signal v_i, in (4),

$$\mathbb{E}_i\big[W_i\big] = -\varphi_i + \delta_i\Big(v_i - \pi - \frac{\delta_i}{\kappa}\Big) - C - \frac{2\,\delta_i}{\kappa} \sum_{j=0}^{M-1} \mathbb{E}_i\Big[\mathbb{1}_{\{\varphi_{(j)}<\varphi_i<\varphi_{(j+1)}\}}\, \Delta_{(j+1:M-1)}\Big]\,,$$

together with the equilibrium priority fees (Proposition 3), trading volumes (Proposition 2), and liquidity (Proposition 5), to obtain for each $i \in \{1, \dots, M\}$:

$$\mathbb{E}\big[W_i \mid v_i\big] = -\frac{2}{\kappa^\star}(M-1)\left(\int_0^{\delta^\star(v_i)} x^2\,dG(x) + \delta^\star(v_i)\int_{\delta^\star(v_i)}^{\overline{\delta}} x\,dG(x)\right) + \delta^\star(v_i)\left(v_i - \pi - \frac{\delta^\star(v_i)}{\kappa^\star}\right) - C.$$

Using that $\delta^\star(v_i) = 0$ for $v_i < \underline{v}_M$ and $\delta^\star(v_i) = \kappa^\star\tilde{\delta}(v_i)$ for $v_i \geq \underline{v}_M$, this can be written as

$$\mathbb{E}\big[W_i \mid v_i\big] = \kappa^\star\Bigg[\tilde{\delta}(v_i)\big(v_i - \pi - \tilde{\delta}(v_i)\big) - 2\,(M-1)\left(\int_0^{v_i}\tilde{\delta}(u)^2\,dF(u) + \tilde{\delta}(v_i)\int_{v_i}^{\overline{v}}\tilde{\delta}(u)\,dF(u)\right)\Bigg] - C.$$

At stage zero, signals have not yet been realized and traders are ex ante symmetric. If $v_i < \underline{v}_M$, then $\delta^\star(v_i) = 0$ and $\varphi_i = 0$, so the payoff is $-C$. For $v_i \geq \underline{v}_M$, the expected wealth is

$$\mathbb{E}[W_i \mid v_i \geq \underline{v}_M] = -\,C\,(1 - F(\underline{v}_M)) + \kappa^\star\int_{\underline{v}_M}^{\overline{v}}\tilde{\delta}(v)\big(v - \pi - \tilde{\delta}(v)\big)\,dF(v) - 2\,\kappa^\star(M-1)\int_{\underline{v}_M}^{\overline{v}}\left[\int_{\underline{v}_M}^{v}\tilde{\delta}(u)^2\,dF(u) + \tilde{\delta}(v)\int_{v}^{\overline{v}}\tilde{\delta}(u)\,dF(u)\right]dF(v).$$

We now show that $\mathbb{E}[W_i]$ converges to a finite negative limit as $M \to \infty$. First, by Proposition 5, $\kappa^\star$ converges to a finite constant as $M \to \infty$.

Consider

$$(M-1)\int_{\underline{v}_M}^{\overline{v}}\int_{\underline{v}_M}^{v}\tilde{\delta}(u)^2\,dF(u)\,dF(v).$$

Interchanging the order of integration yields

$$\begin{aligned}\int_{\underline{v}_M}^{\overline{v}}\int_{\underline{v}_M}^{v}\tilde{\delta}(u)^2\,dF(u)\,dF(v) &= \int_{\underline{v}_M}^{\overline{v}}\int_{u}^{\overline{v}}\tilde{\delta}(u)^2\,dF(v)\,dF(u)\\ &= \int_{\underline{v}_M}^{\overline{v}}\tilde{\delta}(u)^2\big(1-F(u)\big)\,dF(u).\end{aligned}$$

Since $1-F(u)\leq 1$, the limit derived in the proof of Proposition 5 implies

$$0\leq \limsup_{M\to\infty}(M-1)\int_{\underline{v}_M}^{\overline{v}}\int_{\underline{v}_M}^{v}\tilde{\delta}(u)^2\,dF(u)\,dF(v)\leq \frac{(\overline{v}-\pi)^2}{8}.$$

Next, consider

$$(M-1)\int_{\underline{v}_M}^{\overline{v}}\int_{v}^{\overline{v}}\tilde{\delta}(v)\tilde{\delta}(u)\,dF(u)\,dF(v).$$

Using the bound $\tilde{\delta}(u)\leq\tilde{\delta}(\overline{v})=\frac{\overline{v}-\pi}{2}$,

$$\begin{aligned}\int_{\underline{v}_M}^{\overline{v}}\int_{v}^{\overline{v}}\tilde{\delta}(v)\tilde{\delta}(u)\,dF(u)\,dF(v) &\leq \frac{\overline{v}-\pi}{2}\int_{\underline{v}_M}^{\overline{v}}\tilde{\delta}(v)\,(1-F(v))\,dF(v)\\ &\leq \frac{\overline{v}-\pi}{2}\int_{\underline{v}_M}^{\overline{v}}\tilde{\delta}(v)\,dF(v).\end{aligned}$$

By the limit derived in Proposition 4,

$$0\leq \limsup_{M\to\infty}(M-1)\int_{\underline{v}_M}^{\overline{v}}\int_{v}^{\overline{v}}\tilde{\delta}(v)\tilde{\delta}(u)\,dF(u)\,dF(v)\leq \frac{(\overline{v}-\pi)^2}{4}.$$

Collecting terms, the stage-zero expected wealth of each trader is

$$\begin{aligned}C=&\kappa^\star\int_{\underline{v}_M}^{\overline{v}}\tilde{\delta}(v)\big(v-\pi-\tilde{\delta}(v)\big)\,dF(v)\\ &-2\,\kappa^\star(M-1)\int_{\underline{v}_M}^{\overline{v}}(1-F(u))\tilde{\delta}(u)^2\,dF(u)\\ &-2\,\kappa^\star(M-1)\int_{\underline{v}_M}^{\overline{v}}\int_{v}^{\overline{v}}\tilde{\delta}(v)\tilde{\delta}(u)\,dF(u)\,dF(v).\end{aligned}$$

The two $(M-1)$ terms remain bounded as $M \to \infty$, while the first integral term converges to zero. Hence,

$$\limsup_{M\to\infty} \mathbb{E}[W_i] < 0.$$

Therefore, if $\mathbb{E}[W_i] > 0$ for $M = 2$, there exists a finite equilibrium number of informed traders, defined as the largest integer M such that $\mathbb{E}[W_i] \geq 0$. $\square$

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