Do Longer Block Times Impair Market Efficiency in Decentralized Markets?

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ABSTRACT

In blockchains, traders bid *priority fees* to compete for queue position at regular intervals known as *block time*. Priority fees reduce trading volumes of informed traders and mitigate adverse selection costs. Longer block times can improve price efficiency by increasing speculative profits and by encouraging traders to acquire information. However, beyond a certain block time, expected losses from adverse selection outweigh the benefits of priority fees, leading to a liquidity freeze—unless uninformed liquidity demand grows sufficiently with block time. In equilibrium, traders only reveal their information immediately before the block is created.

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Blockchain technology is profoundly reshaping the financial landscape; see Harvey (2016); Cong and He (2019). One of the most prominent financial services implemented on blockchain are decentralized exchanges (DEXs), whose trading volume has been increasing to $40 billion as of August 2023. The most popular type of DEXs are automated Market Makers (AMMs), that employ algorithms to support price and trading of digital assets. Existing research on the microstructure of AMMs has analyzed liquidity dynamics, and arbitrage problems (Lehar and Parlour (2021); Capponi and Jia (2021); Barbon and Ranaldo (2021); John, Kogan, and Saleh (2023); Klein, Kozhan, Viswanath-Natraj, and Wang (2023)), as well as compared the microstructure of DEXs to that of traditional exchanges; see Barbon and Ranaldo (2021); Aoyagi and Ito (2021).

In blockchain, transactions are sequenced into blocks.[1] Blocks are built at regular intervals called *slots*, and the duration of a slot is referred to as *block time.* Transactions are not immediately included in blocks, they enter a public *memory pool.* At the end of each slot, a validator selects and sequences transactions from the memory pool based on *priority fees* paid by traders competing for queue position, and sequentially clears the market.[2] Pending transactions in the memory pool are public, therefore competing traders participate in *priority gas auctions* (PGAs) to optimise the position of their transactions in the queue to improve execution prices.

This paper presents a model to describe the economic effects of priority fees and block time on price efficiency, market frictions, and liquidity in DEXs. Here, price efficiency refers to the extent to which DEX prices incorporate available information, and to the variance of the true price conditional on all relevant public information, in line with classical microstructure models (see e.g., Foster and Viswanathan (1996); Huddart, Hughes, and Levine (2001);

[1] A blockchain transaction is a set of user-initiated instructions that modify the blockchain's state. These include digital asset transfers between users, liquidity provision or taking in an AMM, smart contract deployment, and other state-changing operations. In this work, a pending transaction refers to a user-initiated blockchain operation that has not been executed, and a transaction refers to a blockchain instruction which has been executed and added to a block.

[2] In this paper, we do not use blockchain-specific terminology and refer to any blockchain operator involved in the block creation process as a validator.

Calcagno and Lovo (2006)). Market efficiency, in turn, encompasses both price efficiency and the cost of liquidity in the DEX, both determined endogenously in our model.

We model the strategic interactions between takers and suppliers of liquidity for a risky security as a three-stage game. In stage zero, multiple traders decide whether to acquire information. In stage one, a liquidity supplier sets the AMM's reserves. In stage two, informed traders compete either to buy or to sell the security, so losing queue priority to other informed traders in the block leads to adverse price impact. Consequently, traders bid priority fees to compete for queue position.

The informed traders simultaneously determine their priority fees and trading volumes. To determine the priority fees, informed traders balance profits from better execution prices against costs of paying the priority fee to the validator. To determine trading volumes, informed traders balance increased expected profits from trading larger positions against costs and priority fees that increase with order size. In stage one, the liquidity supplier sets the AMM's reserves by balancing revenue from elastic and uninformed liquidity demand against expected losses to informed traders. Our model implies that the expected profits from informed trading decrease in the number of traders competing in the PGA, so the equilibrium number of informed traders is set where speculative profits, net of priority fees, offset the cost of information.

We show that priority fees increase with both the trading volume of informed traders and the number of competitors in the PGA. These factors raise the expected adverse price impact of losing queue priority, which intensifies bidding. In contrast, priority fees decrease with liquidity depth, because deeper liquidity reduces adverse price impact from competitors. However, informed traders set their trading volumes strategically, trading off execution costs, including priority fees, against speculative gains. Trading volumes increase with the monetary value of private information but decrease to zero as competition in the PGA intensifies. In equilibrium, priority fees, accounting for strategically adjusted trading volumes, decrease with the number of informed traders in the memory pool, and increase in the liquidity supply. Our results characterize the distribution of trading volumes within a block, and show that they are associated with higher signals, higher priority fees, and better queue positions. This result is consistent with observed patterns in Uniswap v3, the largest DEX on Ethereum, where the average trading volume of transactions executed early in a block tends to be larger than that of the transactions behind in the queue.

In stage one, the liquidity provider sets the depth of the pool based on the number of competing traders and the distribution of their private information. We show that there exists a threshold for block time beyond which a liquidity freeze occurs. This threshold increases in the aggregate level and elasticity of liquidity demand. This is because longer block times increase the uncertainty faced by liquidity providers and increase expected adverse selection costs. This prediction mirrors that in Glosten and Milgrom (1985), where there are no bid and ask prices if the signals of informed traders are too precise relative to the elasticity of liquidity demand, preventing liquidity suppliers from breaking even (see also Bhattacharya and Spiegel (1991)).

In blockchains, priority fees reduce the speculative profits of informed traders and transfer part of them to validators. We show that for a large enough number of informed traders, liquidity provision always occurs regardless of block time or the strength of private signals. In this case, block time is beneficial to DEXs. These benefits only arise when many informed traders compete, however, this number is constrained in equilibrium. More precisely, in our model, the equilibrium number of informed traders is endogenous and it is set where speculative profits net of execution costs and priority fees equal the cost of acquiring information. These costs may include access to proprietary blockchain or exchange data, deployment of searcher contracts, and blockchain monitoring.

The equilibrium number of informed traders in stage zero determines how much private information enters the DEX and is thus directly linked to price efficiency. Specifically, as more traders compete in the PGA, prices become more informative, because priority fees and trading volumes are fully revealing and they are publicly observable on the blockchain, so they constitute a vehicle for price discovery. Longer block times enhance price efficiency because they improve the profitability of informed trading and encourage information acquisition, driving DEX prices closer to their fundamental value.

However, this effect is not unbounded: beyond a certain block time, expected losses from adverse selection outweigh the benefits, leading to a liquidity freeze. This is because adverse selection costs increase with block time faster than priority fees from increased competition can offset them. As a result, equilibrium outcomes—namely, the number of informed traders, liquidity depth, trading volumes, and priority fees—depend on the magnitude and elasticity of uninformed demand and the cost of information. Finally, under the assumption that longer block times also allow uninformed demand to accumulate, the likelihood of liquidity freeze decreases and price efficiency improves. However, unless uninformed demand grows sufficiently quickly with block time, the risk of liquidity freeze remains.

A key implication of our model is that the potential benefits of longer block time and priority fees come at the cost of slower information dissemination. This occurs because informed traders engage in a strategic timing game, making information dissemination in blockchains periodic because it occurs at the frequency of block creation. Specifically, priority fees can only be revised upward in memory pools, and agents have one last opportunity to revise their priority fees before the creation of the block. We model this final phase as a first-price sealed-bid auction among informed traders. The pending transaction with highest priority fee submitted before the end of the slot acts as a reservation price for the final auction so it reduces the expected wealth of all traders. In equilibrium, private information is revealed only at the end of each slot in blockchains. Our model prediction is observed in practice: transactions with large priority fees, typically associated with informed trading, see Capponi, Jia, and Yu (2023b), are predominantly submitted to the memory pool shortly before the end of each blockchain slot. This is in contrast to the continuous rate of information dissemination in traditional electronic exchanges (see Kyle (1985b); Huddart et al. (2001)). Our result is consistent with the size and timing of priority fees observed in

Ethereum blockchain data.

Our results have implications for blockchain protocol design. There is a fundamental tradeoff between price efficiency and liquidity supply when choosing block time. Longer block times increase price efficiency by incentivizing informed trading but reduce liquidity and raise the risk of liquidity freeze.

Our results on price efficiency in blockchains are related to the literature on preopening and closing auctions in traditional markets. There are fundamental differences between the purpose and mechanics of these sessions and those of blockchain slots. Preopening sessions are uniform price auctions (Budish, Cramton, and Shim (2015)), where clearing prices maximize trading volume, and agents observe partial information (Van Bommel and Hoffmann (2011)). In contrast, priority gas auctions feature discriminatory pricing subject to queue ordering, and they are publicly visible. Despite these differences, similarities exist. Like memory pools, opening sessions do not clear markets until a specific time, and agents can communicate with one another.

Our findings support the *pure-noise hypothesis* of Biais, Hillion, and Spatt (1999), which posits that trading activity before the end of preopening sessions does not contain new information. Additionally, our results are empirically supported by Medrano and Vives (2001), who find that information dissemination accelerates toward the end of preopening sessions (see also Cao, Ghysels, and Hatheway (2000); Davies (2003)). Our model for PGAs is also related to online auctions with hard closing times, such as those run by eBay. Our results align with empirical findings (Roth and Ockenfels (2002); Yang and Kahng (2006)) which show that the proportion of late bidding is significant in these auctions.

Literature Review. The model of this paper is related to the microstructure literature that studies the properties of price and liquidity in traditional electronic exchanges. In particular, our approach shares features of the models in Biais (1993); De Frutos and Manzano (2002) who study traditional markets using multi-stage, inventory-based model in which dealers compete for public order flow. We extend and adapt these models to account for the unique mechanics of DEXs. Unlike traditional markets, where orders execute continuously if liquidity is available and traders compete on speed (O'Hara (1998)), blockchains clear periodically at fixed intervals and traders compete for queue position with priority fees. In contrast, blockchain-based liquidity supply accumulates in a common pool, determining the price of liquidity and revenue which is equally shared among all suppliers. As a result, equilibrium outcomes are primarily driven by competition among traders. Our model is also related to the theory on information processing costs such as that in Grossman and Stiglitz (1980), Verrecchia (1982), and Kyle (1989).

Some studies examine periodic uniform price auctions for market clearing (Madhavan (1992); Budish et al. (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 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, as traders submit fully revealing priority fees. However, blockchains operate with periodic clearing, so the revealing equilibrium is delayed until the end of block time.

Numerous works explore the microstructure of AMMs. Angeris, Evans, and Chitra (2021); Capponi, Iyengar, Sethuraman, et al. (2023a); Milionis, Moallemi, Roughgarden, and Zhang (2022); Cartea, Drissi, and Monga (2023, 2024a) show that AMMs cause losses to liquidity suppliers. Lehar and Parlour (2021) describe competition between AMMs and order books. Hasbrouck, Rivera, and Saleh (2022) show that higher fees in AMMs increase liquidity supply and decrease trading costs. 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. In contrast to this literature, we study DEXs as the interplay of AMMs and the blockchain on which they operate.

The economic incentives for liquidity supply in AMMs are similar to those in market making within limit order books and dealer markets, and many insights from classical models apply (e.g., Ho and Stoll (1983), Glosten and Milgrom (1985)). Moreover, 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.

Crypto-assets and blockchain economics are a growing topic in the literature (Biais, Capponi, Cong, Gaur, and Giesecke (2023b)). John, Rivera, and Saleh (2020) study the equilibrium security of blockchains. Cong, Li, and Wang (2021) analyse 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) 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 tokenisation (Heines, Dick, Pohle, and Jung (2021)).

The remainder of this paper proceeds as follows. In Section I, we describe the features of DEXs that underpin our model. In Section II, we present notation, assumptions, and structure of the model. In Section III, we study the priority fee bidding strategies and trading volumes of informed traders. In Section IV, we analyse the liquidity supply. In Section V, we study price efficiency when information is costly. Finally, in the appendix, we outline the key features of AMMs and blockchains relevant to describe DEX microstructure and which motivate our model assumptions (Appendix A), we describe the mechanics of PGAs in the Ethereum blockchain (Appendix B), and we collect the proofs (Appendix C).

I. Institutional details

The microstructure of DEXs differs fundamentally from that of traditional financial markets. In this section, we outline the defining institutional features of blockchains, DEXs, and priority gas auctions which underpin the framework of our model. Further details are provided in Appendix A and Appendix B.

A. Blockchains

Here, we describe the key elements of blockchain infrastructure relevant to our model. A blockchain is a distributed digital ledger. 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.* For example, the current block time in Ethereum, the main blockchain hosting the most liquid DEXs, is 12 seconds.

The block builder selects pending transactions from the memory pool to create a block. Validators 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 mandatory for inclusion in a block and 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.

Pending transactions in the memory pool are public, so agents may observe adjust their gas fees or resubmit pending transactions to gain queue priority. This *pre-trade transparency* leads to "priority gas auctions" (PGAs), where agents pay priority fees to compete for better queue positions and for better execution prices. As we show below, PGAs and block time are fundamental to the microstructure of DEXs. For additional details on blockchain protocols, see John, Monnot, Mueller, Saleh, and Schwarz-Schilling (2025).

B. Priority gas auctions

The Ethereum blockchain launched in 2015 and currently operates under a proof-of-stake (PoS) protocol. Under PoS, block building time is deterministic, with time divided into fixed 12-second slots, each producing a new block. Next, we describe the mechanics of priority gas auctions in Ethereum, which form the basis of our modelling assumptions. There are three stages in the lifecycle of transactions on the Ethereum blockchain: (i) submission, where an agent sets the transaction details and a gas fee (base fee and priority fee); (ii) storage in the memory pool, where the pending transaction awaits selection by a validator; and (iii) inclusion in a block, or mining, which corresponds to the execution of the transaction.

A key feature of the Ethereum protocol is the *nonce*, which is a counter assigned to each agent and which tracks the number of transactions included in previous blocks. Let n denote an agent's current account nonce. When submitting pending transactions, the agent must specify a nonce for each transaction, and it determines its eligibility for execution: (i) pending transactions with a nonce strictly smaller than n are immediately rejected by the network, (ii) pending transactions with nonce $n + 1$ are eligible for inclusion in the next block, and (iii) pending transactions with a nonce strictly greater than $n + 1$ are placed in a queue and remain pending until all lower-nonce pending transactions are executed.

The nonce mechanism enables agents to cancel or replace a pending transaction. While transactions confirmed by the network cannot be canceled, an agent can modify pending transactions which are in the memory pool, before they are included in a block, by submitting a new one with the same nonce but with a higher priority fee. Ethereum builders, who maximize revenue, will select the pending transaction with the highest gas fee. Consequently, agents can only revise gas fees upward, a key assumption in our model.

II. The model

The mechanics of DEXs are shaped by two key components: (i) the rules of the AMM, which determine the price of liquidity, and (ii) the consensus mechanism of blockchains, which governs the lifecycle of transactions. In this section, we introduce the features of our model to describe the microstructure of DEXs, and our results follow.

A. General features

Our model assumes that trading takes place within an AMM. However, this assumption is not essential. The results extend to any market structure with finite liquidity, where transactions affect quoted prices and thereby impact execution prices of subsequent trades. Consider an AMM that supplies liquidity in a reference security X (e.g., dollar) and in a risky security Y. A trading function Φ defines the combinations of reserves $\{x = \Phi(y), y\}$ that make liquidity suppliers indifferent, i.e., an iso-liquidity curve. As shown in Appendix A, the marginal price of security Y in terms of X, i.e., the price for an infinitesimal volume is $-\Phi'(y)$.

There are three types of agent, a representative liquidity supplier (he) who deposits assets in a liquidity pool, informed traders (she), and uninformed liquidity traders (they) with elastic demand. More precisely, $M > 2$ informed traders hold private information about the future liquidation value of the security. Each trader submits priority fees to compete for queue priority in the next block. In contrast, uninformed liquidity traders do not bid priority fees strategically, so they pay the base fee only, which we set to zero without loss of generality. The liquidity supply in the DEX, and the subsequent trading process, both in the memory pool and in the liquidity pool, are modelled as a game which proceeds as follows.

- *Stage zero*: M out of $L > M$ traders decide whether to pay a fixed cost C to gather private information.
- *Stage one*: the liquidity supplier sets the AMM. Setting the cost of liquidity in the DEX is equivalent to determining the quantity of reserves to deposit in the liquidity pool; see Appendix A.
- *Stage two*: following the creation of the previous block, a new blockchain slot begins. Informed traders obtain private information about the liquidation value V of the security; we refer to this private information as *private signals*. Based on their private signals, traders determine their priority fee bidding strategies and trading volumes. The PGA is an online (English) auction with a hard close at the end of the blockchain slot. Additionally, liquidity traders submit transactions to the memory pool with zero priority fees.

After the liquidity supplier sets the pool, we assume for simplicity that the liquidity supplier does not compete with informed liquidity takers for queue position in the next block. As described below, the liquidity supplier's strategy depends indirectly on the behavior of informed traders; she chooses the cost of liquidity in the AMM based on rational expectations regarding the informed traders' volumes. 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.

At the start of the slot in stage two, each informed trader receives a private signal about the future liquidation value V of the security, drawn from a common and known distribution. A key simplifying assumption in our model is that all informed traders know whether V, after the creation of the block, will be greater or less than V_0, determining the sign of signals and whether traders are buyers or sellers.

Our assumption that informed traders in a given block receive signals of the same sign may at first appear unrealistic. However, we are particularly interested in studying price efficiency and liquidity in situations where the fundamental value of the asset diverges from the quoted price in the DEX. In such cases, the majority of informed traders are either buyers or sellers, and the priority gas auction (PGA) becomes the primary mechanism through which information is incorporated into prices. Our assumption captures this economically significant regime. When the fundamental value of the asset is close to the quoted DEX price, the direction of private signals may be more dispersed. In such cases, when an informed buyer and an informed seller both submit transactions in the same block, each has an incentive to delay execution and allow the other to trade first, as this improves their own execution price. This strategic behavior leads to an equilibrium in which both traders prefer to lose the PGA, resulting in zero priority fees and little informational content in the auction outcome.

At the end of the slot, corresponding to block time, a new block is created with transactions ordered according to the level of priority fees. Specifically, the block executes the transactions of informed traders first, followed by those from uninformed liquidity traders who only pay the base fee.[3] The final liquidation value of the security is then realized, resolving any remaining uncertainty.

The equilibrium of this game is solved by backward induction. At stage two, given some level of liquidity depth and a number M of competing informed traders, the bidding strategies and trading volumes are determined. At stage one, the liquidity supply is determined based on the liquidity supplier's rational expectations of the trading volumes of M informed traders and the uninformed liquidity traders' activity. At stage zero, the number M of informed traders who pay the cost of information is determined such that there is no marginal utility gain from switching between informed and uninformed.

[3] This assumes that informed traders who lose the PGA bid an ϵ-priority fee.

B. The Assumptions

The sequence of events is described in more detail below and is illustrated in Figure 2.

***Stage zero*: information acquisition.** At stage zero, M traders pay the cost of information C, which include expenses for proprietary blockchain data, centralized exchange data, searcher contract deployment, and blockchain monitoring tools.

***Stage one*: liquidity supply.** At stage one, a risk-neutral representative liquidity supplier sets an AMM pool to balance losses to informed traders with fee revenue earned from uninformed liquidity traders.

First, we describe the measure of liquidity used by the liquidity supplier. The marginal price is a reference price in the DEX, and the difference between execution prices and marginal prices represent execution costs, similar to the difference between the mid-price in a limit order book and the execution price obtained from matching resting limit orders. The level of reserves deposited by the liquidity supplier determine the execution costs in the DEX but also the impact of a liquidity taking trade on the marginal price.

More precisely, and as shown in Appendix A, the execution costs for an order of size δ, per unit of security traded, are $\delta/\kappa + \pi$, where π is a proportional fee charged by the AMM,[4] and where we define

$$\kappa = 2/\Phi''(y). \tag{1}$$

for some level y of the reserves in the pool. Similarly, the impact on the marginal price following a buy (resp. sell) transaction of volume δ is $2\,\delta\,\kappa$ (resp. $-2\,\delta\,\kappa$). We prove in Lemma 1 that the trading function is necessarily convex by no-arbitrage. 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 is inversely proportional to the size of the pool, and it measures the price of liquidity. Thus, we refer

[4] See Lehar, Parlour, and Zoican (2024) for a detailed analysis of the implications of fixed proportional fees on the microstructure of AMMs.

to κ as the *depth of liquidity*. Akin to traditional electronic markets, execution costs and price impact defined above increase with the traded volume δ and decrease with the depth of liquidity κ.

For simplicity, we assume that uninformed liquidity traders transact a net volume that sums to zero in expectation, but an absolute expected volume which is elastic. Specifically, the liquidity demanded by buyers is linear in the price $1/\kappa$ (see (A2)), so its expected volume is

$$\frac{N}{2}\,(1-\theta/\kappa)\ ,$$

and the liquidity demanded by sellers is linear in the price $V_0 - 1/\kappa$, so its expected volume is

$$-\frac{N}{2}\,(1-\theta/\kappa)\ .$$

The demand for liquidity at the ask (resp. bid) is characterized by two parameters: $N/2$, which represents the aggregate of all uninformed liquidity traders' private positive (resp. negative) liquidity needs throughout the blockchain slot, and θ, which captures the sensitivity of the buy (resp. sell) liquidity demand to prices. Specifically, increasing (resp. lowering) the ask (resp. bid) $1/\kappa$ by s reduces demand by $N\,\theta\,s/2$, which, when normalized by aggregate demand, is $\theta\,s$. Liquidity demand in our model is similar to the reduced-form demand functions in the models of Garman (1976); Ho and Stoll (1981); Hendershott and Menkveld (2014).[5] Finally, the liquidity supplier's fee revenue, given by the cumulative fees paid by buyers and sellers, is

$$\pi\,N\,(1-\theta/\kappa)\ . \tag{2}$$

The liquidity supplier does not hold the same information about the future liquidation value V of the security as that of informed traders. At stage one, he assumes that with probability $1/2$, the liquidation value V of the security is positive, in which case the informed

[5]The parameter θ can also be interpreted as capturing the competitiveness and fragmentation of the market. As the market becomes more competitive and the value of θ increases, the likelihood that liquidity traders avoid transacting in the AMM increases because cheaper alternatives are available.

traders buy the security and their private signals are drawn from the interval $[\underline{v}, \overline{v}]$ according to a 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 security and their signals are drawn from the interval $[-\overline{v}, -\underline{v}]$, according to the density $f(-x)$.

Let δ denote the total trading volume of informed traders. From the perspective of the supplier, δ is a random variable, whose expected value is zero, and which we assume to be independent of the uninformed liquidity demand. Let $\mathbb{E}$ denote the expectation operator conditional on the liquidity supplier's information at stage one. The liquidity supplier balances fee revenue with expected losses to informed traders.

To compute the expected loss of the liquidity supplier to informed traders, let the initial marginal price be V_0 and let the initial reserves by y_0,[6] and assume the future liquidation value of security Y is $V = -\varphi'(y_0 + \delta)$, where δ is the volume traded by informed traders. Let $y = y_0 + \delta$ denote the AMM's reserves when the price of the security is V in the AMM. The realized adverse selection cost for a liquidity supplier, who holds an offsetting position $-y_0$, when the marginal price in the AMM shifts from V_0 to V as a result of an informed trading volume δ, is

$$-\left(\Phi(y_0) - \Phi(y) - \Phi'(y)(y_0 - y)\right) \approx -\frac{1}{2}\,\Phi''(y)\,(y - y_0)^2 = -\delta^2\,/\kappa\,, \tag{3}$$

see Appendix A for more details.

This loss is commonly referred to as *impermanent loss.* Intuitively, and akin to traditional markets, the impermanent loss (3) is nonpositive because liquidity providers hold more reserves of the security whose price has decreased and less reserves of the security whose price has increased. More precisely in AMMs, after a liquidity-taking transaction of size δ, the LP earns revenue δ/κ due to execution costs (akin to the spread) in (A2), while incurring adverse selection costs $-2\,\delta/\kappa$ due to price impact.

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

[6] Below, we normalize the initial marginal price to zero.

two is

$$-\frac{1}{\kappa}\,\mathbb{E}\left[\delta^2\right] = -\frac{1}{\kappa}\,\mathbb{V}[\delta]\,, \tag{4}$$

which increase with the variance of the informed trading volume, see (A6) in Appendix A.

As shown below, the variance of the informed traders' volumes increases with that of their private signals. Moreover, the variance of signals is closely tied to the length of blockchain slots, i.e., block time. As block time increases, the likelihood of significant changes in the fundamental value of the risky security rises, so longer block times provide traders with more opportunities to observe signals and gather information, including those from competing exchanges; see Figure 1 for an illustration. In the remainder of this paper, we assume that the variance of the signals increases with block time.

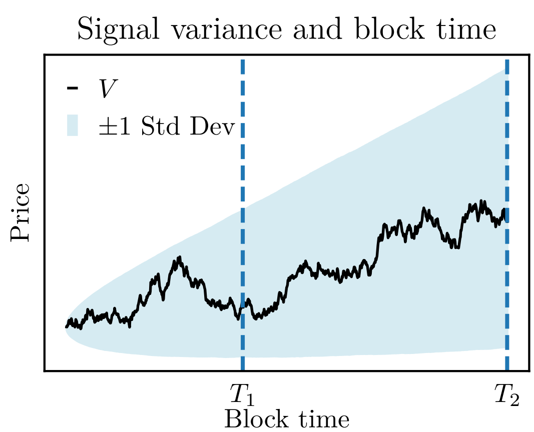


Figure 1. Relationship between the variance of signals and block time: longer block times correspond to increased likelihood of significant changes in the fundamental value of the risky security.

***Stage 2*: liquidity taking.** The depth of liquidity κ influences the execution prices of subsequent trades in the pool. 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 of security

Y. Using the formulas above, the execution price for the trader with queue priority in the block is $V_0 + \delta/\kappa$, after which the new price updates to $V_1 = V_0 + 2\,\delta/\kappa$. Consequently, the execution price for the trader without queue priority is $V_1 + \delta/\kappa = V_0 + 3\,\delta/\kappa$.

In our model, throughout the blockchain slot, informed and uninformed liquidity traders can submit pending transactions to the memory pool. M risk-neutral informed traders compete for queue priority in the next block. PGAs among informed traders are online auctions with a hard close corresponding to the end of the blockchain slot, during which traders can only revise their priority fee bids $\{\varphi_1, \cdots, \varphi_M\}$ upward (similar to an English auction); see Appendix B for more details on the mechanisms of priority fee bidding in Ethereum.

A key implication of pre-trade transparency in memory pools is that traders observe pending pending transactions. In blockchains, traders can sequentially raise their bids throughout the PGA to compete for queue priority. Immediately before block creation, all traders have a final opportunity to revise upward their priority fees. Competition at this round is a first-price sealed-bid auction with a reserve price equal to the highest bid submitted thus far. In the perfect Bayesian equilibrium, traders determine their priority fees $\{\varphi_i, \cdots, \varphi_M\}$ and trading volumes $\{\delta_i, \cdots, \delta_M\}$. The auction of the final round is blind because traders submit transactions immediately before the end of the slot, and it is first-price rather than all-pay, because traders use price limits in their strategies.[7]

An informed trader looking to buy the risky security may find it more profitable to avoid competition in a PGA if sell orders from uninformed traders with better queue position improve her execution price. Recall that transactions with zero priority fees are placed randomly within the block. Thus, if an informed trader chooses to bid a zero priority fee, then on average, an equal number of buy and sell orders from uninformed liquidity demanders

[7] Specifically, each trader submits two pending transactions to the memory pool: one with the equilibrium priority fee and a price limit set to $V_0 + \delta/\kappa$, and another with an ϵ-priority-fee and no price limit. If a trader loses the auction, the pending transaction with the price limit is not executed, while the ϵ-priority-fee pending transaction is. Conversely, if the trader wins the auction, only the pending transaction with the price limit is executed.

are executed before and after her order, while all informed traders' orders are executed before. The expected outcome from avoiding competition is therefore worse than that of losing the PGA, where only half of the informed traders' orders are executed before. As a result, in expectation, avoiding the PGA is never optimal, and informed traders find it strictly more profitable to compete for queue priority.

At the start of the PGA, traders simultaneously observe their private signals $\{v_1, \cdots, v_M\}$ and they know each other's type, i.e., whether they are all buyers or all sellers. Each signal is an independent and noisy realisation of the liquidation value, and it used by the trader to value the risky security. More precisely, the expected liquidation value from the perspective of trader i is

$$\mathbb{E}_i [V] = \mathbb{E} [V \mid v_i] = v_i \, . \tag{5}$$

The estimate of V with the lowest variance is the one conditioned on all available private information $\{v_1, \ldots, v_M\}$. For instance, the sample mean of all signals has variance $\mathbb{V}[v_i]/M$.

At the end of the PGA, a block is created with the transactions of informed and the uninformed liquidity traders. The final value V of the asset is then realized and all randomness is resolved.

III. Price formation, priority fees, and trading volumes

This section studies the priority fee bidding strategy of M informed traders who compete for execution when the liquidity depth in the AMM is κ. Assume that informed traders know that the liquidation value V is positive, so they wish to buy the risky security. The case where informed traders are sellers is symmetric and leads to the same equilibrium priority fee bidding strategies and trading volumes.

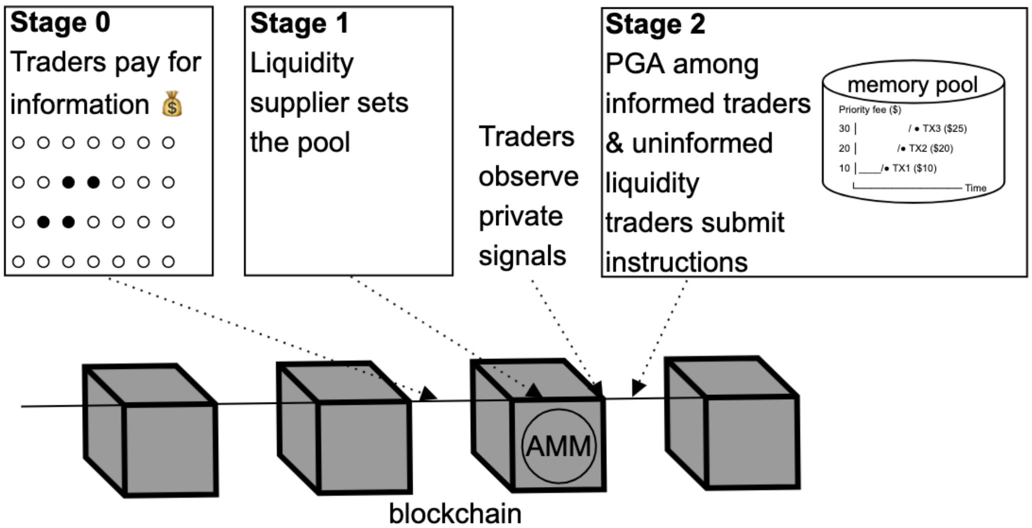


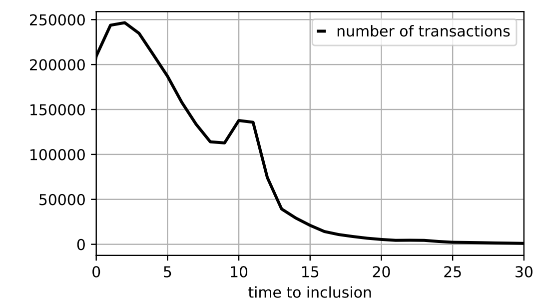
Figure 2. Sequence of events.

A. Price formation

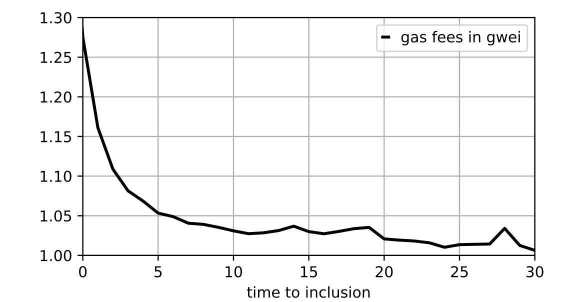
PROPOSITION 1: *The strictly dominant strategy for informed traders is late bidding, i.e., submit priority fees immediately before the end of the blockchain slot.*

The result shows that each informed trader finds it optimal to delay bidding until the last moment because any non-zero bid before the end of the blockchain slot acts as a reservation price for the final auction and reduces expected profits. Proposition 1 also shows that private information is only revealed immediately before the creation of the next block. In practice, this implies that information is disseminated to the market with the same periodicity as that of the creation of blocks, which in Ethereum occurs every 12 seconds. This pattern is observed in practice: transactions with large priority fees, typically associated with informed trading, see Capponi et al. (2023b), are predominantly submitted to the memory pool shortly before the end of each blockchain slot; see Figures 3a and 3b.

This feature of the microstructure of DEXs has implications for price efficiency, defined as the variance of the liquidation value V conditionally on all public information. In traditional electronic exchanges, information can be hidden in orders sent at the frequency of liquidity demand flow, so information is disseminated smoothly at trading frequency; see Kyle (1985b);



(a) Distribution of the average number of transactions as a function of the time (in seconds) between submission to the mempool and inclusion in a block.



(b) Distribution of the average priority fee of transactions as a function of the time (in seconds) between submission to the mempool and inclusion in a block.

Figure 3. Left panel: Distribution of transaction count as a function of timing within the blockchain slot. *Time to inclusion* measures the latency (in seconds) between the arrival of a transaction in the memory pool and its execution, i.e., block inclusion (the value zero on the abscissa is the count of transactions submitted less than one second before the slot ends). Right panel: level of priority fees as a function of timing within the blockchain slot. Data: Ethereum memory pool transactions between 10 and 16 December 2022.

Holden and Subrahmanyam (1992); Foster and Viswanathan (1996); Huddart et al. (2001). In contrast, price discovery in blockchains is a step process where information is only revealed periodically and immediately before each block is created. This property of DEXs, on its own, cannot be deemed inherently beneficial or detrimental to decentralized markets. While long block times delay price discovery, we show below that they can improve price efficiency and liquidity. However, the implications of the staggered information dissemination in DEXs in the presence of a competing venue with continuous clearing and reliable price signals, such as Binance, is beyond the scope of this work.

The study of agent behavior throughout slots in DEXs operating on blockchains resembles the study of agent behavior during preopening sessions of traditional electronic exchanges. In both settings, markets are not cleared until some given time. At the end of preopening sessions, all orders are executed at a 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 only at the end of preopening sessions, but agents can communicate with one another before. However, unlike memory pools, agents 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 et al. (1999) propose several hypotheses regarding the informativeness of preopening prices. Proposition 1 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. Similarly, Medrano and Vives (2001) find that trading volumes and information revelation accelerate toward the end of preopening sessions, providing further empirical support for our results.

B. Priority fees

Proposition 1 shows that it is more profitable for traders to submit their pending transactions at the end of block time. Thus, the PGA reduces to a first-price sealed-bid auction in which traders set their priority fees and trading volumes. This section studies the Bayesian-Nash equilibrium of the PGA. The game is symmetric, so we describe it from the perspective of trader i. Recall that φ_i denotes the priority fee and δ_i denotes the trading volume of trader i.

In what follows, we assume for simplicity that trader i approximates the impact of her competitors' trades on the marginal price based on her own private signal v_i.[8] We characterise the equilibrium priority fees, trading volumes, and liquidity supply in Appendix D without this approximation and show that all results hold, though with more complex expressions.

In stage two, trader i competes against $M-1$ informed traders in the PGA. From the perspective of trader i, the $M-1$ private signals of her competitors are i.i.d. draws from the same distribution. We denote by $\varphi_{(j)}$ the j-th largest bid of the $M-1$ competitors, and

[8] This assumption is further justified by δ_i and δ_{-i} being small relative to the total liquidity supply, so they can be treated as equal to a first-order approximation.

by $v_{(j)}$ the j-th largest private signal. If trader i wins the auction, i.e., if $\varphi_i > \varphi_{(M-1)}$, her buy order is executed first at the unitary price $V_0 + \delta_i/\kappa + \pi = \delta_i/\kappa + \pi$; see (A2). Thus, the trader's terminal wealth in this case is

$$W_i\,(\text{win}) = -\varphi_i - \underbrace{\delta_i\,(\delta_i/\kappa + \pi)}_{\text{initial trade}} + \underbrace{\delta_i\,V}_{\text{inventory}} - \underbrace{C}_{\text{information cost}} . \tag{6}$$

If trader i loses, then we assume that her order is placed randomly among the $M-1$ losing bids, i.e., there are $(M-1)/2$ informed traders' orders executed before her order. The price impact per unit of the security, when transacting a volume δ in the AMM, is $2\,\delta/\kappa$; see Appendix A. Thus, the trader's unitary execution price is

$$\underbrace{2\,\frac{\delta_i}{\kappa}}_{\text{impact of PGA winner}} + \underbrace{2\,\frac{(M-1)\,\delta_i}{2\,\kappa}}_{\text{impact of }(M-1)/2\text{ traders}} + \pi$$

instead (see (A3)), and her terminal wealth is

$$W_i\,(\text{lose}) = -\underbrace{\delta_i\,\left((1+M)\,\delta_i/\kappa + \pi\right)}_{\text{initial trade}} + \underbrace{\delta_i\,V}_{\text{inventory}} - \underbrace{C}_{\text{information cost}} . \tag{7}$$

When submitting a transaction, trader i determines both the priority fee and the volume. At this stage, trader i knows the liquidity depth κ and the number of competing traders, and she recognises that queue priority is secured if her priority fee φ_i is greater than those of her competitors. While trader i does not observe the competitors' priority fees directly, she can compute the probability that her own fee is higher. Denote this probability by $p_i = \mathbb{E}_i[\varphi_i > \varphi_{(M-1)}]$. Before the end of the slot and the creation of the block, the expected utility of the risk-neutral trader is

$$\begin{aligned}\mathbb{E}_i\,[W_i] =& p_i\left(-\varphi_i + M\,\delta_i^2/\kappa\right) - \delta_i\,\left((1+M)\,\delta_i/\kappa + \pi\right) + \delta_i\,v_i - C \\ =& \mathbb{E}_i\,[W_i\,(\text{lose})] + p_i\left(-\varphi_i + M\,\delta_i^2/\kappa\right) ,\end{aligned} \tag{8}$$

and trader i solves the problem

$$\sup_{\delta_i} \sup_{\varphi_i} \mathbb{E}_i \left[W_i \right] \, . \tag{9}$$

The objective function in (9) 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.

The expected wealth in (8) can be interpreted as follows. When trader i loses the PGA, her expected wealth is $\mathbb{E}_i[W_i(\text{lose})]$. However, if she submits a priority fee φ_i, then with probability p_i she gains a surplus from queue priority. This surplus is the difference between the *reservation priority fee* $M\,\delta_i^2/\kappa$ and the priority fee φ_i submitted by the trader in the memory pool. The reservation priority fee $M\,\delta_i^2/\kappa$ represents the fee at which trader i is indifferent between winning or losing the PGA. It corresponds to the price impact that the trader avoids when she secures queue priority in the block. The price impact avoided by the winner increases with the number of informed traders competing in the PGA.

Intuitively, traders buy and sell volumes proportional to their private signals. In the optimisation problem (9), 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 signal v_i.[9]

Recall that this section describes the game when informed traders buy the security. Let $\delta_i = \delta(v_i)$ denote the random variable describing the volume transacted by trader i. By assumption, the trading volume is drawn from the interval $[\underline{\delta}, \overline{\delta}]$ according to the density function

$$g(x) = f\left(\delta^{-1}\left(x\right)\right) \Big/ \delta'\left(\delta^{-1}\left(x\right)\right) . \tag{10}$$

Consequently, from the optimisation problem (9), trader i solves

$$\sup_{\varphi_i} \left\{ p_i \, \left(-\varphi_i + M\,\delta_i^2/\kappa \right) \right\} \tag{11}$$

[9]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 signal 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 signal value.

to obtain her optimal priority fee for a trading volume δ_i. That is, the trader chooses her priority fee to maximize the product of the probability to win the auction and the surplus earned from queue priority. Trader i faces a tradeoff, decreasing the priority fee increases the profit per unit bought but it reduces the probability of obtaining queue priority. This tradeoff is akin to a monopolist who faces a demand curve, or to a dealer who sets bid and ask quotes; see Biais (1993). The problem in (11) is equivalent to a first-price sealed-bid private value auction in which the item's value $M\,\delta_i^2/\kappa$ scales linearly with the number of participants. Here, the object of competition is the adverse price impact that the informed trader avoids by winning the PGA.

When solving for the equilibrium at stage two, informed traders take the depth κ—determined at stage one—as fixed and independent of the priority fee φ_i. In other words, the priority fee does not directly influence the liquidity depth, but has an indirect effect. As shown in the next section, the liquidity supplier accounts for the priority fee and the resulting trading volumes to determine the depth of the AMM's pool.

Trader i expects other traders to employ the increasing priority fee bidding strategy $\varphi(\cdot)$. Therefore, the probability of obtaining queue priority in the block is

$$p_i = \mathbb{P}_i\left[\varphi_i > \varphi_{-i}\right] = \mathbb{P}_i\left[\varphi_i > \varphi_{(M-1)}\right] = \mathbb{P}_i\left[\varphi^{-1}\left(\varphi_i\right) > \delta_{(M-1)}\right] = G\left(\varphi^{-1}\left(\varphi_i\right)\right)^{M-1},$$

where G is the cumulative distribution function corresponding to the density g in (10). Let $H(\cdot) = G(\cdot)^{M-1}$ denote the cumulative distribution function of the second largest trading volume, and let h be the corresponding density function. Consequently, the first-order condition derived from the optimisation problem in (11) is

$$\frac{1}{\varphi'\left(\varphi^{-1}\left(\varphi_i\right)\right)}\,h\left(\varphi^{-1}\left(\varphi_i\right)\right)\left(-\varphi_i + \frac{M\,\delta_i^2}{\kappa}\right) - H\left(\varphi^{-1}\left(\varphi_i\right)\right) = 0\,.$$

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

PROPOSITION 2: *The equilibrium priority fee is*

$$\varphi(\delta_i) = \frac{M}{\kappa}\left(\delta_i^2 - 2\,\frac{\int_{\underline{\delta}}^{\delta_i} x\,G\left(x\right)^{M-1}dx}{G\left(\delta_i\right)^{M-1}}\right). \tag{12}$$

The priority fee is increasing in the trading volume δ_i and in the number of informed traders M, and decreasing in the liquidity depth κ.

When computing her optimal priority fee, trader i uses the reservation priority fee $M\,\delta_i^2/\kappa$ as a baseline. This fee represents the priority fee level that makes her indifferent between winning or losing queue priority. Trader i has an incentive to lower her priority fee to capture a surplus. This is in (12), which shows that trader i applies a discount $2\int_{\underline{\delta}}^{\delta_i} x\,H\left(x\right)dx\big/H\left(\delta_i\right)$ to the reservation priority fee. More precisely, as the value of trader i's private signal v_i increases, the probability that her reservation priority fee exceeds that of other traders also rises. This makes it more likely that she secures queue priority and reduces the need to compete by further raising the priority fee. As a result, trader i applies a larger discount to the reservation priority fee as the value of her private signal increases.

For a fixed trading volume δ, as the number of informed traders increases, the adverse price impact $M\,\delta/\kappa$ also increases, forcing each trader to increase her priority fee $\varphi(\delta)$. Finally, when liquidity supply is abundant, competition diminishes as the cost of losing queue priority becomes less significant.

C. Trading volumes

Substitute the optimal priority fee φ_i in (12) into the objective function (9) to write the optimisation problem

$$\begin{aligned}
&\sup_{\delta_i}\left\{H\left(\delta_i\right)\,\left(-\varphi_i + M\,\delta_i^2/\kappa\right) - (1+M)\,\delta_i^2/\kappa + \delta_i\,\left(v_i-\pi\right) - C + \beta\,R/M\right\}\\
=&\sup_{\delta_i}\left\{F\left(v_i\right)^{M-1}\,\left(-\varphi_i + M\,\delta_i^2/\kappa\right) - (1+M)\,\delta_i^2/\kappa^2 + \delta_i\,\left(v_i-\pi\right)\right\}
\end{aligned} \tag{13}$$

to obtain trader i's optimal trading volume. In what follows, we make the following assumption for simplicity.

ASSUMPTION 1: *Let* $\underline{v} \geq \pi$. *Thus,* $v_i \geq \pi$ *when informed traders are buyers and* $-v_i \geq \pi$ *when informed traders are sellers.*

Assumption 1 ensures that informed traders always execute trades that are expected to be profitable, even after accounting for the transaction fee $\pi\,\delta_i$.

The linear-quadratic 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 priority fee costs they incur on the blockchain when observing a trading signal v_i. Additional trading costs incurred by trader i in the AMM include (i) the execution cost $-\delta_i^2/\kappa$, (ii) the price impact cost $M\,\delta_i^2\left(1-F\left(v_i\right)^{M-1}\right)/\kappa$, which decreases with the probability $F\left(v_i\right)^{M-1}$ of winning the PGA, and (iii) the AMM's proportional transaction fee $\pi\,\delta_i$. Both trading and infrastructure costs increase with trading volume, creating an incentive for trader i to reduce her trading volume δ_i. However, at the end of the slot, when the liquidation value of the asset is realized, trader i holds δ_i units of the risky security, whose expected value is positive. This provides an incentive for trader i to increase her holdings δ_i in the risky security. The next result characterises this tradeoff in equilibrium. In particular, expected speculative profits from higher signals scale linearly in the trading volume, while execution costs scale quadratically, yielding an optimal trading volume level.

PROPOSITION 3: *The equilibrium trading volume is*

$$\delta(v_i) = \kappa\,\tilde{\delta}(v_i) = \kappa\,\frac{v_i-\pi}{2\left(1+M\left(1-F\left(v_i\right)^{M-1}\right)\right)}\,, \tag{14}$$

which is an increasing and continuously differentiable function of the private signal, and which decreases to zero with the number of informed traders M. *In particular, the equilibrium priority fee* $\varphi(\delta(v_i))$ *decreases to zero as the number of informed traders* M *increases.*

In equilibrium, trader i's volume δ_i is linear in the liquidity depth κ, so the trader transacts a *fraction* $\tilde{\delta}_i$ of the pool's liquidity supply. This fraction depends on the observed private signal and the distribution of the competitors' trading signals as follows. The fraction $\tilde{\delta}_i$ increases with the private signal for two reasons. First, the signal v_i is the expected liquidation value from the perspective of trader i, so as v_i rises, the incentive to trade increases because the transaction becomes more profitable. Second, as the value of the signal increases, the likelihood of securing priority in the block at a cost lower than the reservation priority fee $M\,\delta_i^2/\kappa$ increases, encouraging higher trading volumes. In addition, the fraction $\tilde{\delta}_i$ of the pool transacted by trader i also depends on the distribution f of signals. For a fixed private signal v_i, more volatile signals of competitors increase the probability $1 - F(v_i)^{M-1}$ that trader i's signal is lower than that of her competitors, increasing the likelihood of losing the auction. This introduces potential costs, which in turn reduces trading volumes.

Proposition 2 shows that for a fixed trading volume, an increased number of competitors in the PGA increase the adverse price impact $M\,\delta/\kappa$ and drive priority fees up. However, trading volumes are part of the informed traders' equilibrium strategy and they adjust to trading costs, including execution costs and priority fees. In particular, each trader's expected inventory value is unaffected by competition, while priority fees scale linearly with the number of PGA competitors. Thus, in equilibrium, the trading volume $\delta(v)$ in (14) decreases as the number of informed traders increases in anticipation of higher expected priority fees. As a result, the equilibrium priority fees $\varphi(\delta(v))$, accounting for strategically adjusted trading volumes, decrease with the number of informed traders in the memory pool. In the limit, as M approaches infinity, trading volumes and priority fees converge to zero.

Proposition 3 also characterises the distribution of trading volumes within each block. Higher values of private signals correspond to larger trading volumes, and as shown in Proposition 2, they are also associated with higher priority fees and better queue positions. Figure 4 illustrates the average absolute trading volume of transactions across multiple Uniswap v3 pools as a function of their queue position within the block. The figure shows that the average volume of transactions executed first in the block tends to be larger than that of the transactions behind in the queue. This pattern lends empirical support to the findings of our model.

Finally, similar arguments to those in Sections III.B and III.C show that the equilibrium

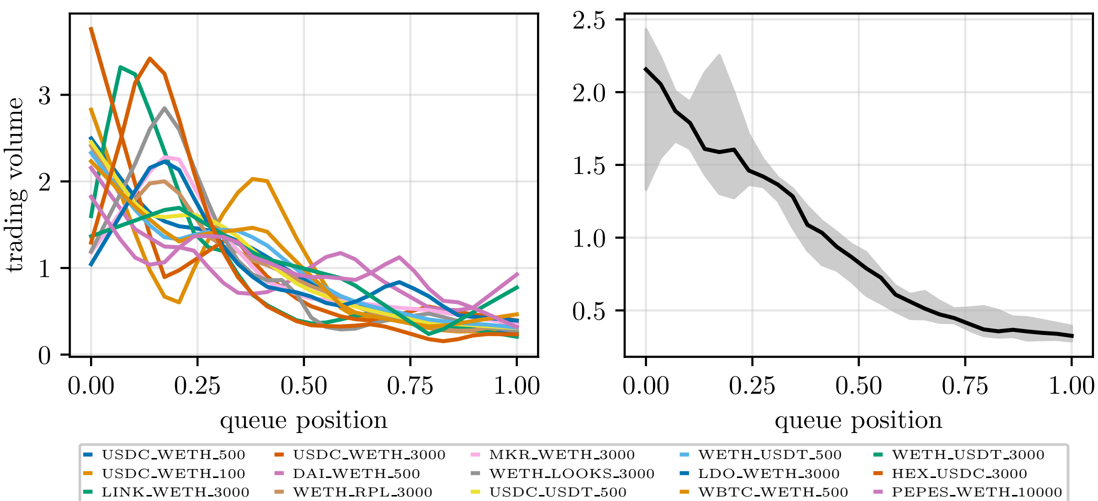


Figure 4. Left panel: Average absolute trading volume as a function of queue position in the block for transactions in multiple Uniswap v3 pools; 0 corresponds to first position and 1 to last position. The transactions are between 1 January 2023 and 31 December 2023 in 15 different Uniswap v3 pools with 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.

priority fees and trading volumes derived earlier also apply when traders wish to sell the security ($V < 0$). The results require only a slight adjustment: replace v_i with $-v_i$. As a consequence, traders are symmetrically aggressive in equilibrium, i.e., they buy or sell the same volumes for signals of equal absolute value and opposite signs.

IV. Equilibrium liquidity supply

This section examines liquidity supply in stage one. The liquidity supplier is risk-neutral and he submits a transaction in the block immediately before the one in which traders compete for execution priority.

As described in Section II.B, the liquidity supplier balances adverse selection losses to informed traders with fee revenue from uninformed liquidity traders. However, he does not know wether the value of the security will increase or decrease, and he assigns a 50% probability to each case. Use (4) and (14), and note that the variance of trading volumes is identical regardless of whether the informed traders are buyers or sellers, to write the expected loss to informed traders as

$$-\mathbb{V}\left[\sum_{1}^{M}\delta_i\right] = -M\,\mathbb{V}\left[\delta_i\right]/\kappa = -M\,\kappa\,\mathbb{V}[\tilde{\delta}_i]\,. \tag{15}$$

In equilibrium, trading volumes of stage two are strategically set to be proportional to the depth of liquidity in the pool, so providing more liquidity in stage one amplifies, on average, the dollar value of the speculative profits of informed traders and, consequently, the expected losses of the liquidity supplier.

The liquidity supplier balances losses to informed traders with fees earned from trading with uninformed liquidity traders. As previously detailed, the net volume of this trading activity is zero, while the absolute volume is elastic and its maximum equals N. Specifically, this amounts to $(1-\theta/\kappa)\,N/2$ in buy quantity and $(1-\theta/\kappa)\,N/2$ in sell quantity, where θ represents the price elasticity of liquidity demand. The optimisation problem of the liquidity supplier, which is solved in the next proposition, is

$$\sup_{\kappa}\left\{\pi\,N\,\left(1-\theta/\kappa\right) - M\,\kappa\,\mathbb{V}[\tilde{\delta}_i]\right\}\,. \tag{16}$$

PROPOSITION 4: *In equilibrium, the supply of liquidity is*

$$\kappa = \sqrt{\frac{\pi\,N\,\theta}{M\,\mathbb{V}[\tilde{\delta}_i]}}\,, \tag{17}$$

where $\tilde{\delta}_i$ is defined in (14). *The liquidity supply increases in the profitability of the uninformed trading flow, and increases in the number of informed traders. The condition for markets to* *remain open is*

$$M\,\mathbb{V}[\tilde{\delta}_i] \leq \frac{\pi\,N}{4\,\theta}\,. \tag{18}$$

In particular, there exists $\overline{M}$ such that for all $M > \overline{M}$, liquidity does not freeze.

The supply of liquidity increases with the profitability of liquidity demand, i.e., with the fee rate π and the demand volume N, and it decreases with demand elasticity. Additionally, the liquidity supplier anticipates that informed traders will transact the fraction (14) of the pool, which determines his own losses. Consequently, he reduces the supply of liquidity when the variance of this fraction increases. From the supplier's perspective—who does not observe private signals—this variance depends on the distribution of the private signals and the number M of competing informed traders. Specifically, the more volatile the signals, the lower the liquidity supply, and the more there are informed traders competing in the PGA, the higher the liquidity supply.

In the limit when M grows to infinity, the term $M\,\mathbb{V}[\tilde{\delta}_i]$ in (18) decreases to zero and supply grows. As a result, in equilibrium, increased competition among informed traders increases liquidity supply, and markets never shut down because of liquidity freeze above a given threshold for M. However, as we show below when endogenising the number of competing traders in the PGA, the value of M is constrained by the cost of acquiring information and by the limited speculative rewards which decrease with competition. Moreover, in practice, the equilibrium liquidity supply is inherently limited by the available pool of liquidity suppliers, so the optimisation problem for liquidity supply is constrained to a range $[0, \overline{\kappa}]$ with $\overline{\kappa} < \infty$.

In practice, Ethereum blockchains operate with slots lasting 12 seconds. The time length of the slot has two opposing effects. One, informed traders submit pending transactions at the end of the slot, which can lead to highly profitable and/or volatile trading signals when considered from the perspective of liquidity suppliers, particularly for risky cryptocurrencies or when competing venues with continuous trading coexist with the DEX. These effects drive liquidity levels down. Two, when slots are long, liquidity demand accumulates, increasing the uninformed demand N and with it the supply of liquidity.

The liquidity supplier's expected payoff is

$$\pi\, N - 2\,\sqrt{M\,\pi\, N\,\theta\,\mathbb{V}[\tilde{\delta}_i]}\,, \tag{19}$$

which establishes the condition (18) for the viability of liquidity provision in AMMs. Condition (18) 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 elasticity 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 signal of informed traders is too precise relative to the elasticity of liquidity demand.

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

$$\mathbb{V}[\tilde{\delta}_i] = \frac{\pi\, N}{4\, M\,\theta}\,, \tag{20}$$

then the minimal liquidity depth, for which the supplier breaks even, is

$$\underline{\kappa}^{\star} = 2\,\theta\,. \tag{21}$$

As demand becomes more elastic, the necessary supply to break even also rises.

Finally, in practice, not all liquidity suppliers are *rational*. Unlike traditional trading venues such as high-frequency limit order books or dealer markets, the permissionless nature of blockchains facilitates entry to provide liquidity, particularly by less sophisticated liquidity suppliers. As a result, strategic liquidity suppliers in AMMs cannot freely set the price of liquidity because they compete with *noise liquidity suppliers*. Let the liquidity already provided by noise liquidity suppliers in the AMM be denoted by κ'. In this context, the strategic liquidity supplier faces the decision of either adding liquidity to reach the target supply $\kappa^\star$ in (17) when $\kappa^\star > \kappa'$, or refraining from further liquidity provision if the existing supply already exceeds $\kappa^\star$. This feature of DEXs may explain the losses observed in practice in current AMMs; see Cartea et al. (2024a).

V. Information acquisition

We study the initial stage where traders decide whether to pay the cost C to acquire private information and participate in blockchain validation. Let L be the total number of traders eligible to acquire information, and let $M \leq L$ be the subset of those who choose to do so. We analyse price efficiency from the perspective of an uninformed individual, defined as the variance of the security's liquidation value V conditional on all public information. This price efficiency is directly related to the number of informed traders who pay the cost of acquiring information. Our analysis shares a similar goal to that in Grossman and Stiglitz (1980) for traditional markets, where the degree of market informativeness and efficiency depends on the information held by informed traders, and their number is endogenously determined.

In blockchains, private information is revealed through the fully revealing priority fee (12) if the trader wins the PGA or through the traded volume (14) if the trader loses the PGA.[10] Each private signal reduces the variance of the security's liquidation value V conditional on all public information.

To illustrate this, consider the following example. Assume the entire pool of L traders acquires information and submits transactions to the memory pool, and assume an uninformed

[10] In blockchains, the number of transactions, and thus the number of informed traders, is limited by the finite size of each block.

individual estimates the liquidation value V as

$$V = \frac{1}{L} \sum_{k=1}^{L} v_i + \varepsilon \,,$$

where ε is unobservable noise with variance σ^2. In this case, the variance of the security's value conditional on all public information is σ^2. As we show below, in the presence of PGAs, only a subset $M \leq L$ of traders pay the information cost C and submit transactions to the memory pool, in which case the variance of the liquidation value V conditional on public information in terms of the variance of private signals $\mathbb{V}[v]$ is given by

$$\mathbb{V}[V \mid \{v_1, \ldots, v_M\}] = \frac{L - M}{L^2}\, \mathbb{V}[v] + \sigma^2,$$

so price efficiency improves as more traders pay the cost of information.

In equilibrium, the number of traders who choose to become informed is constrained by the relative profitability of informed trading and the cost C. At stage zero, the equilibrium number of traders M engaging in informed trading is determined such that the marginal utility gain from switching between informed and uninformed trading is negative. We characterize the equilibrium number of informed traders in the following result.

PROPOSITION 5: *The equilibrium number of informed traders is the integer part of the solution to*

$$C = H(M) = \underbrace{\sqrt{\frac{\pi\, N\, \theta}{M\, \mathbb{V}[\tilde{\delta}\,(v_i)]}}\, \left(\mathbb{E}_0\left[\tilde{\delta}\,\left(v_{(M)}\right)^2\right] - \mathbb{E}_0\left[\tilde{\delta}\,\left(v_{(M-1)}\right)^2\right]\right)}_{\text{trading profits net of execution costs and priority fees}}\,. \tag{22}$$

The function H converges to zero as M goes to infinity. If $H(2) > C$, then there exists $M \geq 2$ that satisfies (22)*. In this case, the equilibrium number of informed traders M increases with the size N and elasticity θ of uninformed liquidity demand. Conversely, M decreases as the information cost C increases.*

The equilibrium number of informed traders characterized in Proposition 5 ensures that the profits from informed trading net of execution costs and priority fees offset the costs of acquiring information. In the equilibrium condition (22), the term

$$\kappa\,\left(\mathbb{E}_0[M\,\delta(v_{(M)})^2] - \mathbb{E}_0[M\,\delta(v_{(M-1)})^2]\right)/M$$

represents the expected profit from winning the auction when the level of liquidity supply is κ.[11] More precisely, at stage zero, $1/M$ is the ex-ante probability of winning the auction. The object of competition in the PGA is the adverse price impact $M\,\delta^2/\kappa$ that the informed trader avoids by winning. In a first-price sealed-bid auction with M competitors, the average winning bid corresponds to the expectation of the second highest private value. Finally, the trading volumes are adjusted by the expected execution costs and priority fees.

Increasing numbers of informed traders enhances price efficiency. Proposition 5 shows that price efficiency decreases as the cost of information C increases. In addition, price efficiency increases with the size of uninformed trading, which incentivizes greater liquidity supply and makes informed trading more profitable. To further understand the effect of the number of competing informed traders on the equilibrium properties of DEXs, note that a key implication of Proposition 3 is that the portion of the pool $\tilde{\delta}_i$ traded by each trader decreases with M, and in the limit when M goes to infinity, informed traders transact an expected fixed portion $\mathbb{E}\left[v_i - \pi\right]/2$ of the pool. In particular, the expected DEX price following the orders of the M informed traders, defined in (A3), is

$$2\,M\,\mathbb{E}\left[\delta_i\right]/\kappa = M\,\mathbb{E}\left[\frac{v_i - \pi}{1 + M\left(1 - F\left(v_i\right)^{M-1}\right)}\right],$$

which converges to $\mathbb{E}\left[v_i - \pi\right]$ as M goes to infinity. Thus, the extent to which DEX prices incorporate available information increases as more informed traders compete in the PGA,

[11] Recall that, at stage zero, the distribution of equilibrium squared trading volumes is identical regardless of whether the informed traders are buyers or sellers.

and in the limit $M \to \infty$, the difference between DEX prices and the price implied by all private information is the AMM's fee rate. Moreover, the variance of the liquidation value V, conditional on all public information, decreases in the number of traders M.

Block time. To study the effect of block time on price efficiency, we consider the simple case where the distribution F of signals v is such that the distribution of $\tilde{\delta} = \delta/\kappa$ is uniform. The portion $\tilde{\delta}(v_i)$ of the pool traded by informed trader i in (14) decreases at a rate $1/M$, so we assume that $\tilde{\delta}(v_i)$ is uniformly distributed on an interval $[0, D/M]$, where D depends only on the maximum signal value $\overline{v}$. Below, we refer to D as block time. The following result presents the equilibrium condition in this case.

COROLLARY 1: *Assume* $\tilde{\delta}$ *is uniformly distributed on the interval* $[0, D/M]$ *with probability* $1/2$ *and uniformly distributed on the interval* $[-D/M, 0]$ *with probability* $1/2$*. The equilibrium condition* (22) *becomes*

$$C = \frac{\sqrt{24\,\pi\,\theta\,N\,M}}{M\,(2 + 3\,M + M^2)}\,D + \frac{\beta}{M}\,R\,, \tag{23}$$

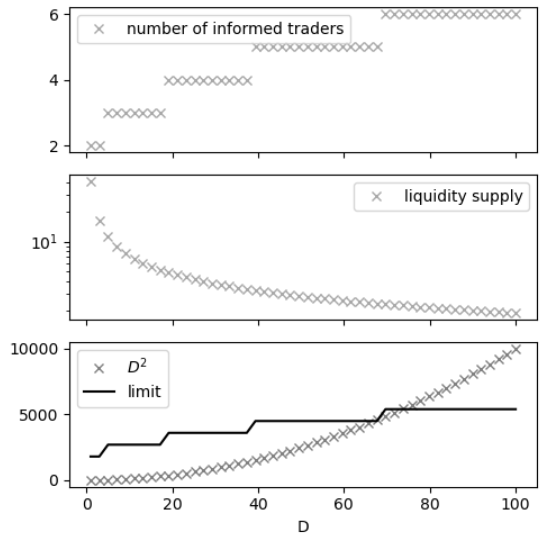
the condition (18) *for markets to remain open is*

$$D^2 \leq \frac{3\,\pi\,N\,M}{\theta}\,, \tag{24}$$

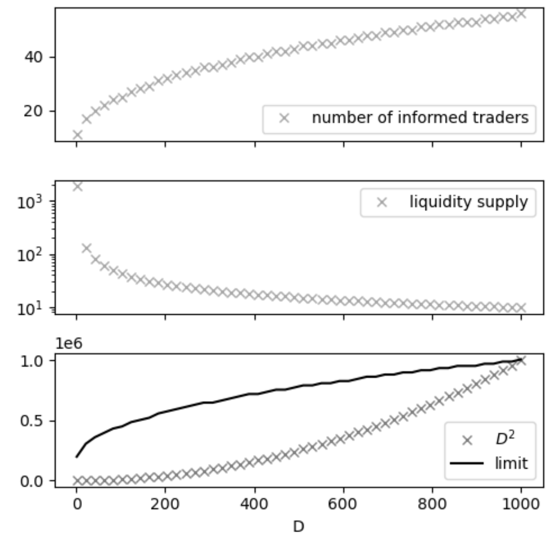
and the equilibrium liquidity supply (17) *is*

$$\kappa^\star = \frac{12}{D}\,\pi\,M\,N\,\theta\,. \tag{25}$$

The equilibrium equation (23) shows that longer block times, i.e., larger values of D, increase the number of informed traders. This is because longer block times enhance the profitability of informed trading and incentivize traders to pay the cost C. In particular, in the case of a uniform distribution, we find that the equilibrium number of informed traders M increases with block time D approximately as $D^{0.4}$.



(a) Low uninformed demand and costly information.



(b) High uninformed demand and cheap information.

Figure 5. Equilibrium number of informed traders (23), liquidity (25), and liquidity freeze condition (24).

However, there is an upper bound on block time D beyond which markets shut down due to a liquidity freeze. Specifically, the equilibrium condition (24) implies that markets remain open only if the block time D is below a threshold $\sqrt{3\,\pi\,N\,M/\theta}$. This threshold increases approximately as $D^{0.2}$, indicating that for any given market configuration, there exists a maximum block time beyond which liquidity freezes. In addition, the equilibrium liquidity supply (25) decreases with block time at a rate $D^{-0.6}$. Consequently, the equilibrium characteristics of DEXs, i.e., the number of informed traders, the depth of liquidity, trading volumes, and priority fees, depend on the level and elasticity of uninformed demand N, the fee rate π, and the cost of information C. Figure 5 illustrates these equilibrium outcomes. In particular, akin to traditional markets, high levels of uninformed demand and cheap costs of information improve market efficiency.

Our findings have implications for the design of blockchain protocols. There is a tradeoff between price efficiency and liquidity supply in DEXs when setting block time. Longer block times improve price efficiency by increasing the profitability of informed trading and by encouraging more traders to pay the information cost C. They however reduce the supply of liquidity and increase the likelihood of liquidity freeze.

Our analysis above assumes that the magnitude of uninformed demand N is fixed and independent of block time D. However, if uninformed demand increases with block time, then the condition for markets to remain open becomes more permissive. In the uniform distribution case, if uninformed demand grows linearly with D, then liquidity supply increases with block time instead of decreasing. Nonetheless, there still exists a critical level of D beyond which liquidity freezes. It can be shown that if uninformed demand grows faster than $D^{1.5}$, then increasing block time leads to higher levels of informed trading, deeper liquidity, and improved price efficiency, without ever triggering a liquidity freeze. However, these benefits come at the cost of slower price dissemination; recall that markets only clear when the block is created after block time. This tradeoff becomes particularly important in the presence of competing trading venues with more frequent price updates.

Our finding that longer block times enhance market efficiency holds when the pool of informed traders L willing to pay for information is large. If L is limited, for example, due to high technological barriers to accessing private information, the number of informed traders in PGAs is capped. Beyond a certain threshold, further increasing block time harms market efficiency.

Finally, when the noise in signals approaches zero ($\overline{\delta} \approx 0$), prices fully incorporate all private observable information, and the profitability of informed trading vanishes. In this case, the only incentive to pay the information cost is the blockchain validation reward. When $\beta = 0$ or $R = 0$, there is no incentive to acquire information, and the only possible equilibrium is one with no informed traders. This finding was originally established in Grossman and Stiglitz (1980) for traditional markets.

VI. Conclusions

This paper studied the microstructure of blockchain-based DEXs. We showed that price efficiency in blockchain-based markets is constrained by the slot structure, with information only revealed at the end of block time (e.g., every 12 seconds in Ethereum). Moreover, we showed that although priority fees introduce a new source of friction and block time slows down price discovery, they benefit DEXs by improving the informativeness of prices when markets clear. We showed that block time presents a tradeoff for DEXs and can either hinder or enhance market efficiency. On the one hand, long block times reduce liquidity supply because providers face prolonged exposure to adverse selection risk. On the other hand, longer block times (i) incentivize informed traders to acquire private information, improving price efficiency, and (ii) allow liquidity demand to aggregate, generating higher fee revenue and deeper liquidity.

Future work will compare the stylized facts of DEXs predicted by our model with empirical observations from blockchain data. Some cryptocurrencies are traded exclusively on blockchains. This provides a unique setting to study DEX microstructure without the influence of traditional trading venues. A further issue to examine is whether the transparency of memory pools and blockchains restricts liquidity providers. Specifically, it is unclear if this transparency hinders their ability to unwind or rebalance positions effectively. Finally, future work should study the impact of MEV and layer 2 blockchains on the properties of DEXs.

Appendix A. Blockchains and automated market makers

Price formation in DEXs arises from the interplay between blockchain protocols and the mechanisms of AMMs. Blockchain protocols govern the lifecycle of transactions from submission to execution. They dictate how information disseminates to the market prior to execution and they determine infrastructure costs, including gas fees paid to validators who ensure network security. On the other hand, AMM mechanisms define the rules of interaction between liquidity takers and suppliers. They determine the price of liquidity and adjust prices based on trading activity.

The microstructure of DEXs differs fundamentally from that of traditional financial markets, and an accurate description of its properties requires modelling the key elements of both the blockchain protocol and the AMM mechanism. In what follows, we outline the defining features of these components, which underpin the framework of our model.

Blockchains

Here, we describe the key elements of blockchain infrastructure relevant to our model. A blockchain is a distributed digital ledger stored by participants—referred to as nodes—within a public network. Any entity can be a node and maintain a copy of the ledger. For a pending transaction to be executed on the blockchain, it must be included in a block created by a *validator*. Blocks are sequentially added to the ledger at regular intervals called *slots*, the duration of which is referred to as *block time*. For example, the current block time in Ethereum, the main blockchain hosting the most liquid DEXs, is 12 seconds. Block time must be long enough to allow for secure and robust confirmation of blocks, a process that 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 decentralisation. Thus, block time is a buffer that balances security and decentralisation.

All blockchain activity is publicly visible. When an agent submits a pending transaction, it is not immediately included in a block. Instead, the pending transaction is broadcast to nodes in the network and stored in their local memory, known as the *memory pool*. The pending transaction propagates through the network until it is visible to all nodes. The block validator, randomly selected at each slot by the blockchain protocol, selects pending transactions from their memory pool to create the next block. Validators 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 is mandatory for inclusion in a block.[12] Base fees are used by the blockchain to regulate network traffic. In contrast, the priority fee is optional, paid exclusively to the validator, and incentivizes transaction inclusion and queue priority in the block. Pending transactions in the memory pool are public, so agents observe the pool's state and adjust their gas fees or resubmit pending transactions to gain queue priority. This *pre-trade transparency* leads to "priority gas auctions" (PGAs), where agents pay priority fees to compete for better queue positions and for better execution prices. PGAs are fundamental to the microstructure of DEXs, so one must consider these costs, and the incentives it creates, in models of these markets. For additional details on blockchain protocols, see John et al. (2025).

Finally, validators have great latitude in deciding which pending transactions to include and in what order, including their own transactions. Ethereum builders, for example, exploit this flexibility to extract revenue through transaction ordering, a practice referred to as miner extractable value (MEV). MEV and PGAs create costs for trading agents, who can choose to bypass public memory pools and submit pending transactions directly to a specific validator. Our model excludes MEV extraction by validators, as blockchain designers actively seek to eliminate it, for instance with layer-2 blockchains; see Sguanci, Spatafora, and Vergani (2021); Gangwal, Gangavalli, and Thirupathi (2023). Similarly, we do not consider private

[12]More precisely, the base fee is *burnt*, 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.

memory pools because they are not frequently used; see Piet, Fairoze, and Weaver (2022).

Automated Market Makers

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 (2021),Capponi and Jia (2021), and Cartea, Drissi, and Monga (2025).

Liquidity takers in DEXs. Assume trading is conducted in an AMM that supplies liquidity x_0 in the reference security X and y_0 in the risky security 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 security 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 security X. Thus, the execution prices per unit of the risky security are

$$\text{price to sell } \delta : \quad \frac{\Phi(y_0) - \Phi(y_0 + \delta)}{\delta}, \qquad \text{price to buy } \delta : \quad \frac{\Phi(y_0 - \delta) - \Phi(y_0)}{\delta}, \tag{A1}$$

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 security Y in terms of X, or simply the price of security 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 (A1). The reserves also determine the impact of a liquidity taking trade on the price. In our models below, the buy and sell prices, per unit of security traded, are

$$\begin{aligned} \text{price to sell } \delta: \quad & \frac{\Phi(y_0) - \Phi(y_0 + \delta)}{\delta} \approx V_0 - \frac{1}{2}\,\delta\,\Phi''(y_0)\,, \\ \text{price to buy } \delta: \quad & \frac{\Phi(y_0 - \delta) - \Phi(y_0)}{\delta} \approx V_0 + \frac{1}{2}\,\delta\,\Phi''(y_0)\,. \end{aligned} \tag{A2}$$

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

$$\begin{aligned} \text{impact after the sell order}: \quad & -\Phi'(y_0 + \delta) - V_0 \approx -\delta\,\Phi''(y_0)\,, \\ \text{impact after the buy order}: \quad & -\Phi'(y_0 - \delta) - V_0 \approx \delta\,\Phi''(y_0)\,. \end{aligned} \tag{A3}$$

Equations (A2) and (A3) 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 (A2) 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 6 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 is inversely proportional to the size of the pool, and we refer to

$$\kappa = 2/\Phi''(y_0) \tag{A4}$$

as the *depth of liquidity*.[13] Thus, execution costs in (A2) are given by δ/κ. Akin to traditional electronic markets, execution costs and price impact, defined in (A2) and (A3), increase with

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

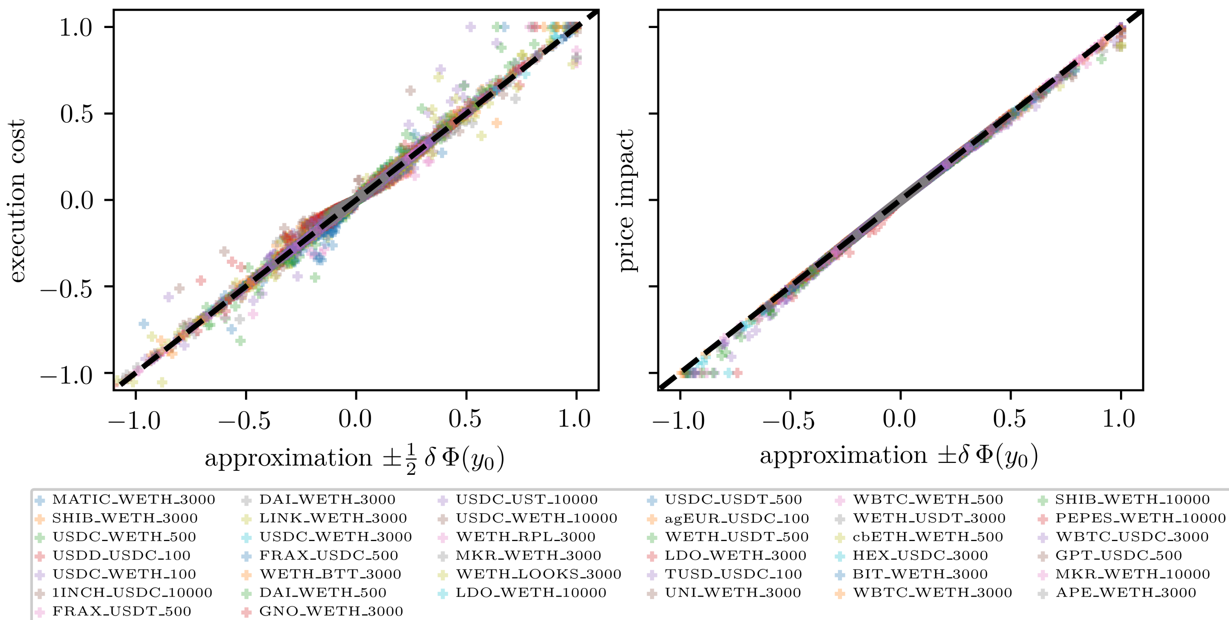


Figure 6. Scatter plots of the execution cost and the price impact of 2.622 million LT transactions against the approximations (A2) and (A3). The transactions are between 1 January 2023 and 31 December 2023 in 38 different Uniswap v3 pools. For each pool, the execution costs and price impacts are scaled between $[0, 1]$ for buy orders and $[-1, 0]$ for sell orders.

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 of security Y. Using the formula for execution costs in (A2) and price impact in (A3), the execution price for the trader with queue priority in the block is $V_0 + \delta/\kappa$, after which the new price updates to $V_1 = V_0 + 2\,\delta/\kappa$. Consequently, the execution price for the trader without queue priority is $V_1 + \delta/\kappa = V_0 + 3\,\delta/\kappa$.

Liquidity suppliers in DEXs. In our model, liquidity supply is determined endogenously. Assume that a representative liquidity supplier sets a pool with depth κ and that the marginal price implied by the pool's reserves is V_0. Next, assume the future liquidation value of security Y is V, and that the total volume δ traded in the pool adjusts the future marginal price $-\varphi'(y_0 + \delta)$ to V. Let $y = y_0 + \delta$ denote the AMM's reserves when the price of the security is V, and let π denote the fixed proportional fee charged by the pool.

LEMMA 1: *By no-arbitrage, the trading function of the AMM is convex. Additionally, the change ΔW_L in the wealth W_L of the liquidity supplier is given by*

$$\Delta W_L = y_0 \; (V - V_0) - (\Phi(y_0) - \Phi(y) - \Phi'(y)(y_0 - y)) + \pi \, \delta \, , \tag{A5}$$

when the marginal price in the AMM shifts from V_0 to V as a result of a liquidity taking order of size δ. The second term in (A5) *is always nonpositive because of the necessary convexity of Φ .*

The change in the wealth of the liquidity supplier can be interpreted as follows. The first term on the right-hand side of (A5) represents the change in wealth had the initial reserves y_0 been held outside the pool. The second term in (A5) 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 impact of informed trading on the LP's wealth. The last term on the right-hand side of (A5) represents the fee revenue.

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

$$-\left(\Phi(y_0) - \Phi(y) - \Phi'(y)(y_0 - y)\right) \approx -\frac{1}{2}\, \Phi''(y) \, (y - y_0)^2 = -\delta^2 \, / \kappa \, , \tag{A6}$$

where κ is the depth of the AMM's liquidity. Intuitively, and akin to traditional markets, the impermanent loss (A6) is nonpositive because liquidity providers hold more reserves of the security whose price has decreased and less reserves of the security 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 (A2), while incurring adverse selection costs $-2\,\delta/\kappa$ due to price impact in (A3).

Appendix B. Priority gas auctions in Ethereum

The Ethereum blockchain launched in 2015 with a proof-of-work (PoW) consensus mechanism. Under PoW, nodes compete to solve complex computational puzzles to earn the right to add the next block. This process made block times random. On 15 September 2022, Ethereum transitioned to proof-of-stake (PoS) with the "merge". Under PoS, participants stake ETH-the native digital currency on Ethereum-to become validators, which eliminates the need for computational puzzles. Block building in PoS is deterministic, with time divided into fixed 12-second slots, each producing a new block.

Next, we describe the mechanics of priority gas auctions in Ethereum, which form the basis of our modelling assumptions. There are three stages in the lifecycle of transactions on the Ethereum blockchain: (i) submission, where an agent sets the transaction details and a gas fee (base fee and priority fee); (ii) storage in the memory pool, where the pending transaction awaits selection by a validator; and (iii) inclusion in a block, or mining, which corresponds to the execution of the transaction.

A key feature of the Ethereum protocol is the *account nonce*, a counter assigned to each agent's account that tracks the number of executed transactions, i.e., the number of transactions included in previous blocks. The nonce prevents replay and double-spending attacks Vujičić, Jagodić, and Ranić (2018). Let n denote an agent's current account nonce. When submitting pending transactions, the agent must specify a nonce for each transaction, and it determines its eligibility for execution: (i) pending transactions with a nonce strictly smaller than n are immediately rejected by the network, (ii) pending transactions with nonce $n+1$ are eligible for inclusion in the next block, and (iii) pending transactions with a nonce strictly greater than $n+1$ are placed in a queue and remain pending until all lower-nonce pending transactions are executed.

The nonce mechanism also enables agents to cancel and replace a pending transaction. While transactions confirmed by the network cannot be effectively canceled, an agent can modify pending transactions which are in the memory pool, before they are included in a block, by submitting a new one with the same nonce but with a higher priority fee. Ethereum builders, who maximize revenue, will always select the pending transaction with the highest gas fee.

Agents might attempt to manipulate this mechanism by submitting a pending transaction with the same nonce but with a deliberately failing execution (e.g., setting a buy price limit at zero), followed by a second pending transaction with the intended original transaction but with lower gas fees. However, failed transactions still incur gas costs. Consequently, agents can only revise gas fees upward, a key assumption in our model.

Appendix C. Proofs

Proof of Lemma 1: Consider the prices to buy and sell a quantity δ in (A2). 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

$$\Phi(y_0) + y_0\, V_0 = \Phi(y_0) - y_0\, \Phi'(y_0)\,.$$

Following a trading volume δ, the new liquidation value is V and the reserves are $y = y_0 + \delta$. Thus, the wealth of the liquidity supplier becomes

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

proving the result. □

Proof of Proposition 1: The PGA is modelled as a first-price online auction with a hard close at the end of the blockchain slot, i.e., the auction runs for a fixed duration T. Using backward induction, we show that late bidding, i.e., submitting priority fees immediately before the end of the slot, is the dominant strategy for competitive informed traders.

Consider a period $[T - \tau, T]$, where $\tau > 0$ is small, which we refer to as the final period. In the final period, each trader has at most one opportunity to revise their priority fee before the auction ends and the block is created. Since priority fees can only be revised upward, let $\widetilde{\varphi} \geq \underline{\delta}$ denote the highest priority fee at the end of round one, i.e., at the end of the first period $[0, T-\tau]$. Thus, the final stage of the auction is a first-price sealed-bid auction with public reserve price $\widetilde{\varphi}$. This auction is a slight variation of the auction analysed in Section III.B solved in Proposition 2. Following similar arguments, we obtain the following result.

PROPOSITION 6: *The equilibrium priority fee of the second stage when the current maximum priority fee at time $T-\tau$ is $\widetilde{\varphi}$ is*

$$\varphi_i^\star = \frac{2}{\kappa}\left(\delta_i^2 - 2\,\frac{\int_{\widetilde{\delta}}^{\delta_i} x\,G\left(x\right)dx}{G\left(\delta_i\right)}\right)\mathbb{1}_{2\,\delta_i^2/\kappa \geq \widetilde{\varphi}}\,, \tag{C1}$$

where $2\,\widetilde{\delta}^2/\kappa = \widetilde{\varphi}$. In particular, the equilibrium priority fee is increasing in the reserve priority fee φ_*

$$\partial_{\widetilde{\varphi}}\varphi^\star = \frac{4\,\widetilde{\varphi}}{\kappa}\,\frac{G\left(\widetilde{\varphi}\right)}{G\left(\delta_i\right)} > 0\,, \tag{C2}$$

and trader i's expected profit is decreasing in $\widetilde{\varphi}$

$$\partial_{\widetilde{\varphi}}\mathbb{E}[W_i] = -\frac{4\,\widetilde{\varphi}}{\kappa}\,G\left(\widetilde{\varphi}\right) > 0\,. \tag{C3}$$

Next, consider the behavior of informed traders during the online auction of round one, i.e., over the interval $[0, T-\tau]$. By Proposition 6 and the description of the PGA in Appendix B, any bid on the priority fee can only increase the current highest bid $\widetilde{\varphi}$. Consequently, no trader has an incentive to bid early in round one because it would decrease their expected terminal wealth; see (C3). Thus, the priority fee remains constant and equal to the starting bid set by the blockchain protocol, which corresponds to the mandatory base fee for inclusion in a block (normalized to zero in our model). Therefore, each informed trader finds it optimal to delay bidding until the last moment. $\square$

Proof of Proposition 2: The first-order condition (FOC) derived from the optimisation problem in (11) is

$$\frac{1}{\varphi'\left(\varphi^{-1}\left(\varphi_i\right)\right)}\, h\left(\varphi^{-1}\left(\varphi_i\right)\right) \times \left(-\varphi_i + \frac{M\,\delta_i^2}{\kappa}\right) - H\left(\varphi^{-1}\left(\varphi_i\right)\right)\,.$$

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

$$\varphi^{'}\left(\delta_i\right) H\left(\delta_i\right) + h\left(\delta_i\right)\varphi_i = g\left(\delta_i\right)\left(M\,\delta_i^2\Big/\kappa\right),$$

or equivalently

$$\varphi\left(\delta_i\right) H\left(\delta_i\right) = M\int_{\underline{\delta}}^{\delta_i}\left(x^2\Big/\kappa\right) g\left(x\right)\,dx = \frac{2}{\kappa}\left[\delta_i^2\, H\left(\delta_i\right) - 2\int_{\underline{\delta}}^{\delta_i} x\, H\left(x\right)\,dx\right],$$

proving the result. □

Proof of Proposition 3: Use the optimal priority fee (12) in the objective (13) to write the expected wealth of trader i as

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

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

$$0 = 2\,\delta_i\,\left(M\,H\left(\delta_i\right) - 1 - M\right)/\kappa + v_i - \pi\,. \tag{C4}$$

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

$$H\left(\delta_i\right) = G\left(\delta_i\right)^{M-1} = \left(\int_{\underline{\delta}}^{\delta_i}\frac{f\left(\delta^{-1}\left(x\right)\right)}{\delta'\left(\delta^{-1}\left(x\right)\right)}\,dx\right)^{M-1} = \left(\int_{\underline{v}}^{v_i} f\left(y\right)\,dy\right)^{M-1} = F\left(v_i\right)^{M-1}\,.$$

Rearranging (C4) one obtains

$$\delta\left(v_i\right)=\kappa\,\frac{v_i-\pi}{2\left(1+M\left(1-F\left(v_i\right)^{M-1}\right)\right)}\,.$$

$\square$

Proof of Proposition 4: The first order condition from optimisation problem (16) of the liquidity supplier is

$$0=\pi\,N\,\theta/\kappa^2-M\,\kappa\,\mathbb{V}[\tilde{\delta}_i]\,,$$

which provides the optimal liquidity depth (17) of the AMM. Thus, the wealth of the liquidity supplier is

$$\begin{aligned}\mathbb{E}\left[W_L\right]&=\left(\pi\,N\,-\,\sqrt{M\,\pi\,N\,\theta\,\mathbb{V}[\tilde{\delta}_i]}\right)-\sqrt{M\,\pi\,N\,\theta\,\mathbb{V}[\tilde{\delta}_i]}\\&=\pi\,N-2\sqrt{M\,\pi\,N\,\theta\,\mathbb{V}[\tilde{\delta}_i]}\,,\end{aligned}$$

proving the result. $\square$

Proof of Proposition 5: The wealth of trader i when they win or lose the PGA while M informed traders are competing is given in (6) and (7). At stage zero, the private signals have not been observed yet, so the expected validation reward is equivalent when trader i wins or loses the auction, and it corresponds to the distribution of the highest observed signal among M observations, thus

$$\mathbb{E}_0\left[W_i\left(\text{win}\right)\right]=\mathbb{E}_0\left[W_i\left(\text{lose}\right)\right]+\mathbb{E}_0\left[-\varphi\left(v_{(M)}\right)+M\,\delta_i^2/\kappa\right]\,.$$

Moreover, the probability of observing the highest signal and winning the auction is $1/M$, so the expected wealth of trader i, when they pay the cost C is

$$\begin{aligned}&\frac{M-1}{M}\,\mathbb{E}_0\left[W_i\,(\text{lose})\right]+\frac{1}{M}\,\mathbb{E}_0\left[W_i\,(\text{win})\right]\\=&\mathbb{E}_0\left[W_i\,(\text{lose})\right]+\frac{1}{M}\,\mathbb{E}_0\left[-\varphi\left(\delta\left(v_{(M)}\right)\right)+M\,\delta\left(v_{(M)}\right)^2/\kappa\right],\end{aligned}$$

where $v_{(M)}$ denotes the highest observed signal, whose cumulative distribution function is $F(\cdot)^M$. If trader i does not pay C to gather private information and participate in blockchain validation, then her expected wealth is

$$\mathbb{E}_0\left[W_i\,(\text{lose})\right]+C-\frac{\beta}{M}\,\left(\mathbb{E}_0\left[\varphi\left(\delta\left(v_{(M)}\right)\right)\right]+R\right)\,,$$

because she does not pay C but she also loses the expected validation reward. Thus, trader i invests in informed trading whenever

$$C<\frac{1}{M}\,\mathbb{E}_0\left[-\varphi\left(\delta\left(v_{(M)}\right)\right)+M\,\delta\left(v_{(M)}\right)/\kappa\right]+\frac{\beta}{M}\,\left(\mathbb{E}_0\left[\varphi\left(v_{(M)}\right)\right]+R\right)\,.$$

Using (12), this condition can be written as

$$C<\frac{1}{M}\,\mathbb{E}_0\left[\frac{2\,M}{\kappa}\frac{\int_{\underline{\delta}}^{\delta\left(v_{(M)}\right)}x\,G\left(x\right)^{M-1}\,dx}{G\left(\delta\left(v_{(M)}\right)\right)^{M-1}}\right]+\frac{\beta}{M}\,R\,,$$

and the equilibrium condition corresponds to equality in the equation above. Next, we prove that

$$2\,\mathbb{E}_0\left[\frac{\int_{\underline{\delta}}^{\delta\left(v_{(M)}\right)}x\,G\left(x\right)^{M-1}\,dx}{F\left(v_{(M)}\right)^{M-1}}\right]=\mathbb{E}_0\left[\delta^2\left(v_{(M-1)}\right)\right]-\mathbb{E}_0\left[\delta^2\left(v_{(M)}\right)\right].\qquad\text{(C5)}$$

To prove the above equality, we derive the expressions for the expected trading volumes corresponding to the highest and second highest private signals, which are distributed according to, respectively, $F(\cdot)^M$ and $M\,F(\cdot)^{M-1} - (M-1)\,F(\cdot)^M$. Using integration by parts, write

$$\begin{aligned}\mathbb{E}_0\left[\delta^2\left(v_{(M)}\right)\right] =& \int_{\underline{v}}^{\overline{v}} \delta^2(x)\; d\left(F(x)^M\right)\, dx\\ =&\overline{\delta}^2 - 2\int_{\underline{v}}^{\overline{v}} \delta(x)\;\delta'(x)\; F(x)^M\; dx\,,\end{aligned} \tag{C6}$$

and

$$\begin{aligned}\mathbb{E}_0\left[\delta^2\left(v_{(M-1)}\right)\right] =& \int_{\underline{v}}^{\overline{v}} \delta^2(x)\; d\left(M\,F(x)^{M-1} - (M-1)\;F(x)^M\right)\, dx\\ =&\overline{\delta}^2 + 2\int_{\underline{v}}^{\overline{v}} \delta'(x)\;\delta(x)\;\left((M-1)\;F(x)^M - M\,F(x)^{M-1}\right)\, dx\,,\end{aligned} \tag{C7}$$

proving (C5). Finally, use the equilibrium liquidity supply (17) to obtain the equilibrium condition (22) in the statement of the result.

Next, to show that $H(M)$ converges to zero as M goes to infinity, first write

$$\tilde{\delta}(x) = \frac{V(x)-\pi}{2\left(1+M\left(1-F(x)^{M-1}\right)\right)} \leq \frac{\overline{V}-\pi}{2\,(1+M)} \leq \frac{\overline{V}-\pi}{2\,M}\,,$$

for all $x \leq \overline{v}$, so $\sqrt{\frac{\pi\,N\,\theta}{M\,\mathbb{V}[\tilde{\delta}(v_i)]}}$ grows in M at most at a rate $\sqrt{M}$. Moreover, use (C6), (C7), and the fact that the trading volume is finite, to obtain that $\mathbb{E}_0\left[\tilde{\delta}^2\left(v_{(M)}\right)\right] - \mathbb{E}_0\left[\tilde{\delta}^2\left(v_{(M-1)}\right)\right]$ converges at a rate $M\,a^M$ for $a<1$, so the first term of $H(M)$ converges to zero as M goes to infinity. It is straightforward to see that $\beta\,R/M$ also converges to zero because β and R are fixed, proving the result. □

Proof of Corollary 1: To obtain the result, it is enough to write the expectation of the squared highest trading volume as

$$\mathbb{E}_0\left[\tilde{\delta}^2\left(v_{(M)}\right)\right] = \int_{\underline{\delta}}^{\overline{\delta}/M} x^2 d\left(F(x)^M\right) dx = \frac{\overline{\delta}^2}{M\,(2+M)}$$

and

$$\mathbb{E}_0 \left[\tilde{\delta}^2 \left(v_{(M-1)} \right) \right] = \int_{\underline{\delta}}^{\overline{\delta}/M} x^2 d \left(M \, F(\cdot)^{M-1} - (M-1) \, F(\cdot)^M \right) dx = \frac{M-1}{M \, (2 + 3 \, M + M^2)} \overline{\delta}^2 \, .$$

□

Appendix D. Equilibrium priority fees and trading volumes without impact approximation

This section solves the game described in Sections III and IV under the assumption that each trader's impact is determined by their trading signal. Without loss of generality, we present the results for the case of two informed trader i and j.

If trader i wins the auction, i.e., if $\varphi_i > \varphi_j$, her buy order is executed first, and her execution price is $V_0 - \delta_i/\kappa = -\delta_i/\kappa$; see (A2). Conversely, if trader j's order is executed first, i.e., if $\varphi_i < \varphi_j$, then trader i's execution price is $\delta_i/\kappa + 2, \delta_j/\kappa$ instead; see (A3). The corresponding wealth expressions for trader i in both cases are given by

$$\begin{cases} W_i\,(\text{win}) = & -\varphi_i - \delta_i\,\left(\delta_i/\kappa + \pi\right) \quad + \delta_i\, V \\ W_i\,(\text{lose}) = & -\delta_i\,\left(\delta_i/\kappa + 2\,\delta_j/\kappa + \pi\right) \quad + \delta_i\, V\,. \end{cases} \tag{D1}$$

In contrast to the model in the main text, the adverse price impact $2, \delta_j/\kappa$ from losing priority is now a random variable. The expected wealth of trader i is given by

$$\mathbb{E}_i\left[W_i\right] = \int_{\underline{v}}^{\overline{v}} \mathbb{1}_{\varphi_i > \varphi_j}\left(-\varphi_i + 2\,\delta_i\,\delta_j/\kappa\right)\, f\left(x\right)\, dx - \delta_i^2/\kappa - 2\,\delta_i\,\mathbb{E}_i\left[\delta_j\right]/\kappa + \delta_i\,\left(v_i - \pi\right)\,, \tag{D2}$$

where $\mathbb{E}_i\left[\delta j\right]$ represents trader i's expectation of trader j's trading volume, conditional on their own private information.

As in the main model, one can show that $\partial_{\delta_i\, v_i} \neq 0$, implying that the optimal trading volume depends on the private signal, and it is thus a random variable. Let g denote its density and G its cumulative distribution function. Similarly, $\partial_{\varphi_i\, \delta_i} \neq 0$, so the priority fee is a function of the trading volume or equivalently a function of the private signal. Trader i determines the optimal priority fee by solving

$$\sup_{\varphi_i}\left\{\int_{\underline{v}}^{\overline{v}} \mathbb{1}_{\varphi_i > \varphi_j}\left(-\varphi_i + 2\,\delta_i\,\delta_j/\kappa\right)\, f\left(x\right)\, dx\right\}\,. \tag{D3}$$

Unlike the main model, the problem (D3) corresponds to a symmetric first-price sealed-bid common value auction, where the item's value is $2\,\delta_i\,\delta_j/\kappa$. Common value auctions typically involve a winner's curse, where bidders risk overestimating the item's value. Here, trader i does not consider the naive expectation of the item's value $2\,\delta_i, \delta_j/\kappa$, but instead considers the expected value of the item conditional on the event of winning; see Chapter 4 of Menezes and Monteiro (2005) for similar problems. The optimal priority fee is characterized in the following result.

PROPOSITION 7: *The equilibrium priority fee is*

$$\varphi_i^\star = \frac{2}{\kappa}\left(\delta_i^2 - 2\,\frac{\int_{\underline{\delta}}^{\delta_i} x\,G(x)\,dx}{G(\delta_i)}\right). \tag{D4}$$

The priority fee increases in the trading volume.

Proof. Assume trader j uses the priority fee bidding strategy φ. The expected payoff of trader i is

$$\int_{\underline{\delta}}^{\varphi^{-1}(\varphi_i)} \left(-\varphi_i + 2\,\delta_i\,x/\kappa\right)\,g(x)\,dx = -\varphi_i\,G\left(\varphi^{-1}(\varphi_i)\right) + 2\,\delta_i/\kappa \int_{\underline{\delta}}^{\varphi^{-1}(\varphi_i)} x\,g(x)\,dx\,.$$

The first-order condition from problem (D3) is

$$\frac{1}{\varphi'\left(\varphi^{-1}(\varphi_i)\right)}\left(-\varphi_i + 2\,\delta_i\,\varphi^{-1}(\varphi_i)\Big/\kappa\right) g\left(\varphi^{-1}(\varphi_i)\right) - G\left(\varphi^{-1}(\varphi_i)\right) = 0\,.$$

In equilibrium, trader i employs the same strategy, in which case $\varphi^{-1}(\varphi_i) = \delta_i$. This gives

$$g(\delta_i)\left(2\,\delta_i^2\Big/\kappa\right) = G(\delta_i)\;\varphi'(\delta_i) + \varphi(\delta_i)\;g(\delta_i) \implies G(\delta_i)\;\varphi(\delta_i) = \int_{\underline{\delta}}^{\delta_i} g(x)\left(2\,x^2\Big/\kappa\right)\,dx\,.$$

Applying integration by parts yields the result in (D4). □

In equilibrium, the priority fee as a function of trading volume take a similar for to that in Section III. However, the relationship between trading volume and the trading signal differs, and the distribution of equilibrium trading volumes is different from that in (10). For consistency, we continue to denote the distribution of the trading signal by g, despite it now representing a different distribution. In what follows, we employ the notation

$$V_i(v) = \mathbb{E}_i \left[V \mid v_i = v \right] = \int \mathbb{E} \left[V \mid v_i = v, v_j = x \right] \, f\left(x\right) \, dx \quad \text{and} \quad V_i'(v) = \partial_v V_i(v) \, .$$

The next result characterises the equilibrium trading volume and demonstrates that it retains the same properties as those established in Proposition 3 and the main model in the text.

PROPOSITION 8: *The equilibrium trading volume is*

$$\delta_i^\star = \delta\left(v_i\right) = e^{F(v_i)} \left(\underline{\delta} + \frac{\kappa}{2} \int_{\underline{v}}^{v_i} e^{-F(x)} V_i'\left(x\right) dx \right) \, , \tag{D5}$$

where $\underline{\delta} = \frac{\kappa}{2} \left(V_i(0) - \pi \, e^{-1}\right) + \frac{\kappa}{2} \int_{\underline{v}}^{\overline{v}} e^{-F(x)} V_i(x) \, f(x) \, dx > 0$. *The trading volume is an increasing and continuously differentiable function of the private signal.*

Proof. Use the priority fee (D4) to write trader i's wealth (D2) as

$$\mathbb{E}_i \left[W_i \right] = \frac{4}{\kappa} \int_{\underline{\delta}}^{\delta_i} x \, G\left(x\right) \, dx - \frac{2}{\kappa} \, \delta_i \int_{\underline{\delta}}^{\delta_i} G\left(x\right) \, dx - \delta_i^2 / \kappa - 2 \, \delta_i \, \mathbb{E}_i \left[\delta_j \right] / \kappa + \delta_i \, \left(V_i - \pi \right) \, .$$

The first-order condition for the optimal trading volume is

$$0 = \frac{2}{\kappa} \delta_i \, \left(G\left(\delta_i\right) - 1 \right) - \frac{2}{\kappa} \int_{\underline{\delta}}^{\delta_i} G\left(x\right) \, dx - 2 \, / \kappa \int_{\underline{v}}^{v_i} \delta_j\left(x\right) \, f\left(x\right) \, dx + V_i - \pi \, .$$

In equilibrium, both traders employ the same trading volume function δ. Use $G\left(x\right) = F\left(\delta^{-1}\left(x\right)\right)$ and the first-order condition to write the following equation for δ:

$$0 = -\frac{2}{\kappa} \delta\left(v_i\right) - \frac{2}{\kappa} \int_{v_i}^{\overline{v}} \delta\left(y\right) \, f\left(y\right) \, dy + V_i(v_i) - \pi \, .$$

This yields the boundary condition $\delta(\overline{v}) = \kappa(V_i(\overline{v}) - \pi)/2$. Differentiating with respect to v_i gives the ordinary differential equation

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

whose solution is

$$\delta(v_i) = e^{F(v_i)} \left(c + \frac{\kappa}{2} \int_{\underline{v}}^{v_i} e^{-F(x)} V_i'(x)\, dx \right) .$$

The boundary condition at $v_i = 0$ gives $c = \underline{\delta} = \delta(0)$ and the boundary condition at $v_i = \overline{v}$ gives

$$\underline{\delta} = \frac{\kappa}{2} \left(V_i(0) - \pi\, e^{-1} \right) + \frac{\kappa}{2} \int_{\underline{v}}^{\overline{v}} e^{-F(x)} V_i(x)\, f(x)\, dx\, ,$$

which is positive by Assumption 1. Finally, the derivative of the equilibrium trading volume is

$$\delta'(v_i) = \frac{\kappa}{2} V_i'(v_i) + e^{F(v_i)} \left(\underline{\delta} + \frac{\kappa}{2} \int_{\underline{v}}^{v_i} e^{-F(x)} V_i'(x)\, dx \right)$$

which is positive. □

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