Open Data, Order-Flow Privacy, and Market Quality

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Outline

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2. Model Setup
3. Trading Equilibrium
4. Endogenous Data Sales
5. Optimal Data Design
6. Empirical Evidence
7. Conclusion

Data antitrust is a global regulatory trend

Regulators increasingly intervene to dismantle information monopolies:

- **US.** SEC *Market Data Infrastructure Rule*: competing consolidators.
- **EU.** 2020 in-depth review of the LSEG / Refinitiv acquisition.
- **China.** 2023 antitrust action ending an exclusive bond-data agreement.

The common belief behind "Open Data" initiatives:

turning data monopolies into competitive markets improves market quality.

This paper identifies a critical oversight in this view.

Open Data involves two different types of data

Opening data, in practice, involves two different kinds of data:

Fundamental data

Signals about asset value.

e.g. Open banking, credit histories.

Reduces information asymmetry.

Non-fundamental data

Signals about trading.

e.g. Real-time order, PFOF-style data.

Exposes trading intentions.

This paper

Does competition in data markets always improve market quality, once data includes non-fundamental order-flow information?

We frame the answer as the open data paradox in capital markets:

1. Extend **Kyle (1985)**: traders may acquire data on the size of noise trading.
2. Introduce an **upstream data market**; compare six data market structures.
3. Characterize the optimal data design: selective openness.
4. Test predictions using **China's 2023 bond-data antitrust** intervention.

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Kyle (1985) with two types of data

A single risky asset with terminal value $\theta \sim N(0, \tau_\theta^{-1})$, prior mean normalized to 0.

- N **potential rational traders.** Risk-neutral, submit market orders x_i.
- **Noise traders.** Submit an aggregate random order $u \sim N(0, \tau_u^{-1})$, independent of θ.
- **Competitive market maker.** Observes only aggregate order flow $y = \sum_i x_i + u$, sets $p(y) = \mathbb{E}[\theta \mid y]$ (zero expected profit).

Upstream data sellers can produce two signals:

Fundamental data

$$s_f = \theta + \epsilon_f, \quad \epsilon_f \sim N(0, \tau_f^{-1})$$

helps form a belief about θ.

Non-fundamental data

$$s_n = u + \epsilon_n, \quad \epsilon_n \sim N(0, \tau_n^{-1})$$

Not useful on its own: $u \perp \theta$.

Information structure: four trader types

The data market partitions the N rational traders into four types:

Type	Information set	Mass
FN-type	$\{s_f, s_n\}$, the full package	N_{fn}
F-type	$\{s_f\}$, fundamental only	N_f
N-type	$\{s_n\}$, order-flow only	N_n
U-type	$\varnothing$, uninformed	N_u

Two sufficient statistics summarize the information structure:

$$M \equiv N_f + N_{fn} \quad \text{(fundamental access)}, \qquad K \equiv N_n + N_{fn} \quad \text{(order-flow access)}.$$

Six data-sales regimes

"Open Data" means non-discriminatory *access*, not free data. Sellers monetize access.

	Integrated (one seller, both)	**Segmented** (one data type each)
Monopoly	I. Integrated monopoly	II. Segmented monopoly
Competition	IV. Integrated competition	III. Segmented competition
Asymmetric	V. & VI. Generalist vs. specialist (overlap in s_f or s_n)	

- **Integration.** Whether one seller controls both data types (internalization).
- **Competition.** Whether ≥ 2 sellers operate within a data market.
- **Asymmetric oligopoly.** A generalist vs. a specialist.

Timing and equilibrium

The game has three stages:

- $t = 0$. **Data-market competition.** Each data provider chooses the quantity of data to supply, (N_{fn}, N_f, N_n), to maximize its ex-ante profit.
- $t = 1$. **Trading.** Traders realize their types, observe signals, and submit orders simultaneously.
- $t = 2$. **Pricing.** The market maker observes y, sets $p(y)$; payoffs realize.

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The unique linear equilibrium

Take the information structure (N_{fn}, N_f, N_n, N_u) as given. **Linear strategies:**
F-type: $x^f = \beta_f \hat{\theta}_f$ with $\hat{\theta}_f \equiv \mathbb{E}[\theta \mid s_f]$;
N-type: $x^n = \gamma_n \hat{u}_n$ with $\hat{u}_n \equiv \mathbb{E}[u \mid s_n]$;
FN-type: $x^{fn} = \beta_{fn} \hat{\theta}_f + \gamma_{fn} \hat{u}_n$;
U-type: $x^u = 0$.

Proposition 1

Let $M \equiv N_f + N_{fn}$ and $K \equiv N_n + N_{fn}$. A unique symmetric linear equilibrium exists:

$$\beta = \frac{1}{\lambda(M+1)}, \qquad \gamma = -\frac{1}{K+1}, \qquad \lambda = \frac{\sqrt{M}}{M+1}\sqrt{\frac{\tau_f}{\tau_\theta(\tau_f+\tau_\theta)}}\,\frac{1}{\sqrt{h(K)}},$$

where $h(K)$ is the residual noise in order flow, strictly decreasing in K.

Proposition 1: four key findings

1. **Linear additivity.** $\beta_f = \beta_{fn}$ and $\gamma_n = \gamma_{fn}$, and $x^{fn} = x^f + x^n$: holding one signal does not change how a trader uses the other.

2. **Trading against expected noise.** $\gamma = -\frac{1}{K+1} < 0$: traders with s_n trade *against* the noise they predict.

3. **Profitable without fundamental information.** A non-fundamental trader earns rents, even without any knowledge about fundamentals, both ex-ante and ex-post.

4. **Fundamental data always matters.** If $M = 0$, order flow carries no information, $\lambda = 0$, and all order-flow rents vanish. The value of s_n comes from the price impact.

Non-fundamental data is independently profitable

The market maker cannot separate informed orders from noise, so she prices *all* order flow the same way, $p = \lambda y$. A trader who observes u knows part of that price move is "wrong" and bets against it.

Example: $M = K = 1$, perfect signals, $\tau_\theta = \tau_u = 1 \Rightarrow \lambda = 1,\ \beta = 0.5,\ \gamma = -0.5$.

	x^f	x^n	y	p	Non-fund. profit $(\theta - p)\, x^n$
State 1: $\theta = 2,\ u = +1$ (same sign)	1	-0.5	1.5	1.5	-0.25
State 2: $\theta = 2,\ u = -1$ (opposite sign)	1	$+0.5$	0.5	0.5	$+0.75$

When u aligns with θ, the trade is on the wrong side but the mispricing is small. When u opposes θ, the mispricing is large and the trade is on the right side.

Gains exceed losses $\Rightarrow$ strictly positive expected profit, with zero fundamental knowledge.

Data access and market quality

How do fundamental access (M) and order-flow access (K) move market quality?

Market-quality measure	$M \uparrow$	$K \uparrow$
Market depth $MD = 1/\lambda$	$\uparrow$	$\downarrow$
Informational efficiency IE	$\uparrow$	$\rightarrow$ no effect
Order-flow volatility $\mathrm{Var}(y)$	$\uparrow$	$\downarrow$
Noise-trader welfare W_{noise}	$\uparrow$	$\uparrow$

- Order-flow data hurts depth yet does nothing for price discovery.
- Low volatility need not mean a liquid market: $K \uparrow$ lowers both volatility and depth.

The value of data

Ex-ante expected profit of a j-type trader: $\pi_j \equiv \mathbb{E}\big[\,\mathbb{E}[x^j(\theta - p) \mid \mathcal{I}_j]\,\big]$.

The value of data is the difference in π_j with and without access: $v_f \equiv \pi_{fn} - \pi_n$, $v_n \equiv \pi_{fn} - \pi_f$.

$$v_f(M,K) = \frac{\tau_f}{\tau_\theta(\tau_f+\tau_\theta)}\,\frac{1}{\lambda(M+1)^2}, \qquad v_n(M,K) = \frac{\tau_n}{\tau_u(\tau_u+\tau_n)}\,\frac{\lambda}{(K+1)^2}.$$

- **Additivity:** $\pi_{fn} = \pi_f + \pi_n$.

Data sales generate externalities among buyers

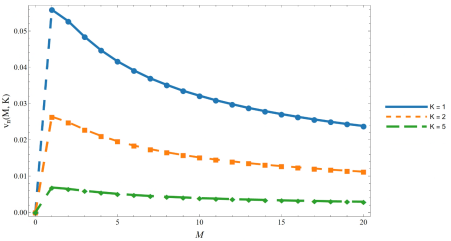
Strategic substitutability

$$\frac{\partial v_f}{\partial M} < 0, \quad \frac{\partial v_f}{\partial K} < 0, \quad \frac{\partial v_n}{\partial K} < 0.$$

Each extra informed trader imposes a negative externality on the others.

Non-monotone externality in M

$v_n = 0$ at $M = 0$; jumps to its global max at $M = 1$; then strictly falls for $M > 1$.



Value of non-fundamental data $v_n(M, K)$.

A monopolist has an incentive to internalize this externality and restrict sales.

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Why study data-market structure?

Regulating data products is hard: vendors repackage equivalent information. A more feasible regulatory method is to intervene structure of the data market.

We vary the data market along two dimensions:

- **Monopoly vs. competition.** How many sellers operate within a data market? With ≥ 2 sellers, each internalizes only a fraction of any externality.
- **Integrated vs. segmented operation.** Does one seller control both data types?

An seller may internalize two externalities:

- **Own-market dilution.** Selling more of a data type lowers its own marginal value: informed traders' rents are spread thinner.
- **Cross-market externality.** The two data types are strategic substitutes.

Equilibrium data sales across the six regimes

Regime	(M, K)	Economic content
I. Integrated monopoly	$(1, 0)$	internalizes externality; suppresses s_n
II. Segmented monopoly	$(1, \geq 1)$	s_n seller ignores the externality
III. Segmented competition	(N, N)	full saturation once ≥ 2 sellers
IV. Integrated competition	$(\leq N, N)$	partial internalization
V. Asym. oligopoly (s_f)	$(\geq 1, \leq K^{II})$	generalist may self-segment
VI. Asym. oligopoly (s_n)	$(1, N)$	s_f stays monopolistic

- A fundamental-data monopolist always sells to one trader ($M = 1$).
- With ≥ 2 non-cross-selling sellers, they sell as much data as possible: non-linear Cournot.

No single regime is optimal

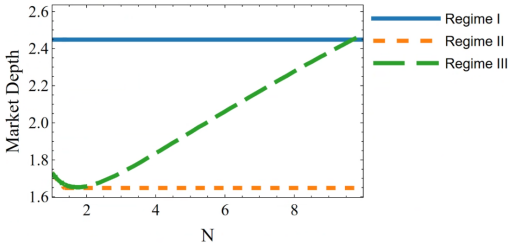
The optimality of data market structures depend on measures of financial market quality:

- **Informational efficiency:** $IE^I = IE^{II} \leq IE^{III}$. Competition always wins.
- **Market depth:** $MD^{III} \leq MD^I$ iff $N \leq \widehat{N}$. Monopoly wins in small markets.
- **Order-flow volatility:** minimized by the *segmented monopoly*.
- **Noise-trader welfare:** $W^I_{\text{noise}} < W^{II}_{\text{noise}} \leq W^{III}_{\text{noise}}$. Competition wins.

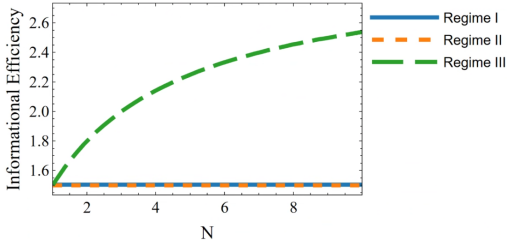
where $\widehat{N} = 1 + 2\rho_n + \sqrt{4\rho_n^2 + 3\rho_n}$, with $\rho_n \equiv \tau_n/\tau_u$, increasing in ρ_n.

The optimal regime depends on the regulator's objective and on market size N.

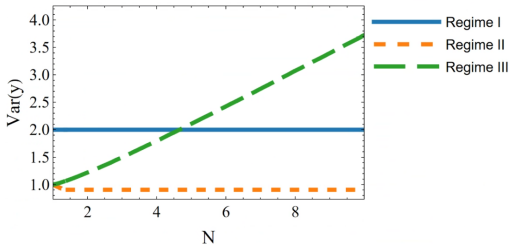
Market size N and market quality



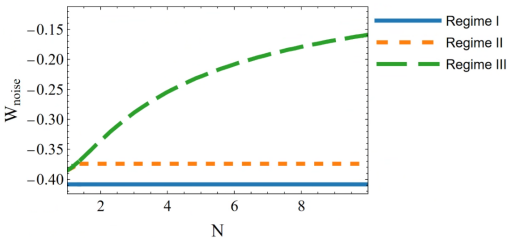
(a) Market depth



(b) Informational efficiency



(c) Order-flow volatility



(d) Noise-trader welfare

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Is the open data paradox unavoidable?

The six regimes generate only a limited collection of allocations (M, K).

Let a regulator choose (M, K) directly, subject to the equilibrium pricing of Proposition 1. The objective is an *institutional mandate*:

$$W(M,K) = \alpha\, IE + \beta\, MD + \gamma\, W_{\text{noise}} - \zeta\, \text{Var}(y), \qquad (\alpha,\beta,\gamma,\zeta) \in \mathbb{R}^4_+.$$

- α, β: price discovery and liquidity.
- γ: retail-investor welfare. ζ: order-flow-volatility penalty.

Selective openness

Proposition: selective openness

Under an efficiency–liquidity mandate ($\alpha, \beta > 0$, $\gamma = \zeta = 0$), the regulator's problem has a unique maximizer

$$(M^*, K^*) = (N, 0) :$$

full fundamental access, full order-flow suppression. It *weakly dominates every one of the six regimes* in both *IE* and *MD*.

- The open data paradox reflects the *bundling* of fundamental access with order-flow disclosure.
- Implementing $(N, 0)$ requires competition in fundamental data, while restricting order-flow data sales.
- **Robustness region $\mathcal{R}$.** For $\gamma > 0, \zeta > 0$, there exists $\mathcal{R} \neq \emptyset$, the set of weights $(\alpha, \beta, \gamma, \zeta)$ for which $(N, 0)$ remains the unique optimum. It is an open neighborhood of the pure efficiency–liquidity slice $\{(\alpha, \beta, 0, 0)\}$.

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A natural experiment: China's interbank bond market

Setting. About 80% of bond trading; few participants and broker-reliant, hence a small-N market.

The monopoly. A dominant data vendor (*Firm S*) held a decade-long exclusive agreement with one of six major brokers (*Broker X*), becoming the only platform aggregating all six brokers' real-time quote and transaction data.

The shock, March 2023. China's first data antitrust action banned exclusivity clauses; within days, rival platforms integrated Broker X's data.

A clean, exogenous shift: data monopoly $\rightarrow$ data competition.

Empirical design

Difference-in-differences, bond-month panel, 2021–2025; 700 bonds, 24,025 obs.

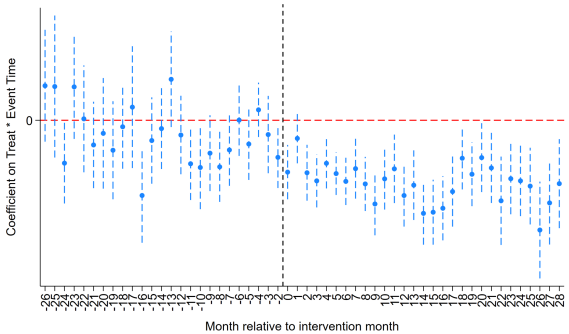
$$Y_{it} = \alpha + \beta\,(Treat_i \times Post_t) + \gamma X_{it} + \mu_i + \lambda_t + \varepsilon_{it}$$

- **Treat:** bonds ever matched by Broker X before the intervention.
- **Post:** March 2023 and later.
- **Informational efficiency:** price deviation $= \left|\frac{\text{close price}-\text{valuation}}{\text{valuation}}\right|$.
- **Liquidity:** turnover = volume / outstanding market value.
- Controls: rating, maturity, duration, convexity, type; bond & month FE; SE clustered by bond.

Result 1: informational efficiency improved

	(1)	(4)
$Treat \times Post$	-0.011^{***}	-0.004^{***}
	(0.001)	(0.001)
Controls / FE	No	Yes
Observations	24,025	24,025

Outcome: price deviation.



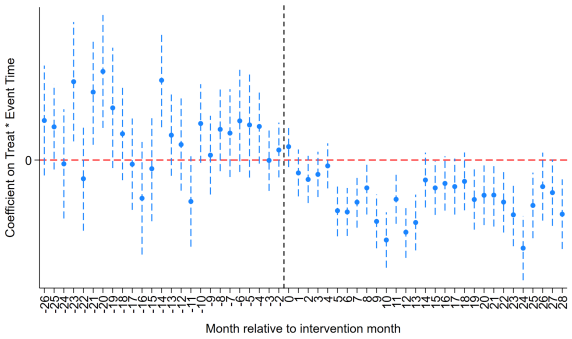
Event study: price deviation.

Price deviations fell 30 to 40 bps, immediate and persistent.

Result 2: market liquidity declined

	(1)	(4)
Treat × *Post*	−0.158***	−0.042***
	(0.010)	(0.014)
Controls / FE	No	Yes
Observations	24,025	24,025

Outcome: turnover.



Event study: turnover.

Turnover declined steadily: the open data paradox

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Conclusion

- Data market structure governs the type of data released.
- Fundamental and non-fundamental data have distinct, interacting effects: competition aids price discovery but can harm liquidity, the open data paradox.
- A regulator can escape the paradox through selective openness: open fundamental data fully, withhold or coarsen order-flow data.
- China's 2023 bond-data antitrust confirms the trade-off: efficiency $\uparrow$, turnover $\downarrow$.
- Open Data is not unambiguously welfare-improving. Optimal regulation must account for data type, market size and structure.

Thank you!

Comments and questions welcome.