PRIVATE BRIEF

Brief 55+

Beyond the AI Conspiracy: A Diagnostic for Coordination

September 2025

Demo: https://acd-monitor.vercel.app/
Code Repository: https://github.com/yomarfrancisco/acd-monitor
Product specification: https://github.com/yomarfrancisco/acd-monitor/blob/main/docs/product_spec_v2.2.md:

Summary

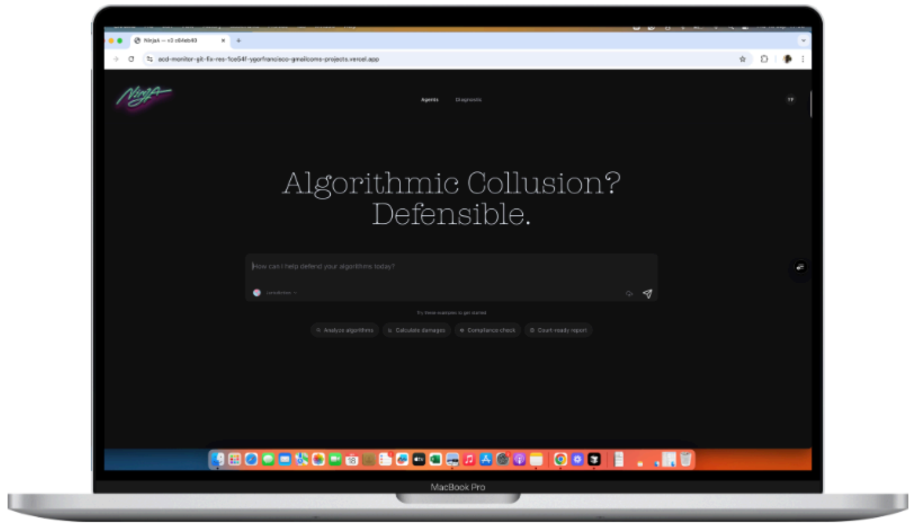
Enforcement agencies face an acute challenge in distinguishing legitimate algorithmic competition from anticompetitive coordination. Current approaches rely on theoretical speculation without systematic methodology, creating regulatory uncertainty that chills innovation while potentially missing genuine coordination.

The **Algorithmic Coordination Diagnostic** (ACD) framework provides objective, empirically grounded tools for this distinction. Drawing on advances in causal inference and continuous validation techniques, the ACD tests whether algorithmic pricing relationships remain **invariant** across market environments — a key signature of coordination — or **adapt** dynamically as competitive conditions change.

This methodology is particularly powerful in data-intensive sectors (Airlines, Hospitality, E-commerce, Shipping and Logistics, Real-Estate, Digital Advertising, Gaming, Telecommunications, Insurance and Financial Services) where algorithmic sophistication, public pricing and data density enable robust statistical analysis. The framework

- Enables firms to **continuously monitor** their algorithmic pricing for coordination risks *before* regulatory scrutiny,
- Offers competition authorities **evidence-based investigation** criteria, and
- Gives courts and compliance experts analytically rigorous evidence that moves beyond superficial parallelism.

Not merely conceptual, the diagnostic is productionised in a minimal functional demo, "Ninja": an agent-driven protocol that interprets econometric results and generates court-ready outputs that regulators, firms, and judges can easily understand and act on: https://acd-monitor.vercel.app/.



1. Introduction

The regulatory obsession with algorithmic pricing continues: the European Commission, the CMA, and the OECD persist in warning that pricing algorithms facilitate collusion by increasing transparency and reducing deviation incentives.[1] Commissioner Vestager was adamant that companies "cannot escape responsibility for collusion by hiding behind a computer program."[2] The enforcement rhetoric has intensified despite a notable absence of robust **empirical evidence** supporting "worst-case" theoretical predictions.

RBB's **Brief 55** demonstrated that these regulatory fears rest on highly stylised game-theoretic conditions that ignore the complexity of real markets.[3] The essential economic logic of the coordination problem — that individual incentives to deviate remain powerful even with algorithmic pricing — has not changed. Real markets continue to exhibit product differentiation, cost heterogeneity, demand volatility, entry threats, and other features that destabilise coordination.

What has emerged is a dangerous **enforcement gap**. Regulators face political pressure to act against algorithmic pricing but lack systematic methodology for distinguishing *legitimate competitive adaptation* from *actual coordination*. This creates a perverse situation where firms face investigation risk simply because their algorithms generate parallel pricing patterns — regardless of whether those patterns reflect competition or collusion.

While these concerns apply broadly, the enforcement challenge has become most acute in high-frequency, data-rich sectors — e.g., airlines, e-commerce, digital advertising, gaming, telecommunications, hotels, cryptocurrency and financial services — where algorithmic sophistication and open (API-sourced) pricing creates both the greatest coordination risks and the most robust opportunities for empirical analysis.

The current state of enforcement is unsustainable:

1. OECD (2017), Algorithms and Collusion: Competition Policy in the Digital Age, DAF/COMP(2017)4.

2. Vestager, M. (2017), Algorithms and Competition, Bundeskartellamt 18th Conference on Competition, 16 March 2017.

3. RBB Brief 55 (2018), Automatic Harm to Competition? Pricing algorithms and coordination

1. Courts cannot adjudicate complex algorithmic pricing cases without proper diagnostic tools, and
2. Firms cannot operate under the threat that any parallel algorithmic behaviour will be presumed anticompetitive.

What is urgently needed is a **Structured Diagnostic Approach** — one that enables firms to proactively audit their pricing algorithms while providing regulators with systematic methodology that can distinguish competitive from coordinated algorithmic behaviour.

2. The Economics of Environment Sensitivity

The diagnostic framework rests on a fundamental asymmetry between competitive and coordinated conduct that connects directly to classic coordination problems in oligopoly theory. Schelling demonstrated that successful coordination requires **focal points** — obvious strategies that provide common understanding.[4] Green and Porter showed that sustainable coordination needs effective **monitoring** and **punishment** mechanisms.[5] These foundational insights remain valid in algorithmic environments and create specific empirical signatures that the ACD framework detects.

- ➔ Competitive firms face genuine uncertainty about optimal responses to **ongoing environmental changes.** Cost shocks, demand shifts, competitor entry, and regulatory changes require case-by-case evaluation of profit-maximising strategies. This uncertainty naturally generates **variation** in competitive responses across different market environments. A competitive algorithm responding to a cost shock will exhibit different pricing relationships than the same algorithm responding to a demand surge or competitive entry.
- ➔ Coordinated firms, by contrast, benefit from predictable **invariant response** patterns that provide focal points for sustained cooperation. Environmental sensitivity would destabilise coordination by creating ambiguity about appropriate responses. *If firms have agreed that Company A should raise prices by 3% whenever Company B raises by 5% for instance, introducing environment-specific variations would undermine this coordination mechanism by creating uncertainty about when and how much to respond.*

This insight draws on recent advances in causal inference[6] and established industrial organisation literature demonstrating that successful tacit coordination requires common understanding of "the rules of the game." Environmental sensitivity undermines such understanding because it requires firms to continuously renegotiate appropriate responses to changing conditions — precisely the type of complex contingent contracting that makes coordination difficult to sustain.

Synthesis: **coordination requires invariance; competition generates adaptation.** This principle provides the foundation for an empirically testable diagnostic framework.

.4. Schelling, T.C. (1960), The Strategy of Conflict, Harvard University Press.

5. Green, E.J. and Porter, R.H. (1984), "Noncooperative Collusion under Imperfect Price Information," Econometrica, 52(1), 87-100.

6. Peters, J., Bühlmann, P. & Meinshausen, N. (2016), "Causal inference by using invariant prediction: identification and confidence intervals," Journal of the Royal Statistical Society: Series B, 78(5), 947-1012.

3. The Enforcement Problem

Even allowing for oligopolistic market structure, product homogeneity and transparent pricing (including interseller price verification), the central challenge lies in regulators' inability to distinguish between two fundamentally different phenomena:

- **Parallel behaviour** arising from competitive adaptation to transparent market conditions
- **Parallel behaviour** reflecting genuine coordination

Competition law has *long* recognised that parallel conduct alone **does not** constitute evidence of agreement or concerted practice.[7] The 'Wood Pulp' judgment established this principle decades ago, yet enforcement agencies appear to have forgotten this lesson when AI enters the picture. The speed and sophistication of algorithmic responses can create pricing patterns that superficially resemble coordination even when they result from entirely independent competitive decision-making.

7. Case C-89/85, A. Ahlström Osakeyhtiö and others v Commission (Wood Pulp) [1993] ECR I-1307.

3.1. The theoretical obsession

Current enforcement approaches rely heavily on "grim" and "stick-and-carrot" models that demonstrate algorithmic coordination is possible under sufficiently large discount factors (i.e., perspectives about the future) and infinitely high renegotiation costs .[8] These models typically assume perfect transparency, instantaneous responses, infinite period games, static discount rates and simplified market structures that bear little resemblance to real competitive environments.

8. Salcedo, B. (2015), "Pricing Algorithms and Tacit Collusion"; Calvano, E. et al. (2020), "Artificial Intelligence, Algorithmic Pricing and Collusion," American Economic Review, 110(10), 3267-3297.

While such models provide valuable insights into potential coordination mechanisms (e.g. Reinforcement Learning might lead to algorithmic rationalization through trial and error that following a price leader is yield-enhancing, even without explicitly communicating or colluding), they cannot substitute for empirical analysis of realised dynamic market behaviour. The problem is compounded by regulators' tendency to treat theoretical possibility as empirical inevitability, leading to enforcement approaches that presume guilt rather than requiring proof of anticompetitive algorithmic conduct.

3.2. The enforcement vacuum

What is missing from current practice is systematic methodology for examining real market data to determine whether algorithmic behaviour exhibits competitive or coordinated characteristics. This creates several problems:

- **Firms** face regulatory uncertainty that chills innovation in pricing systems
- **Courts** are asked to adjudicate cases without proper economic frameworks
- Genuine coordination may escape detection because enforcers focus on **superficial parallelism**
- **Resources are wasted** investigating spurious correlations rather than systematic patterns

4. Enter 'The Algorithmic Coordination Diagnostic'

The ACD framework addresses this enforcement gap by providing systematic methodology for distinguishing competitive from coordinated algorithmic behaviour, grounded in recent advances in causal inference and econometric modelling while remaining practical for courtroom application.

4.1. Environment partitioning approach

The framework *first* partitions pricing data into distinct "environments" based on observable changes in market conditions. These environments vary by sector (and by implication 'algorithm-type;):

- **Airlines**: Route-level demand elasticity shifts, fuel price changes, slot constraints, seasonal capacity adjustments, weather disruptions
- **E-commerce platforms**: Inventory cycles, search algorithm updates, promotional calendars, supply chain disruptions, customer behaviour changes
- **Digital advertising**: Keyword seasonality, conversion changes, budget cycles, platform policy changes, competitive intensity shifts
- **Financial services**: Market volatility regimes, regulatory announcements, liquidity stress, arbitrage opportunities, interest rate cycles

The diagnostic methodology adapts to different algorithmic architectures — from simple rule-based price matching to complex reinforcement learning systems — with environment sensitivity expectations calibrated to each algorithm type's coordination risk profile. **The economic logic is straightforward**: if algorithmic pricing reflects genuine competitive adaptation, firms' pricing relationships should vary across different market environments. Coordinated behaviour should exhibit *structural stability* that persists regardless of environmental changes.

4.2. Continuous monitoring and dynamic validation

Building on advances in sequential inference, the ACD framework then incorporates continuous monitoring using **Variational Method of Moments** (VMM) techniques adapted from financial risk management. This approach enables firms to monitor their pricing algorithms in real-time for coordination patterns while providing regulators with tools that:

- **Detect deterioration in real-time** without requiring pre-defined environmental categories
- **Discover environments endogenously** by detecting structural breaks in pricing relationships
- **Provide dynamic confidence scoring** with evolving confidence intervals
- **Reduce gaming potential** by avoiding fixed environmental definitions

4.3. Invariance testing

Both approaches apply **Invariant Causal Prediction (ICP)** techniques to test whether price relationships between competitors remain structurally stable.[9] This provides formal statistical tests for whether observed relationships are "invariant"

9. Giordani, P. & Kohn, R. (2008), "Efficient Bayesian inference for multiple change-point and mixture innovation models," Journal of Business & Economic Statistics, 26(1), 66-77.

(suggesting coordination) or "environment-sensitive" (consistent with competition).

Example: *Two South African fuel retailers using algorithmic pricing. If Company A consistently raises prices by R2 per litre whenever Company B raises by R3 per litre — regardless of whether the trigger is a crude oil shock, holiday weekend, or new competitor entry — this invariant relationship suggests coordination. If responses vary systematically (R1.5 during cost shocks, R2.5 during demand surges, no response to new entry), this environment-sensitivity indicates competitive adaptation.*

4.4. Multi-layer validation

The framework incorporates complementary validation approaches:

- **Information flow analysis**: Identifies consistent price leadership patterns vs. dynamic competitive responses
- **Network analysis**: Maps how pricing influence propagates through competitive networks
- **Regime-switching detection**: Identifies distinct periods of pricing behaviour coinciding with specific events
- **Statistical confidence mapping**: Translates statistical significance into enforcement guidance (95%+ warrants investigation, 90-95% suggests monitoring, lower levels indicate competition)

5. Empirical Validation

Beyond these forward-looking implementation possibilities, the ACD framework gains credibility through retrospective application to documented coordination cases.

The CMA poster frames investigation (2015)[10]

Online sellers agreed to use similar algorithmic pricing strategies to coordinate prices on Amazon. Applying ACD retrospectively:

- **Environmental analysis**: The market experienced seasonal demand variations, Amazon policy changes, and new seller entry
- **Invariance testing**: Coordinating firms maintained highly stable pricing relationships across environments, while non-coordinating competitors showed significant variation
- **Multi-layer validation**: Would have revealed consistent price leadership patterns and structural relationship stability
- **Implication**: ACD would have flagged this case based on invariant relationships, providing objective basis for investigation

U.S. v. Airline Tariff Publishing Co.

Carriers used a computerised system to signal pricing intentions. ACD-style analysis would have examined whether fare relationships remained invariant across route-specific demand shocks, fuel price changes, and competitive entry. Competitive airlines would have shown different sensitivities to business vs. leisure demand, fuel hedging positions, and slot constraints, while coordinating

10. CMA (2015), Online Pricing of Posters and Frames, Decision of 4 December 2015.

carriers would have maintained stable relationships regardless of environmental factors.

6. Implementation and Commercial Applications

6.1. Implementation roadmap

- **Phase 1 (Months 1-6)**: Pilot validation with retrospective analysis of known cases and methodology refinement
- **Phase 2 (Months 7-12)**: Regulatory sandbox with pilot applications, court protocols, and training programs
- **Phase 3 (Year 2)**: Industry compliance programs with proactive auditing and continuous monitoring
- **Phase 4 (Year 3)**: Full deployment as standard investigative tool with international harmonisation.

6.2. Commercial opportunities

- **For firms developing pricing systems** (from rule-based matching to ML ensemble methods): Proactive compliance audits, real-time monitoring for regulatory risk, algorithm design guidance, early warning systems for potentially problematic patterns
- **For competition authorities**: Objective investigation criteria, reduced false positives, court-friendly evidence, proportionate enforcement
- **For merging parties**: Structured coordinated effects assessment, empirical basis for rebutting theories, proactive compliance assessment
- **For litigation**: Quantitative evidence against conspiracy claims, strengthened expert testimony, structured defence against allegations

6.3. Real-time compliance monitoring for firms

The ACD framework's primary commercial application enables firms to apply the methodology **proactively**, transforming regulatory compliance from reactive defense to continuous risk management through:

- **Regulatory preparedness** with documented competitive behaviour
- **Risk management** through early pattern detection
- **Competitive advantage** via optimised yet clearly competitive pricing strategies
- **Algorithm design** integration ensuring competitive characteristics from inception

6.4. Advanced Implementation: Incentive-Aligned Enforcement

Rather than viewing gaming as a limitation, adoption by regulators transforms the ACD into a market mechanism for enforcement. The framework enables a modular algorithmic bounty component (i.e. think of this as an algorithmic leniency program) where market participants earn rewards (fiat or token-based) by contributing validated moment conditions to the VMM framework, making enforcement endogenous and adaptive.

- **Prisoner's Dilemma Inversion:** Bounty systems reverse coordination

payoffs by rewarding defection through coordination reporting. When algorithms profit from detecting rivals' coordination, Nash equilibria shift toward competitive behavior.
- **Endogenous Learning:** Market participants (including competition authorities) can contribute moment conditions that improve system-wide detection accuracy. This ensures only statistically meaningful contributions receive compensation while the framework adapts with scale.
- **Information Asymmetry Exploitation:** Coordinating firms possess precise information about their own patterns. Bounty systems transform this inside knowledge from a coordination asset into a competitive liability as rivals monetize detection capabilities.

This approach transforms enforcement from external regulatory oversight into an adaptive market mechanism that aligns private detection incentives with competitive objectives.

7. Limitations and Challenges

The ACD framework should be understood as an analytical tool to inform economic assessment rather than a definitive legal test.

- **Technical limitations**: Requires high-frequency pricing data over extended periods; works best where price is the main competitive variable; relies on observable environmental changes; statistical outputs require expert interpretation
- **Sector-specific challenges**: Most effective in data-intensive sectors with frequent pricing decisions and opportunity for repeated AI interaction; limited application in traditional industries with infrequent changes; mixed effectiveness in highly differentiated markets
- **Legal adaptation**: Different jurisdictions have varying coordination standards; designed to supplement rather than replace traditional analysis; cross-border cases may require harmonised approaches

8. Academic Robustness and Policy Acceptance

The framework's success depends on regulatory acceptance and judicial confidence, supported by:

- **Established econometric principles** widely accepted in academic and policy circles
- **Conservative application** focusing initially on clear cases with observable variation
- **Methodological transparency** enabling full disclosure and peer review
- **Complementary evidence** strengthening rather than superseding existing investigative tools

Addressing potential criticisms: The framework complements traditional market structure analysis, acknowledges real-world competitive pressures preserve competition even in algorithmic environments, and makes gaming prohibitively complex through multi-layer validation.

9. Conclusions

The current state of algorithmic pricing enforcement represents a failure of evidence-based policy. Regulators have allowed theoretical speculation to drive enforcement without developing tools to distinguish competition from coordination, risking condemnation of efficient innovation while missing genuine collusion.

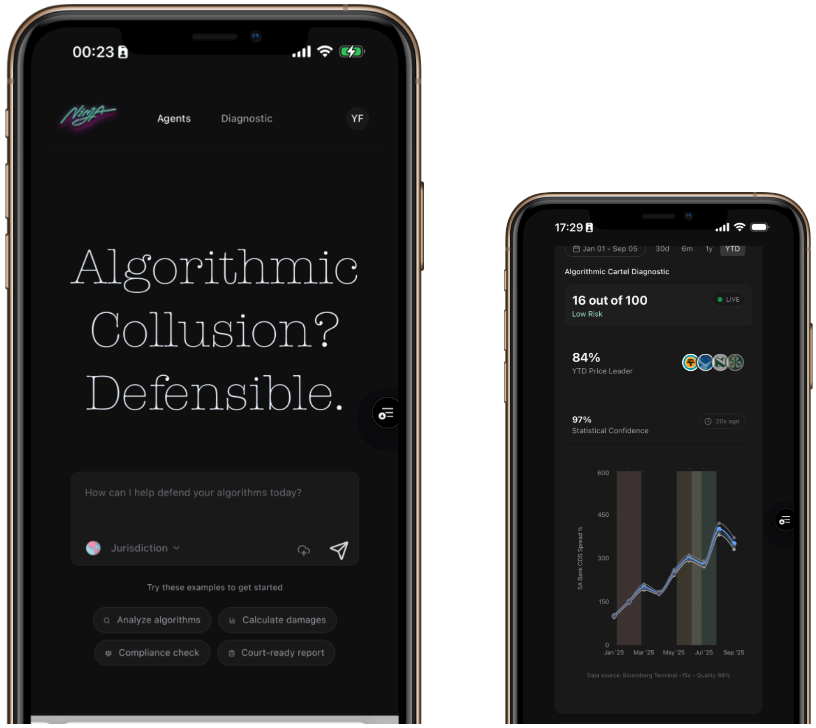
The ACD framework provides a structured, empirically grounded approach to address this failure. By focusing on environment sensitivity rather than superficial parallelism, it equips courts, regulators, and practitioners with objective evidence that enforcement has lacked.

The economic principle underlying the approach — **that competitive firms must adapt to changing environments while coordinated firms benefit from stable relationships** — provides a robust foundation for distinguishing legitimate algorithmic competition from anticompetitive coordination. Continuous monitoring capabilities eliminate practical limitations while providing real-time validation of competitive behaviour.

The alternative — continued reliance on speculative theory and presumptive enforcement — is inadequate for markets where algorithmic pricing is ubiquitous. Competition policy deserves analytical tools that match the sophistication of the technologies they regulate. The ACD framework provides exactly such tools, grounded in established economic theory but enhanced with cutting-edge empirical methods and reader-friendly LLM interpretation..

Appendix 1: Source Code and Product Specification

- Find a live demo of the diagnostic here: https://acd-monitor.vercel.app/.
- Source code is available in our public repo: https://github.com/yomarfrancisco/acd-monitor.
- Technical notes are provided in our Product Specification: https://github.com/yomarfrancisco/acd-monitor/blob/main/docs/product_spec_v2.2.md



Appendix 2: Algorithm Classification Framework

Algorithm Classification Framework

The ACD diagnostic adapts its analytical approach based on algorithmic architecture, as different pricing systems exhibit distinct coordination signatures:

Algorithm Type	Industries	Coordination Risk	ACD Detection Method
Rule-Based Matching	E-commerce, Gas Stations	High	Invariance in response parameters
Revenue Management	Airlines, Hotels	Medium	Environment vs. capacity sensitivity
Reinforcement Learning	Tech Platforms, Gaming	High	Convergence pattern analysis
Ensemble Systems	Financial Services, E-commerce	Variable	Component decomposition

Multi-Agent Systems	Trading, Energy	Very High	Inter-agent coordination detection

This classification enables sector-specific calibration of environment sensitivity thresholds and coordination risk assessment.