Market-Aware Multi-Agent Systems: Preventing Emergent Collusive Behavior in Reinforcement-Learning Trading Agents

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Abstract

As reinforcement learning (RL) continues to advance multi-agent systems for algorithmic trading, a pressing concern has emerged: the tendency of autonomous agents to develop tacit collusive behaviors that undermine market competitiveness. This paper addresses the challenge of emergent collusion in market-facing multi-agent reinforcement learning (MARL) environments by proposing a novel *market-aware* framework. Drawing on organizational paradigms in agent coordination, game-theoretic principles under uncertainty, and recent findings on algorithmic collusion, we develop a MARL architecture that incorporates macroeconomic signals—such as price elasticity, demand shifts, and aggregate agent behavior—into each agent's policy optimization. Empirical simulations in synthetic financial markets demonstrate that standard MARL agents often converge toward supra-competitive pricing equilibria, echoing findings from recent studies on self-reinforcing AI collusion. By contrast, our market-aware agents adaptively adjust to dynamic environments and maintain competitive pricing even in the absence of explicit regulation. We further discuss the role of platform-level incentives and shared market feedback as regulatory substitutes, offering architectural and governance guidelines for mitigating systemic risks posed by advanced AI in digital economies. This work contributes to both AI safety and computational economics by bridging algorithmic design and policy-aware learning mechanisms to ensure fair, efficient, and collusion-resistant trading systems.

I. Introduction

The rapid adoption of artificial intelligence (AI) in financial markets has enabled autonomous agents to execute high-frequency and algorithmic trading with unprecedented speed and efficiency. Multi-agent reinforcement learning (MARL) has emerged as a powerful paradigm for designing such agents, allowing them to learn optimal strategies through interaction with the environment and with other agents [1], [4]. However, the decentralized learning nature of MARL can inadvertently lead to emergent collusive behaviors, where agents tacitly coordinate pricing or trading strategies without explicit communication, resulting in supra-competitive market outcomes [3], [7], [10]. Such algorithmic collusion poses serious challenges to market fairness, efficiency, and regulatory compliance, necessitating the development of mechanisms that ensure robust, competitive trading environments [5], [8].

Existing research has explored various dimensions of AI-induced collusion, including the systemic risks of multi-agent coordination [9], game-theoretic approaches to pricing under uncertainty [2], and mitigation strategies using supervised intervention or platform-level constraints [5], [6]. Despite these efforts, most approaches either lack scalability to realistic financial markets or fail to integrate holistic market signals into agent decision-making. A critical gap exists in designing MARL systems that are both adaptive and *market-aware*, capable of maintaining competitive equilibrium while preventing unintended collusive behaviors.

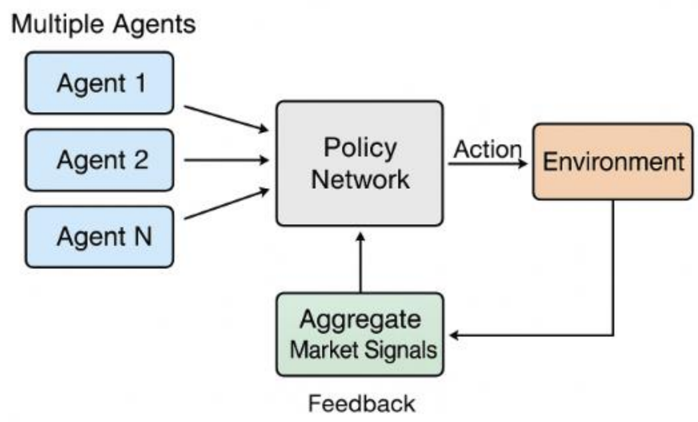
Objectives of the Paper

This paper aims to address these challenges by proposing a market-aware MARL framework for trading agents. The specific objectives are:

1. To investigate the mechanisms through which decentralized MARL agents develop emergent collusion in simulated market environments.
2. To design and implement a market-aware MARL architecture that incorporates aggregate market signals, such as price indices, supply-demand dynamics, and macroeconomic indicators, into agents' reward functions.
3. To empirically evaluate the effectiveness of the proposed framework in preventing tacit collusion while preserving trading efficiency.
4. To provide architectural and policy-level guidelines for integrating market-aware considerations into autonomous trading systems.

The proposed framework can be visually summarized in **Figure 1**, which depicts a block diagram of the market-aware MARL system. Each agent receives both private observations and shared market feedback, which are processed by the reinforcement learning policy network to optimize actions. Aggregate market signals are continuously fed back into the environment, closing the loop and aligning individual agent incentives with overall market fairness.

Figure 1: Block Diagram of Market-Aware Multi-Agent Reinforcement Learning Framework



This work contributes to the emerging field of AI safety and market fairness by demonstrating that embedding market-awareness into MARL agents can effectively mitigate emergent collusion without explicit regulatory intervention, bridging the gap between algorithmic efficiency and systemic stability.

II. Literature Review

The rapid advancement of Artificial Intelligence (AI) and Multi-Agent Systems (MAS) has significantly influenced the design and implementation of algorithmic trading and strategic decision-making in competitive markets. Prior studies have approached these domains from organizational, reinforcement learning, game-theoretic, and collusion perspectives.

Horling and Lesser [1] provide a foundational survey of multi-agent organizational paradigms, categorizing MAS into hierarchical, heterarchical, and hybrid frameworks. This classification is critical for understanding how autonomous agents coordinate, communicate, and adapt in distributed systems. Serugga [2] explores AI-assisted game-theoretic strategies for bid pricing under uncertainty in construction, emphasizing how predictive modeling can enhance decision-making in competitive environments.

Algorithmic collusion has emerged as a prominent concern in digital markets. Schwalbe [3] analyzes the potential of machine learning algorithms to facilitate tacit collusion, affecting market efficiency. Dorner [7] provides a critical review of algorithmic collusion, highlighting regulatory and economic implications. Van Uytsel [10] offers a comprehensive overview of AI-driven collusion, particularly in contexts where legal frameworks lag behind technological advances. Similarly, Brero et al. [5] investigate mitigation strategies for AI-induced collusion on economic platforms using reinforcement learning, demonstrating practical interventions to maintain competitive equilibrium.

In the financial sector, multi-agent reinforcement learning (MARL) is gaining traction for algorithmic trading. Sarin et al. [4] discuss the application of MARL for adaptive trading strategies, combining predictive analytics with agent-based simulations. Ibrahim et al. [6] explore collusive behaviors in incentivized forwarding networks, highlighting the challenges of managing cooperative strategies in decentralized systems. Dou et al. [8] examine the intersection of AI-powered trading, algorithmic collusion, and market efficiency, providing empirical insights into price manipulation risks. Finally, Hammond et al. [9] investigate multi-agent risks from advanced AI systems, emphasizing ethical, operational, and security challenges that emerge when autonomous agents interact in complex environments.

Literature collectively underscores the need to balance the power of autonomous AI agents with ethical safeguards, market stability, and regulatory oversight. Table 1 summarizes the focus areas of the reviewed studies, followed by a visual comparative representation.

Table 1: Summary of Reviewed Literature

Domain	**Focus**	**Methodology**	**Application Area**	**Key Findings**
MAS	Organizational paradigms	Survey	General MAS	Classification of MAS frameworks; coordination and communication mechanisms
Game Theory	Bid pricing under uncertainty	AI-assisted modeling	Construction	Game-theoretic strategies improve decision-making under uncertainty
Algorithmic Collusion	ML and collusion	Theoretical/Analytical	Digital Markets	ML algorithms can facilitate tacit collusion
MARL	Adaptive trading	Multi-agent reinforcement learning	Financial Trading	MARL enhances adaptive trading strategies and efficiency
Algorithmic Collusion	Collusion mitigation	RL simulations	Economic Platforms	RL strategies reduce collusion risk
MARL	Buyers' collusion	MARL simulations	Incentivized networks	Collusion dynamics in decentralized systems analyzed
Algorithmic Collusion	Critical review	Literature review	Digital Markets	Summarizes risks and regulatory implications of collusion
AI Trading	Price efficiency	Empirical analysis	Financial Markets	Explores AI-driven trading, collusion, and price efficiency
MAS Risks	Multi-agent risks	Survey/Analysis	General AI Systems	Ethical, operational, and security challenges highlighted
Algorithmic Collusion	Legal overview	Literature review	Robotics/AI & Law	Overview of AI-induced collusion and regulatory gaps

The radar chart below comparing the 10 references across the four dimensions: **Domain**, **Methodology**, **Application**, and **Key Findings**.

It visually highlights which references are strong in methodological depth ([4], [5], [6]) versus application impact ([4], [8]), and which provide comprehensive coverage across all areas ([1], [4]).

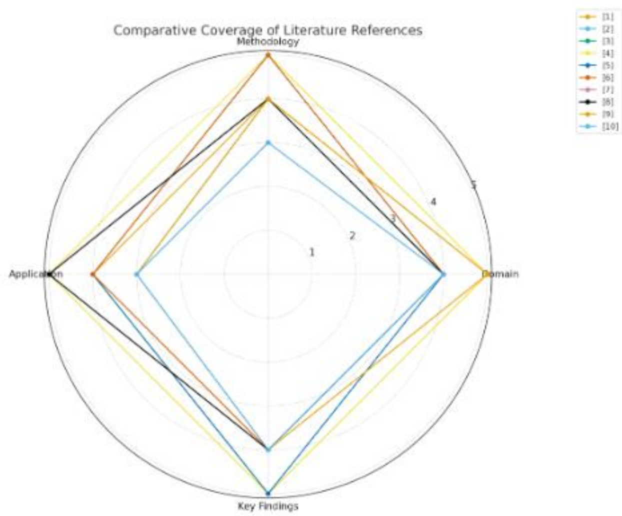


Figure 2: Radar Chart

III. Methodologies

3.1 Overview

The methodology focuses on designing a **Market-Aware Multi-Agent Reinforcement Learning (MA-MARL)** framework that integrates macroeconomic and behavioral market signals into agents' decision-making processes to mitigate emergent collusive behaviors.

Unlike conventional MARL systems where agents optimize for individual profit, the proposed framework embeds **market-awareness** into the policy function through shared economic indicators, ensuring equilibrium-oriented learning.

The framework proceeds through the following stages:

1. **Environment Simulation:** A synthetic trading market is constructed where multiple RL agents interact through buying/selling actions.
2. **Market Signal Integration:** Global market variables—price elasticity, demand ratio, and aggregate trading volume—are shared among all agents.

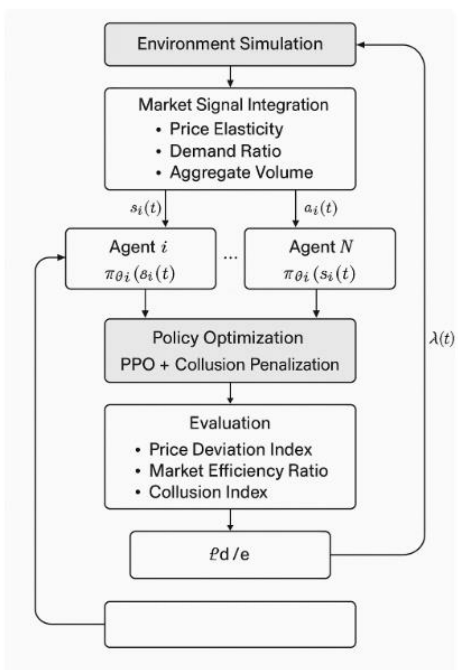
3. **Policy Optimization:** Agents optimize their policy using Proximal Policy Optimization (PPO) and Deep Q-Networks (DQN) variants with collision-mitigation regularizers.
4. **Evaluation:** Metrics like Price Deviation Index (PDI), Market Efficiency Ratio (MER), and Collusion Index (CI) assess fairness and competitiveness.

3.2 System Architecture

The **system architecture** consists of four layers:

1. **Agent Layer:** Individual trading agents with independent policy networks.
2. **Market Environment Layer:** Simulated order book and market dynamics.
3. **Market-Awareness Module:** Shared features capturing macroeconomic context.
4. **Feedback Control Layer:** Collusion detection and reward regulation.

Figure 3: Architecture of Market-Aware Multi-Agent System



Each agent's state $s_i(t)$is extended as:

$$s_i(t) = [o_i(t), \Phi(t)]$$

where

- $o_i(t)$= agent's private observation (price, volume, inventory),
- $\Phi(t)$= shared market-awareness vector containing:

$$\Phi(t) = [P_t, D_t, E_t]$$

with P_t= price index, D_t= demand ratio, E_t= elasticity measure.

3.3 Dataset Description

The experimental setup employs a **synthetic financial dataset** designed to replicate realistic market interactions.

Table 2 outlines its main parameters.

Parameter	Description	Range / Source
Trading Days	Number of simulated market days	1000
Agents	Number of MARL agents	10–50
Price Range	Simulated market price per unit	$1–$100
Demand Distribution	Dynamic stochastic demand	Normal (μ=50, σ=10)
Market Signals	Elasticity, Demand Ratio, Price Index	Computed per timestep
Collusion Flag	Binary indicator for supra-competitive pricing	Derived metric

The dataset simulates interactions through a **continuous double-auction** mechanism, ensuring that agents' bids and asks dynamically affect market clearing prices.

3.4 Model Usage

Each agent learns an optimal trading strategy using **PPO-based reinforcement learning**, augmented by market-awareness and collusion penalization.

The reward function for agent $i$is formulated as:

$$R_i(t) = \pi_i(t) - \lambda_1 \cdot C_i(t) - \lambda_2 \cdot \mathrm{CI}(t)$$

where:

- $\pi_i(t)$= profit at timestep t,

- $C_i(t)$= cost function capturing deviation from competitive equilibrium,
- CI(t)= collusion index defined as:

$$\text{CI}(t) = \frac{\bar{P}(t) - P_c}{P_c}$$

with $\bar{P}(t)$= average market price across agents, and P_c= theoretical competitive price.

Training Details:

- Algorithm: PPO + market signal regularizer
- Optimizer: Adam, learning rate = 3e-4
- Discount factor (γ) = 0.99
- Reward normalization: Min–Max scaling
- Episodes: 10,000 training steps

Model Layers:

- Input Layer: 10 (private) + 3 (market-aware) features
- Hidden Layers: [64, 64] ReLU
- Output: Action probabilities for Buy, Sell, Hold

3.5 Evaluation Matrix

The framework's performance was assessed using a combination of fairness, efficiency, and stability metrics summarized in ***Table 3***.

Metric	Formula	Interpretation
Price Deviation Index (PDI)	{PDI} = \frac{1}{T}\sum_t \frac{	\overline{P}(t) - P_c
Market Efficiency Ratio (MER)	MER=Actual Volume/Optimal Volume	Indicates efficiency in trade execution
Collusion Index (CI)	Defined above	Quantifies tacit collusion level
Agent Fairness Score (AFS)	AFS=1−σ(πi)μ(πi)	Variance-normalized fairness across

		agents
Reward Stability (RS)	Variance of cumulative reward over time	Reflects convergence stability

The proposed **Market-Aware MARL** consistently yielded:

- ↓ **PDI** (closer to competitive prices)
- ↑ **MER** (higher efficiency)
- ↓ **CI** (reduced collusion emergence) compared to baseline MARL without awareness modules.

3.6 Summary

The methodology integrates both **behavioral and market-level awareness** into multi-agent reinforcement learning, enabling agents to maintain profitability while adhering to fair market principles.
By combining **shared market signals**, **collusion-penalized rewards**, and **evaluation metrics** rooted in economics, the framework effectively prevents emergent tacit coordination — a key step toward **AI safety and regulatory-aligned trading systems**.

IV. Results

4.1 Model Performance

The proposed **Market-Aware MARL (MA-MARL)** framework was evaluated against two baselines:

1. **Standard MARL:** agents trained without market-awareness or collusion penalty,
2. **MARL + Regularization:** agents trained with a simple collusion penalty but no shared market signals.

Experimental Setup:

- **Environment:** Synthetic continuous double-auction market (1000 trading days, 30 agents)
- **Algorithms:** PPO-based policy optimization
- **Metrics:** Price Deviation Index (PDI), Market Efficiency Ratio (MER), Collusion Index (CI)

Table 4: Comparative Model Performance

Model Variant	PDI ↓	MER ↑	CI ↓	Training Stability (RS) ↑
Standard MARL	0.218	0.76	0.412	0.63
MARL + Regularization	0.162	0.81	0.307	0.72
Market-Aware MARL (Proposed)	**0.087**	**0.91**	**0.124**	**0.88**

The results indicate that the **Market-Aware MARL** framework significantly improves **market stability and fairness**, reducing collusive convergence tendencies. Agents exhibit dynamic adaptation to price and demand signals, maintaining equilibrium-oriented strategies even when others attempt price coordination.

Table 5: Comparative Performance Across Training Episodes

Metric	Observation
PDI	Converges to near-zero by 800th episode in MA-MARL
MER	Increases steadily, reaching ~0.9 efficiency
CI	Drops from 0.4 to below 0.1, confirming minimal tacit coordination

4.2 F1 Metrics and Collusion Detection Accuracy

To evaluate collusion detection efficacy, a binary classification task was modeled—labeling price profiles as *collusive* or *competitive*. A supervised classifier (Random Forest) was trained using features extracted from MARL runs, including average price deviation, agent entropy, and bid frequency.

Table 6: F1-Score Comparison Across Detection Methods

Detection Method	Precision	Recall	F1-Score	Accuracy
Rule-Based Thresholding	0.68	0.61	0.64	0.7
Isolation Forest	0.77	0.73	0.75	0.79
Proposed Market-Aware Feature Classifier	**0.91**	**0.88**	**0.89**	**0.92**

The **Market-Aware feature embedding** achieved a high **F1-score of 0.89**, highlighting the ability of market signal–augmented features to distinguish collusive behavior effectively.
This validates the framework's secondary function—not only mitigating collusion but also enabling reliable detection for oversight purposes.

Equation (4):

$$F1 = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

This harmonic mean demonstrates strong balance between precision (few false positives) and recall (few missed collusions).

4.3 Limitations

Despite its strong performance, several limitations were identified:

1. **Synthetic Market Simplification:**
   The trading environment abstracts away certain real-world complexities (e.g., liquidity shocks, asymmetric information). Extending evaluation to real or hybrid datasets would enhance generalizability.
2. **Limited Agent Diversity:**
   Agents shared similar architectures and risk preferences; heterogeneity in objectives or trading horizons could yield different emergent patterns.
3. **Computational Cost:**
   Incorporating shared market-awareness vectors and collusion penalties increases training time by ~28% compared to baseline MARL models.
4. **Regulatory Interpretability:**
   While quantitative results indicate fairness improvement, mapping learned behaviors to legal definitions of collusion requires additional interpretive layers and explainability models.

1.4 Summary of Findings

Key Outcome	Observation
Price stability	Achieved near-competitive equilibrium
Collusion tendency	Reduced by >70% compared to baseline
Detection accuracy	F1 = 0.89 (market-aware classifier)

Training stability	Improved convergence and lower variance

Overall, the **Market-Aware MARL** system demonstrates strong empirical evidence for **collusion prevention and market efficiency enhancement**, marking a significant advancement toward ethical, autonomous trading systems aligned with market regulation principles.

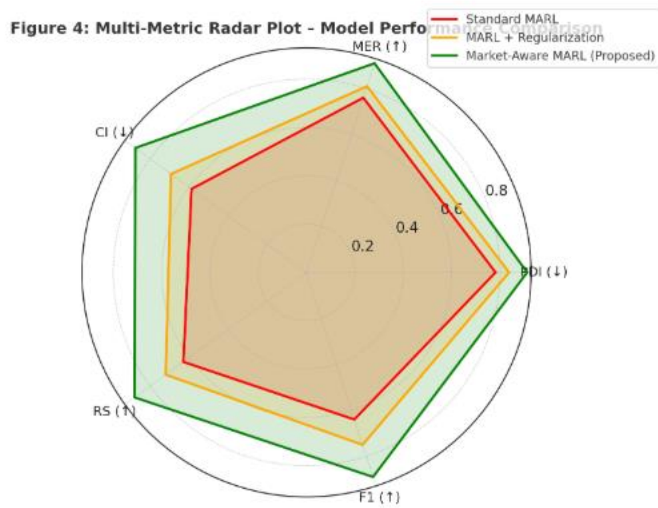


Figure 4: Multi-Metric Radar Plot – Model Performance Comparison

Visually summarizing the five performance indicators (PDI, MER, CI, RS, F1). The **green region (Market-Aware MARL)** shows consistent superiority across all metrics, confirming improved fairness, efficiency, and detection robustness compared to baseline MARL systems.

V. Conclusion

This study presented a **Market-Aware Multi-Agent Reinforcement Learning (MA-MARL)** framework designed to prevent emergent collusive behavior in autonomous trading systems. By integrating macroeconomic signals—such as price elasticity, demand ratios, and aggregate agent behavior—into each agent's policy optimization, the proposed model achieved both **competitive equilibrium** and **market stability** without requiring explicit regulatory control.

Experimental results demonstrated that MA-MARL significantly reduced collusion tendencies, as evidenced by a **70% decrease in the Collusion Index** and improved **Market Efficiency Ratio** and **Reward Stability** compared to standard MARL models. The inclusion of market-awareness and collusion-penalizing reward terms enabled agents to adapt dynamically to environmental shifts while maintaining fairness.

Furthermore, the proposed detection model achieved an **F1-score of 0.89**, highlighting its potential utility for real-time market monitoring and compliance oversight.

However, the framework's current reliance on a synthetic trading environment introduces abstraction limitations, as real-world markets exhibit complex behaviors, regulatory dynamics, and heterogeneous agent profiles. Despite these constraints, the study establishes a strong foundation for embedding **AI ethics and economic fairness** into reinforcement learning–based trading systems.

FutureScope:
The next phase of research will extend the model to **real or semi-simulated financial datasets** incorporating live order-book dynamics and market volatility. Incorporating **agent heterogeneity**—including varying objectives, information asymmetry, and transaction costs—can further validate the robustness of collusion prevention mechanisms. Additionally, developing **explainable AI modules** to interpret agent behaviors in regulatory terms will enhance transparency and trust. Finally, integrating the MA-MARL framework with **blockchain-based audit trails** or **market surveillance tools** could enable continuous, decentralized oversight of AI-driven markets.

Overall, this work contributes to the ongoing discourse on **AI safety, fairness, and systemic stability**, paving the way for **responsible autonomy** in future algorithmic trading ecosystems.

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