Redesigning Anti-Manipulation and Anti-Fraud Regulation in Financial Derivatives Markets: Artificial Intelligence Applications in Judicial Precedents

1. Mohammad. Saboorifard*: PhD Candidate, School of Law and Political Science, Allameh Tabataba'i University, Tehran, Iran. Email: MohammadSaboorifard1402@gmail.com (Corresponding Author)
2. Ali. Emami Meibodi
3. Abbas. Kazemi Najafabadi: Associate Professor of Law, School of Law and Political Science, Allameh Tabataba'i University, Tehran, Iran

*Correspondence: MohammadSaboorifard1402@gmail.com

Abstract

Financial derivatives markets play a fundamental role in contemporary financial systems by enabling risk transfer, hedging, speculation, arbitrage, and price discovery across securities, commodities, currencies, interest rates, and energy products. However, the growing complexity, speed, and technological sophistication of these markets have increased their vulnerability to manipulation and fraud. Practices such as spoofing, layering, wash trading, artificial settlement-price pressure, pump-and-dump schemes, benchmark distortion, and algorithmic market abuse create serious challenges for courts and regulators. Traditional judicial approaches usually depend on proving manipulative conduct, intent, causation, artificial price, and investor harm, yet these elements are difficult to establish in markets where misconduct may be distributed across thousands of orders, multiple accounts, high-frequency strategies, communication networks, and cross-market positions. This article examines how artificial intelligence can contribute to redesigning anti-manipulation and anti-fraud regulation in financial derivatives markets by strengthening judicial analysis and improving regulatory enforcement. The study argues that AI can assist courts and regulators through pattern recognition, anomaly detection, order-book analysis, sentiment analysis, network analysis, legal precedent review, and harm calculation. These applications can make hidden manipulative conduct more visible, reconstruct trading sequences, support the inference of intent, estimate artificial price impact, and improve proportionality in sanctions. At the same time, the use of AI in judicial and regulatory contexts must be governed by transparency, explainability, auditability, data reliability, and human oversight. AI should not replace judicial reasoning or due process; rather, it should function as an auxiliary evidentiary and analytical tool. The article concludes that an AI-supported regulatory model can help transform anti-manipulation law from a reactive and fragmented system into a more preventive, integrated, evidence-based, and technically informed framework for protecting the integrity of derivatives markets.

Keywords: Financial Derivatives Markets; Market Manipulation; Financial Fraud; Artificial Intelligence; Judicial Precedents; Algorithmic Trading; Anti-Manipulation Regulation; Market Surveillance

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1. Introduction

Financial derivatives markets have become one of the central infrastructures of contemporary financial systems because they transform uncertainty into tradable risk and allow market participants to hedge, speculate, arbitrage, and allocate exposure across time, assets, and jurisdictions. Unlike spot markets, where the exchange of an asset and payment is generally immediate or near-immediate, derivatives markets are built around future performance, conditional obligations, and the transfer of risk associated with an underlying asset. This underlying asset may be a commodity, stock, interest rate, currency, index, credit event, or energy product, and this structural connection between the derivative and the underlying market makes derivatives highly influential in price discovery and risk management. In oil and energy markets, for example, futures and options can help producers, refiners, exporters, importers, and institutional investors manage exposure to volatile price movements, and this function is especially important because oil prices are affected by geopolitical tension, supply shocks, demand expectations, monetary conditions, and strategic inventory decisions. The logic of derivatives as risk-transfer mechanisms has been emphasized in financial engineering literature, where such instruments are not merely speculative devices but mechanisms for distributing uncertainty among parties with different risk preferences and expectations (Sayah & Saleh Abadi, 2004). Derivatives also provide a structured means for managing exposure in commodity markets, including oil markets, where price fluctuation can have direct consequences for national economies, corporate planning, and investment decisions (Derakhshan, 2013). At the same time, the economic power of derivatives comes from their leverage, liquidity, and connection to expectations, and these same qualities can make derivatives markets vulnerable to manipulation and fraud when traders use artificial strategies to distort price, volume, or market appearance.

The transformation of derivatives markets has also been intensified by algorithmic trading, high-frequency trading, automated order placement, and machine-driven decision-making. Traditional financial markets were once shaped primarily by human traders, brokers, and institutional strategies, but modern trading environments increasingly involve automated systems that can submit, modify, and cancel large volumes of orders at speeds beyond ordinary human capacity. High-frequency trading has altered the temporal structure of markets by making microseconds relevant to price formation, liquidity provision, and order-book dynamics (Aldridge, 2010). This transformation creates a regulatory difficulty because manipulative conduct may now occur through sequences of orders that are individually lawful but collectively deceptive. For example, a trader may place large orders without genuine execution intent to create a false impression of supply or demand, cancel them before execution, and profit from the reaction of other traders. Similarly, algorithmic strategies may be used to generate artificial volume, trigger stop-loss orders, exploit liquidity gaps, or influence settlement prices in futures and options markets. These forms of misconduct are difficult to assess through traditional legal reasoning alone because the evidence is not always contained in a single transaction or statement; rather, it is distributed across order books, price charts, execution timestamps, communication networks, volatility patterns, and cross-market relationships. Therefore, the modern challenge of anti-manipulation and anti-fraud regulation is not only to prohibit abusive conduct but also to develop technical and evidentiary methods capable of detecting, reconstructing, and explaining such conduct before courts and regulatory authorities.

Market manipulation in derivatives markets is particularly dangerous because it can distort the relationship between the derivative contract and its underlying asset. Derivatives are often used for risk management, but they can also amplify price effects because a relatively small margin position may control a much larger notional exposure. Financial engineering literature explains that derivatives make it possible to separate ownership, exposure, leverage, and risk allocation in ways that are economically useful but legally complex (Michael, 2011). When a trader manipulates the price of a futures contract, option, swap, or related benchmark, the effect may not remain limited to that contract. It can influence settlement prices, margin calls, hedging decisions, physical commodity prices, and the expectations of uninformed traders. In oil and commodity markets, such distortions may affect not only speculative positions but also commercial contracts, inventory valuations, transportation decisions, and national revenue planning. The conceptual foundation of derivatives shows that these instruments are intended to manage risk, not manufacture artificial prices, and this distinction is essential for legal analysis (Khan & Iqbal, 2010). However, the boundary between aggressive trading and manipulation is often unclear. A large trade may be legitimate if it reflects genuine economic exposure, but the same trade may be manipulative if it is designed to mislead the market, create artificial pressure, or move price away from competitive supply and demand. This difficulty explains why courts have historically focused on intent, causation, artificial price, and fraudulent conduct, although these elements remain hard to prove in fast and complex markets.

Artificial intelligence offers a new way to address this difficulty because it can process large, heterogeneous, and high-frequency datasets that are beyond the practical capacity of human review. Artificial intelligence is not a single technique but a broad field concerned with designing systems capable of perception, reasoning, learning, decision-making, and problem-solving in complex environments (Russell & Norvig, 2021). In the context of derivatives regulation, AI can assist in identifying abnormal trading patterns, detecting suspicious order behavior, mapping relationships among market participants, comparing historical precedents, analyzing legal documents, and estimating losses or illicit gains. Machine learning is especially relevant because it enables systems to improve performance by learning patterns from data rather than relying solely on manually programmed rules (Mitchell, 1997). Pattern recognition methods can classify market behavior into normal and abnormal categories, detect clusters of suspicious trading, and distinguish random volatility from structured manipulation (Duda et al., 2012). Probabilistic machine learning can also help courts and regulators manage uncertainty by estimating the likelihood that a given sequence of market events reflects manipulation rather than ordinary trading noise (Murphy, 2012). These capacities do not eliminate the need for judicial reasoning, but they can provide courts with more objective and technically grounded evidence.

The importance of AI is not limited to detection. It can also improve judicial precedent by helping judges and regulators understand how similar patterns have been treated in previous cases, how statutory elements have been interpreted, and whether penalties are proportionate to harm and illicit benefit. Traditional judicial analysis often relies on documentary evidence, expert testimony, trade records, and regulatory reports. These remain essential, but modern manipulation cases require a more integrated evidentiary architecture. AI can combine market microstructure analysis, sentiment analysis, network analysis, and legal analytics to reconstruct the factual sequence of manipulation. Deep learning models can identify complex nonlinear patterns in financial data that may not be visible through ordinary statistical review (Goodfellow et al., 2016). Neural networks can be used for classification, prediction, and anomaly detection in environments where the relationship between inputs and outcomes is difficult to specify manually (Haykin, 1999). Reinforcement learning may also be relevant because automated trading strategies operate in dynamic environments where agents learn from reward, feedback, and market response (Sutton & Barto, 1998). The later development of reinforcement learning further shows how sequential decision-making can be modeled in complex environments, which is highly relevant to algorithmic trading and regulatory simulation (Sutton & Barto, 2018). The objective of this article is to examine how artificial intelligence applications can be used to redesign anti-manipulation and anti-fraud regulation in financial derivatives markets by strengthening judicial analysis, improving evidentiary standards, and supporting more proportionate and technically accurate court precedents.

2. Financial Derivatives Markets and the Conceptual Foundations of Manipulation and Fraud

Financial derivatives are contractual instruments whose value is derived from the value, movement, or occurrence of another asset, index, rate, commodity, or event. Their fundamental function is to transfer risk between parties that have different expectations, exposures, and risk capacities. A futures contract obliges parties to buy or sell an underlying asset at a predetermined price on a future date, while an option gives the holder the right, but not the obligation, to buy or sell an asset under defined conditions. Swaps allow parties to exchange cash flows based on interest rates, currencies, commodities, or other variables, and forwards operate as customized agreements outside organized exchanges. These instruments are central to financial engineering because they separate price exposure from direct ownership and enable risk to be allocated through contract rather than physical transfer (Sayah & Saleh Abadi, 2004). Their usefulness is especially visible in commodity and oil markets, where producers and consumers face substantial uncertainty about future prices and require instruments to stabilize expectations and cash flows (Derakhshan, 2013). In investment management, derivatives are also used to construct synthetic positions, hedge portfolios, increase or reduce exposure, and implement complex strategies that cannot easily be achieved through spot transactions alone (Farhadi & Shariat Panahi, 2011). However, the same characteristics that make derivatives efficient also increase their vulnerability to abuse. Leverage allows a trader to influence a large exposure with limited capital.

Settlement mechanisms can make specific time windows or benchmark prices highly sensitive to strategic trading. Cross-market links can allow manipulation in one market to affect another. These structural features mean that derivatives regulation must focus not only on contractual validity but also on market integrity.

The conceptual distinction between legitimate risk management and manipulation depends on whether market conduct reflects genuine economic purpose or artificial interference with price formation. A trader may take a large futures position because of a real hedging need, a macroeconomic view, or a speculative belief about future prices. Such conduct is not manipulative merely because it affects the market. Market prices are supposed to respond to supply, demand, information, and liquidity. The legal problem arises when trading conduct is designed to create a false appearance of supply or demand, mislead other market participants, distort settlement prices, or produce an artificial price that would not have existed under normal competitive conditions. Financial derivatives literature recognizes that these instruments can redistribute risk efficiently, but it also recognizes that their complexity can create informational asymmetry between sophisticated and unsophisticated participants (Michael, 2011). This asymmetry becomes legally significant when one party intentionally uses superior technology, market power, or information to deceive others rather than to participate in genuine price discovery. In Islamic and comparative financial engineering discussions, the legitimacy of financial contracts is often linked to transparency, real economic purpose, and avoidance of excessive uncertainty or deception (Khan & Iqbal, 2010). Although modern derivatives markets are not governed by one uniform normative system, the underlying concern is similar: a market cannot be fair if prices are manufactured through fictitious activity rather than real supply, demand, and information.

Manipulation and fraud are related but not identical concepts. Fraud generally involves deception, misrepresentation, concealment, or misleading conduct that causes another party to act to its detriment. Manipulation, by contrast, may occur through trading behavior itself, even without an explicit false statement. A trader who spreads false information about a company, commodity shortage, or regulatory event may commit fraud by misleading market participants through information. A trader who places and cancels large orders to create artificial demand may commit manipulation through conduct. In practice, both often overlap because manipulative trading usually communicates a false signal to the market. A false order, artificial volume, wash trade, or coordinated price movement tells other participants something untrue about market interest. The technical complexity of modern trading makes this distinction more difficult because signals may emerge from patterns rather than statements. High-frequency trading environments intensify this problem because market participants react to order-book signals quickly, and an artificial signal may influence price even if it exists for only a short period (Aldridge, 2010). In such markets, the manipulator may not need to persuade investors through public announcements; it may be enough to generate machine-readable signals that trigger other algorithms, stop-loss orders, or liquidity responses.

Several common forms of market manipulation are particularly relevant to derivatives markets. Spoofing occurs when a trader places orders without the intention of execution in order to create a false impression of supply or demand. Layering is similar but often involves multiple orders placed at different price levels to build artificial pressure. Wash trading involves transactions that create the appearance of activity without genuine change in beneficial ownership. Pump-and-dump schemes inflate prices through coordinated promotion or artificial demand before insiders sell at a profit. Market cornering occurs when a participant accumulates enough control over a commodity or derivative position to influence price. Settlement manipulation occurs when traders attempt to affect the price used to settle futures, options, or swaps. Benchmark manipulation, such as manipulation of reference rates, can affect vast numbers of contracts tied to the benchmark. These strategies differ in technique, but they share a common logic: they interfere with price formation by creating false signals or artificial scarcity, demand, supply, or sentiment. Pattern recognition theory is highly relevant here because manipulation can be understood as a recurring class of abnormal behavior embedded in market data (Bishop, 2006). Classification methods can help distinguish ordinary trading from suspicious activity by identifying features such as cancellation rates, order imbalance, abnormal volume, repeated timing, and deviation from historical baselines (Duda et al., 2012). Such methods are not legal conclusions by themselves, but they can provide a factual basis for judicial and regulatory analysis.

The role of intent remains one of the most difficult elements in manipulation cases. Legal systems often require proof that the trader intended to deceive the market or create an artificial price. Yet intent is rarely visible directly. It must be inferred from conduct, communication, profit patterns, order placement, cancellation behavior, market context, and the absence of legitimate economic explanation. Traditional legal methods infer intent from witness testimony, documents, and circumstantial evidence. In derivatives markets, however, the relevant circumstantial evidence may be deeply technical. For example, if a trader repeatedly places large orders on one side of the book, cancels them before execution, and simultaneously executes smaller trades on the opposite side, this pattern may support an inference of manipulative intent. Machine learning can assist by identifying whether such behavior is statistically unusual, repeated, profitable, and inconsistent with normal execution strategies (Murphy, 2012). Artificial intelligence can also compare the conduct with known manipulation typologies and historical enforcement patterns. Earlier conceptions of artificial intelligence emphasized the capacity of machines to reason, search, and solve problems in structured domains (Nilsson, 1998). In market abuse cases, that capacity can be adapted to reconstruct sequences of conduct and support legal inference. Still, AI cannot replace the legal requirement that courts evaluate evidence, credibility, causation, and responsibility.

Another central issue is artificial price. In theory, a manipulated price is one that differs from the price that would have existed absent the manipulative conduct. In practice, this is difficult to establish because markets move for many reasons, including news, liquidity, macroeconomic expectations, inventory data, geopolitical events, and ordinary volatility. Oil markets are especially difficult because price movements may reflect supply shocks, refinery demand, shipping constraints, currency changes, or strategic reserves (Derakhshan, 2013). Therefore, a sudden movement outside a normal price channel is not automatically manipulation. The legal question is whether the movement was caused by artificial conduct. AI can assist by constructing counterfactual models that estimate expected price behavior under normal conditions and compare actual price movement with that baseline. Neural networks and other learning models can capture nonlinear relationships between variables and identify deviations that may not be visible through simple linear models (Haykin, 1999). Deep learning can process large-scale historical data, order-book sequences, and market indicators to detect subtle departures from ordinary market dynamics (Goodfellow et al., 2016). However, courts must require explainability because a model that simply labels conduct as suspicious without showing why may not satisfy due process. The value of AI lies in making market complexity intelligible, not in replacing legal proof with opaque prediction.

3. Anti-Manipulation and Anti-Fraud Rules in Judicial and Regulatory Practice

Anti-manipulation and anti-fraud rules are designed to protect market integrity, investor confidence, and the fairness of price formation. In derivatives markets, these rules must address both informational deception and conduct-based distortion. A legal system that focuses only on false statements may fail to capture spoofing, layering, wash trading, settlement manipulation, or artificial order-book pressure. Conversely, a legal system that prohibits all aggressive trading too broadly may discourage liquidity provision, hedging, and legitimate speculation. The challenge is to design rules that identify harmful artificiality without criminalizing ordinary market participation. This balance is particularly important in derivatives markets because traders often take large positions, use leverage, and act on expectations about future price movements. Investment management literature emphasizes that informed trading, speculation, and hedging are ordinary components of market activity (Farhadi & Shariat Panahi, 2011). Therefore, the law must distinguish between informed price discovery and manipulative price distortion. Financial engineering literature similarly shows that derivatives are used to manage exposure and transfer uncertainty, so regulation must preserve their economic function while preventing abusive practices (Michael, 2011). This requires precise legal standards, strong surveillance mechanisms, and evidentiary tools capable of explaining complex trading behavior.

In judicial practice, manipulation has often been analyzed through a combination of conduct, intent, causation, and artificial price. The first element concerns whether the defendant engaged in a manipulative act or deceptive scheme. The second concerns whether the defendant acted intentionally, knowingly, or recklessly. The third concerns whether the conduct caused market distortion or investor harm. The fourth concerns whether the resulting price was artificial or fictitious. These elements are conceptually useful, but they are difficult to apply in modern derivatives markets. A manipulative strategy may involve thousands of orders, multiple accounts, different exchanges, automated algorithms, and cross-market positions. The evidence may include trade logs, order-book data, chat messages, emails, benchmark submissions, news releases, and social media signals. Traditional judicial reasoning can examine this evidence, but it may struggle to identify the hidden pattern connecting the data. Pattern classification methods can support the analysis by organizing complex evidence into recognizable categories of behavior (Duda et al., 2012). Probabilistic learning can assist where the issue is not absolute certainty but the likelihood that a sequence of events reflects manipulation rather than chance (Murphy, 2012). However, courts must ensure that these technical tools are translated into legally meaningful concepts such as intent, causation, reliance, harm, and proportionality.

The United States provides one of the most developed legal and regulatory frameworks for market manipulation in securities and derivatives markets. Federal securities law, commodity law, and post-crisis reforms all contribute to the prohibition of deceptive and manipulative conduct. The Securities Exchange Act, the Commodity Exchange Act, CFTC regulations, SEC rules, and Dodd-Frank reforms reflect a regulatory effort to address both fraud and manipulation across securities, futures, swaps, and commodities. In commodity and futures markets, the regulatory concern is especially strong because derivatives prices can affect physical commodity markets and broader economic expectations. High-frequency trading adds an additional layer of complexity because manipulative intent may be embedded in algorithmic design and order behavior rather than expressed in ordinary language (Aldridge, 2010). In this context, courts and regulators must ask whether a trading sequence had a legitimate execution purpose or whether it was designed to deceive other market participants. AI can help by identifying patterns such as repeated order placement and cancellation, abnormal order-to-trade ratios, strategic timing around settlement windows, and coordinated behavior across accounts. Machine learning, as a discipline, provides tools for learning from past examples and detecting patterns that can generalize to new cases (Mitchell, 1997). This is particularly valuable for regulators who must identify evolving manipulation strategies before they become widespread.

Canadian and Iranian legal contexts reveal a broader comparative issue: market manipulation is increasingly global, while regulation remains jurisdictionally fragmented. Derivatives transactions, algorithmic trading, and commodity-linked financial products often cross borders, but enforcement authority is still tied to national regulators and courts. This creates difficulties when manipulation involves offshore accounts, foreign trading venues, international benchmark prices, or coordinated conduct across jurisdictions. In oil and energy markets, the problem is even more complex because physical production, transportation, storage, futures trading, and financial speculation may occur in different jurisdictions (Derakhshan, 2013). A manipulation strategy may affect a domestic market even if parts of the conduct occur abroad. Therefore, comparative regulation must move toward greater integration, data-sharing, and common evidentiary standards. The financial engineering literature shows that risk itself is internationally transferable through derivatives, and this means that abusive conduct can also transmit harm across borders (Sayah & Saleh Abadi, 2004). Where one jurisdiction lacks advanced surveillance tools or clear anti-manipulation standards, manipulators may exploit regulatory gaps. This is why judicial precedent should not be studied only as a national legal artifact but also as part of an emerging global system of market integrity.

One of the weaknesses of current judicial practice is the lack of sufficiently objective criteria for identifying artificial price. Courts often rely on expert testimony and circumstantial evidence, but expert opinions may conflict, and judges may not have the technical background needed to evaluate complex market data. A price may move sharply because of legitimate information, liquidity shortage, or ordinary volatility. It may also move because of manipulation. The difference is not always visible from the price chart alone. AI can assist by integrating price movement with volume, order-book data, sentiment, cross-market indicators, and participant behavior. Pattern recognition and machine learning models can establish a baseline of normal market behavior and identify deviations from that baseline (Bishop, 2006). Deep learning models can capture more complex relationships among variables, such as the interaction between news sentiment, trading volume, volatility, and order cancellation patterns (Goodfellow et al., 2016). These tools can help courts determine whether the price movement was merely unusual or whether it was linked to a manipulative sequence. However, legal systems should not treat AI output as automatically decisive. The court must ask whether the model is reliable, whether the data are complete, whether the methodology is explainable, and whether the inference corresponds to legal elements.

Another major weakness concerns proportionality in penalties. Manipulation and fraud sanctions may include civil fines, disgorgement, restitution, trading bans, imprisonment, and corporate compliance obligations. Yet penalties can vary widely, and courts may lack a consistent formula for measuring illicit gain, market harm, investor loss, and deterrence. Derivatives manipulation can produce direct profits for the manipulator, indirect losses for counterparties, and broader market distortion that is difficult to quantify. A trader who manipulates a settlement price may affect many contracts without directly transacting with every injured party. AI can assist by estimating the time window of manipulation, measuring abnormal price impact, identifying affected transactions, calculating illicit profit, and modeling counterfactual prices. Probabilistic machine learning provides a framework for estimating uncertainty and explaining the confidence level of such calculations (Murphy, 2012). Neural networks can also model complex market relationships, although their use in court must be accompanied by interpretability safeguards (Haykin, 1999). The goal is not to make punishment mechanical but to make it more consistent, evidence-based, and proportionate. A redesigned regulatory system should use AI to support sentencing and sanctioning decisions while preserving judicial discretion and procedural fairness.

Judicial precedent itself can also be improved through AI. Courts develop anti-manipulation doctrine through repeated interpretation of statutory terms such as deception, artificial price, intent, recklessness, causation, and market harm. However, precedents may be inconsistent when different courts interpret similar conduct differently or when legal doctrine fails to keep pace with new trading technologies. Artificial intelligence can support legal research by identifying patterns across cases, summarizing judicial reasoning, detecting inconsistencies, and comparing factual scenarios. Earlier AI research emphasized symbolic reasoning, problem-solving, and knowledge representation (Nilsson, 1998). Contemporary AI expands this capacity through machine learning, natural language processing, and large-scale data analysis (Russell & Norvig, 2021). In judicial contexts, these tools can help courts understand whether a particular manipulation strategy resembles spoofing, wash trading, benchmark manipulation, or another recognized form of abuse. They can also help regulators draft clearer rules based on observed judicial difficulties. Nevertheless, AI-assisted precedent analysis must be used carefully because legal reasoning is normative as well as predictive. A court should not decide a case merely because similar cases had similar outcomes; it must also justify its decision according to law, evidence, fairness, and due process.

4. Artificial Intelligence Applications for Redesigning Judicial Analysis and Market Regulation

Artificial intelligence can redesign anti-manipulation and anti-fraud regulation by transforming the way suspicious conduct is detected, interpreted, presented, and evaluated in judicial proceedings. The first and most direct application is market surveillance. Traditional surveillance systems often rely on predefined rules, thresholds, or manual review, such as identifying unusually large trades, abnormal price movements, or suspicious communication. These methods remain useful, but they are insufficient when manipulation is adaptive, algorithmic, and distributed across many small actions. AI systems can learn from historical data and continuously update their understanding of normal and abnormal behavior. Machine learning provides the methodological foundation for systems that infer patterns from data rather than depend only on static human instructions (Mitchell, 1997). Pattern recognition methods can classify trading behavior into categories such as ordinary hedging, aggressive speculation, spoofing, layering, wash trading, or settlement manipulation (Duda et al., 2012). Probabilistic learning can assign likelihoods to competing explanations, helping regulators distinguish between random market volatility and structured manipulation (Murphy, 2012). In this sense, AI does not merely accelerate surveillance; it changes surveillance from reactive inspection to proactive detection.

Anomaly detection is one of the most important AI applications in derivatives regulation. An anomaly is not automatically illegal, but it is a signal that behavior deviates from a learned or expected baseline. In a futures market, anomalies may include sudden spikes in trading volume, abnormal order cancellation, repeated price movements near settlement, unusual bid-ask pressure, or price departures from historically stable channels. In oil derivatives markets, anomalies must be interpreted carefully because legitimate price movement may occur due to inventory reports, geopolitical news, supply disruptions, or macroeconomic expectations (Derakhshan, 2013). Therefore, an AI system should not treat all unusual movement as manipulation. It should integrate multiple variables, including price, volume, volatility, order-book depth, spread, timing, participant identity, and external information. Pattern recognition models can identify whether the observed event resembles known manipulation patterns (Bishop, 2006). Deep learning can be especially useful when the relevant pattern is nonlinear and distributed across time-series data, order flows, and textual signals (Goodfellow et al., 2016). However, for judicial use, anomaly detection must be explainable. A regulator may use a black-box alert for internal investigation, but a court requires a clear explanation of what was abnormal, why it mattered, and how it connects to legal elements.

Order-book analysis is another essential AI function. Many forms of manipulation do not appear only in executed trades but in orders that are placed, modified, layered, and canceled. Spoofing and layering are examples of conduct where the manipulator uses the order book as a communication device. The trader creates a visible but false impression of supply or demand, waits for other market participants or algorithms to react, and then cancels the false orders before execution. High-frequency trading makes this strategy especially dangerous because order-book signals can influence other algorithms within extremely short timeframes (Aldridge, 2010). AI can analyze order-to-trade ratios, cancellation speed, repeated placement patterns, directional imbalance, execution asymmetry, and profitability following cancellations. Neural network models can process sequential order-book data and identify suspicious temporal patterns (Haykin, 1999). Reinforcement learning is also conceptually relevant because algorithmic traders operate as agents in dynamic environments, learning which actions generate profitable responses (Sutton & Barto, 2018). If manipulative algorithms learn to exploit regulatory thresholds, surveillance systems must also learn adaptively. This creates an arms race between market abuse and market supervision, and AI-based regulation becomes necessary because static rules cannot adequately respond to adaptive misconduct.

Sentiment analysis and natural language processing can address manipulation that operates through information rather than orders alone. Fraudulent schemes may involve false announcements, misleading financial statements, rumors, social media campaigns, coordinated promotional messages, or deceptive narratives about supply, demand, corporate performance, or commodity shortages. AI can analyze news articles, social media posts, financial reports, trader communications, and public statements to detect sudden sentiment shifts that coincide with unusual trading behavior. Artificial intelligence research has long emphasized the importance of representing and interpreting information in ways that support reasoning and decision-making (Russell & Norvig, 2021). In modern financial markets, textual information is not separate from trading; it is part of the market environment that shapes expectations and automated responses. A pump-and-dump scheme, for example, may involve coordinated positive sentiment followed by abnormal volume and insider selling. A commodity manipulation scheme may involve false information about supply constraints while related futures positions are being accumulated. Machine learning models can connect textual signals with trading data to identify whether information events and market activity are suspiciously synchronized (Murphy, 2012). Courts can use such analysis to evaluate whether public statements were part of a broader manipulative strategy.

Network analysis is particularly important for detecting collusion and coordinated manipulation. Manipulators rarely act in isolation when the objective is to move a large market or create a sustained artificial price. They may use multiple accounts, related entities, brokers, funds, chat groups, or cross-market positions. Network analysis can map relationships among traders, communication channels, beneficial owners, order flows, and profit patterns. Pattern classification can then identify clusters of accounts that behave in a coordinated way even when formal ownership links are concealed (Duda et al., 2012). AI can detect repeated sequences where several accounts place orders in the same direction, cancel at similar times, trade around the same settlement windows, or profit from the same artificial movement. This is important for judicial proof because collusion may not be directly admitted in documents. Courts may need to infer coordination from behavior. Earlier machine learning theory explains that learning systems can generalize from observed examples to unseen cases (Mitchell, 1997). In legal terms, this means AI can identify patterns of coordination that resemble past manipulation cases even when the specific actors and instruments differ. However, network inference must be handled cautiously because correlation is not conspiracy. The court must require corroboration, explanation, and opportunity for challenge.

AI can also improve the proof of causation. In manipulation cases, causation asks whether the defendant's conduct actually produced the artificial price, investor loss, or market distortion. This is difficult because market prices are affected by multiple simultaneous forces. A defendant may argue that the price movement resulted from ordinary supply and demand, external news, or market volatility rather than manipulation. AI can help by constructing counterfactual models. These models estimate what the price, volume, or liquidity pattern would likely have been absent the suspicious conduct. Probabilistic machine learning is useful because it can express uncertainty rather than pretend to provide absolute certainty (Murphy, 2012). Deep learning can model complex dependencies among market variables, although its outputs must be interpreted carefully in court (Goodfellow et al., 2016). For example, if a crude oil futures contract moves sharply after a sequence of large non-genuine orders, an AI model can compare the movement with similar historical periods, relevant news, order-book conditions, and cross-market indicators. If the model shows that the movement is highly inconsistent with normal behavior and closely linked to the suspicious orders, this supports causation. The final legal conclusion remains judicial, but the evidentiary foundation becomes stronger.

A further contribution of AI concerns intent. Legal systems often struggle to prove intent because a manipulator can claim that orders were legitimate, cancellations were ordinary, or profits were coincidental. AI cannot read the trader's mind, but it can identify behavioral evidence from which intent may be inferred. Repeated placement and cancellation of large orders without execution, consistent profitability on the opposite side, concentration around sensitive settlement windows, use of multiple accounts, and absence of legitimate hedging rationale may support an inference of manipulative purpose. Reinforcement learning theory is helpful in understanding how agents choose actions to maximize rewards over time (Sutton & Barto, 1998). In algorithmic trading, a strategy may learn that certain order-book signals trigger profitable market reactions, and if the strategy is designed or maintained for that purpose, intent may be inferred from design, knowledge, and repeated use. The updated reinforcement learning framework further demonstrates how sequential decisions can be optimized through interaction with an environment (Sutton & Barto, 2018). This matters because market manipulation is often sequential. The manipulator acts, observes market response, adapts, and acts again. AI can reconstruct this sequence and show whether the conduct reflects accidental activity or systematic exploitation.

AI can also support proportionate penalties by measuring harm and illicit benefit more accurately. In many manipulation cases, punishment depends on the amount gained, the amount lost by victims, the duration of the scheme, the number of affected participants, and the seriousness of market disruption. Yet these quantities are difficult to calculate in derivatives markets because losses may be dispersed across many traders and instruments. Financial engineering literature shows that derivatives can transmit exposure through complex contractual structures (Sayah & Saleh Abadi, 2004). A manipulated futures settlement price may affect options, swaps, margin requirements, hedging strategies, and physical commodity contracts. AI can identify affected transactions, estimate abnormal price impact, calculate unjust enrichment, and distinguish manipulation-related losses from ordinary market risk. Neural networks and probabilistic models can support estimation where direct observation is incomplete (Haykin, 1999). Pattern recognition can identify the period during which manipulation was active and separate it from normal market behavior (Bishop, 2006). Such analysis can help courts impose fines, disgorgement, restitution, and trading restrictions that correspond more closely to actual harm. This does not remove judicial discretion; it gives discretion a more rigorous evidentiary basis.

AI applications can also assist in legal research and precedent analysis. Courts deciding manipulation cases must interpret statutes, regulations, prior judgments, and administrative decisions. Inconsistent precedent can produce uncertainty for traders and regulators. AI can search large legal databases, identify similar cases, summarize judicial reasoning, compare legal standards, and highlight contradictions. Artificial intelligence has historically included the development of systems capable of search, reasoning, and knowledge representation (Nilsson, 1998). Modern AI extends these capabilities through natural language processing and machine learning (Russell & Norvig, 2021). In the context of derivatives manipulation, AI can help judges understand whether a case resembles spoofing, benchmark manipulation, insider trading, wash trading, or legitimate market-making. It can also help regulators identify where statutory language is too vague, where courts disagree on intent, or where penalties lack consistency. Nevertheless, judicial precedent is not merely data. It contains normative judgments about fairness, responsibility, due process, and market integrity. Therefore, AI should be treated as a legal intelligence tool, not as an autonomous judge.

The proposed regulatory framework should therefore integrate AI into four connected stages: detection, evidentiary reconstruction, judicial evaluation, and regulatory reform. In the detection stage, AI monitors trading data, order books, sentiment, and networks to identify suspicious activity. In the evidentiary reconstruction stage, AI explains the sequence of conduct, estimates artificial price impact, identifies affected parties, and supports expert analysis. In the judicial evaluation stage, courts use AI-assisted evidence to assess intent, causation, artificial price, harm, and proportionality. In the regulatory reform stage, lawmakers and regulators use accumulated AI findings to refine definitions, improve surveillance rules, harmonize sanctions, and update compliance obligations. This framework must be governed by safeguards. AI models should be transparent, auditable, explainable, and subject to adversarial challenge. The data used must be reliable, complete, and lawfully obtained. False positives must be minimized because over-enforcement can chill legitimate trading. Model bias must be controlled because surveillance should not unfairly target certain traders, markets, or strategies. The final decision must remain with human courts and regulators. AI can reveal patterns, but law must determine responsibility.

5. Conclusion

Financial derivatives markets are indispensable to modern finance because they allow risk to be priced, transferred, hedged, and managed across time and across markets. Their economic usefulness, however, is inseparable from their legal vulnerability. The same leverage, liquidity, speed, and complexity that make derivatives efficient also make them attractive instruments for manipulation and fraud. When a trader or group of traders creates artificial price pressure, false volume, deceptive order-book signals, or coordinated misinformation, the harm extends beyond private profit and loss. It undermines market integrity, weakens investor confidence, distorts price discovery, and can affect related physical markets, especially in commodities and energy.

Traditional anti-manipulation and anti-fraud rules remain necessary, but they are no longer sufficient by themselves. Courts and regulators have relied on concepts such as manipulative conduct, intent, causation, artificial price, investor harm, and proportionality of punishment. These concepts remain legally essential, but their application has become increasingly difficult in markets shaped by algorithmic trading, high-frequency strategies, complex derivatives, cross-market positions, and enormous quantities of data. A manipulative scheme may no longer appear as a single false statement or an easily visible transaction. It may appear as a sequence of orders, cancellations, communications, price movements, sentiment shifts, and coordinated behavior distributed across multiple markets and accounts. Judicial reasoning must therefore become more technically informed without losing its normative and procedural character.

Artificial intelligence can play a decisive role in this transformation. It can detect suspicious trading patterns, identify abnormal price and volume movements, analyze order-book behavior, reconstruct market sequences, map networks of coordination, examine textual sentiment, compare judicial precedents, and estimate illicit gains or market harm. These functions can help courts and regulators move from abstract suspicion to evidence-based reconstruction. AI can also assist in distinguishing ordinary volatility from artificial price movement, legitimate speculation from manipulative pressure, and aggressive trading from deceptive market conduct. In this way, AI can make anti-manipulation law more precise, more consistent, and more responsive to the realities of modern derivatives markets.

The most important contribution of AI is not that it replaces judges, regulators, experts, or legal doctrine. Its contribution is that it can make hidden market behavior visible and measurable. It can translate complex trading data into patterns that courts can evaluate. It can support the proof of intent by identifying repeated strategic conduct. It can support the proof of causation by modeling counterfactual price behavior. It can support proportionality by estimating harm, profit, and the duration of manipulation. It can support precedent by showing how similar cases have been treated and where judicial reasoning has become inconsistent. These capacities can help redesign anti-manipulation and anti-fraud regulation from a reactive model into a more preventive, analytical, and evidence-based system.

At the same time, the use of AI in judicial and regulatory settings must be limited by due process, transparency, explainability, and human oversight. A black-box model cannot become a substitute for legal reasoning. A statistical anomaly cannot automatically become proof of guilt. A predictive output cannot replace the court's duty to evaluate evidence, hear objections, assess credibility, and justify its decision. AI must therefore be used as an auxiliary instrument that strengthens legal analysis rather than displaces it. Its outputs should be explainable, auditable, contestable, and connected to recognized legal elements.

The redesign of derivatives market regulation should therefore combine technological capacity with legal safeguards. Regulators should adopt AI-based surveillance systems capable of real-time monitoring and cross-market analysis. Courts should develop evidentiary standards for AI-assisted proof in manipulation and fraud cases. Legislators should refine anti-manipulation definitions so that they address both traditional deception and algorithmic market abuse. Penalty systems should become more proportionate by using better methods for calculating illicit profit, investor loss, and systemic harm. International cooperation should also be strengthened because derivatives markets operate across borders while enforcement remains largely national.

Ultimately, artificial intelligence should be understood as a means of restoring the connection between legal judgment and market reality. Financial markets have become too fast, too complex, and too data-intensive for traditional evidentiary methods to operate alone. If carefully governed, AI can help courts and regulators identify manipulation more accurately, punish fraud more proportionately, and protect the integrity of derivatives markets more effectively. The future of anti-manipulation regulation should not be purely technological, nor should it remain purely traditional. It should be a legally accountable, technically informed, and institutionally integrated system in which AI supports the central purpose of financial law: fair, transparent, and trustworthy markets.

Ethical Considerations

All procedures performed in this study were under the ethical standards.

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Conflict of Interest

The authors report no conflict of interest.

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