AIFS0046

Written evidence submitted by Maximilian Goehmann

Introduction and Statement of Interest

This paper responds to the UK Parliament's call for evidence by examining a critical and overlooked risk in financial markets: the impact of disputed or phantom data on automated trading systems (ATS) that use artificial intelligence (AI). These data issues can quietly disrupt the financial system, increasing the risk of rapid and widespread market instability. This submission is designed for policymakers and regulators, and its findings have direct implications for the Financial Conduct Authority (FCA), the Bank of England (BoE), and UK policymakers concerned with AI and financial market stability.

The insights and recommendations in this paper are based on my doctoral research at the London School of Economics (LSE). That research investigated how small but frequent data errors — what I call 'disputed data' — are formed and contribute to systemic fragility. Motivated by extreme market events like the 2010 Flash Crash, I used real-world trading data and examples aiming to uncover how today's automated trading systems are vulnerable not only to major technical failures but also to small data issues that accumulate unnoticed. This paper explains how these risks emerge and what can be done to manage them in order to uphold a capitalistic free market.

It argues that current regulatory frameworks — in the UK and internationally — focus heavily on AI/algorithmic oversight while largely neglecting the quality and governance of financial data inputs, despite the centrality of data reliability to AI systems and market stability. The submission recommends a potential regulatory response, including real-time data quality monitoring, improved transparency across financial data supply chains, data-centric stress testing for AI models, and a certification framework for trusted financial data providers. Together, these measures would help reduce systemic risks associated with AI-driven trading, safeguard the stability and resilience of UK and international financial markets as AI adoption and the markets continues to grow.

Glossary of key terms:

Terms	Definition/Explanation
Disputable data	Market data that may be incorrect, duplicated, or missing

Phantom data	Errors in market data that look real but are not (Daraio et al., 2022)
NBBO quotes	The best available price from different exchanges built from different quotes to build the national best quote
Automated Trading Systems	Computer programs that make trades without human input
AI-generated signals	Market decisions made automatically using AI
Self-reinforcing feedback loop	A cycle where one mistake causes more mistakes
Tightly coupled system	A system where everything is connected and reacts instantly
Herding behaviour	When many trading systems react in the same way to the same signal
Fleeting opportunities	Extremely short-lived chances to act or profit in financial markets, often lasting only milliseconds

2. Table of Contents

3. Executive Summary

The growing adoption of AI and ML in financial services has led to the rapid expansion of ATS across global financial markets. These systems are increasingly relied upon to execute trades at speeds and frequencies far beyond human capability, with over 60% to 70% of trades now conducted algorithmically (Goldman Sachs, 2016). AI-driven trading systems — including those powered by reinforcement learning (RL) and other advanced algorithms — offer enhanced speed, efficiency, and data processing capacity, enabling firms to capitalize on fleeting opportunities (Kraus & Feuerriegel, 2017; Olorunnimbe & Viktor, 2023). However, these same capabilities have also introduced new risks to financial stability, market transparency, and systemic resilience.

The core of these risks lies in the data environments underpinning AI-based ATS. While financial markets operate under stringent regulatory frameworks that emphasize transparency and data integrity (Feyen et al., 2022; Wachter et al., 2017), a critical assumption persists across the industry — that the data used by AI trading systems is inherently accurate and reliable. This assumption has been largely unchallenged, despite mounting evidence that data quality issues can directly contribute to market instability (Wang & Strong, 1996; Clay, 2014).

Historical cases such as the 2010 Flash Crash demonstrate how algorithmic trading, driven by flawed data inputs and amplified by feedback loops between algorithmic systems, can trigger rapid and unpredictable market failures (Kirilenko et al., 2017). These incidents highlight the vulnerability of tightly coupled financial systems, where high-frequency trading (HFT) algorithms process thousands of orders per second based on real-time data feeds (Johnson et al., 2013). The speed and scale of these transactions leave little room for human intervention once faults propagate through the system (Perrow, 1999). Employees of a financial intuition famously were rumoured trying to unplug their trading system during the Flash Crash. When data containing errors, omissions, or duplications — termed for this paper ‘disputable data’— enters ATS systems, the consequences at the minimum could lead to wrongly informed decisions.

Disputable data refers to financial data that lack real-world correspondence, often originating from errors in the data aggregation and transmission processes between exchanges, data suppliers, and trading firms. These data points are particularly problematic in aggregated quote data such as NBBO data (SEC, 1934) — a benchmark dataset used by many AI trading systems — where slight inaccuracies can distort pricing models, liquidity forecasts, and risk assessments (Patterson et al., 2014). In financial markets, accurate price information is essential for informed trading decisions. The term NBBO (National Best Bid and Offer) refers to the best available buying (bid) and selling (offer) prices for a stock at any given moment across different stock exchanges. Automated Trading Systems (ATS) rely on NBBO data, rapidly executing trades without human intervention based on these continuously updated price quotes. Despite the well-established importance of data quality, existing regulatory and operational frameworks focus primarily on ensuring the accuracy of algorithms and their outputs, rather than scrutinizing the integrity of the data inputs that underpin them (Horneber & Laumer, 2023; MacKenzie, 2009).

The preliminary findings of my research — which examines live and historical NBBO datasets — reveal concrete evidence of disputable data formation: duplicated quotes, missing values, and incorrect price aggregations introduced not by trading firms themselves, but by data suppliers acting as intermediaries between exchanges and trading platforms to consumers and financial institutions. Hence, data points are disputable. In greater detail once could argue that these data points form phantom data points. This term refers to financial information that appears real but is actually the result of technical errors — for example, repeated or out-of-date trading quotes. These errors often arise during the process of collecting, combining, or distributing market data. A prime example would be that a duplicated price quote might be treated by a trading algorithm as a new market signal. In a high-speed trading environment, this can trigger unnecessary or incorrect trades, which then influence other systems, amplifying the error. The issue is not just solely technical. It goes to the heart of financial stability. If many trading systems act on false signals at the same time, the market can swing dramatically in seconds — without any real-world economic reason.

Motivated by this phenomenon the researcher contacted data providers for a comment who in response shifted the responsibilities to the exchanges. To compare the data, data sets were also requested from the contributing exchanges to compare if and how faulty data was being delivered. The exchanges complied and the preliminary comparison resulted in the following table.

The table below illustrates a comparison between the official NBBO quotes provided directly by exchanges and quotes distributed by third-party data providers. Each row represents a precise timestamp, showing the exact moment when the price quotes were recorded, while each column lists the timestamp (t), the bid exchange (bx), the ask exchange (ax), the bid price (bp), and the ask price (ap):

[redacted]	t	bx	ax	bp	ap	bs	as	c	q	
	1639146659836	11	10	104.1	104.61	5	1	1	1139667	
	1639146659992	11	10	104.1	104.61	5	1	1	1140279	<= Phantom Quote
	1639146660299	11	10	104.1	104.61	3	1	1	1142367	

[redacted]	Timestamp-short	Bid-Exchange-ID	Ask-Exchange-ID	Bid-price	Ask-price	Bid-size	Ask-size
	1639146659836	11.0	10.0	104.1	104.61	5.0	1.0
	1639146660299	11.0	10.0	104.1	104.61	3.0	1.0

The table above showcases that, under unknown conditions, the supplier failed to form the correct NBBO quote. In this instance values were duplicated, creating phantom data. The NBBO quote marked by the '?' does not exist if the NBBO quote is aggregated correctly from the data provided by the exchanges. Upon on closer investigation, one realises that the previous quote just had been simply duplicated (marked by the '1'). Further comparisons of data revealed that this phenomenon is not an anomaly but rather a repeating pattern.

Although only one quote in the above shown example had been duplicated which might appear negligible, it can have substantial financial consequences in high-volume markets like the U.S., where daily trading exceeds $341.9 billion (Nasdaq, 2024). In this context, even a minor data inaccuracy can trigger erroneous forecasts leading an ATS to buy the wrong quantity at the wrong time, potentially causing significant financial losses and contributing to market volatility (Gomber et al., 2017).

A prime example is the previous mentioned 2010 Flash Crash, where a series of rapid trades triggered by ill-informed ATS feedback loops led to a sudden $1 trillion drop in market value within minutes (Kirilenko et al., 2017). A cascading failure which destabilised the entire market (Chen and Wei, 2015).

Hence, the risks posed by faulty financial data in AI trading systems extend beyond individual firm losses to broader financial stability risks. AI trading models trained on flawed data may misprice assets, amplify herding behaviour, and could create artificial liquidity crises, particularly in periods of market stress (Quilk, 2025; Aldridge, 2013). These risks are exacerbated by the increasing reliance on third-party data providers, leading to challenges in traditional regulatory framework (Arner et al., 2017). Without effective oversight, the systemic impact of disputable data and data-related algorithmic failures can grow.

These errors were not only undetected at the time, but were also normalized within the operational environment, meaning they were treated as acceptable deviations rather than red flags requiring correction (Perrow, 2011). This normalization of faulty data reflects a broader systemic issue: the absence of real-time oversight and audit mechanisms to verify the accuracy and provenance of financial data feeding into AI models (Bello et al., 2023).

Further, empirical evidence from the doctoral research supports this concern. A pilot study conducted on a random historical NBBO dataset identified that approximately 2.5% of all quotes can be classified as disputable data — erroneous quotes generated by system processes rather than genuine reflective market quotes Analysis demonstrated a statistically significant correlation ($r = 0.65$, $p < 0.05$) between these disputable data points and volatility spikes, illustrating how erroneous data triggers could amplify market instability.

Key Risks Identified:

1. **Disputable Data Formation – root cause:** Faulty, duplicated, or missing financial data — e.g. introduced through third-party data suppliers — is passed unnoticed into AI trading systems, where it can distort decision-making processes.

2. **Algorithmic Herding & Feedback Loops — result of disputable data:** When multiple AI trading models rely on similarly flawed data, they could generate herding behaviour, reinforcing inaccurate pricing signals and magnifying volatility (Fu et al., 2023).

3. **Tightly Coupled System Fragility — amplified by disputable data:** In high-frequency environments, minor data faults can rapidly propagate through interconnected trading algorithms, causing systemic instability (Perrow, 1999; Kirilenko et al., 2017).

4. **Absence of Data Oversight Frameworks — regulatory gap:** Current regulatory frameworks emphasize algorithmic transparency but neglect the need for continuous real-time verification of financial data quality and provenance (MacKenzie, 2009; Office for Financial Research, 2016; Wachter et al., 2017).

Conclusion and Need for Policy Action

As AI adoption accelerates across financial markets, the systemic risks arising from disputable data in AI trading systems demand urgent regulatory attention. The UK has an opportunity to lead in developing a comprehensive AI data governance framework for financial markets — one that includes addressing data quality assurance, supplier transparency, and real-time oversight mechanisms for AI inputs. By enhancing data governance, regulators can strengthen the resilience of AI trading systems, mitigate systemic risks, and ensure that AI contributes to market stability rather than amplifying wrongfully caused volatility for financial institutions and the average citizen. Crucially, such a framework would also help preserve market efficiency by ensuring that trading algorithms are built on reliable and accurate inputs, while simultaneously raising the barrier for actors with malicious intent who may seek to exploit data vulnerabilities.

Here, are three recommendations:

1. Real-Time Data Oversight: The FCA could oversee the licensing regime for data providers, incorporating data quality standards into its existing Senior Managers and Certification

Regime (SM&CR) for regulated firms. For example, the SEC introduced the Market Access Rule (Rule 15c3-5), requiring real-time risk management controls for algorithmic trading systems. A similar approach could be taken for real-time data quality auditing in AI-driven trading.

2. Data Stress Testing for AI Models: The Bank of England (BoE) could implement mandatory stress tests that simulate data anomalies — such as duplicated quotes, missing values, and inconsistent timestamps — would ensure that AI trading models can detect or withstand such anomalies without triggering self-reinforcing failures. This approach aligns with the ECB's existing stress-testing frameworks, which assess banks' ability to cope with various shocks (ECB, 2024).

3. Data Quality Certification: Data suppliers should be held to clearer standards and required to certify the accuracy of their data. For example, the PSR mandates certification of payment data integrity for financial institutions. This model could be expanded to create a certification framework for financial data providers as the responsibilities as of March are shifted anyway to the FCA.

4. AI in Financial Markets: A Growing Systemic Risk?

4.1 The Rise of AI-Driven Trading

The increasing sophistication of these systems stems from their integration of machine learning algorithms, including deep learning and reinforcement learning techniques, which allow ATS to learn from historical and real-time data to refine trading strategies dynamically (Chen et al., 2018; Millea, 2021). By analysing market microstructure patterns, sentiment data, and economic indicators, these models optimise decision-making in milliseconds, adjusting order flows, position sizes, and risk exposures in near real-time.

This evolution from static, pre-programmed algorithms to adaptive learning systems has accelerated the overall pace of market activity, compressing price discovery processes into ever shorter windows (Yadav, 2015). In high-frequency trading (HFT) environments, AI-driven ATS now trade per second often competing for microscopic price advantages (Aldridge, 2013). This shift has not only boosted liquidity provision (Menkveld & Zoican, 2017) but has also created an operational environment in which even minor data discrepancies can have cascading impacts on entire market segments.

The reliance on AI trading models comes with an implicit assumption that quote data provided by exchanges is an accurate reflection of price development between all market participants — an assumption that has been challenged by empirical evidence from past market disruptions and emerging research on financial data quality (Wang & Strong, 1996; Batini & Scannapieco, 2016). AI models depend on continuous data feeds from both exchanges and third-party data suppliers, including data aggregators responsible for constructing NBBO quotes (U.S. Congress, 1934). These data streams form the informational foundation upon which trading decisions are made.

However, data imperfections — including latency issues or incomplete updates — frequently go undetected in real-time environments. These undisputed data points may appear isolated in traditional systems but in tightly coupled, high-frequency trading networks, they can propagate rapidly and distort collective decision-making across multiple trading firms (Perrow, 1999; Kirilenko et al., 2017).

The increased outsourcing of data acquisition to third-party suppliers, often acting as intermediaries between exchanges, brokers, and trading firms, further exacerbates these risks (McCahery & De Roode 2018). Many AI systems have little visibility into how data is generated, validated, or transmitted, creating a critical blind spot in existing governance frameworks. This absence of transparent, auditable data supply chains introduces systemic vulnerabilities, especially during periods of heightened market volatility.

In summary, the rise of AI-driven trading has not only redefined market efficiency but also introduced new forms of operational fragility. These systems now rely on data environments where errors may go unnoticed until they trigger collective instability, underscoring the need to address data quality risks as part of any comprehensive approach to managing AI in financial markets (Gomber et al., 2017; FSB, 2017; Mosaic Smart Data 2024).

4.2 The Case of Instability: Lessons from the 2010 Flash Crash

The 2010 Flash Crash remains a defining moment in the evolution of automatic-driven trading and a stark illustration of the systemic risks embedded in modern, automated financial markets. On 6 May 2010, the U.S. equity market experienced a near-instantaneous collapse, wiping out approximately $1 trillion in market value within minutes, only for prices to recover almost as quickly (Kirilenko et al., 2017).

Subsequent investigations identified several contributing factors, including algorithmic trading strategies that amplified volatility through rapid order cancellations and re-submissions (SEC., 2010; Leuchtkafer, 2016; Min & Borch, 2021). At the heart of the incident were tightly coupled, high-speed trading environments, where AI models continuously adapted to signals from other AI models, amplifying herding behaviour and accelerating price dislocations (Johnson et al., 2013). In such systems, even minor data discrepancies — such as inconsistent bid-ask spreads or delayed quote updates — can distort price discovery processes, particularly when multiple models depend on the same flawed data streams (Gomber et al., 2017; Tivnan, 2018; Lin et al. 2019).

In a more recent example in the UK, 2020, the London Stock Exchange (LSE) experienced a market-wide trading outage, disrupting transactions in FTSE 100 and FTSE 250 stocks for over 90 minutes. The issue stemmed from a data feed malfunction within the LSE's Millennium Exchange trading system, which failed to properly distribute market data, leading to an operational halt (Financial Times, 2020). The incident highlighted the fragility of AI-driven and automated trading infrastructure, where data inconsistencies can trigger cascading failures across high-frequency trading (HFT) systems.

This incident underscores the need for real-time AI data validation frameworks to ensure market stability, particularly as financial markets become increasingly reliant on automated trading platforms and AI-generated signals. A specific data-related failure I identified in the preliminary research relates to disputable data that is, pricing information that may be incorrect, duplicated, or missing - embedded within NBBO quotes. These errors - caused by duplicated or missing data points introduced during the aggregation process by data suppliers - directly impacted the pricing signals upon which AI models relied. If models were to act on non-existent price movements, their actions could further trigger AI responses across the ecosystem, creating possibly a self-reinforcing feedback loop (Zhong et al., 2018; Sidley Austin LLP, 2024). This phenomenon fits into Perrow's (1999) Normal Accident Theory (NAT), which posits that in systems characterised by both tight coupling and complex interactions, accidents are inevitable. In such systems, small failures can escalate into cascading breakdowns due to the system's intrinsic structural properties. In the case of the Flash Crash, human traders, compliance teams, and regulators lacked the ability to intervene effectively, as the collapse occurred at speeds that outpaced both manual oversight and existing risk controls (Perrow, 2011; Kirilenko et al., 2017).

The normalisation of disputable data within the operational processes of data suppliers, trading firms, and exchanges can be another key contributor to future incidents such as the Flash Crash. Qualitative findings indicated that disputable data such as duplicated quotes are treated as minor technical artefacts rather than systemic risks, reflecting a broader cultural acceptance of data imperfections in high-frequency environments.

The Flash Crash is thus more than a historical event — it is a warning of how AI-driven trading systems, operating in fragmented data environments, can amplify seemingly minor errors into catastrophic failures. Without robust data governance frameworks for real-time data quality assurance, improved transparency in data supply chains, and systemic risk monitoring tailored to AI-driven trading, the risk of future flash crashes remains alarmingly high (Wachter et al., 2017; Floridi & Taddeo, 2016).

5. The Hidden Risks of AI in Financial Trading

5.1. Disputable Data and the Fragility of AI-Driven Systems

AI-driven ATS depend heavily on continuous streams of accurate, high-frequency data. These data flows, sourced from exchanges, brokers, and third-party data suppliers, are the foundation upon which trading algorithms form their decisions, ranging from order execution to risk management and portfolio rebalancing (IMF, 2024; PyQuant News, 2024).

However, my research — specifically analysing NBBO data — has revealed the persistent presence of disputable data. Unlike conventional data noise or latency errors — which are often temporary and detected through basic filtering — these data points mirror valid financial data in structure, allowing it to pass undetected into trading algorithms.

This issue is particularly acute in tightly coupled trading environments, where data is aggregated, transmitted, and acted upon within milliseconds, leaving no meaningful window for quality control (Perrow, 1999). Initial findings from doctoral research show that certain NBBO quotes were formed using duplicated bid and ask prices, likely resulting from faulty data aggregation logic at the data supplier level.

The presence of disputable data increases fragility across the entire financial system in three keyways:

- Mispricing: Trading algorithms operating on faulty data make misinformed trading decisions, contributing to asset mispricing (Zhang, 2021).
- Liquidity Distortions: When ATS systems react to non-existent price signals, they adjust order books, which can reduce genuine market liquidity and deepen order book imbalances (Gomber and Gesell., 2009; Martin, 2018).
- Feedback Amplification: Disputable data can trigger trading responses across multiple systems, creating a reinforcing feedback cycle that amplifies minor errors into system-wide volatility spikes (Kirilenko et al., 2017).

The absence of standardised, real-time data quality controls between exchanges, data suppliers, and trading firms means phantom data propagates unchecked, posing a latent but substantial risk to financial stability (FSB, 2017; Arner et al., 2017).

5.2. Algorithmic Herding and the Synchronisation Risk in AI Markets

AI trading models, particularly those using ML and RL, rely on common data sources, often from a small set of large data providers (Liu et al, 2022; Ye et al., 2024). This creates the risk of algorithmic herding, where different firms' trading models converge on identical data signals, magnifying their collective response to perceived market changes (Fu et al., 2023; McGeever, 2024).

During periods of market stress, this synchronisation can rapidly destabilise prices, as multiple algorithms simultaneously adjust their strategies based on the same (potentially faulty) inputs (Kirilenko et al., 2017). When disputable data or incomplete information enters this shared data pool, it acts as a systemic 'false signal' that disproportionately influences all algorithms at once (Wang & Strong, 1996; MacKenzie, 2021).

The use of reinforcement learning techniques can exacerbate this synchronisation risk. These systems continuously update their trading logic based on recent experiences, meaning one bout of phantom data can permanently alter the model's perception of market conditions, embedding faulty logic into future trading decisions (Lopez de Prado, 2018; Yuan et al., 2020).

This effect is particularly pronounced in high-frequency environments, where the overwhelming volume of trades reduces the weight of fundamental analysis, increasing reliance on short-term technical signals derived from streaming data feeds (Aldridge, 2013). Consequently, algorithmic herding combined with faulty data amplifies short-term volatility and can trigger cascading order cancellations and liquidity shocks, as witnessed during the 2010 Flash Crash (Kirilenko et al., 2017; Gomber et al., 2017)

The combination of disputable data, algorithmic herding, and feedback loops forms a self-reinforcing risk cycle, where each distorted price signal becomes both a trigger for further trading and a validation for existing positions. This fragile equilibrium makes financial markets more susceptible to sudden breakdowns, even in the absence of external shocks (Benhabib et al., 2018; Zhong et al., 2018; MacKezie, 2021).

---

6. Third-Party Risks & Regulatory Gaps

6.1. Third-Party Dependencies and the Data Supply Chain Blind Spot

A key structural vulnerability underpinning these risks lies in the increasing dependence of trading firms on third-party data suppliers, who aggregate and distribute data from multiple exchanges and offer them via APIs. These suppliers — including both established financial data vendors and newer fintech platforms — operate in a high-pressure, real-time environment, where data is collected, standardised, and transmitted under extremely tight latency requirements (sub-millisecond in some cases) (Lewis, 2014; Budish et al., 2015; O'Hara, 2015).

The operational environment at these suppliers, as revealed through preliminary document analysis in the doctoral research, reflects a combination of systemic blind spots and normalised shortcuts. In several cases, disputable data or anomalies — including duplicated quotes and partial quote construction errors — were dismissed as harmless artefacts or transient glitches, rather than symptoms of systemic fragility (Perrow, 1999).

The original research revealed that disputable data often originate from the interfaces between exchanges and data suppliers. Comments from data suppliers' employees and analysis of real-time quote streams demonstrated that errors introduced during data aggregation — particularly in the creation of the NBBO — are rarely flagged in real-time and often propagate downstream to ATS with no clear accountability between exchanges, suppliers, or trading firms. This lack of data provenance and validation oversight creates a systemic blind spot, where erroneous data can trigger cascading failures across tightly coupled systems without any actor having full visibility or responsibility.

This organisational normalisation of deviance, a phenomenon where repeated low-impact errors are gradually accepted as part of normal operations, prevents proactive remediation and systematic oversight (Perrow, 2011). It also obscures accountability, as data suppliers, exchanges, and trading firms all can potentially presume the data they receive has been quality-checked by someone else in the chain (Burkholder et al., 2023).

Despite the centrality of data quality to AI trading performance, there are no clear regulatory requirements mandating real-time data audits at the supplier level, nor transparency obligations requiring data suppliers to disclose quality assurance processes or detected anomalies in the UK (Department for Science, 2023; FCA, 2022). This regulatory gap leaves

AI trading firms blind to critical vulnerabilities in their core data feeds, magnifying the risk of sudden and severe disruptions (CEPS, 2019; FSB, 2024).

6.2. The Need for Data-Centric Risk Governance

Existing financial regulations, including MiFID II in the EU and FCA guidelines in the UK, largely focus on the transparency and accountability of trading algorithms themselves. These frameworks rightly emphasise the importance of explainability and risk controls within the AI models, but they underemphasise the systemic importance of data governance in algorithmic trading (FCA, 2018; ESMA,2021).

The absence of holistic data quality regulation leaves a critical gap in the financial sector's AI risk management framework. Without continuous monitoring of data flows, real-time detection of phantom data, and regulatory audits of data suppliers' aggregation and validation processes, the stability of AI trading systems will remain at risk. Markets could become inefficient and invite faulty players that might even abuse the loopholes which is a threat for free capitalist markets in general.

A data-centric approach to AI regulation is therefore essential — one that treats data quality assurance and supply chain transparency as core pillars of systemic financial market stability, equal in importance to algorithmic oversight and rules such as insider trading (FMSB, 2020; uTrade Algos, 2024).

Conclusion of Section 6

These identified gaps in data governance and third-party oversight align with broader policy concerns already recognised within the UK regulatory ecosystem. The FCA's Artificial Intelligence Public-Private Forum (AIPPF) has highlighted data quality as a fundamental enabler of trustworthy AI, while the Bank of England and FCA's joint work on AI and Machine Learning in Financial Services has emphasised the importance of data reliability in high-frequency environments. The recommendations in the following section build on these foundational insights, offering targeted proposals to enhance data governance specifically within AI-driven trading environments. By embedding data-centric oversight into the UK's evolving AI regulatory framework, policymakers can ensure a more resilient, future-proof financial system that upholds the integrity of a free market.

---

7. Recommendations for Government and Regulators

7.1. Establishing Real-Time Data Quality Oversight and Accountability

The UK's regulatory framework for financial markets has evolved to incorporate the oversight of ATS, particularly in areas such as algorithmic transparency, stress testing, and market abuse prevention. However, these efforts remain largely focused on the models themselves, rather than the underlying data flows that feed those models (PRA, 2018; FCA, 2018; FCA, 2024).

As demonstrated by the disputable data phenomenon uncovered in the prior research, financial data — particularly consolidated market data such as NBBO quotes — is subject to a complex supply chain that includes exchanges, third-party data aggregators, and trading firms. Each layer introduces the potential for errors and offers opportunities for ill-intend, yet there is currently no regulatory requirement for continuous, real-time data quality auditing at any point in this chain to the authors knowledge (Ding et al., 2014; EY, 2021).

Recommendation of possible actions:

- United States (SEC): The SEC introduced the Market Access Rule (Rule 15c3-5), requiring real-time risk management controls for algorithmic trading systems. A similar approach could be taken for real-time data quality auditing in AI-driven trading.
- The FCA could oversee the licensing regime for data providers, incorporating data quality standards into its existing Senior Managers and Certification Regime (SM&CR) for regulated firms.
- Require all financial data suppliers serving regulated financial institutions to implement real-time anomaly detection and reporting systems, covering both structural anomalies (missing fields, duplications) and contextual anomalies (implausible price movements).
- Introduce data quality audits for all firms providing data to AI-driven trading systems, with audit reports accessible to both financial regulators and client firms.
- Establish a data anomaly incident reporting framework, requiring data suppliers to notify regulators and clients when systemic anomalies (e.g., duplicated NBBO quotes) are detected, even if no immediate market impact is identified.

This shift from reactive to preventive data oversight could significantly reduce the risk of silent propagation of phantom data through interconnected trading models, while ensuring continuous market efficiency. It further aligns data oversight with the risk management expectations already imposed on algorithmic systems themselves. One notable example is the Basel Committee on Banking Supervision’s Principles for Effective Risk Data Aggregation and Risk Reporting, commonly known as BCBS 239. Established in January 2013, BCBS 239 aims to strengthen banks’ risk data aggregation capabilities and internal risk reporting practices, thereby enhancing risk management and decision-making processes within financial institutions. However, achieving full compliance remains an ongoing challenge, necessitating continuous efforts from both banks and supervisory authorities in the respecting countries (BCBS 239, 2013)

7.2. Data-Centric Stress Testing for AI Trading Models

Current stress-testing requirements for algorithmic trading systems focus primarily on market scenarios (volatility spikes, liquidity shortages) and model failures (overfitting, excessive order flows). However, stress tests rarely examine the impact of corrupted, missing, or disputable data on algorithmic behaviour — despite clear evidence that such data anomalies can trigger cascading failures (Min et al., 2021).

Recommendation of possible actions

- European Central Bank (ECB): The ECB introduced AI model stress-testing protocols in financial institutions to evaluate AI-driven liquidity risks. Applying this approach to data quality stress testing would improve model resilience. Notably, the ECB conducted a cyber resilience stress test on 109 directly supervised banks in 2024, assessing how banks respond to and recover from cyberattacks. While this exercise focused on cyber resilience, the methodology could be adapted to evaluate AI-driven liquidity risks, thereby improving model resilience (ECB, 2024).
- Implementing mandatory stress tests that simulate data anomalies — such as duplicated quotes, missing values, and inconsistent timestamps — would ensure that AI trading models can detect or withstand such anomalies without triggering self-reinforcing failures. This approach aligns with the ECB's existing stress-testing frameworks, which assess banks' ability to cope with various shocks (ECB, 2024).
- Expanding stress-testing frameworks to include data supply chain disruptions is crucial. Disruptions in supply chains, whether due to cyberattacks or other factors, can have significant implications for financial stability. The ECB's cyber resilience stress test, which assessed banks' responses to severe but plausible cybersecurity events, serves as a pertinent example of incorporating such scenarios into stress-testing exercises (ECB, 2024).

Integrating data quality considerations into stress-testing protocols can be crucial for enhancing the resilience of AI-driven trading systems. The ECB's proactive stance in conducting various stress tests, including those assessing cyber resilience, provides a valuable framework that can be adapted to address data quality issues. By implementing these recommended actions, regulators and financial institutions can better anticipate and mitigate risks associated with data anomalies, thereby safeguarding financial stability.

7.3. Building a Data Quality Certification Framework

Financial regulators have already introduced codes of conduct for algorithmic trading (under MiFID II) and ethical guidelines for AI usage, but no equivalent framework exists in the UK for certifying the quality and transparency of financial data sources used by AI systems.

Given the centrality of data to AI trading performance — and the potential for faulty data to compromise not just individual firms but entire markets — regulators could establish a certification process for high-quality financial data services. The current courses on assessing data quality to promote better data management practices by the UK Government are a good step but not a preventive measure for inefficacies to ensure the pillars of an efficient capitalistic free market (Government Data Quality Hub, 2022).

Recommendation of possible actions:

- UK Payment Systems Regulator (PSR): The PSR mandates certification of payment data integrity for financial institutions. This model could be expanded to create a certification framework for financial data providers as the responsibilities as of March are shifted anyway to the FCA.
- The Bank of England, in its systemic risk oversight role, could incorporate data-centric stress testing into its Financial Policy Committee's broader stress-testing programmes for systemically important institutions rather than just assessing the resilience of the UK banking systems in the traditional sense of economic shocks and financial metrics.
- Develop a voluntary certification scheme for financial data providers, awarding "Trusted Data Supplier" status to firms demonstrating superior data governance, anomaly detection, and transparency practices (Mahanti, 2021).
- Align certification criteria with international standards for data quality management (BCBS, 2013), ensuring that certified data providers meet objective, auditable standards for data accuracy, timeliness, and reliability.

Implementing these recommendations could significantly enhance data quality and transparency in the UK's financial sector while not overregulating the financial market. However, recent developments, such as the planned abolition of the PSR, necessitate careful consideration of which regulatory bodies will assume responsibility for these initiatives. Aligning certification frameworks with international standards and encouraging the use of certified data sources would further bolster the integrity and reliability of financial data, benefiting both institutions and consumers.

April 2025

8. References

Aldridge, I. (2013). *High-Frequency Trading: A Practical Guide to Algorithmic Strategies and Trading Systems.* Wiley.

Arner, D. W., Barberis, J., & Buckley, R. P. (2017). FinTech, RegTech, and the Reconceptualization of Financial Regulation. *Northwestern Journal of International Law & Business*, 37(3), 371-413.

Barki, H., Rivard, S., & Talbot, J. (1988). An Information Systems Keyword Classification Scheme. *MIS Quarterly*, 12(2), 299-322.

Basel Committee on Banking Supervision. (2013). Principles for effective risk data aggregation and risk reporting (BCBS 239). Bank for International Settlements. Available at: https://www.bis.org/publ/bcbs239.pdf

Batini, C., & Scannapieco, M. (2016). *Data Quality: Concepts, Methodologies and Techniques.* Springer.

Bello, O.A., Ogundipe, A. and Mohammed, D. (2023). 'AI-driven approaches for real-time fraud detection in US financial transactions: Challenges and opportunities', European Journal of Computer Science and Information Technology, 11(6), pp. 84–102. Available at: https://eajournals.org/ejcsit/vol11-issue-6-2023/ai-driven-approaches-for-real-time-fraud-detection-in-us-financial-transactions-challenges-and-opportunities/.

Benhabib, J., Liu, X. and Wang, P. (2018). 'Information production in financial and real sides of the economy and self-fulfilling uncertainties', Journal of Economic Theory, 177, pp. 358–398. Available at: https://xuewenliu.com/pdf/Information%20production%20in%20financial%20and%20real%20sides.pdf.

Biais, B., Foucault, T., & Moinas, S. (2015). Equilibrium High-Frequency Trading. *Journal of Financial Economics*, 116(2), 292-313.

Budish, E., Cramton, P., & Shim, J. (2015). The High-Frequency Trading Arms Race: Frequent Batch Auctions as a Market Design Response. The Quarterly Journal of Economics, 130(4), 1547-1621.

Burkholder, G., Malik, N., & Forsythe, G. (2023). 'Fixing the finance data supply chain'. EY.

Cabrera, B. (2021). Data Quality in High-Frequency Trading Environments: Challenges and Solutions. *Journal of Trading*, 16(2), 45-53.

Cai, C. W., & Zhu, C. (2016). Fraud Detection in Financial Markets Using Machine Learning Approaches. *Finance Research Letters*, 19, 56-62.

Centre for European Policy Studies (CEPS). (2019). Artificial intelligence and cybersecurity: Technology, governance, and policy challenges. European Defence Agency. Available at: https://eda.europa.eu/docs/default-source/documents/ceps-tfr-artificial-intelligence-and-cybersecurity.pdf.

Chen, Q., & Wei, S. X. (2015). Modeling Market Dynamics with High-Frequency Data: Evidence from the Flash Crash. *Journal of Empirical Finance*, 33, 150-165.

Chen, Y., Zhou, X., & Dai, H. (2018). A LSTM-based Method for Stock Return Forecasting Using High-Frequency Data. *IEEE Access*, 6, 77259-77267.

Clay, B. (2024). ‘Benefits and risks of using AI in trading’, Blueberry Markets, 7 August. Available at: https://blueberrymarkets.com/market-analysis/benefits-and-risks-of-using-ai-in-trading/.

Daraio, C., Bonaccorsi, A., & Simar, L. (2022). Phantom Data and Its Implications for Efficiency Analysis. *Journal of Productivity Analysis*, 57(1), 1-23.

Department for Science, Innovation & Technology. (2023). A pro-innovation approach to AI regulation. GOV.UK.

Demirer, R., & Liao, Y. (2019). Crash Sensitivity and Market Efficiency: Evidence from Emerging Markets. *Emerging Markets Review*, 39, 100635.

Ding, S., Hanna, J., & Hendershott, T. (2014). How Slow Is the NBBO? A Comparison with Direct Exchange Feeds. Financial Review, 49(2), pp.313-332. Available at: https://faculty.haas.berkeley.edu/hender/nbbo.pdf.

European Central Bank. (2024). Cyber resilience stress testing from a macroprudential perspective. [online] Available) at: https://www.ecb.europa.eu/press/financial-stability-publications/macroprudential-bulletin/html/ecb.mpbu202502_01~f4914a46c1.en.html

European Central Bank (2024). Stress tests - ECB Banking Supervision. [online] Available at: https://www.bankingsupervision.europa.eu/activities/stresstests/html/index.en.html.

European Securities and Markets Authority (ESMA), 2021. MiFID II review report on algorithmic trading. ESMA. Available at: https://www.esma.europa.eu/sites/default/files/library/esma70-156-4572_mifid_ii_final_report_on_algorithmic_trading.pdf.

EY. (2021). Fixing the Finance Data Supply Chain. EY. Available at: https://www.ey.com/en_us/insights/financial-services/finance-transformation-fixing-the-finance-data-supply-chain

Feyen, E., Frost, J., Gambacorta, L., Natarajan, H. and Saal, M. (2022). Fintech and the future of finance: Market and policy implications. Washington, DC: World Bank. Available at: https://documents1.worldbank.org/curated/en/099450005162250110/pdf/P17300600228b70070914b0b5edf26e2f9f.pdf.

Financial Conduct Authority (FCA). (2018). Algorithmic Trading Compliance in Wholesale Markets. FCA. Available at: https://www.fca.org.uk/publications/multi-firm-reviews/algorithmic-trading-compliance-wholesale-markets.

Financial Conduct Authority. (2022). FS22/1: Accessing and using wholesale data.

Financial Conduct Authority (FCA). (2024). Market Watch 79: Newsletter on market conduct and transaction reporting issues. FCA. Available at: https://www.fca.org.uk/publications/newsletters/market-watch-79.

Financial Markets Standards Board (FMSB). (2020). The critical role of data management in the financial system. FMSB. Available at: https://fmsb.com/wp-content/uploads/2020/05/The-critical-role-of-data-management-in-the-financial-system.pdf.

Financial Stability Board. (2017). 'Artificial intelligence and machine learning in financial service'. Available at: https://www.fsb.org/2017/11/artificial-intelligence-and-machine-learning-in-financial-service/.

Financial Stability Board (FSB), 2024. The financial stability implications of artificial intelligence in financial services. Financial Stability Board. Available at: https://www.fsb.org/uploads/P14112024.pdf.

Financial Times. (2020). Exchange operators face scrutiny after bout of outages in 2020.

Floridi, L., & Taddeo, M. (2016). What is Data Ethics? *Philosophical Transactions of the Royal Society A*, 374(2083), 20160360.

Fu, T., Alexakis, C., & Zhang, X. (2023). 'Does algorithmic trading induce herding?', International Journal of Finance & Economics, 28(1), pp. 123–138. Available at: https://onlinelibrary.wiley.com/doi/abs/10.1002/ijfe.3085.

Gomber, P., Koch, J. A., & Siering, M. (2017). Digital Finance and FinTech: Current Research and Future Research Directions. *Journal of Business Economics*, 87(5), 537-580.

Goldstein, M. A., Kumar, P., & Graves, F. (2019). Computerized and High-Frequency Trading. *Financial Management*, 48(1), 5-38.

Goldman Sachs. (2016). What percentage of trading is algorithmic? Analyzing Alpha. Available at: https://www.quantifiedstrategies.com/what-percentage-of-trading-is-algorithmic.

Government Data Quality Hub. (2022). New courses on assessing data quality. GOV.UK. Available at: https://www.gov.uk/government/news/new-courses-on-assessing-data-quality

Horneber, J., & Laumer, S. (2023). Trusting the Unknown: Transparency and Trust in AI Systems. *Journal of Strategic Information Systems*, 32(1), 101719.

International Monetary Fund. (2024). ‘Artificial intelligence can make markets more efficient—and more volatile’, IMF Blog, 15 October. Available at: https://www.imf.org/en/Blogs/Articles/2024/10/15/artificial-intelligence-can-make-markets-more-efficient-and-more-volatile.

Johnson, N., Zhao, G., Hunsader, E., Meng, J., Ravindar, A., Carran, S., & Tivnan, B. (2013). Abrupt Rise of New Machine Ecology Beyond Human Response Time. *Scientific Reports*, 3, 2627.

Khan, S., & Yairi, T. (2018). A Review on the Application of Deep Learning in System Health Management. *Mechanical Systems and Signal Processing*, 107, 241-265.

Khan, Z., Lew, Y. K., & Park, B. I. (2019). Institutional Legitimacy and Norms-Based CSR Marketing Practices: Insights from MNE Subsidiaries’ Cross-National Transfer of CSR Practices. *Journal of Business Research*, 98, 98-105.

Kirilenko, A. A., Kyle, A. S., Samadi, M., & Tuzun, T. (2017). The Flash Crash: High-Frequency Trading in an Electronic Market. *Journal of Finance*, 72(3), 967-998.

Kraus, M., & Feuerriegel, S. (2017). Decision Support from Financial Disclosure Statements via Deep Learning. *Decision Support Systems*, 104, 38-48.

Lewis, M. (2014). Flash Boys: A Wall Street Revolt. W.W. Norton & Company.

Lin, C.-F., Chaio, C.-H. and Wang, B. (2019). ‘The impact of post-trade transparency on price efficiency and price discovery: Evidence from the Taiwan Stock Exchange’, Managerial Finance, 45(8), pp. 1069–1085. Available at: https://epublications.marquette.edu/fin_fac/133/.

Liu, X.-Y., Xia, Z., Rui, J., Gao, J., Yang, H., Zhu, M., Wang, C.D., Wang, Z. and Guo, J. (2022). ‘FinRL-Meta: Market Environments and Benchmarks for Data-Driven Financial Reinforcement Learning’, arXiv preprint arXiv:2211.03107. Available at: https://arxiv.org/abs/2211.03107.

Leuchtkafer, D. (2016). ‘Bibliography on high-frequency trading’. Available at: https://www.sec.gov/comments/s7-02-10/s70210-129.pdf.

López de Prado, M. (2018). ‘The 10 Reasons Most Machine Learning Funds Fail’, The Journal of Portfolio Management, 44(6), pp. 120–133. Available at: https://jpm.pm-research.com/content/44/6/120.

MacKenzie, D. (2009). Material Markets: How Economic Agents are Constructed. Oxford University Press.

MacKenzie, D. (2021). ‘Flash crashes and the social dynamics of algorithmic trading’, Social Studies of Science, 51(6), pp. 834–855. Available at: https://pubmed.ncbi.nlm.nih.gov/34612758/.

MacKenzie, D. (2021). ‘Normal accidents and high reliability in financial markets’, Social Studies of Science, 51(6), pp. 834–855. Available at: https://journals.sagepub.com/doi/abs/10.1177/03063127211048515 (Accessed: 16 March 2025).

Mahanti, R. (2021). *Data Governance: Creating Value from Information Assets.* Packt Publishing.

Martins, C.J.L. (2018) ‘Toxic liquidity – is it here to stay?’, Bank i Kredyt, 49(1), pp. 1–16. Available at: https://scispace.com/pdf/hidden-and-fast-liquidity-hidden-orders-and-high-frequency-4ycit86ayo.pdf.

McCahery, J.A. and De Roode, F.A. (2018). ‘Governance of financial services outsourcing: Managing misconduct and third-party risks’, ECGI Working Paper Series in Law, (417/2018). Available at: https://www.ecgi.global/sites/default/files/working_papers/documents/finalmccaheryderoode1.pdf.

McGeever, J. (2024). ‘For markets, AI efficiency may bring volatility’, Reuters, 17 October. Available at: https://www.reuters.com/markets/markets-ai-efficiency-may-bring-volatility-mcgeever-2024-10-17/

Menkveld, A.J. and Zoican, M.A. (2017). ‘Need for speed? Exchange latency and liquidity’, The Review of Financial Studies, 30(4), pp. 1188–1228. Available at: https://academic.oup.com/rfs/article/30/4/1188/2966376.

Millea, M. (2021). Reinforcement Learning in Financial Market Trading: A Review and Future Directions. *Journal of Financial Data Science*, 3(2), 34-52.

Min, B.H. and Borch, C. (2021). Systemic failures and organizational risk management in algorithmic trading: Normal accidents and high reliability in financial markets. Social Studies of Science, 51(6), pp.897-922.

Mosaic Smart Data. (2024). ‘Research reveals two thirds of banks struggle with data quality and integrity’. Available at: https://mosaicsmartdata.com/research-reveals-two-thirds-of-banks-struggle-with-data-quality-and-integrity/.

Nasdaq Trader. (2024). Daily market summary. Nasdaq.

Office of Financial Research. (2016). Developing best practices for regulatory data collections. Washington, DC: U.S. Department of the Treasury. Available at: https://www.financialresearch.gov/viewpoint-papers/files/OFRvp-2016-01_Best-Practices-Data-Collection.pdf.

O’Hara, M. (2015). High-Frequency Trading and its Impact on Markets. Financial Analysts Journal, 71(1), 18-39.

Olorunnimbe, M., & Viktor, H. (2022). Reinforcement Learning in Algorithmic Trading: A Survey. *AI Review*, 55, 481-508.

Olorunnimbe, R.O. and Viktor, H.L. (2023). ‘A systematic review of deep learning applications in the stock market’, Artificial Intelligence Review, 56(1), pp. 123–158. Available at: https://link.springer.com/article/10.1007/s10462-022-10226-0.

Patterson, S., Aldridge, I. and Krehbiel, T. (2014). ‘How slow is the NBBO? A comparison with direct exchange feeds’, Journal of Trading, 9(3), pp. 35-45. Available at: https://www.researchgate.net/publication/261410999_How_Slow_Is_the_NBBO_A_Comparison_with_Direct_Exchange_Feeds.

Perrow, C. (1999). *Normal Accidents: Living with High-Risk Technologies.* Princeton University Press.

Perrow, C. (2011). The Next Catastrophe: Reducing Our Vulnerabilities to Natural, Industrial, and Terrorist Disasters. Princeton University Press.

Prudential Regulation Authority (PRA). (2018). Algorithmic Trading. Bank of England. Available at: https://www.bankofengland.co.uk/prudential-regulation/publication/2018/algorithmic-trading.

PyQuant News. (2024), ‘AI models in high-frequency trading’, PyQuant News, 25 June. Available at: https://www.pyquantnews.com/free-python-resources/ai-models-in-high-frequency-trading.

Qlik. (2025). ‘Data quality is not being prioritized on AI projects, a trend that 96% of U.S. data professionals say could lead to widespread crises’, Business Wire, 12 March. Available at: https://www.businesswire.com/news/home/20250312530068/en/Data-Quality-is-Not-Being-Prioritized-on-AI-Projects-a-Trend-that-96-of-U.S.-Data-Professionals-Say-Could-Lead-to-Widespread-Crises.

Sidley Austin LLP. (2024). ‘Artificial intelligence in financial markets: Systemic risk and market abuse concerns’, Butterworths Journal of International Banking and Financial Law, December. Available at: https://www.sidley.com/en/insights/newsupdates/2024/12/artificial-intelligence-in-financial-markets-systemic-risk-and-market-abuse-concerns.

Strong, D. M., Lee, Y. W., & Wang, R. Y. (1997). Data Quality in Context. *Communications of the ACM*, 40(5), 103-110.

Tivnan, B.F., Slater, D., Thompson, J.R., Bergen-Hill, T.A., Burke, C.D., Brady, S.M., Koehler, M.T.K., McMahon, M.T., Tivnan, B.F. and Veneman, J.G. (2018). ‘Price discovery and the accuracy of consolidated data feeds in the U.S. equity markets’, Journal of Risk and Financial Management, 11(4), p. 73. Available at: https://www.mdpi.com/1911-8074/11/4/73.

U.S. Congress. (1934). Securities Exchange Act of 1934.

U.S. Securities and Exchange Commission (2020) 'Staff report on algorithmic trading in U.S. capital markets'. Available at: https://www.sec.gov/files/algo_trading_report_2020.pdf.

uTrade Algos. (2024). Understanding the importance of data quality in algo backtesting. uTrade Algos. Available at: https://www.utradealgos.com/blog/understanding-the-importance-of-data-quality-in-algo-backtesting.

Wachter, S., Mittelstadt, B., & Floridi, L. (2017). Why a Right to Explanation of Automated Decision-Making Does Not Exist in the General Data Protection Regulation. *International Data Privacy Law*, 7(2), 76-99.

Wang, R. Y., & Strong, D. M. (1996). Beyond Accuracy: What Data Quality Means to Data Consumers. *Journal of Management Information Systems*, 12(4), 5-33.

Yadav, Y. (2015) 'How algorithmic trading undermines efficiency in capital markets', Vanderbilt Law Review, 68(6), pp. 1607–1671. Available at: https://scholarship.law.vanderbilt.edu/vlr/vol68/iss6/3/.

Ye, J., Goswami, B., Gu, J., Uddin, A. and Wang, G. (2024) 'From Factor Models to Deep Learning: Machine Learning in Reshaping Empirical Asset Pricing', arXiv preprint arXiv:2403.06779. Available at: https://arxiv.org/abs/2403.06779.

Yuan, Y., Wen, W. and Yang, J. (2020) 'Using Data Augmentation Based Reinforcement Learning for Daily Stock Trading', Electronics, 9(9), p. 1384. Available at: https://www.mdpi.com/2079-9292/9/9/1384.

Zhang, X. (2021). 'Mispricing and algorithm trading', Information Systems Research, 32(4), pp. 1184–1199. Available at: https://pubsonline.informs.org/doi/abs/10.1287/isre.2021.0570.

Zhong, L.X., Xu, W.J., Chen, R.D., Zhong, C.Y., Qiu, T., Ren, F. and He, Y.X. (2018) 'Self-reinforcing feedback loop in financial markets with coupling of market impact and momentum traders', Physica A: Statistical Mechanics and its Applications, 493, pp. 301–310. Available at: https://ideas.repec.org/a/eee/phsmap/v493y2018icp301-310.html.