US Centre Summer Research Grant

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ProjectTitle: A Quantitative and Qualitative Investigation of Disputable Data in NBBO Datasets

Summary of Project:

This project explored the formation of 'disputable data' through National Best Bid and Offer (NBBO) quotes from U.S. stock markets.

Itemployed a quantitative pilot study deploying anomaly detection on historical 2010 NBBO data, revealing possible anomalies such as duplicated or out-of-sequence price quotes. These disputable data points demonstrate the divergence of consolidated NBBO feeds from actual market conditions. Furthermore, a qualitative analysis was deployed surveying market stakeholders to understand the possible causes and persistence of disputable data. Findings indicate that these data points are often viewed as minor occurrences rather than systemic problems.

Together, these studies highlight a possible vulnerability in algorithmic trading as the success of trading algorithms relies on the quality of the data they process. Therefore, enhancing data integrity and quality in the NBBO supply chain is essential for maintaining free and competitive financial markets in the era of AI-based trading.

1. Introduction

Financial markets are increasingly driven by high-speed, algorithm-based trading systems, which conduct approximately 60% of today's trades (Groette, 2024). While these Automated Trading Systems (ATS) can enhance efficiency by acting in milliseconds, they also pose new risks to market stability. This is because they rely substantially on accurate data inputs. Here, even minor errors can lead algorithms astray, as seen in the May 6, 2010, 'Flash Crash,' where faulty data contributed to extreme market fluctuations within minutes (Kirilenko et al., 2017). Events like this highlight the critical importance of data integrity for financial stability.

Amid concerns about systemic risks, this research focuses on specifically disputable data points. In other words, market data that seems legitimate but can mislead algorithms. These data points can include duplicate quotes, stale prices, and baseless values that may prompt ill- informed trades. In a high-frequency environment, for example, even a brief false signal can trigger rapid automated responses before human intervention (Wang & Strong, 1996).

The NBBO consolidates the best available prices across U.S. exchanges and is essential for fair, transparent pricing (SEC, 1934). However, its assembly from multiple exchanges offers room for potential inaccuracies, such as discrepancies between public and direct exchange feeds. Hence, this project aims to introduce an investigation into possible disputable data in NBBO feeds and identify possible sources.

2. Empirical Studies

2.1 Pilot Study 1 - Empirical Detection of NBBO Data Anomalies

The initial empirical pilot study investigates historical and live NBBO datasets to detect possible disputable data. As mentioned above, these refer to data points that appear valid but are technically erroneous, such as duplicated quotes, missing values, and incorrect price aggregations. Crucially, it has to point out that these data points stem not from the trading firms themselves but are possibly created by the supply chain between third-party data providers and exchanges (Cai et al., 2018). This study, thus, sought to understand whether NBBO data delivered by suppliers diverged from the original exchange data and whether such deviations were systematic.

Methodology:

The study employed a comparative design of live and historic datasets in order to assess the accuracy of NBBO data which aligns with similar studies such as Ding (2014). These datasets were obtained from data providers and from exchanges. Each NBBO data record contained the timestamp (t), bid exchange (bx), ask exchange (ax), bid price (bp), and ask price (ap). The comparison revealed whether supplier-distributed NBBO quotes matched the official exchange records. Hence, it allowed the author essentially to do a side-by-side evaluation of each timestamped record.

Errors were classified into distinct anomaly categories:

- Duplicated quotes, where a previously recorded entry was simply repeated;
- Missing values, where an expected NBBO update was absent;

	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	
	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			

An example of this is presented in *Table 1*, where the duplicate NBBO quote was tagged with red. It was observed in the supplier's live feed but not in the historic data set.

Results:

The comparative analysis outlined revealed that within the feed of NBBO data, occasionally disputable data is carried through to the end user. What initially appeared to be an isolated occurrence turned out to be a recurring pattern across multiple days and datasets. Even though some duplications involved only a single quote, such data points can cause consequences in high-volume markets such as the U.S., where daily equity trading exceeds $341.9 billion (NASDAQ, 2024). These, even minor inaccuracies, may be misinterpreted by ATS as fresh market signals, leading to erroneous trades and feedback loops.

Empirical evidence from the pilot study reinforced this concern. Approximately 2.5% of all quotes in a randomly sampled NBBO dataset were classified as disputable, i.e. system-generated disputable data rather than genuine market quotes. Statistical analysis revealed a significant correlation between these disputable data points and volatility spikes ($r = 0.65$, $p < 0.05$).

The risks posed by disputable market data extend beyond firm-level losses. If many trading systems act on false signals simultaneously, systemic effects could emerge, such as artificial liquidity crises, asset mispricing, or amplified herding behaviour (Aldridge, 2013). These challenges are exacerbated by the increasing reliance on data providers and the absence of real- time oversight mechanisms. According to Bello et al. (2023), disputable data, as the one found above, underscores the need for systems capable of verifying the provenance and accuracy of data feeding into AI models.

2.2 Pilot Study 2 – Organisational Analysis of Data Supplier Practices

The second pilot study investigated the human and organisational factors underlying the formation of disputable data. Whereas the first pilot study documented the types of anomalies that occur in NBBO datasets, this study attempted to explore why they arise within the financial data supply chain in the first place. To address this question, the analysed industry documents were used to capture organisational practices and cultural attitudes towards data integrity (Astrix Technology Group, 2019; Atlan. 2023).

Methodology:

The qualitative approach employs documentary analysis. Documents include email chains, industry reports and technical publications (e.g., SEC and FIA reports, internal emails where available, and regulatory guidelines) were reviewed to contextualise the interview insights.

Results:

Two interrelated findings emerged from the pilot study.

First, a culture of 'normalisation of deviance' was evident in data operations. Employees acknowledged that small anomalies (e.g., duplicated quotes or momentary outages) were often treated as glitches or problems carried through from exchanges rather than as potential issues that required remediation. One email chain noted that 'if it doesn't disrupt trading, it is usually dismissed as a one-off.' Other available documentary evidence supported this account: internal vendor reports labelled recurrent anomalous records (such as fleeting locks or crosses) as 'network latency artefacts,' with no follow-up investigation. Over time, such tolerance becomes part of the daily routine, embedding possible disputable data as an accepted feature ofthe feed rather than an exception.

Second, data quality is decentralised throughout the supply chain. The exchanges, the SIPs or consolidators and the vendors are all parties involved in the National Best Bid and Offer (NBBO) process by which quotes are produced by exchanges, aggregated by the SIPs or consolidators, and emitted by vendors as feeds. Each layer to some extent assumes that responsibilities lie with another actor. For example, one vendor email stated that 'If the exchange sends it to us, we pass it along, we don't alter their data.' Similarly, exchanges pointed to compliance with reporting rules and delegated responsibility for consistency to the vendor. This diffusion creates governance gaps, allowing disputable data to pass through unchecked.

This organisational analysis suggests that the persistence of disputable data is not only a technical artefact but is underpinned by cultural norms and less strong accountability structures. A study by Ghafoori (2023) emphasizes the importance of understanding and measuring risk culture to develop interventions that improve risk culture in organizational settings However, minor anomalies were tolerated unless they seem to escalate into crises, and the absence of regulatory mandates reinforces this reactive posture (Feldberg, 2020). As the data supply chain has become increasingly complex, financial markets are becoming more vulnerable to systemic risks arising from overlooked data points. The qualitative findings thus complement the empirical results of *Pilot Study 1* by revealing how organisational practices and regulatory blind spots enable phantom data to circulate unchecked.

3. Discussion Contribution and Impact

This summer research project has contributed to both academic literature and practical discussions in financial technology governance.

Academic contribution: The project developed an empirical taxonomies of real-world market data disputable data in a consolidated feed. Additionally, the integration of quantitative anomaly detection with qualitative inquiry is methodologically very helpful to address complex problems such as this (Dewasiri et al., 2018). It demonstrates the value of a mixed-methods approach to uncover not just the 'what' type of disputable data, but the 'how'; an approach aligned with emerging critical perspectives on fintech that consider socio-technical systems as a whole. These findings will feed directly into the researcher's PhD dissertation, informing at least two chapters (one on technical analysis of disputable data points, and one on institutional responses). The author anticipates preparing a journal article focusing on the NBBO anomaly detection results, which can contribute to the literature on market data quality and high-frequency trading inefficiencies.

Policy and industry impact: Although a pilot, the research has already spurred conversations with stakeholders about improving data governance. The insights were shared with regulatory experts, aligning with growing regulatory interest in AI and algorithmic trading risks. A concrete impact is that the researcher submitted written evidence to a UK parliamentary inquiry on AI in financial services, using findings from this project to advocate for data quality oversight measures (such as real-time feed auditing and certification of data providers). The project's emphasis on data-centric risk governance, ensuring that data streams are trustworthy, has been well received. In industry terms, the findings suggest that trading firms should demand greater transparency from their data vendors and possibly invest in fail-safes (like cross- checking multiple data sources) to mitigate data risk as similar measures can enhance the performance of organisations according to Ferilli et al. (2024).

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