

Advancing Quantamental Investment Frameworks through Large Language Model Reasoning Integrating Textual Sentiment Volatility and Structured Financial Statement Analytics

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Abstract

The evolution of asset management has increasingly converged toward the "quantamental" approach, a paradigm that seeks to synthesize the systematic rigor of quantitative modeling with the nuanced, discretionary depth of fundamental analysis. Despite significant advancements in computational finance, traditional models often struggle to reconcile high-frequency unstructured data, such as news sentiment and social media volatility, with the periodic, structured nature of corporate financial statements. This research paper proposes an advanced architectural framework for quantamental investment that leverages the reasoning capabilities of Large Language Models (LLMs) to bridge this cognitive gap. By treating LLMs not merely as sentiment extractors but as sophisticated reasoning engines capable of multi-modal data synthesis, the proposed system integrates textual sentiment volatility with longitudinal financial statement analytics. The discussion focuses on the system-level design, examining the structural trade-offs between computational latency and reasoning depth, the governance of algorithmic decision-making, and the socio-technical implications of deploying autonomous reasoning agents within global financial infrastructures. We further explore the robustness of these systems against data poisoning and hallucination, the sustainability of large-scale inference in financial contexts, and the policy frameworks required to ensure market fairness and systemic stability. Through extensive conceptual analysis and systemic evaluation, this study demonstrates that the integration of generative reasoning into quantitative pipelines facilitates a more holistic understanding of market dynamics, ultimately enhancing the resilience and interpretability of modern investment strategies in an increasingly complex digital economy.

Keywords:

Quantamental Investment, Large Language Models, Financial Statement Analytics, Sentiment Volatility, Systemic Robustness, Socio-Technical Infrastructure.

1. Introduction

The contemporary investment landscape is characterized by an unprecedented deluge of data, where the traditional boundaries between fundamental and quantitative analysis have become increasingly porous [31]. This shift has given rise to the quantamental investment paradigm, which attempts to combine the scalability and objectivity of machine learning with the deep contextual understanding of human analysts [22]. However, the practical implementation of such frameworks faces significant structural hurdles, particularly in how disparate data streams are harmonized. While quantitative models excel at processing structured time-series data from financial statements, they often fail to capture the ephemeral and reflexive nature of market sentiment [11]. Conversely, qualitative fundamental analysis provides deep insight into corporate strategy and industry positioning but lacks the capacity to process information at the scale and speed required by modern high-frequency markets [24]. The emergence of Large Language Models (LLMs) represents a transformative inflection point in this trajectory, offering a mechanism to automate the reasoning processes that previously required human intervention [32].

The central challenge in modern quantamental frameworks is the reconciliation of textual sentiment volatility with structured financial analytics [12]. Sentiment is often noisy, prone to rapid reversals, and frequently decoupled from the underlying economic reality of a firm [10]. Financial statements, while grounded in audited reality, are lagging indicators that provide a retrospective view of corporate health [20]. Integrating these two domains requires a reasoning layer capable of understanding how a sudden spike in negative sentiment—perhaps due to a regulatory investigation or a geopolitical event—interacts with a firm’s balance sheet strength or cash flow resilience. This paper explores the system-level architecture necessary to host such a reasoning engine, prioritizing the infrastructure and governance protocols that ensure these models remain robust in the face of adversarial market conditions [1]. By moving beyond simple sentiment scores to a more comprehensive reasoning-based approach, investment systems can better anticipate structural shifts in market regimes and manage the inherent risks of automated capital allocation [28].

Furthermore, the deployment of LLM-based reasoning in finance is not merely a technical challenge but a socio-technical one [26]. It involves the interplay of complex algorithms, human stakeholders, and regulatory environments [17]. As these systems become more integrated into the core of global financial infrastructures, questions regarding transparency, accountability, and systemic fairness become paramount [3]. The tendency of generative models to hallucinate or produce biased outputs poses a significant risk to market integrity [25]. Therefore, the architecture of a quantamental system must include rigorous governance frameworks and ethical guardrails. This study addresses these concerns by analyzing the trade-offs between model complexity and interpretability, the sustainability of the

energy-intensive compute required for LLM inference, and the long-term policy implications of a market increasingly driven by machine reasoning [8].

2. Theoretical Underpinnings of Quantamental Synthesis

The transition from purely quantitative or qualitative methods to a synthesized quantamental framework is driven by the limitations of each approach in isolation [6]. Quantitative finance, historically rooted in the efficient market hypothesis and subsequent behavioral critiques, relies on historical data to project future price movements. These models are highly effective in stable market regimes but often experience catastrophic failure during black-swan events or structural breaks where historical correlations collapse [4]. The primary weakness of these systems is their lack of semantic context; they can identify a pattern but cannot understand the "why" behind it [18]. On the other hand, fundamental analysis seeks to establish the intrinsic value of an asset through an exhaustive review of economic indicators, industry trends, and management quality [15]. While this provides a robust intellectual foundation for long-term investing, it is inherently limited by human cognitive bandwidth and is often susceptible to cognitive biases such as overconfidence or anchoring.

LLMs provide a unique bridge between these two schools of thought by functioning as high-dimensional semantic processors [30]. Unlike traditional Natural Language Processing (NLP) tools that rely on dictionary-based sentiment analysis, LLMs utilize transformer-based architectures to understand context, sarcasm, and complex causal relationships within financial discourse. This allows the system to evaluate how textual data influences the interpretation of structured data [7]. For instance, an LLM can analyze an earnings call transcript to detect subtle shifts in management tone regarding debt obligations, subsequently adjusting the risk weight of the structured leverage ratios found in the company's 10-K filings [14]. This reasoning capability mimics the work of a senior analyst but operates at the scale of an entire market. The theoretical advantage of this synthesis lies in its ability to reduce information asymmetry and improve the price discovery process by integrating non-linear, qualitative insights into systematic workflows [33].

However, the integration of LLM reasoning into quantamental frameworks introduces new theoretical complexities regarding market reflexivity [19]. As more institutional players adopt similar reasoning agents, the market itself begins to reflect the biases and logic of these models. If multiple LLMs interpret a specific textual event in the same way, it may lead to crowded trades and increased systemic volatility [9]. This phenomenon suggests that the "alpha" generated by such systems may be ephemeral, shifting from the discovery of information to the speed and sophistication of the reasoning engine itself. The theoretical focus must therefore shift from simple predictive accuracy to the robustness of the reasoning process and its ability to maintain performance across diverse economic cycles and information environments [16].

3. Architectural Framework for Multi-Modal Reasoning

The design of a quantamental system utilizing LLM reasoning requires a sophisticated multi-layered architecture that can handle the ingestion, normalization, and synthesis of heterogeneous data types [13]. At the foundational layer, the infrastructure must support high-throughput data pipelines for both structured financial metrics and unstructured textual streams. This involves the use of distributed ledger technologies or high-performance cloud databases capable of maintaining the temporal integrity of data. The structured data component typically includes balance sheets, income statements, and cash flow data, which must be cleaned and standardized to ensure comparability across different jurisdictions and accounting standards. Simultaneously, the unstructured data component ingests news feeds, social media, regulatory filings, and transcriptions of executive speeches [2].

The second layer of the architecture is the reasoning engine, where the LLM resides. Unlike traditional machine learning pipelines where features are engineered and fed into a regressor, this framework uses the LLM to perform "chain-of-thought" reasoning [29]. The model is prompted to evaluate the structured financial health of a company in the context of the current sentiment environment. For example, the system might be tasked with determining if a high level of sentiment volatility is a precursor to a credit rating downgrade given the current liquidity ratios of the firm. This requires the LLM to have access to a large vector database of historical market contexts and financial principles, allowing it to provide a rational justification for its conclusions [21]. This interpretability is a critical system-level requirement, as it allows human overseers to audit the decision-making process of the autonomous agent.

The final layer is the execution and risk management module, where the reasoning outputs are converted into actionable investment signals [23]. This layer must navigate the trade-offs between the conviction of the LLM's reasoning and the constraints of the existing portfolio. Structural trade-offs are most evident here; a deeper, more comprehensive reasoning process may yield better insights but at the cost of higher computational latency. In fast-moving markets, the delay caused by an LLM's inference time could result in missed opportunities or increased slippage [5]. Therefore, the architecture often employs a tiered approach, where a smaller, faster model provides preliminary filters, and a larger, more sophisticated model performs deep-dive analysis on a subset of high-conviction targets. This hierarchical design ensures both scalability and depth, maintaining the system's robustness in varied market conditions.

4. Integrating Textual Sentiment Volatility

Textual sentiment in financial markets is not a monolithic entity but a dynamic and volatile signal that reflects the aggregate psychological state of market participants [27]. Traditional sentiment analysis often focuses on the "polarity" of a text—whether it is positive or negative. However, in a quantamental context, the volatility of that sentiment is often more informative than the mean. High sentiment volatility suggests a lack of consensus among investors, which often precedes significant price movements or shifts in liquidity [35]. By employing LLMs to monitor the variance in sentiment across multiple sources, the proposed framework can identify periods of heightened uncertainty that traditional quantitative models might miss.

The reasoning engine analyzes the source and nature of this volatility [22]. It distinguishes between "noise," such as social media-driven speculative fervor, and "signal," such as varying interpretations of a complex regulatory change. For instance, when a company releases a sustainability report, the initial sentiment may be positive due to environmental commitments, but subsequent analysis of the fine print by industry experts may introduce negative volatility [34]. An LLM-driven system can synthesize these conflicting viewpoints, assessing the credibility of the sources and the potential impact on the company's long-term valuation. This involves a deep understanding of the socio-technical landscape in which the information is disseminated, including an awareness of how algorithmic trading bots might react to certain keywords.

Moreover, sentiment volatility is intrinsically linked to market reflexivity [11]. The framework must account for the fact that the sentiment expressed in news and social media is often a reaction to price movements, rather than a cause. A robust reasoning engine must be able to de-convolve these relationships, identifying when sentiment is leading the market and when it is merely following [12]. This requires a longitudinal perspective, where the LLM compares current sentiment patterns with historical analogs to determine the likelihood of a sustained trend or a mean reversion. By integrating these qualitative insights into the structured analytics of the portfolio, the system can better calibrate its exposure to volatile assets, enhancing the overall stability of the investment strategy.

5. Structured Financial Statement Analytics and Reasoning

While sentiment provides the "pulse" of the market, structured financial statements provide its "anatomy" [20]. Traditional quantitative analysis of these statements involves the calculation of ratios—such as Price-to-Earnings, Debt-to-Equity, and Return on Invested Capital—and comparing them against historical norms or peer averages. However, these metrics often lack context [33]. A high debt-to-equity ratio might be a sign of distress for a mature company in a declining industry, but it could be a rational strategy for a high-growth firm in a capital-intensive sector. The integration of LLM reasoning allows the system to perform a more nuanced evaluation of these structured metrics by incorporating the narrative context found in the management discussion and analysis sections of financial reports [14].

The reasoning engine is capable of performing multi-period trend analysis, identifying subtle changes in accounting policies or revenue recognition methods that might signal future problems [18]. For example, if a company consistently reports growing accounts receivable while revenue growth slows, an LLM can flag this as a potential "red flag" for aggressive accounting, even if the primary quantitative filters do not trigger an alert. The system evaluates the quality of earnings by cross-referencing the structured data with textual evidence of market share gains, competitive pressures, and cost-cutting initiatives. This holistic view ensures that the quantitative metrics are interpreted through the lens of fundamental reality.

Furthermore, the system-level challenge in structured analytics is the handling of missing or delayed data [28]. In many emerging markets or for smaller-cap stocks, financial reporting may be less frequent or less transparent. The LLM can fill these gaps by inferring the likely financial state of a company based on secondary data sources, such as industry reports, supply chain data, and competitor announcements. This "imputation through reasoning" allows the quantamental framework to maintain broad coverage without sacrificing the depth of its analysis. However, this process must be carefully governed to prevent the model from over-extrapolating or inventing data, a risk that is inherent in generative architectures [25]. Robustness is maintained through a "human-in-the-loop" or a multi-agent verification system where different model instances cross-check each other's financial logic.

6. Systemic Robustness and Guardrails against Hallucination

One of the most significant risks in deploying LLMs for financial decision-making is the phenomenon of hallucination—where the model generates plausible-sounding but factually incorrect information [13]. In a high-stakes environment like investment management, a single hallucinated fact regarding a company's debt levels or a regulatory ruling could lead to disastrous capital allocation decisions. System-level robustness, therefore, requires the implementation of multi-layered guardrails designed to detect and neutralize such errors before they reach the execution stage. This involves the use of "Grounding" techniques, where the LLM's reasoning is strictly tethered to a verifiable knowledge base of audited financial data and official news sources.

A key architectural strategy for ensuring robustness is the "Reasoning-Verification" split [1]. In this setup, one LLM agent generates a hypothesis or an investment thesis, while a second, independent agent is tasked with finding contradictory evidence or identifying logical fallacies in the first agent's output. This adversarial approach mimics the peer-review process in academia or the "red-teaming" exercises in cybersecurity. Additionally, the system must include deterministic checks. For instance, if the LLM suggests that a company is a good buy because its revenue doubled, a deterministic module should automatically verify this claim against the structured financial data. If a discrepancy is found, the system flags the output for human review and prevents automated execution.

Robustness also extends to the model's performance under adversarial conditions, such as data poisoning or "prompt injection" attacks [26]. If an external actor intentionally spreads misinformation to manipulate the LLM's sentiment analysis, the system must be resilient enough to recognize the anomaly. This can be achieved through diversity in data sources and the use of consensus-based reasoning, where the model compares information from multiple independent providers [34]. Furthermore, the system must be robust against "regime shifts" in the market. A reasoning engine trained on a decade of low interest rates might struggle in a high-inflation environment. Continuous fine-tuning on recent data and the inclusion of historical economic "memory" are essential for maintaining the system's relevance and accuracy over time.

7. Governance, Ethics, and Algorithmic Accountability

The delegation of financial reasoning to autonomous agents necessitates a robust governance framework to manage the ethical and legal implications [15]. Algorithmic accountability is a central concern; when an automated system makes a trade that results in significant losses or contributes to market instability, it must be possible to trace the decision back to a specific reasoning chain. The "black box" nature of early neural networks is unacceptable in modern finance [3]. Therefore, the proposed quantamental framework prioritizes "Explainable AI" (XAI), where the LLM provides a natural language justification for every signal it generates. This documentation serves not only as an audit trail for regulators but also as a learning tool for human analysts to understand the system's logic and biases [21].

Governance also involves the management of bias [17]. LLMs are trained on vast datasets that reflect existing human biases, including those related to gender, race, and geography. In a financial context, this could manifest as biased credit scoring or the systematic undervaluing of firms in certain regions. The architecture must include active bias-mitigation strategies, such as de-biasing the training data or implementing fairness constraints in the reasoning prompts. Moreover, the deployment of these systems must be transparent to stakeholders. Investors have a right to know how much of their capital is being managed by autonomous reasoning agents and what the "kill-switch" protocols are in the event of systemic failure.

Ethical considerations also extend to the impact of these systems on market fairness [17]. If only the largest and most technologically advanced firms can afford to deploy high-end LLM reasoning engines, the information gap between institutional and retail investors will widen, potentially undermining the integrity of public markets. Policymakers must consider whether access to certain types of AI-driven market intelligence should be regulated to ensure a level playing field. Additionally, the role of the human analyst is fundamentally changed. Rather than being replaced, the analyst becomes a "governor" of the system, focusing on high-level strategy, ethical oversight, and the management of edge cases that the AI cannot handle [22].

8. Infrastructure, Deployment, and Sustainability

The physical and digital infrastructure required to support LLM-driven quantamental investment is substantial [30]. Unlike simple quantitative models that can run on standard server hardware, LLMs require massive amounts of compute, typically provided by clusters of high-end Graphical Processing Units (GPUs) or specialized Tensor Processing Units (TPUs). For an investment firm, the choice between building an on-premise infrastructure or relying on cloud providers involves a trade-off between control and scalability. On-premise solutions offer better data security and lower latency for execution but require significant capital expenditure and specialized talent for maintenance. Cloud-based solutions offer virtually unlimited scale but introduce third-party risks and potential latency issues during periods of high market activity.

Deployment strategies must also address the temporal nature of financial data [1]. The system

must be capable of "online learning" or frequent updates to incorporate new information without forgetting historical context. This requires a sophisticated versioning system for both the models and the data they consume. Furthermore, the deployment must be global to capture opportunities across different time zones and markets. This necessitates a distributed architecture where regional reasoning agents can operate locally but share insights with a central coordinator. Such a "federated reasoning" model can improve latency and ensure that regional market nuances are captured effectively.

Sustainability is an increasingly critical component of system design [8]. The energy consumption associated with training and running large-scale generative models is immense, raising concerns about the carbon footprint of AI-driven finance. Responsible firms must prioritize "green AI" initiatives, such as using more efficient model architectures (e.g., pruned or quantized models), utilizing data centers powered by renewable energy, and optimizing the frequency of model inference. The long-term viability of these systems depends on their ability to deliver alpha without imposing an unsustainable environmental or social cost. This involves a shift from "brute force" scaling—simply using larger models—to "intelligent scaling," where the system uses the minimum necessary compute to achieve the desired reasoning depth.

9. Socio-Technical Implications and Future Perspectives

The widespread adoption of LLM reasoning in investment management will have profound socio-technical implications [26]. One major concern is the potential for increased market "herding." If a dominant set of LLMs are all trained on similar data and use similar reasoning patterns, they may all converge on the same trades simultaneously [9]. This could lead to flash crashes or extreme liquidity droughts as all autonomous agents attempt to exit a position at once. The socio-technical system must therefore be designed to encourage "cognitive diversity" among reasoning agents, perhaps by using different base models or varied prompt engineering strategies to ensure a range of market perspectives.

Looking forward, the integration of LLMs with other emerging technologies, such as Quantum Computing and the Internet of Things (IoT), will further transform quantamental frameworks [33]. Quantum algorithms could potentially solve complex portfolio optimization problems that are currently computationally intractable, while IoT data—such as satellite imagery of retail parking lot density or real-time shipping logs—could provide a "ground truth" to verify the claims made in corporate financial statements. The LLM would serve as the central reasoning hub, synthesizing these disparate and high-dimensional data streams into a coherent investment narrative. This vision of "Autonomous Fundamental Analysis" represents the logical conclusion of the quantamental evolution [19].

Furthermore, the relationship between human intelligence and machine intelligence will continue to evolve [19]. We may see the rise of "cyborg" investment teams, where human intuition and machine reasoning are so deeply integrated that they are indistinguishable. This will require new organizational structures and communication protocols to ensure that the

strengths of both are maximized. The ultimate goal is a more resilient and efficient financial system that can better allocate capital to productive uses while managing the systemic risks of a complex, interconnected world. The journey toward this goal will require ongoing collaboration between technologists, financiers, and regulators to ensure that the advancement of machine reasoning serves the broader interests of society.

10. Conclusion

The integration of Large Language Model reasoning into quantamental investment frameworks represents a significant leap forward in the quest to harmonize quantitative rigor with fundamental depth. By moving beyond simple sentiment analysis to a multi-modal reasoning approach, these systems can better navigate the complexities of modern financial markets, identifying subtle risks and opportunities that traditional models miss. However, the deployment of these systems is not without significant challenges. The structural trade-offs between depth and speed, the risks of hallucination and bias, and the immense infrastructure requirements all demand a sophisticated and disciplined approach to system design.

A robust quantamental architecture must prioritize transparency, governance, and sustainability. It must be built on a foundation of high-quality, grounded data and protected by rigorous, multi-layered guardrails. As we move toward a future where autonomous reasoning agents play an increasingly central role in global finance, the focus must remain on ensuring that these systems are not only profitable but also stable, fair, and accountable. By fostering a socio-technical environment that values both human oversight and machine intelligence, we can build an investment landscape that is more resilient to the uncertainties of the digital age. This research contributes to that goal by providing a comprehensive blueprint for the next generation of reasoning-driven investment systems, laying the groundwork for further exploration into the intersection of artificial intelligence and systemic financial health.

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