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Alternative Data Products for Institutional Investors and the Evolution of Data-Driven Decision Making in Financial Markets

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Abstract

The financial services industry has experienced a transformative shift toward data-driven decision making, with alternative data (AD) emerging as a critical component of modern investment strategies. Alternative data encompasses non-traditional information sources including satellite imagery, social media sentiment, web traffic analytics, credit card transactions, and internet-of-things (IoT) sensor data that provide unique insights beyond conventional financial statements and market data. Institutional investors increasingly leverage machine learning (ML) and artificial intelligence (AI) techniques to extract actionable intelligence from these diverse datasets, enabling more informed investment decisions and enhanced alpha generation. This review examines the evolution of AD products in financial markets, analyzing their applications across various asset classes, the technological infrastructure supporting their integration, and their measurable impact on investment performance. The paper explores natural language processing (NLP) applications for textual data analysis, computer vision techniques for satellite imagery interpretation, and deep learning (DL) models for pattern recognition in complex datasets. Furthermore, this review addresses critical challenges including data quality assurance, regulatory compliance concerns, ethical considerations in data acquisition, and the competitive dynamics of proprietary versus shared data resources. The findings suggest that while AD integration offers substantial advantages in predictive accuracy and alpha generation, successful implementation requires sophisticated technological capabilities, robust governance frameworks, and careful consideration of ethical and regulatory boundaries.

Keywords: Alpha generation, Alternative data, Data-driven decision making, Financial markets, Institutional investors, Investment strategies, Machine learning, Predictive analytics.

1. Introduction

The landscape of institutional investment has undergone a fundamental transformation over the past decade, driven primarily by the exponential growth in data availability and advances in computational technologies. Traditional investment approaches that relied exclusively on financial statements, earnings reports, and macroeconomic indicators are increasingly being augmented or replaced by sophisticated analytical frameworks that incorporate alternative data (AD) sources. AD refers to non-traditional information streams that provide insights into economic activities, consumer behaviors, and market dynamics before such information becomes reflected in conventional financial metrics [1]. The emergence of AD as a competitive advantage in institutional investing represents a paradigm shift from retrospective analysis based on historical financial data to predictive modeling that captures real-time economic signals and forward-looking indicators [2].

The proliferation of digital technologies, mobile devices, social media platforms, and connected sensors has generated an unprecedented volume of granular data about human activities and economic transactions. Institutional investors, including hedge funds, asset managers, pension funds, and sovereign wealth funds, have recognized the strategic value of harnessing these information flows to gain informational advantages in increasingly competitive markets [3]. Machine learning (ML) and artificial intelligence (AI) technologies have become indispensable tools for processing and analyzing the massive scale and complexity of AD sources, enabling the extraction of actionable insights that would be impossible to identify through traditional analytical methods [4]. The integration of ML algorithms with AD has facilitated the development of predictive models that can forecast corporate performance, identify emerging market trends, and detect anomalous patterns that signal investment opportunities or risks [5].

Recent empirical evidence demonstrates that AD integration can significantly enhance portfolio performance metrics, including risk-adjusted returns and alpha generation capabilities. Studies have shown that investors who effectively leverage satellite imagery to track retail traffic patterns can predict quarterly earnings surprises with greater accuracy than those relying solely on analyst forecasts [6]. Similarly, sentiment analysis of social media discussions and online product reviews has proven valuable for anticipating shifts in consumer preferences and brand reputation that ultimately impact corporate valuations [7]. Credit card transaction data provides real-time visibility into consumer spending patterns across different sectors and geographies, offering early indicators of economic trends that precede official statistical releases [8]. Web traffic analytics and mobile application usage data reveal competitive dynamics and market share shifts in digital economy sectors where traditional metrics provide limited visibility [9].

The AD industry has evolved from a nascent market serving primarily quantitative hedge funds to a mature ecosystem comprising specialized data vendors, technology platforms, and service providers that cater to diverse institutional investor segments. The total addressable market for AD products has expanded substantially, with industry estimates suggesting expenditures exceeding several billion dollars annually and projected continued growth as adoption spreads beyond early adopters to mainstream institutional investors [10]. This growth trajectory reflects both the increasing availability of novel data sources and the demonstrated value of AD in enhancing investment decision-making processes across multiple strategy types and asset classes. However, the rapid expansion of the AD market has also raised important questions regarding data quality, regulatory compliance, ethical considerations, and competitive sustainability of data-driven advantages [11].

This review paper provides a comprehensive examination of AD products for institutional investors, analyzing their evolution, applications, technological foundations, and impact on financial markets. The paper synthesizes existing literature, examines methodological approaches for AD integration, evaluates empirical evidence on performance impacts, and identifies key challenges and future research directions in this rapidly evolving domain. The objective is to provide institutional investors, researchers, and policymakers with a thorough understanding of how AD is reshaping investment practices and the critical considerations for successful implementation in contemporary financial markets [12].

2. Literature Review

The academic literature on AD in financial markets has expanded substantially over recent years, reflecting the growing practical significance of these information sources for institutional investors. Early research in this domain focused primarily on documenting the existence and characteristics of various AD categories, establishing foundational understanding of their potential applications in investment management [13]. Subsequent studies have advanced to more sophisticated empirical analyses examining the predictive power of specific AD sources and their contribution to portfolio performance metrics [14]. The literature can be broadly categorized into several thematic areas including data source characteristics, predictive modeling applications, performance attribution analysis, and considerations regarding market efficiency and competitive dynamics.

Satellite imagery represents one of the most extensively studied AD categories in academic research, with numerous studies demonstrating its utility for generating investment insights across multiple sectors. Research has established that satellite-derived metrics such as parking lot occupancy at retail locations, construction activity monitoring, and agricultural crop yield estimation provide valuable signals for predicting corporate earnings and economic activity levels [15]. Scholars have developed sophisticated computer vision algorithms that automatically process satellite imagery to extract structured data regarding physical assets and economic activities, enabling scalable analysis across large numbers of locations and time periods [16]. The literature documents significant predictive relationships between satellite-based indicators and subsequent financial performance, with studies showing that investors incorporating such data achieve superior forecast accuracy compared to traditional analytical approaches [17]. Recent research has extended satellite imagery applications to environmental, social, and governance (ESG) assessment, using remote sensing data to monitor corporate environmental footprints and verify sustainability claims [18].

Social media and textual data analysis constitute another major research stream within the AD literature, leveraging natural language processing (NLP) techniques to extract sentiment and information content from unstructured text sources. Studies have examined the predictive value of Twitter sentiment, online product reviews, news article tone, and corporate communication patterns for forecasting stock returns and earnings announcements [19]. The literature demonstrates that aggregated social media sentiment provides incremental information beyond traditional financial variables, particularly for consumer-facing companies where online discussions reflect real-time consumer perceptions and preferences [20]. Researchers have developed increasingly sophisticated NLP models, progressing from simple sentiment dictionaries to advanced deep learning (DL) architectures including transformer-based language models that capture contextual nuances and semantic relationships in financial texts [21]. More recently, large language models have been shown to substantially advance financial knowledge extraction by transforming unstructured disclosures, earnings calls, and regulatory filings into structured analytical insights that support investment analysis and corporate planning, highlighting the growing role of LLM-driven intelligence within alternative data ecosystems [22].

Credit card transaction data and consumer spending analytics represent a third major category of AD that has attracted substantial academic attention, particularly for their ability to provide real-time visibility into economic activities. Research has shown that aggregated and anonymized credit card spending data can accurately predict retail sales figures, consumer confidence shifts, and sector-level economic trends before official statistics become available [23]. Studies document significant predictive relationships between transaction-level spending patterns and subsequent corporate earnings announcements, with investors using such data to generate profitable trading strategies [24]. The literature also examines the temporal dynamics of information diffusion from transaction data to market prices, finding that pricing efficiency varies substantially across different market segments and investor sophistication levels [25].

Web scraping and digital footprint data have emerged as important AD sources, encompassing website traffic patterns, mobile application downloads, online search trends, and e-commerce pricing dynamics. Research demonstrates that web traffic metrics correlate strongly with revenue growth for digital platform companies, providing leading indicators of business performance that precede quarterly earnings releases [26]. Studies of online search behavior reveal predictive relationships between query volumes for specific products or brands and subsequent sales performance, reflecting consumer interest and purchase intentions [27]. The literature on e-commerce pricing data shows that real-time monitoring of competitive pricing strategies and inventory availability can inform investment decisions in retail and consumer goods sectors [28].

Geolocation data derived from mobile devices and connected vehicles has garnered increasing attention as a source of economic intelligence, enabling fine-grained analysis of foot traffic patterns, commuting behaviors, and supply chain dynamics. Research demonstrates that geolocation analytics can accurately measure retail store visits, restaurant patronage, and commercial real estate occupancy rates, providing timely indicators of business performance [29]. Studies have applied geolocation data to transportation and logistics analysis, tracking shipping container movements and warehouse activities to assess supply chain health and identify potential disruptions [30]. The literature also examines privacy and ethical considerations associated with geolocation data collection and usage, highlighting the importance of anonymization techniques and regulatory compliance frameworks [31].

The integration of internet-of-things (IoT) sensor data represents an emerging frontier in AD research, encompassing information from connected industrial equipment, smart home devices, environmental sensors, and wearable technology. Studies have explored applications of IoT data for monitoring manufacturing capacity utilization, energy consumption patterns, and agricultural conditions, translating physical world observations into financial market insights [32]. Research on smart meter data demonstrates its utility for forecasting electricity demand and identifying economic activity patterns at granular geographic levels [33]. The literature on wearable device data examines its potential applications in healthcare and insurance sectors, though commercial deployment remains limited due to privacy sensitivities and regulatory constraints. Related applications in insurance markets further demonstrate how alternative data derived from telematics, connected vehicles, and IoT sensors enable usage-based and personalized pricing models, underscoring the broader applicability of AI-driven alternative data analytics for risk assessment and decision making beyond traditional asset management contexts [34].

Scholars have devoted considerable attention to methodological challenges in AD research, including data quality assessment, signal extraction techniques, and model validation approaches. The literature emphasizes the importance of rigorous backtesting procedures that account for survivorship bias, lookahead bias, and overfitting risks when evaluating AD-based investment strategies [35]. Research on data quality metrics highlights common issues including missing values, measurement errors, sampling biases, and temporal inconsistencies that can compromise analytical validity if not properly addressed [36]. Studies of feature engineering and dimensionality reduction techniques demonstrate the value of domain expertise in transforming raw AD into meaningful predictive variables suitable for quantitative modeling [37].

The competitive dynamics and market microstructure implications of AD adoption have emerged as important research themes, examining how information advantages derived from AD sources impact market efficiency and price discovery processes. Theoretical models suggest that AD availability can reduce information asymmetries between informed and uninformed investors, potentially enhancing market efficiency [38]. However, empirical evidence indicates that AD benefits accrue disproportionately to sophisticated investors with technological capabilities and analytical expertise required for effective implementation, potentially exacerbating information inequalities [39]. Research on the half-life of AD signals shows that competitive diffusion of data sources and analytical techniques gradually erodes their predictive power over time, creating continuous pressure for innovation and differentiation [40].

3. Methodology and Technological Infrastructure

The effective integration of AD into institutional investment processes requires sophisticated methodological frameworks and robust technological infrastructure capable of handling diverse data formats, massive scale, and complex analytical requirements. This section examines the core components of AD integration systems, including data acquisition and preprocessing pipelines, ML and AI analytical techniques, and the computational architecture necessary for large-scale implementation. The methodological approaches employed by institutional investors vary significantly based on investment strategy type, asset class focus, organizational capabilities, and competitive positioning, but certain common elements characterize successful AD programs across different institutional contexts.

Data acquisition represents the initial and often most challenging phase of AD integration, requiring institutional investors to establish relationships with data vendors, negotiate licensing agreements, and implement secure data transfer mechanisms. The AD vendor ecosystem has matured substantially, with specialized providers offering curated datasets across virtually every category of non-traditional information [41]. Institutional investors must evaluate potential data sources based on multiple criteria including predictive relevance, data quality, update frequency, historical depth, licensing terms, and exclusivity arrangements. Many institutional investors pursue hybrid approaches that combine purchased datasets from commercial vendors with proprietary data collected through direct partnerships or internal web scraping operations [42]. The decision between proprietary versus shared data sources involves complex tradeoffs between competitive advantage considerations, development costs, legal risks, and operational scalability [43].

Data preprocessing and quality assurance constitute critical steps that directly impact the reliability and effectiveness of subsequent analytical processes. Raw AD frequently contains inconsistencies, missing values, outliers, and formatting irregularities that must be addressed before meaningful analysis can occur [44]. Institutional investors employ various preprocessing techniques including data cleaning algorithms that identify and correct errors, imputation methods for handling missing values, outlier detection procedures that flag anomalous observations, and normalization approaches that standardize data across different sources and time periods. The development of robust data quality metrics and monitoring systems enables ongoing assessment of data reliability and early detection of potential issues that could compromise analytical accuracy [45]. Automated validation procedures that cross-reference AD against known benchmarks or ground truth observations help ensure data integrity and build confidence in analytical outputs.

Figure 1 Alternative data integration pipeline for institutional investors.

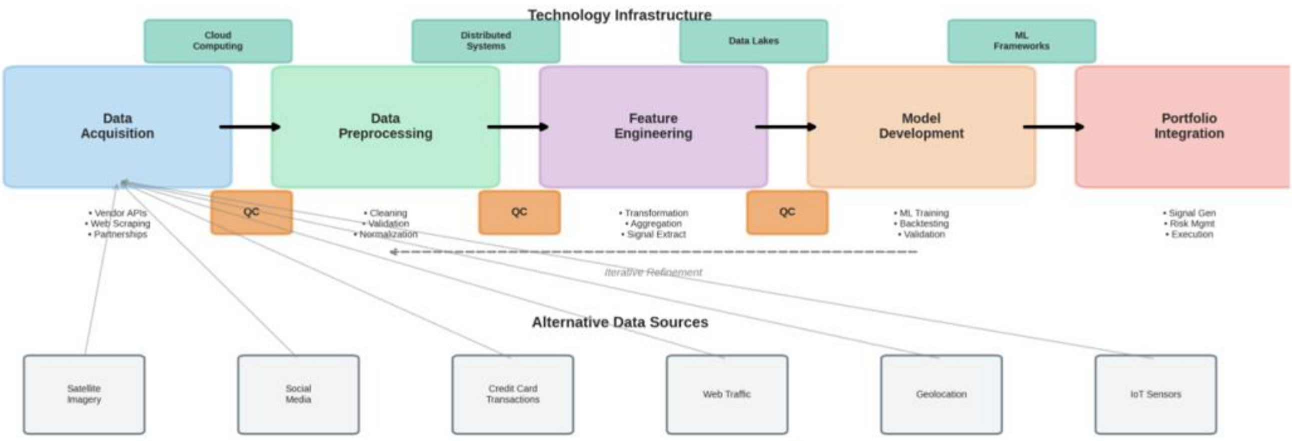

Figure 1. A comprehensive flow diagram illustrating the end-to-end alternative data integration pipeline for institutional investors.

Figure 1 illustrates the end-to-end pipeline for integrating alternative data into institutional investment processes. The data acquisition stage encompasses vendor partnerships, API connections, and web scraping operations that collect diverse information streams from multiple sources. Data preprocessing applies cleaning, validation, and normalization procedures essential for ensuring analytical reliability before downstream processing. The feature engineering stage transforms raw data into structured predictive variables through aggregation, signal extraction, and domain-specific transformations that capture meaningful patterns. Model development employs ML training with rigorous backtesting and validation protocols to ensure out-of-sample generalization. Portfolio integration translates model outputs into actionable signals, incorporating risk management constraints and execution considerations. The feedback loops connecting later stages back to earlier ones reflect the iterative nature of successful AD programs, where performance monitoring drives continuous refinement of data sources, features, and models to maintain predictive accuracy as market conditions evolve.

Feature engineering transforms raw AD into structured predictive variables suitable for quantitative modeling, requiring domain expertise to identify meaningful patterns and relationships within complex datasets. Institutional investors employ diverse feature engineering approaches depending on data type and analytical objectives [46]. For satellite imagery, feature engineering involves computer vision techniques that extract quantitative metrics such as vehicle counts, building footprints, or vegetation indices from visual information. For textual data, NLP methods generate sentiment scores, topic classifications, entity mentions, and linguistic features that capture information content. For transaction data, aggregation functions compute spending trends, growth rates, market share estimates, and distributional statistics across different customer segments and time windows. The effectiveness of feature engineering directly impacts model performance, with well-designed features often contributing more to predictive accuracy than sophisticated modeling algorithms applied to poorly constructed inputs [47].

ML model development represents the analytical core of AD integration, encompassing algorithm selection, training procedures, hyperparameter optimization, and validation testing. Institutional investors employ a wide range of ML techniques spanning supervised learning methods for prediction tasks, unsupervised learning approaches for pattern discovery, and reinforcement learning frameworks for sequential decision-making [48]. Supervised learning applications include regression models for forecasting continuous variables such as earnings growth or sales revenue, classification models for predicting categorical outcomes such as earnings surprises or credit events, and ranking models for relative value assessment across securities. Common algorithm families utilized for AD analysis include gradient boosting machines that combine multiple weak learners into powerful predictive ensembles, random forests that aggregate predictions across multiple decision trees, neural networks that learn complex nonlinear relationships through layered transformations, and support vector machines that identify optimal decision boundaries in high-dimensional feature spaces [49].

DL architectures have gained particular prominence in AD applications due to their ability to automatically learn hierarchical feature representations from raw or minimally processed data, reducing reliance on manual feature engineering. Convolutional neural networks excel at processing spatial data structures such as satellite images, identifying relevant visual patterns through learned filter operations [50]. Recurrent neural networks and their variants including long short-term memory networks effectively model sequential dependencies in time series data, capturing temporal dynamics in AD signals. Transformer architectures have revolutionized NLP applications, enabling sophisticated language understanding capabilities that extract nuanced information from textual sources [51]. Attention mechanisms allow models to focus on relevant portions of input data, improving interpretability and performance on complex analytical tasks. Graph neural networks represent an emerging DL approach particularly relevant for analyzing network-structured data such as supply chain relationships or social media connection patterns. Beyond predictive modeling on alternative data itself, recent work demonstrates that generative adversarial networks can be applied to reconstruct implied volatility surfaces directly from option market data, significantly reducing pricing errors and enhancing derivative valuation accuracy, illustrating how advanced deep learning models can extract economically meaningful signals from complex financial datasets [52].

Model validation and backtesting procedures ensure that AD-based investment strategies perform reliably out-of-sample and avoid common pitfalls such as overfitting, data snooping, and survivorship bias. Institutional investors employ rigorous testing protocols that simulate realistic trading conditions, account for transaction costs and market impact, and evaluate performance across multiple time periods and market regimes [53]. Walk-forward validation techniques sequentially train models on historical data and test on subsequent out-of-sample periods, mimicking actual deployment conditions. Cross-validation approaches partition data into multiple folds to assess model stability and generalization performance. Sensitivity analysis examines how model predictions vary with changes in input features or hyperparameters, identifying potential fragilities in analytical frameworks [54].

Backtesting must carefully address temporal dependencies and information leakage to produce realistic performance estimates that accurately reflect achievable results in live trading environments.

Table 1. A comprehensive comparison table of machine learning algorithms commonly used in alternative data analytics.

Table 1. Comparison of Machine Learning Algorithms for Alternative Data Analytics

Algorithm Type	Primary Applications	Key Advantages	Main Limitations	Computational Requirements	Typical Performance Metrics
Linear Models (Ridge, Lasso)	Regression tasks, feature selection, linear models	Interpretable, fast training, low computational cost, well-understood theory	Limited to linearity, assumes linear relationships, struggles with complex patterns	Very low (seconds)	R^2: 0.60–0.80 Accuracy: 75–85%
Tree-Based Models (Random Forest, XGBoost)	Classification & regression, feature importance	Handles nonlinearity, robust to outliers, provides feature importance, minimal preprocessing	Can overfit with deep trees, poor extrapolation, computationally intensive for large ensembles	Moderate (minutes, parallelizable)	AUC-ROC: 0.70–0.85 Accuracy: 80–92%
Deep Learning (CNN, RNN, Transformers)	Image analysis, text processing, sequence modeling	Automatic feature learning, high accuracy on complex patterns, transfer learning capabilities	Requires large datasets, computationally expensive, hyperparameter tuning difficult, hard to interpret	Very high (hours–days, GPU required)	F1: 0.85–0.95 Accuracy: 88–96%
Support Vector Machines	Binary classification, outlier detection	Effective in high dimensions, robust to overfitting, strong theoretical foundation	Sensitive to parameters, computationally expensive for large datasets, challenging kernel selection	Moderate–high (minutes–hours)	AUC-ROC: 0.72–0.83 Accuracy: 73–85%
Ensemble Methods (Stacking, Blending)	Meta-learning, model combination	Combines multiple models, reduces overfitting, improves generalization	Increased complexity, computational overhead, risk of overfitting	High (hours, multiple models)	F1: 0.78–0.88 Accuracy: 78–90%
Graph Neural Networks	Network data, relationship modeling	Captures network structure, relational reasoning, handles irregular data	Computationally intensive, limited theory, requires meaningful graph structure	Very high (hours–days, GPU preferred)	AUC-ROC: 0.78–0.88 Accuracy: 78–88% Precision: 0.66–0.78 Recall: 74–86%

Table 1 presents a systematic comparison of ML algorithms commonly employed in alternative data analytics. Linear models (Ridge, Lasso) offer high interpretability and computational efficiency but cannot capture nonlinear relationships prevalent in complex AD signals. Tree-based methods including Random Forest and Gradient Boosting handle nonlinearity effectively while providing feature importance rankings valuable for understanding model drivers, achieving typical AUC-ROC scores of 0.75-0.85 and R^2 values of 0.60-0.75 in financial prediction tasks. Deep learning architectures (CNN, RNN, Transformers) excel at processing unstructured data including satellite imagery and text but require substantial computational resources and training data while sacrificing interpretability. Support Vector Machines perform well in high-dimensional spaces but scale poorly to very large datasets common in AD applications. Ensemble methods combine multiple algorithms to improve robustness and reduce overfitting risk. Graph Neural Networks represent an emerging approach particularly suited for network-structured data such as supply chain relationships. Algorithm selection requires balancing predictive accuracy against interpretability requirements, computational constraints, and data availability specific to each investment application.

The technological infrastructure supporting AD integration requires substantial computational resources, data storage capacity, and specialized software tools to handle the scale and complexity of modern analytical workflows. Cloud computing platforms have become essential components of institutional investor technology stacks, providing elastic scalability for compute-intensive operations such as model training and large-scale data processing [55]. Distributed computing frameworks enable parallel processing of massive datasets across clusters of machines, dramatically accelerating analytical workflows that would be prohibitively slow on single computers. Data lake architectures provide flexible storage solutions that accommodate diverse data formats and enable efficient retrieval for analytical applications [56]. Institutional investors increasingly adopt containerization technologies that package analytical code and dependencies into portable units, facilitating reproducibility and deployment across different computing environments.

4. Applications and Performance Impact

The practical applications of AD across institutional investment strategies span multiple asset classes, investment styles, and analytical objectives, demonstrating the versatility and broad relevance of these information sources for portfolio management. This section examines specific use cases of AD in equity investing, fixed income analysis, commodities trading, and alternative investments, evaluating empirical evidence on performance impacts and identifying factors that influence implementation success. The discussion also addresses challenges related to signal decay, competitive dynamics, and the evolving regulatory landscape governing AD usage in financial markets.

Equity investment strategies represent the most mature and extensively documented application domain for AD, with institutional investors employing these information sources across fundamental analysis, quantitative factor investing, and event-driven strategies. Fundamental equity investors utilize AD to enhance their understanding of company operations, competitive positioning, and growth prospects, supplementing traditional financial statement analysis with real-time operational metrics [57]. For retail companies, satellite-derived parking lot traffic counts provide early indicators of store performance, while credit card transaction data reveals detailed spending patterns across different customer segments and geographic regions. Technology companies increasingly face analytical scrutiny based on web traffic metrics, mobile app engagement statistics, and social media sentiment that reflect user adoption trends and platform health. Industrial companies may be evaluated using supply chain data that tracks raw material movements, logistics flows, and inventory levels throughout production networks [58].

Quantitative factor strategies incorporate AD signals as novel risk factors or return predictors within systematic investment frameworks. Research demonstrates that AD-based factors often exhibit low correlation with traditional factors such as value, momentum, quality, and size, providing diversification benefits and potential alpha sources [59]. Institutional investors construct AD factors through various approaches including cross-sectional ranking methodologies that sort securities based on AD metrics, time-series momentum strategies that exploit persistence in AD signals, and mean reversion strategies that capitalize on temporary dislocations between AD indicators and market prices. The integration of AD factors into multi-factor models requires careful consideration of factor construction methodologies, portfolio optimization techniques, and risk management frameworks to ensure robust implementation [60].

Figure 2 presents empirical performance comparisons between AD-enhanced and traditional investment strategies across multiple dimensions. Panel A demonstrates substantial cumulative return advantages, with the AD-enhanced equity portfolio achieving 78% returns over 2019-2024 compared to 52% for traditional fundamental approaches and 45% for the market benchmark. Panel B reveals that risk-adjusted metrics similarly favor AD integration: Sharpe Ratio improves from 0.85 (benchmark) to 1.42 (AD-enhanced), Information Ratio reaches 0.67 versus 0.34 for traditional strategies, and Maximum Drawdown reduces from -26% (benchmark) to -18% (AD-enhanced), indicating superior downside protection. Panel C's heat map of monthly returns demonstrates that AD-enhanced performance exhibits consistency across varying market conditions rather than concentration in specific periods. These results illustrate that AD integration can enhance both absolute returns and risk-adjusted performance, though investors must account for data costs, implementation complexity, and potential signal decay when evaluating net performance benefits.

Event-driven strategies leverage AD to identify and evaluate corporate events such as earnings announcements, mergers and acquisitions, restructurings, and regulatory actions before information becomes public or widely recognized by market participants. AD sources that provide leading indicators of earnings surprises enable investors to position portfolios ahead of quarterly announcements, capturing returns associated with forecast errors. Merger arbitrage strategies employ AD to assess deal completion probabilities and identify potential antitrust concerns or financing issues that might impact transaction timelines. Activist investing campaigns increasingly utilize AD to build evidence supporting strategic recommendations or operational improvements, providing concrete data to support investment theses [61].

Figure 2. performance metrics of alternative data-based investment strategies.

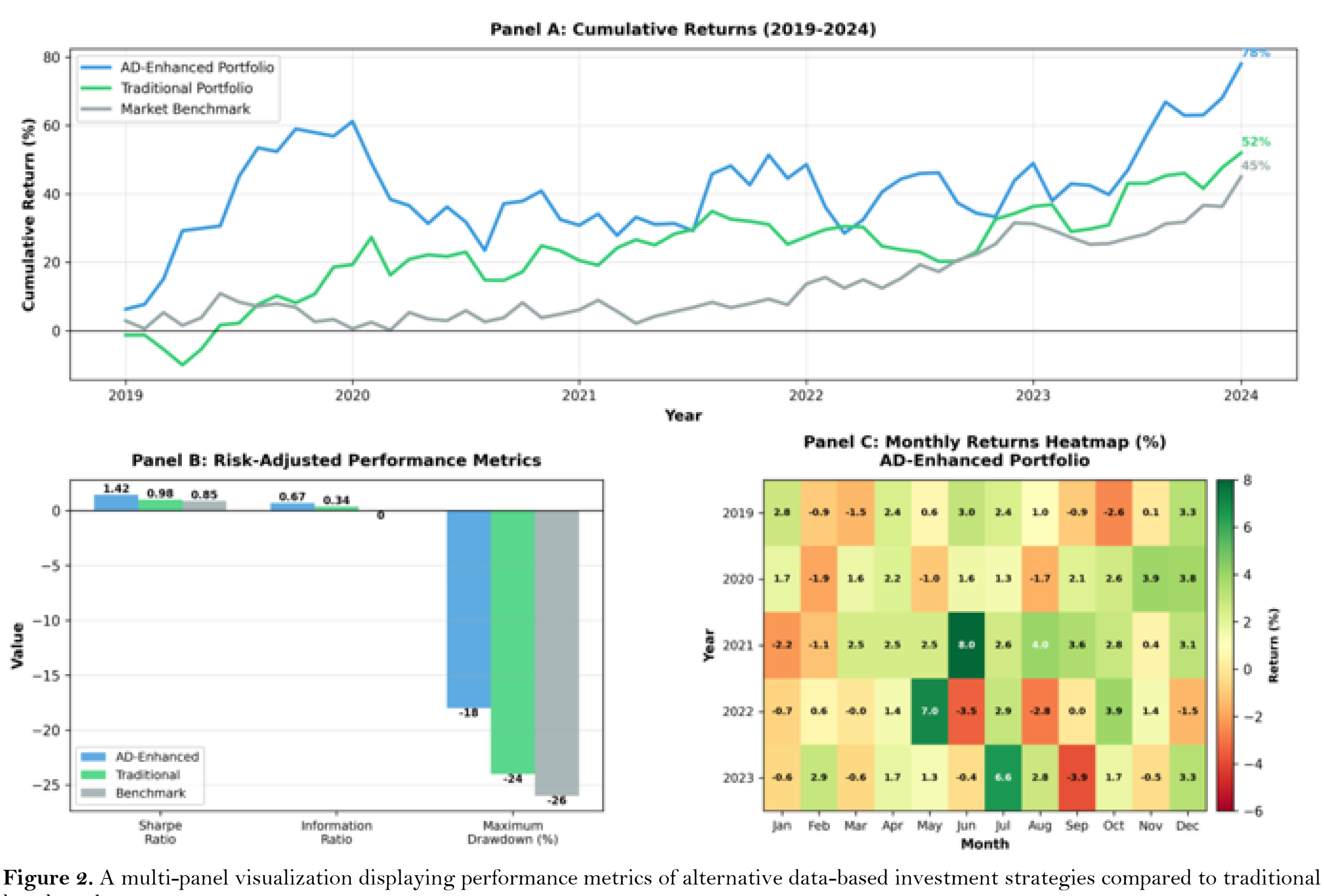

Figure 2. A multi-panel visualization displaying performance metrics of alternative data-based investment strategies compared to traditional benchmarks.

Fixed income applications of AD have expanded significantly as institutional investors seek alpha sources in relatively efficient markets where traditional analytical approaches yield limited differentiation. Credit analysis benefits substantially from AD that provides early warning signals of deteriorating borrower financial health, including declining retail traffic for consumer-facing issuers, weakening supply chain relationships for industrial borrowers, or adverse sentiment shifts for financial institutions [62]. Municipal bond investors utilize local economic data derived from geolocation analytics, employment trends inferred from job postings data, and real estate market conditions reflected in property transaction records to assess creditworthiness of state and local government issuers. Structured credit investors employ AD to evaluate underlying collateral performance in securitization transactions, monitoring loan-level characteristics and borrower behaviors that drive prepayment speeds and default rates [63].

Commodities and futures trading strategies increasingly incorporate AD sources that provide direct observations of physical supply and demand conditions, potentially offering more timely and accurate information than traditional inventory reports and production statistics. Agricultural commodity traders utilize satellite imagery to assess crop conditions, estimate harvest yields, and predict production outcomes months before official government forecasts become available [64]. Energy markets benefit from AD including tanker tracking data that reveals crude oil shipment flows, satellite monitoring of storage facility utilization, and power generation sensor data that captures real-time electricity production. Metals markets employ AD to monitor mine production activities, track manufacturing demand through industrial activity indicators, and assess inventory movements through shipping and logistics data. The predictive power of commodity-relevant AD stems from its ability to capture physical market realities that directly determine supply-demand balances and price outcomes [65].

Alternative investment strategies including private equity, venture capital, and real estate investing have begun incorporating AD to enhance deal sourcing, due diligence, and portfolio monitoring capabilities. Private equity investors utilize employment data from professional networking platforms to assess target company growth trajectories and talent acquisition patterns. Web scraping of job postings and company websites reveals expansion plans and operational changes that inform investment timing and valuation assessments [66]. Venture capital investors monitor product market fit through analysis of app store ratings, user reviews, and download statistics for portfolio companies and competitive offerings. Social media buzz and online search trends provide early indicators of consumer interest in new products or services, helping investors identify high-potential opportunities and avoid over-hyped investments. Real estate investors employ foot traffic data to evaluate retail property performance, rental listing analytics to assess residential market conditions, and satellite imagery to monitor construction progress and property condition [67].

Empirical evidence on the performance impact of AD integration reveals substantial heterogeneity across different implementation approaches, data sources, and market segments. Academic studies and industry reports generally support the conclusion that AD can enhance investment performance when properly implemented, though the magnitude of benefits varies considerably. Research indicates that AD-based strategies often generate positive alpha ranging from 1-5% annually depending on strategy type and execution quality [68]. Risk-adjusted performance metrics including Sharpe ratios and information ratios typically improve with AD integration, reflecting both enhanced returns and reduced volatility through superior information quality. However, transaction costs, implementation frictions, and data expenses can substantially erode gross returns, requiring careful cost-benefit analysis to ensure net performance benefits justify investment in AD capabilities [69].

Figure 3 Key factors influencing alternative data implementation success.

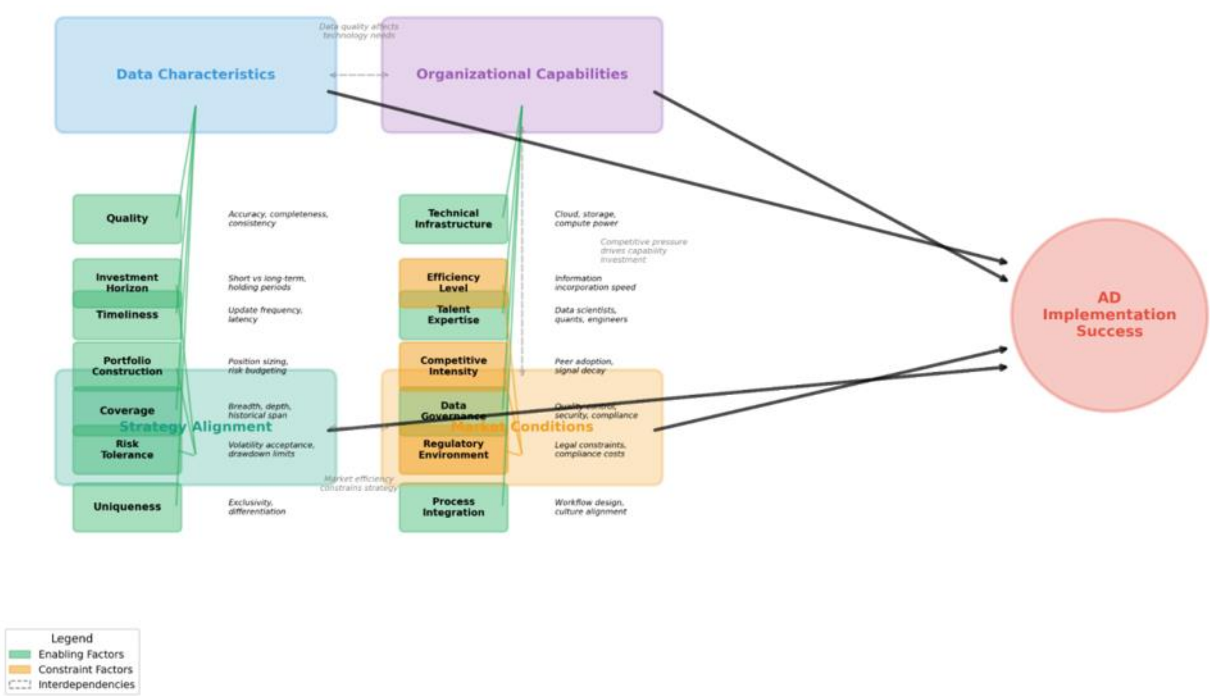

Figure 3. An analytical framework diagram illustrating the key factors influencing alternative data implementation success.

The sustainability of AD-derived alpha represents a critical consideration for institutional investors evaluating long-term strategic commitments to these capabilities. Research on signal decay patterns demonstrates that AD advantages tend to erode over time as information sources become more widely available and analytical techniques diffuse across market participants [70]. The half-life of AD alpha varies substantially across different data types, with highly proprietary or difficult-to-analyze sources maintaining predictive power longer than easily accessible or straightforward signals. Institutional investors pursuing sustained AD advantages must continuously invest in innovation, identifying new data sources, developing advanced analytical techniques, and maintaining technological leadership relative to competitors. The dynamic nature of the AD landscape creates ongoing pressure for capability development and strategic adaptation [71].

Figure 3 presents an analytical framework identifying the key factors that determine alternative data implementation success. Data characteristics—including quality, timeliness, coverage, and uniqueness—establish the foundational potential of AD sources, as even sophisticated analytics cannot overcome fundamentally flawed or commoditized inputs. Organizational capabilities encompassing technical infrastructure, talent expertise, data governance, and investment process integration determine whether institutions can effectively translate data potential into actionable investment signals. Market conditions including efficiency level, competitive intensity, and regulatory environment shape the external context within which AD advantages can be captured and sustained. Strategy alignment ensures that AD investments match investment horizon, portfolio construction approaches, and risk tolerance, avoiding mismatches where short-term signals inform long-horizon strategies or vice versa. The framework emphasizes that implementation success requires simultaneous strength across all four dimensions; excellence in data characteristics alone proves insufficient without organizational capabilities to exploit them, while strong capabilities deliver limited value when applied to low-quality data or misaligned strategies.

Regulatory considerations increasingly influence AD adoption decisions and implementation approaches, as policymakers and enforcement agencies examine potential issues related to insider information, market manipulation, personal data privacy, and fair access to market-relevant information. Institutional investors must carefully evaluate whether specific AD sources might constitute material non-public information subject to securities law restrictions [72]. The use of personal data in investment analytics raises privacy concerns and compliance obligations under regulations such as the General Data Protection Regulation in Europe and various state privacy laws in the United States. Institutional investors implement compliance frameworks including legal review processes, data provenance tracking, and ethical guidelines to ensure AD usage adheres to applicable laws and industry standards. Regulatory uncertainty in this evolving domain requires prudent risk management and ongoing monitoring of policy developments that might impact permissible AD applications [73].

5. Conclusion

The integration of AD into institutional investment processes represents a fundamental transformation in how financial markets operate and how investment decisions are formulated. This review has examined the evolution, applications, and implications of AD for institutional investors, highlighting both the substantial opportunities these information sources provide and the significant challenges associated with their effective implementation. The analysis demonstrates that AD has progressed from a specialized tool employed by quantitative hedge funds to a mainstream capability adopted across diverse institutional investor types and investment strategies. The expanding universe of available data sources combined with advances in ML and AI technologies continues to create new possibilities for extracting investment insights from non-traditional information.

The evidence presented throughout this review indicates that AD can meaningfully enhance investment performance when properly integrated into analytical and decision-making frameworks. Empirical research consistently demonstrates that AD provides predictive signals regarding corporate performance, economic trends, and market dynamics that complement or exceed traditional information sources. The ability to access real-time or near-real-time data about physical activities, consumer behaviors, and business operations enables more timely and accurate investment decisions compared to reliance on backward-looking financial statements and lagging economic indicators. Institutional investors who successfully harness AD capabilities achieve competitive advantages through superior information quality, earlier identification of investment opportunities, and more effective risk management.

However, the successful implementation of AD capabilities requires substantial organizational commitments spanning technological infrastructure, analytical expertise, data governance, and strategic alignment with investment processes. The technological requirements for handling diverse data formats, massive scale, and complex analytics demand significant capital investment and ongoing operational support. Recruiting and retaining personnel with specialized skills in data science, ML, software engineering, and domain expertise presents human capital challenges for many institutional investors. Establishing robust data governance frameworks that ensure quality, security, and compliance adds operational complexity but remains essential for managing risks associated with AD usage. Perhaps most critically, effective AD integration requires thoughtful alignment with investment philosophy, strategy objectives, and organizational capabilities rather than wholesale adoption of technologies or data sources without clear strategic rationale.

The competitive dynamics of the AD landscape present important strategic considerations for institutional investors evaluating their positioning in this evolving environment. While early adopters of AD enjoyed substantial advantages from accessing novel information sources ahead of competitors, the gradual diffusion of data availability and analytical capabilities has compressed some of these advantages over time. Institutional investors must continuously innovate to maintain differentiation, either through proprietary data development, advanced analytical techniques, or superior integration with investment processes. The decision between pursuing cutting-edge AD capabilities versus accepting competitive parity in a maturing landscape involves tradeoffs between potential returns, required investments, and risk tolerance that vary across institutions based on their specific circumstances and objectives.

Regulatory and ethical dimensions of AD usage will likely assume increasing prominence as policymakers and society more broadly grapple with appropriate boundaries for data collection, analysis, and application in financial contexts. Institutional investors must proactively address concerns regarding personal privacy, information fairness, and market integrity to maintain social license for AD activities and avoid regulatory restrictions that could constrain valuable applications. Industry self-regulation through ethical guidelines and best practices may help demonstrate responsible stewardship of data resources and forestall more prescriptive regulatory interventions. The development of transparent standards for data sourcing, anonymization, and usage could benefit the entire ecosystem by establishing clear boundaries and building public confidence in AD applications.

Looking forward, several trends will likely shape the continued evolution of AD in institutional investing. The ongoing proliferation of connected devices, digital platforms, and sensor networks will generate ever-expanding volumes of potentially relevant data, creating both opportunities and challenges for institutional investors. Advances in AI technologies including large language models, multimodal learning systems, and automated machine learning will further enhance capabilities for extracting insights from complex unstructured data. The potential emergence of synthetic data, privacy-preserving analytics techniques, and decentralized data marketplaces may address some current limitations while introducing new considerations. Climate-related data sources will gain prominence as investors increasingly integrate environmental factors into investment processes and reporting requirements expand for climate risk disclosure. The competitive landscape will continue evolving as traditional data vendors, technology companies, and new entrants compete for share in the growing AD market.

In conclusion, AD represents a permanent feature of the institutional investment landscape rather than a temporary phenomenon, fundamentally changing how investors gather information and make decisions. While specific data sources and analytical techniques will continue to evolve, the core principle of leveraging diverse information sources to gain investment insights will remain central to competitive success in financial markets. Institutional investors must develop sustained capabilities in data analytics, maintain organizational agility to adapt to rapidly changing technologies and data sources, and uphold ethical standards that preserve trust and legitimacy. Those institutions that successfully navigate these challenges while capitalizing on AD opportunities will be best positioned to deliver superior investment performance in increasingly complex and competitive financial markets.

References

Mitra, G., Hoang, K. T., Gladilin, A., Chu, Y., Black, K., & Mani, G. (2023). Alternative data: Overview. In *Handbook of alternative data in finance* (Vol. I, pp. 1–28). Elsevier.

Bartram, S. M., Branke, J., De Rossi, G., & Motahari, M. (2021). Machine learning for active portfolio management. *Journal of Financial Data Science, 3*(3), 9–30. https://doi.org/10.3905/jfds.2021.1.065

Mami, E. (2023). The role of sovereign wealth funds in natural resource-rich countries: A systematic meta-narrative review. *Journal of International Business Policy, 6*(3), 356–371. https://doi.org/10.1057/s42214-023-00153-3

Lin, H., & Liu, W. (2025). Symmetry-aware causal-inference-driven web performance modeling: A structure-aware framework for predictive analysis and actionable optimization. *Symmetry, 17*(12), Article 2058. https://doi.org/10.3390/sym17122058

Jiang, F., Liu, Y., Meng, L., & Zhang, H. (2024). Deep learning, textual sentiment, and financial market. *Information Technology and Management.* Advance online publication. https://doi.org/10.1007/s10799-024-00399-6

Katona, Z., Painter, M. O., Patatoukas, P. N., & Zeng, J. (2025). On the capital market consequences of big data: Evidence from outer space. *Journal of Financial and Quantitative Analysis, 60*(2), 551–579. https://doi.org/10.1017/S0022109024000215

Ajjoub, C., Walker, T., & Zhao, Y. (2021). Social media posts and stock returns: The Trump factor. *International Journal of Managerial Finance, 17*(2), 185–213. https://doi.org/10.1108/IJMF-04-2019-0141

Dang, T. T., Hoang, K. N., Thanh, L. B., Thuy, T. N. T., & Quoc, C. N. (2023). Constructing and understanding customer spending prediction models. *SN Computer Science, 4*(6), Article 852. https://doi.org/10.1007/s42979-023-02085-6

Yang, S. (2024). *Motivated extrapolative beliefs.* SSRN. https://doi.org/10.2139/ssrn.4753510

Shangguan, X. (2025). Digital museum exhibits based on big data. In *Frontier computing: Proceedings of FC 2024* (Vol. 1, Article 1355, p. 325). Springer.

Yang, J., Zeng, Z., & Shen, Z. (2025). Neural-symbolic dual-indexing architectures for scalable retrieval-augmented generation. *IEEE Access. (Early access; DOI not yet assigned)*

Gao, W. (2024, December). Analysis of the key elements in mergers and acquisitions cases. In *Proceedings of the 3rd International Conference on Public Service, Economic Management and Sustainable Development (PESD 2024)* (pp. 312–320). Atlantis Press.

Bybee, L., Kelly, B. T., Manela, A., & Xiu, D. (2020). *The structure of economic news* (NBER Working Paper No. 26648). National Bureau of Economic Research. https://doi.org/10.3386/w26648

Villota Miranda, J. (2024, June). Predicting market reactions to news: An LLM-based approach using Spanish business articles. In *Generative AI in Finance Conference.* John Molson School of Business, Montréal.

Fuster, A., Goldsmith-Pinkham, P., Ramadorai, T., & Walther, A. (2022). Predictably unequal? The effects of machine learning on credit markets. *Journal of Finance, 77*(1), 5–47. https://doi.org/10.1111/jofi.13053

Clement, M., Lee, J., & Yong, K. O. (2019). A new perspective on post-earnings-announcement drift: Using a relative drift measure. *Journal of Business Finance & Accounting, 46*(9–10), 1123–1143. https://doi.org/10.1111/jbfa.12396

Ke, Z. T., Kelly, B. T., & Xiu, D. (2019). *Predicting returns with text data* (NBER Working Paper No. 26186). National Bureau of Economic Research. https://doi.org/10.3386/w26186

Joseph, O. A., & Falana, A. (2021). Artificial intelligence and firm performance: A robotic taxation perspective. In *The fourth industrial revolution: Implementation of artificial intelligence for growing business success* (pp. 23–56). Springer. https://doi.org/10.1007/978-3-030-60711-1_2

Bao, Y., Ke, B., Li, B., Yu, Y. J., & Zhang, J. (2020). Detecting accounting fraud in publicly traded U.S. firms using a machine learning approach. *Journal of Accounting Research, 58*(1), 199–235. https://doi.org/10.1111/1475-679X.12292

Bellstam, G., Bhagat, S., & Cookson, J. A. (2021). A text-based analysis of corporate innovation. *Management Science, 67*(7), 4004–4031. https://doi.org/10.1287/mnsc.2020.3702

Mitchell, W. C. (2024). Business cycles. In *Business cycle theory* (Part II, Vol. 8, pp. 225–241). Routledge.

Zhang, X., & Wang, M. (2025). Large language models for financial knowledge extraction: Analytical insights and corporate planning support. *Mathematical Modeling and Algorithm Application, 6*(2), 44–56.

Napier, C. J. (2023). Using accounting records as historical data sources. In *Handbook of historical methods for management* (pp. 140–155). Edward Elgar Publishing.

Chen, S., Wang, Y., Zhang, H., & Zhou, J. (2025). Music sentiment and the cross-section of stock returns in the U.S. *Transactions on Economics, Business and Management Research, 15*, 399–406.

National Guideline Centre (UK). (2022). *Evidence review: Patient information and support.* NICE.

Green, T. C., Huang, R., Wen, Q., & Zhou, D. (2019). Crowdsourced employer reviews and stock returns. *Journal of Financial Economics, 134*(1), 236–251. https://doi.org/10.1016/j.jfineco.2019.03.009

Rahman, D., Haque, A., Kabir, M., & Bin Hasan, M. S. (2024). Firm-level political risk and equity issuance. *Journal of International Financial Markets, Institutions and Money, 91*, Article 101944. https://doi.org/10.1016/j.intfin.2024.101944

He, J., Tian, X., Yang, H., & Zuo, L. (2020). Asymmetric cost behavior and dividend policy. *Journal of Accounting Research, 58*(4), 989–1021. https://doi.org/10.1111/1475-679X.12315

Huang, S., Huang, Y., & Lin, T.-C. (2019). Attention allocation and return co-movement: Evidence from repeated natural experiments. *Journal of Financial Economics, 132*(2), 369–383. https://doi.org/10.1016/j.jfineco.2018.12.005

Akey, P., Gupta, N., & Lewellen, S. (2025). *Politics and finance* (ECGI Finance Working Paper, forthcoming). European Corporate Governance Institute.

Anh Thu, P., Quang Huy, P., & Huu Tuan Anh, L. (2023). Is related party transactions linked to accounting comparability? Evidence from emerging markets. *Cogent Business & Management, 10*(1), Article 2163094. https://doi.org/10.1080/23311975.2022.2163094

Kim, C., Wang, K., & Zhang, L. (2019). Readability of 10-K reports and stock price crash risk. *Contemporary Accounting Research, 36*(2), 1184–1216. https://doi.org/10.1111/1911-3846.12453

Brockman, P., Chung, D. Y., & Snow, N. M. (2023). Search-based peer groups and commonality in liquidity. *Review of Finance, 27*(1), 33–77. https://doi.org/10.1093/rof/rfac018

Sun, T., & Wang, M. (2025). Usage-based and personalized insurance enabled by AI and telematics. *Frontiers in Business and Finance, 2*(2), 262–273.

Loughran, T., & McDonald, B. (2024). Measuring firm complexity. *Journal of Financial and Quantitative Analysis, 59*(6), 2487–2514. https://doi.org/10.1017/S0022109023000586
Ma, M., Pan, J., & Stubben, S. (2020). The effect of local tournament incentives on firms' performance, risk-taking decisions, and financial reporting decisions. *The Accounting Review, 95*(2), 283–309. https://doi.org/10.2308/accr-52503
Abbas Zadeh Amiri, R., Bazzaz Zadeh Torbati, H. R., Abbaszadeh, M. R., Mehrazin, A., & Karimi, M. (2025). The impact of economic policy uncertainty on stock liquidity with a focus on the role of financial disclosure. *Iranian Journal of Accounting, Auditing and Finance, 9*(4), 101–125.
Zhang, X., Lu, F., Tao, R., & Wang, S. (2021). The time-varying causal relationship between the Bitcoin market and internet attention. *Financial Innovation, 7*(1), Article 66. https://doi.org/10.1186/s40854-021-00282-8
Chen, X., Hilary, G., & Tian, X. (2025). Mandatory data breach disclosure and insider trading. *Journal of Business Finance & Accounting, 52*(5), 2091–2110. https://doi.org/10.1111/jbfa.12643
Clarke, J., Chen, H., Du, D., & Hu, Y. J. (2020). Fake news, investor attention, and market reaction. *Information Systems Research, 32*(1), 35–52. https://doi.org/10.1287/isre.2020.0959
Bhagwat, V., Cookson, J. A., Dim, C., & Niessner, M. (2025). *The market's mirror: Revealing investor disagreement with large language models* (FEB-RN Research Paper No. 107).
Wei, Y., Jia, N., & Bonardi, J.-P. (2023). Corporate political connections: A multidisciplinary review. *Journal of Management, 49*(6), 1870–1910. https://doi.org/10.1177/01492063221132235
Wijayanti, H., Supian, S., Chaerani, D., & Shuib, A. (2024). Robust goal programming as a novelty asset–liability management modeling in non-financial companies: A systematic literature review. *Computation, 12*(11), Article 220. https://doi.org/10.3390/computation12110220
Yang, S., Ding, G., Chen, Z., & Yang, J. (2025). GART: Graph neural network-based adaptive and robust task scheduler for heterogeneous distributed computing. *IEEE Access*.
Sutiene, K., Schwendner, P., Sipos, C., Lorenzo, L., Mirchev, M., Lameski, P., … Cerneviciene, J. (2024). Enhancing portfolio management using artificial intelligence: Literature review. *Frontiers in Artificial Intelligence, 7*, Article 1371502. https://doi.org/10.3389/frai.2024.1371502
Coqueret, G., & Guida, T. (2020). *Machine learning for factor investing: R version*. Chapman & Hall/CRC.
Boubaker, S., Ni, X., & Yin, D. (2025). *Inalienable human capital and debt choice* (FEB-RN Research Paper No. 55).
Chen, Y., Bredin, D., Potì, V., & Matkovskyy, R. (2022). COVID risk narratives: A computational linguistic approach to the econometric identification of narrative risk during a pandemic. *Digital Finance, 4*(1), 17–61. https://doi.org/10.1007/s42521-021-00053-3
Dey, P., Dev, S., & Phelan, B. S. (2023). CombineDeepNet: A deep network for multistep prediction of near-surface $PM_{2.5}$ concentration. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 17*, 788–807. https://doi.org/10.1109/JSTARS.2023.3319621
Avramov, D., Cheng, S., & Metzker, L. (2023). Machine learning vs. economic restrictions: Evidence from stock return predictability. *Management Science, 69*(5), 2587–2619. https://doi.org/10.1287/mnsc.2022.4438
Ning, Y., Yang, S., & Xiao, Z. (2024). Manager sentiment, stock returns, and the evolving information environment in post-IPO firms. *Journal of Economics and Finance, 48*(1), 238–261. https://doi.org/10.1007/s12197-023-09641-3
Ge, Y., Wang, Y., Liu, J., & Wang, J. (2025). GAN-enhanced implied volatility surface reconstruction for option pricing error mitigation. *IEEE Access*.
Barber, B. M., Huang, X., Odean, T., & Schwarz, C. (2022). Attention-induced trading and returns: Evidence from Robinhood users. *The Journal of Finance, 77*(6), 3141–3190. https://doi.org/10.1111/jofi.13173
Easley, D., López de Prado, M., O'Hara, M., & Zhang, Z. (2021). Microstructure in the machine age. *The Review of Financial Studies, 34*(7), 3316–3363. https://doi.org/10.1093/rfs/hhab019
Xu, X., & Liu, W. H. (2024). Forecasting the equity premium: Can machine learning beat the historical average? *Quantitative Finance, 24*(10), 1445–1461. https://doi.org/10.1080/14697688.2024.2364123
Kelly, B. T., Kuznetsov, B., Malamud, S., & Xu, T. A. (2025). *Artificial intelligence asset pricing models* (NBER Working Paper No. 33351). National Bureau of Economic Research. https://doi.org/10.3386/w33351
Leippold, M., Wang, Q., & Zhou, W. (2022). Machine learning in the Chinese factor zoo. *Journal of Financial Economics, 145*(2), 64–82. https://doi.org/10.1016/j.jfineco.2022.04.006
Cong, L. W., Tang, K., Wang, J., & Zhang, Y. (2021). *AlphaPortfolio: Direct construction through deep reinforcement learning and interpretable AI*. SSRN. https://doi.org/10.2139/ssrn.3554486
Dixon, M. F., Polson, N. G., & Goicoechea, K. (2022). Deep partial least squares for empirical asset pricing. *arXiv*. https://arxiv.org/abs/2206.10014
Kelly, B., & Xiu, D. (2023). Financial machine learning. *Foundations and Trends® in Finance, 13*(3–4), 205–363. https://doi.org/10.1561/0500000064
Giglio, S., & Xiu, D. (2021). Asset pricing with omitted factors. *Journal of Political Economy, 129*(7), 1947–1990. https://doi.org/10.1086/713936
Wang, Y., Ding, G., Zeng, Z., & Yang, S. (2025). Causal-aware multimodal transformer for supply chain demand forecasting: Integrating text, time series, and satellite imagery. *IEEE Access*.
Kozak, S., Nagel, S., & Santosh, S. (2020). Shrinking the cross-section. *Journal of Financial Economics, 135*(2), 271–292. https://doi.org/10.1016/j.jfineco.2019.05.008
Wu, W., & You, J. (2025, May). Machine learning approaches to picking A-shares stocks: A comparative analysis. In *2025 Joint International Conference on Automation-Intelligence-Safety (ICAIS) & International Symposium on Autonomous Systems (ISAS)* (pp. 1–8). IEEE.
Schmidt, J. (2025). The influence of short-term subjective expectations on stock price movements. *Financial Markets and Portfolio Management*. Advance online publication.
Noordermeer, B., & Vorst, P. (2025). The informativeness of balance sheet disaggregations: Evidence from forecasting operating assets. *Management Science*. Advance online publication.
Zhao, R., Xiong, X., Ma, J., Zhang, Y., & Zhang, Y. (2025). Baidu News and the return volatility of Chinese commodity futures: Evidence for the sequential information arrival hypothesis. *Financial Innovation, 11*(1), Article 80. https://doi.org/10.1186/s40854-025-00533-9
Cevik, E., Kirci Altinkeski, B., Cevik, E. I., & Dibooglu, S. (2022). Investor sentiments and stock markets during the COVID-19 pandemic. *Financial Innovation, 8*(1), Article 69. https://doi.org/10.1186/s40854-022-00364-1
Sun, Y., Wu, M., Zeng, C., & Peng, Z. (2021). The impact of COVID-19 on the Chinese stock market: Sentimental or substantial? *Finance Research Letters, 38*, Article 101838. https://doi.org/10.1016/j.frl.2020.101838
Liu, J., Wang, J., & Lin, H. (2025). Coordinated physics-informed multi-agent reinforcement learning for risk-aware supply chain optimization. *IEEE Access, 13*, 190980–190993. https://doi.org/10.1109/ACCESS.2025.3534976
Fu, X. (2023, August). The impact of investor sentiment on stock returns. In *International Conference on Economic Management and Green Development* (pp. 1361–1370). Springer Nature Singapore. https://doi.org/10.1007/978-981-99-3262-6_140
Dhakal, S. P., Nankervis, A., & Burgess, J. (2023). *The future of work in the Asia Pacific*. Routledge.
Xu, X., & Zhang, Y. (2024). Network analysis of price comovements among corn futures and cash prices. *Journal of Agricultural & Food Industrial Organization, 22*(1), 53–81. https://doi.org/10.1515/jafio-2023-0062