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Forecasting meets Portfolio Theory: A Bibliometric Approach to Decision-Making under Uncertainty

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Financial decision-making increasingly requires navigating model uncertainty, estimation risk, and structural instability. Although forecasting and portfolio theory have evolved largely in parallel, both fields have developed complementary strategies for managing uncertainty through techniques such as shrinkage, model averaging, and robust optimisation. This study examines their methodological convergence through a bibliometric and thematic analysis of 489 peer-reviewed publications published between 2000 and 2025. A hybrid framework is introduced that integrates co-occurrence analysis, bibliographic coupling, fractional authorship attribution, and machine learning-based semantic clustering. Comparing a classical pipeline employing principal component analysis and K-Means with a nonlinear alternative based on uniform manifold approximation and projection combined with hierarchical density-based clustering enables an evaluation of trade-offs in cluster quality, stability, and interpretability. The analysis identifies six dominant conceptual clusters, including adaptive weighting, regularisation, and ensemble strategies, spanning both domains and reflecting a shared orientation towards robustness and ambiguity-tolerant decision-making. The research concludes by outlining opportunities for cross-disciplinary integration and proposing targeted research directions to enhance robustness, adaptability, and interpretability in forecasting and financial decision-making.

Introduction

In an era of growing financial complexity and uncertainty, institutions face increasing pressure to design decision-making strategies that remain robust despite data limitations, estimation error, and structural change. Whether designing economic policies, allocating capital in volatile markets, or selecting forecasting models, the challenge lies not only in extracting insights from data but also in managing ambiguity and exercising human judgement under incomplete information (Petropoulos et al., 2018). Psychological research further shows that such decisions are not purely rational; they are influenced by cognitive biases, heuristics, and prior beliefs that can undermine decision quality across domains such as forecasting, investment, and financial risk management (Athota et al., 2023).

Uncertainty itself is multifaceted and emerges at different stages of the decision-making pipeline. It can be classified as (i) Sample uncertainty, the variability in data samples that leads to different parameter estimates; (ii) Parameter uncertainty, the sensitivity of parameter values to

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estimation methods or initial conditions; and (iii) Model uncertainty, reflecting the inherent limitations of any single model in capturing the complexity of the underlying process (Kourentzes et al., 2019). These challenges are especially relevant in forecasting and investment contexts, where decisions rely on historical data to form expectations about the future. In practice, choices are made not with perfect knowledge but with estimates. As Barroso and Saxena (2022) note: 'In a more realistic setting, investors have to make their portfolio decisions in a context of uncertainty, with estimates learned from a sample instead of the true input.'

This adds a further layer of risk to the decision process, as overconfidence in model outputs and limited understanding of uncertainty can degrade outcomes. The tension between simplicity and complexity is also reflected in the relationship between statistical inference and human reasoning. Sophisticated solutions may promise accuracy, yet remain bound by their assumptions, whereas simpler heuristics, though biased, can offer rapid and often effective guidance, particularly in noisy or constrained environments (Brighton and Gigerenzer, 2015). Empirical studies show that greater complexity does not always yield better results (e.g., Fildes and Petropoulos, 2015; Green and Armstrong, 2015), prompting growing interest in methods that combine diverse sources of information through alternative weighting schemes.

In parallel, regulatory initiatives, such as the European Union's Artificial Intelligence Act (European Commission, 2020), together with recent academic research, including regulatory-aligned frameworks like SAFE and KAIRI, have placed increasing emphasis on transparency, interpretability, accuracy, fairness, sustainability, and risk management in complex predictive systems (Giudici et al., 2024b; Giudici and Raffinetti, 2023). Financial institutions are progressively integrating machine-learning methods and generative artificial intelligence into applications such as fraud detection, credit scoring, trading, investment processes, regulatory compliance, governance, and anomaly detection. In this context, explainable artificial intelligence (XAI) approaches have been developed to clarify how forecasting models generate predictions, assess risk, and relate input variables to model outputs (Giudici and Raffinetti, 2021), with important implications for trust and accountability in financial decision-making (e.g., Arsenault et al., 2025; Coussement et al., 2024; Giudici et al., 2024a). However, much of the XAI literature focuses on explaining individual models, rather than addressing uncertainty arising from competing, empirically similar alternatives within broader decision-making systems. Consequently, important questions remain regarding how transparency, robustness, and decision quality jointly emerge in complex financial environments.

In response to uncertainty and the limits of relying on a single 'best' model, both forecasting and portfolio theory have developed strategies to combine multiple inputs to improve decision quality. These aggregation methods offer several advantages across both domains: (i) Pooling heterogeneous information promotes diversification, reducing forecast error in predictive settings (Kang et al., 2022) and portfolio risk in financial applications (Pham et al., 2022), with ambiguity serving as a measure of diversity in both cases; (ii) Incorporating heterogeneous models or assets increases resilience to structural breaks and regime shifts in both time-series forecasting (Rossi, 2021) and investment allocation (Ciciretti and Bucci, 2023); (iii) Combining models or assets that capture different aspects of the underlying process helps mitigate misspecification bias and estimation uncertainty, enhancing robustness (Bravo and Ayuso, 2021; Bravo et al., 2021; Zhang et al., 2022); and (iv) Aggregation improves temporal stability, reducing fluctuations in forecast updates (Godahewa et al., 2025) and variability in portfolio returns (Cesarone et al., 2020).

Beyond these shared benefits, both fields have converged on common methodological tools to address uncertainty and instability. Shrinkage techniques regularise parameter estimates, such as forecast combination weights or covariance matrices, by pulling them towards stable targets, reducing estimation variance and improving robustness. These include linear (Ledoit and Wolf, 2003a, b, 2004) and nonlinear approaches (Ledoit and Wolf, 2017, 2021, 2022). Similarly, robust optimisation frameworks acknowledge that inputs are estimated with error. Rather than optimising around a single-point estimate, they seek solutions that perform well across a range of plausible values within an uncertainty set, improving out-of-sample performance in both financial allocation and predictive modelling (Ghahtarani et al., 2022; Roccazzella et al., 2022). Convex optimisation provides the mathematical foundation for these strategies, yielding efficient and globally optimal allocations, whether in portfolio weights or forecast combinations, under well-defined objectives and constraints (Bertsimas and den Hertog, 2022; Post et al., 2019).

Despite these advances, evidence from both domains shows that simple heuristics often match or outperform complex optimisation-based methods. In forecasting, this phenomenon, known as the 'forecast combination puzzle', occurs because simple averages are often more robust to estimation error (Blanc and Setzer, 2020; Chan and Pauwels, 2018; Stock and Watson, 2004). In portfolio research, naïve diversification through equal weighting similarly outperforms mean–variance optimisers in out-of-sample tests, particularly under short samples, structural breaks, or model misspecification (DeMiguel et al., 2009; Peng and Linetsky, 2024). These results highlight a key insight: robustness and stability often arise not from complexity, but from simplicity and aggregation.

Although forecast combination and portfolio theory share several methodological foundations, their literatures have largely evolved in parallel, with limited integration. To date, no bibliometric research has systematically mapped their intersection. Previous research have focused on one domain or the other, leaving open the question of how innovations diffuse across fields (e.g., Salo et al., 2024; Wang et al., 2023). This gap constrains our understanding of convergence, which should not be seen merely as coincidental overlap in statistical techniques. Rather, it reflects a deeper epistemic shift: both fields are moving towards ambiguity-tolerant, adaptive decision-making, where uncertainty is managed through aggregation, shrinkage, and robustness. This research advances the argument that convergence between forecasting and portfolio theory represents a shared rethinking of how uncertainty is conceptualised and addressed across disciplines. This type of bibliometric analysis has previously been used to document methodological convergence across distinct research domains, including molecular imaging and robotic surgery (Taha et al., 2026), climate change and oncology (Gupta et al., 2025), social media analytics and capital markets (Long and Guo, 2025), blockchain-enabled sustainable finance (Roy and Zaher, 2025), and energy transition and green finance (Xu et al., 2024). These precedents reinforce the value of cross-domain integration and motivate the present study's focus on the intersection of forecasting and portfolio theory, where such convergence remains underexplored.

Accordingly, the present research formulates four research questions (RQ) designed to provide the first systematic bibliometric mapping of conceptual and methodological convergence between forecasting and portfolio theory:

- **RQ1:** What evidence exists for conceptual and methodological convergence between forecasting and portfolio theory in their treatment of uncertainty?

- **RQ2:** Which thematic structures and methodological tools have defined this intersection, and how have they changed over the past two decades?
- **RQ3:** In what ways do key publications, authors, journals, institutions, and countries act as conceptual bridges between the two literatures?
- **RQ4:** How are bibliometric interpretations of convergence shaped by different methodological choices, such as clustering algorithms and scholarly impact attribution?

In response to the challenges and gaps identified above, this research offers four contributions: (i) First, it provides a bibliometric and thematic analysis of more than two decades of research, mapping conceptual and methodological intersections between the two bodies of literature; (ii) Second, it develops a hybrid methodological framework combining established techniques, such as keyword-based screening, co-occurrence analysis, bibliographic coupling, and network visualisation, with machine learning-based semantic clustering. Specifically, we compare a classical baseline pipeline consisting of principal component analysis (PCA) followed by K-Means clustering, widely used in bibliometric and text-mining studies, with a recent nonlinear alternative combining Uniform Manifold Approximation and Projection (UMAP) with hierarchical density-based spatial clustering of applications with noise (HDBSCAN). To our knowledge, this is the first bibliometric study to apply the UMAP +HDBSCAN pipeline, and few analyses have explicitly contrasted classical and nonlinear clustering methods. This allows for a methodological reflection on the strengths and limitations of alternative clustering strategies, rather than treating them as black-box tools; (iii) Third, we address the bias in scholarly impact assessment by comparing full and fractional methods of authorship attribution, enabling a normalised and comparative evaluation of individual and institutional contributions that accounts for differences in collaboration intensity across fields; and (iv) Finally, we identify knowledge gaps and outline future research directions, including empirical blind spots, underexplored cross-disciplinary opportunities, and methodological pathways through which tools developed in one field may inform the other. Special emphasis is placed on enhancing robustness, adaptability, and interpretability in complex and uncertain environments. Taken together, these contributions provide not only a systematic account of how forecasting and portfolio theory have converged to date but also a foundation for future research that extends the analysis to new datasets, tests the stability of thematic clusters, and explores practical cross-domain applications in financial decision-making.

The remainder of the paper is organised as follows. Section 'Bibliometric and Analytical Methodology' describes the bibliometric methodology and data collection procedures. Section 'Bibliometric Findings and Thematic Mapping' presents the results, identifying thematic overlaps, collaboration networks, and prevailing methodological trends. Section 'Main Conclusions and Contributions' provide the conclusions of the study. Section 'Research Constraints and Future Research Directions' outlines the limitations and discusses the future outlook.

Bibliometric and Analytical Methodology

This research conducts a bibliometric analysis to systematically examine how the fields of forecasting and portfolio theory address decision-making under uncertainty. The bibliometric approach provides a structured framework to map the intellectual landscape of both fields, identify major research areas and their interconnections, trace theoretical overlaps, track the evolution of research topics, and highlight influential contributions, institutions, and journals. It also enables the identification of research gaps and emerging directions, providing evidence-based insights for research policy and strategic decision-making.

This analysis draws on the Scopus database, with records extracted on 18th April 2025. Scopus was selected as the primary data source because it offers the broadest and most consistent coverage of forecasting, portfolio theory, economics, finance and operational research. It also provides rich metadata, especially for author keywords and affiliations, which are essential for advanced bibliometric, clustering, and network analyses. In response to common alternatives in bibliometric research, we also considered the use of Web of Science. Preliminary tests indicated that, for these target fields, Web of Science offers narrower coverage and less complete metadata for keywords and affiliations compared to Scopus. Moreover, merging multiple databases can introduce duplicate records, inconsistent metadata, and citation mismatches, which can undermine the reliability of semantic and network analyses, especially with non-linear techniques. In line with bibliometric methodology guidelines, we prioritised methodological coherence and data consistency by relying on a single, well-curated source (Donthu et al., 2021). The overall bibliometric workflow, including search strategy, screening, and analytical steps, is summarised in Fig. 1.

Search Strategy and Screening. A targeted search was conducted in Scopus to capture publications reflecting the intersection in forecasting and portfolio theory. The search query was designed to maximise conceptual relevance and methodological specificity by combining key terms from both domains. Publications were included if the search terms appeared in the title, abstract, author keywords, or indexed keywords. The search was limited to peer-reviewed English-language publications published between 2000 and 2025 and indexed under 'Business, Management and Accounting', 'Economics, Econometrics and Finance' and 'Mathematics'. This period was selected to ensure metadata consistency and analytical reliability, as Scopus indexing for author keywords, abstracts, and affiliations is notably less complete prior to 2000. Although relevant studies may appear in adjacent fields or earlier periods, these restrictions ensured a coherent, methodologically focused corpus.

Earlier foundational works (e.g., Bates and Granger, 1969; Markowitz, 1952) are not directly captured in the initial screening due to metadata limitations. However, their intellectual influence can be traced through citation and bibliographic coupling analyses, as well as explicit discussion within the narrative review. Thus, the convergence argument is supported by both recent bibliometric trends and the enduring legacy of classic contributions. The complete search query was:

Scopus Search Query Used.

(TITLE-ABS-KEY ("forecast combin*" OR "ensemble lear*" OR "forecast pooling" OR "model averaging")
OR TITLE-ABS-KEY ("portfolio optimi?ation" OR "mean-variance" OR "asset allocation"))
AND TITLE-ABS-KEY ("uncertaint*" OR "shrinkage" OR "regulari?ation" OR "estimation error" OR "misspecification" OR "model selection")
AND PUBYEAR > 1999 AND PUBYEAR < 2026
AND (LIMIT-TO (PUBSTAGE, "final"))
AND (LIMIT-TO (SUBJAREA, "ECON") OR LIMIT-TO (SUBJAREA, "BUSI") OR LIMIT-TO (SUBJAREA, "MATH"))
AND (LIMIT-TO (LANGUAGE, "English"))

Source: Authors' Preparation.

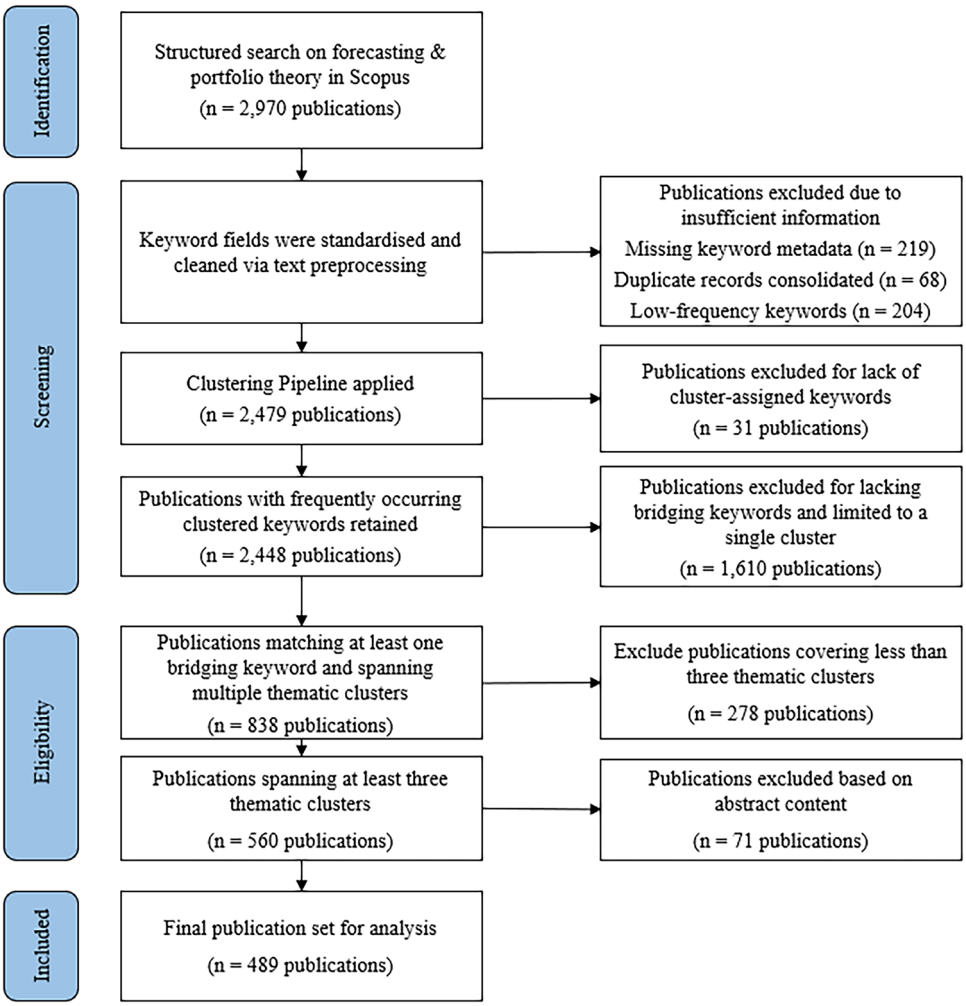


Fig. 1 Methodological Workflow for Bibliometric Screening. Source: Authors' Preparation.

Initial searches that combined forecasting and portfolio terms with high-level uncertainty keywords proved overly restrictive, returning few results, while broader queries yielded large volumes of publications lacking methodological specificity. The final query was iteratively refined to balance inclusiveness with conceptual focus, ensuring that the resulting dataset represented research at the methodological intersection of forecasting and portfolio theory. Research Screening followed the PRISMA-inspired workflow depicted in Fig. 1. The initial Scopus search returned 3056 records. However, publications with incomplete or malformed metadata were excluded during the data import process, resulting in a final dataset of 2970 publications. All records were subsequently analysed in Python.

Data Cleaning and Keyword Preprocessing. The conceptual landscape and thematic structure of the literature were examined through content analysis of author-assigned and Scopus-indexed keywords. After data extraction, bibliographic records were standardised and filtered to maintain analytical consistency. Publications lacking both author-supplied and Scopus-indexed keyword fields were excluded ($n = 219$). Surplus metadata rows arising from duplicate publication identifiers were subsequently consolidated ($n = 68$) to ensure one analytical record per study prior to keyword analysis (Fig. 1).

A text normalisation pipeline was then implemented in Python using the Natural Language Toolkit for tokenisation and lemmatisation. All keywords were converted to lowercase, punctuation was removed, and spelling was standardised to British English using a curated dictionary. Rule-based filters were applied to eliminate metadata tags, classification codes, and noise terms such as 'JEL codes' and numeric-only strings, which improved semantic consistency across entries.

A two-step frequency-based keyword filtering process was implemented to support robust clustering and appropriate thematic mapping: (i) First, a minimum occurrence threshold was applied to exclude rare or idiosyncratic terms from the dataset; (ii) Second, cumulative frequency percentile trimming was used to retain only the most representative keywords, specifically those representing the top 90% of total usage. As a result of this additional filtering, a further 204 publications were excluded for lacking keywords that met the frequency threshold. Sensitivity analyses were conducted by testing a range of filtering parameters, with details and results presented in Section 'Keyword Clustering Methodology' and in Table A1 in the Supplementary Results. This approach minimised the influence of infrequent terms on the semantic structure while preserving the field's core vocabulary for analysis. At the end of this stage, the dataset comprised 2479 publications suitable for further analysis.

Keyword Clustering Methodology. Clustering was undertaken using two complementary pipelines to ensure both methodological robustness and thematic interpretability. The first pipeline,

employing PCA followed by K-Means clustering, serves as a widely recognised benchmark in bibliometric research (e.g., Narvaez-Montoya et al., 2023). The second combines transformer-based semantic embeddings, non-linear dimensionality reduction via UMAP, and density-based clustering with HDBSCAN. This pipeline is designed to address the challenges of clustering complex, high-dimensional, and context-dependent keyword data.

The PCA+K-Means pipeline transforms the keyword-feature matrix into a set of uncorrelated components using PCA, which captures the dominant directions of variance in the data (Ayesha et al., 2020). These principal components are then clustered using K-Means, a method that partitions the data by minimising within-cluster variance and assigning each point to the nearest cluster centroid (Saxena et al., 2017). This approach is a standard benchmark in bibliometrics, offering reproducibility and interpretability. However, K-Means is less suited to semantic keyword data with uneven or overlapping clusters, sensitive to outliers, and requires the number of clusters to be set in advance.

The UMAP+HDBSCAN pipeline applies recent advances in natural language processing to more effectively capture semantic similarity among keywords. Each unique keyword, following standardisation and filtering, was embedded in a high-dimensional semantic space using the `all-MiniLM-L6-v2` sentence transformer model. This method encodes context and word relationships beyond simple string similarity, supporting nuanced grouping of related concepts. Dimensionality reduction was performed using UMAP, which preserves both global and local data structure within the embedding space (Healy and McInnes, 2024). Clustering was then conducted with HDBSCAN, an algorithm that identifies clusters of varying size and density without requiring the number of clusters to be specified in advance (Campello et al., 2013). This pipeline was selected for several reasons: (i) Transformer-based embeddings provide richer semantic representations than frequency-based approaches (Abdalgader et al., 2024); (ii) UMAP and HDBSCAN have demonstrated strong performance in handling non-convex, high-variance, and sparse data (Healy and McInnes, 2024); and (iii) Topic modelling methods (e.g., Latent Dirichlet Allocation, BERTopic), while effective for full-text or abstract analysis, are less suitable for short keyword lists and often yield less interpretable results. Accordingly, such topic modelling methods were considered during the review but ultimately excluded. Embedding-based clustering is recommended for such corpora (Abdalgader et al., 2024).

Clustering performance was evaluated using standard internal validation indices: (i) The silhouette coefficient, which measures the similarity of each point to its own cluster relative to others (Rousseeuw, 1987); (ii) The Davies–Bouldin index, which reflects the average similarity between clusters (Davies and Bouldin, 1977); and (iii) The Caliński–Harabasz score, which compares between-cluster to within-cluster variance (Caliński and Harabasz, 1974). For a comprehensive review of clustering validation methods, see Ullmann et al. (2022). Clustering in both pipelines was conducted on the set of keywords defined by the filtering process described in Section 'Data Cleaning and Keyword Preprocessing'. For each pipeline, key parameters were systematically varied as part of a comprehensive grid search. Clustering was then performed using only the keywords that satisfied the criteria associated with each parameter configuration. This unified approach ensured that all clustering solutions were based on a consistent and representative core vocabulary for the field. Details of the top-performing parameter combinations are provided in Table A2 of the Supplementary Results.

Across the full parameter grid, the UMAP+HDBSCAN pipeline generally achieved higher internal clustering quality scores than the PCA+K-Means baseline. These indices are used here as comparative diagnostics rather than absolute measures of clustering optimality, and are known to be sensitive to cluster number and size distribution. The best-performing UMAP +HDBSCAN configuration (`min_occurrence` = 10, `keyword_percent` = 85, `n_neighbors` = 10, `n_components` = 15, `min_cluster_size` = 15) achieved a silhouette score of 0.692, a Davies–Bouldin index of 0.478, and a Caliński–Harabasz score of 391.89, but yielded only five clusters. Although this solution maximised internal validation metrics, it provided limited thematic granularity; qualitative inspection revealed that conceptually distinct topics were frequently merged. Balancing quantitative and qualitative criteria, we selected a configuration that maintained strong internal validation while offering improved thematic resolution. The final solution (`min_occurrence` = 5, `keyword_percent` = 90, `n_neighbors` = 15, `n_components` = 10, `min_cluster_size` = 20) achieved a silhouette score of 0.662, a Davies–Bouldin index of 0.439, and a Caliński–Harabasz score of 591.47, resulting in eleven semantically coherent clusters. Table 1 highlights each thematic cluster together with its most representative keywords, illustrating the thematic structure and interpretability of the selected solution. Representative keywords reflect the final assignment, including cases where conceptually relevant 'noise' keywords were manually reviewed and reassigned to appropriate clusters.

At the publication level, papers were retained in the analysis only if they contained at least one keyword assigned to a thematic cluster. This stage resulted in the exclusion of 31 papers, with 2448 publications proceeding to subsequent analyses. The selected configuration maintained strong internal validation while offering greater thematic resolution, enabling a more nuanced and interpretable mapping of the research landscape.

Identification of Bridge Papers and Conceptual Theme Mapping. Building on the validated eleven-cluster thematic structure, the Health and Biomedical Applications cluster was excluded as it falls outside the scope of the present study, and the analysis therefore focuses on the remaining ten domains. We then sought to identify publications that serve as conceptual bridges across multiple research areas. A 'bridge paper' is defined as a publication whose keyword set spans multiple distinct thematic clusters, indicating integration across areas such as forecasting, optimisation, uncertainty modelling, and decision-making. Beginning with the 2448 publications retained after keyword clustering, we applied a targeted filter using a set of conceptually relevant keywords associated with aggregation, robustness, optimisation, and uncertainty. The targeted keyword set comprised 'forecast combination', 'forecast aggregation', 'combining forecasts', 'shrinkage', 'shrinkage estimation', 'robust optimisation', 'ensemble learning', 'ensemble methods', 'equal-weighted portfolio', 'simple average', 'convex optimisation', 'model uncertainty', and 'parameter uncertainty'. Publications that did not contain any of these targeted keywords were excluded from further consideration. Additionally, to ensure genuine interdisciplinarity, only publications that were associated with at least two of the ten defined clusters were retained. This dual screening process resulted in a focused subset of 838 candidate publications for subsequent analysis.

Robustness of the 'bridge paper' identification was evaluated by testing different minimum thresholds for the number of thematic clusters represented in each publication's keyword set. While our operational definition required publications to span at least two clusters, further inspection revealed that this baseline often captured publications with only marginal thematic overlap. To

Table 1 Thematic Clusters and Representative Keywords.

Thematic Cluster	Representative Keywords
Risk Metrics and Financial Risk	risk assessment, risk management, risk perception, conditional value at risk, value at risk, risk analysis, risk aversion, ambiguity aversion, estimation risk, financial risk
Forecasting and Predictive Modelling	forecasting, forecast combination, prediction, time series, performance, volatility forecasting, probabilistic forecasting, prediction interval, density forecast, forecast evaluation
Optimisation Algorithms and Metaheuristics	optimisation, robust optimisation, linear programming, multiobjective optimisation, dynamic programming, quadratic programming, stochastic optimisation, convex optimisation, evolutionary algorithm, heuristic method
Probabilistic and Stochastic Processes	stochastic system, stochastic model, stochastic programming, entropy, markov process, markov chain, random process, gaussian process, stochastic dominance, state space model
Model Selection and Ensemble Techniques	model selection, model, mathematical model, dynamic model, factor model, model misspecification, model combination, model selection criterion, mixture model, generalised additive model
Machine Learning and Artificial Intelligence	ensemble learning, machine learning, deep learning, neural network, classification, random forest, artificial intelligence, clustering, support vector machine, reinforcement learning
Health and Biomedical Applications	article, meta analysis, clinical trial, empirical analysis, dose response, research design, longitudinal study, randomised controlled trial, empirical study, treatment outcome
Uncertainty and Estimation Error	uncertainty analysis, uncertainty, model uncertainty, uncertainty quantification, parameter uncertainty, parameter estimation, sensitivity analysis, uncertainty modelling, error, confidence interval
Bayesian inference and model evaluation	bayesian network, bayesian analysis, bayesian inference, bayesian estimation, posterior distribution, bayesian modelling, bayesian approach, causal inference, bayesian learning, empirical bayes
Portfolio Theory and Asset Allocation	portfolio optimisation, portfolio selection, asset allocation, optimal portfolio, portfolio theory, portfolio management, diversification, robust portfolio optimisation, portfolio construction, asset management
Macroeconomics and Business Topics	financial market, economics, finance, economic growth, stock market, inflation, macroeconomics, supply chain, economic policy, renewable energy

Source: Authors' Preparation.

enhance conceptual integration, we examined higher thresholds: applying a three-cluster minimum identified 560 papers, while raising the requirement to four, five and six clusters resulted in 338, 169 and 69 papers, respectively, but risked excluding substantively integrative contributions and limiting coverage of relevant methodological strands. The three-cluster threshold was therefore selected as providing the most appropriate balance between conceptual breadth and thematic focus, ensuring that retained publications exhibited genuine cross-domain integration while remaining feasible for qualitative inspection.

Following the identification of 'bridge papers', we conducted a manual screening of titles and abstracts to ensure substantive cross-domain integration, resulting in the exclusion of 71 publications and a final set of 489 'bridge papers'. Next, a higher-level synthesis was performed to consolidate the ten data-driven clusters into six overarching conceptual themes. This mapping relied on structured expert judgement, considering the dominant methodological focus, decision-theoretic role, and uncertainty-handling strategy characterising each cluster. Clusters were grouped when they exhibited strong conceptual proximity, shared methodological foundations, or played complementary roles within the broader forecasting–decision pipeline. This process yielded six mutually distinct yet interrelated conceptual categories, each representing a coherent strategy for managing uncertainty and guiding decision-making in forecasting and portfolio theory. The final themes are summarised in Table 2. These are denoted as Decision-Making and Managing Estimation Error under Uncertainty (DMEEU), Stochastic and Robust Aggregation Methods (SRAM), Shrinkage and Regularisation Approaches (SR), Model Averaging under Uncertainty (MAU), Time-Varying and Adaptive Combinations (TVAC), and Simplicity vs. Complexity: Heuristic Methods vs. Optimisation (SC).

We then examined the stability of the conceptual mapping across stricter thresholds, focusing on subsets comprising papers that spanned at least four, five or six clusters. Although only the three-cluster subset was manually screened, theme assignments for the higher-threshold groups were retained using the same mapping for comparative purposes. The results reported in Table A3 in the Supplementary Results indicate that the relative thematic composition remains stable as the threshold increases. For instance, MAU accounts for 38.5% of papers at the three-cluster threshold and remains within a comparable range at higher thresholds (33.6% at four clusters and 36% at five clusters), while SRAM consistently represents around one-quarter of publications across all thresholds. This pattern supports the internal coherence of the six-theme structure and confirms the three-cluster threshold as an appropriate analytical foundation for the bibliometric synthesis.

This curated corpus forms the analytical foundation for examining how forecasting and portfolio theory intersect in addressing decision-making under uncertainty.

Bibliometric Findings and Thematic Mapping

Descriptive Overview and Thematic Composition. Building on the corpus of literature and the established thematic framework, this section presents the core findings of the bibliometric analysis. Its purpose is to examine how the academic literature has addressed the challenge of decision-making under uncertainty through the methodological lenses of forecast combination and portfolio theory. Based on the selected body of work, Table 3 provides a descriptive overview, including key bibliometric indicators such as publication volume, average citations, co-authorship patterns, and the distribution of publications across the six conceptual themes.

The research corpus comprises 489 peer-reviewed publications authored by 1841 unique contributors. On average, each publication involved 3.76 authors and 1.93 institutions, indicating a strong trend towards collaborative research. The proportion of internationally co-authored publications, at 22.01%, together with an average annual growth rate of 5.48% between 2000 and 2025, further underscores the increasingly global and interconnected nature of research in this area. In terms of publication type, the corpus is dominated by journal articles (404), complemented by

Table 2 Conceptual Themes Identified in the Literature.

Theme	Description
Decision-Making and Managing Estimation Error under Uncertainty (DMEEU)	Frameworks that explicitly model and manage estimation risk and uncertainty in decision processes in both forecasting and portfolio theory. Includes parameter learning, regime detection, and uncertainty propagation in optimisation or predictive models.
Stochastic and Robust Aggregation Methods (SRAM)	Methods for addressing uncertainty and model misspecification using stochastic and robust optimisation, distributional robustness, or worst-case hedging. Includes robust mean–variance portfolios, distributionally robust forecasting, and aggregation under ambiguous or misspecified conditions.
Shrinkage and Regularisation Approaches (SR)	Techniques focused on mitigating overfitting and estimation error through shrinkage and regularisation. Includes penalisation strategies for forecast weights, sparse portfolio designs, and shrinkage approaches in high-dimensional settings.
Model Averaging under Uncertainty (MAU)	Strategies that avoid model selection by averaging between models to reduce overfitting and spread model risk. Encompasses Bayesian Model Averaging (BMA), Frequentist Model Averaging (FMA), stacking with static meta-models, and other static ensemble approaches.
Time-Varying and Adaptive Combinations (TVAC)	Approaches that dynamically adjust combination weights (e.g., Dynamic Model Averaging (DMA), Dynamic Model Selection (DMS), Drift-Aware Dynamic Ensemble) or model selection based on new information. Includes rolling window updates and performance-based weighting in changing environments.
Simplicity vs. Complexity: Heuristic Methods vs. Optimisation (SC)	Comparative studies between simple heuristics and complex optimisation methods in uncertain or data-limited settings. Emphasis on robustness, interpretability, and sample efficiency.

Source: Authors' Preparation.

Table 3 Summary Statistics of the Bibliometric Corpus.

Description	Results
Time Span	2000–2025
Total Publications	489
Annual Growth rate (%)	5.48
Average Publication Age (Years)	7.63
Average Citations per Publication	17.88
Unique Keywords (Author+Indexed)	2787
Total Authors	1841
Average Authors per Publication	3.76
Average Institution per Publication	1.93
International Co-Authorships (%)	22.01
Unique Journals and Conferences	249
Publication Type: Articles	404
Publication Type: Conference Papers	76
Publication Type: Reviews	6
Total Publications in: MAU	188
Total Publications in: SRAM	121
Total Publications in: SR	78
Total Publications in: TVAC	48
Total Publications in: DMEEU	35
Total Publications in: SC	19

Source: Authors' Preparation.

76 conference papers and a small subset of 6 review articles. These works appear across 249 distinct journals and conference proceedings, reflecting the interdisciplinary scope of research spanning economics, finance, operations research, statistics, and computational sciences. Table 4 lists the 20 leading journals by publication count, along with key metadata including disciplinary classification, impact rankings, citation metrics, and thematic contributions within the research corpus.

The corpus also contains more than 2500 unique keywords, drawn from both author-supplied and indexed sources, reflecting the conceptual and methodological diversity that characterises research on uncertainty in forecasting and investment contexts. Examination of the thematic structure reveals that the leading category is MAU, with 188 publications, followed by SRAM with 121. SR accounts for 78 publications, while TVAC appears in 48. Less frequent are DMEEU and SC, comprising 35 and 19 publications, respectively. This distribution indicates a prevailing emphasis on model aggregation and regularisation as strategies to address uncertainty, leaving scope for further exploration of adaptability, estimation risk and simplicity. Table A4 in the Supplementary Results presents a selection of representative recent studies from the Scopus-indexed corpus, illustrating the methodological contributions and thematic overlaps within each of the six identified clusters. The resulting thematic structure underscores how research in forecast combination and portfolio theory, though historically developed in parallel, confronts fundamentally similar challenges and increasingly adopts convergent solutions.

Temporal and Conceptual Dynamics. Figure 2 provides a temporal perspective on this convergence. Panel (A) shows a steady increase in publication volume, particularly after 2010, while Panel (B) reveals a concentration of citations around model averaging and robust methods, which have dominated the literature since the early 2010s. The most recent publication window includes all records indexed up to the extraction date, offering an up-to-date perspective while maintaining methodological consistency. Recent developments in shrinkage, adaptive, and heuristic methods further indicate a shift towards uncertainty-based frameworks. Overall, the field appears to be expanding and reconfiguring around methodological strategies that explicitly address estimation error and structural instability.

The temporal patterns in Fig. 2 highlight strong growth in research output and citations, but do not reveal how conceptual relationships between themes evolve over time. To address this limitation, we construct time-specific keyword co-occurrence networks for successive 5-year windows and analyse the resulting inter-theme interactions within each period. These network-level interactions are then aggregated at the thematic level to quantify cross-thematic co-occurrence intensity, providing a direct measure of thematic convergence over time, as summarised in Fig. 3. To focus explicitly on cross-cluster interplay, within-theme co-occurrences are excluded from this aggregation, while the full

Table 4 Top-Contributing Journals in the Bibliometric Corpus.

JN	CP	MF	AR	SR	HI	NP	TC	AC	CPY	AY	MT
J. of Econometrics	Netherlands	Economics and Quant. Methods	4	Q1	198	29	2545	88	4	2001–2025	MAU
J. of Forecasting	United Kingdom	Management and Analytics	2	Q1	71	20	310	16	1	2009–2024	MAU
European J. of Operational Research	Netherlands	Operations Research	4	Q1	319	19	671	35	1	2000–2024	SRAM
Lecture Notes in Computer Science	Germany	Computer Science	–	Q2	499	12	69	6	1	2004–2025	SRAM
Energy Economics	Netherlands	Energy Economics	3	Q1	230	11	695	63	6	2014–2023	MAU
International J. of Forecasting	Netherlands	Management and Analytics	3	Q1	126	10	399	40	3	2011–2023	MAU
J. of Banking and Finance	Netherlands	Finance	3	Q1	211	9	352	39	3	2008–2020	SR
Applied Economics	United Kingdom	Economics	2	Q2	121	8	26	2	1	2010–2024	MAU
Energy	United Kingdom	Energy and Engineering	–	Q1	274	7	358	51	5	2014–2024	MAU
Energies	Switzerland	Energy and Engineering	–	Q1	175	7	211	30	4	2016–2023	MAU
J. of Business and Economic Statistics	United Kingdom	Economics and Statistics	4	Q1	122	6	433	72	5	2009–2024	MAU
Empirical Economics	Germany	Economics and Statistics	2	Q1	71	6	59	10	1	2014–2021	MAU
Proceedings of Machine Learning Research	Netherlands	Computer Science	–	–	125	6	15	3	1	2020–2023	MAU
Management Science	United States	Management and Analytics	4*	Q1	303	6	809	135	8	2009–2024	SR
J. of Industrial Management and Optimisation	United States	Management and Analytics	1	Q3	44	5	16	3	1	2020–2023	DMEEU
Computational Statistics and Data Analysis	Netherlands	Computer Science	3	Q1	138	5	78	16	1	2007–2019	MAU
Technometrics	United Kingdom	Computer Science	–	Q2	96	5	347	69	3	2002–2024	MAU
J. of Asset Management	United Kingdom	Finance	2	Q2	26	5	59	12	1	2013–2023	SRAM
Physics A	Netherlands	Physics and Maths	–	Q2	195	4	72	18	4	2019–2023	SRAM
Econometric Reviews	United States	Economics	3	Q1	68	4	70	18	1	2010–2023	MAU

Source: Authors' Preparation.
JN Journal Name; *CP* Country of Publisher; *M* Main Field (Scimago+ABS); *AR* ABS Rank 2024; *SR* Scimago Rank 2024; *HI* H-index (Scimago 2024); *NP* Number of Publications; *TC* Total Citations; *AC* Average Citations per Publication (TC/NP); *CPY* Citations per Publication per Year (AC/(AY-1)); *AY* Active Years (Earliest-Latest); *MT* Main Thematic Contribution.

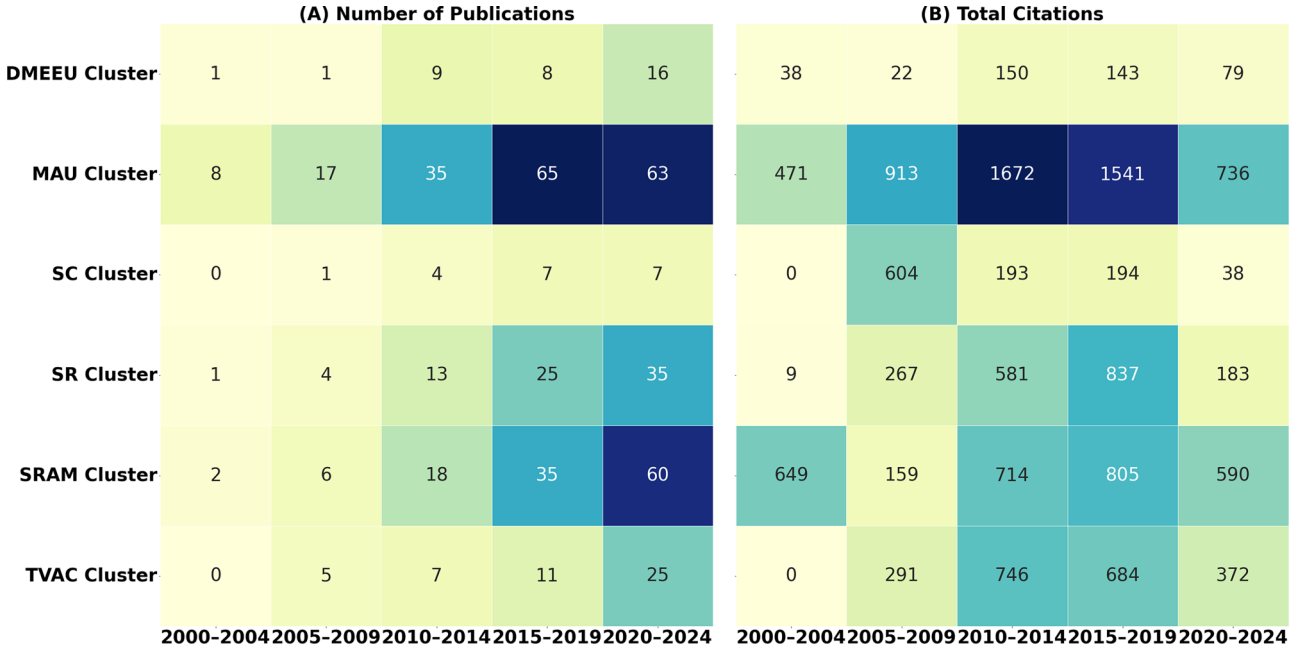


Fig. 2 Thematic Trends in Research Output and Citations. Source: Authors' Preparation. **Note**: The final bin (2020–2024) includes publications through 18th April 2025, reflecting the date of data extraction.

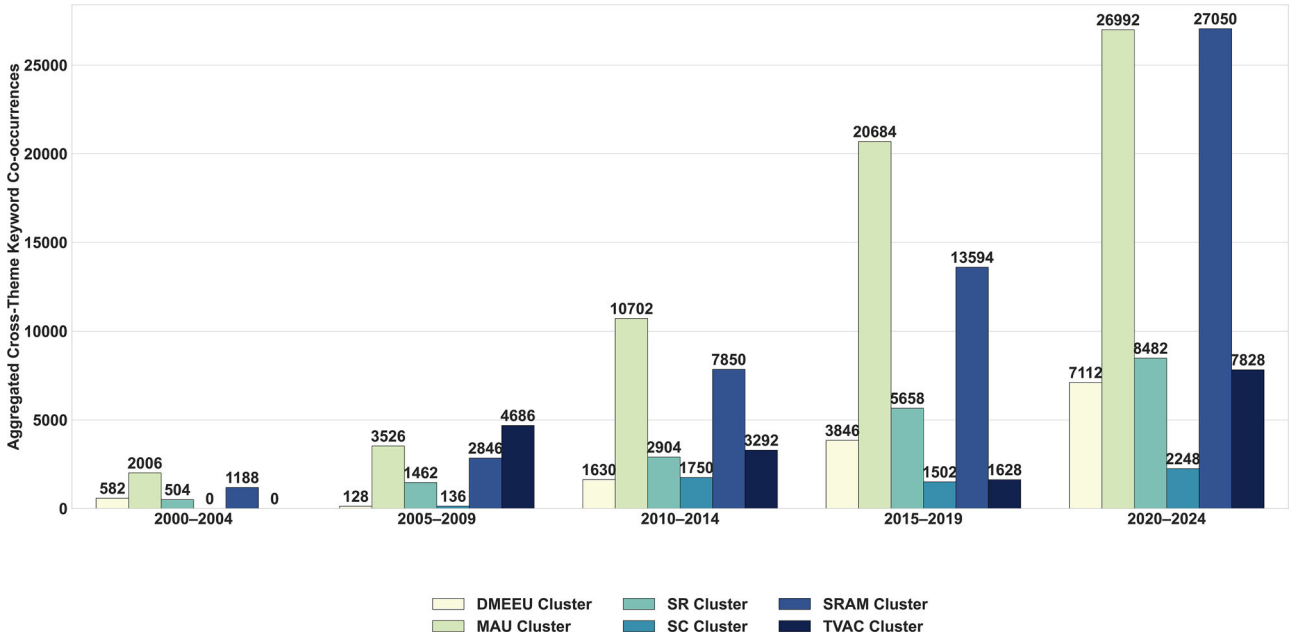


Fig. 3 Temporal Evolution of Inter-Thematic Co-Occurrence Intensity. Source: Authors' Preparation. **Note**: Bars show the aggregated cross-theme co-occurrence intensity of keywords associated with each conceptual cluster across successive five-year periods, based on time-specific keyword co-occurrence networks. Within-theme co-occurrences are excluded to emphasise thematic convergence.

theme-by-theme interaction matrices, including within-theme links, are reported in Fig. B1 in the Supplementary Results.

Figure 3 shows a steady increase in cross-cluster interaction over time, indicating growing thematic convergence across the six conceptual strands. Inter-theme co-occurrence is minimal in the early 2000s (near zero across clusters) but rises after 2010, reaching several hundred aggregated cross-theme interactions per cluster in the most recent periods. This growth is driven mainly by the MAU and SRAM clusters, whose associated keywords display the strongest and most persistent interactions with other themes throughout the post-2010 period. SR also becomes more interconnected, while TVAC and DMEEU increasingly link forecasting- and portfolio-based methods in later periods. In contrast, heuristic approaches remain relatively peripheral, with consistently lower cross-theme interaction levels. Overall, the figure documents a shift from largely theme-specific development toward a more integrated methodological landscape focused on robustness, combination, and adaptive decision-making under uncertainty.

Complementing this view, Table 5 summarises the dominant drivers of cross-theme interaction in each period. Rather than

Table 5 Dominant Drivers of Cross-Theme Interaction over Time.

Time Period	Dominant Driver	Representative Keywords	Interpretation of Cross-Theme Dynamics
2000–2004	Computational and statistical foundations	computer simulation, Monte Carlo methods, approximation theory, regression analysis	Cross-theme interaction is driven by shared computational tools, with limited integration between forecasting and decision-making frameworks.
2005–2009	Explicit modelling of uncertainty	uncertainty analysis, model uncertainty, Bayesian model averaging, Bayesian networks	Uncertainty emerges as a common conceptual focus, enabling early links between predictive accuracy and robust decision criteria.
2010–2014	Forecasts as decision inputs	forecasting, forecast combination, portfolio optimisation, financial data processing	Forecast outputs increasingly inform optimisation and allocation decisions, strengthening links between forecasting and portfolio research.
2015–2019	Integrated combination and optimisation	forecast combination, forecasting, portfolio optimisation, investment, stochastic systems	Combination methods and optimisation frameworks co-evolve, indicating methodological consolidation across domains.
2020–2024	Ensemble and machine-learning-based robustness	ensemble learning, learning systems, machine learning uncertainty analysis	Learning-based ensembles accelerate convergence by providing scalable tools for robustness and adaptivity under persistent uncertainty.

Source: Authors' Preparation.
Note: Keywords are illustrative examples drawn from the top ten period-specific cross-theme contributors. Top 10 rankings and cross-theme weights are reported in Supplementary Results Table A5.

introducing additional quantitative measures, the table characterises how the structure of inter-theme connectivity evolves over time by associating periods of increased interaction with representative methodological developments and keyword groups. This structured summary supports the interpretation of the convergence patterns identified in Fig. 3 by linking periods of intensified cross-theme interaction to the dominant methodological themes and representative keyword groups characterising each phase of the literature's development.

A common concern across the six themes is how to combine multiple imperfect sources of information to improve decision-making under uncertainty. MAU is more extensively developed in forecasting, where approaches such as BMA and FMA are employed to address model uncertainty by combining predictions from multiple models (Bravo et al., 2023; D'Andrea, 2022; Kejzlar et al., 2023). Portfolio research adopts a similar approach, blending predictive signals or strategies that emphasise economic implications, including utility gains and improvements in out-of-sample performance (Baştürk et al., 2019). Kynigakis and Panopoulou (2022) demonstrate that portfolios constructed from combined forecasts of diverse machine learning models consistently outperform single-model and naïvebenchmarks. These findings suggest that averaging, whether across models or signals, serves as a practical hedge against structural instability.

Robust frameworks are being extended in both domains to confront misspecification and ambiguity. In portfolio theory, robust optimisation frameworks are widely applied to prioritise performance under worst-case scenarios, typically using uncertainty sets around inputs such as expected returns or covariances (Kobayashi et al., 2023). Bayesian approaches further refine these frameworks by incorporating prior beliefs and parameter uncertainty into the optimisation process. For instance, Zapata et al. (2025) integrate Bayesian priors with ellipsoidal robust optimisation to model parameter uncertainty in a structured way, enhancing diversification and stability relative to classical mean–variance portfolios. In contrast, forecasting approaches typically pursue predictive robustness through ensemble diversity and uncertainty-aware modelling, rather than formal optimisation under ambiguity (Dai et al., 2024). Both fields converge on a shared objective: designing decision rules that remain reliable when models or inputs are uncertain.

SR approaches reflect a common methodology across both literatures: they impose structure on high-dimensional estimation problems by shrinking weights towards stable baselines. This mitigates instability when the number of predictors or assets exceeds the available data. Instead of fully optimised weights, these methods favour well-conditioned solutions that trade small amounts of bias for substantial reductions in estimation error. Roccazzella et al. (2022) extend portfolio theory to forecast combinations, treating model weights as asset allocations and using the forecast error covariance matrix in the optimisation process. Their fixed-weight approach applies shrinkage, non-negativity constraints, and penalties that discourage large deviations from a baseline, paralleling how robust optimisation stabilises portfolio choices under uncertainty. Complementing this, Wu et al. (2024) introduce a non-convex ℓ_1/ℓ_2 regularisation framework for sparse portfolio selection, showing how fractional norms and efficient solvers can stabilise high-dimensional asset allocations under estimation error. Their approach, which balances sparsity and performance without requiring convexity, aligns with the growing interest in structured regularisation across robust forecasting and portfolio optimisation.

TVAC methods allow weights to adapt dynamically as new information becomes available, reflecting the assumption that no single model or asset remains optimal over time. They prioritise flexibility in environments characterised by structural breaks or regime shifts. Zhao (2021) provides a systematic Monte Carlo analysis of forecast combination methods under structural instability, showing that algorithms differ in their robustness to breaks, shocks, and evolving forecast performance. Large candidate pools can undermine sophisticated weighting schemes, leaving simple averaging relatively effective. This finding aligns with subsequent adaptive approaches such as Zhang et al. (2021), who employ DMA and DMS to forecast U.S. stock market volatility, demonstrating the benefits of time-varying weights; and Li et al. (2023), who show that DMA enhances both predictive accuracy and portfolio allocation when accounting for model and parameter uncertainty.

Empirical evidence from both domains indicates that simple rules often rival or outperform more sophisticated optimisation-based approaches, particularly when data are limited or uncertainty is high. Soule et al. (2024) provide new evidence for the 'forecast combination puzzle', demonstrating that even when expert skill and correlation are known, estimation error in small samples can cause complex weighting schemes to underperform equal weighting. They propose a 'common correlation' heuristic

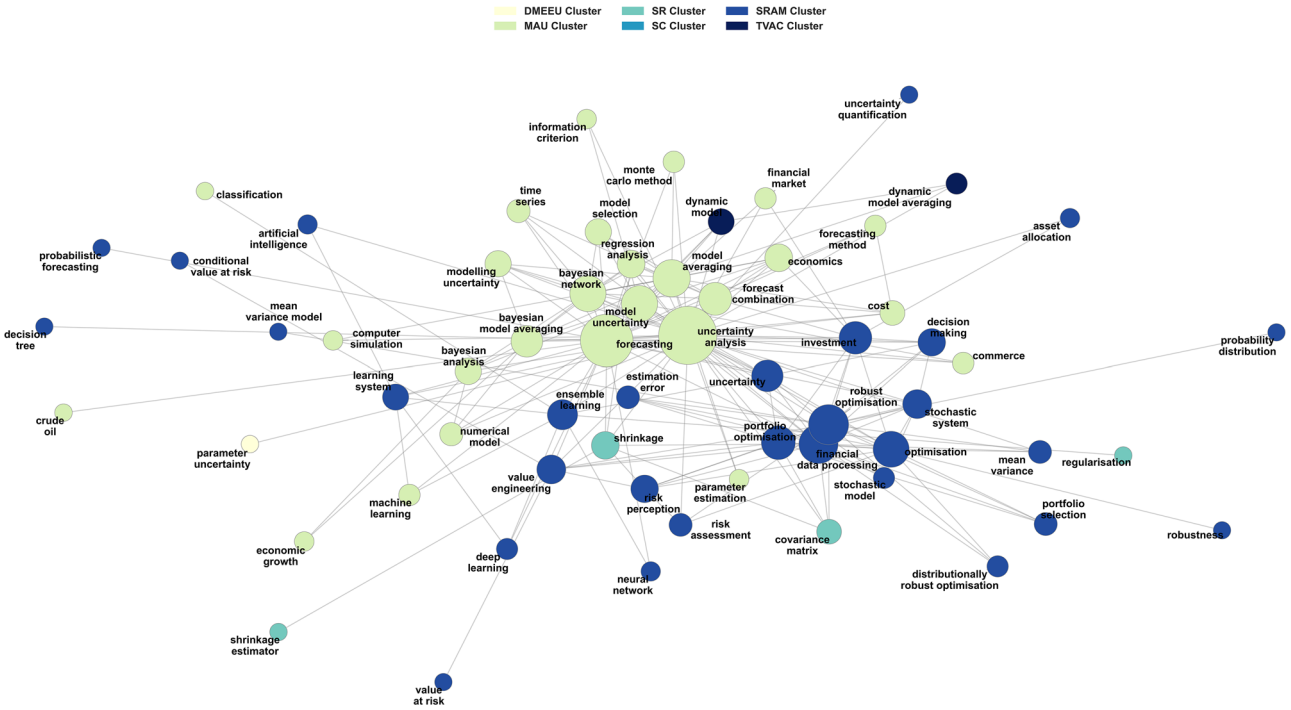


Fig. 4 Thematic Keyword Co-Occurrence Network. Source: Authors' Preparation. **Note**: Visualisation restricted to the 100 most frequent keywords (from Scopus and author-assigned fields), displaying only pairs that co-occur in at least five publications.

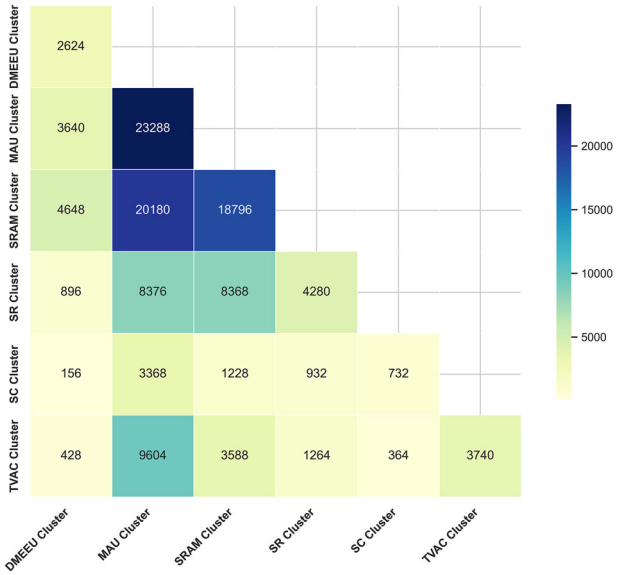


Fig. 5 Heatmap of Co-Occurrence Intensity Between Conceptual Themes. Source: Authors' Preparation.

that balances skill-based weights with robustness to estimation noise, outperforming both variance- and covariance-based methods on macroeconomic and experimental forecast data. Peng and Linetsky (2024) extend this simplicity-over-complexity argument to portfolio optimisation, introducing the partially egalitarian portfolio selection (PEPS) framework. Rather than fully optimising all weights, PEPS shrinks a selected subset towards equality, offering a tractable alternative to classical Markowitz methods. These findings reinforce a broader insight: under deep parameter uncertainty, robustness and parsimony frequently lead to more stable and effective decisions.

A growing stream of research adopts a behavioural perspective, asking how agents should act when uncertainty is persistent (e.g., Kontosakos et al., 2024; Shahbab and Zaman, 2024). Rather than treating calibration and decision-making as separate stages, this view reflects a more realistic and policy-relevant approach in which beliefs evolve dynamically and strategies adapt accordingly. Recent contributions exemplify this shift. Xidonas et al. (2025) propose a hybrid framework that combines simple forecasting methods with multiple-criteria decision aiding, generating dynamically updated PROMETHEE II rankings from forward-looking indicators. These scores guide both asset allocation and macroeconomic forecasting, offering a robust and adaptive process that accommodates estimation error and evolving signals. The approach aligns with the DMEEU theme, illustrating how forecast-informed strategies can support flexible, uncertainty-aware decision-making without decoupling model calibration from implementation.

Conceptual Structure and Thematic Convergence. This section examines the conceptual structure of the literature and the extent of thematic convergence between forecasting and portfolio theory. Figures 4 and 5 jointly illustrate the structural and thematic convergence between the two literatures in addressing decision-making under uncertainty. Both fields face the challenge of aggregating information from multiple, often conflicting, models or sources, and they converge on similar methodological solutions centred on the principles of combination, robustness, and adaptivity.

Figure 4 presents the thematic co-occurrence network constructed from the standardised keywords of the corpus. The network visualises the conceptual structure of the literature by linking keywords that frequently appear together within the same publication. Node size represents degree centrality, the number of unique terms to which a keyword is connected, while edge thickness indicates the frequency of co-occurrence. Each keyword

Table 6 Global Distribution of Publications.

Country	Total Publications	Share of Total Publications (%)	Fractional Contribution (%)
United States	132	19.61	20.41
China	104	15.45	17.26
United Kingdom	74	11	10.53
Germany	38	5.65	5.70
Australia	34	5.05	4.39
Italy	33	4.90	5.24
Canada	27	4.01	3.73
Netherlands	19	2.82	3.00
Switzerland	14	2.08	1.88
Hong Kong	12	1.78	1.34

Source: Authors' Preparation.

is assigned a dominant theme, with node colours denoting its thematic classification.

To focus on the most salient methodological terms, the corpus was filtered to include only publications containing at least one of the 100 most frequent keywords drawn from both Scopus and author-assigned fields. This prioritised recurring and thematically central concepts while filtering out idiosyncratic terms. From this filtered subset, a co-occurrence matrix was computed, and the resulting network includes only keyword pairs that co-occur at least five times, enhancing clarity and thematic focus. Although the network was simplified for readability, all quantitative analyses, including co-occurrence (Fig. 5), degree centrality, and thematic clustering, were performed using the complete set of keywords from the full corpus of 'bridge papers'.

At the top of this structure lies 'uncertainty analysis' (degree centrality = 0.4659), which is connected to terms from every thematic group. It plays a pivotal role in both fields, linking shared concerns such as model reliability, estimation error and robustness. Similarly, 'forecasting' (0.3317) and 'model uncertainty' (0.2441) are widely connected and central to managing uncertainty across domains.

Bayesian approaches are among the most prominent high-degree terms, including 'Bayesian network' (0.2344), 'Bayesian model averaging' (0.2136) and 'Bayesian analysis' (0.0926). These underscore a shared emphasis on probabilistic reasoning and the use of prior updating to improve forecast accuracy and manage portfolio uncertainty. Model combination constitutes another core link: whether through 'ensemble learning' (0.1931), 'forecast combination' (0.1820), or 'model averaging' (0.1784), the central idea is to integrate diverse sources of information to enhance performance. Such approaches are common to both forecasting and investment research and appear consistently across all thematic areas.

Optimisation frameworks provide a practical foundation for this convergence. Keywords such as 'robust optimisation' (0.1558), 'portfolio optimisation' (0.1658) and 'financial data processing' (0.1813) illustrate how mathematical tools are applied to manage uncertainty and guide decision-making. Even less frequent terms, including 'constrained optimisation' (0.0265), remain closely linked to robustness and forecasting, highlighting their broad relevance. These optimisation strategies are often embedded within stochastic frameworks such as 'stochastic system' (0.1389) and 'stochastic model' (0.0772), which incorporate time evolution and distributional assumptions into the decision-making process, reflecting the methodological requirements of forecasting and long-horizon portfolio design.

Methods that stabilise estimation, including 'shrinkage' (0.1134), 'regularisation' (0.0711), and 'covariance matrix' (0.0956), highlight the adoption of tools aimed at mitigating instability in high-dimensional settings. These are complemented by machine learning-related terms, such as 'learning system' (0.1543), 'machine learning' (0.1149), and 'neural network' (0.0815), which indicate the growing integration of computational approaches to enhance robustness and adaptability.

Figure 5 complements this network-level representation by providing a static, corpus-wide view of thematic co-occurrence aggregated over the full sample period. Together, these figures provide a holistic view of cross-domain integration and the methodological convergence between forecasting and portfolio theory.

Strong structural connections emerge between model averaging, stochastic and robust frameworks, and adaptive methods, indicating that these approaches are frequently applied together across the literature. In particular, the MAU–SRAM coupling forms the dominant structural backbone of the field, while TVAC exhibits a notably strong connection with MAU. This pattern highlights the role of time-varying and adaptive methods as a key interface through which forecasting and portfolio methodologies interact. SR remains meaningfully connected to both MAU and SRAM, reflecting their stabilising role in high-dimensional and uncertain environments. In contrast, SC and DMEEU methods appear structurally peripheral, displaying comparatively weak interactions both within and across themes. Overall, Fig. 5 characterises the long-run conceptual architecture of the field by distinguishing structurally central clusters from more marginal ones.

Geographic and International Collaboration. The methodological convergence is shaped by the broader research environment in which it occurs. Table 6 presents the ten leading countries, out of a total of 51, that contribute to both literatures, based on the institutional affiliations of all contributing authors. The United States leads by volume, followed by China and the United Kingdom, while most other countries make only moderate contributions.

However, volume alone does not reflect the relative weight of each country's contribution in collaborative contexts. Figure 6 offers a complementary perspective using fractional authorship counting, whereby a co-authored publication is assigned proportionally to each of its authors, with the total weight of the publication summing to one. This approach normalises the contribution of authors across different articles and research areas, providing a normalised and complementary perspective on individual and institutional input that accounts for differences in collaboration intensity across fields, particularly when comparing research output across fields with differing collaboration patterns. In doing so, it prevents the over-representation of researchers active in highly collaborative disciplines.

This method reinforces the dominant position of countries such as the United States (20.41%) and China (17.26%) within the literature. At the same time, it provides a more balanced view of global participation by correcting for collaboration intensity, thereby highlighting meaningful contributions from countries that may be underrepresented in raw publication counts. The resulting distribution reveals a broad, albeit uneven, pattern of international engagement in this cross-disciplinary field.

Although both publication volume and fractional contribution highlight concentration, they overlook potential patterns of collaboration. Figure 7 addresses this limitation by presenting the co-authorship network, which visualises international collaboration across countries.

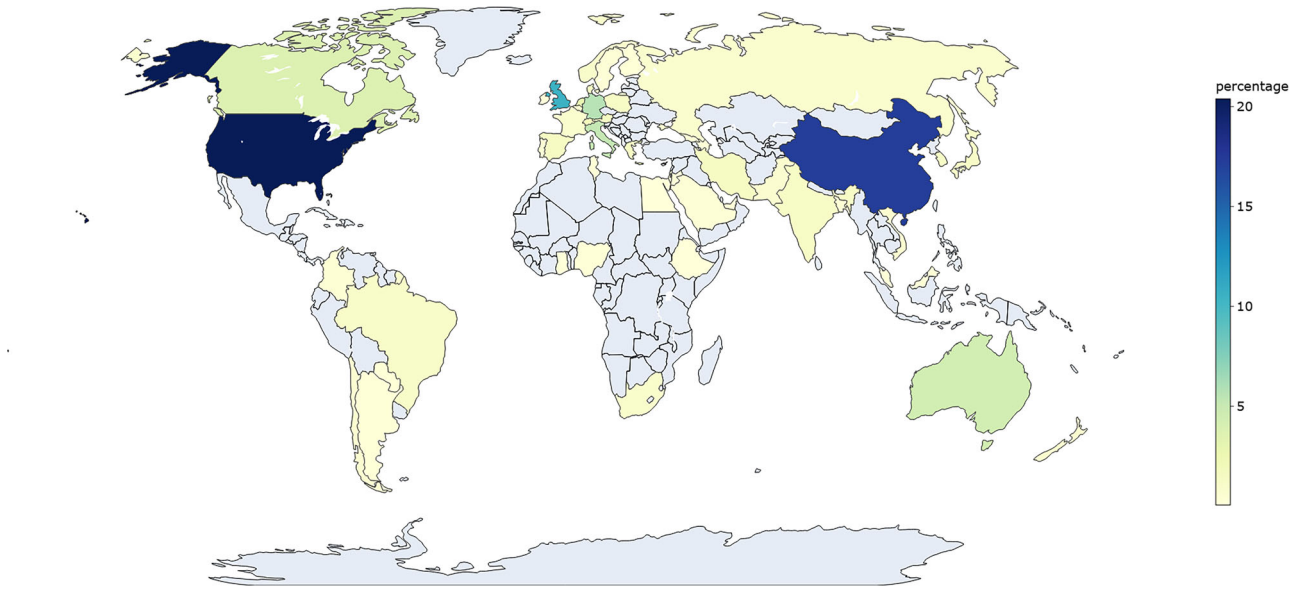


Fig. 6 Country-Level Research Share Adjusted for Fractional Counting. Source: Authors' Preparation.

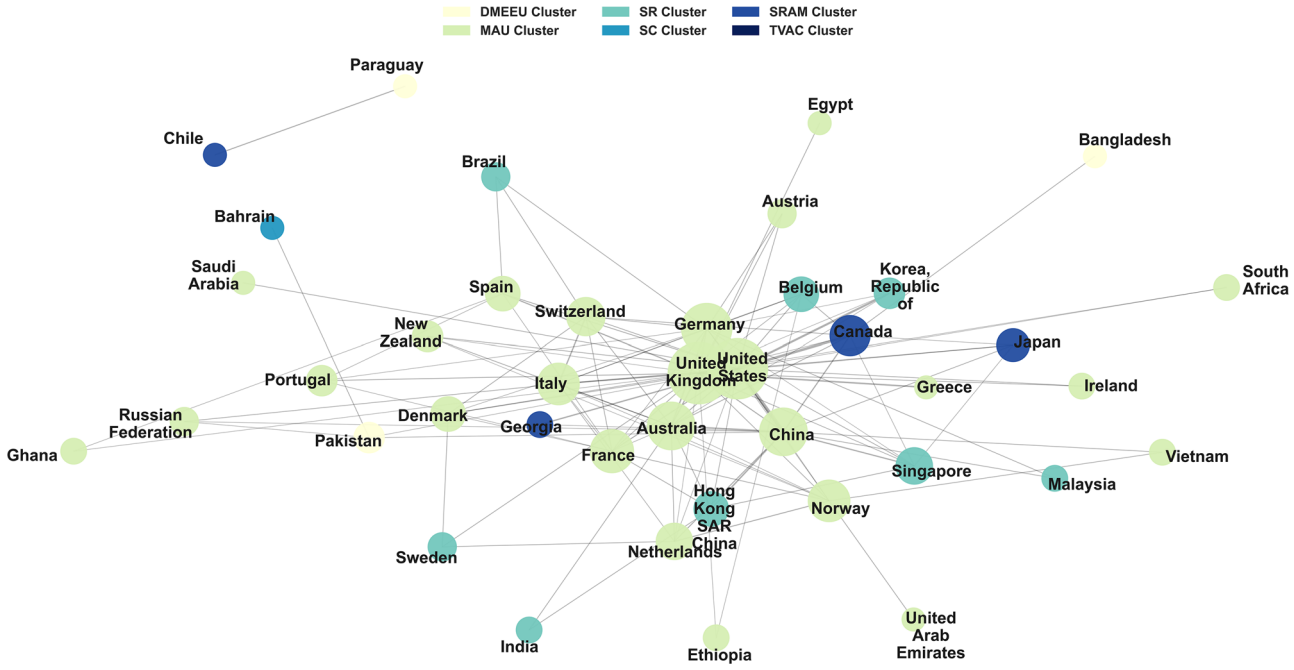


Fig. 7 International Co-Authorship Patterns in Forecasting and Portfolio Research. Source: Authors' Preparation. **Note**: Results produced used fractional counting (authorship).

The resulting network reveals that international collaboration plays a pivotal role in connecting research efforts worldwide. In Europe, Germany, France, and the United Kingdom form a closely linked group, reinforcing the continent's strong internal cohesion. China extends its partnerships across Asia and beyond, actively collaborating with countries such as Singapore, India, and Australia, the latter serving as a bridge to Oceania. North America also exhibits a dense network, with Canada and the United States maintaining strong ties both within the region and across continents. Although countries in Africa and South America appear less central, the presence of Brazil, South Africa, and Ghana underscores emerging participation and the potential for greater integration into the global research ecosystem.

Institutional Contributions and International Collaboration. Following the analysis of geographic contributions, this section shifts focus to the institutional level, providing a more detailed view of where research in both fields is produced and how collaborative structures emerge between institutions. The analysis of author affiliations identifies a total of 594 unique institutions contributing to the field. This broad institutional base reflects the cross-disciplinary and globally distributed nature of the literature, which encompasses technical universities, business schools, policy research centres, and central banks. Such diversity underscores the widespread academic and policy interest in forecasting and portfolio theory, as well as the varied institutional contexts in which this research is undertaken.

Table 7 Institutional Distribution of Publications.

Institution	Country	Total Publications	Share of Total Publications (%)	Fractional Contribution (%)
CAS	China	16	1.70	1.19
EUR	The Netherlands	10	1.06	0.82
NUST	China	9	0.96	0.82
DU	United States	7	0.74	0.97
NB	Norway	6	0.64	0.34
CU	United States	6	0.64	0.69
UNSW	Australia	6	0.64	0.85
US	Scotland	6	0.64	0.53
UW	United States	6	0.64	1.04
AUEB	Greece	6	0.64	0.87
SJU	China	6	0.64	0.43
LU	United Kingdom	6	0.64	0.73
NUS	Singapore	5	0.53	0.36
UG	Iran	5	0.53	1.04
ICL	United Kingdom	5	0.53	0.8

Source: Authors' Preparation.
CAS Chinese Academy of Science; *EUR* Erasmus University Rotterdam; *NUST* Nanjing University of Science and Technology; *DU* Duke University; *NB* Norges Bank; *CU* Columbia University; *UNSW* University of New South Wales; *US* University of Strathclyde; *UW* University of Wisconsin; *AUEB* Athens University of Economics and Business; *SJU* Southwest Jiaotong University; *LU* Lancaster University; *NUS* National University of Singapore; *UG* University of Guilan; *ICL* Imperial College of London.

Table 7 presents the fifteen most prominent institutions, ranked by total publication output, alongside their percentage share of all publications and their fractional contribution, which adjusts for co-authorship. As in the preceding analysis, fractional counting assigns each institution a proportional share of a co-authored publication, providing a normalised measure of research involvement that adjusts for variation in co-authorship intensity.

The table highlights a diverse yet concentrated landscape of institutional contributions to the literature, with the Chinese Academy of Sciences leading both in total publications (16) and in fractional contribution (1.19%), indicating not only prolific output but also substantive engagement in co-authored work. Notably, Erasmus University Rotterdam and Nanjing University of Science and Technology follow in publication volume, while institutions such as Duke University and the University of Wisconsin stand out for their high fractional contributions relative to their total output (0.97% and 1.04%, respectively, on just seven and six publications). This pattern suggests more centralised authorship roles within their collaborations.

Similar dynamics can be observed among other institutions with smaller publication counts but notable fractional impact, such as the University of Guilan (five publications, 1.04%) and Lancaster University (six publications, 0.73%). The disparity between total publications and fractional contributions underscores the value of adjusting for co-authorship, as institutions such as Norges Bank (Norway) and the University of Strathclyde may appear equally productive in raw counts yet show lower fractional shares (0.34% and 0.53%, respectively).

These patterns mirror the national trends discussed earlier, in which China, the United States, and the United Kingdom dominate in terms of institutional presence. However, the application of fractional counting remains essential for uncovering underlying variations in authorship concentration, distinguishing between broad participation and deep, leading contributions. As collaborative structures intensify in quantitative disciplines, full-count metrics risk overstating influence, particularly for institutions involved only peripherally in multiple projects. Fractional analysis, by contrast, provides a more granular and equitable perspective on institutional impact.

This sets the stage for the next part of the analysis, which examines how these institutions connect and collaborate through co-authorship networks, revealing the structural relationships underpinning knowledge production in the field. Figure 8 visualises the institution-level co-authorship network, where nodes represent institutions and edges denote co-authored publications between them. The visualisation includes only institutions that have collaborated with at least four others to ensure clarity and interpretability. Additionally, isolated nodes and sparse connections were excluded to emphasise the core collaborative structure of the field. Each institution is colour-coded according to its dominant research theme, defined by the most frequent thematic assignment across its publications. This allows the network to capture not only the density of collaborations but also the thematic architecture of the field, illustrating how institutions cluster around shared methodological orientations.

The joint distribution of degree centrality and thematic connectivity highlights a subset of institutions that function as true hubs of collaboration within the field. These institutions not only exhibit high co-authorship frequency but also operate across multiple methodological areas, suggesting a structurally integrative role.

The co-authorship network reveals a layered and collaborative architecture that links methodological themes in forecast combination and portfolio theory. A prominent cluster is anchored by Erasmus University Rotterdam (0.0425), the University of Strathclyde (0.0255), and the University of Maryland (0.0191), which maintain dense ties across the SR, MAU, and TVAC clusters. Their collaborations span European and North American institutions, with a shared focus on shrinkage techniques, ensemble learning, and adaptive model selection. This group functions as a methodological hub bridging econometric regularisation and time-varying forecasting approaches.

A second, thematically expansive cluster is led by the Chinese Academy of Sciences (0.0594), the most central node in the network, together with the Capital University of Economics and Business (0.0106) and Xiamen University (0.0170). These institutions contribute across the SRAM, SR, MAU, and SC clusters, focusing on robust aggregation, high-dimensional estimation, and heuristic simplification. The Chinese Academy of Sciences also performs a transnational role, linking East Asian scholarship with collaborators in Europe and North America.

A third configuration centres on Nanjing University of Science and Technology (0.0191) and the University of Melbourne

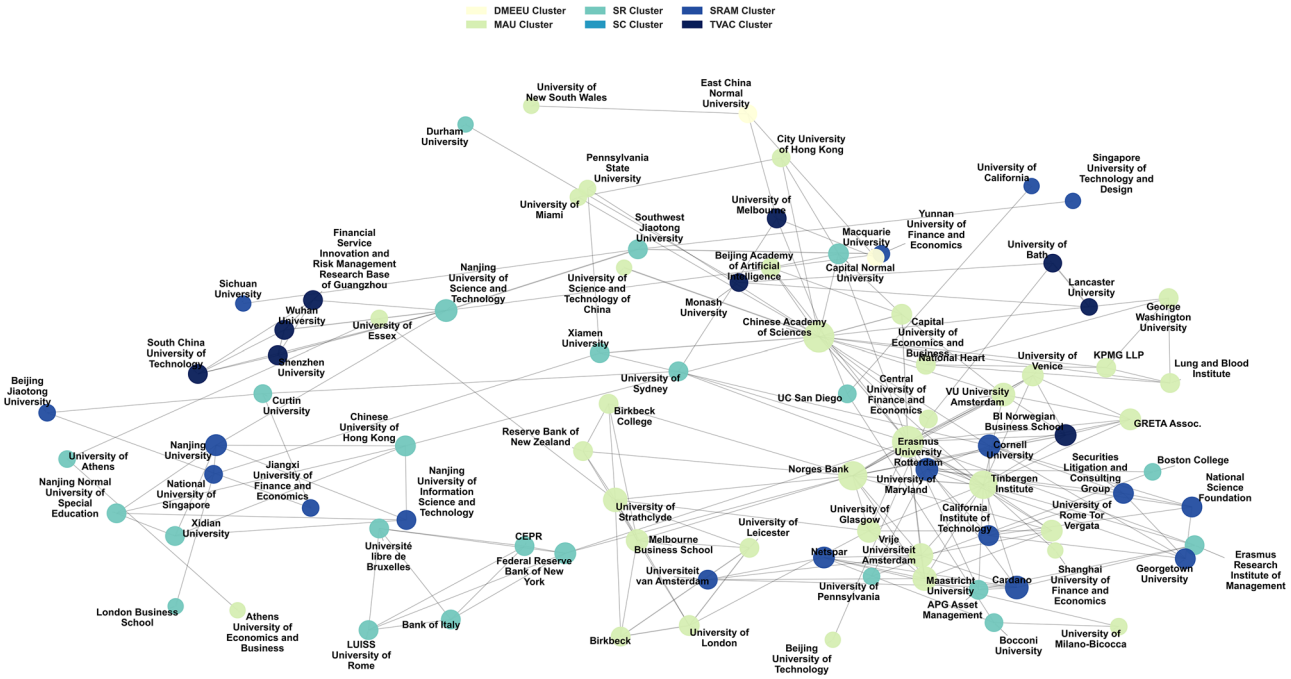


Fig. 8 Institutional Collaboration Network in Forecasting and Portfolio Research. Source: Authors' Preparation. **Note**: Results are based on fractional counting of authorship. Only institutional pairs with at least four co-occurrences are shown.

(0.0106), the only two institutions represented in five clusters. Although their degree centrality is moderate, their broad thematic engagement positions them as integrative actors that connect specialised subfields such as robust optimisation, estimation error control, and adaptive combinations. Their role underscores the importance of institutions that operate across disciplinary boundaries despite limited direct connectivity.

Another cluster emerges at the intersection of academic and applied research, involving the National University of Singapore (0.0170), Shanghai University of Finance and Economics (0.0085), and Curtin University (0.0106). These institutions are situated within or adjacent to the SR, MAU, and SRAM clusters, contributing to developments that integrate econometrics, decision theory, and machine learning. Their collaborations reflect a growing interest in algorithmic model weighting, regularised portfolio construction, and data-driven uncertainty quantification.

In contrast, institutions such as Columbia University (0.0170), Vrije Universiteit Amsterdam (0.0191), and Maastricht University (0.0191) occupy more intermediate positions within the collaboration network. While not central hubs in terms of thematic breadth, they remain embedded in the main European research core, with specialised contributions linking MAU to SR or SRAM. Their targeted co-authorships reinforce domain-specific knowledge and facilitate selective cross-theme diffusion, particularly within the European research space.

Taken together, the network reveals a topology in which geographic concentration, methodological breadth, and collaborative connectivity intersect. Highly central institutions serve as both thematic and regional bridges, facilitating cross-pollination between robust aggregation methods, adaptive forecasting, and regularised estimation. At the same time, more focused contributors enrich specific domains, sustaining methodological rigour and diversity. The visual representation further highlights the presence of cohesive regional hubs, particularly in Europe and East Asia, as well as multi-cluster linkages that reflect the interdisciplinary evolution of the field.

Structural Connectivity: Bibliographic Coupling. Following the thematic and geographical mapping of the literature, Fig. 9 presents the fifteen most frequently cited contributions within the corpus, based on the number of times they are referenced across the 489 publications analysed.

Unsurprisingly, the corpus includes foundational contributions such as Bates and Granger (1969), who introduced the idea of combining forecasts to improve accuracy, and Markowitz (1952), who developed the mean–variance framework for portfolio optimisation. These seminal works underpin many of the subsequent developments in forecast combination and portfolio research. A clear distinction can be drawn between two main categories: (i) Statistical and econometric approaches such as shrinkage (Tibshirani, 1996), robust estimation (Hansen, 2008), and model averaging (Hoeting et al., 1999; Raftery et al., 1997); and (ii) Frameworks that directly address forecasting accuracy or investment decision-making, particularly in contexts characterised by structural instability or limited information (Hjort and Claeskens, 2003; Jagannathan and Tongshu, 2003). The most frequently cited publications also include influential studies on the trade-off between simplicity and complexity in forecasting (Stock and Watson, 2004) and portfolio theory (DeMiguel et al., 2009).

Figure 10 presents the bibliographic coupling network constructed from the selected corpus. The underlying premise of bibliographic coupling is that publications influenced by a similar body of prior work are more likely to exhibit methodological alignment. To improve matching accuracy despite citation variation, the reference data were subjected to a cleaning and deduplication process. This involved standardising abbreviations, harmonising journal names, and grouping reference variants into canonical forms using fuzzy string-matching techniques.

Indirect relationships between citation variants were captured by applying transitive closure through a Union–Find algorithm. This approach enabled references linked through chains of fuzzy matches to be grouped into single canonical clusters, ensuring a

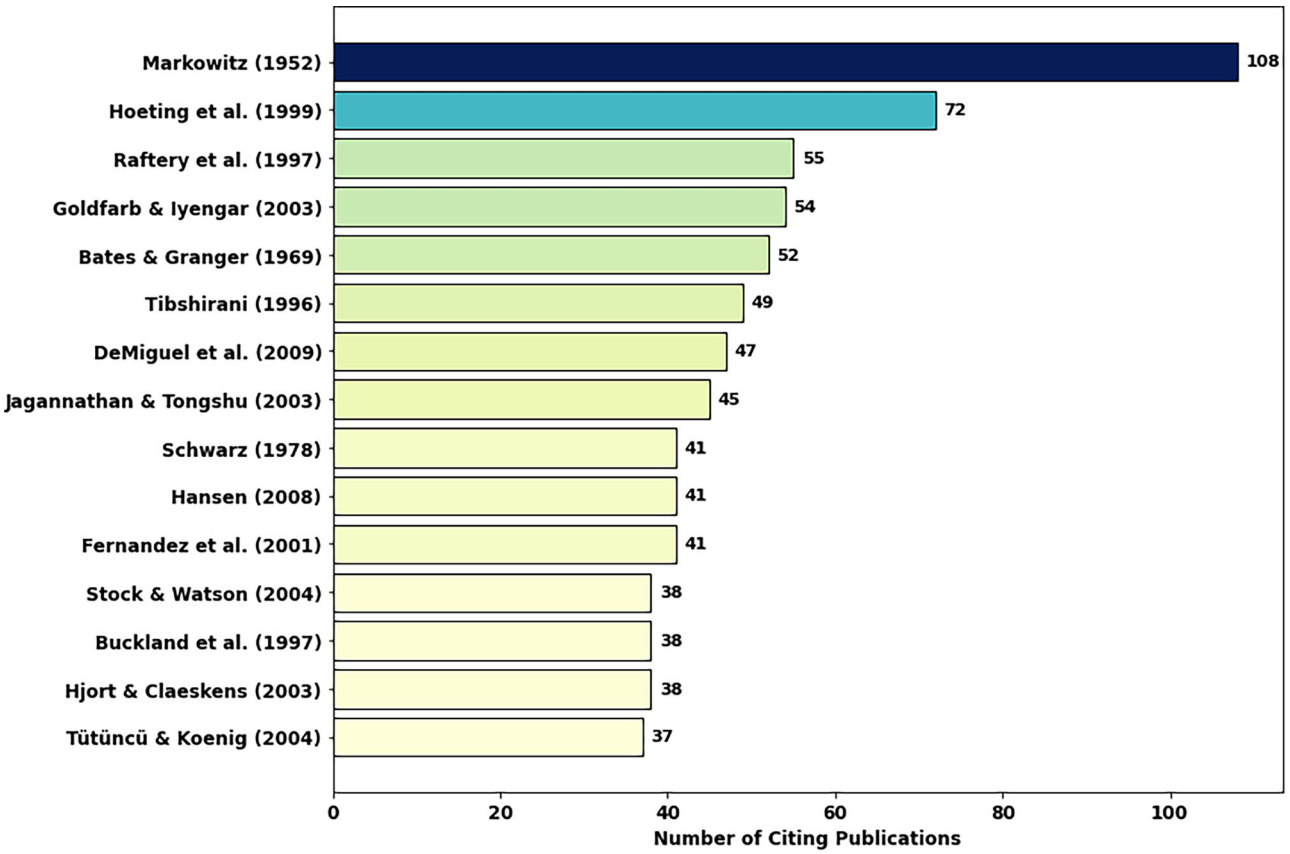


Fig. 9 Core References by Citation Frequency in the Corpus. Source: Authors' Preparation. **Reference list**: Markowitz (1952); Hoeting et al. (1999); Raftery et al. (1997); Goldfarb and Iyengar (2003); Bates and Granger (1969); Tibshirani (1996); DeMiguel et al. (2009); Jagannathan and Tongshu (2003); Schwarz (1978); Hansen (2008); Fernandez et al. (2001); Stock and Watson (2004); Buckland et al. (1997); Hjort and Claeskens (2003); and Tütüncü and Koenig (2004).

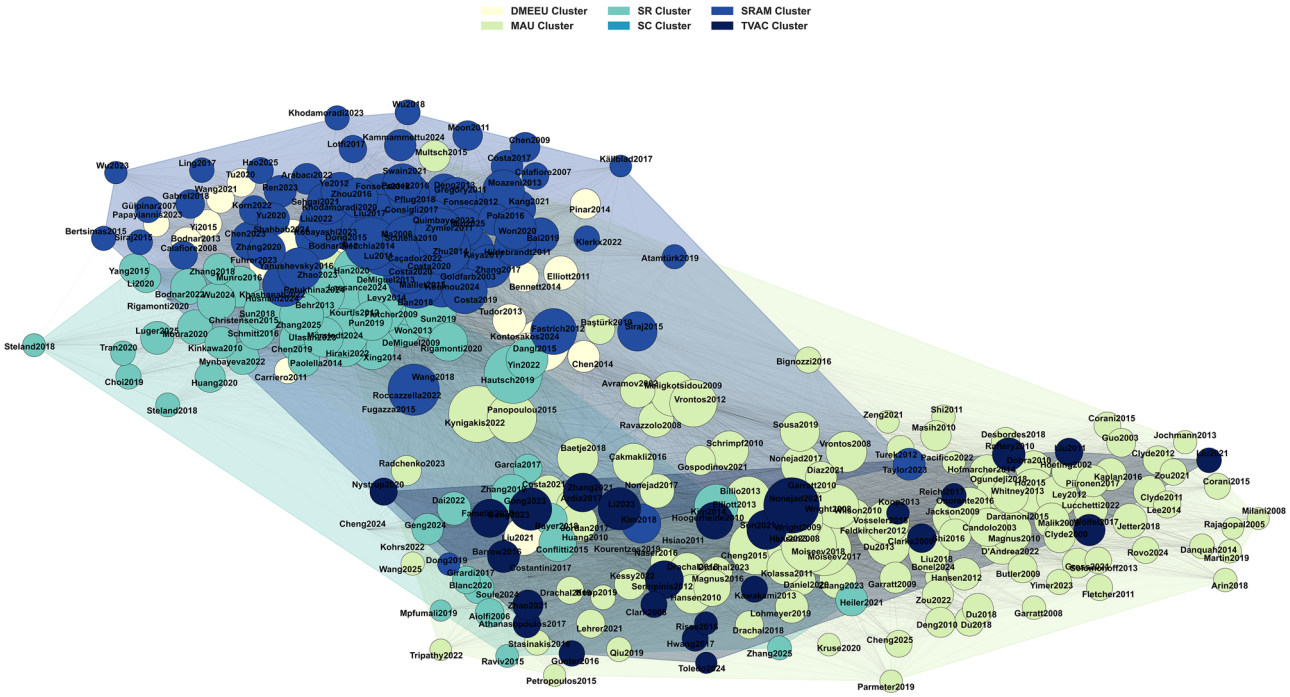


Fig. 10 Bibliographic Coupling Network of Conceptual Themes in Decision-Making under Uncertainty. Source: Authors' Preparation. **Note**: Network edges represent publication pairs with a weighted degree of 85.

comprehensive and robust consolidation of semantically equivalent citations. Bibliographic coupling was then computed by identifying all publication pairs that shared at least one of these standardised references. Unlike co-occurrence analysis, which clusters publications based on conceptual keywords, bibliographic coupling reveals structural proximity grounded in shared references. This method uncovers methodological connections even across distinct themes, exposing foundational overlaps that keyword-based clustering may overlook.

For visual clarity, Fig. 10 retains only edges with a weighted degree of at least 85, corresponding to the 80th percentile of the weighted degree distribution. This percentile-based filter ensures that the network highlights intellectually central publications with strong structural connectivity while reducing noise from weakly coupled or peripheral nodes. The layout reflects relative proximity based on bibliographic coupling, with node size indicating connectivity and colour representing the dominant conceptual theme. Thematic areas were outlined using convex hulls to visualise overlapping research domains.

Within the bibliographic coupling network, DeMiguel et al. (2013) emerge as the most central node under the SR theme, exhibiting the highest weighted degree with 583 shared references across the corpus. It is followed by Kynigakis and Panopoulou (2022), associated with the MAU theme, with 531 shared references. Nonejad (2021), representing the TVAC theme, holds 512 shared references, while Caçador et al. (2022), associated with the SRAM theme, follow with 508. Lastly, Dangl et al. (2015), linked to the DMEEU theme, and DeMiguel et al. (2009), under the SC theme, record weighted degrees of 457 and 383, respectively.

The SR cluster displays strong internal coherence, grounded in shared concerns with estimation error, high dimensionality, and portfolio stability. Lassance et al. (2024b) and Petukhina et al. (2024) are among the most densely interconnected contributions within the cluster, sharing twelve and thirteen references, respectively, with closely related works. Both address estimation risk via regularisation, albeit through different methods, yet converge on the goal of enhancing allocation robustness in non-Gaussian and high-dimensional settings. Cross-cluster connections also emerge, reflecting shared foundational influences. One such link connects DeMiguel et al. (2013) and Husnain et al. (2024) from the SC cluster, who share eight key references related to estimation error, constraints, and Bayesian frameworks (e.g., Frost and Savarino, 1986; Jagannathan and Tongshu, 2003; Ledoit and Wolf, 2004; Markowitz, 1952). Despite methodological differences, both pursue portfolio stability under uncertainty. Similarly, a connection with Kontosakos et al. (2024) in the DMEEU cluster reveals a shared interest in shrinkage, model uncertainty, and utility-based frameworks (e.g., Garlappi et al., 2007; Kourtis et al., 2012; Wang, 2005), underscoring a common emphasis on decision quality under parameter risk.

The MAU cluster centres on combination approaches under uncertainty, with emphasis on ensemble learning, predictive performance, and robustness to misspecification. A strong bibliographic connection links Kynigakis and Panopoulou (2022) with Zhang et al. (2021) from the TVAC cluster, who share eight references spanning combination methods (e.g., Kelly and Pruitt, 2015; Rapach et al., 2010) and empirical research on return forecasting and allocation (e.g., Campbell and Thompson, 2008; Welch and Goyal, 2008). Further convergence arises between MAU and SR, particularly through shared references that connect model averaging with robust covariance estimation, such as the approach proposed by Mörstedt et al. (2024) (e.g., DeMiguel et al. 2009; Jagannathan and Tongshu, 2003; Ledoit and Wolf, 2004; Markowitz, 1952). While their techniques differ, both aim to improve out-of-sample performance by mitigating model risk and estimation error.

The TVAC cluster focuses on dynamic frameworks that adapt to shifting predictor relevance, typically through time-varying parameter models and Bayesian updating. At its centre, Nonejad (2021) and Pacifico (2022) from the MAU cluster share ten references, including foundational works on dynamic Bayesian modelling and model averaging (e.g., Carriero et al. 2019; Koop and Korobilis, 2013; Raftery et al., 1997), frequently applied in contexts of forecast instability and structural change. A further connection links Nonejad (2021) to Yin (2022) from the SR cluster, based on four shared references concerning return predictability and structural breaks (e.g., Dangl and Halling, 2012; Rapach et al., 2010). While Nonejad (2021) provides a methodological synthesis of DMA for addressing forecast instability, Yin (2022) applies partial least squares to extract supervised forecast factors from a high-dimensional predictor set, demonstrating substantial portfolio gains in terms of Sharpe ratios and certainty-equivalent returns. This connection reinforces the link between adaptive forecast combination techniques and their capacity to improve portfolio decisions under structural uncertainty.

The SRAM cluster is characterised by robust portfolio strategies that explicitly account for model uncertainty, distributional ambiguity, and adverse risk scenarios. At its core, Caçador et al. (2022) and Quimbayo et al. (2023) share twelve references spanning robust optimisation, tail-risk measures, and worst-case allocation frameworks (e.g., Ben-Tal and Nemirovski, 1998; Bertsimas et al., 2011; Chopra and Ziemba, 1993; Fabozzi et al., 2007). Both move beyond classical mean–variance optimisation, incorporating conditional value-at-risk and Omega-based objectives to address parameter uncertainty and non-Gaussian risk. Cross-cluster links highlight the breadth of this robustness perspective: Husnain et al. (2024) from the SC cluster shares references on heuristic allocation and constrained diversification (e.g., DeMiguel et al., 2009; Jagannathan and Tongshu, 2003), while Shahbab and Zaman (2024) of the DMEEU cluster draws on robust optimisation principles (e.g., Garlappi et al., 2007; Goldfarb and Iyengar, 2003) to formulate decision rules resilient to parameter uncertainty and limited information. These connections reveal a shared ambition to design portfolio strategies that remain effective under structurally unstable or adversarial environments.

The DMEEU cluster is unified by concerns with decision quality under model and estimation uncertainty, often incorporating perspectives from Bayesian decision theory, robust optimisation, and utility-based evaluation. A strong bibliographic connection links Dangl et al. (2015) to Hautsch and Voigt (2019) from the SR cluster, with eight shared references. The latter extends this tradition by embedding parameter and model uncertainty into a dynamic portfolio optimisation framework that leverages high-frequency data and Bayesian predictive distributions. Both studies cite foundational contributions on shrinkage and predictive learning under uncertainty (e.g., Garlappi et al., 2007; Ledoit and Wolf, 2003a, b), and demonstrate how structural constraints can serve as implicit regularisers. Further convergence arises with Roccazzella et al. (2022) from the SRAM cluster, who shares six references with the above and explicitly frames forecast combination as a constrained optimisation problem analogous to portfolio allocation. Their approach draws on high-dimensional risk management techniques (e.g., DeMiguel et al., 2009; Jagannathan and Tongshu, 2003), including shrinkage-based estimators, and reinforces the theoretical analogy between robust forecast combination and portfolio theory. Collectively, these studies exemplify the methodological convergence between forecasting and asset allocation, showing how constrained, uncertainty-aware strategies sustain decision quality under volatile regimes.

The SC cluster revolves around the trade-off between heuristic diversification strategies and complex optimisation under uncertainty. This theme is distinguished by its critical stance towards overreliance on plug-in optimisation and its emphasis on performance under parameter instability and estimation error. DeMiguel et al. (2009) exhibits strong bibliographic ties to contributions in the SR cluster, notably Petukhina et al. (2024) and Lassance et al. (2024b), with fifteen and eight shared references, respectively. Among these, foundational works on shrinkage estimators, the role of constraints, and the instability of optimal weights foreground the practical risks of estimation error (e.g., Jagannathan and Tongshu, 2003; Ledoit and Wolf, 2004; Michaud, 1989). Further convergence is observed with Roccazzella et al. (2022) from the SRAM cluster, who share six references, including Chopra and Ziemba (1993), Ledoit and Wolf (2003a), and Jorion (1986). These foundational works highlight how estimation error can bias optimal allocations and motivate alternatives such as Bayes–Stein shrinkage and robust optimisation. Their use of constrained or distributionally aware methods parallels the logic of forecast combination under model ambiguity, reinforcing the growing intersection between aggregation strategies in forecasting and portfolio theory.

Main Conclusions and Contributions

Forecast combination and portfolio theory have long addressed the challenge of decision-making under uncertainty, often through parallel developments in statistical and optimisation techniques designed to manage estimation error, structural change, and incomplete information. Across the corpus, we observe not only convergence in tools such as shrinkage, model averaging, and robust optimisation, but also a shared emphasis on combining noisy, partial, or unstable signals to improve decision quality. This thematic alignment is reinforced by bibliometric patterns. High-centrality institutions and publications frequently span multiple conceptual clusters, and methodological influence tends to flow across rather than within disciplinary boundaries. Bibliographic coupling further reveals common reference foundations between areas that otherwise appear distinct, highlighting conceptual bridges that are not always captured through keywords or co-authorship networks. These findings point to the emergence of a cross-disciplinary methodological core with a growing focus on uncertainty-aware and decision-sensitive strategies.

Beyond thematic alignment, the analysis reveals a structurally integrated research landscape. Institutions, journals, and collaboration networks increasingly span disciplinary boundaries, reinforcing the methodological convergence observed at the conceptual level. A small but influential group of institutions, particularly in China, Europe, and North America, plays a central role in this integration by connecting research across econometrics, machine learning, and financial engineering. These organisations contribute to multiple thematic clusters and promote the diffusion of techniques such as ensemble learning, robust optimisation, and adaptive regularisation across distinct application areas. Collaboration patterns suggest a layered and globally distributed research architecture, where knowledge exchange is driven more by shared methodological goals than by disciplinary traditions. This structural convergence supports a more unified approach to uncertainty, in which tools originally developed within a specific field increasingly inform decision-making practices in others.

The findings of this research carry practical implications for multiple stakeholder groups, including researchers, financial institutions, and policymakers. Within the academic community, the convergence between forecasting and portfolio theory provides a unified foundation for developing robust, adaptive, and decision-aware modelling frameworks. The thematic and structural patterns identified here also highlight areas that remain underdeveloped relative to their conceptual potential, particularly time-varying combinations and decision-sensitive optimisation. For financial institutions, methodological tools such as DMA and distributionally robust portfolio design offer practical means of improving decision quality in environments characterised by model uncertainty, structural instability, and estimation risk. These approaches support more transparent and defensible investment practices across both strategic allocation and real-time execution. Policymakers can also benefit from this methodological alignment, particularly through adaptive and uncertainty-aware frameworks that enhance macroeconomic monitoring, policy design, and crisis response, especially in contexts where single-model systems struggle to capture evolving structural dynamics.

Taken together, the evidence indicates that methodological convergence in this literature is not merely descriptive, but functional. It reflects a deeper realignment of tools and principles designed to support resilient, transparent, and adaptive decision-making under uncertainty. Forecasting and portfolio theory, though historically distinct, are increasingly united in their treatment of uncertainty as an inherent and persistent feature of decision environments rather than a nuisance to be eliminated. Future progress will depend on deepening this integration and translating theoretical complementarities into practical innovations that enhance stability, interpretability, and responsiveness in uncertain environments. In this respect, convergence represents more than the diffusion of techniques; it signals an epistemic shift towards decision-making frameworks that are structurally robust, context-aware, and inherently adaptive.

Research Constraints and Future Research Directions

This research provides a structured account of thematic, methodological, and institutional convergence across forecasting and portfolio theory. Several limitations should nonetheless be acknowledged. First, bibliometric analyses depend on the coverage and structure of the underlying database. Although Scopus offers broad coverage and rich metadata, differences in indexing practices, language representation, and disciplinary scope may limit the visibility of relevant contributions, particularly from adjacent fields. Second, citation-based indicators are shaped by field-specific norms, self citation practices, and publication recency, which may affect interpretations of scholarly prominence. Third, keyword- and citation-based clustering, while effective for high-level mapping, may not fully capture latent methodological connections not reflected in titles, abstracts, or bibliographic metadata. Fourth, the search query remains sensitive to alternative formulations that could lead to variations in corpus composition. Finally, authorship attribution relies on simple $1/n$ fractional counting, which assumes equal contributions and does not account for author order or contribution statements; consequently, relative prominence under fractional counts may differ from full publication counts for countries or institutions frequently involved in large research consortia.

Despite these constraints, the analysis offers a coherent foundation for advancing research at the intersection of forecasting, portfolio theory, and decision-making under uncertainty. The evidence of conceptual convergence identified in this study points toward several promising directions for future research. In particular, further work could combine bibliometric mapping with empirical benchmarking to assess how alternative aggregation, regularisation, and robustness strategies perform in applied forecasting and portfolio settings. Extending the analysis to

Table 8 Structured Future Research Agenda.

Research Stream	Conceptual Context	Observed Gap	Future Research Directions	Representative References
Unified weight optimisation under estimation risk	Forecast combination and portfolio selection framed as a unified constrained optimisation problem, with applications to forecast aggregation and high-dimensional asset allocation under estimation risk.	Although forecast combination and portfolio optimisation are unified through constrained and regularised weight estimation, most approaches rely on static penalties and fixed reference structures. Regularisation strengths and shrinkage targets are treated as exogenous and time-invariant, limiting adaptability to structural change and evolving dependence patterns. Uncertainty representations remain passive with respect to downstream decisions.	Develop adaptive and decision-aware weight optimisation frameworks in which regularisation strength, reference targets, or constraints evolve dynamically. Move beyond fixed ℓ_1/ℓ_2 penalties toward state-dependent or hierarchical regularisation schemes that integrate learning, optimisation, and uncertainty updating, enabling aggregation rules to respond endogenously to structural instability.	Bodnar et al. (2023); Roccazzella et al. (2022); Shi et al. (2025)
Strategy aggregation and portfolio construction	Portfolio construction and risk management through the combination of multiple allocation principles, with emphasis on robustness, diversification, and strategic asset allocation.	Existing strategy combination methods operate primarily at the strategy level, treating allocation rules as indivisible blocks. This limits granularity and flexibility, constraining exposure control and reducing robustness to heterogeneous asset-level risk, correlation dynamics, and structural change.	Develop asset-level strategy aggregation frameworks that combine the outputs of multiple allocation principles at the individual asset level. Such approaches should enable dynamic reweighting of asset exposures, flexible incorporation of constraints and preferences, and targeted robustness where estimation risk or instability is most pronounced.	Kan et al. (2022); Lassance et al. (2024a, 2024b)
Decision-aware forecast aggregation	Forecast aggregation in settings where predictive outputs directly inform allocation, policy, or operational decisions, including portfolio choice and resource allocation.	Forecast combination methods typically optimise predictive accuracy or error variance without accounting for the structure, costs, or asymmetries of downstream decisions. Although decision-focused learning explicitly optimises decision quality, it has not yet been systematically integrated into forecast aggregation or ensemble weighting schemes.	Develop decision-aware forecast aggregation frameworks that integrate decision-focused learning objectives into the estimation of combination weights. Design task-specific surrogate losses encoding risk preferences, asymmetric costs, and operational constraints, and embed them within ensemble aggregation to align predictive combination with downstream decision performance.	Anis and Kwon (2025); Butler and Kwon (2023); Costa and Iyengar (2023); Elmachtoub and Grigas (2022)

Table 8 (continued)

Research Stream	Conceptual Context	Observed Gap	Future Research Directions	Representative References
Robust optimisation and uncertainty modelling	Robust forecasting and portfolio allocation under model uncertainty, structural change, and information asymmetry.	Classical robust aggregation frameworks treat uncertainty sets as fixed and exogenous, constructed independently of the decisions they inform. Although recent work has linked robust optimisation to bilevel formulations, decision-dependent uncertainty sets have not yet been systematically developed or integrated into aggregation frameworks.	Develop decision-dependent and endogenous uncertainty sets within robust aggregation frameworks using hierarchical and bilevel optimisation formulations. Extend robust and distributionally robust aggregation schemes to allow uncertainty representations to adapt to modelling or allocation decisions, while addressing tractability and uncertainty-set design challenges.	Beck et al. (2023); Goerigk et al. (2025); Kobayashi et al. (2023)
Combination methods in trading and execution-sensitive strategies	Application of forecast combination to statistical arbitrage, pair-trading, and other real-time trading strategies requiring fast execution and interpretability.	Combination frameworks remain underexplored in statistical arbitrage and pair-trading contexts, where execution speed, interpretability, and robustness to structural breaks are critical. Concerns persist that complex aggregation schemes may introduce opacity and operational fragility in real-time settings.	Extend combination frameworks to statistical arbitrage and pair-trading strategies, emphasising interpretable and computationally efficient architectures. Balance robustness and predictive accuracy with execution feasibility, ensuring adaptability to regime shifts without sacrificing transparency.	Huck (2010); Krauss (2017)
Explainable and decision-aware aggregation	Forecast and portfolio aggregation in settings where transparency, interpretability, and accountability are essential for decision-making, particularly in financial time series and risk-sensitive environments.	Many advanced forecasting and optimisation methods operate as black boxes, limiting interpretability and trust in downstream financial decisions. Existing XAI frameworks have rarely been integrated with aggregation-based forecasting or portfolio construction, leaving a gap between predictive performance and explainable decision support.	Develop explainable aggregation frameworks that combine forecast or strategy averaging with transparent, decision-oriented explanations. This includes linking aggregation weights to interpretable features, uncertainty measures, or decision impacts, and integrating post-hoc explainability tools to support trust, communication, and regulatory accountability in financial decision-making.	Arsenault et al. (2025); Coussement et al. (2024); Giudici et al. (2024b); Giudici and Raffinetti (2023)

Source: Authors' Preparation

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additional data sources, such as Web of Science or domain-specific repositories, would also help evaluate the robustness of the observed patterns to alternative coverage and indexing conventions.

More broadly, future research will benefit from moving beyond disciplinary silos and adopting context-aware frameworks that explicitly accommodate model uncertainty, structural instability, and the dynamics of real-time decision-making. Furthermore, developments in XAI and related regulatory frameworks underscore the growing importance of transparency, interpretability, and accountability in risk-sensitive financial environments. Rather than seeking universally dominant methods, the emerging literature suggests the value of adaptive, decision-focused approaches whose effectiveness depends on data availability, uncertainty structure, and downstream objectives. Building on the thematic synthesis developed here, Table 8 summarises a set of forward-looking research directions that highlight concrete opportunities for theoretical development and applied innovation at the interface of forecasting and portfolio theory.

Data availability

The data analysed in this study were obtained from the Scopus database. In addition to the original publication records, the study generated processed datasets, screening outputs, clustering results, bibliometric mapping outputs, and analysis code supporting the full workflow. These materials, including the search strategy, inclusion and exclusion documentation, database export files, and all scripts used for data cleaning and network analysis, have been provided to the referees and editors for the purposes of peer review. Access is granted subject to Scopus licensing conditions.

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Author contributions

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Competing interests

The authors declare no competing interests.

Ethical approval

This article does not contain any studies with human participants or animals performed by any of the authors.

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