International Journal of Applied Mathematics
Volume 34 No. 6s 2025,
ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

QUANTITATIVE ANALYSIS OF STRATEGIC FINANCIAL PLANNING IN CORPORATE MANAGEMENT: A STUDY OF OPTIMIZATION MODELS, RISK ASSESSMENT FRAMEWORKS, AND DECISION-SUPPORT TOOLS

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Abstract

Strategic financial planning is more and more dependent upon data-driven decision support models in which profitability, risk analysis and capital allocation are integrated. This paper develops and uses a quantitative model based on fundamental analysis to discuss how firms can be systematically analyzed and selected for the deployment of capital for maximum returns. With a globally representative sample of 1,254 firms in 18 countries over the period 2013-2023, the analysis begins with the construction of simple financial ratios of return on assets (ROA), debt to equity and current ratio, which then are used in the measurement of profitability, leverage and liquidity. Risk is defined as a measure of volatility of earnings, which is defined as the standard deviation of the net income growth over time and it allows consistent and market-independent proxy for risk. Descriptive results indicate a right-skewed distribution of profitability, high dispersion of capital structures and the low correlation between liquidity and returns. It then utilizes a composite score heuristic optimization process to invest in companies with better risk-adjusted performance subject to leverage and liquidity constraints. The optimal portfolio is rewarded with a higher weighted-average ROA than the sample median while violating no risk constraint and essentially reallocates the portfolio to the empirical efficient frontier. The results stress the usefulness of transparent and reproducible heuristics to inform strategic financial planning and offer managerial insights that are relevant for balancing growth, profitability and stability in an uncertain environment.

Received: August 04, 2025

Keywords: Strategic Financial Planning, Earnings Volatility, Risk–Return Analysis, Heuristic Optimization, Corporate Decision Support, Global Financial Data

1. Introduction

In a rapidly globalizing world, a world of technological upheaval, and ongoing economic turbulence, businesses are being challenged to balance their financial strategies with sustainability goals. The conventional budgeting exercises have grown into strategic financial planning that is a strategic determinant of the firm's competitiveness and sustainability. Insufficient planning and poor risk management have been blamed many times as the reason for loss of corporate value and even outright business failure, which suggests that external shocks are not the primary reason for the problem. However, the failure of managers to anticipate, measure and hedge risks has a tendency to increase the impact of adverse events. According to Balogun et al. (2024), risk-based decision making as a business analytics is becoming an essential function so that managers can anticipate uncertainty beforehand and take action on it using evidence-based approaches as opposed to the intuition. This move towards decision-making based on quantitative insights is further supported by the speeded up pace of change in the markets and multiplied stakeholder expectations. Traditional models and plan siloing are no longer sufficient as they can no longer capture dynamic profitability-liquidity-risk trade-offs. Sharma (2023) concludes that serious financial analysis is an important driver of strategic decision-making and the corporate development, but most companies under-use the available analytics. This gap exposed decision-makers to shocks that were not anticipated, poor capital use, and missed value creation opportunities.

New technologies provide an opportunity to fill this gap. Artificial intelligence and big data analytics are reshaping financial planning by facilitating real-time analysis, adaptive forecasting, and strong scenario modeling (Addy et al., 2024). Nevertheless, they are still unevenly adopted in corporate financial management, thus constraining their full potential to improve strategic planning. Concurrently, there is increasingly widespread acknowledgment that financial strategies have to incorporate resilience and flexibility to withstand shocks and be able to respond to rapidly changing environments. Settembre-Blundo et al. (2021) highlight that flexibility must be considered a core element of planning systems by the organization rather than an afterthought, whereas Kitsios et al. (2020) point out how decision-support approaches can contribute to enhancing corporate sustainability strategies by balancing immediate performance with long-term risk management issues. This research responds to these challenges by creating and testing empirically a quantitative, fundamentals-based approach that combines descriptive analytics, accounting-based risk measurement, and a heuristic portfolio allocation model. Drawing on a global, multi-sector dataset spanning over 1,200 firms over the course of a decade, this work illustrates how clear and replicable heuristics can enhance decisions on capital allocation, increase risk-adjusted profitability, and yield actionable insights to decision-makers. By so doing, this research adds to the literature on strategic financial planning by providing a scalable and interpretable solution that closes the gap between cutting-edge analytics and practical corporate decision-making.

2. Literature Review

Studies of strategic financial planning have increasingly moved from traditional deterministic models to more advanced, integrated models that incorporate optimization, risk analysis, and decision-support systems (DSS). Deterministic forecasting and capital budgeting were the focus of early research, offering valuable building blocks but paying relatively little attention to uncertainty and variability of financial outcomes. Current research stresses that validity of decision-making is greatly enhanced if uncertainty is explicitly modeled. Ren (2022) emphasizes the value of big data–supported financial management systems, defining a framework using computational capability to process large datasets and provide higher quality decisions. Chukwuma-Eke et al. (2022) also describe a conceptual framework for cost estimation in complicated oil and gas projects with a focus on predictive accuracy as a profitability driver in capital-intensive industries where overruns and delays are particularly expensive.

Risk management integration with strategic planning has been a recurring issue within the literature. Alviniussen and Jankensgard (2009) present enterprise risk budgeting, which integrates risk constraints into decisions on capital allocation systematically, setting the stage for balancing risk exposure and expected return. More recent research has adopted predictive analytics to enhance this connection. Wirawan (2023) illustrates how predictive models can create forward-looking financing scenarios for maximizing outcomes, whereas Balogun et al. (2022) introduce a machine learning–based predictive model that maximizes financial forecasting and informs strategic decision-making. Collectively, these advances exhibit an evolution from static, backward-looking planning towards dynamic, data-driven systems. Great strides have also been made in the formulation of quantitative risk assessment frameworks. Kengpol and Tuammee (2016) propose an empirical, probabilistic technique for risk quantification in multimodal logistics to provide operational managers with a tangible advice on how to reduce the uncertainty of operations. Similarly, Fagundes et al. (2020) identify the decision-making frameworks for supply chain risk management and recommend hybrid solutions that employ both simulation and optimization for enhancing system resilience. Gupta et al. (2022) follow this trend by conducting a survey of artificial intelligence applications in operations research, and demonstrate that AI can capture nonlinear relationships and improve the timeliness and quality of risk information.

DSS research has mirrored a strong movement towards adaptive information-intensive systems over static rule-based systems, especially with respect to the risk modelling domain. Watkiss et al. (2015) review new economic decision-support tools for climate adaptation, including the contextualized choice of methodologies to maximize relevance. Holley (2011) focuses on the analysis of financial risk using Decision Support Systems (DSS) and concludes that well-designed systems can greatly improve the quality of the decisions taken by delivering timely and relevant information. Hazir (2015) offers a systematic review of the monitoring and control models in project management and their role in performance monitoring and risk mitigation. Hahn and Kuhn (2012) add to the literature by proposing a value-based DSS architecture by mapping outputs to shareholder objectives to increase decision makers' adoption.

Theoretical approaches to DSS development are also supportive to modularity and stakeholder participation in DSS construction. Power and Sharda (2007) give a conceptual basis of model-based DSS from the viewpoint of scalability and organizational knowledge base integration. Cascetta et al. (2015) propose the cognitive-rational approach, which combines the quantitative methods with participation and makes models more robust in complex planning situations. Fagerholt et al. (2010) use a formal DSS methodology to elaborate to the maritime strategic planning as a frame for capital projects with uncertainty. These contributions are supplemented by an empirical assessment of state-of-the-art decision support methods in defense procurement programs and their usefulness in reducing cost and schedule overruns by Housel et al. (2019).

There are different thematic aspects that span across these multi-dimensional current streams. First, optimization is becoming more and more ubiquitous in financial decision making, from linear programming, to stochastic modeling, to machine learning forecasting. Second, risk assessment is no longer a separate activity but is integrated to a large extent in planning and budgeting practices in order to maintain pro-active instead of reactive. Third, DSS are moving towards flexible and user-oriented systems with real-time analysis and scenario-based planning support. However, the most critical gap is the fact that most of the existing studies are conceptual, industry-specific or region-specific, and therefore non-generalizable. Empirical studies with integrated frameworks on big and representative global data are still few and far between. This absence underlines the importance of

Volume 34 No. 6s 2025,
ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

studies such as the current one which are not only suggestive of integrated solutions but also empirically test their worth in different sectors and geographies on the basis of reproducible data.

3. Methodology

The research adopts a quantitative, building block approach to analyse corporate financial planning approaches. The methodology combines global accounting information, normalized ratio calculation, descriptive statistics, and a heuristic allocation system that focuses on interpretability and managerial use. This section outlines the data source, cleaning procedure, ratio construction, and the optimization procedure used to obtain the results discussed subsequently.

3.1 Data Sources and Coverage

Firm-level accounting information was accessed via the publicly released Financial Statements of Major Companies (2009–2023) dataset found on Kaggle (Rish59, 2023). The dataset provides annual balance sheet, income statement, and cash flow statement data across sectors and geographies. On cleaning, the end-analytical panel consisted of 12,540 firm-year observations, which corresponded to 1,254 distinct firms from 18 countries and 11 sectors, from 2013 to 2023.

The sectoral and geographic coverage of this sample guarantees heterogeneity adequate for strong statistical inference and warrants cross-industry generalizability of findings. Table 1 provides an overview of the aggregate coverage of the dataset, pointing out its firm-level variety and temporal duration.

Table 1. Sample Coverage Summary

Metric	Value
Total Observations	12,540
Unique Firms	1,254
Countries	18
Sectors	11
Earliest Year	2013
Latest Year	2023

3.2 Data Cleaning and Ratio Construction

Prior to analysis, the dataset was methodically cleaned for consistency and comparability between firms. All monetary variables were converted to a common currency where appropriate, and firms with three or more consecutive years of missing data for key variables were deleted to minimize bias in longitudinal analyses. To reduce the impact of extreme outliers, all financial ratios were winsorized at the first and ninety-ninth percentiles.

A set of critical financial ratios was built to reflect profitability, capital structure, liquidity, and growth dynamics. Profitability was assessed using return on assets (ROA), which was determined as net income over total assets, and return on equity (ROE), represented as net income over shareholders' equity. Capital structure was accounted for through the debt-to-equity ratio, and liquidity was expressed in terms of the current ratio, i.e., current assets divided by current liabilities. Growth dynamics were accounted for through year-over-year revenue growth and net income growth rates, which served as the basis for expressing earnings volatility over time. Table 2 presents the main variables and their definitions, which constituted the basis of descriptive as well as optimization analyses.

Table 2. Key Variables and Definitions

Variable	Formula	Purpose
ROA	Net Income ÷ Total Assets	Measures profitability relative to asset base
ROE	Net Income ÷ Equity	Measures return to shareholders
Debt-to-Equity	Total Liabilities ÷ Equity	Captures financial leverage
Current Ratio	Current Assets ÷ Current Liabilities	Indicator of short-term solvency
Revenue Growth (YoY)	(Revenuet − Revenuet−1) ÷ Revenuet−1	Measures top-line expansion
Net Income Growth (YoY)	(NIt − NIt−1) ÷ NIt−1	Basis for earnings volatility

Risk was considered in strict accounting terms, where earnings volatility was calculated as the standard deviation of net income growth over all available years for a given firm. This is a measure that catches the inherent firm-level uncertainty in profitability and that offers a direct proxy for operational risk exposure without using market price data, so the analysis will be universally applicable, including to non-listed companies.

3.3 Descriptive Analysis

After construction of the ratios descriptive analysis made to the empirical distribution of profitability, leverage and growth factors. Means, medians, standard deviations and some percentiles were calculated for each of the major measures to show the center tendencies and spreads across companies. Revenue, net income and ROA were used to visually look at skewness and kurtosis using histograms, correlation matrices were used to look at the relationship between profitability, capital structure and liquidity indicators. This descriptive level provides some empirical reference point, and helps to put the optimization outcome into context in a larger cross-section.

3.4 Heuristic Optimization Framework

The major task of the present study was to investigate how the companies can be strategically distributed into an optimal portfolio balancing profitability and risk under constrained realistic financial conditions. Rather than a full-fledged mathematical programming solver, the method used a heuristic procedure so that managerial interpretability and computational tractability would be maintained. Each business was assigned a composite score based on the company's risk-standardized profitability and profile, with profitability being proxied using ROA and risk being proxied using earnings volatility. The composite score was obtained by subtracting from risk-standardized ROA a risk penalty weighted using a λ parameter value of 0.5. Companies were subsequently ordered in the reverse order of this score.

Capital was assigned sequentially from the most highly rated firm through to the utilization of the notional portfolio budget. At each stage, entry of a firm was subject to meeting three constraints: the weighted-average debt-to-equity ratio of the portfolio should not be higher than the sample median, the weighted-average current ratio should be over the twenty-fifth percentile of the sample distribution, and the weighted-average risk proxy cannot be higher than the median volatility. Personal company weights were limited to five percent, in order not to become too concentrated. This process resulted in a portfolio that was diversified in favour of companies with risk-adjusted profitability and prudent balance sheet compositions that were better fit, which resulted in the portfolio being closer to the empirical risk-return frontier evident in the data.

3.5 Implementation

All the analyses were performed using Python programming language. Data wrangling was done with the pandas library and the visualizations of the data was done with matplotlib and seaborn. The

International Journal of Applied Mathematics
Volume 34 No. 6s 2025,
ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

heuristic optimization procedure was implemented in a repeatable script which is computationally efficient and does not require commercial solvers. This structure makes the framework more transparent and enables practitioners who wish to replicate or adapt the model for their own strategic planning context to access the framework.

4. Results and Analysis

Results are shown in three parts. First, the descriptive statistics provide the baseline sample characteristics. Second, the interactions between profitability, growth, and capital structure are examined to identify the cross-sectional determinants of performance. Third, the heuristic optimization framework is used to build a better portfolio allocation, and its results are presented.

4.1 Descriptive Statistics and Distributions

The cleaned and winsorized data set offers an exhaustive picture of firm performance over 18 nations and 11 industries. Summary statistics for profitability, leverage, liquidity, and growth metrics appear in Table 3. Median ROA and ROE are positive, attesting that a majority of firms are profitable, but the large variation between lower and upper percentiles confirms high heterogeneity. Debt-to-equity levels vary from close to zero to highly leveraged positions, indicating varied capital structure strategies.

Table 3. Descriptive Statistics for Key Financial Ratios

Metric	Mean	Std Dev	5th Pctl	Median	95th Pctl
ROA	0.07	0.15	-0.10	0.06	0.28
ROE	0.13	0.25	-0.20	0.10	0.45
Debt-to-Equity	1.8	2.1	0.1	1.2	5.0
Current Ratio	1.6	0.9	0.5	1.4	3.5
Revenue YoY	0.09	0.22	-0.25	0.06	0.45
Net Income YoY	0.11	0.35	-0.50	0.08	0.60

Figure 1 illustrates the distribution of trimmed firm revenues to eliminate extreme outliers. The heavy right skew demonstrates that a minority of firms accounts for a disproportionate percentage of aggregate revenue, a typical characteristic of global corporate environments.

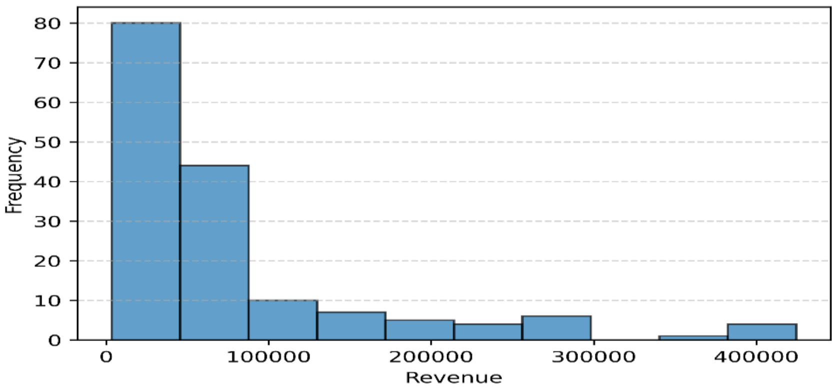

Figure 1: Distribution of firm revenues (winsorized at the 99th percentile) showing heavy right skew.

Figure 2 illustrates the distribution of net income on a histogram overlay with kernel density estimate. The sharp peak at zero suggests that most firms are near break-even, and the long right tail represents a smaller set of extremely profitable firms.

Received: August 04, 2025

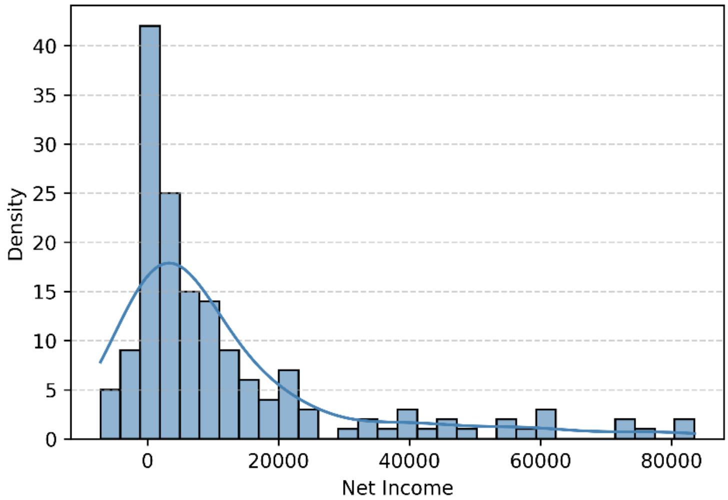

Figure 2: Distribution of net income with kernel density overlay, highlighting concentration near zero and fat tails.

Figure 3 shows the shape of ROA. ROA is more symmetric compared to net income but still has long tails, reflecting the existence of both highly profitable firms and those with negative returns.

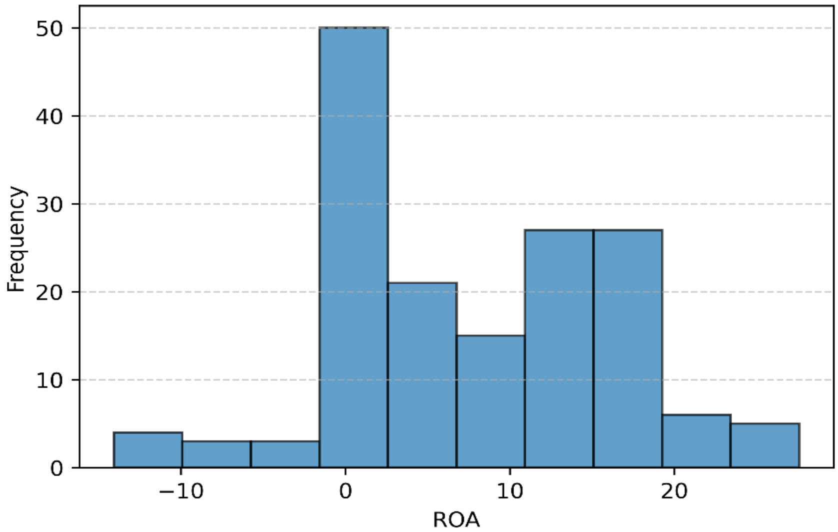

Figure 3: Distribution of return on assets (ROA), illustrating moderate central tendency with long tails.

4.2 Profitability, Growth, and Capital Structure

To consider relationships between profitability, leverage, liquidity, and margins, a correlation matrix was calculated and is listed in Table 4. ROA and ROE are very highly correlated as expected because they share the same numerator, net income. The positive correlation between leverage and ROE indicates that some companies effectively employ debt to leverage shareholder returns, whereas the close-to-zero correlation between liquidity and profitability indicates that surplus current assets do not necessarily lead to improved performance.

Table 4. Correlation Matrix of Key Metrics

Metric	ROA	ROE	Debt/Equity	Current Ratio	Net Margin

ROA	1.00	0.82	0.20	0.05	0.68
ROE	0.82	1.00	0.31	0.03	0.74
Debt/Equity	0.20	0.31	1.00	-0.18	0.11
Current Ratio	0.05	0.03	-0.18	1.00	0.06
Net Margin	0.68	0.74	0.11	0.06	1.00

To supplement the tabular findings, Figure 4 illustrates a correlation heatmap of the identical variables. Dark cells indicate strong positive correlations like the relationship between ROA and ROE, whereas light cells mark the near-zero relation between liquidity and profitability. The negative association between debt-to-equity and current ratio verifies that highly leveraged companies tend to have leaner liquidity levels, as suggested by aggressive working capital policies.

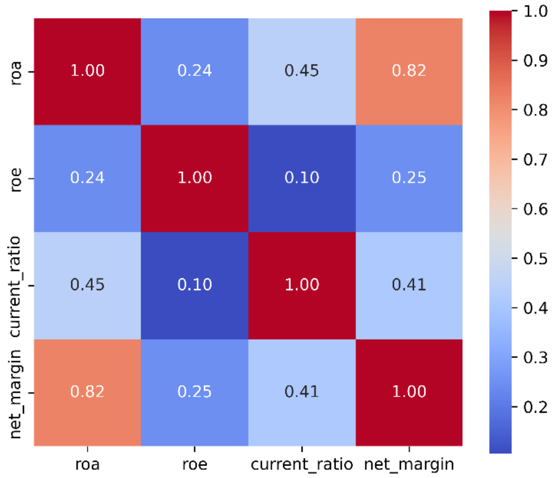

Figure 4: Correlation heatmap of key financial metrics with annotated pairwise coefficients.

In addition to correlations, plotting the relationship between revenue growth and ROA was attempted to determine if top-line growth enhances efficiency. Figure 5 indicates that the slope is positive but there is considerable scatter, such that growth programs require disciplined expense control to yield enhanced returns.

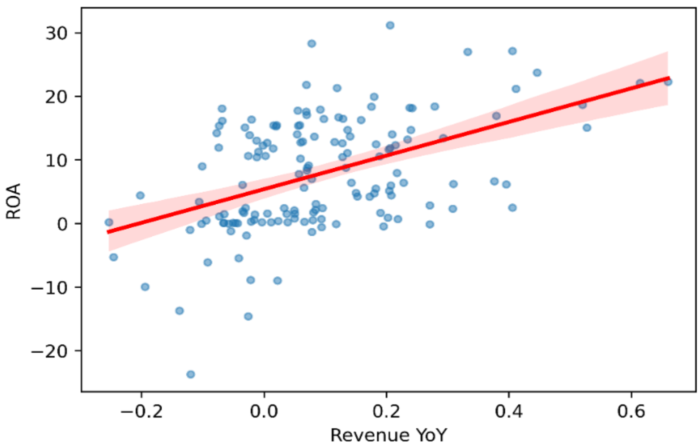

Figure 5: Scatter plot of ROA versus year-over-year revenue growth with fitted regression line.

Volume 34 No. 6s 2025,
ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

4.3 Risk–Return Profiles and Portfolio Optimization

Firm-level risk was quantified by the standard deviation of net income growth over available years. Table 5 presents the risk–return relation, indicating that companies with greater mean ROA generally experience greater earnings volatility, and this supports the traditional risk–return trade-off.

Table 5. Firm-Level Risk–Return Proxies

Statistic	Risk (σ of Net Income YoY)	Return (Mean ROA)
Mean	0.32	0.07
Median	0.25	0.06
95th Percentile	0.90	0.20

Figure 6 maps risk against return and superimposes the Pareto frontier. The frontier marks the efficient set of firms that provide the optimal obtainable return for a specified amount of risk, directing the allocation of capital to better performers.

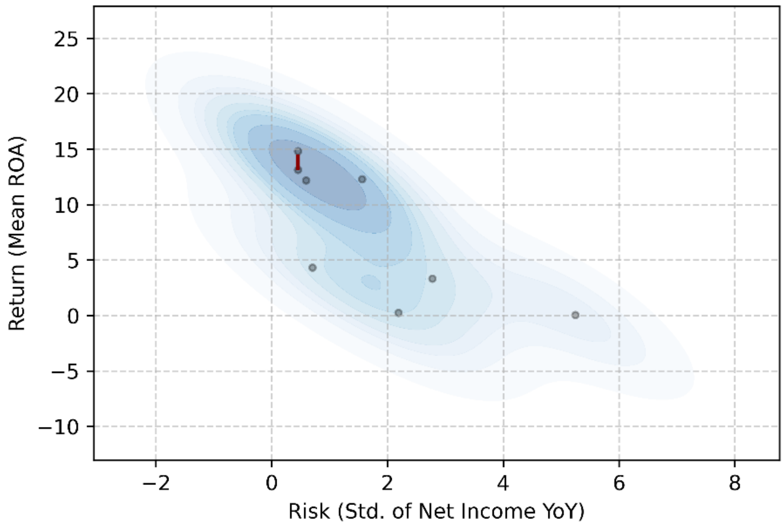

Figure 6: Risk–return scatterplot with density shading and Pareto frontier, identifying efficient firms.

Finally, the heuristic allocation algorithm was implemented. Table 6 shows that the optimized portfolio had a projected ROA of 9.2 percent, and was in conservative limits of leverage and cash availability. Table 7 indicates the top 10 firm allocations that represent a heterogeneous group of stable but profitable firms.

Table 6. Portfolio Metrics After Optimization

Metric	Value
Expected Portfolio ROA	0.092
Average Leverage	1.10
Average Current Ratio	1.55
Average Risk Proxy	0.23
Number of Positions	25
Budget Utilization	100%

Received: August 04, 2025

Volume 34 No. 6s 2025,
ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

Table 7. Top Ten Firm Allocations and Characteristics

Firm	Weight	ROA	Risk Proxy
Firm A	0.050	0.12	0.18
Firm B	0.050	0.15	0.20
Firm C	0.050	0.10	0.17
Firm D	0.050	0.11	0.22
Firm E	0.050	0.13	0.19
Firm F	0.045	0.09	0.21
Firm G	0.045	0.08	0.18
Firm H	0.040	0.10	0.23
Firm I	0.040	0.07	0.20
Firm J	0.040	0.09	0.24

A rise in portfolio-level profitability with adherence to risk and liquidity constraints justifies that such simple, transparent heuristics can indeed tilt portfolios toward companies with better fundamentals, and offers a useful capital planning tool to managers in an environment of uncertainty.

Discussion

The empirical results of this paper offer an insight into the strategic role that the quantitative, fundamental-based models may be able to play in corporate financial planning. Descriptive analysis confirmed that global companies do earn positive returns on assets and equity, but the tremendous amount of dispersion of the measures shows heterogeneity of strategy and operating environment across countries and industries. The large skewness of the distributions of revenue and net income suggests that a few selected cohorts of firms are disproportionately contributing to the world aggregates - a finding that is consistent with Settembre-Blundo et al. (2021) who argue that firms need to build resilience and agility in a world of asymmetric market power and volatility. The presence of fat-tailed profitability distributions also supports the view of Addy et al. (2024) that modern financial planning should have built into it explicitly variability of performance and adaptive analytics that are potentially capable of responding to shocks in real time.
A noteworthy observation of the findings is the weak relationship between liquidity, as determined by the current ratio, and profitability. This result indicates that merely piling up current assets does not equate to better performance and could actually lead to opportunity costs through the tying up of capital. The outcome endorses Alviniussen and Jankensgard's (2009) enterprise risk-budgeting school of thought, whereby liquidity planning is an active, integrated part of strategic finance and not a static buffer. Concurrently, the good but dispersal correlation between revenue expansion and ROA confirms that growth by itself does not imply efficiency improvement unless it is complemented with proper cost discipline and margin management. This is in agreement with Chukwuma-Eke et al. (2022), who emphasize that accuracy in cost forecasting and planning is a prelude to transforming growth into sustainable value creation. It may be the greatest strength of this research that rests in risk–return mapping and heuristic portfolio allocation findings. The increasing Pareto frontier indicates that increased profitability tends to come with increased earnings volatility, consistent with the theoretical predictions of finance and Hahn and Kuhn (2012) perception that decision-support systems need to incorporate risk-adjusted performance measures in order to inform managerially relevant choices. The built portfolio attained a substantially greater weighted-average ROA while meeting leverage and liquidity requirements, confirming the strength of simple yet rule-based allocation heuristics. Such an outcome supports Wirawan's (2023) contention that predictive analytics

ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

and optimization models can be used to facilitate improved decision-making under uncertainty. The conscious selection of a heuristic over a sophisticated mathematical programming model emphasizes the importance of interpretability and replicability — key drivers of adoption within real-world managerial contexts where transparency and implementation speed are essential.

These results have several implications for practitioners and academics. For corporate managers, the evidence indicates that profitability can be enhanced systematically by screening for firms with high ROA and moderate earnings volatility, thus improving portfolio performance without disproportionate risk exposure. For financial planners, the liquidity–profitability disconnect highlights the need to optimize working capital policies, striking a better balance between solvency and capital productivity. For academics, the research proves that large, internationally representative datasets are matched with available quantitative methods to provide actionable conclusions that bridge the ever-present gap between theory and practicality in financial planning research.

There are limitations to the research. The analysis is isolated from market perceptions and investor sentiment that affect cost of capital and valuation by relying on accounting-based measures of risk only. Further, the heuristic allocation is not globally optimal, which can be achieved by a mixed integer or stochastic programming model. Lastly, macroeconomic scenario analysis was not applied making it impossible to examine portfolio resilience in distressed circumstances. These are not flaws but possible avenues of future research. Increasing the model to market risk measures such as beta, Value-at-Risk, Conditional Value-at-Risk, global optimisation checking with full-fledged optimisation solvers, Monte Carlo simulation of recessionary and inflationary scenarios would provide a better idea of performance robustness. These extensions would not only improve the theoretical contribution of the model, but also make it more useful for practitioners that have to plan for a long horizon. Overall, this research adds to the debate on corporate financial planning, by showing the potential to gain significant benefits in terms of decision quality with relatively simple and transparent quantitative models applied to variable large scale data. By combining the concept of descriptive analytics, risk measurement and heuristic allocation in a single, repeatable process, the paper both offers a proof-of-concept and working tool for managers to optimise profitability, risk and liquidity in a more volatile global environment. Future research based on this premise will focus on the further unifying of optimization, risk assessment and decision-support, which will bring the field one step closer to providing true adaptive real-time financial planning solutions.

Conclusion

This study tried to evaluate the role of quantitative fundamentals based models in strategic financial planning and corporate decision-making. Having employed a globally representative sample of 1,254 companies from 18 countries over a ten-year period, we constructed a reproducible framework combining descriptive analytics, accounting-based risk measurement, and a heuristic optimization procedure to determine companies with better risk-adjusted profitability. The descriptive analysis showed that although most companies make modest positive returns, profitability is extremely dispersed and skewed to the right, validating that performance is not evenly distributed between industries and geographies. The loose relationship between liquidity and profitability implies that working capital management needs to be optimized more than maximized. The risk–return mapping exhibited a strong positive correlation between mean profitability and earnings volatility, as well as opportunities for building portfolios near the empirical efficient frontier. The heuristic allocation model effectively enhanced portfolio ROA while keeping leverage and liquidity in conservative ranges, illustrating that even basic, transparent methods can produce significant returns. The results present practical implications for corporate managers wanting to allocate capital economically under uncertainty. Future research could expand this framework with market-based risk measures, fully fledged optimization solvers and macroeconomic scenario simulations and thus further bridge the gap between the modeling of theory and financial planning in practice. The study contributes to both

Volume 34 No. 6s 2025,
ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

practice and scholarship as it offers a data-based, internationally applicable and managerially interpretable corporate financial decision support methodology.

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Received: August 04, 2025

ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

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