Reassessing Risk Integration in Investment Appraisal: A Comparative Evaluation of Traditional and Simplified Analytical Models

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ABSTRACT

This study provides a systematic examination and critical evaluation of prevailing methodologies for incorporating risk into investment appraisal and project planning. It advances the argument that inadequate recognition or improper integration of risk—often arising from the use of flawed or overly complex analytical models—can materially distort decision outcomes and undermine project viability. Using a desk-research approach, the study analyzes cash-flow estimates from five projects drawn from the authors' tutorial archive. The project parameters were assessed using discounted cash-flow (DCF) techniques and risk metrics generated through Monte Carlo simulation, Mean-Relative Regression (MRR) analysis, and Enyi's simplified statistical risk model, which also produced the distribution of risk around mean cash flows. The findings reveal that the more sophisticated models not only pose practical challenges in application but also yield inconsistent results. In contrast, the risk-distribution insights produced by Enyi's simplified statistical model offer clearer, more coherent guidance for investment planning and project-appraisal decision makers. The study contributes to the literature by highlighting the value of simplified, transparent risk-integration frameworks in enhancing the reliability of capital-investment decisions.

Keywords: Investment appraisal; Discounted cash flow; Risk modeling; Monte Carlo simulation; DCF; Mean relative regression.

JEL Classifications: M40, M41, C1, G31, G32

INTRODUCTION

Investment appraisal is a central component of strategic financial decision-making, yet it remains one of the most challenging tasks faced by managers and analysts. The difficulty stems from its inherently forward-looking orientation: decisions must be made today based on expectations about an uncertain future. Economic volatility, political instability, technological disruption, demographic shifts, and evolving consumer behavior all introduce layers of uncertainty that can materially affect project outcomes. Within this context, risk represents the possibility that anticipated benefits may not be realized, while uncertainty reflects the absence of complete knowledge about future events. ISO 31000 captures this relationship succinctly by defining risk as the "effect of uncertainty on objectives."

In capital investment decisions, failing to recognize or appropriately incorporate risk can lead to systematic overestimation of project viability. Many corporate failures and abandoned projects can be traced to inadequate risk assessment or the use of models that obscure rather than illuminate the true distribution of possible outcomes. Although probability theory and statistical tools offer mechanisms for quantifying risk, their practical application varies widely in complexity and interpretability. Traditional measures—such as standard deviation, coefficient of variation, and regression-based approaches—provide useful insights but often require assumptions that may not hold in dynamic business environments.

More sophisticated frameworks, including those derived from the work of Modigliani and Miller, attempt to capture systematic and financial risk through constructs such as beta (β). While theoretically robust, these models demand a level of technical expertise and data availability that many organizations, particularly in emerging markets, may not possess. As a result, managers frequently rely on simplified heuristics or deterministic projections that fail to capture the full spectrum of risk exposure.

In project appraisal, two categories of risk are especially salient: the risk of failing to achieve projected cash flows and the risk of failing to realize broader project objectives. Although related, the former typically exerts a more immediate and measurable influence on investment outcomes. Understanding how different modeling approaches capture these risks is therefore essential for improving the reliability of capital budgeting decisions.

Despite the proliferation of risk-integration techniques—ranging from Risk-Adjusted Discount Rates (RADR) and Certainty Equivalent Adjustments (CEA) to Scenario Analysis and Monte Carlo simulation—many remain mathematically demanding, computationally intensive, or difficult to interpret. Monte Carlo simulation, for example, is widely praised for its ability to incorporate stochastic variability (probabilistic measurement based on a given dataset pattern or trend), yet its effective use requires assumptions about probability distributions and a level of statistical literacy that many practitioners lack. Even with modern software, the interpretive burden remains substantial.

Given these challenges, there is a growing need for risk-assessment frameworks that balance analytical rigor with practical accessibility. This study responds to that need by evaluating traditional and advanced risk-integration models alongside a simplified statistical approach designed to enhance interpretability without sacrificing methodological soundness.

The need for this study

A wide range of methodologies for identifying and modeling the probability of project failure within the framework of risk assessment have been advanced in prior research. Such methods include *Risk Adjusted Discount Rate (RADR), Certainty Equivalent Adjustments (CEA), Scenario and Sensitivity Analysis (SASA),* and *Probability Simulation (PS),* otherwise known as *Monte Carlo simulation,* among others (Brealey et al., 2017; Trigeorgis, 1996; Rubinstein & Kroese, 2016). However, many of these approaches are characterized by considerable mathematical and computational complexity, and despite their sophistication, they frequently fall short of delivering actionable or context-specific solutions. Among the most prominent techniques is the Monte Carlo simulation, which has been extensively lauded for its capacity to incorporate stochastic variability into project evaluation. Nevertheless, its effective application presupposes a high level of mathematical proficiency that often exceeds the expertise of the average manager. Although advances in computational tools have facilitated the execution of the tens of thousands of iterative runs required by the method, the interpretive demands and the limitation of incorrect probabilistic distributions remain substantial (Jorion, 2006). Other methods of estimating risk include the use of quantile regressions which in themselves are no less easier to understand and apply as the Monte Carlo simulation and other stochastic based methods (Coughing et al., 1991; Guikema & Goffelt, 2008; Huang, 2012; Wang et al., 2025; Linstone & Turoff, 2011).

The issues with Monte Carlo and other risk analysis methods

Monte Carlo analysis is widely used to model uncertainty and evaluate complex systems; however, it may produce misleading or false conclusions under certain conditions. One major limitation arises when incorrect or unrealistic probability distributions are assigned to input variables, since simulation outputs are directly dependent on the validity of these assumptions (Law & Kelton, 2000). Similarly, poor quality or insufficient empirical data used to estimate model parameters can bias simulation outcomes and reduce their reliability (Robert & Casella, 2004). Monte Carlo simulations may also generate inaccurate results when correlations among variables are ignored, particularly in financial and risk analysis contexts where interdependencies significantly influence outcomes (Jorion, 2006). Furthermore, model misspecification or oversimplified assumptions can distort results even when large numbers of simulations are performed (Hull, 2018). Additional sources of error include an insufficient number of simulation iterations, which may prevent convergence to stable probability estimates (Ross, 2013), as well as misinterpretation of probabilistic outputs by decision-makers who may treat simulated results as deterministic forecasts rather than probability-based estimates (Taleb, 2007).

Quantile regression also follows the stochastic route like the Monte Carlo method but grounded on the use of multiple regression analysis with overloaded errors of residuals and the difficulty in locating the most appropriate region of the dataset from which to set the mean (Coughing et al., 1991; Guikema & Goffelt, 2008). The problem of the use of coefficient of variation on the other hand is in it's close affinity with the standard deviation which is swayed to any direction by the presence of outliers or huge data deviations from the general trend.

The objective of the study

Consequently, this paper proposes a streamlined, yet statistically robust, risk modeling framework designed to bridge the gap between methodological rigor and managerial accessibility. The objective is to reconcile theoretical rigor with practical applicability and to furnish decision-makers with a practical analytical instrument that enables systematic evaluation of risk exposure in newly proposed projects, thereby enhancing the reliability of investment appraisal and supporting more informed strategic choices.

Literature Review

Investment appraisal fundamentally seeks to identify, rank, and select projects capable of generating value under conditions of uncertainty. Traditional capital budgeting frameworks rely heavily on discounted cash flow (DCF) techniques, with net present value (NPV) serving as the dominant decision criterion. NPV is computed by discounting expected future cash flows at the firm's cost of capital (Brealey, Myers, & Allen, 2017). However, the presence of risk complicates this process by influencing both the magnitude and timing of cash flows as well as the appropriate discount rate. When risk is inadequately incorporated, project valuations may become distorted, leading to inefficient capital allocation and suboptimal strategic outcomes (Dixit & Pindyck, 1994).

This review synthesizes theoretical and empirical perspectives on risk recognition, risk integration, and the conceptual frameworks that underpin modern risk-adjusted investment appraisal. It provides the foundation for the comparative evaluation of traditional and simplified analytical models undertaken in this study.

Risk Recognition in Business and Project Proposals

In contemporary business environments characterized by volatility and rapid change, the ability to recognize risk early in the investment proposal stage is a strategic necessity. Effective risk identification enhances budgeting accuracy, strengthens contingency planning, and supports more resilient project design. Flyvbjerg (2021) highlights the pervasive influence of "optimism bias," whereby planners systematically underestimate costs and overestimate benefits. Rigorous risk recognition serves as a corrective mechanism against such cognitive distortions.

Risk recognition also plays a critical role in building investor confidence. Hillson (2017) argues that transparent communication of risks fosters a "risk-aware culture," enhancing stakeholder trust and improving access to capital. Moreover, early identification of uncertainties enables organizations to embed strategic flexibility—often conceptualized as "real options"—into project design, allowing managers to adapt decisions as new information emerges (Trigeorgis & Reuer, 2017).

Ultimately, risk recognition is not about eliminating uncertainty but about making informed, strategically aligned decisions. As Knight (2012) famously noted, profit is the reward for bearing uncertainty that cannot be insured or fully predicted.

Importance of Integrating Risk into Investment Appraisals

Integrating risk into investment appraisal is essential for ensuring that capital budgeting decisions reflect the true distribution of potential outcomes. Graham and Harvey (2001) demonstrate that ignoring risk leads to biased

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return estimates and increases the likelihood of financial underperformance. Incorporating risk also ensures alignment between project selection, organizational risk tolerance, and long-term strategic objectives.

Risk adjustment is particularly important because capital budgeting decisions are made under uncertainty. Without explicit risk adjustments, firms may systematically overinvest in high-variance projects and underinvest in safer but value-enhancing alternatives (Mun, 2015). By embedding risk into appraisal models, organizations improve decision transparency, enhance the credibility of assumptions, and ensure that downside exposures are adequately considered.

Concept of risk in investment appraisal

In investment appraisal, risk is typically defined as the variability of actual cash flows and project outcomes around their expected values. This variability may arise from market volatility, technological disruption, regulatory changes, or macroeconomic fluctuations. Consequently, robust appraisal frameworks must consider both expected values and the dispersion of outcomes.

Risk in capital budgeting is commonly decomposed into three categories:

i. **Stand-alone risk:** the variability of project cash flows in isolation.

ii. **Corporate risk:** the project's contribution to the firm's overall risk profile.

iii. **Market (systematic) risk:** the portion of risk that cannot be diversified away and is relevant to shareholders in well-diversified portfolios.

Systematic risk is frequently measured using beta (β) within the Capital Asset Pricing Model (CAPM), which links expected returns to market-related risk factors (Van Horne et al., 2008).

Importance of adjusting for risk

Risk adjustment is necessary for three key reasons:

1. **Avoiding biased project evaluation:** Expected cash flows without dispersion measures systematically overstate the attractiveness of uncertain projects. Risk analysis enables decision-makers to differentiate between projects with identical expected NPVs but different risk profiles.

2. **Improving transparency and accountability:** Explicit modeling of volatility, correlations, and probability distributions makes assumptions visible and testable, enabling stakeholders to evaluate downside risk and the likelihood of achieving strategic targets (Broadie et al., 2015; Huang, 2012).

3. **Aligning appraisal with modern finance theory:** Techniques such as risk-adjusted discount rates, certainty equivalents, and simulation methods ensure consistency between project evaluation, cost of capital estimation, and portfolio-level risk management.

Modern portfolio theory provides the conceptual foundation for many of these adjustments. Markowitz (1952) formalized the trade-off between expected return and variance, while the CAPM (Sharpe, 1964; Lintner, 1965) links expected returns to systematic risk. The Arbitrage Pricing Theory (Ross, 1976) extends this logic to multiple risk factors. Although these models offer valuable insights, they rely on assumptions—such as market completeness and asset tradability—that may not hold for idiosyncratic project risks or non-marketable assets.

Theoretical Risk Framework

Risk is a multidimensional concept interpreted differently across disciplines. Three major theoretical perspectives dominate contemporary risk scholarship: rational choice, socio-cultural, and psychopolitical frameworks.

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Rational Choice Perspective

The rationalist tradition conceptualizes risk as a quantifiable function of probability and consequence. Rooted in the work of Bernoulli (1738) and formalized by Von Neumann and Morgenstern (1944), this perspective assumes that individuals make decisions by maximizing expected utility. Risk is treated as an objective phenomenon that can be measured and managed through statistical and economic tools.

Socio-Cultural Perspectives

Beck (1992) "Risk Society" thesis (1992) and Giddens (1999) theory of Reflexive Modernity argue that modernity has produced new categories of "manufactured risks"—global, irreversible hazards arising from technological and industrial advancement. These risks differ fundamentally from historical "natural risks" and require new governance structures.

Douglas and Wildavsky (1982) extend this view by proposing the Cultural Theory of Risk, which posits that risk perception is shaped by social norms, group identities, and institutional structures. Different social groups prioritize different risks based on their cultural orientations.

Psychopolitical Perspectives

Drawing on Foucault's concept of governmentality, psychopolitical theories view risk as a mechanism of social regulation. Rose (1996) argues that labeling behaviors as "high risk" enables institutions to shape individual conduct and manage populations. In this view, risk is not merely a technical construct but a tool of governance.

METHODOLOGY

This study adopts a **desk-research approach**, drawing on cash-flow estimates from five proposed projects previously evaluated by the lead author. These projects were subjected to comparative investment appraisal and risk assessment using both traditional discounted cash-flow (DCF) techniques and three distinct risk-quantification models: **Monte Carlo simulation**, **Mean-Relative Regression (MRR)** analysis, and **Enyi's simplified statistical risk model**.

The DCF framework was used to determine baseline project viability, while the three risk-assessment techniques were applied to quantify the uncertainty inherent in the projected cash flows. Monte Carlo simulation provides a stochastic representation of cash-flow variability; MRR offers a regression-based measure of relative dispersion; and Enyi's simplified model evaluates risk through the coefficient of variation and the distribution of cash-flow deviations around the mean.

MRR is particularly useful because it allows flexible evaluation of covariate effects on a survival-type cash-flow variable while retaining interpretability on the time scale (He et al., 2020). As Peng (2021) notes, MRR—similar to quantile regression—offers stable computation and intuitive interpretation, making it suitable for project-level risk analysis.

Model formulation

The following notations are used throughout the analysis:

m = mean cash flow

a_t = annual cash flow for time t.

p_t = probability of cash flow (a_t) occurring

prs = project realization risk

rv = risk associated with loss of money value (purchasing power)

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cs = project chance of success

td = total discounted cash flow of all estimates and residual value

tu = total undiscounted cash flow of all estimates and residual value

ocs = over all chance of project success

ha = highest annual cash flow

$\hat{a}_t$ = $\hat{y}$ = predicted annual cash flow for time *t*.

mrr_risk = Mean relative regression risk

RSS = residual sum of squares

TSS = total sum of squares

e = residual

t = time or cash flow period

With MRR, the annual cash flow projections which becomes the predictor variable will be regressed against the outcome variable computed using the formula for m, â, with the associated risk computed using the RSS and TSS as follows:

$m = (\sum_t^n a_t) / n$ (1)

$\hat{a}_t = a_t(a_t/m)$ (2)

$mrr\_risk = 1 - \frac{RSS}{TSS}$ (3)

$TSS = (y - \bar{y}1)^T(y - \bar{y}1)$ (4)

$e = y - \hat{y}$ (5)

$RSS = e^Te$ (6)

$td = \sum_{t=1}^n a_t(1+i)^{-t}$ (7)

$tu = \sum_{t=1}^n a_t$ (8)

$rv = 100 - \{(\frac{1-td}{tu} 100)$ (9)

$prs = \{\sqrt{\sum(p_t(a_t - m)^2)}\} / m$ (10)

$cs = 100 - rv$ (11)

$ocs = cs(1 - prs)$ (12)

Enyi’s Simplified Statistical Risk Model

Enyi’s model evaluates project risk using the **coefficient of variation (CV)**, computed as:

$CV = \sigma/m$ (13)

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$Rd_u = [(ha – (m + σ)) / CV] * 100$ (14)

$Rd_l = [(m – (la + σ) / CV] * 100$ (15)

where:

σ is the standard deviation of the cash-flow distribution.

Rd_u is the upper limit risk.

Rd_l is the lower limit risk.

ha is the highest cash flow value.

la is the lowest cash flow value.

m is the mean cash flow.

Beyond computing CV, the model examines the **distribution of covariations around the mean**, enabling identification of whether risk is skewed toward downside or upside outcomes. This directional insight supports more nuanced project ranking and decision-making.

Computational Tools

Monte Carlo simulations and MRR analyses were performed using **ValuStats (VSP) version 2.0**, which supports iterative simulation, regression modeling, and statistical diagnostics. Enyi's simplified model was computed manually and verified using spreadsheet-based statistical functions.

Data and Analysis

This section presents the empirical data used in the comparative appraisal of the five sampled projects and applies the three risk-assessment techniques—Monte Carlo simulation, Mean-Relative Regression (MRR), and Enyi's simplified statistical risk model. The analysis proceeds in three stages: (1) statistical risk modeling, (2) integration of cash-flow realization risk with project actualization risk, and (3) application of DCF metrics to evaluate overall project viability.

Statistical Risk Modeling

Statistical risk modeling decomposes the risk metrics associated with each project to provide a clearer understanding of the magnitude and direction of risk exposure. Table 1 presents the cash-flow streams for the five projects, along with their frequency distributions, mean values, standard deviations, and coefficients of variation.

Table 1: Cash-Flow Listing and Descriptive Statistics for Five Projects

Stream	Project 1 (F)	Project 2 (F)	Project 3 (F)	Project 4 (F)	Project 5 (F)
1	45,000 (3)	2,000 (2)	3,000 (2)	2,500 (3)	55 (17)
2	50,000 (3)	3,000 (3)	3,500 (4)	3,000 (3)	155 (15)
3	55,000 (6)	4,000 (5)	4,000 (8)	3,500 (7)	255 (11)
4	60,000 (5)	5,000 (5)	4,500 (4)	4,200 (4)	355 (14)
5	65,000 (3)	6,000 (5)	5,000 (2)	5,500 (3)	455 (12)

6–10	—	—	—	555–955	—
Mean	55,000	4,000	4,000	3,715	418.5
Std. Dev.	6,305	1,280.63	547.72	916.12	289.25
Coefficient of Variation (%)	11.36	29.11	13.69	24.66	69.12

The coefficient of variation (CV) provides a normalized measure of dispersion, enabling comparison across projects with different cash-flow magnitudes. Project 5 exhibits the highest CV (69.12%), indicating substantial volatility relative to its mean cash flow.

Table 2: Project Risk Distribution Analysis

Metric	**Project 1**	**Project 2**	**Project 3**	**Project 4**	**Project 5**
Highest Value	65,000	6,000	5,000	5,500	955
Upper Risk Deviation	3,695	319.37	452.28	868.88	247.25
Upper Limit Value	61,305	5,680.63	4,547.72	4,631.12	707.75
Mean	55,000	4,400	4,000	3,715	418.5
Lower Limit Value	48,695	3,119.37	3,452.28	2,798.88	129.25
Lower Risk Deviation	3,695	1,119.37	452.28	298.88	74.25
Lowest Value	45,000	2,000	3,000	2,500	55
Standard Deviation	6,305	1,280.63	547.72	916.12	289.25
Risk Level (CV %)	11.36	29.11	13.69	24.66	69.12
Total Risk Deviation	7,380	1,438.74	904.56	1,167.76	321.50
Top-Limit Risk	5.68 (50%)	6.46 (22.2%)	6.85 (50%)	18.35 (74.4%)	53.16 (76.9%)
Bottom-Limit Risk	5.68 (50%)	22.65 (77.8%)	6.85 (50%)	6.31 (25.6%)	15.96 (23.1%)
Risk Characteristic	Even	Bottom-heavy	Even	Top-heavy	Top-heavy

The distribution analysis reveals that

1) Projects 1 and 3 exhibit even risk distribution.
2) Project 2 is bottom-heavy, indicating greater downside exposure.
3) Projects 4 and 5 are top-heavy, suggesting a higher likelihood of achieving upper-bound cash flows.

MRR regression results (details omitted for brevity) produced risk estimates of 9.8%, 8.2%, 7.4%, 21.3%, and 27.75% for Projects 1–5, respectively.

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Inter-Phasing Cash Flow Realization Risk with Project Actualization

Cash-flow realization risk must be integrated with project actualization risk to obtain a comprehensive risk profile. While DCF techniques adjust for the time value of money, they do not inherently validate the reliability of projected cash flows. The following key questions arise:

1) How accurate are the projected cash flows?

2) Have all uncertainties and impediments been accounted for?

3) What is the probability that the project will achieve its intended outcomes?

These are the questions that shall be addressed to illustrate this integration using the case-study project as analyzed using both cash-flow realization risk and DCF metrics.

Case-Study Project Parameters: Initial cost: $200,000; **Project life:** 10 years; **Discount rate:** 17.5%; **Cash flows:** 22,000; 34,000; 47,500; 58,000; 68,500; 79,000; 92,000; 102,000; 112,000; 120,000.

Cash-Flow Realization Risk

The journey to computing the risk inherent starts with - Mean cash flow: **$73,500** Standard deviation: **$31,595.89** Coefficient of variation: **43%**

The risk distribution analysis metrics are detailed as follows:

Highest cash flow: 120,000

Lowest cash flow: 22,000

Upper limit: 105,095.89

Lower limit: 41,904.11

Upper deviation: 14,904.11

Lower deviation: 19,904.11

Total deviation: 34,808.22

The risk allocation between the top limit risk (the probability of not attaining the highest cash flow) and the bottom limit risk (the probability of not getting to the lowest cash flow projection) are as follows:

Top-limit risk: **18.4% (42.8% of total risk)**

Bottom-limit risk: **24.6% (57.2% of total risk)**

Interpretation

The risk distribution around the mean cash flow for the case project is **bottom-heavy**, meaning the project is more likely to achieve higher cash flows than to fall to the minimum projection.

DCF Analysis of the Projections

The DCF analysis metrics for the case-study project are: Total discounted cash flows (td): $271,643.05; Total undiscounted cash flows (tu): **$735,000**; NPV at 17.5%: **$71,643.05**; NPV at 22.5%: **$16,562.95**; IRR: **24%**

Project Actualization Risk

Using the formulas in section 3 we compute the risk metrics for the case study project as follows:

Risk of loss of purchasing power: $rv = 36.96\%$

Project chance of success: $cs = 63.04\%$

Overall chance of success: $ocs = 0.6304\times(1-0.43) = 35.93\%$

Overall project risk: $100-35.93 = 64.07\%$

Risk-adjusted discount rate range:

Lower bound: $17.5\%\times1.3593 = 23.8\%$

Upper bound: $17.5\%\times1.6406 = 28.7\%$

Since the IRR (24%) exceeds the lower bound, the project retains a **fair chance of success**.

The case study project's overall analysis metrics are presented in the following table for clarity:

Metric	**Value**
Risk of loss of purchasing power	36.96%
Mean cash flow	$73,500
Standard deviation	$31,595.89
Coefficient of variation	43%
Chance of success	63.04%
Risk-adjusted chance of success	35.93%
Overall project risk	64.07%
Risk-adjusted discount range	23.8% – 28.7%
Net Present Value (NPV)	$71,643.05
Internal Rate of Return (IRR)	24%
Allowable risk premium	6.5%
% of allowable risk premium utilized	58.04%

RESULTS

A comprehensive set of analytical procedures was applied to evaluate the viability and risk characteristics of the five sampled projects and the case-study project. The results presented in this section integrate outputs from the Monte Carlo simulation, Mean-Relative Regression (MRR) analysis, and Enyi's simplified statistical risk model. Together, these methods provide a multidimensional view of project risk—capturing not only the magnitude of uncertainty but also its distribution around expected cash-flow values. The findings highlight areas of convergence and divergence across the three modeling approaches and offer insights into how each method informs investment appraisal under uncertainty.

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Monte Carlo Risk Analysis

To evaluate the uncertainty inherent in the case-study project, a Monte Carlo (MC) simulation was conducted using 10,000 iterations. Each annual cash-flow value was modeled as a normally distributed variable with a standard deviation of 10% to reflect plausible variability in project performance (see figure 1). The simulation produced the following key results:

Mean NPV: $71,658.66

Probability (NPV > 0): 100%

Breakeven discount rate (MC-derived IRR): 24.38%

Implied risk premium: 11.52%

These results indicate that, under simulated uncertainty, the project maintains a positive NPV across all iterations at discount rates up to 24.38%. The MC-derived risk premium (11.52%) closely aligns with the 11.5% premium estimated using the simplified statistical risk model, suggesting convergence between the two approaches.

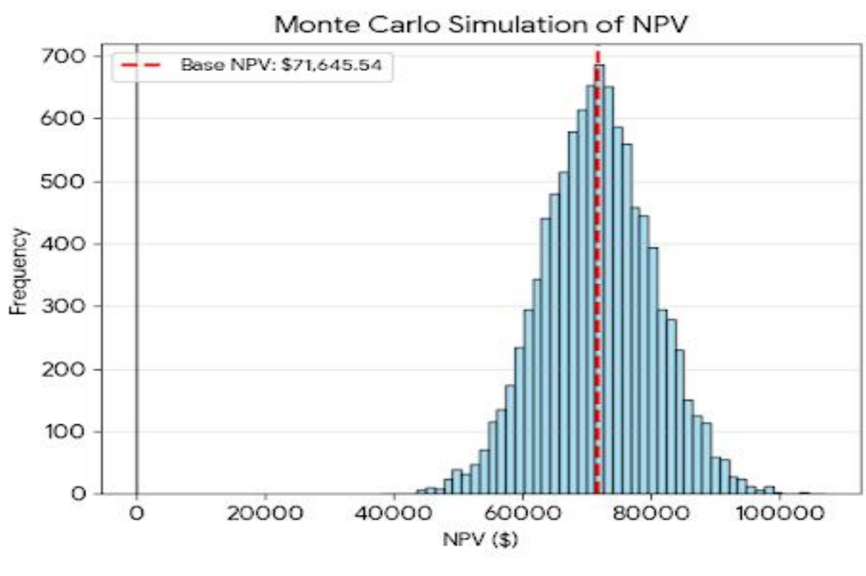
Statistical Risk Distribution

The risk-distribution analysis in Tables 1 and 2 reveals important differences in the behavior of the five projects as outlined in the following section:

Projects 1 and 3 exhibit **even risk distribution**, meaning the likelihood of deviating above or below the mean cash flow is symmetrical. However, **project 2** is **bottom-heavy**, with 22.65% of its 29.11% total risk concentrated below the mean, implying a relatively low probability of falling below the lower cash-flow threshold.

Projects 4 and 5, on the other hand, are **top-heavy**, with 74.4% and 76.9% of their respective risks concentrated above the mean, suggesting that these projects are more likely to underperform relative to their highest projections.

Figure 1: Monte Carlo Risk Simulation Chart



Source: ValuStats (VSP) 2.0

The MRR regression results further quantified project risk with the following results: **Project 1:** 9.8%; **Project 2:** 8.2%; **Project 3:** 7.4%; **Project 4:** 21.3%; and **Project 5:** 27.75%

Case-Study Project: Integrating Risk Premiums and DCF Metrics

The case-study project requires a risk premium of 28.7%−17.5% = 11.5%. However, because the project's IRR is **24%**, only 24%−17.5% = 6.5% of the required premium can be absorbed without rendering the project unviable. This represents **58.04%** of the required risk premium. The DCF results are NPV **(17.5%):** $71,643.05; **NPV (22.5%):** $16,562.95; and **IRR:** 24%.

Comparative Evaluation of the Three Risk Models on the Case Study Project

Table 3 summarizes the risk estimates generated by the Monte Carlo simulation, MRR analysis, and Enyi's simplified statistical model.

Table 3: Comparison of Risk Figures Across Models

Model	Project 1	Project 2	Project 3	Project 4	Project 5
Monte Carlo	13%	24%	12.5%	25.1%	48%
MRR	9.8%	8.2%	7.4%	21.3%	27.75%
Enyi's Model	11.36%	29.11%	13.69%	24.66%	69.12%

Other key Observations on the metrics of the case-study project

Other key information revealed by the case-study project analysis are outlined for clarity as follows:

1. **Monte Carlo and Enyi's model** produce broadly comparable results, especially for Projects 1, 3, and 4.
2. **MRR** consistently yields lower risk estimates and appears less sensitive to extreme variations, making it less precise for ranking high-volatility projects.
3. **Enyi's model** provides the most granular insight into risk directionality (top-heavy vs. bottom-heavy), which neither MC nor MRR explicitly captures.
4. **Project 5** consistently emerges as the riskiest across all models, with Enyi's model highlighting its extreme volatility (69.12%).

DISCUSSION

The results highlight important differences in how the three risk-assessment models capture project uncertainty and how these insights can guide investment decision-making.

Interpretation of Monte Carlo Results

The Monte Carlo simulation confirms the robustness of the case-study project under uncertainty. A 100% probability of NPV > 0 suggests that the project is resilient across a wide range of possible outcomes. The MC-derived breakeven rate of 24.38% closely matches the project's IRR (24%), reinforcing the reliability of the DCF results. The MC-implied risk premium of 11.52% also aligns closely with the 11.5% premium derived from Enyi's simplified statistical model, suggesting that the latter provides a credible approximation without requiring intensive computation.

Interpretation of Risk Distribution Patterns

The risk-distribution analysis provides deeper insight into the directional nature of project risk. This indicates that even-risk projects (1 and 3) offer balanced upside and downside potential, making them stable investment options while bottom-heavy projects (like Project 2) are more likely to achieve higher cash flows than to fall below minimum thresholds, making them particularly attractive. Top-heavy projects (4 and 5), on the other hand, exhibit high downside risk, with a strong likelihood of underperforming relative to their highest projections.

This directional insight is critical because traditional DCF metrics do not reveal whether risk is skewed toward upside or downside outcomes. The Enyi's simplified statistical model fills this gap by showing not only how much risk exists but also where it lies relative to expected performance.

Integrating Risk Premiums with DCF Metrics

The case study project demonstrates the importance of integrating risk premiums into DCF analysis. While the required premium is 11.5%, only 6.5% can be absorbed without exceeding the project's IRR. This highlights a key managerial insight, which warns that risk premiums must be applied judiciously and that excessive adjustments can lead to the rejection of viable projects.

The simplified statistical model, on the other hand, provides a structured way to determine an appropriate premium, thereby avoiding arbitrary adjustments that distort investment decisions.

Implications for Project Selection

From the results in tables 1 and 2, the implications for project selection are that **Projects 1, 2, and 3** are more attractive because they exhibit either even or bottom-heavy risk distributions, meaning they are more likely to achieve or exceed their mean cash-flow projections. Project 2, on a closer observation, appears particularly strong, with only a 22.2% risk of not achieving its highest cash-flow value—lower than the 50% risk observed for Projects 1 and 3. **Projects 4 and 5**, with more than 70% of their risk concentrated above the mean, are more likely to underperform and therefore present less favorable investment prospects.

This demonstrates the value of statistical risk modeling: by examining the direction and magnitude of risk around the mean, managers can make more informed investment decisions beyond what traditional DCF metrics reveal.

Comparative Performance of the Three Models

The three models differ in sensitivity and interpretive value, for while Monte Carlo simulation is the most comprehensive but requires advanced tools and assumptions about probability distributions, MRR identifies relative risk levels but tends to understate risk magnitude and lacks directional insight, while Enyi's simplified model offers a practical balance—easy to compute, directionally informative, and closely aligned with MC results.

Overall, Enyi's simplified model emerges as the most accessible and decision-useful tool for practitioners who require robust risk insights without the complexity of advanced simulation techniques.

CONCLUSION

Effective recognition and integration of risk are indispensable components of investment planning, project appraisal, and project execution. Ignoring risk in capital-investment decisions is analogous to navigating an aircraft without a compass—possible, but dangerously uninformed. Equally problematic is the use of inappropriate or misleading risk metrics. As Dixit and Pindyck (1994) caution, flawed risk measures can misguide investors into accepting projects that should be rejected or abandoning opportunities that are fundamentally sound.

This study demonstrates that while sophisticated models such as Monte Carlo simulation and Mean-Relative Regression (MRR) offer valuable insights, they often require technical expertise and computational resources that may not be readily available to practitioners. In contrast, Enyi's simplified statistical risk model provides a practical, transparent, and analytically robust alternative. Beyond its ease of application, the model offers an important additional advantage: it reveals the direction of risk distribution around the mean cash-flow projection. This directional insight—whether risk is top-heavy, bottom-heavy, or evenly distributed—enables decision-makers to understand not only how much risk exists but also where that risk lies relative to expected performance.

The findings of this study reinforce the argument that simplified, well-structured risk-integration frameworks can produce decision-useful results comparable to more complex models. By enabling managers to quantify risk, interpret its distribution, and incorporate it meaningfully into investment appraisal, such models enhance the reliability of capital-budgeting decisions and support more resilient strategic planning.

Declarations

Ethical Approval and Consent to Participate

This research did not involve any human or animal subjects. The study exclusively utilized available investment cash flow projections used for tutorial purposes only. According to the Babcock University Research and Ethics Committee (BUREC) guidelines, research using tutorial archived documents is exempt from ethical scrutiny that applies to studies involving direct contact with humans or animals.

Consent for Publication

No personalized details, images, or videos of any individuals were used in the preparation of this document; thus, no consent for publication is required.

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Data Availability

The data used for the analysis in this study are available from the corresponding author upon request.

Conflict of Interest

The authors have no conflict of interest to declare.

Authors' Contributions

The first author wrote the manuscript, the second author proofread the manuscript, the third author supplied the literature, and the fourth and fifth authors performed the analysis and effected the pre-submission suggested corrections.

Declaration of Generative AI and AI-assisted Technologies

This study has not used any generative AI tools or technologies in the preparation of this manuscript.

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