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A Technical Framework for Monte Carlo-Based Coal Mining Valuation

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ABSTRACT

Coal mining valuation must represent uncertainty from price cycles, output and cost variability, policy constraints, exchange rates, and capital market risk. Deterministic discounted cash flow remains a useful baseline but yields false precision for cyclical commodity businesses. A desk-based framework for Monte Carlo simulation in coal mining valuation is developed by synthesising valuation theory, mining risk literature, commodity price modelling, and simulation-based decision analysis across five stages: problem identification, free cash flow to firm mapping, input classification, distribution assignment, and output interpretation. Four blocks are integrated (operating assumptions, financial assumptions, simulation design, output interpretation) with seven stochastic drivers under lognormal, triangular, or truncated normal distributions: coal benchmark price, selling price realisation, production volume, operating margin, weighted average cost of capital, terminal multiple, and exchange rate. Interpretation rests on P10, P50, and P90 percentiles with sensitivity ranking rather than a single point estimate, supported by eleven matrices. Application is demonstrated on an export-oriented producer on the Indonesia Stock Exchange. Seaborne benchmark prices for 2001 to 2024 calibrate to a reversion speed of 0.328 and a 2.12 year shock half-life. Across ten thousand trials, value per share spans IDR 30,356 (P10) to IDR 75,048 (P90), median IDR 45,879, with the deterministic estimate 3.5% above the median and benchmark price years accounting for 72.5% of output variance. The approach supports mining economics teaching, preliminary investment risk screening, and empirical research.

Keywords: *coal valuation; discounted cash flow; free cash flow to firm; Monte Carlo simulation; probabilistic framework*

Introduction

Coal mining companies operate under high uncertainty. Firm value depends not only on reserves and production capacity but also on coal price cycles, operating costs, exchange rates, domestic policy obligations, environmental requirements, capital structure, and investor risk perception. These features separate coal valuation from the valuation of stable non-commodity firms.

Discounted cash flow remains among the most widely used valuation methods because it links firm value to expected future cash flow discounted at an appropriate cost of capital (Danielson, 2023; Rodríguez, 2024). In a standard free cash flow to firm model, the analyst estimates revenue, operating profit, tax, capital expenditure, working capital, terminal value, and discount rate, producing an enterprise value and, after debt and cash adjustment, an equity value.

The limitation of deterministic valuation becomes material in cyclical commodity sectors. Such models rest on a single set of assumptions: one price forecast, one production scenario, one operating margin, one discount rate. The result can be false precision, a model that looks exact while its inputs remain uncertain. In commodity valuation this is not a minor technical weakness, since it can reverse the direction of the conclusion.

Benchmark coal prices move in pronounced cycles driven by demand shocks, supply constraints, delayed capacity response, and investment cycles that pass directly into issuer profitability (Endri et al., 2021; Prakoso & Faturohman, 2024). Prices rise sharply during energy shocks and fall when supply adjusts or demand weakens. Treating peak-cycle prices as permanent overstates intrinsic value; treating trough-cycle prices as permanent understates long-term value. Both errors match the valuation-trap problem in cyclical and commodity-firm valuation (Markovic et al., 2025).

Mining literature treats uncertainty as central to resource-sector analysis, spanning commodity prices, grade, reserves, production volume, capital expenditure, operating cost, exchange rate, taxation, environmental cost, and discount rate. Monte Carlo simulation has therefore been used to evaluate mining projects under economic uncertainty, since it translates uncertain inputs into a range of outcomes rather than one deterministic number (Kamel et al., 2023; Markovic et al., 2025; Pawlak & Wiśniewski, 2024). In the Indonesian setting, Trijayanto and Hakam (2025) show that deterministic discounted cash flow does not fully capture price volatility and carbon pricing exposure, while Sunardi et al. (2023) find that domestic coal price policy moves issuer valuation directly.

Stochastic price modelling reinforces the probabilistic approach. Alfeus and Collins (2023) represent thermal coal production and logistics through stochastic processes and show that the optionality embedded in a coal operation can be valued once price dynamics are modelled explicitly. Prakoso and Faturohman (2024) apply static and dynamic stochastic price models to Indonesian mining project valuation and report that the treatment of price uncertainty changes project value. Correlation structure between inputs also shapes the realism of risk analysis, because valuation variables seldom move independently (Ardian & Kumral, 2021; Markovic et al., 2025).

For listed miners, uncertainty is a capital-market issue as much as an operational one, since value emerges from the interaction between commodity prices, issuer-level operating assumptions, capital structure, currency exposure, investor risk premium, and market benchmark. Skogsvik et al. (2023) argue that discounted cash flow valuation can incorporate risk states rather than unconditional expected cash flows alone. Buchanan (2025) connects mineral-project valuation with share-performance metrics in listed mineral companies, showing that technical and market valuation are related but not identical.

This article develops a technical framework for applying Monte Carlo simulation to coal mining valuation and demonstrates it on one coal producer listed on the Indonesia Stock Exchange, exposing the mechanics on observed data: calibration of the price process, assignment of distributions, treatment of correlation between inputs, and reading of simulated output. The article is not an equity research report. It does not test whether the market price of any issuer is correct and offers no investment recommendation, and the values reported remain conditional on the assumptions adopted here.

The research problem is therefore: how can Monte Carlo simulation be structured as a technical framework for communicating valuation uncertainty in coal mining companies? The objective is a simplified framework linking operating assumptions, financial assumptions, simulation design, and output interpretation, examined once on observed data. The contribution is methodological and educational, providing a practical model architecture and one documented demonstration for mining-economics students, analysts, and researchers who face valuation risk in cyclical coal businesses.

Research Methods

This article develops a technical framework through desk-based synthesis of valuation theory, mining-risk literature, commodity-price modelling, and simulation-based decision analysis. No field survey, interview, or laboratory test is conducted, and all data used in the demonstration are secondary and publicly available. The output is conceptual and methodological. Valuation figures in the demonstration illustrate how the framework behaves under the stated assumptions and are not an equity valuation opinion on any issuer.

The development process runs in five stages: identifying the valuation problem in coal mining companies, mapping the deterministic discounted cash flow structure, classifying uncertain valuation inputs, assigning candidate probability distributions to selected uncertain variables, and defining interpretation rules for Monte Carlo output.

The basic valuation model uses the free cash flow to firm approach. Enterprise value is expressed as follows:

$$EV = \sum_{t=1}^{n} \frac{FCFF_t}{(1 + WACC)^t} + \frac{TV_n}{(1 + WACC)^n}$$

Where (EV) is enterprise value, $(FCFF_t)$ is free cash flow to firm in year (t), $(WACC)$ is the weighted average cost of capital, and (TV_n) is the terminal value at the end of the projection period. This structure follows standard corporate valuation logic (Damodaran, 2012; Danielson, 2023; Koller et al., 2020). Free cash flow to firm is defined as follows (Damodaran, 2012; Rodríguez, 2024):

$$FCFF = EBIT(1 - T) + D\&A - CAPEX - \Delta NWC$$

Where *(EBIT)* is earnings before interest and tax, *(T)* is the corporate tax rate, $D\&A$ is depreciation and amortization, *(CAPEX)* is capital expenditure, and ΔNWC is the change in net working capital. For coal mining firms, this formula must be interpreted with attention to stripping activity, mine development, sustaining capital expenditure, reclamation obligations, reserve depletion, and mine-life constraints. The weighted average cost of capital is expressed as follows (Danielson, 2023; Rodríguez, 2024):

$$WACC = \left(\frac{E}{V}\right) K_e + \left(\frac{D}{V}\right) K_d (1 - T)$$

Where *(E)* is equity value, *(D)* is debt value, *(V)* is total capital, (K_e) is the cost of equity, (K_d) is the cost of debt, and *(T)* is the tax rate. The cost of equity may be estimated using the capital asset pricing model (Franc-Dąbrowska et al., 2021):

$$K_e = R_f + \beta \times ERP$$

Where (K_e) is the cost of equity, (R_f) is the risk-free rate, (β) is the equity beta, and (ERP) is the equity risk premium. CAPM rests on Sharpe (1964) and Lintner (1965), while the leverage adjustment to equity beta follows Hamada (1972). Emerging-market valuation demands care with country risk premium and currency consistency, since inconsistent discount-rate assumptions distort value: local-currency cash flows require a local-currency discount rate, and USD cash flows require a USD-consistent one (Damodaran, 2012; Lilford, 2023).

The Monte Carlo component enters after the deterministic model is defined. Uncertain variables become probability distributions, and repeated simulation produces a distribution of enterprise value, equity value, and intrinsic value per share for listed companies. Results are read through percentiles and sensitivity analysis rather than a single point estimate.

No single software package is prescribed. Spreadsheets, statistical packages, or dedicated risk-analysis software all serve, provided that model structure, assumptions, distributions, correlation treatment, and output interpretation remain transparent and reproducible. Where correlated assumptions are required, Iman and Conover (1982) offer one statistical basis for inducing rank correlation among input variables. The stochastic component rests on the mean-reverting representation of commodity prices demonstrated by Schwartz (1997). The coal benchmark price is therefore treated as a risk driver reverting towards a long-run central tendency rather than as a fixed forecast, with process parameters calibrated on historical price series before simulation (Sauvageau & Kumral, 2018; Alfeus & Collins, 2023).

The demonstration in subsection 1.11 follows the same five stages. There the benchmark price process is calibrated by regressing the first difference of the log benchmark price on its lagged level, yielding the persistence parameter, the speed of reversion as the negative natural logarithm of that parameter, the implied long-run price level, and the residual volatility. Dispersion therefore widens with the projection horizon while the central path converges towards the long-run level. Serial correlation among annual price draws is imposed as the persistence parameter raised to the absolute difference between the two years, preventing consecutive years from being drawn independently. Every simulation uses ten thousand trials with Latin hypercube sampling and a fixed random seed, so the run can be repeated and audited. Trial count, sampling method, and seed are treated as reportable items, because a percentile that has not stabilised across repeated runs is not a usable output.

Table 1. Framework Development Stages

Stage	Main Activity	Expected Output
1	Identify coal mining valuation problem	Problem boundary and valuation objective
2	Map deterministic DCF structure	Baseline FCFF-WACC model
3	Classify uncertain inputs	List of deterministic and stochastic variables
4	Assign probability distributions	Simulation-ready input model
5	Interpret Monte Carlo output	P10, P50, P90, sensitivity, and boundary notes

Source: synthesised from Kamel et al. (2023), Ronyastra et al. (2024), and Markovic et al. (2025).

Results and discussion

1.1 Valuation Risk in Coal Mining Companies

Coal mining valuation carries several layers of risk. The first is commodity-price risk. Coal price drives revenue directly and also shapes margin, working capital, capital spending, and investor sentiment. Price cycles are long and volatile, which makes single-price assumptions insufficient (Endri et al., 2021; Sunardi et al., 2023).

The second layer is operational risk. Production may depart from plan because of geological conditions, equipment availability, rainfall, hauling distance, stripping ratio, contractor performance, and permit constraints. Volume alone is not enough for coal companies; calorific value, sulfur, ash, and moisture also govern selling price and market access.

The third layer is cost risk. Operating cost moves with fuel prices, contractor rates, labor, spare parts, overburden removal, hauling, barging, port charges, royalties, and environmental obligations. A higher coal price therefore need not lift company value proportionally when costs rise alongside it.

The fourth layer is financial risk, covering discount rate, capital structure, cost of debt, exchange rate, and equity risk premium. Small changes in WACC can produce large changes in present value, especially when terminal value contributes a large share of enterprise value (Danielson, 2023; Franc-Dąbrowska et al., 2021).

The fifth layer is regulatory and policy risk: domestic market obligation, royalty regulation, export policy, environmental and reclamation requirements, and carbon-transition pressure. These affect both cash flow and valuation multiple. Coal mining valuation should therefore be treated as a risk-based estimation problem rather than a fixed calculation.

Table 2. Valuation Risk Layers in Coal Mining Companies

Risk Layer	Typical Variables	Valuation Effect
Commodity price risk	Benchmark coal price, market cycle, demand shock	Directly affects revenue and margin
Operational risk	Production, coal quality, stripping ratio, logistics	Changes volume, ASP, and operating cost
Financial risk	WACC, beta, cost of debt, exchange rate	Changes present value and equity value
Policy risk	DMO, royalty, export policy, carbon pressure	Changes cash flow and terminal multiple
Terminal risk	Mine life, reserve depletion, exit multiple	Changes residual value and valuation range

Source: synthesised from Endri et al. (2021), Lilford (2023), Sunardi et al. (2023), and Markovic et al. (2025).

1.2 Deterministic DCF as Baseline Model

Deterministic DCF remains necessary because it supplies the economic structure of valuation, linking production, price, cost, tax, investment, and discount rate into one coherent system. Without that structure, simulation has no economic foundation.

The model should nevertheless be treated as a baseline rather than a final answer. Its main weakness in coal valuation is dependence on fixed assumptions. A single output looks precise, yet the precision may be artificial, because the value shifts materially once coal price, margin, WACC, terminal multiple, or exchange rate moves.

A practical model therefore separates architecture from input certainty. The architecture may follow FCFF-WACC logic while the inputs are tested through distributions or scenarios. This keeps the model economically grounded and reduces the false precision of a single deterministic output.

Table 3. Deterministic DCF Components in Coal Mining Valuation

Component	Function in Valuation	Main Risk
Coal price	Determines benchmark revenue potential	Commodity cycle and price shock
ASP realization	Converts benchmark price into issuer selling price	Coal quality, contract type, DMO, export mix
Production volume	Determines sales volume	Operational disruption and reserve constraints
Operating margin	Converts revenue into operating profit	Cost inflation and stripping variation
WACC	Discounts future cash flow	Beta, ERP, debt cost, currency, country risk
Terminal value	Captures residual firm value	Mine life, resource depletion, multiple risk

Source: synthesised from Damodaran (2012), Koller et al. (2020), Danielson (2023), and Rodríguez (2024).

1.3 Proposed Monte Carlo Valuation Architecture

The framework rests on four integrated blocks: operating, financial, simulation, and interpretation. The structure keeps the valuation model tractable while retaining the main uncertainty drivers.

The operating block starts from coal-price assumptions. Benchmark price should not be treated as company selling price. Average selling price must be adjusted through a realization ratio, since coal quality, domestic-market exposure, contract structure, and export mix differ across companies.

The financial block converts operating assumptions into free cash flow and present value through WACC, terminal value, net cash or net debt, and currency conversion. Currency consistency matters here. USD cash flows require a discount rate built on USD assumptions, while local-currency cash flows require a risk-free rate, inflation, and discount-rate structure that follow local-currency logic.

The simulation block turns uncertain inputs into probability distributions. The analyst defines which variables are uncertain, which distributions apply, and whether the variables should be correlated, because valuation inputs are rarely independent. Coal price, margin, exchange rate, and terminal multiple may move together under stressed market conditions (Iman & Conover, 1982; Ardian & Kumral, 2020).

The interpretation block translates simulation output into decision-support information. A single value is not enough. P10, P50, and P90 are more informative because they show downside, central, and upside valuation conditions.

Table 4. Proposed Monte Carlo Valuation Architecture

Block	Main Elements	Purpose
Operating block	Coal price, ASP realization, production, margin	Estimates revenue and operating cash flow
Financial block	FCFF, WACC, terminal value, net debt, currency	Converts operating output into firm and equity value

Simulation block	Input distributions, correlation, repeated trials	Generates valuation distribution
Interpretation block	P10, P50, P90, sensitivity ranking	Communicates valuation-risk profile

Source: synthesised from Sauvageau and Kumral (2018), Kamel et al. (2023), and Markovic et al. (2025).

1.4 Input Classification and Distribution Logic

The framework separates deterministic inputs, fixed for modelling convenience or relatively stable, from stochastic inputs, those carrying material uncertainty and high valuation impact. Distribution choice should follow economic logic and data availability. A triangular distribution suits early-stage work where minimum, most likely, and maximum values can be defined, and its shape is easy to explain. A lognormal distribution suits price variables that cannot fall below zero and may carry upside skewness. A truncated normal suits discount rates, where extremely low or extremely high WACC values are unrealistic. Whatever is chosen should be documented plainly. A complex distribution does not by itself improve valuation quality; where data are weak, simpler assumptions are more transparent and more defensible. This matters in mining valuation, because sophistication can manufacture a false sense of accuracy when the assumptions are not grounded.

Table 5. Classification of Valuation Inputs

Input Type	Examples	Treatment
Deterministic inputs	Tax rate, shares outstanding, base reporting currency	Fixed unless scenario requires change
Semi-stochastic inputs	CAPEX, working capital, depreciation	Fixed in simple model or simulated in advanced model
Stochastic inputs	Coal price, ASP realization, margin, WACC, terminal multiple, FX	Converted into probability distributions

Source: synthesised from Ardian and Kumral (2020, 2021) and Markovic et al. (2025).

Table 6. Suggested Distribution Design

Variable	Suggested Distribution	Reason
Coal benchmark price	Lognormal or mean-reverting path	Price cannot be negative and may show skewness
ASP realization ratio	Triangular	Reflects minimum, most likely, and maximum realization
Production volume	Triangular	Reflects operational range
EBITDA margin	Triangular	Captures cost and profitability variation
WACC	Truncated normal	Allows uncertainty but avoids unrealistic rates
Terminal multiple	Triangular	Captures valuation-multiple uncertainty
Exchange rate	Triangular or lognormal	Captures currency translation risk

Source: synthesised from Franc-Dąbrowska et al. (2021), Alfeus and Collins (2023), Prakoso and Faturohman (2024), and Pawlak and Wiśniewski (2024).

1.5 Coal Price and ASP Treatment

Coal price is usually the most important input in coal mining valuation, shaping revenue, margin, reserve economics, mine planning, and investor perception. Benchmark price and company selling price are not the same thing: realized price depends on calorific value, sulfur, ash, moisture, contract terms, market destination, and policy constraints. A technical framework should therefore keep the benchmark separate from ASP realization, the benchmark carrying market direction while the realization ratio converts it into a company-specific selling price. Two producers may face one benchmark and still book different revenue. Mean-reverting price logic avoids projecting today's price permanently into the future. Schwartz (1997) provides the foundation for stochastic commodity-price modelling, and mining applications such as Sauvageau and Kumral (2018) show that calibrated stochastic processes support risk-based cash-flow analysis; Alfeus and Collins (2023) and Prakoso and Faturohman (2024) report the same behaviour for thermal coal. For a framework paper, defining the modelling logic is enough without estimating a final company-specific parameter. Coal price is therefore a risk driver, not a fixed forecast, and valuation output must show the range of value generated by different price paths and realization assumptions.

1.6 WACC and Discount-Rate Treatment

WACC drives the present value of future cash flows. In coal mining it carries systematic risk, leverage, debt cost, tax shield, currency basis, country risk, and sector cyclicality, and standard references require the discount rate to match the risk and the currency of the cash flows being discounted (Danielson, 2023; Lilford, 2023). Cost of equity may be estimated by CAPM, with beta capturing sensitivity to market risk (Sharpe, 1964; Lintner, 1965), still the working standard for cost-of-equity estimation in energy-sector firms (Franc-Dąbrowska et al., 2021); where leverage differs materially across companies, beta can be adjusted through the Hamada framework (Hamada, 1972). Beta in emerging-market commodity firms is not always stable. A short return window may capture one phase of the cycle rather than structural risk. The framework therefore treats WACC as a stochastic or semi-stochastic variable, with a truncated normal distribution representing discount-rate uncertainty while excluding unrealistic values, so the model can show how valuation responds as WACC moves within a reasonable range. Lilford (2023) stresses that natural-resource valuation must be explicit about discounting, risk, and uncertainty, because these choices materially affect value.

1.7 Terminal Value and Mine-Life Constraint

Terminal value is often among the most sensitive components of a DCF. Non-resource businesses may use perpetual growth or an exit multiple; coal mining demands more caution because the asset is finite, reserves deplete, and mine life can constrain long-term cash-flow generation. A terminal EV/EBITDA multiple serves in a simplified model provided it is bounded and read conservatively. Where remaining mine life is limited, terminal value should be adjusted, since perpetuity-based discounting misstates a finite-life asset (Danielson, 2023). Advanced models can carry reserve depletion, production scheduling, reclamation cost, and real options; the mining valuation literature shows that flexibility and uncertainty materially affect resource-asset value (Brennan & Schwartz, 1985; Kamel et al., 2023; Pawlak & Wiśniewski, 2024; Alghani & Hakam, 2025). Terminal value should therefore not be handled mechanically. It should be tested through sensitivity analysis and, where possible, folded into the simulation block; a valuation conclusion driven almost entirely by terminal value should be reported with caution.

1.8 Output Interpretation: P10, P50, P90, and Sensitivity

Monte Carlo simulation produces many valuation outcomes, and the useful output is the distribution rather than the average alone. P10, P50, and P90 serve as practical summaries: they communicate downside, central, and upside conditions without pretending that the future reduces to one exact number. The probability that intrinsic value exceeds a benchmark needs careful reading. It is not the probability that a share price will rise, only how often simulated intrinsic value clears a selected reference point under the model assumptions, and intrinsic value and market price are related but not identical. Sensitivity ranking matters as much. If coal price dominates output variance, the analyst should concentrate on price assumptions; if WACC dominates, on beta, the risk-free rate, the ERP, and the cost of debt; if ASP realization dominates, on coal quality, contract structure, and domestic-market exposure. This logic follows simulation-based risk communication in mining valuation (Kamel et al., 2023; Markovic et al., 2025; Ronyastra et al., 2024; Sauvageau & Kumral, 2018).

Table 7. Interpretation of Simulation Outputs

Output	Meaning	Use
P10	Downside percentile	Indicates conservative valuation condition
P50	Median percentile	Indicates central valuation condition
P90	Upside percentile	Indicates optimistic valuation condition
Mean	Average simulated value	Useful but sensitive to skewness

Output	Meaning	Use
Probability above benchmark	Share of simulated values above reference point	Diagnostic tool, not return forecast
Sensitivity ranking	Contribution of input variables to output variance	Identifies key valuation drivers

Source: synthesised from Kamel et al. (2023), Ronyastra et al. (2024), and Markovic et al. (2025).

1.9 Framework Application Categories

The framework applies to different types of coal mining company. Rather than report company-specific results, this article classifies the application categories, which keeps the treatment methodological while still showing how the framework works in practice. An export-oriented producer calls for closer attention to seaborne benchmark prices, foreign exchange, and export ASP realization. A domestic-exposure producer calls for attention to the domestic market obligation, pricing constraints, and policy stability. A structurally changing company calls for normalization, because historical financial statements may no longer represent the future business profile. The classification lets the framework be used without empirical claims about any one issuer. Applying it to selected companies remains a separate research design, with explicit data, assumptions, calibration procedures, and validation steps. The illustrative application in Subsection 1.11 falls within this limit; it demonstrates the mechanics on one issuer and does not constitute an empirical claim about that issuer.

Table 8. Application Categories for Coal Mining Valuation

Category	Characteristics	Main Modelling Focus
Export-oriented producer	High exposure to seaborne coal market	Benchmark price, FX, export ASP realization
Domestic-exposure producer	Significant domestic-market obligation	Domestic pricing, policy constraint, margin stability
Low-rank coal producer	Lower calorific value coal	ASP discount, logistics, market access
Integrated coal-energy company	Linked to power generation or downstream assets	Segment separation and transfer-pricing logic
Structurally changing company	Major divestment, merger, or restructuring	Normalized data and post-event comparability

Source: synthesised from Endri et al. (2021), Sunardi et al. (2023), and Trijayanto and Hakam (2025).

1.10 Boundary Conditions and Ethical Use

Monte Carlo simulation improves how valuation is communicated, but it does not remove uncertainty. Output quality follows assumption quality: weak assumptions produce weak results however advanced the simulation. Five boundary conditions apply to this framework. It is intended for preliminary valuation-risk analysis and mining-economics education; it does not replace technical due diligence, geological modelling, reserve audit, legal review, or environmental assessment; it offers no trading recommendation; it does not prove that a market price is wrong; and it requires transparent documentation of assumptions. Those limits carry an ethical obligation. Analysts should not present simulation output as certainty, and should state the assumptions, the distribution choices, the data limitations, and the boundaries of interpretation. That is the purpose of probabilistic valuation: to make uncertainty visible rather than hide it behind a single deterministic value.

Table 9. Boundary Conditions for Using the Framework

Boundary	Explanation	Practical Control
Not a trading model	The framework does not forecast stock returns	Use results as valuation-risk diagnostics only
Not a reserve audit	The model does not verify geological reserves	Use audited reserves or technical reports when available
Assumption-dependent	Output depends on input distributions	Document each assumption and data source
No market-efficiency test	Benchmark comparison does not prove mispricing	Avoid overclaiming undervaluation or overvaluation
Requires reproducibility	Simulation must be transparent	Report model structure, trials, and sensitivity logic

Source: synthesised from Lilford (2023), Skogsvik et al. (2023), and Buchanan (2025).

Illustrative Application of the Framework

The preceding subsections define the framework and its limits; this one demonstrates its behaviour when executed once on observed data. A single issuer was chosen rather than a portfolio because the aim is to expose the mechanics, not to compare companies: an export-oriented coal producer listed on the Indonesia Stock Exchange, the first category in Table 8 and the one for which a seaborne benchmark price is the economically appropriate driver. Every boundary condition in Table 9 continues to apply to the figures below.

Operating and financial inputs come from audited annual financial statements for 2015 to 2024; calibration uses the seaborne thermal coal benchmark observed each December from 2001 to 2024. Regressing the first difference of the log benchmark price on its lagged level gives a slope of −0.279 (SE 0.133; $t = -2.09$; $p = 0.049$), significant at the five per cent level but with low explanatory power ($R^2 = 0.173$). The implied speed of reversion is 0.328, the half-life of a price shock 2.12 years, and the long-run price level USD 97.36 per ton. The projection is anchored on the Indonesian benchmark coal price for December 2024, USD 122.51 per ton for the 6,322 kcal/kg GAR grade. Because that anchor lies above the long-run level, the projected mean path declines from USD 123.19 per ton in 2025 to USD 117.05 in 2029 while dispersion widens. The series is strongly right-skewed (skewness 2.99, kurtosis 11.62), which supports a lognormal rather than a symmetric distribution for the price driver. Table 10 records the data sources and the resulting input specification.

Table 10. Empirical Inputs and Simulation Specification

Item	Source or basis	Specification
	Data sources	
Benchmark price series	Seaborne thermal coal benchmark, December observation each year	2001 to 2024, used to calibrate the price process
Starting benchmark price	Indonesian benchmark coal price, 6,322 kcal/kg GAR, Ministerial Decree 339.K/MB.01/MEM.B/2024	USD 122.51 per ton, December 2024
Operating and financial data	Audited annual financial statements	2015 to 2024
Equity risk premium	Damodaran country risk dataset, January 2026	6.69% total for Indonesia
Risk-free rate	Ten-year United States government bond yield	4.39%
Stochastic drivers		
Benchmark price 2025 to 2029	Lognormal	Mean 123.19 declining to 117.05 USD per ton; standard deviation 47.64 rising to 66.40
ASP realisation ratio	Triangular	0.50 / 0.84 / 1.05 times benchmark price
Production volume	Triangular	19.4 / 21.5 / 23.7 million tonnes
Operating margin	Triangular	0.13 / 0.28 / 0.50
Weighted average cost of capital	Truncated normal	Mean 16.02%, standard deviation 1.00%, bounds 8% to 20%
Terminal multiple	Triangular	3.5 / 4.5 / 6.0 times EBITDA
Exchange rate	Triangular	14,500 / 16,157 / 18,500 IDR per USD
Run setting		
Trials, sampling, seed	Fixed for reproducibility	10,000 trials, Latin hypercube sampling, fixed seed
Correlation among price years	Persistence rule	Persistence parameter raised to the absolute difference between years

Source: Author construction.

The simulation was executed with ten thousand trials using Latin hypercube sampling and a fixed random seed. Seven stochastic drivers were defined, which is exactly the set identified in Table 6 with no additions. Serial correlation among the five annual price draws was imposed using the persistence parameter from the calibration, so that consecutive years are not drawn independently. The discount rate was estimated using a risk-free rate of 4.39% for cash flows denominated in United States dollars and a total equity risk premium of 6.69% for Indonesia, which gives a weighted average cost of capital of 16.02%.

Table 11. Calibration Result and Simulated Output

Item	Value	Note
Price process calibration		
Observations	24	Annual, 2001 to 2024
Regression slope	−0.2793 (SE 0.1334)	First difference of log price on lagged level
t-statistic and p-value	−2.09; 0.049	Significant at the five per cent level
Coefficient of determination	0.173	Low, reported as a limitation
Speed of reversion	0.3276	Negative natural logarithm of persistence
Long-run price level	97.36 USD per ton	Implied by intercept and slope
Half-life of a shock	2.12 years	Natural logarithm of two over reversion speed
Simulated output		
Deterministic baseline	47,464	IDR per share
P10	30,356	IDR per share
P50	45,879	IDR per share
P90	75,048	IDR per share
Mean	50,257	IDR per share
Standard deviation	19,521	IDR per share
Skewness	1.55	Right-tailed output distribution
P90 to P10 ratio	2.47	Width of the central eighty per cent range
Deterministic relative to P50	3.50%	Point estimate above the median
Observed market price	28,000	IDR per share
Share of outcomes above market price	94.30%	Distribution position, not a mispricing test

Table 11 reports the outcome. Simulated value spans IDR 30,356 per share at the tenth percentile to IDR 75,048 at the ninetieth, a P90/P10 ratio of 2.47, with a median of IDR 45,879. The deterministic baseline of IDR 47,464 lies 3.5% above that median, which is what the framework anticipates: a right-skewed price driver entered as one central assumption yields a point estimate above the median of its distribution, so the deterministic figure is not a neutral central case. The output distribution is likewise right-skewed (skewness 1.55), placing the simulated mean of IDR 50,257 above the median, so the mean alone would overstate the central case. Figure 1 plots the distribution with the percentile markers, the deterministic baseline, and the observed market price of IDR 28,000 per share, which 94.3% of simulated outcomes exceed. That proportion locates the model output against one benchmark on a single observation date, conditional on the assumptions adopted here; it is neither a test of market efficiency nor a probability of mispricing, following the boundary condition stated in Table 9.

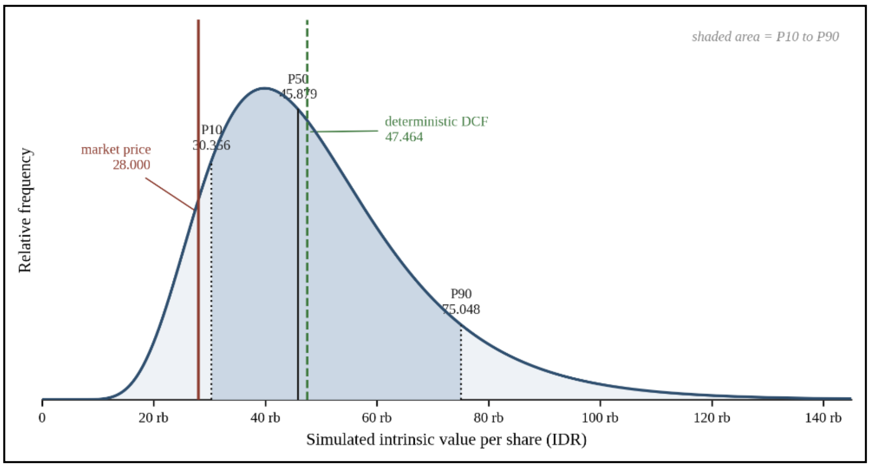

Figure 1. Simulated distribution of intrinsic value per share

Figure 2 ranks the drivers by contribution to output variance. The four benchmark price years account for 72.5%, while the highest-ranked issuer-specific variable, operating margin, contributes 13.8%. Effort allocation follows from this: refining an operating assumption while the price process remains crudely specified will not improve the valuation range materially, because the variance originates there. Three limitations qualify the demonstration. The benchmark series uses one December observation per year rather than an annual average, a coarse proxy for within-year price behaviour; twenty-four annual observations make a short window for estimating mean reversion, which the low coefficient of determination reflects; and reclamation and mine-closure obligations are discussed in the framework but not modelled as an explicit terminal liability in this run. Each would need addressing before the output could be read as an empirical valuation result rather than a demonstration of framework mechanics.

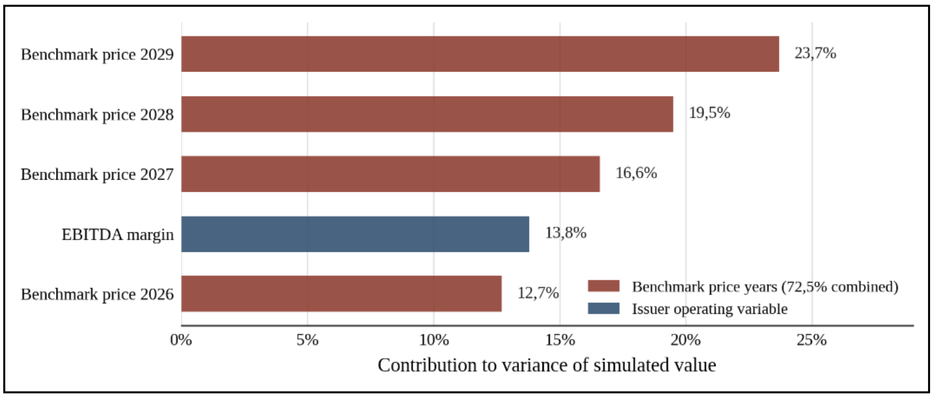

Figure 2. Contribution of each stochastic driver to the variance of simulated value

Conclusion

A technical framework for applying Monte Carlo simulation to coal mining valuation is developed here. It begins with a deterministic FCFF-WACC structure, then converts seven uncertain variables into probability distributions: coal benchmark price, ASP realization, production volume, operating margin, WACC, terminal multiple, and exchange rate. Valuation is therefore communicated as a range, where P10, P50, and P90 describe downside, central, and upside conditions, while sensitivity ranking identifies the variables that move value most.

Demonstration on one export-oriented coal producer listed on the Indonesia Stock Exchange produced an upper decile 2.47 times the lower decile, a deterministic point estimate 3.5% above the simulated median, and benchmark price years accounting for most of the output variance. Market mispricing is not tested and no investment recommendation is given. The contribution is methodological: a practical valuation architecture with one documented worked demonstration, usable for mining-economics teaching, preliminary investment-risk screening, and future empirical research. Coal mining valuation is best treated as a risk-based estimation problem. Monte Carlo simulation does not remove uncertainty; it structures, quantifies, and communicates it more clearly.

Suggestion

Future research should extend the demonstration to a larger sample of coal producers, using annual average benchmark prices rather than single year-end observations, a longer calibration window, higher-frequency price data, issuer-specific ASP realization, stochastic exchange rates, and carbon-pricing risk. Reserve-side treatment also needs strengthening through an explicit terminal liability for reclamation and mine closure, reserve-life modelling, and a cumulative production constraint tied to audited reserves. Comparison of deterministic DCF, Monte Carlo simulation, and real-options valuation remains open.

Linking valuation output to market-price behaviour is worthwhile for listed issuers, yet belongs in a separate predictive, event-study, or market-efficiency design rather than inside a valuation framework paper. For practitioners, value should be communicated as a range rather than a single target price. For students, the framework serves as a teaching device for showing how uncertainty moves mining-company value.

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