Monte Carlo Simulations for Scenario Analysis in Financial Modeling

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2nd March 2024

Abstract

The document intends to contend the conventional deterministic approach of scenario analysis as a means of capturing the uncertainties in modeling practices. Instead, it advocates for a stochastic approach, specifically Monte Carlo simulations, as a more nuanced decision-making tool to achieve corporate finance objectives. The study employs a comparative analysis between conventional and simulations-based approaches for the optimal capital structure analysis on a case company – Clearway Energy Inc.(CWEN) – as a proxy to reach its assertation.

Introduction

"The almost impenetrable mist of any forecast."

- Ross G. Walker.[1]

Much of what we do in corporate finance and valuation boils down to how we try to capture the uncertainty of the future in our models. Often, we proceed with a heuristic approach of punching in input numbers that can reasonably be argued as a reflection of the future outcome. A conventional 'what-if' analysis is then brought in as a handy tool to adjust for plausible variance in that outcome by painstakingly changing inputs one at a time and tabulating them under three scenarios – the best case, the base case, and the worst case. This $n * 3$ matrix is presented as the range of possibilities, with which we further proceed by planning for the worst while wishing for the best outcome to occur.

A fatal flaw in this conventional approach is not the mathematics that underlies the model but the idea that three sets of scenario inputs are meant to capture the high level of uncertainty associated with those inputs. The result is an illusion of precision while presuming that each set of inputs carries the same probability of occurrence. For instance, suppose that, as per our model, the most likely estimate is a healthy return of 20%. This output is generated based on what we plug in as our most likely point estimate for each input. Suppose we have five input

[1] Hertz (1961)

variables, and each of our estimated inputs has a 70% probability of occurring. This results in a probability of only about 16% (0.70^5) for our expected outcome to be a reality. Add in the biases of the practitioner conducting the analysis, and the 'most likely' outcome now becomes rather unlikely. This rather trivial example shows that a set of outcomes depends solely on sets of combinations of input variables, which in themselves have an inherent likelihood of occurrence. Once we factor in the varying probabilities of each input and the increasing number of inputs on which the outcome depends, an analyst's task becomes more akin to that of a soothsayer.

Surely, there is a more holistic approach that factors in uncertainty in our modelling practices and does not shy away from facing it head-on.

About three decades ago, without access to large amounts of data and heavy computing power, doing simulations would have been daunting, both in economic and computing terms. For its time, point estimates made sense; today, we have access to abundant data and massive computing power, where even a million simulations can be done with relative ease (Damodaran, 2016). The methodology used in this article was first proposed by Dr David B. Hertz in the 1964 edition of the Harvard Business Review, wherein an alternative technique was proposed for calculating the risks entailed in a corporate endeavour – replacing point estimates with frequency distributions for each of the input variables influencing the outcome (Hertz, 1979). This article extends the proposed methodology, urging practitioners to adopt distributions and simulations instead of point estimates and conventional tabulated scenario analysis practices.

For the remainder of this paper, as a means of demonstrating the implementation of theory into analytical practice, the article will estimate an optimal leverage ratio based on static trade-off theory – where the tax benefits of debt balance the costs associated with default risks of debt, assuming transaction costs are negligible (Fama and French, 2002). We take a case example of a renewable energy yieldco. – Clearway Energy (CWEN), and use Excel to create a deterministic base-case model, and use Python to conduct 10,000 simulations and visualize output distribution and data.

The paper will be broken down into three sections – Theoretical background necessary and methodology used in calculating relevant input factors for the base-case model; introduction and modelling of the case study - Clearway Energy Inc. (CWEN); and a comparative analysis between conventional and simulation-based scenario analysis.

1 Theoretical background

1.1 Optimal capital structure

Capital structure is the firm's mix of debt and equity that enables it to optimize its financing decisions. Since the development of the irrelevance theorem and its revised iterations by Modigliani and Miller (1958), several theories have been proposed to solve the capital structure puzzle as proposed by Myers (1984) – how do firms choose their capital structure decisions?

However, our analysis adopts the static trade-off framework and assumes proactive managers seeking to achieve their target capital structure. Additionally, we assume the transactional costs related to recapitalization are minimal enough to enable the firm to adjust its capital structure if the benefits of those adjustments outweigh the costs of those adjustments. These assumptions are made as these distortions are irrelevant to our paper's objectives.

The static trade-off theory posits that firms have or aim to achieve an optimal debt-to-equity ratio where the tax benefits of debt balance the default and agency costs of debt. At that optimal leverage ratio, the weighted cost of financing is at its minimal, advertently maximizing firm value. According to Leary and Roberts (2005), corporate financing policy is mainly consistent with the trade-off theory, thus enabling us to model our case's target capital structure in line with this theoretical framework.

The conventional methodology of calculating the weighted average cost of capital (WACC) of a firm is in line with the M&M theorem, where we make use of the capital asset pricing model (CAPM) to determine the required return on equity (i.e., cost of equity), and use the coverage ratios as a proxy to determine a synthetic credit rating and further, the default spread of the debt (Damodaran, 2024). This will give us a deterministic model to conduct our recommended stochastic sensitivity analysis approach.

$$WACC \;=\; R_E \,\frac{E}{E+D} \;+\; R_D\,(1-T)\,\frac{D}{E+D} \tag{1}$$

1.2 Risk-free rate

The risk-free rate is a rate of return offered by a default-free asset; however, every asset has some probability of default, so we use the yield on long-term governmental fixed-income security (for example, US10TY) as a proxy for a rate offered by a risk-less asset. Depending on the currency of choice for the analysis, attaching a default spread of that currency would serve our purpose. The estimates of these default spreads are open source (Damodaran, 2023). Ideally, an asset with a negligible covariance with the market is preferred.

1.3 Cost of equity

Shareholder equity, being junior to roughly all claims on the value of a firm, is the most expensive source of financing. Estimating the cost of the residual claim is a daunting task in itself. Most practitioners use the asset pricing model; however, several models are proposed to capture the uncertainty inherent in the equity risk. Fama and French (1993) three-factor model and multi-factor models are some examples; However, according to Bartholdy and Peare (2005), CAPM performs equally as well relative to other factor models for estimating expected equity returns. For our analysis, we will use the conventional asset pricing model to factor in the cost of equity.

$$R_E = R_f + \beta (R_m - R_f) \tag{2}$$

1.3.1 Beta (β)

Beta measures the relative returns of a security compared to the return of a benchmark market index. In practice, beta is considered a proxy for measuring an individual firm's business and financial risk.

Several prior assumptions are made before calculating a firm's beta – the benchmark index, regression time frame, and data collection frequency. However, this raw beta has a significant bias, as shown by Koller et al. (2010).

In order to improve the quality of relative risk (Beta), practitioners implement adjusted beta whereby firm value is broken down into steady-state value and the present value of growth opportunities (PVGO). According to Blume (1975), as firms mature, the majority of the firm value comes from steady-state value, and the betas, in turn, converge more towards 1.0, implying growth that is in line with the market. Therefore, an adjustment of raw beta is made as per chosen weights of steady-state and PVGO value.

Additionally, the beta can be further improved by breaking down the beta as per the industry in which the firm operates; however, for the purposes of this paper, the bottom-up beta process is out of context. For our purposes, we will be using an industry-average beta approach.

1.3.2 Equity risk premium (ERP)

ERP is the premium above the risk-free rate investors demand to invest in equity markets. The ERP intends to capture investors' perception of systematic risk associated with investing in broader equities – macroeconomic risks, political risks, inflationary risks, etc. On Wall Street, the equity risk premium ranges between 5% to 8% (Rosenbaum and Pearl, 2018). For our purposes, we take the equity risk premium of 5.5% as recommended by Kroll (2024).

1.4 Cost of debt

The cost of debt is the effective after-tax rate a firm has to pay on its long-term debts.

For conventional investment grade fixed-income securities, yield-to-maturity (YTM) (i.e., the current yield) of the trading bond can be considered as a cost of raising additional funds through the debt capital markets.

In the absence of current market data, an alternative approach is used by estimating default spreads with its current (or implied) credit rating at the target capital structure. According to Damodaran (2007), in the absence of a credit rating, the firm's interest coverage ratio can be used as a proxy to estimate a synthetic credit rating and derive an implied default spread for calculating the pre-tax cost of debt.

1.4.1 Synthetic ratings and default spreads

The inherent risk associated with equity in a company is secondary; our primary concern is whether the company is able to service the interest payments and principal repayments. Therefore, we must focus our attention on firm liquidity and cash-at-hand from operations and internal sources to service the interest expenses.

According to Moody's (2013) rating measurement criteria for highly capital-intensive industries – the cash-based interest coverage ratio – is an essential measure of a utility's ability to cover its borrowed capital costs. The numerator of the metric is cash flow from operations before working capital changes plus interest expense (Pre-WC CFO), with the denominator being the interest expense. Based on this metric, Moody's has assigned ratings, which will be used as a synthetic rating to assign a default spread. Each rating has an implicit default spread attached to it, and with every drop in the credit rating, the model increases the default spread (See Appendix C.2.1).

1.5 Monte Carlo simulations

The Monte Carlo simulation is a numerical stochastic technique that employs randomly sampling input variables from their respective probability distributions to generate output results. The technique is capable of obtaining numerical solutions to problems that are too complicated to solve analytically. By drawing upon the law of large numbers, where the expected value of an outcome can be reliably approximated by taking the sample mean of simulated outcomes, Monte Carlo simulation provides a robust approach to tackling uncertainty (KU Leuven, 2023).

As an extension of capital structure analysis, generating multiple simulated outcomes based on probabilistic inputs instead of static point estimates would lead to a more complete evaluation of uncertainty related to future outcomes.

1.5.1 Simulations-based modeling approach

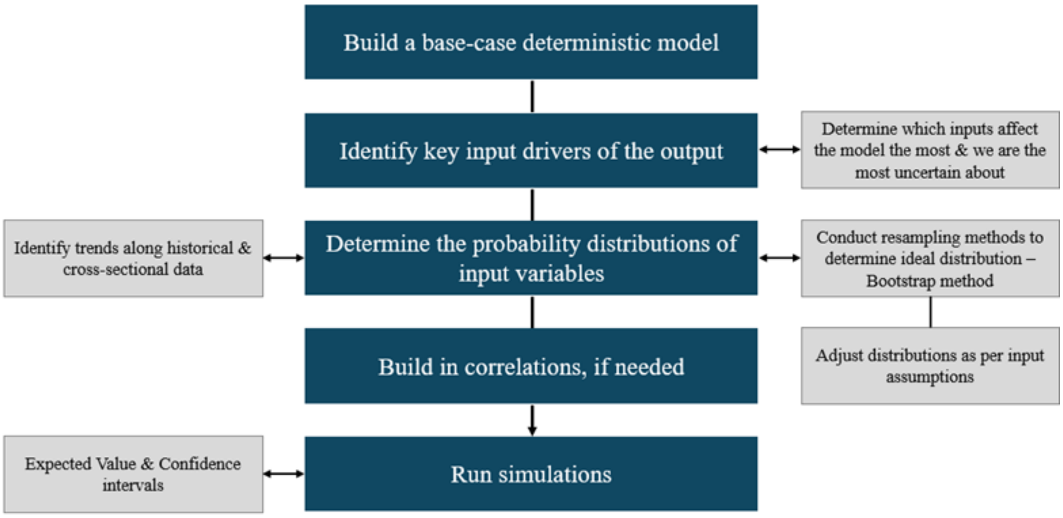


Figure 1: Simulations-based modeling approach

We begin by building a deterministic base-case model unadjusted for risk. To integrate the model with the simulations' Python code, we should follow conventional modelling practices, such as colour-coding inputs and formulas, stacking inputs along a single column, and avoiding hard-coded data to debug or make changes quickly, if necessary.

Once the model is built out, identify the key input drivers that significantly change the output. This could be done by tinkering with the inputs and checking which inputs affect our output the most. In addition, factor in the variables that have a relatively high uncertainty factor among practitioners (Damodaran, 2016). The input variables chosen as stochastic inputs are assigned distributions, whereas the remaining variables can be factored in as point estimates in our model.

When inputting point estimates while doing our three-case scenario analysis, we factor in industry growth, macroeconomic forecasts, trends in historical and cross-sectional data, and a lot of other implicit factors. Similarly, intuition and judgment can be used to assign distributions instead of point estimates. Histograms and other visualizing methods of historical and cross-sectional data can be utilized to estimate a distribution. For instance, if we take cross-sectional and time-series data of profit margins of retail stores across the United States, and the data shows that the margins are in the range of 2% to 6% with a normal distribution, then it is probably ideal to take a normal distribution with an expected value of 4% and a standard deviation of 1%. Assuming there are some structural changes within the sector or any firm-specific characteristics that separate it from the average, the distribution can be skewed to align with those factors. To bring in some statistical sophistication, Kolmogorov–Smirnov or the Shapiro–Wilk test can be conducted on the data to check whether our data is normally distributed.

If our data is limited to a small sample size, resampling techniques such as bootstrapping can be conducted to estimate the distribution and summary statistics, such as mean and standard deviation of the true population.

We can now run 10,000 or 100,000 simulations by iteratively changing inputs as per their assigned distributions and determining the expected value and percentile-based confidence interval of our output. The output distribution can then be used to quantify the likelihood of a point estimate to occur.

2 Case study - Clearway Energy (CWEN)

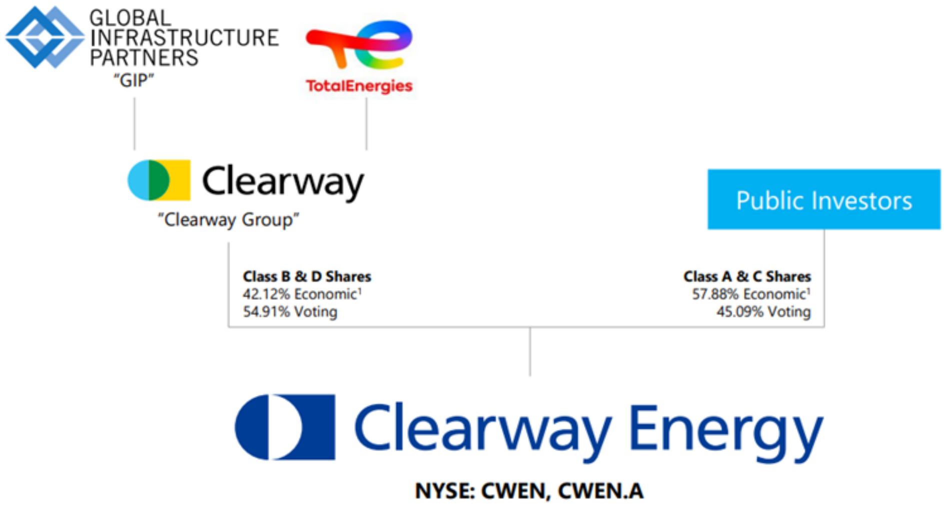


Figure 2: Clearway Energy Corporate Structure

Like most of the utility-scale renewable energy developers, Clearway Energy Inc. is a publicly traded yieldco. that operates and manages a portfolio of energy assets with predictable, long-term cash flows. The majority of its revenues are derived from long-term power purchase agreements (PPAs) with utilities to offtake the capacity generated by its energy assets. The company has a strong sponsor backing of Global Infrastructure Partners (GIP), an independent infrastructure fund manager, and TotalEnergies, a global French multi-energy company. The ownership is split between publicly traded Class A (CWEN.A) and Class C (CWEN) shares, and the privately held Class B and Class D shares, each with their respective rights over control and economics of the firm (See fig. 2) (Clearway Energy, 2024a).

2.1 Base-case model - Capital structure and WACC schedule(Excel)

The objective of the cost of capital schedule is to determine an optimum leverage ratio where the cost of capital (WACC) is minimized.

The following subsections are intended to dissect and explain the individual components of the model - market value of firm debt & equity, cost of debt iterative schedule, and cost of capital schedule.

2.1.1 Market value of firm debt and equity

The model values the firm's debt and equity based on its market value instead of its book value. The market capitalization[2] of the firm is based on the share prices of its class A and class C shares, as of the valuation date. (See Appendix B.1)

The fully diluted shares outstanding consist of a cumulative share count of 202.08 million common stock, with none in convertibles, options, warrants, or restricted stock units (RSUs)[3].(See Appendix A)

The market value of firm debt includes all interest-bearing liabilities and is broken down into corporate-level debt, non-recourse project-level debt, and operating lease commitments (See Appendix B.2). The corporate-level senior debt is discounted at a pre-tax cost of debt of 6.95% (See Appendix B.2.1); the project-level non-recourse debt is discounted at 9%[4].

The total market value of firm equity and debt (including operating lease commitments) is at $4.6 billion and $7.5 billion respectively, giving us a market value debt-to-total capitalization of 61.4%.

2.1.2 Cost of debt schedule

The model lays out the after-tax cost of debt at every debt level in the cost of debt schedule[5]. The interest expense is tied to the credit rating, which is tied to the cash coverage ratio, which affects the default spread, and thus the interest expense. We have a loop. Hence, to resolve this, the schedule implements an iterative approach to determine the default spread at a debt level as recommended by Damodaran (2012) (See Appendix C.2.2). The marginal tax rate is adjusted to account for the marginal tax benefit of debt[6]. At a certain debt level, the interest expense exceeds earnings before interest and taxes (EBIT)[7], where the benefit of interest deductibility cannot be fully realized (See Appendix C.2).

2.1.3 Cost of capital schedule

The cost of capital schedule gives the cost of capital at every debt ratio. As the debt level rises the levered beta of the firm rises, further increasing the cost of equity (See Appendix C.1). Cost of debt has a similar affect, however at a debt level of 30%, the cost of capital is minimized at 7.05%, giving us an optimal financing mix of 30% debt and 70% equity (See Appendix C).

[2]The market value per share of privately held class B and class D shares consists of a control premium of 5% over the publicly traded class A and class C shares. According to Lease et al. (1983), shares with higher voting rights per share trade at about 5-10% premium to that of non-voting shares.

[3]RSUs issued by the firm are already accounted for as vested in common share count due to the valuation being a standalone valuation

[4]Project-level debt discount rate comes from a July 3, 2023 project-debt transaction which offered a fixed annual rate of 9%(Clearway Energy, 2024a)

[5]The project-level debt financing costs are not considered, and the cost of debt schedule does not adjust for differences in term structures for conventional debt and project debt.

[6]The model does not account for the tax equity and other non-debt tax shields (NDTS) benefits.

[7]The model does not account for implicit financing cost benefits derived due to strong sponsor backing. In addition, no other implicit costs incurred due to ratings drop are considered.

Considering the current firm debt ratio stands at about 62% debt ratio, the firm should consider an equity recapitalization of about \$3.8 billion, to stabilize its debt ratio at 30%, and lower cost of capital by about 50 basis points (bps).

2.2 Stochastic approach - Monte Carlo simulations

To conduct our simulations-based scenario analysis, we begin by identifying our key input drivers of cost of capital. Our cost of capital model is built around four input drivers that we are uncertain about: Market risk (risk-free rate, equity risk premium) and company-specific risk (Pre-WC CFO, EBIT).

2.2.1 Input probability distributions

Risk-free rate As recessionary fears subsided by the end of 2023 and core inflation has fallen sharply from its pandemic peak, Federal Open Market Commission (FOMC) has signaled that the Federal Reserve will begin with its cautious rate cuts during 2024. According to Goldman Sachs (2024) forecasts, the FOMC intends to deliver on its rate cuts of 25 bps per quarter, bringing the feds fund rate to about 3.5-3.75% at equilibrium. However, according to Federal Reserve (2024) January statement, the primary goal is to bring the inflation down to the target 2%, and any direct or indirect inflationary risks would lead the committee to adjust its monetary policy. The economic outlook remains uncertain; however, investors expect steady rate cuts in the coming quarter. From its 2023-Q4 high of about 5%, US 10-year treasury yield has steadily fallen to 4.3% as of the valuation date. Therefore, we assume a triangular distribution with a lower limit of 3.75%, an upper limit of 5.25%, and a mode of 4%.

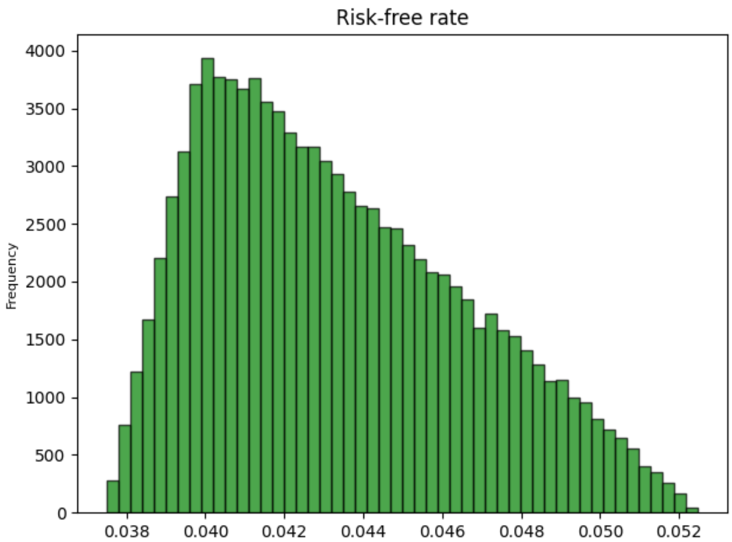


Figure 3: Estimated risk-free rate distribution

Equity risk premium As interest rate uncertainty begins to subside, and a scenario of a 'soft-landing' seems more likely, the equity markets are pricing in significant rate cuts. With the S&P 500 and the Dow Jones Industrial average reaching new highs, the risk premiums associated with the post-pandemic uncertainty are beginning to being priced away. According to Kroll (2024), the US equity risk premium is being reaffirmed at 5.5% but can be lowered in the near future.

We assume a negatively (left) skewed normal distribution with a mean of 5.5% and a standard deviation of 0.5%.

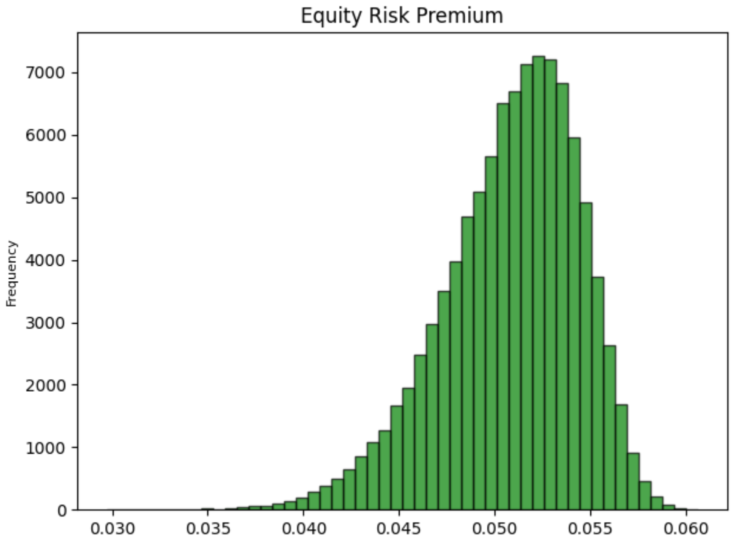


Figure 4: Estimated equity risk premium distribution

Pre-working capital cashflow from operations (Pre-WC CFO) As per the company's recent earnings call and management guidance, the cashflow available for distribution (CAFD) is projected to reach \$395 million for 2024, from \$349 million in 2023. Two utility-scale solar projects have achieved commercial operations which will help drive higher CFO and CAFD for 2024 and beyond. The hikes in PPA prices during 2023 are expected to be maintained throughout 2024, which will be able to support higher earnings growth. Given that the interest expenses will steadily decline in the short-term as construction debt gets replaced by cash equity, tax equity, and other forms of permanent financing, the CFO, as a result, will also increase (Clearway Energy, 2024b).

With a three-year average pre-WC CFO at around \$750 million, we assume a positively (right) skewed normal distribution with a mean of \$750 million and a standard deviation of \$30 million.

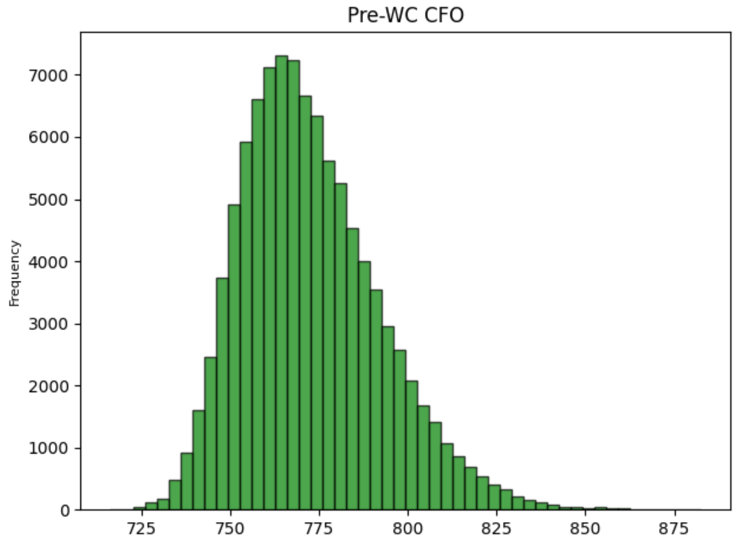


Figure 5: Estimated Pre-WC CFO distribution

2.2.2 Input correlations and constraints

EBIT The very nature of random sampling implies that values will be randomly chosen from a given distribution without any correlation to how a value is sampled from another input distribution. For example, if a higher operating income input is sampled from its distribution and assuming the operating costs are constant, there are no constraint built in the model that prevents sampling of a lower turnover input from its respective distribution; this sort of random sampling without factoring in the correlation between related input variables will significantly distort the model's output. Therefore, there is a need to explicitly build in such correlations in our simulations.

In our case, correlation between EBIT and pre-WC CFO is factored in by analysing historical data on a quarterly basis, and cross-sectional data across the sector. We have assumed a ratio between EBIT and pre-WC CFO as a stochastic input variable that will correlate sampling of cashflow input with an EBIT input. Due to lack of a large sample size, we have implemented resampling method of bootstrapping data to generate an approximated summary statistics and distribution (See Appendix: D and fig: 6).

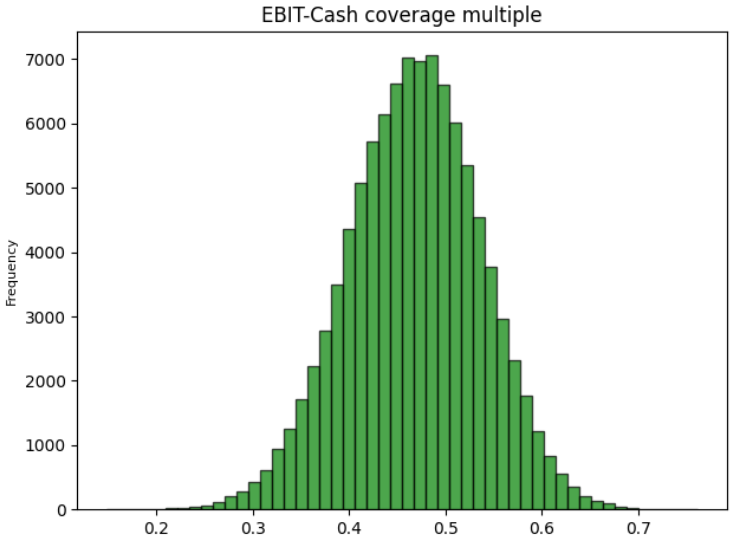


Figure 6: Bootstrapped EBIT/Pre-WC CFO multiple histogram

To give a conclusive example, assume that the model samples a pre-WC CFO of $775 million, and based on normally distributed correlation multiple (EBIT/Pre-WC CFO), a multiple of 0.5x is sampled; ceteris paribus, an EBIT of $387.5 million is then indirectly sampled. Note that the model will now never sample a negatively related EBIT to any pre-WC CFO sampled input due to this built-in correlation.

2.2.3 Run simulations

Once the deterministic model is built out and reviewed; once the input variables and its distribution align with the practitioner's assumptions; and the constraints and correlations are factored in, we can now let the computer do the heavy-lifting and run our simulations. For our purposes, we run 10,000 simulations using Python and integrate it with Excel using the xlwings library. However, there are user-friendly alternatives that do not require proficiency in the Python language; Oracle's Crystal Ball Excel add-in uses the same mechanic with a more intuitive and user-friendly dashboard interface.

3 Results

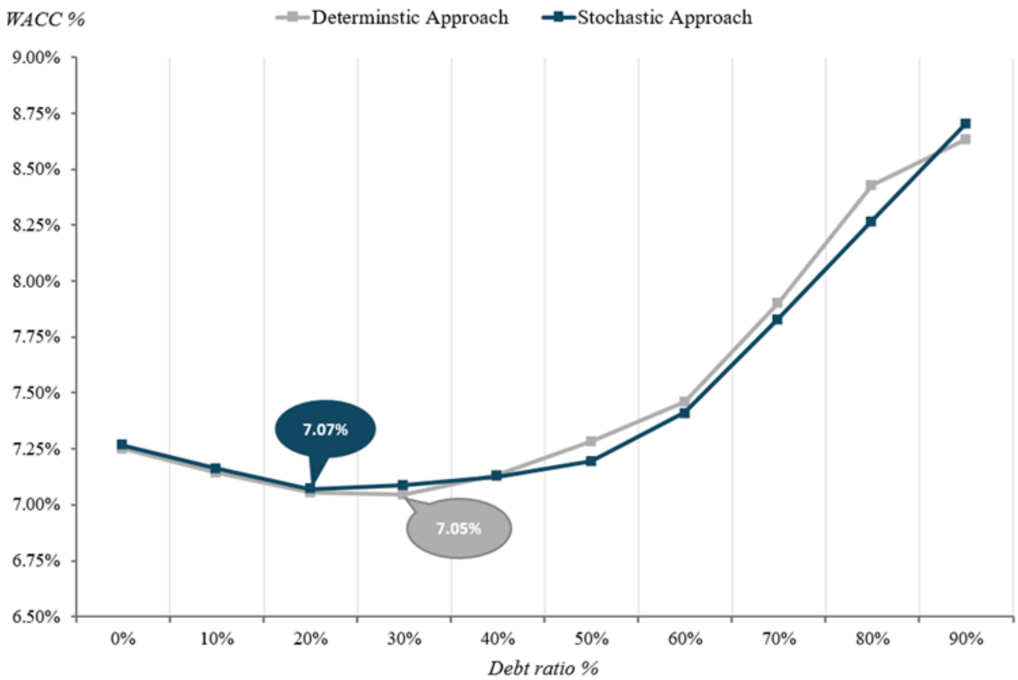


Figure 7: Simulation-based vs Conventional WACC at every leverage ratio

The simulations result in an expected cost of capital of 7.07% at a leverage ratio of 20% compared to a base-case cost of capital of 7.05% at a leverage ratio of 30% when done using the conventional deterministic method. However, the difference of 2 bps is almost negligible and can be disregarded.

This result is quite obvious as our input distributions are centered around the same base-case point estimate. Then, why bother with simulations?

The reasons are twofold – the constraint of 2-dimensionality of conventional sensitivity table; and lack of probability level of the outcome.

3.1 N-dimensionality of simulation-based what-if analysis & probability level of outcome

A serious limitation of conventional sensitivity analysis is the fact that the table can only factor in a range of possibilities for one or two input variables, while the remaining input variables are kept constant. This limitation significantly undermines the complexity of interaction and dependencies of input variables, and their effect on the outcome. Consequently, crucial insights may be overlooked, leading to biased or incomplete assessment of risks associated with the outcome.

Simulations and a distributions-based sensitivity analysis factors in the stochastic nature of all input variables used in the model, leading to an n-dimensional and a more holistic scenario analysis.

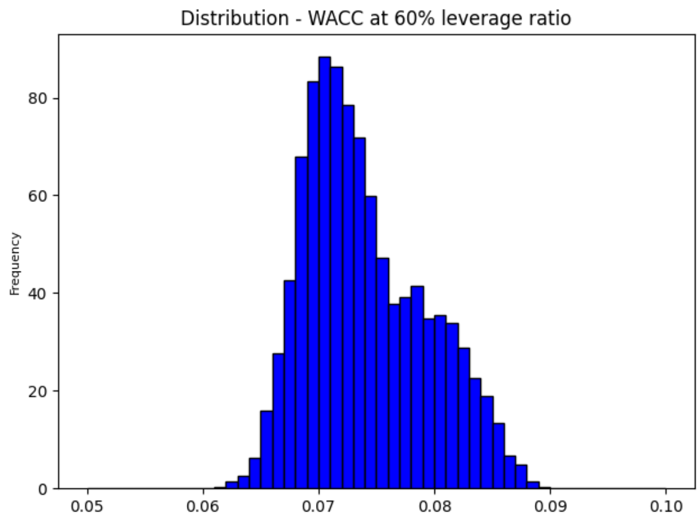
In our case, let us assume that CWEN intends to assess the range of what would be the hurdle rate (WACC) at their current leverage ratio of about 60%. From our conventional 2-dimensional sensitivity approach, we keep the Pre-WC CFO and EBIT constant, while spreading out the risk-free rate between 3.25-5.25%, and the market risk premium between 5.0-5.50%.

Sensitivity Analysis - WACC at 60% leverage ratio

		Risk-free rate				
		3.25%	3.75%	4.25%	4.75%	5.25%
Equity Risk Premium	5.00%	6.47%	6.80%	7.30%	8.08%	8.58%
	5.25%	6.59%	6.92%	7.42%	8.20%	8.70%
	5.50%	6.71%	7.04%	7.54%	8.32%	8.82%

Figure 8: Conventional sensitivity analysis data table

The result is a difference of about 2.35 percentage points between the minimum and maximum value. This spread can be trimmed down by reducing the interval between values of input variables. However, it is important to note that neither does the table account for the variability in company-specific inputs, nor does it provide decision makers with any insight on the probability of the outcomes occurring.



(a) WACC distribution at 60% leverage ratio

Percentile-based probability table

Percentile	WACC value
5%	6.59%
10%	6.81%
20%	6.94%
30%	7.06%
40%	7.17%
50%	7.30%
60%	7.44%
70%	7.65%
80%	7.90%
90%	8.19%
95%	8.51%

(b) Percentile-based WACC

Figure 9: Simulations-based sensitivity analysis output

In contrast, the simulations-based approach factors in the stochastic nature of all input variables that affect the outcome range, while providing decision makers with a richer outcome assessment. According to figure 9b, the expected hurdle rate at the current capital mix would be about 7.30%.

Questions that could have not been answered before, can now be answered. Suppose, the management wants to assess whether they should take on project with an internal rate of return (IRR) of 8%; figure 8 gives us a broad range of plausible outcomes, yet it provides no assessment of the likelihood of whether our project would be a net positive or not. However, figure 9b says that as per our estimate, we can be about 80% certain that the hurdle rate will fall below 7.90%, providing us with a holistic assessment of our question.

4 Conclusion

This document aims to drive home a crucial point: In the realm of financial modeling, confronting uncertainty head-on is not just advisable; it is absolutely imperative. We must fully grasp that the input estimates we rely on are nothing more than educated guesses. Failing to account for the vast range of potential inputs makes even the most sophisticated models merely an illusionary endeavour.

In addition, the suggestion of merely substituting point estimates with distributions is rather a minor adjustment; however, the implication is a significant and holistic improvement to our corporate analysis toolkit.

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Appendix - Excel Model & Python Code

A Fully diluted shares outstanding

Shares Outstanding			
$ and shares in million, except share price			
End of fiscal year	31/12/23		
Most recent quarter end date	02/11/23		
Valuation date	08/02/24		
Current share price - Class A	$21.48		
Current share price - Class C	$23.43		
Fully diluted shares outstanding			
Basic shares outstanding	Shares	source	Filing date
Class A	34.614	10-Q	02/11/23
Class B	42.739	10-Q	02/11/23
Class C	82.386	10-Q	02/11/23
Class D	42.337	10-Q	02/11/23
Restricted stock/RSUs	-	DEF 14A	17/03/23
Options/Warrants	0	10-K	11/02/23
Convertible debt	0	10-K	11/02/23
Convertible preferred stock	0	10-K	11/02/23
Fully diluted shares outstanding	**202.075**		

A.1 Options/Warrants

Options/Warrants			
$ and shares in million, except share price	Class A	Share price	$21.48
	Class C	Share price	$23.43
Stock options - TSM			
Tranche	Outstanding options	Exercise price	In-the-$ options
Class A	-	-	-
Class C	-	-	-
Net shares from exercised options			**0**

B Market Value of firm debt & equity

Market Value - Debt & Equity	
Unlevered beta	0.56
Levered beta	1.28
D/E	1.62
D/(D+E)	61.8%
Market Capitalization	4,680
MV of LT debt (incl. Lease commitments)	7,574
Market Value of Firm Debt & Equity	**12,253**

B.1 Market capitalization

Equity Value per share class			
$ and shares in million, except share price			
	Diluted shares #	Share price	Equity value
Class A	34.61	$21.48	$743.51
Class B	42.74	$23.58	$1,007.68
Class C	82.39	$23.43	$1,930.30
Class D	42.34	$23.58	$998.21
Market Capitalization			**$4,679.70**

B.2 Market value of firm debt

Market Value of Debt	
Book value of corporate debt	2,125
Pre-tax cost of debt	6.38%
Weighted average maturity of corporate debt	5.96
Interest expense on LT corporate debt	88.19
PV of LT corporate debt	**1,895.9**
Book value of project debt	4,326
Interest expense on LT project debt	269.8
Project-level cost of debt	9.00%
PV of LT project debt (incl. Interest exp)	**5,120.8**
PV of Operating lease commitments	**557**
MV of LT Debt (incl. Operating lease commitments)	**$7,573.68**

B.2.1 Corporate debt

Senior debt schedule						
Corporate senior debt	Year	**Book value**	Coupon	**Interest**	Weight	**Weighted maturity**
2028 Senior Notes	4	850	4.75%	40.4	40.0%	1.60
2031 Senior Notes	7	925	3.75%	34.7	43.5%	3.05
2032 Senior Notes	8	350	3.75%	13.1	16.5%	1.32
Total		**2,125**		**88.2**		**5.96**

B.2.2 Project-level debt

Project-debt schedule			
Non-recourse project-level debt (excl. Interest exp)	Year	Book value	PV
Due 2024	1	410	376.1
Due 2025	2	382	321.5
Due 2026	3	361	278.8
Due 2027	4	399	282.7
Due 2028	5	388	252.2
There-after		2,386	1773.4
Total		**4,326**	**3284.7**

B.2.3 Operating lease commitments

Lease schedule		
Operating lease commitments	Year	PV
2024	1	30
2025	2	30
2026	3	31
2027	4	32
2028	5	31
Thereafter		831
Imputed interest		(428)
Total		**557**

C Cost of capital schedule

General Information	
Company Name	Clearway Energy, Inc.
Ticker	CWEN.A; CWEN
Stock Exchange	New York Stock Exchange
Fiscal Year Ending	December 31
Valuation date	08/02/24
Moody's Corporate Rating	Ba2
Average sector unlevered beta	0.56
Marginal Tax rate	21.0%

Cost of capital schedule				
Debt ratio	**Beta**	**Cost of Equity**	**After-tax cost of debt**	**WACC**
0%	0.56	7.25%	3.76%	7.25%
10%	0.61	7.52%	3.76%	7.14%
20%	0.67	7.86%	3.85%	7.06%
30%	**0.75**	**8.29%**	**4.14%**	**7.05%**
40%	0.85	8.87%	4.53%	7.14%
50%	1.00	9.68%	4.89%	7.29%
60%	1.22	10.90%	5.17%	7.46%
70%	1.59	12.93%	5.75%	7.90%
80%	2.33	16.98%	6.29%	8.43%
90%	4.54	29.15%	6.35%	8.63%

C.1 Cost of equity schedule

Cost of equity schedule			
Debt/Capital	**D/E**	**Levered Beta**	**Cost of Equity**
0%	0.00%	0.56	7.25%
10%	11.11%	0.61	7.52%
20%	25.00%	0.67	7.86%
30%	42.86%	0.75	8.29%
40%	66.67%	0.85	8.87%
50%	100.00%	1.00	9.68%
60%	150.00%	1.22	10.90%
70%	233.33%	1.59	12.93%
80%	400.00%	2.33	16.98%
90%	900.00%	4.54	29.15%

C.2 Cost of debt schedule

Cost of debt schedule							
Debt ratio	$ Debt	Interest expense	Cash coverage ratio	Bond rating	Pre-tax cost of debt	Adj. Marginal Tax rate	After-tax cost of debt
0%	$0	$0.0	-	Aaa	4.76%	21.0%	3.76%
10%	$1,225	$58.3	14.5x	Aaa	4.76%	21.0%	3.76%
20%	$2,451	$119.3	7.6x	Aa2	4.87%	21.0%	3.85%
30%	$3,676	$192.6	5.1x	A2	5.24%	21.0%	4.14%
40%	$4,901	$276.4	3.8x	Baa2	5.64%	19.7%	4.53%
50%	$6,127	$353.8	3.2x	Baa3	5.78%	15.4%	4.89%
60%	$7,352	$434.5	2.8x	Ba1	5.91%	12.5%	5.17%
70%	$8,577	$547.2	2.4x	Ba2	6.38%	9.9%	5.75%
80%	$9,803	$671.0	2.2x	Ba3	6.85%	8.1%	6.29%
90%	$11,028	$754.9	2.0x	Ba3	6.85%	7.2%	6.35%

C.2.1 Synthetic rating & default spreads table

Synthetic rating and default spreads			
if cash flow coverage ratio is			
>	<= to	Bond rating	Corporate default spread
8.0x	+∞	Aaa	0.59%
6.0x	8.0x	Aa2	0.70%
5.5x	6.0x	A1	0.92%
5.0x	5.5x	A2	1.07%
4.5x	5.0x	A3	1.21%
4.0x	4.5x	Baa1	1.34%
3.5x	4.0x	Baa2	1.47%
3.0x	3.5x	Baa3	1.61%
2.7x	3.0x	Ba1	1.74%
2.4x	2.7x	Ba2	2.21%
2.0x	2.4x	Ba3	2.68%
1.7x	2.0x	B1	3.14%
1.4x	1.7x	B2	3.61%
1.0x	1.4x	B3	5.24%
-	1.0x	Caa	10.15%

C.2.2 Iterative cost of debt schedule

Pre-tax cost of debt as per ratings spread										
D/(D+E)	0%	10.0%	20.0%	30.0%	40.0%	50.0%	60.0%	70.0%	80.0%	90.0%
D/E	0%	11%	25%	43%	67%	100%	150%	233%	400%	900%
$ Debt	0.0	1225.3	2450.7	3676.0	4901.4	6126.7	7352.0	8577.4	9802.7	11028.0
Pre-WC CFO + interest exp	785	843	904	978	1,061	1,139	1,220	1,332	1,456	1,540
Interest expense	0	58	119	193	276	354	435	547	671	755
Cash Coverage ratio	-	14.46x	7.58x	5.08x	3.84x	3.22x	2.81x	2.43x	2.17x	2.04x
Synthetic rating	Aaa	Aaa	Aa2	A2	Baa2	Baa3	Ba1	Ba2	Ba3	Ba3
Pre-tax cost of debt	4.76%	4.76%	4.87%	5.24%	5.64%	5.78%	5.91%	6.38%	6.85%	6.85%

Python code

D Bootstrapping EBIT/Pre-WC CFO multiples data (See fig. 5.)

```
def bootstrap(data,n_samples,statfunc):
     data = np.array(data)
     resampled_stat = []
     for k in range(n_samples):
         index = np.random.randint(0,len(data),len(data))
         sample = data[index]
         bstat = statfunc(sample)
         resampled_stat.append(bstat)
     return np.array(resampled_stat)

cfo_ebit_ratio_data = historical_data.range('F17:F43').value
bootstrap_data = bootstrap(cfo_ebit_ratio_data,100000,np.mean) # 100,000 samples
conf_int = np.percentile(bootstrap_data,[0.5,99.5])

# Descriptive Statistics - Bootstrapped data
print('Empirical mean: %.4f' %np.mean(bootstrap_data))
print('99% Confidence interval : ',conf_int)
print('Standard deviation: %.5f'%(np.std(bootstrap_data)))

# Plotting bootstrapped data histogram
plt.hist(bootstrap_data,bins=50,color='g',edgecolor='black',alpha=0.7)
plt.title('EBIT-Cash coverage multiple')
plt.ylabel('Frequency',fontsize=8)
plt.tight_layout()
plt.show()
```

E Pre-tax cost of debt schedule code

E.1 Default spread per credit rating

```
def add_spread(rating):
     if rating in cache:
         return cache[rating]
     else:
        for i in range(5,20):
            if rating != df_spread.cells(i,'E').value:
                pass
            else:
                spread = df_spread.cells(i,'F').value
                cache[rating] = spread
                return spread
```

Figure E.1: Memoization & function to add default spread as per credit rating (Appendix C.2.1)

E.2 Pre-tax cost of debt iteration (Appendix C.2.2)

```
def pre_tax_cod_iteration():
     list_ratings = sheet4.range('E9:M9').value
     list_rate_iter_1 = []
     for rating_1 in list_ratings:
         real_spread = add_spread(rating_1)
         list_rate_iter_1.append(risk_free + real_spread)
      sheet4.range('E10:M10').value = list_rate_iter_1
```

Figure E.2: Code to iteratively change default spread as recommended by Damodaran (2012)

F Simulations

F.1 Input distributions

```
def change_inputs():# Distributions of inputs (Risk-free rate, ERP, CFO-Pre WC)
     global risk_free
     risk_free = r.triangular(0.0375,0.055,0.04) # risk-free rate
     # ERP - Source: Kroll Report
     equity_risk_prm = skewnorm.rvs(-3,loc=0.055,scale=0.0055)
     # CFO/EBIT ratio - estimated by bootstrapping
     ebit_CFO_ratio = r.normalvariate(0.4678,0.06866)
     cfo_pre_wc = skewnorm.rvs(3.5,loc=750,scale=40) #CFO Pre-WC
     input_lst = [risk_free,equity_risk_prm,ebit_CFO_ratio,cfo_pre_wc]
     input_sheet.range('E13').options(transpose=True).value = input_lst
```

Figure F.1: Function to change input distribution assumptions

F.2 Simulations code snippet

```
lst_outputs = []
#Simulations
for i in range(10000):
    change_inputs()
    sheet4.range('E10:M10').options(transpose=True).value = 0.01
   for j in range(3):
       pre_tax_cod_iteration()
    lst_outputs.append(input_sheet.cells(27,'G').value)

plt.hist(lst_outputs,bins=50,color='blue',range=[0.05,0.1])
plt.title('Distribution - WACC at 60% leverage ratio')
plt.ylabel('Frequency',fontsize=8)
plt.tight_layout()
plt.show()

# Descriptive Statistics - Output
print(np.mean(lst_outputs), np.std(lst_outputs))
print(np.percentile(lst_outputs,[0,10,20,30,40,50,60,70,80,90]))
print(np.percentile(lst_outputs,[2.5,97.5]))
```