Resilience Under Pressure: Statistical Stress Testing Models for Company Valuation

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1 - INDEX

2 - INTRODUCTION

2.1 - Context and Motivation

In the world of finance, valuing a company accurately is one of the most critical tasks for investors, analysts, and decision-makers. Among the various valuation methods, the Discounted Cash Flow (DCF) model is one of the most widely used and theoretically grounded. It estimates the intrinsic value of a company based on the present value of its expected future cash flows, offering a forward-looking and company-specific approach.

However, while the DCF model is conceptually robust, its practical application faces a major challenge: it relies heavily on assumptions about the future. Projections of revenue growth, operating margins, reinvestment needs, and discount rates are all subject to uncertainty. Even small changes in these inputs can lead to significantly different valuation outcomes. As a result, a single-point DCF estimate often gives a false sense of precision, hiding the fact that it is built on inherently uncertain forecasts.

To deal with this uncertainty, analysts increasingly look to probabilistic methods that can incorporate risk and variability directly into the valuation process. One such approach is the Montecarlo simulation. By generating a large number of random but plausible scenarios for the key input variables, Montecarlo methods allow us to transform the traditional DCF from a static estimate into a dynamic distribution of possible outcomes. This provides not only an expected valuation, but also a deeper understanding of the risks and confidence levels associated with the investment.

This thesis is motivated by the desire to bridge the gap between theoretical finance and practical uncertainty. It aims to explore how the integration of Montecarlo simulation into the DCF framework can lead to more realistic and informative company valuations, helping investors make decisions that better reflect the complex and unpredictable nature of financial markets.

This thesis is closely integrated with the accompanying Excel file, which constitutes the core of the practical application of the methodologies discussed. To fully grasp the model’s logic, structure, and outputs, it is crucial to explore the Excel workbook directly rather than relying solely on the written content. The file is publicly available on my GitHub repository <https://github.com/SnappierCape/SnappierCape-Public>, and a detailed guide to its structure and use can be found in Section 6.2 – An Overview of the Excel Model.

Please note that due to the intensity of the Montecarlo simulation (10,000 iterations), the main version of the Excel file is computationally demanding and may perform slowly on low-end hardware. For this reason, a second version of the file is also provided, in which the Montecarlo data table contains fixed values. This allows for smooth navigation and exploration of the model structure without requiring significant processing power.

2.2 - Assumption Uncertainty

The traditional Discounted Cash Flow (DCF) method, despite being widely accepted in financial analysis, presents a fundamental limitation: it is deterministic in nature. This means that all key input variables, such as revenue growth, operating margins, tax rates, capital expenditures, and the discount rate, must be fixed based on assumptions made by the analyst. These assumptions, however, are often uncertain and difficult to estimate with high confidence, especially when the time horizon extends over many years.

In practical terms, the DCF model produces a single-point estimate of a company's intrinsic value. While this value can be useful, it offers no information about how sensitive it is to changes in the underlying assumptions, nor does it quantify the level of uncertainty embedded in the projection. As a result, investors and analysts may be misled by a valuation that appears precise, but is in fact highly sensitive and potentially unreliable.

The core problem this thesis addresses is how to incorporate uncertainty into the valuation process in a structured and transparent way. Specifically, how can we move from a static, single-value DCF output to a more realistic model that reflects a range of possible outcomes, while preserving the analytical rigor of the original method?

To solve this, the thesis proposes the integration of Montecarlo simulation into the DCF framework. This allows for the generation of thousands of different valuation scenarios by assigning probability distributions to the key inputs. The result is not just one estimate of value, but a full distribution, from which we can derive probabilities, confidence intervals, and risk measures, leading to more informed and resilient investment decisions.

2.3 - Objective of the Thesis

This probabilistic approach allows for a deeper understanding of valuation outcomes. Rather than simply stating that a company is worth a specific amount, the model provides a range of values, each with an associated likelihood. This offers more informative insights into the expected return, downside risk, and confidence intervals of a valuation, which can support better decision-making for investors, portfolio managers, and financial analysts.

To accomplish this, the thesis will:

- Build a standard DCF model for a selected publicly traded company based on historical data and reasoned assumptions.
- Define the key input variables most sensitive to change and assign to them realistic probability distributions.
- Implement the Montecarlo simulation using Excel.
- Analyze and interpret the results of the simulation, with a focus on the distribution of outcomes, the identification of risk drivers, and the comparison with the classic deterministic DCF result.

In addition to the technical implementation, the thesis also aims to contribute to the academic and practical literature by illustrating the value of integrating simulation-based methods into traditional financial models in general. By doing so, it promotes a more nuanced and informed approach to valuation, one that acknowledges and embraces uncertainty rather than oversimplifying it.

2.4 - Methodology Summary

To address the limitations of traditional Discounted Cash Flow (DCF) analysis and introduce a probabilistic dimension into valuation, this thesis adopts a structured methodology combining financial modeling, statistical analysis, and computational simulation.

The first step involves building a classic DCF model for a selected publicly traded company. This model projects the company's free cash flows over a ten-year horizon based on key financial assumptions: revenue growth, operating margins, capital expenditures, changes in working capital, and tax rates. A terminal value is then added, and the total is discounted to present value using a chosen cost of capital. This baseline model serves as the reference point and provides the structure into which uncertainty will later be introduced.

In the second step, the most critical input variables, those that have the greatest impact on the valuation result, are identified. Rather than keeping these inputs fixed, the methodology assigns to each one a probability distribution that reflects its expected behavior and possible deviations. For example, revenue growth might follow a normal distribution, while the terminal growth rate might be modeled with a triangular distribution constrained to plausible values.

The core of the methodology is the implementation of a Montecarlo simulation. Using Excel and its apposite functions, the model generates thousands of valuation scenarios by drawing random values from the defined distributions for each input. Each iteration produces a different possible intrinsic value for the company, depending on the combination of assumptions. The full set of simulations results in a distribution of outcomes, from which statistical indicators, mean, median, percentiles, confidence intervals, are extracted and analyzed.

Finally, the output is interpreted to draw insights into the valuation's sensitivity, the level of uncertainty, and the implications for decision-making. The probabilistic DCF model is compared to the deterministic version to highlight the additional information gained through the simulation process. Graphs such as histograms or cumulative probability plots are used to visualize and explain the results clearly.

Overall, the methodology combines theoretical rigor with practical applicability. It allows for a more comprehensive understanding of company value, accounting for the uncertainty and variability inherent in financial forecasting. This approach aims to improve the quality of financial decisions by offering a transparent and realistic valuation framework that embraces uncertainty instead of ignoring it.

2.5 - Structure of the Thesis

This thesis is organized into seven main chapters, each designed to guide the reader through the theoretical foundations, methodological development, practical implementation, and final results of the research project.

- **Chapter 2 – Introduction**
  This opening chapter presents the context and motivation behind the study, outlines the research problem, states the main objective, briefly summarizes the methodology, and explains the overall structure of the thesis. It provides the reader with a clear understanding of what to expect in the following chapters and the rationale behind the research approach.

- **Chapter 3 – The Discounted Cash Flow (DCF) Framework**
  This chapter reviews the theoretical foundations of the DCF method. It describes how free cash flows are projected, how the discount rate is determined, and how the terminal value is calculated. It also discusses the strengths and limitations of the DCF model, particularly with regard to its sensitivity to assumptions and the absence of probabilistic interpretation.

- **Chapter 4 – Montecarlo Simulation Framework**
  This section introduces the Montecarlo method and its application to financial modeling. It explains the logic behind random sampling, the role of probability distributions, and the advantages of simulation in handling uncertainty. Key concepts such as convergence, number of iterations, and interpretation of output distributions are covered to provide a technical foundation for the model implementation.

- **Chapter 5 – Literature Review**
  This chapter surveys existing academic and professional literature on DCF

modeling, valuation under uncertainty, and the use of Montecarlo simulations in finance. It identifies gaps in traditional approaches, reviews relevant empirical studies, and positions the current thesis within the broader context of financial modeling research.

- **Chapter 6 – Model Development**
  In this practical chapter, the baseline DCF model is built using real financial data from a selected company. Assumptions are made for each key input, and sensitivity analysis is conducted to identify the most influential variables. These variables are then assigned appropriate probability distributions. The Montecarlo simulation is implemented in Excel, and technical aspects are briefly discussed.

- **Chapter 7 – Results and Discussion**
  This chapter presents the outcomes of the simulation. It includes graphical representations of the value distribution, analysis of key statistical metrics (e.g., mean, median, standard deviation, percentiles), and comparison with the classic deterministic DCF result. It also discusses the implications of the findings for valuation practice and decision-making under uncertainty.

- **Chapter 8 – Conclusion and Key Considerations**
  The final chapter summarizes the main insights from the thesis, reflects on the methodological contributions, and suggests areas for future research. It also highlights the importance of incorporating probabilistic thinking into financial analysis and outlines potential extensions of the model to other contexts or asset classes.

Each chapter is designed to build on the previous one, moving from theoretical background to technical implementation and concluding with critical interpretation. This structure ensures a logical flow and supports both academic rigor and practical relevance throughout the thesis.

3 - DCF FRAMEWORK

3.1 - Theoretical Foundations of the DCF Valuation

The Discounted Cash Flow (DCF) method is a fundamental valuation technique used to estimate the intrinsic value of a company based on its expected future cash flows. It is grounded in the time value of money principle, which asserts that a sum of money today is worth more than the same sum in the future due to its potential earning capacity. This approach is particularly suited for valuing firms with predictable and stable cash flows, and it is widely used by analysts, investors, and corporate finance professionals.

At its core, the DCF method involves forecasting the future free cash flows (FCFs) that a company is expected to generate, and discounting them back to their present value using an appropriate discount rate, typically the Weighted Average Cost of Capital (WACC). The sum of these discounted cash flows represents the estimated intrinsic value of the firm.

The DCF formula can be expressed as follows:

$$ENTERPRISE\ VALUE = \sum_{t=1}^{n} \frac{FCF_t}{(1+r)^t} + \frac{TV}{(1+r)^t}$$

Where:

- FCF_t = Free Cash Flow in year t
- r = Discount rate (WACC)
- n = Length of the explicit forecast period
- TV = Terminal Value, representing the value of all future cash flows beyond year n

The terminal value can be estimated using either the perpetuity growth method (also called the Gordon Growth Model) or the exit multiple method. In this thesis, an average of the two methods will be used.

The forecasted free cash flows are derived from projections of revenues, operating expenses, taxes, and investments in capital expenditures and working capital. Each of these components relies on assumptions that must be carefully justified and consistent with the company's historical performance and industry outlook.

Since this thesis is implemented using Excel, the DCF model will be built with a clear, modular structure. Key inputs and assumptions, such as revenue growth rates, EBIT margins, and capital reinvestment ratios, will be linked directly to the FCF calculations, allowing for flexibility and transparency in the simulation phase. Excel's built-in functions and data tables will be used to carry out the valuation mechanics, and Montecarlo simulation will later be integrated through random number generation and scenario iteration.

In summary, the DCF method provides a structured framework for valuing a company based on its fundamentals. However, its reliability is heavily dependent on the accuracy and robustness of the assumptions used. In the next chapters, we will address how to handle this uncertainty by applying simulation techniques to complement and strengthen the valuation process.

3.2 - Free Cash Flows to the Firm (FCFF) – Definitions and Calculations

Free Cash Flow to the Firm (FCFF) is the central component of the Discounted Cash Flow (DCF) valuation model. It measures the cash available to all providers of capital, both equity holders and debt holders, after accounting for the necessary investments required to maintain and grow the business. Unlike accounting profits, FCFF focuses on actual cash generation, making it a robust metric for assessing intrinsic value.

3.2.1 - Definition of FCFF

The standard formula for FCFF is as follows:

$$
\begin{aligned}
FCFF = EBIT \times (1 - Tax\ Rate) + Depreciation\ and\ Amortization \\
- Capital\ Expenditures - \Delta Working\ Capital
\end{aligned}
$$

Where:

- $EBIT$ = Earnings Before Interest and Taxes, a proxy for core operating profitability.
- $Tax\ Rate$ = The effective corporate tax rate, used to calculate Net Operating Profit After Tax (NOPAT).
- $Depreciation\ and\ Amortization$ Non-cash expenses added back to reflect actual cash flow.
- $Capital\ Expenditures$ = Represent long-term investments in fixed assets.
- $\Delta Working\ Capital$ = Reflects the annual change in net working capital needed to support operations.

3.2.2 - Calculation in Excel

In this thesis, the entire FCFF forecast and valuation will be constructed in Excel. The following steps will guide the model-building process:

- Project revenues over a 10-year horizon based on growth assumptions.
- Apply an EBIT margin to estimate operating profit.
- Calculate NOPAT as:

$$NOPAT = EBIT \times (1 - Tax\ Rate)$$

- Add back Depreciation and Amortization, either as a percentage of revenue or based on historical fixed asset data.
- Deduct Capital Expenditures, typically forecasted as a percentage of revenue or guided by past investments.
- Deduct $\Delta Working\ Capital$, estimated using a fixed ratio relative to revenue or directly projected from current asset and liability accounts.

The result is a yearly series of projected FCFFs, which will be discounted to the present using the Weighted Average Cost of Capital (WACC).

3.2.3 - Terminal Value Calculation

The Terminal Value (TV) represents the value of all cash flows generated beyond the forecast horizon. In this thesis, to reduce the bias and limitations of using a single approach, an average of two common methods will be used to calculate the terminal value:

3.2.3.1 - Perpetuity Growth Method

Assumes that free cash flow grows at a constant rate g forever.

$$TV_{PG} = \frac{FCFF_{n+1}}{r - g}$$

3.2.3.2 - Exit Multiple Method

Assumes the business is sold at the end of year nnn for a multiple of a financial metric such as EBITDA or EBIT.

$$TV_{EM} = EBITDA_n * Exit\ multiple$$

The final Terminal Value will be the average of the two estimates.

This hybrid approach enhances the robustness of the valuation by combining a forward-looking growth assumption with a market-based exit value, helping mitigate the limitations of each method when used in isolation.

3.3 - The discount rate: Weighted Average Cost of Capital (WACC)

The Discounted Cash Flow method relies on the principle of time value of money, future cash flows are worth less than present cash flows. To account for this, all projected Free Cash Flows to the Firm (FCFF) must be discounted back to their present value using a rate that reflects the opportunity cost of investing in the firm. This rate is known as the Weighted Average Cost of Capital (WACC).

3.3.1 - Definition and Purpose

WACC represents the average rate of return demanded by all the firm's capital providers, weighted by their relative contributions to the capital structure. It captures both the cost of debt and the cost of equity, adjusted for the company's leverage. Mathematically:

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

Where:

- E = Market value of equity
- D = Market value of debt
- K_e = Cost of equity
- K_d = Cost of debt
- T = Corporate tax rate

3.3.2 - Estimating WACC in Excel

In this project, all components of WACC will be estimated manually in Excel using reasonable assumptions or publicly available data for the company being analyzed.

3.3.2.1 - Cost of Equity

The cost of equity reflects the return required by investors to hold the company’s stock. It is typically estimated using the Capital Asset Pricing Model (CAPM):

$$K_e = r_f + \beta * (r_M - r_f)$$

Where:

- r_f = Risk-free rate (e.g., yield on 10-year government bonds)
- β = Measure sensitivity of the company stock prices relative to the market
- r_M = Expected market return

All these inputs will be sourced from market data and inserted into Excel. The beta can be taken from financial websites or calculated using historical regression.

3.3.2.2 - Cost of Debt

The cost of debt is the effective interest rate the company pays on its borrowings. It can be estimated from:

- The interest rate on outstanding bonds or loans
- An average yield on similar-rated corporate debt
- A peer's comparison

For the sake of this study, the cost of debt will be taken from external sources.

3.3.2.3 - Capital Structure

The relative weights of equity and debt should be based on market values, not book values. In Excel, market capitalization is typically used for equity, while the market value of debt can be estimated using face value or by adjusting for bond pricing if data is available.

3.3.2.4 - Corporate Tax Rate

The tax shield on interest expense reduces the effective cost of debt. The corporate tax rate can be taken from the company's annual report or financial databases or can be estimated from the ratio between income tax and pretax income.

3.3.2.5 - Why WACC Matters

WACC serves as the hurdle rate for evaluating the firm's cash flows. It reflects the minimum return the firm must generate to satisfy both shareholders and creditors. A firm that generates returns above its WACC is creating value, while one that earns below WACC is destroying it.

WACC is used to:

- Discount all projected FCFFs to their present value
- Discount the terminal value to its present value

Choosing a realistic and consistent WACC is critical to obtaining a fair and accurate company valuation.

4 - MONTECARLO SIMULATION FRAMEWORK

4.1 - Introduction to the Montecarlo Simulation

Montecarlo simulation is a powerful computational technique used to model and analyze systems that involve uncertainty. Originally developed during the 1940s as part of the Manhattan Project, the method was named after the Montecarlo Casino in Monaco due to its reliance on randomness and probability. Since then, it has become a standard tool in various scientific and engineering fields, including finance, where it is widely applied to simulate uncertain outcomes and assess risk.

At its core, a Montecarlo simulation allows analysts to understand the range of possible outcomes in a model that includes random variables. Rather than relying on fixed inputs, the simulation assigns probability distributions to uncertain assumptions and generates thousands of possible scenarios by drawing random values from those distributions. This results in a range of outputs that reflect the probabilistic nature of the real world.

In finance, uncertainty is inherent in almost every valuation process. Future revenues, costs, tax rates, market growth, and discount rates are never known with certainty. Traditional financial models often simplify this complexity by using single-point estimates for each assumption. While this makes models easier to compute and interpret, it ignores the natural variability of each input and can lead to misleading results.

Montecarlo simulation addresses this limitation by introducing randomness into the modeling process. It allows for a more comprehensive view of potential outcomes by replacing single estimates with distributions. In the context of discounted cash flow (DCF) valuation, this approach makes it possible to generate a probability distribution of the company's intrinsic value, rather than a single, deterministic figure.

This chapter introduces the basic principles of Montecarlo simulation and explains how it works, step by step. In the next sections, we will explore how to define random variables and choose appropriate probability distributions for each key input. Then, we will walk through the simulation process as implemented in Excel, highlighting its application to DCF modeling. Finally, we will briefly discuss how Montecarlo methods are used more broadly in financial analysis, risk management, and decision-making.

By incorporating randomness in a structured and statistical way, Montecarlo simulation makes valuation models more realistic and informative. It transforms uncertainty from a source of concern into a key component of analysis.

4.2 - Random Variables and Probability Distributions

At the heart of any Montecarlo simulation lies the concept of randomness. To simulate uncertain outcomes, the model must replace fixed numerical inputs with *random variables*, variables that can take on different values according to a predefined probability distribution. Each distribution reflects the nature and range of uncertainty surrounding the variable in question.

Understanding the various types of probability distributions is essential for building realistic simulations. The choice of distribution affects the behavior of the model and ultimately the conclusions drawn from it. Below are some of the most commonly used distributions in financial simulations:

4.2.1 - Normal Distribution

The normal distribution (or Gaussian distribution) is one of the most widely used in statistical modeling. It is symmetric, bell-shaped, and fully defined by two parameters: the mean (expected value) and the standard deviation (volatility or uncertainty). It is particularly useful when modeling variables that naturally fluctuate around a central average, such as inflation, interest rates, or mature business growth.

However, normal distributions may sometimes underestimate the probability of extreme events (so-called "fat tails"), which can be a drawback in risk-sensitive applications.

4.2.2 - Lognormal Distribution

The lognormal distribution is used for variables that cannot be negative and tend to grow exponentially over time, such as revenues, asset prices, or operating income. In a lognormal distribution, the natural logarithm of the variable is normally distributed.

This distribution is positively skewed, meaning it allows for a long right tail — a characteristic that reflects the real-world possibility of unusually large positive outcomes, while ensuring the variable remains strictly positive.

4.2.3 - Uniform Distribution

The uniform distribution is the simplest probability model: all values within a specified range are equally likely. It is defined by a minimum and a maximum. Though rarely used in sophisticated models, it can be useful for sensitivity testing or when there is very limited information about a variable's behavior.

4.2.4 - Triangular Distribution

The triangular distribution is often used when only limited data is available, but a reasonable estimate of the minimum, most likely, and maximum value can be made. It is defined by three parameters:

- Minimum value
- Most likely value (mode)
- Maximum value

This distribution is easy to implement in spreadsheets and offers a flexible way to model asymmetric uncertainty, making it popular in project finance and early-stage forecasting.

4.2.5 - Beta and PERT Distributions

The beta distribution is very flexible and can take many shapes, depending on its parameters. A specific form of this, the PERT distribution (Program Evaluation and

Review Technique), is often used to model expert estimates where minimum, maximum, and most likely values are known. The PERT distribution is smoother and less abrupt than the triangular distribution, and it tends to give more weight to the most likely value.

4.2.6 - Discrete Distributions

In some cases, variables are best modeled as discrete distributions, where a small number of specific outcomes are possible, each with an assigned probability. This is useful, for example, when simulating tax rate changes, binary policy decisions, or market regimes.

4.2.7 - Why the Choice of Distribution Matters

The selection of the appropriate distribution plays a central role in how the simulation behaves. Each distribution carries different assumptions about risk and variability. For example, a normal distribution implies that extreme values are rare and symmetric around the mean, while a lognormal distribution acknowledges that large upside deviations are more likely than downside ones, and that the variable cannot go below zero.

Using the wrong distribution can lead to misleading results, especially in financial models where uncertainty compounds over time. Therefore, selecting and justifying the correct distribution for each variable is one of the most critical steps in building a reliable Montecarlo model.

In this section, we have introduced the most common distributions available for modeling uncertainty. In Chapter 6, we will discuss how to choose the most appropriate distribution for each specific input in a DCF model, including revenue growth, margins, capital expenditures, and other financial assumptions.

4.3 - Simulation Process

Montecarlo simulation transforms a deterministic valuation model into a probabilistic one by introducing randomness into key inputs and running the model repeatedly to generate a distribution of possible outcomes. This section outlines the general process of setting up and running a Montecarlo simulation for a DCF (Discounted Cash Flow) valuation, using a spreadsheet environment like Microsoft Excel.

4.3.1 - Identify Uncertain Inputs

The first step is to pinpoint the variables in the DCF model that are subject to uncertainty and have a significant impact on the final valuation. These typically include:

- Revenue growth rates
- Operating margins (EBIT or EBITDA)
- Capital expenditures
- Working capital changes
- Tax rate
- Terminal growth rate
- Discount rate (WACC)

Each of these variables will later be replaced by a random number generator that draws from a defined probability distribution, as discussed in Section 3.2.

4.3.2 - Define Probability Distributions

For each uncertain input, a specific probability distribution must be assigned. This step defines how the variable will behave across different simulation iterations, whether it is centered around a most likely value, skewed to allow for extreme scenarios, or capped within defined bounds.

Although the exact choice of distributions will be discussed in Chapter 6, the simulation process cannot proceed until each random variable has a distribution to draw from.

4.3.3 - Generate Random Samples

In Excel, random values for each variable can be generated using built-in functions such as:

- RAND() for uniform distributions
- NORM.INV(RAND(), mean, stdev) for normal distributions
- LOGNORM.INV(RAND(), mean, stdev) for lognormal distributions
- Etc

Each simulation iteration involves generating a new set of input values from these distributions.

4.3.4 - Recalculate the DCF Model

Once a complete set of inputs is generated, the DCF model is recalculated using those inputs to compute the implied company value. This includes:

- Projecting free cash flows over the forecast horizon
- Estimating the terminal value
- Discounting all cash flows to the present using the WACC
- Summing the results to obtain the equity or enterprise value

This process mimics how an analyst would perform a traditional DCF manually, but it is done automatically for thousands of different input scenarios.

4.3.5 - Repeat the Process Many Times

To achieve statistically meaningful results, the simulation must be repeated a large number of times, typically 1,000 to 10,000 iterations, depending on the complexity of the model and available computing power.

Each iteration produces a different valuation outcome. These outcomes form the basis for analyzing the uncertainty around the DCF valuation.

4.3.6 - Analyze the Results

Once the simulations are complete, the resulting valuation outcomes are collected and analyzed to create a distribution of values. From this, we can derive:

- The mean or median estimated value
- Standard deviation and variance to measure dispersion
- Percentiles (e.g., 5th, 25th, 75th, 95th) to construct confidence intervals
- Histograms or density plots to visualize the spread of valuations

This probabilistic output helps the analyst understand not just a single "fair value," but the range and likelihood of different outcomes, offering a much richer view of valuation risk and opportunity.

Montecarlo simulation, therefore, introduces a structured approach to modeling uncertainty and capturing the full range of potential values. The next section will explore its broader applications in the world of finance, beyond DCF modeling.

4.4 - Other applications in Finance

Montecarlo simulation is a versatile and widely used tool in financial analysis due to its ability to model uncertainty, incorporate randomness, and estimate probability distributions of outcomes. While this thesis focuses on its application to DCF valuation, the technique is also employed across a broad range of financial domains. Below are some of the key areas where Montecarlo methods are commonly applied:

4.4.1 - Risk Management and Value-at-Risk (VaR)

One of the most common applications is in measuring the market risk of a portfolio through Value-at-Risk. By simulating thousands of future price paths for financial assets based on their historical volatilities and correlations, analysts can estimate the probability distribution of portfolio returns. From this, they determine the potential loss over a certain period with a given confidence level (e.g., a 5% chance of losing more than X in one day).

4.4.2 - Option Pricing and Derivatives Valuation

Montecarlo simulation is particularly useful for pricing complex financial derivatives that lack closed-form solutions, such as exotic options or path-dependent instruments. In this context, the simulation generates multiple scenarios for the underlying asset's price trajectory over time, and then the derivative's payoff is calculated for each scenario and averaged.

4.4.3 - Portfolio Optimization and Asset Allocation

Investors can use simulations to test the performance of different asset allocations under a wide range of economic and market scenarios. This allows for stress-testing portfolio strategies and identifying allocations that offer the best trade-off between expected return and risk.

4.4.4 - Credit Risk Analysis

In credit risk modeling, Montecarlo methods simulate default scenarios and potential losses on a loan portfolio. These simulations incorporate uncertainties in borrower behavior, economic cycles, interest rate fluctuations, and recovery rates after default.

4.4.5 - Pension Fund Forecasting and Actuarial Modeling

Actuaries and pension fund managers use Montecarlo simulation to model uncertain future outcomes such as mortality rates, inflation, salary growth, and investment returns. This helps in estimating the solvency and sustainability of pension schemes over long time horizons.

4.4.6 - Project Finance and Capital Budgeting

In corporate finance, when evaluating large investment projects, Montecarlo simulation can model uncertainties in cash inflows, costs, and external variables (e.g., commodity prices or exchange rates). This enables firms to assess the range of possible Net Present Values (NPV) and better understand the project's risk profile.

4.4.7 - Forecasting and Scenario Analysis

Beyond valuation, Montecarlo techniques are often used to enrich forecasting models for revenues, earnings, or macroeconomic indicators. Simulating various paths under different assumptions helps analysts assess the likelihood of different outcomes and make more informed decisions.

4.4.8 - Conclusion

These applications show the breadth and flexibility of Montecarlo simulation in finance. Whether used for pricing, risk management, forecasting, or valuation, the technique provides a structured way to deal with uncertainty, especially in complex environments where linear models fall short.

In the next chapter, we turn to the academic literature that has explored and refined the use of Montecarlo simulation in valuation contexts.

5 - LITERATURE REVIEW

5.1 - Academic Studies on DCF and Uncertainty

The Discounted Cash Flow (DCF) method has long been a cornerstone of valuation in both academic theory and professional practice. Its strength lies in its foundation on economic principles such as the time value of money and the concept of intrinsic value. However, several studies have highlighted its limitations when it comes to dealing with uncertainty and forecasting errors.

One of the central critiques is that the DCF method, when used in its deterministic form, tends to provide a single-point estimate that fails to capture the variability inherent in financial forecasting. As emphasized by Damodaran (2006), even small changes in key inputs such as growth rates, margins, or the discount rate can lead to large swings in valuation. This sensitivity makes DCF both powerful and potentially misleading if input assumptions are not handled carefully.

Several academic works have proposed methods to incorporate uncertainty more systematically. For instance, Copeland, Koller, and Murrin (2000) suggest the use of stochastic techniques and sensitivity testing to understand how different assumptions impact valuation results. While helpful, these techniques remain limited in that they consider only a small number of predefined cases, rather than the full spectrum of possible outcomes.

Another approach that has gained attention in literature is the probabilistic modeling of future cash flows, which allows analysts to move from fixed input values to probability distributions. This shift enables the calculation of a range of potential valuations rather than a single estimate, offering a more nuanced view of value. While earlier adoption of such techniques was mostly theoretical, the increasing availability of computing power and spreadsheet tools like Excel has made these methods more accessible to practitioners.

In summary, the academic consensus acknowledges that while DCF remains a valid and robust method for valuation, it must be supplemented with tools that allow for a more realistic treatment of uncertainty. This opens the door to simulation techniques, such as Montecarlo analysis, as a natural extension to the traditional model.

5.2 - Montecarlo Simulation in Valuation Models

The application of Montecarlo simulation to valuation models has steadily grown in relevance, particularly as practitioners and researchers seek to better understand the impact of uncertainty on investment decisions. Unlike traditional DCF models that rely on point estimates for each input, Montecarlo techniques allow for the inclusion of variability by assigning probability distributions to key assumptions and running simulations to obtain a range of possible outcomes.

Early academic discussions of this approach appeared in the 1990s and 2000s, as computing capabilities became more widely available. One of the foundational texts that introduced simulation to valuation is by Hertz (1964), who suggested using probabilistic models to account for uncertainty in capital budgeting decisions. Since then, the concept has evolved and been incorporated into more complex valuation frameworks.

A commonly cited advantage of Montecarlo simulation in finance is its ability to generate a full distribution of possible firm values, rather than a single result. This enables analysts to assess not just an expected value, but also the volatility of that value, in essence, providing a confidence interval around the valuation. This has proved especially useful in valuing early-stage companies, firms in cyclical industries, or businesses with volatile cash flows.

Montecarlo methods have also been explored as a decision-support tool, helping investors assign probabilities to different outcomes and incorporate risk tolerance into their evaluation process. This probabilistic perspective aligns well with modern portfolio theory and risk-adjusted valuation.

Although these techniques are not yet universally adopted in practice, partly due to complexity or lack of familiarity, their benefits are increasingly recognized both in academia and in the investment industry. The next step in this thesis is to leverage these insights to build a model that incorporates uncertainty directly into the DCF framework.

6 - MODEL DEVELOPMENT

6.1 - Data Collection and Company Selection

The company chosen for the application of the Montecarlo-enhanced DCF model is Nvidia Corporation. The selection is based on both practical and analytical reasons. From a practical standpoint, Nvidia is currently the second-largest company in the world by market capitalization, which ensures a wide availability of high-quality financial data, analyst forecasts, and commentary. This makes the construction of a detailed valuation model more feasible and reliable.

On a personal level, Nvidia is also present in my investment portfolio, which provides an additional motivation to study the company in depth. An accurate valuation of a held asset is not only academically interesting but also useful in the context of real-world investment decision-making.

From an analytical point of view, Nvidia is a particularly compelling subject due to the intense debate surrounding its valuation. Some market participants and analysts argue that the stock is significantly overvalued, pricing in unrealistic future growth, while others view it as still undervalued, given the company’s leadership in AI-related hardware and data center technology. This divergence in opinion makes it an ideal case for a probabilistic valuation approach like the Montecarlo simulation, which can capture the full range of outcomes instead of relying on a single point estimate.

Additionally, Nvidia has experienced extraordinary recent growth, driven by the rapid adoption of artificial intelligence and its associated infrastructure. At the same time, the stock has also seen sharp corrections, reflecting the market's uncertainty about the sustainability of its performance. These dynamics make it especially important to account for uncertainty in the valuation process, and further justify the use of a Montecarlo simulation to explore the risk and reward embedded in the stock price.

6.2 - An Overview of the Excel Model

The foundation of this project is an Excel-based valuation model, structured to clearly separate raw data, model mechanics, assumptions, and outputs. This section serves as a brief guide to navigating the Excel file and understanding the flow of information through its various components. Each sheet has a specific role in supporting both the deterministic and the stochastic versions of the DCF model.

- **Data**
  This sheet contains the raw historical financial data, sourced from FactSet. It includes the last ten reporting periods as well as the first quarter of 2026. No modification or calculation occurs here; it serves as the primary input source.

- **Financials**
  This is a cleaned and restructured version of the income statement, balance sheet, and cash flow statement. The format is designed to be more readable and suitable for analysis. In particular, the year 2026 is partially projected based on Q1 data, using straightforward linear extrapolation unless otherwise specified.

- **Assumptions**
  This sheet gathers all the user-defined inputs for the model, including long-term growth rates (TGR), revenue growth projections, risk-free rates, and cost of capital components. All editable cells are highlighted in yellow to allow for quick adjustment and experimentation without altering the core formulas, cells not highlighted in yellow are NOT supposed to be modified. This worksheet contains also a chart showing the last 10 periods revenues as well as the forecasted 10 periods (the red ones), to allow for a quick eye-check of the assumptions on revenues growth, which is the main and most important item to estimate.

- **Wacc**
  Here, the weighted average cost of capital (WACC) is calculated based on the parameters entered in the "Assumptions" sheet. It includes separate inputs for the cost of equity and the cost of debt, and accounts for the company’s capital structure.

- **Distributions**
  This sheet introduces uncertainty into the model. Each key variable that is subject to forecasting risk is adjusted using random values drawn from probability distributions. These distributions are selected and parameterized in

later sections, and this sheet acts as the dynamic link between user inputs and stochastic valuation.

- **Standard DCF**
  This is the traditional, deterministic DCF valuation model, built using the base-case assumptions from the "Assumptions" sheet. It serves as the control scenario, offering a single-point estimate of intrinsic value with no randomness.

- **DCF with Uncertainty**
  This version of the DCF model mirrors the standard one, but pulls inputs from the "Distributions" sheet instead of fixed assumptions. It is used to produce one randomized valuation path, and forms the basis for the simulation.

- **Montecarlo**
  This is where the actual Montecarlo simulation takes place. Excel generates 10 thounsand randomized valuations by repeatedly running the stochastic DCF using the uncertain variables, under the “Montecarlo” data table. The results are summarized with descriptive statistics and visualized through histograms and charts, providing a full distribution of possible outcomes for the company’s intrinsic value, in the “light” version of the workbook, meant for low-end hardware, the Montecarlo interactive data table is replaced by fixed values, appartaining to a real simulation scenario.

Together, these sheets offer a modular and transparent structure that supports both deterministic and probabilistic valuation, making the model easy to update, audit, and extend.

6.3 - Projection of Financial Statement Items

In order to estimate the intrinsic value of Nvidia over a ten-year forecast horizon, a series of forward-looking assumptions were made for key components of the financial statements. The methodology adopted seeks a balance between empirical consistency and realistic forward projections, while maintaining transparency and simplicity. The projected values are derived from historical patterns and economic intuition, and are structured to be both dynamic and adjustable within the Excel model.

The following items were selected for forecasting:

- **Revenues**
  Future revenues are projected using a declining growth rate model. Starting from the growth rate observed in the most recent periods, a fixed decay factor is applied year by year. This allows the model to reflect the common pattern in mature companies of slowing revenue expansion as they scale, while still incorporating momentum from previous performance.

- **EBIT (Earnings Before Interest and Taxes)**
  EBIT is modeled as a percentage of revenues. The starting value is the historical average EBIT margin over the past ten periods. To incorporate a moderate improvement over time, a slight positive adjustment factor is added annually, based on the assumption that Nvidia, like many large technology firms, may gain operational efficiency as it grows.

- **Tax Rate**
  Rather than using an effective tax rate from a single year, the average of the absolute tax rates from the past ten periods is used. This method smooths out any anomalies or outliers due to one-off effects (e.g., tax credits or extraordinary losses) and reflects a more stable, expected effective tax burden for the future.

- **Depreciation & Amortization (D&A)**
  D&A is forecast as a fixed percentage of revenues, using the historical average from the observed period. This assumption is consistent with the generally stable relationship between asset base and operating size, especially in a hardware-intensive company like Nvidia.

- **EBITDA**
  EBITDA is calculated directly using the previously forecasted EBIT and D&A. Since these are derived from revenues and historical operating patterns,

EBITDA reflects the combined trends of both operating efficiency and capital structure.

- **Capital Expenditures (CapEx)**
  CapEx is assumed to maintain a constant ratio relative to revenues, following the average historical percentage. The logic behind this choice lies in the discretionary nature of CapEx spending: companies tend to align investment intensity with current business performance, particularly in technology sectors where growth and reinvestment are closely tied.

- **Change in Net Working Capital (ΔNWC)**
  ΔNWC is notoriously volatile and difficult to predict, as it is influenced by various internal and external factors such as inventory cycles, payment terms, and supply chain disruptions. To simplify, it is projected as a constant percentage of revenues, derived from the historical average. While this approach does not capture short-term fluctuations, it provides a consistent and scalable estimate over the forecast period.

Required discount rates, starting values, and other necessary items are linked from the “Baseline values” in the “Distributions” sheet of from the “Assumptions” sheet. This structure ensures that the financial statements evolve consistently and remain analytically linked to observable historical trends. It also allows for quick scenario testing by adjusting a small set of intuitive assumptions, which is essential for both deterministic and Montecarlo simulations.

6.4 - Baseline DCF Implementation

The Excel model includes a standard implementation of the Discounted Cash Flow (DCF) method, following conventional procedures widely adopted in corporate finance and equity valuation. The sheet labeled *“Standard DCF”* performs the valuation using the projected Free Cash Flows (FCFs) obtained from the previously described forecast assumptions.

The process is straightforward and transparent, with all intermediate steps clearly laid out. The FCFs for each of the ten forecasted years are calculated and then discounted to present value using the Weighted Average Cost of Capital (WACC) estimated separately.

The only element that deviates slightly from the textbook formulation is the calculation of the terminal value (TV). Rather than relying on a single method, the model computes TV using both the perpetual growth method (based on a long-term terminal growth rate, or TGR) and the exit multiple method (applying a terminal EBITDA multiple to the projected EBITDA in the final forecast year). The final terminal value is taken as the average of these two approaches, to mitigate the limitations and potential bias associated with either method when used in isolation.

This hybrid approach aims to strike a balance between theoretical rigor and market-based realism, while preserving the simplicity and interpretability of the model.

6.5 - Chosen Distributions

In this section, we describe the specific probability distributions assigned to each of the uncertain inputs in the DCF model, along with the reasoning behind each choice. The objective was to reflect the real-world behavior of each variable as faithfully as possible while maintaining tractability for implementation in Excel.

- **WACC – Truncated Normal Distribution**
  The Weighted Average Cost of Capital was modeled using a truncated normal distribution. This choice reflects the fact that WACC tends to fluctuate mildly around a central expected value, but it cannot drop below a minimum threshold. Truncating the distribution prevents unrealistic negative or near-zero discount rates, which would significantly distort the valuation.

- **Terminal Growth Rate (TGR) – Triangular Distribution**
  The terminal growth rate was assigned a triangular distribution with a conservative lower bound, an expected most likely value, and an upper bound that reflects optimistic long-term economic scenarios. This choice allows flexibility within a bounded range and is well-suited for inputs where historical volatility is low but expert judgment is available.

- **Revenue Growth Rate – Normal Distribution with Decay Factor**
  Rather than using a fixed distribution across all forecast years, revenue growth is modeled with a truncated normal distribution whose mean decays over time. The expected growth rate of each future year is based on the previous year's value, introducing a smoothing effect that mirrors how fast-growing companies often stabilize over time. This approach reduces the likelihood of generating unrealistic exponential growth paths across the projection period.

- **EBIT as a % of Revenue – Truncated Normal with Small Growth Factor**
  EBIT margin was also modeled as a truncated normal distribution. The mean for each year is based on the previous year's value, with a slight upward adjustment to reflect potential long-term operational improvements. The truncation ensures that the margin remains within a realistic, non-negative range, while still allowing modest variability year to year.

- **D&A as a % of Revenue – Triangular Distribution**
  Depreciation and Amortization, expressed as a percentage of revenue, typically exhibits limited volatility and tends to follow a relatively stable trend for mature firms. A triangular distribution captures this behavior by concentrating values around a central mode while allowing for occasional deviation within historical bounds.

- **Tax Rate – Truncated Normal Distribution**
  The tax rate is one of the most difficult item to apply uncertainty too: while in real-world scenarios can fluctuate aggressively, and can also assume negative values at times, usually these outliers tend to cancel out over time, and allowing these observations in the model might influence too much the final results. The effective tax rate was modeled using a truncated normal distribution with particularly wide bounds to reflect its usual behavior while preventing extreme outliers. This distribution captures the common variation observed due to deferred taxes, changing jurisdictions, or policy changes, while keeping results within a realistic range.

- **CapEx as a % of Revenue – Triangular Distribution**
  Capital expenditures were modeled using a triangular distribution. This

approach reflects the fact that CapEx decisions are typically made annually based on expected revenues and strategic needs, and they tend to cluster around a typical value with occasional deviations. The triangular distribution captures this behavior well by incorporating a most likely value and reasonable bounds without allowing for extreme outliers.

- **Change in NWC as a % of Revenue – Truncated Normal Distribution**
  The change in Net Working Capital was modeled using a truncated normal distribution. Given its historical volatility and the potential for both positive and negative values, the truncation ensures values remain within a realistic and manageable range. This distribution reflects the unpredictable nature of working capital changes while preventing the simulation from being skewed by extreme outliers.

- **EV/EBITDA Sector Multiple – Normal Distribution**
  The sector EV/EBITDA multiple was modeled using a standard normal distribution centered on the historical sector average. This choice captures the fluctuations due to shifting investor sentiment and macroeconomic cycles, assuming a symmetric range of possible outcomes around the expected multiple.

6.6 - Application of Uncertainty in the DCF Model

In this section, the methodology through which uncertainty is incorporated into the valuation model is explained in detail. The core idea is to move from a deterministic discounted cash flow (DCF) approach, where a single estimate for each input produces a single valuation, to a probabilistic framework that accounts for the natural variability of the model's key drivers. This is achieved through the implementation of a Montecarlo simulation, which generates a distribution of possible intrinsic values for the stock based on the specified volatility of selected inputs.

The implementation is structured across three interconnected sheets within the Excel file: "Distributions", "DCF with Uncertainty", and "Montecarlo".

- **"Distributions" Sheet**
  The "Distributions" sheet is responsible for generating random realizations of

each uncertain input in the model, based on the probability distributions described in Section 6.5 – Chosen Distributions. For each of these variables, such as WACC, terminal growth rate (TGR), revenue growth, EBIT margin, tax rate, and others, a formula is applied that simulates a value drawn from its assigned distribution. These formulas rely on Excel's native random number functions, which ensure that each input is re-randomized every time the workbook is recalculated.

- **"DCF with Uncertainty" Sheet**

  The "DCF with Uncertainty" sheet is where the actual valuation is computed based on the randomly generated inputs from the "Distributions" sheet. All the volatile assumptions, such as revenue growth rate, operating margins, and capital expenditures, are linked directly to their corresponding randomized cells. As a result, this sheet performs a complete DCF calculation for one specific scenario with a combination of unuque realizations for each input each time the workbook refreshes.

  The structure of this sheet mirrors that of a traditional DCF, with forecasted cash flows computed over a ten-year horizon, followed by the estimation of the terminal value using both the terminal growth method and the exit multiple method. The average of these two estimates forms the final terminal value. Free cash flows are then discounted using the randomly generated WACC to obtain the present value of the firm. Consequently, the result of this sheet is a single intrinsic value estimate, which reflects the specific combination of input values drawn in that instance.

  Every time the sheet is refreshed, a new set of input variables is generated, resulting in a new intrinsic value estimate. This setup effectively creates a mechanism for simulating a large number of independent valuation scenarios, each with its own combination of assumptions.

- **"Montecarlo" Sheet**

  The final stage of the simulation process is conducted in the "Montecarlo" sheet. Here, the randomization framework is extended from single-scenario analysis to full-scale probabilistic simulation. The intrinsic value computed in the “DCF with Uncertainty” sheet is referenced as the target output, and the simulation is conducted by generating 10,000 independent valuations of the firm.

This is achieved through an Excel “Data table” function that repeatedly recalculates the workbook and records the resulting value. In each iteration, the random input values are regenerated in the “Distributions” sheet, a new valuation is calculated in the “DCF with Uncertainty sheet”, and that output is stored in the “Montecarlo sheet”.

Once the 10,000 simulations have been completed, the sheet compiles the data into a frequency distribution, illustrated in 2 charts with different class grouping width, allowing the user to visualize the shape and spread of the valuation outcomes. Summary statistics such as the mean, median, standard deviation, and selected percentiles (e.g., 10th, 25th, 75th, 90th) are computed to provide insight into the distribution’s central tendency and dispersion.

This approach enables a more robust understanding of the firm's intrinsic value by explicitly modeling the uncertainty inherent in the key assumptions. Rather than producing a single-point estimate, the model provides a full probability distribution of possible valuations, offering a more nuanced basis for investment decisions. For example, one could determine the likelihood that the stock is undervalued relative to its current market price or assess the risk associated with different valuation scenarios.

In summary, the integration of uncertainty into the DCF model via the “Distributions”, “DCF with Uncertainty”, and “Montecarlo” sheets transforms a static valuation tool into a dynamic, simulation-based framework. This methodology enhances both the realism and the decision-making utility of the DCF model in the presence of uncertain market and business conditions.

7 - RESULTS DISCUSSION

7.1 - Discussion of Assumptions

This section outlines and justifies the assumptions used to construct the Discounted Cash Flow (DCF) model prior to applying Montecarlo simulation. The goal was to ground each input in observable reality while allowing enough flexibility to reflect uncertainty and variability. All assumptions were either derived from historical data, calculated from financial statements, or estimated based on credible external sources and reasoned judgment. Where applicable, volatility parameters, bounds, and growth or decay factors were determined using common sense, past trends, and publicly available information.

- **Terminal Growth Rate (TGR) – 3%**
  The terminal growth rate was set at 3%, which is broadly consistent with long-term GDP growth in developed economies. This conservative assumption avoids overstating the long-term potential of the firm and ensures a grounded valuation.

- **Revenue Growth Rate – 36% Initial Value (with Decay)**
  The revenue growth rate starts at 36%, based on NVIDIA’s Compound Annual Growth Rate (CAGR) over the past five years. However, this rate is subject to a significant decay factor, applied progressively across the 10-year forecast horizon. This approach reflects the recent sales boom the company experienced, while acknowledging that such extraordinary growth is unlikely to persist indefinitely.

- **EBIT as a Percentage of Revenue – 45%**
  The EBIT margin was set at 45%, based on the company’s historical average over the last ten fiscal periods. This value captures NVIDIA’s high profitability and operational efficiency, while future margin changes are governed by a small growth factor to reflect potential business optimization.

- **Depreciation & Amortization (D&A) as a Percentage of Revenue – 2.6%**
  Depreciation and amortization were assumed to be 2.6% of revenue, again

derived from historical data. As this item tends to follow relatively stable patterns, it is treated with minimal volatility.

- **Tax Rate – 12%**
  The effective tax rate was set at 12%, which reflects NVIDIA's average over the past decade. This choice acknowledges the company's ability to optimize its tax position across jurisdictions while remaining within a realistic long-term range.

- **Capital Expenditures (CapEx) as a Percentage of Revenue – -3.5%**
  CapEx was modeled at -3.5% of revenues, based closely on the firm's historical capital allocation patterns. While the value can vary significantly in practice, the estimate assumes that capital investment remains proportionate to sales trends and strategic expansion.

- **Change in Net Working Capital as a Percentage of Revenue – -3%**
  The change in net working capital, a notoriously volatile and company-specific item, was assumed to average -3% of revenues, based on historical figures. Despite its variability, using the historical average helps smooth its effect in the model and reflects the company's general working capital management approach.

- **Sector EV/EBITDA Multiple – 18**
  An EV/EBITDA multiple of 18 was chosen for use in the terminal value calculation, derived from extensive web research and financial databases. This value reflects prevailing market sentiment for the semiconductor and AI-related technology sector.

- **Market Expected Return – 8%**
  The expected return of the overall market was set at 8%, in line with long-run average returns of the S&P 500 index. This serves as a key input in estimating the cost of equity.

- **Risk-Free Rate – 4.4%**
  The risk-free rate was set at 4.4%, based on the current yield of U.S. 10-year

Treasury bonds as of June 8, 2025. This rate anchors the cost of capital in a realistic benchmark tied to prevailing macroeconomic conditions.

- **Beta – 2**
  The beta coefficient was set at 2, based on various reputable web sources. This relatively high value is consistent with NVIDIA's exposure to high-growth, high-volatility sectors such as AI, semiconductors, and GPUs.

- **Cost of Debt – 2.5%**
  The cost of debt was estimated at 2.5%, using information gathered from market data, debt issuances, and web research. It reflects favorable borrowing conditions typical for a well-capitalized technology leader like NVIDIA.

- **Market Capitalization and Share Price – Factual Data**
  The company's market capitalization and current share price were sourced directly from financial databases and updated as of June 8, 2025. These values do not require estimation.

Across all assumptions, when uncertainty had to be incorporated, the ranges (upper and lower bounds), volatilities, decay factors, and incremental growth trends were determined using a combination of historical behavior, reasonable forecasting logic, and available data. This structured yet flexible approach allowed the model to incorporate realistic scenarios while remaining transparent and interpretable.

7.2 - Statistical Analysis of Simulation Results

This section presents a detailed statistical analysis of the output generated by the Montecarlo simulation of the DCF model. The simulation, run for 10,000 iterations, incorporates uncertainty in the key financial and valuation inputs, as discussed in previous sections. The purpose of this analysis is to understand the behavior of the estimated intrinsic value distribution for NVIDIA's stock and to draw meaningful conclusions regarding its valuation relative to the current market price.

Please note that, since every time the Excel workbook is opened all the random numbers are recalculated, it is almost impossible to replicate the exact results that I based this section on. However, due to the high number of simulations (10.000), every new result obtained opening the workbook or refreshing manually is very close to the ones presented here.

The following tables report the core descriptive statistics, distribution shape characteristics, percentiles and ranges, and a comparison between market valuation and simulated values. Each measure is accompanied by an interpretive commentary to contextualize the results.

7.2.1 - Core Descriptive Statistics

- **Mean (170.09):**
  The average intrinsic value estimated across all simulated scenarios is significantly higher than both the current share price (124) and the deterministic DCF output (58). This highlights the substantial effect of incorporating uncertainty into the valuation process and indicates that the expected value of the stock, under uncertain conditions, may be considerably underestimated by traditional single-scenario DCF models.

- **Median (130.93):**
  The median value also exceeds the current share price, though it remains lower than the mean. This suggests a positively skewed distribution where the majority of the outcomes lie below the mean but are influenced by a few extremely high valuations.

- **Standard Deviation (304.21):**
  The model produces a very wide dispersion of outcomes, implying significant volatility in the potential intrinsic value of the stock. This level of uncertainty is consistent with the high-growth and high-risk profile of a technology company like NVIDIA.

- **Coefficient of Variation (1.79):**
  With a value greater than 1, this relative measure confirms that the dispersion is extremely high in relation to the mean, further underscoring the uncertainty in estimating intrinsic value.

- **Variance (92,545.23):**
  The large variance reaffirms the extreme variability and spread of simulated valuations.

7.2.2 - Shape of the Distribution

- **Skewness (56.82):**
  The distribution is heavily positively skewed, indicating the presence of rare, extremely high-value outcomes. Such outcomes typically result from combinations of optimistic assumptions (e.g., sustained revenue growth, low discount rates), which although unlikely, are not impossible under high uncertainty.

- **Kurtosis (4,549.83):**
  The distribution exhibits very heavy tails, suggesting that extreme values occur more frequently than in a normal distribution. This leptokurtic behavior is a hallmark of financial simulations involving asymmetric upside potential.

7.2.3 - Percentiles and Ranges

- **Range (25,116.40):**
  The wide range between minimum and maximum simulated values reflects the expansive set of possible valuation outcomes. The presence of a maximum value above 25,000 implies the existence of outlier scenarios, which may or may not be economically plausible.

- **5th Percentile (41.78):**
  This threshold indicates that 5% of scenarios produce an intrinsic value below 41.78, offering insight into the downside risk profile. Notably, this is lower than both the median and current market price, indicating a tangible possibility of overvaluation under unfavorable conditions.

- **95th Percentile (400.77):**
  Conversely, this value shows that in 5% of cases, the intrinsic value exceeds 400. Such scenarios likely stem from a combination of favorable growth dynamics and cost structures.

- **Interquartile Range (IQR = 122.20):**
  The middle 50% of the distribution spans from 78.05 (25th percentile) to 200.25 (75th percentile), reflecting a substantial variability even among the more central outcomes. This again reinforces the notion of broad uncertainty across the valuation spectrum.

7.2.4 - Market Valuation Comparison

- **Probability (DCF > Market Price) = 52.61%**
  Just over half of the simulated outcomes suggest that the intrinsic value of the stock exceeds its current market price of 124. This implies a slight undervaluation in relative terms. However, the proximity to the 50% threshold indicates that this finding is not robust and should be interpreted cautiously.

- **Probability (DCF < Market Price) = 47.39%**
  Nearly half of the simulations suggest overvaluation. This near-balance of probabilities highlights the importance of scenario-based analysis when making investment decisions, especially in volatile sectors.

7.2.5 - Key Takeaways

- The deterministic DCF model (without uncertainty) estimated NVIDIA’s intrinsic value at $58, well below the current share price of $124, implying a strong overvaluation.

- However, when uncertainty was introduced via Montecarlo simulation, the distribution of possible intrinsic values changed substantially: the mean valuation rose to $170, and the median to $131, both above the current market price. This shift suggests that the company may actually be slightly undervalued in probabilistic terms, contrary to the deterministic conclusion.

- The distribution exhibits high variability, with a standard deviation over $300 and a very long right tail (skewness of 56.8), indicating the potential for rare but extremely high valuations under optimistic scenarios.

- A majority of simulated outcomes (52.61%) resulted in valuations higher than the current market price, compared to 47.39% below it—further suggesting a marginal tilt toward undervaluation.

7.2.6 - Conclusion

The introduction of uncertainty into the DCF model not only broadened the range of possible valuation outcomes but also fundamentally altered the narrative around NVIDIA’s stock. While a single-point estimate suggested the company was dramatically overvalued, the stochastic analysis indicates that such a conclusion may be overly simplistic and misleading.

By accounting for variability in key inputs, such as revenue growth, profit margins, and discount rates, the Montecarlo simulation revealed that the expected value of the company is likely higher than what a traditional DCF would imply. In doing so, it exposed the limitations of deterministic models when applied to dynamic, high-growth firms, and reinforced the importance of probabilistic thinking in investment analysis.

In summary, what appeared to be a significant overvaluation under a static approach was reinterpreted as a case of mild undervaluation once uncertainty was properly accounted for, illustrating the critical role of simulation techniques in modern equity valuation.

8 - CONCLUSION AND IMPORTANT CONSIDERATIONS

8.1 - Summary of the Work

This thesis explored the integration of uncertainty into the traditional Discounted Cash Flow (DCF) valuation framework through the application of Montecarlo simulation. After presenting the foundational concepts of DCF analysis, we identified its deterministic nature as a key limitation, particularly in light of the variability and subjectivity inherent in its input assumptions.

To address this, we developed a probabilistic DCF model in Excel, assigning appropriate probability distributions to key variables such as revenue growth, margins, tax rates, and discount factors. These distributions were sampled across 10,000 iterations, generating a range of potential outcomes and offering a more nuanced view of the intrinsic value of a company.

The case study on NVIDIA illustrated how the introduction of uncertainty not only expanded the range of plausible valuations but also altered the conclusion of the investment analysis, shifting from a strong overvaluation signal to a moderate undervaluation under certain probability thresholds.

8.2 - Model Limitations

While the integration of uncertainty through Montecarlo simulation significantly enhances the traditional DCF framework, the model presented in this thesis is not without its limitations. These constraints stem both from the structural nature of the model itself and from the technical limitations of the Excel environment in which it was developed.

One of the primary limitations lies in the simplicity of the probabilistic assumptions. Although the model incorporates uncertainty through the use of carefully chosen probability distributions, the calibration of these distributions, such as their means, bounds, and volatility, relied heavily on historical averages, common sense, and qualitative web research. In the absence of advanced statistical inference or robust historical datasets, these inputs may not fully capture the true behavior of the variables under consideration, particularly in highly volatile or structurally changing industries.

Another significant constraint is rooted in the nature of Excel as a simulation platform. While accessible and flexible, Excel is not optimized for large-scale probabilistic modeling. The computational load introduced by generating and processing thousands of random scenarios often results in significant performance issues. This includes file sluggishness, delayed recalculations, and in some cases, outright instability or data corruption. These issues not only limit the scalability of the simulation but also introduce the risk of technical errors that may compromise the reliability of the results.

Moreover, Excel's built-in random number generation and distribution functions, while sufficient for basic modeling, lack the statistical sophistication and precision found in more specialized environments like R or Python. For instance, certain distribution shapes or inter-variable correlations are either difficult to implement or impossible to replicate accurately within Excel's architecture. Additionally, the Montecarlo simulation in this model assumes independence across all variables and across time, an assumption that may not hold true in real-world financial dynamics, where many inputs are interdependent or exhibit autocorrelation.

The deterministic nature of the core DCF logic also remains intact at the structural level. While inputs are varied across simulations, the logic of the forecast and valuation model is fixed. This means that scenario-specific behaviors—such as cost structure adjustments in low-growth environments or tax effects during operating losses, are not dynamically modeled but instead implicitly absorbed into the probabilistic input ranges.

In summary, while the model succeeds in enhancing valuation realism by introducing probabilistic inputs, it remains a simplification of a far more complex reality. Its accuracy is ultimately bounded by the quality of its assumptions, the independence of its variables, and the technical limitations of the software used. These constraints must be acknowledged when interpreting its results, especially in the context of real-world investment decision-making.

8.3 - Possible Model Extensions and Future Improvements

The probabilistic DCF model presented in this thesis represents a significant evolution of the traditional valuation framework. However, there are numerous avenues for refinement and enhancement that could further improve its accuracy, efficiency, and analytical depth. These future improvements can be grouped into three main areas: technical upgrades, methodological enhancements, and integration with advanced analytics.

8.3.1 - Technical Upgrades and Platform Migration

While Excel was chosen for its accessibility and transparency, it is not the ideal environment for large-scale stochastic modeling. Migrating the model to a more robust programming environment such as Python or R would offer several advantages. These include improved computational speed, better memory management, and access to advanced statistical libraries.

For example, Python’s NumPy and SciPy libraries would allow more accurate random sampling and distribution fitting, while Pandas and Matplotlib could streamline data manipulation and visualization. Moreover, simulation runtimes could be drastically reduced, enabling more extensive and complex scenario testing, including time-dependent correlations and multi-step dependencies.

8.3.2 - Methodological Enhancements

From a methodological standpoint, the model could be improved by introducing more sophisticated probabilistic structures. One promising direction would be the incorporation of correlated inputs, particularly between revenue growth, margins, and capital expenditures. These variables often move together in real-world corporate dynamics, and modeling them independently may produce implausible scenario combinations.

Another enhancement could involve implementing regime-switching behavior or conditional logic based on scenario characteristics. For example, if revenue growth drops below a certain threshold, the model could trigger a different cost structure or investment behavior. This would increase realism in low-probability tail scenarios, which often drive significant valuation insights.

8.3.3 - Integration of Machine Learning Techniques

A more forward-looking avenue for development lies in the integration of machine learning techniques to automate and refine input estimation. For instance, supervised learning algorithms could be trained on historical data to estimate future growth rates, margins, or capital structure behavior based on macroeconomic indicators, financial ratios, or industry trends.

Additionally, unsupervised methods such as clustering could be used to identify comparable companies or sector patterns that inform model parameters.

These techniques, if properly trained and validated, could vastly increase the objectivity and predictive power of the valuation process, though they would also introduce challenges related to data availability, overfitting, and interpretability.

8.3.4 - Real-Time Integration and Automation

Finally, future iterations of this model could benefit from real-time data integration. By linking the valuation model to APIs from financial data providers, it would be possible to update inputs dynamically as market conditions evolve. This would allow analysts to maintain a “living” valuation tool, especially useful in fast-moving or high-volatility sectors.

Furthermore, automating the Montecarlo simulation process, triggered by scheduled updates or significant market events, would ensure that valuation distributions remain relevant and up to date without constant manual intervention.

8.3.5 - Conclusion

These proposed extensions represent both technical and conceptual improvements to the current model. They highlight a pathway toward more sophisticated, data-driven valuation tools that can better account for the complexity and uncertainty of financial markets. While not trivial to implement, such innovations would significantly enhance the analytical depth, adaptability, and decision-making utility of the DCF framework.

8.4 - Final Thoughts and Ethical Considerations

The integration of probabilistic methods, such as Montecarlo simulations, into traditional valuation frameworks like the Discounted Cash Flow (DCF) model represents a meaningful step toward a more nuanced understanding of investment uncertainty. However, it is crucial to stress that probabilistic valuation should not be misconstrued as a guarantee of accuracy or predictive power. These tools serve to highlight a range of potential outcomes rather than provide definitive answers. Their value lies in their ability to support deeper insight and more informed decision-making, not in eliminating risk or ambiguity.

The responsibility for interpreting and communicating the outputs of such models rests squarely on the shoulders of the analyst. It is not enough to present a distribution of outcomes; the assumptions, limitations, and context behind the model must be clearly understood and transparently conveyed to stakeholders. Misinterpretation of probabilistic data, or an overreliance on model outputs without critical analysis, can lead to misguided conclusions and poor financial decisions.

Ultimately, valuation is a human process, subject to judgment, uncertainty, and interpretation. While the use of advanced tools and simulations can enhance precision, they should not obscure the fact that financial forecasting involves assumptions about the future that are, by nature, uncertain. It is essential to resist the temptation to reduce valuation to a mechanical or purely quantitative exercise. Ethical practice in finance demands both technical competence and thoughtful reflection on the broader implications of the methods used.

This work, while technical in nature, should be viewed as part of a larger conversation on how best to represent uncertainty, exercise judgment, and uphold integrity in financial analysis.

8.5 - Disclaimer

The model presented in this thesis has been developed exclusively for academic and illustrative purposes. It is designed to explore the potential of integrating Montecarlo simulation techniques into the Discounted Cash Flow (DCF) valuation method, with the goal of providing a more probabilistic view of future stock valuations under uncertainty.

All assumptions, inputs, and estimations, both deterministic and stochastic, are based on publicly available data, historical averages, or general research, and should not be interpreted as professional investment advice or financial recommendations. The model does not account for all possible risks, real-world constraints, or behavioral and macroeconomic shocks that could significantly alter valuation outcomes.

Furthermore, while every effort has been made to ensure the model's internal consistency and logical rigor, the use of Microsoft Excel as a development platform introduces certain limitations in terms of computational performance, statistical flexibility, and error handling. As such, results may vary depending on user modifications, system specifications, or spreadsheet conditions.

The author disclaims any responsibility for financial decisions, investment strategies, or market operations that may be derived, directly or indirectly, from this work. Any attempt to replicate or apply this model to real-world securities should be done with extreme caution, and only in conjunction with thorough independent analysis and professional judgment.

Copy trading, model replication for speculative purposes, or reliance on the presented valuation outputs without a full understanding of the underlying mechanisms is strongly discouraged.

9 - BIBLIOGRAPHY

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