Beyond DCF: Enhancing Business Valuation in Emerging Markets through Monte Carlo Simulation Techniques

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Introduction

Emerging markets are expected to be one of the fastest-growing and dynamic business environments in today's global economy. For instance, despite the impact of the Covid-19 pandemic and the Russian-Ukraine war, the World Economic Outlook report in October 2023 projects Sub-Saharan Africa (SSA) to grow at 3.3% and 4.0% in 2023 and 2024, respectively, compared to, for example, a stable 1.1% growth for advanced economies. This growth potential has caught the attention of global investors who are seeking new investment opportunities and higher returns.

However, due to their unique characteristics, such as regulatory uncertainties, political instability, and data reliability issues, valuing businesses in emerging markets can be a complex and challenging process. Traditional valuation methods, such as the Discounted Cash Flow and Market Multiples, often have shortcomings when it comes to capturing the complex and unpredictable nature of the market. As a result, new and innovative approaches are worth considering to provide investors, analysts, and other stakeholders with more accurate and reliable options for valuations. One such technique that has gained significant attention is **Monte Carlo Simulation**. This approach provides a powerful means of modelling complex systems and generating a range of possible outcomes that can inform strategic decision-making.

In this thought leadership article, we explore the major limitations of the traditional valuation methods in emerging markets and highlight the benefits of the Monte Carlo Simulation technique in addressing these limitations. We also discuss the implementation of the approach with real-life cases, and highlight its potential limitations and challenges. Finally, we consider the future of business valuation in emerging markets, exploring emerging trends and new techniques that are likely to shape the field in the years to come.

Emerging Markets

Emerging markets have become a focal point of global economic growth, and SSA is no exception. Despite the region's socio-economic and political challenges, it has been a major focus of the investment world.

According to the World Bank, Foreign Direct Investment (FDI) net inflows in SSA from 2015 to 2019 averaged 3.8% of their GDP. Although it reduced to 2.6% in 2020, the average FDI inflows in 2021 and 2022 increased to 3.6%.

The SSA region is expected to continue to experience significant economic growth, although this growth is likely to be uneven across countries in the region. Rapid urbanisation, a growing middle class, and a youthful population are driving the growth of consumer markets, infrastructure, and financial services. In addition, emerging markets are generally considered as "segmented markets" due to their low level of financial integration with the rest of the world. This limits the transmission of global shocks into their financial markets, thereby creating diversification opportunities for international investors.

Nevertheless, investing in emerging markets is not without risk, as these markets could be characterised by greater uncertainty and volatility. For instance, the political landscape in these markets can be unpredictable, with significant changes in policy or regulations that can affect market conditions. Additionally, data availability and reliability can be a challenge, and there may be variations in accounting and financial reporting standards that require additional diligence. Also, the risk premium for investing in emerging markets can be relatively challenging to estimate, making it difficult to determine the appropriate discount rate to apply when calculating the present value of future cash flows. Thus, determining the value of businesses in emerging markets can be a daunting task, with unique challenges that must be considered.

Emerging markets often lack the transparency and efficiency of developed markets, making it difficult to obtain accurate market data for valuation purposes. Economic, political, and social risks can be significant, and the unique cultural and regulatory environments of these markets can require additional consideration. Therefore, analysts must apply a range of valuation techniques and approaches to accommodate the specific challenges posed by the markets.

In the next section, we will discuss the limitations of conventional valuation techniques, such as the discounted cash flow and market multiples, and how emerging market conditions require new approaches, such as the Monte Carlo simulation, to address these limitations and improve the reliability of business valuations.

Conventional Valuation Techniques

In emerging markets, the challenges faced in business valuation could be far more complex than in advanced markets. Conventional valuation techniques such as the Discounted Cash Flow and Market Multiples are still commonly used in these markets despite their limitations in addressing the unique issues faced. These limitations could lead to mispricing and an inaccurate valuation of businesses, creating a significant challenge for analysts and investors alike. In this section, we discuss the limitations of these conventional valuation techniques, and how they fall short in providing a comprehensive valuation that considers the complex nature of the markets. We would not be discussing the Asset-Based Approach.

Discounted Cash Flow (DCF) Approach: This approach is widely used in business valuation to determine the intrinsic value of businesses, and several types of DCF models are available to analysts and researchers, including the Free Cash Flow (FCF) Model, the Residual Income Model, and the Dividend Discounted Model (DDM). The FCF Model determines the value of a business as the present value of expected cash flows freely available to providers of capital, while the Residual Income Model sums the current book value of equity and the present value of expected residual income. The DDM, on the other hand, determines the value of a business as the present value of expected dividends payable to shareholders.

The DCF model is a widely used methodology in business valuation, but its application in emerging markets poses significant challenges. One major limitation of the DCF model is the difficulty in forecasting cash flows with reasonable accuracy due to the significant macroeconomic uncertainties, weak institutions, political instability and lack of transparency in financial reporting in most emerging markets.

This challenge is compounded by the limited availability of reliable financial data, making it challenging to generate accurate cash flow projections. Another significant limitation of the DCF model is the difficulty in determining an appropriate discount rate. In more advanced markets, the Capital Asset Pricing Model (CAPM) is widely used to determine an appropriate discount rate.

However, the assumptions underlying the CAPM, such as the availability of a risk-free rate and the efficient market hypothesis, does not usually hold in emerging markets. For instance, in SSA, the lack of well-established stock markets makes it difficult to estimate accurate market risk premia and the stock beta statistics, which are key components of the CAPM. Additionally, the high level of systemic risks in the region coupled with limited availability of long-term treasury instruments, makes it challenging to estimate an appropriate risk-free rate that matches investors' preferred investment horizon for the purposes of the valuation.

While the CAPM is still being used by several analysts in emerging markets, significant adjustments are made to input parameters to align with local market and economic circumstances.

Market-Based Approach: Market-based approaches are widely employed for business valuation and encompass methods such as Comparable Company Analysis (CCA) and Precedent Transaction Analysis (PTA). CCA entails comparing the financial ratios or multiples of analogous publicly traded firms to the subject firm. Conversely, PTA involves scrutinising financial ratios or multiples of comparable historical transactions involving similar companies to the target firm. Notably, S&P Capital IQ is a valuable resource that provides a comprehensive database for screening for comparable companies and precedent transaction data, which are critical for conducting market-based valuations. In many valuation exercises, these multiples are used to corroborate the DCF models rather than as a standalone valuation of the subject company.

The market-based approach has its limitations despite its popularity in business valuation. For instance, the use of market-based multiples may not always provide accurate valuation estimates, particularly in emerging markets where the information asymmetry due to low level of financial disclosure is a significant challenge. Furthermore, finding comparable companies whose prices reflect underlying fundamentals is a significant challenge due to low levels of trading activities on the stock markets in the region. Once identified, differences in financial reporting framework also make the needed adjustments cumbersome.

These limitations may lead to unreliable valuation estimates and potentially inaccurate investment decisions. Monte Carlo simulation remains a valuable tool for addressing some of these limitations hence improving the accuracy of business valuations.

Introducing Monte Carlo

Justification

Monte Carlo is a numerical technique for evaluating integrals, especially high-dimensional integrals, for which no close-form solution is available.

Suppose you have an integral of a function $f(x)$ over a specific domain or sample space Ω, represented as:

$$V = \int_{\Omega} f(x)dx$$

The Monte Carlo method involves randomly sampling points within the domain Ω. These random points are generated according to a known probability distribution. For each sampled point x_i, you evaluate the function $f(x_i)$ at that point. You then calculate the average of the function values obtained to arrive at an expected value as an approximation for the integral. This is shown below:

$$V \approx \frac{1}{N}\sum_{i=1}^{N} f(x_i)$$

where N is the total number of random samples.

Interestingly, the Monte Carlo method is consistent with the **Fundamental Asset Pricing Formula (FAPF)** which states that the value of an asset is the present value of its expected future cash flows:

$$\boldsymbol{Value\ of\ Asset = PV\{\mathbb{E}[Asset\ Cash\ Flows]\},}$$

Where $\mathbb{E}$ is a probability measure, and PV, the present value.

The FAPF forms basis for valuation and pricing of all financial assets including all types of derivatives, equity and fixed income instruments.

In the context of business valuation, the integral V represents the present value of expected future cash flows generated by the business over a specified investment horizon, which is essentially the intrinsic value of the business. This is the value being estimated through the Monte Carlo method, given the uncertainty and variability associated with the cash flows.

The function $f(x)$ represents the underlying financial model (cash flow generating model) which calculates the future cash flows generated by the business at a particular point in time, denoted as x. The financial model can be based on either the FCF, Residual Income or Dividends.

The x represents time, indicating different points in the future at which cash flows are expected to occur. Ω represents the investment horizon or the time period over which the business valuation is being conducted. It defines the range of possible future time points (years), or time steps (more generally), for which you want to estimate the cash flows and their present values.

The larger the N, the lower the approximation error (standard error) hence the better the estimate of the value of the business or asset whose integral is being evaluated.

Monte Carlo & Conventional Techniques

As we just established, one area where the Monte Carlo method can be particularly useful in finance is in business valuation. By treating the intrinsic value of a business as a random variable, we can use Monte Carlo Simulation to model the potential range of outcomes for a given set of inputs.

For instance, in the DCF, the intrinsic value of a business depends on the business' expected future cash flows and the discount rate used to discount those cash flows, both of which may be difficult to estimate. Additionally, future cash flows are driven by several variables including sales revenue, operating costs, capex, working capital and more, each of which can be treated as a random variable with a probability distribution that can be modelled accordingly.

By simulating thousands of possible outcomes for each variable and analysing the resulting distribution of intrinsic values generated based on an assumed financial model, the Monte Carlo simulation provides a comprehensive picture of the range of possible values that a business may be worth, and their probability distributions.

Monte Carlo simulation is not intended to replace the conventional DCF model, but rather to enhance its precision and relevance. One way to use Monte Carlo simulation in the context of business valuation, is to combine it with one of the DCF models such as the FCF model, Dividend Discount Model, or Residual Income Model. These models provide a basis for forecasting cash flows, which can then be used as inputs in the Monte Carlo simulation to generate a range of possible valuations.

By using this approach, analysts can take into account the inherent uncertainty in cash flow forecasts and other key inputs, which can improve the accuracy and robustness of the valuation results. Additionally, Monte Carlo simulation can produce confidence intervals for the valuation results at a given level of confidence, which can aid in decision-making and risk management.

Stochastic Processes

Introduction

It is important to note that Monte Carlo simulation relies on stochastic processes or models to generate random paths that represent the possible future values of a random variable.

To understand how Monte Carlo simulation is used in asset pricing, it is important to understand stochastic processes. A stochastic process is a variable that changes randomly over time. In statistical hypothesis testing, if x is a random variable with a mean μ and a standard deviation σ, then

$$x = \mu + z\sigma$$

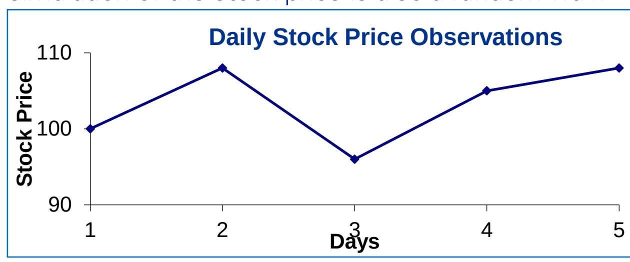
where z represents a stochastic or random term sampled from the standard normal distribution. The inclusion of z renders x a stochastic process.

It can be concluded that, since x is stochastic, the change in x or the derivative of x, dx, is also stochastic. This fundamental concept is critical to modelling stock price returns, which follows a stochastic process.

Key Concepts in Stochastic Processes

Random Walk

Let us continue further to analyse the behaviour of a stock price. Consider the metaphorical term "drunkard's walk", where a drunken person takes random steps in random directions, with no bias towards any particular direction. The movement of the drunken person is completely random, and there is no pattern to his steps. In a similar way, the movement of the stock price is a random walk, with no discernible trend or pattern. Consider the graph below for a traded stock's price observed over a 5-day period. Every daily movement in the stock price is a random walk. It follows that, each daily simulation of the stock price is also a random walk



In a random walk process, the assumption is that the stock price follows a path that is completely random and unpredictable. There are no trends or patterns in the price movement, which means that the future value of the stock price cannot be predicted based on past prices. Each new step in the process is independent of the previous steps. This contrasts with trending process, where the price movement is influenced by a systematic trend or pattern, making it possible to predict the future value of the stock price based on past prices.

Markov Process

Another important concept to note is the Markov Property and Markov Processes. The Markov Property is a fundamental concept in stochastic processes that states that the future state of a system depends only on the present state and not on any past states. In the context of stock prices, this means that the future value of a stock price in a random walk process depends only on the current price and not on any past prices. The Markov Property implies that the probability distribution of the stock price at any particular future time is not dependent on the particular path followed by the stock price in the past.

This makes the random walk process a Markov Process, which can be modelled using a Markov chain. In a Markov chain, the current stock price is a state, and the probability of transitioning to a new price state depends only on the current state. This makes it possible to simulate the future stock price using Monte Carlo simulation techniques.

Stochastic processes used in Monte Carlo simulations

There are two broad stochastic processes often used in Monte Carlo simulations for business valuation, namely, Arithmetic Brownian Motion and Geometric Brownian Motion.

Arithmetic Brownian Motion (ABM)

This process assumes that the stock price follows a random walk with a drift, where drift refers to the average rate of return on the stock. This process implies that the stock price will randomly increase or decrease in small increments over time, and the expected rate of return on the stock will remain constant over time. The stochastic differential equation (SDE) for ABM is given by:

$$dS = \mu dt + \sigma dZ \;\; \ldots . equation\ (1)$$

where dS is the differential or change in the stock price, μ is the expected rate of return or drift, σ is the volatility or standard deviation of the stock returns, dt is the instantaneous time increment, and dZ is the random shock. ABM simulations occasionally result in negative asset prices.

Geometric Brownian Motion (GBM):

This process assumes that the logarithmic returns of an asset follows a Brownian motion with a constant drift and volatility. It incorporates a geometric component, meaning that the asset prices can exhibit exponential growth or decay over time but will never be zero, unlike the ABM. The SDE for the GBM is given by:

$$dS = \mu S dt + \sigma S dZ \;\; \ldots . equation\ (2)$$

where dS is the differential or change in the stock price, μ is the expected rate of return or drift, σ is the volatility or standard deviation of the stock price, S is the current stock price, dt is the time increment, and dZ is the random shock.

Within this discussion, we centred our analysis on GBM as the preferred stochastic process, specifically the SDE that models the behaviour of asset prices.

The Monte Carlo Approach

The GBM model, which is a widely used stochastic process in finance describes the dynamics of stock prices, interest rates, and other financial variables. In the context of stock price modelling, the GBM model assumes that the rate of return on the stock follows a normal distribution, with the mean and variance of the distribution being constant over time. There are two main types of GBM models: the continuous-time GBM and the discrete-time GBM. The continuous-time GBM is the most commonly used model, and it assumes that the asset price changes continuously over time, whereas the discrete-time GBM assumes that the asset price changes only at specific points in time, hence increasing the approximation error.

Discrete-Time

In discrete-time GBM, time is divided into discrete intervals, and the stochastic process is simulated at each interval. The time step is typically chosen to be small enough to capture the essential features of the process, but large enough to keep computation time manageable. Specifically, the time step should match the period of return used, could be daily or weekly. For example, suppose an analyst wants to simulate the stock price over a 6-month period with daily time-steps. In this case, the time step Δt will be ${}^{1}/_{126}$. The accuracy of the simulation can be significantly impacted by the size of the time step, with smaller time steps generally leading to more accurate results but also longer computation time.

The SDE for the discrete-time GBM is obtained by replacing dt with Δt and dS with ΔS in $equation\ (2)$. This gives us:

$$\Delta S = \mu S \Delta t + \sigma S \varepsilon \sqrt{\Delta} t \ldots . equation\ (3)$$

where $\varepsilon\sqrt{\Delta t}$ is used as an approximation for the dZ term, representing the change in Wiener process in discrete time.

We can deduce that the stock price at time $t + \Delta t$, $S_{t+\Delta t}$ is equal to the stock price at time t, S_t plus the change in stock price, which is given by ΔS:

$$S_{t+\Delta t} = S_t + \Delta S$$

We can substitute $equation\ (3)$ into the equation for $S_{t+\Delta t}$ to get:

$$S_{t+\Delta t} = S_t + \mu S_t \Delta t + \sigma S_t \varepsilon \sqrt{\Delta} t \ldots \ldots equation\ (4)$$

It's important to note that $equation\ (4)$ is for the discrete-time GBM.

Continuous-Time

The continuous-time GBM assumes that the stock price is continually compounded at a constant expected rate of return, and the volatility is constant and independent of the stock price.

Consider the SDE in $equation\ (2)$. That is the standard process followed by the stock price. The term μSdt is known as the drift (deterministic component) and the term σSdZ is known as the diffusion or stochastic term (random component). The dZ term represents the change in the Wiener process. This stochastic process describes the instantaneous change dS in the stock price S as time changes infinitesimally dt.

However, analysing the process for dS in its original form can be difficult due to the stochastic term dZ, which can be rewritten as $\varepsilon\sqrt{dt}$. Also, in this process, the values of μ and σ are dependent on the future value of the stock price, making it challenging to model. To address this issue, a transformation of dS is required. In other words, the SDE must be solved to arrive at a closed-form solution for the stock price.

Solving the SDE

By applying Ito's lemma to $equation\ (2)$, we get:

$$d(\log S) = \left(\mu - {}^{1}/_{2}\,\sigma^2\right)dt + \sigma dZ \ \ldots\ldots equation\ 5$$

Integrating the above equation between 0 and T, we get:

$$\int_0^T d(\log S) = \int_0^T \left(\mu - {}^{1}/_{2}\,\sigma^2\right)d\tau + \int_0^T \sigma dZ$$

Evaluating further:

$$\log S_T - \log S_0 = \left(\mu - {}^{1}/_{2}\,\sigma^2\right)T + \sigma(Z_T - Z_0)$$

From the laws of logarithms:

$$\log\left(\frac{S_T}{S_0}\right) = \left(\mu - {}^{1}/_{2}\,\sigma\right)T + \sigma(Z_T - Z_0)$$

Assuming $Z_0 = 0$, and taking exponential function of both sides, the exact solution for the SDE (the stock price model) in $equation\ (2)$ is as follows.

$$S_T = S_0 \exp\left[\left(\mu - {}^{1}/_{2}\,\sigma^2\right)T + \sigma Z_T\right] \ldots\ldots equation\ (6)$$

From $equation\ (6)$ above, the expected return $(\mu - {}^{1}/_{2}\,\sigma^2)$ is constant and so is the volatility σ, with both being independent of the stock price S_0.

The Z_T term can be modelled as a random variable sampled from the standard normal distribution with a mean of 0 and standard deviation of $\sqrt{T}$. We can use Excel to generate random variables using the formula:

$$Z_T = NORMSINV(Rand()) \times \sqrt{T}$$

where $Rand()$ enables us to sample from a standard uniform distribution.

In addition, the final stock price S_T is lognormally distributed. This means that the natural logarithm of the final stock price $\log S_T$ follows a normal distribution with mean $\log S_0 + (\mu - {}^{1}/_{2}\,\sigma^2)T$, and variance $\sigma^2 T$.

Mathematically, we can write this as:

$$\log(S_T) \sim N\left[\log S_0 + \left(\mu - {}^{1}/_{2}\,\sigma^2\right)T, \sigma\sqrt{T}\right] .. eqn\ (7)$$

Taking the exponential function of both sides, we can also express S_T as :

$$S_T = exp\left\{N\left[\log S_0 + \left(\mu - {}^{1}/_{2}\,\sigma^2\right)T, \sigma\sqrt{T}\right]\right\} \ldots eqn\ (8)$$

where N is the normal distribution with mean $[\log S_0 + (\mu - {}^{1}/_{2}\,\sigma^2)T]$ and variance $\sigma\sqrt{T}$.

We have now derived our GBM model that constitutes the stochastic process underlying the Monte Carlo Simulation for our business valuation exercise.

Implementation of the GBM Model

Step 1: Define the problem

Identify the objective of the valuation and the entity whose value is to be determined. For instance, the objective may be to determine the intrinsic value of a business by conducting a business valuation.

Step 2: Analyse Data

Conduct a thorough analysis of the historical performance of the entity being valued, focusing on the financial variables that are relevant to the chosen valuation method such as Free Cash Flow to Equity (FCFE) or Residual Income (RI) models. This analysis may include variables such as revenue, operating costs, capex, working capital, taxes, cost of equity, etc. Compute the mean and standard deviation of each variable from historical data.

Step 3: Simulate Variables

Simulate the possible future values for each variable using the GBM Model. This involves generating correlated random values from the appropriate distribution (mainly the standard uniform distribution) for each selected financial statement variable. The correlation among the variables can be incorporated using Cholesky lower triangular decomposition.

Using the generated correlated random values and the statistics for each variable (the initial value, mean and standard deviation), apply the continuous-time GBM model to simulate the possible paths that each variable could take in the future over a defined investment horizon and a specified time step. Simulate the cost of equity and the terminal sustainable growth rate as uncorrelated random variables.

Step 4: Develop Financial Model

Specify the valuation model underlying the Monte Carlo, such as the FCFE or RI model. For example, for a manufacturing firm, the financial model using the FCFE method may be:

$$
\begin{aligned}
&FCFE \\
&= Revenue\ - Operating\ costs \\
&- Capital\ expenditures \\
&\pm Changes\ in\ Working\ Capital \\
&\pm Changes\ in\ Net\ Borrowings \\
&- Interest\ expense(post - tax)
\end{aligned}
$$

The Monte Carlo model will then generate possible outcomes for the intrinsic values of the company by determining the FCFE for each path and discounting them to arrive at their present values. Terminal value assumptions should also be incorporated for each path.

Step 5: Analyse the Results

After running the Monte Carlo simulation, we can analyse the simulated intrinsic value results using statistical tools such as histograms to visualize the distribution of the outputs. We can also calculate descriptive statistics such as the mean, median, standard deviation, and skewness to better understand the distribution.

Additionally, we can perform probabilistic analysis such as defining a confidence interval to estimate the range of values that the intrinsic value is likely to fall within. This analysis can help us make more informed investment decisions based on the risk and return characteristics of the investment opportunity.

Estimating Input Parameters

- **Historical financial data:** The mean and standard deviation of the financial variables used in the GBM model can be calculated from the historical financial data of the company. For example, if we are using the FCFE model to value a manufacturing company, we can use the historical data on revenue, operating costs, capital expenditures, and changes in working capital to calculate the mean and standard deviation of each variable. We can then use these statistics to simulate the future values of these variables using Monte Carlo simulation.
- **Industry benchmarks:** In cases where historical financial data is not available or limited, industry benchmarks can be used to calibrate input parameters. For example, if we are valuing a start-up company that has not yet generated any revenue, we can use industry benchmarks to estimate the revenue growth rate and operating margins. We can then simulate the future values of these variables using Monte Carlo simulation.
- **Non-normality of data distribution:** In many cases, the distribution of financial data is non-normal, meaning that it does not follow a Gaussian or normal distribution. One way to address this issue is to transform the data using techniques such as logarithmic transformations to make the data distribution more normal. For example, when valuing a technology company with highly skewed revenue data, the analyst can apply a logarithmic transformation.
- **Time horizon and frequency:** The time horizon and frequency of the data used in calibrating input parameters are critical in business valuation. The time horizon should be selected based on the investment objective, while the frequency should be selected based on the nature of the data. For instance, if the objective of the valuation is to determine the intrinsic value of a company over the next five years, then the time horizon should be set at five years, and the frequency of the data should be annual or quarterly, depending on the availability of data.
- **Dealing with outliers:** Outliers are data points that are significantly different from the rest of the data and can significantly impact the mean and standard deviation of the data. When calibrating input parameters for business valuation, outliers must be identified and handled appropriately. One way to handle outliers is to winsorize the data by capping extreme values at a certain percentile. For example, when valuing a real estate company, the analyst may identify outliers in property values and cap the values at the 95th percentile to prevent extreme values from skewing the mean and standard deviation.
- **Accounting for uncertainty:** Business valuation involves significant uncertainty, which can impact the calibration of input parameters. One way to account for uncertainty is to use a range of possible values for each variable instead of a single point estimate. This can be done using techniques such as sensitivity analysis, which involves varying each variable within a range of possible values to determine how it impacts the overall valuation result. For example, when valuing a pharmaceutical company, the analyst may use a range of possible success rates for the company's pipeline drugs to account for the uncertainty surrounding drug development.

Barriers in Monte Carlo

- **Data Availability and Quality:** Monte Carlo simulation relies heavily on historical financial data to calibrate input variables and generate projections. However, data availability and quality can be a major barrier to conducting accurate simulations. For example, if a company has limited historical financial data or has recently undergone a significant change in its business model, such as a merger or acquisition, it may be difficult to accurately simulate future performance. Similarly, if a company operates in an emerging market with limited financial reporting requirements, it may be challenging to obtain reliable financial data.
- **Parameters and Distribution:** Monte Carlo simulation involves making assumptions about the probability distributions and correlation coefficients of the input variables. Choosing appropriate probability distributions and correlation coefficients can be a complex and time-consuming process. For example, if the analyst is valuing a company in the pharmaceutical industry, they may need to consider the probability distribution of the success rates for the company's drug pipeline.

The analyst may also need to consider the correlation between different input variables, such as revenue growth and operating margins.

- **Model Complexity:** Emerging markets can be particularly challenging for Monte Carlo simulation due to the rapid changes and fluctuations in factors such as political instability, exchange rates, and regulations. These factors can make it difficult to accurately model future performance. For example, if the analyst is valuing a company operating in an emerging market with a rapidly changing political landscape, they may need to consider the probability of changes in government policy and the impact that these changes could have on the company's performance.
- **Updates and Adjustments**: Monte Carlo simulation is not a one-time exercise. As new data becomes available, the simulation model may need to be updated and adjusted to reflect changing market conditions. For example, if a company experiences a significant change in its business model or if new financial data becomes available, the simulation model may need to be adjusted to accurately reflect these changes.
- **Interpretation and communication:** The output of Monte Carlo simulation can be complex and difficult to interpret for non-experts. It is essential that the analyst can communicate the results of the simulation in a clear and understandable way to stakeholders. For example, the analyst may need to present the simulation results in the form of a probability distribution or a range of possible values to convey the level of uncertainty associated with the valuation.

To address these potential barriers, analysts can use a variety of techniques such as scenario analysis, stress testing, and sensitivity analysis to test the robustness of the simulation model and ensure that it accurately reflects the underlying economic reality. It is also important for analysts to continually update and adjust the simulation model as new data becomes available to ensure that it accurately reflects changing market conditions.

Monte Carlo in Action: Valuing Commercial Banks using GBM Model

We provide a step-by-step approach to determining the fair value of the top 5 banks in Ghana. We assume that there is no synergistic benefit or cost associated with combining these banks. Also, there is no inter-company transaction that should be eliminated. All analysis and modelling were done in Python.

Step 1: Define the problem

The objective of this exercise is to demonstrate the application of Monte Carlo in determining the fair value of the top 5 banks in Ghana by conducting a business valuation. We intend to apply the FCFE Model. The banks were ranked and selected on the basis of asset size. Note that, this exercise is just for demonstration purpose and should therefore not be misconstrued as a reflection of the true valuation of the banks. The business valuation date is December 31, 2021. The adjacent table gives additional information on the respective banks:

Banks	2021: Total Assets (GHS' M)	2021: Earnings (GHS' M)
GCB	18,260	557
Ecobank	17,857	579
Absa	16,038	693
Stanbic	14,043	405
Fidelity	13,350	342
Total	**79,547**	**2,575**

Step 2: Analyse Data

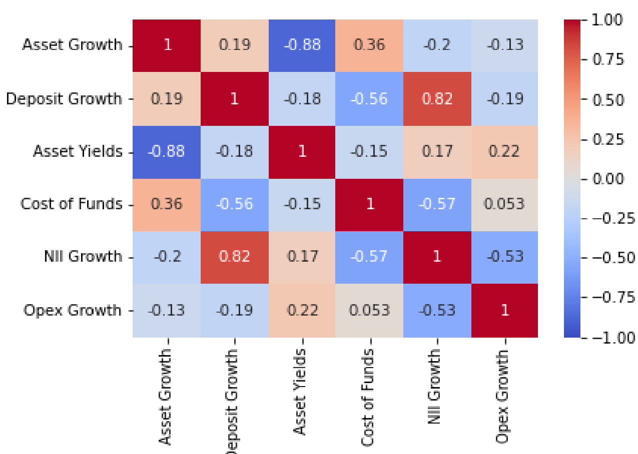
We considered the 7 year (2015 – 2021) aggregate historical financial data of the banks for our analysis. The key aggregate financial statement variables of importance for our analysis are summarised in the table below:

Variables	2015	2016	2017	2018	2019	2020	2021
Earning Asset Yields	20%	21%	17%	17%	15%	15%	15%
Cost of Funds	3.76%	3.41%	3.29%	3.37%	3.14%	3.17%	3.05%
Non-Interest Income	1,067,	1,278	1,367	1,581	2,004	1,990	2,475
Operating Expense	1,630	1,946	2,238	2,587	2,972	3,566	3,791
Impairment Loss	419	453	366	320	515	688	711
Earning Assets (Loans & Inv.)	16,331	17,012	22,778	27,960	36,713	44,740	52,636
Deposits & Borrowings	18,271	22,913	28,014	34,666	47,411	53,268	65,172

Variables	Initial value	Mean	Volatility
Growth in Asset Yield	-2%	-4%	7%
Growth in Cost of Funds	-4%	-3%	4%
Growth in Non-Interest Income	24%	15%	10%
Growth in Operating Expense	6%	15%	4%
Impairment Loss Rate (% of Earn. Assets)	-12%	-7%	22%
Growth in Earning Assets	18%	22%	10%
Growth in Deposits & Borrowings	22%	24%	7%

The mean and the standard deviation of each variable was computed on the basis of movements (or growth) in the historical values of the variables.

The objective is to model the movement in the variables rather than the variables themselves. The summary statistics are shown in the table adjacent.



The correlation heatmap reports a strong negative correlation between growth in earning assets and growth in asset yields, representing a trade-off between generating interest income from earning assets and maintaining profitability.

A strong positive correlation between deposit growth and growth in non-interest income (NII growth) may be attributable to an increased ability to earn higher fee-based income from enhanced customer-base or customer deposits.

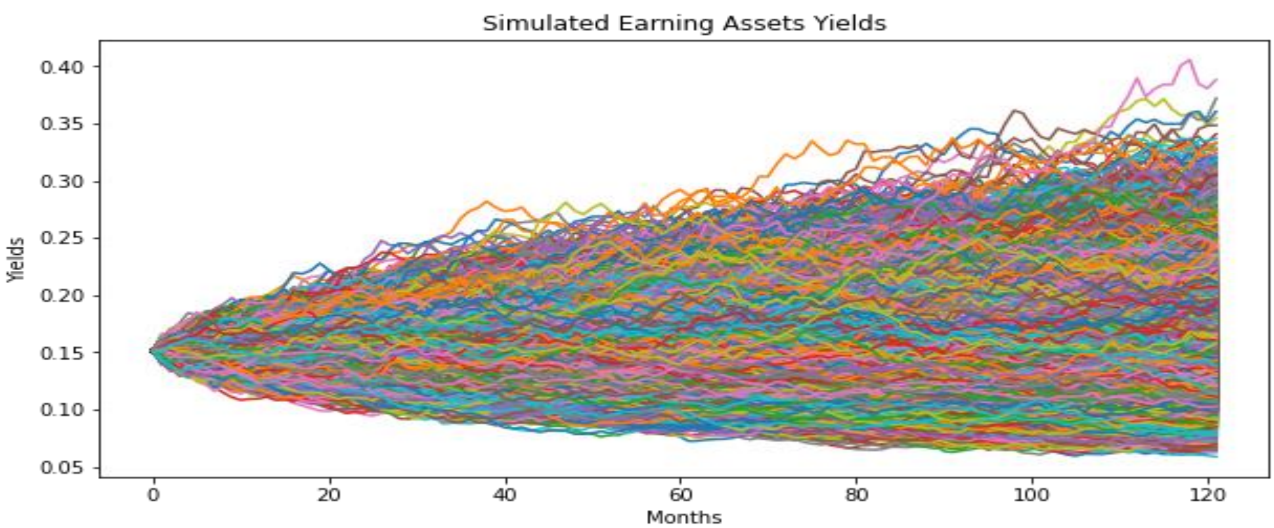
An extremely weak correlation between growth in cost of funds and growth in operating expense (opex) is predictable because cost of funds are mainly driven by market interest rates while the latter, by size and operating efficiency.

Monte Carlo in Action: Valuing Commercial Banks using GBM Model

Step 3: Simulate Variables

Assuming normal distributions for each variable, we generate independent random numbers conforming to the standard normal distribution. Our analysis of the correlation matrix has revealed significant correlations between various pairs of variables featured in the financial statements of the banks. Consequently, it is imperative to incorporate the historical correlation of these variables into the independent random numbers generated for simulation. To achieve this, we transformed the correlation matrix into a lower triangular matrix after verifying its positive semi-definiteness, which entails that all the eigenvalues of the matrix are non-negative.

We utilized **equation (6)**, the continuous-time GBM model, to run 40,000 simulations on each variable over a 10-year forecast horizon projected on a monthly basis (120 months). The GBM model was supplied with the initial variable value, the mean, the volatility, and the correlated random variables. The resulting output of one of the variables, future earning asset yield, based on the statistical properties, is visualised in the accompanying graph. Note that there are stochastic interest rate models such as Vasicek which can be calibrated to simulate more reliable paths for earnings asset yield.



Note, we simulated impairment loss rate, cost of equity, and sustainable long-term growth rate independently, as we did not observe any significant correlations among them. Although it could be argued that impairment loss rate may correlate with some financial statement variables, its inclusion resulted in our correlation matrix being non-positive semi-definite. It is worth noting that, in simulating asset yields, cost of funds, impairment loss rate, cost of equity, and long-term sustainable growth rate using the GBM model, we assumed that the change in each of these variables is driftless. This is crucial because we expect the future values of these variables to revert to the historical mean. Therefore, introducing a drift would scale estimate in a manner that would not achieve the desired outcome.

Step 4: Develop Financial Model

In this phase, we proceed to construct a basic financial model centred on the FCFE. This model serves as the bedrock for the Monte Carlo Simulation, which in turn facilitates the estimation of the fair value of the banks. Specifically, the FCFE model is formulated as:

FCFE = interest income – interest expense + non interest income – operating expense – impairment loss – taxes – transfer to statutory reserves.

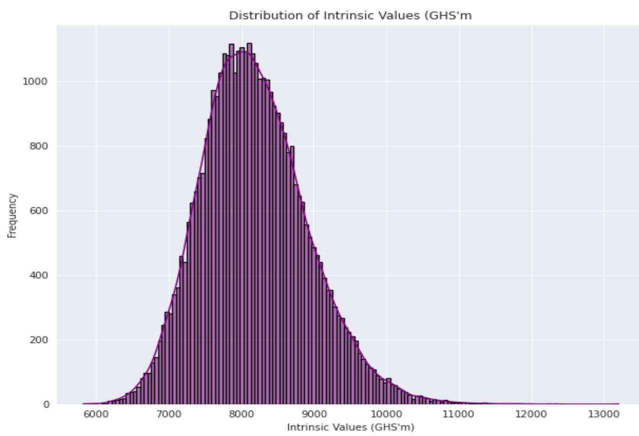
By leveraging the 2-dimensional simulations developed for each independent variable (40,000 x 120), we

Monte Carlo in Action: Valuing Commercial Banks using GBM Model

Step 4: Develop Financial Model (cont'd)

simulate the FCFE. As a result, the FCFE itself was generated as a 2-dimensional dataset, with each value representing an estimate of the FCFE at a specific point in time. Leveraging the simulated FCFE values alongside the simulated terminal value, we discount these figures by the simulated cost of equity for each simulation, and sum them together. This framework allows for generation of an estimate for the fair value of the banks in each simulation, which forms the basis for subsequent analysis.

The resulting fair values of the banks are then represented on a histogram, which provides a visualisation of the simulations' outputs. As shown below, the distribution of the simulated fair values resembles a log-normal distribution.



This approach enables us to evaluate the distribution of fair values across simulations and assess the extent to which they align with our underlying assumptions.

Overall, the FCFE model, in conjunction with Monte Carlo simulation, provides a comprehensive framework for estimating the fair value of the banks, while also offering a high degree of precision and flexibility in the valuation process.

Step 5: Analyse the Results

Descriptive Statistics	GHS' M
Mean	8,183
Median	8,126
Standard Deviation	734
75th Percentile	8,640
95th Percentile	**9,480**

Multiples	GHS'M
Fair Value (GHS' M)	8,183
Book Value (GHS' M)	10,696
Earnings after Tax (GHS' M)	2,575
Trailing Price/Book	0.77x
Trailing Price/Earnings	**3.18X**

The GBM model estimates the fair value of the top 5 banks at GHS 8.2 billion as of 31 December, 2021. The aggregated book value of equity and net earnings were GHS 10.7 billion and GHS 2.6 billion for the period. These correspond to a P/B multiple of 0.77 and a P/E multiple of 3.18.

While the assets and liabilities of banks are often reported at their fair values, a P/B ratio below 1 can still be justified from a residual income standpoint. Despite an average return on equity (ROE) of 24% in 2021 for the top 5 banks, the expected cost of equity of 29% suggests that these leading banks will not generate sufficient economic profits to offset the required rate of return expected by equity investors and therefore, eroding value over time.

The Future of Business Valuation in Emerging Markets

- **Machine Learning & AI:** One of the most exciting developments in business valuation is the application of Machine Learning and Artificial Intelligence (AI) to the valuation process. Machine Learning algorithms can be trained on large datasets of financial and non-financial data to identify patterns and relationships that can inform the valuation of a company. For example, machine learning algorithms can be used to analyse a company's financial statements, news articles, and social media activity to identify key drivers of value and potential risks. This can lead to a more comprehensive and accurate valuation of a company, particularly in cases where traditional financial metrics may not be sufficient.
- **New Valuation Techniques:** Traditional valuation methods such as DCF models have limitations in capturing the value of strategic options and other real options that are commonly found in emerging markets. Real option analysis, for example, is a valuation technique that recognizes the value of flexibility and options that a company has in terms of its strategic choices. This approach can help investors to better evaluate the potential value of a company's investments in R&D, market expansion, or new technology. Another example is contingent claims analysis, which uses option pricing theory to value companies with complex capital structures or contingent liabilities, such as those found in emerging markets.
- **Multi-Criteria Decision Analysis:** In emerging markets, traditional financial metrics may not always capture the full spectrum of value drivers. Multi-criteria decision analysis (MCDA) provides a framework for evaluating investment opportunities based on multiple criteria, including financial and non-financial factors. For example, in valuing a company in the renewable energy sector, the analyst may consider criteria such as the company's environmental impact, social responsibility, and governance practices, in addition to traditional financial metrics.
- **Integrating Environmental, Social and Governance Factors (ESG):** ESG is becoming critical in business valuation. Companies that prioritize sustainability and social responsibility may have a competitive advantage in the long term, and analysts must consider these factors when valuing such companies. For example, ESG factors can be incorporated into the discounted cash flow model by adjusting the discount rate to reflect the company's ESG risks and opportunities.
- **Addressing Data Limitations:** Data limitations are a common challenge in emerging markets, where data may be incomplete or unreliable. To address this challenge, investors may need to rely on alternative data sources or use statistical techniques to estimate missing data. For example, satellite imagery can be used to estimate crop yields in agriculture, while social media data can be used to estimate consumer sentiment in retail.

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