

MINERVA INVESTMENT MANAGEMENT SOCIETY

Quantitative Research Division



A Data-Driven DCF Valuation Framework

Integrating SMM-Based Growth Dynamics into Valuation

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Abstract

The present framework is inspired by the simulation-based DCF valuation approach proposed by Botta (2026), who introduces the use of the Simulated Method of Moments to estimate growth dynamics and integrate them into a discounted cash flow framework. Traditional DCF valuations often rely on deterministic or judgmental growth assumptions, particularly in the explicit forecast period and terminal value calculation. Such assumptions may generate internally inconsistent projections and provide limited information about valuation uncertainty. To address this issue, we model revenue growth as a mean-reverting stochastic process and estimate its structural parameters (the long-run mean, persistence and innovation volatility), by minimizing a weighted quadratic distance between empirically observed moments and their model-implied counterparts obtained through Monte Carlo simulation. The estimated process is then exploited into a DCF framework to generate cash-flow projections, terminal value estimates and Monte Carlo valuation distributions. Using Microsoft Corporation as an empirical application, the results show a long-run log growth estimate of approximately 10.45%, low persistence in growth shocks (not significant) and moderate innovation volatility of 6.71%. The implied DCF valuation yields an intrinsic value of approximately 620.57\$ per share, compared with a market price of 422.79\$. However, the valuation remains highly sensitive to terminal growth and discount rate assumptions, therefore the proposed framework should mainly be seen as a different methodology for making a bridge between historical growth dynamics, cash-flow projections and valuation uncertainty in a statistically coherent way.

1 Empirical Setting

1.1 Data Framework

The empirical application is conducted on Microsoft Corporation (MSFT). The dataset combines accounting information, market data and valuation inputs. The accounting data consist primarily of quarterly revenues over the period 2012–2026, which are used to estimate the stochastic growth process.

Data are obtained from FactSet Fundamentals and publicly available financial information from Yahoo Finance. Market data and valuation inputs are measured as of April 17, 2026 ¹.

Quarterly revenue observations are used instead of free cash flow growth for the estimation of the structural growth process. Revenues provide a smoother measure of the firm’s underlying operating activity, whereas free cash flow may be affected by short-term fluctuations arising from working capital changes, tax payments, capital expenditure and many other factors. Consequently, revenue growth is used as a proxy for the firm’s long-run operating growth dynamics, while free cash flow is used as the cash-flow base in the DCF valuation.

Let R_t denote revenue in quarter t . The empirical growth rate is computed as the log difference of revenue:

$$g_t = \Delta \log(R_t) = \log(R_t) - \log(R_{t-1}).$$

When quarterly data are used, the resulting growth estimates are annualized to make them consistent with the annual DCF projection horizon. This allows the structural growth parameters estimated from quarterly observations to be incorporated into an annual valuation framework. The use of quarterly revenues increases the number of observations relative to annual data and improves the statistical identification of our parameters of interest in the growth process.

All monetary variables are expressed in USD billions, except for the stock price, which is expressed in USD per share. Shares outstanding are reported in billions. The main valuation inputs are summarized in Table 1.

Table 1: Market Data and Valuation Inputs

Variable	Symbol	Value
Valuation date	–	April 17, 2026
Stock price	P_0	\$422.79
Shares outstanding	N	7.42563B
Market capitalization	$P_0 \times N$	\$3,139.5B
Weighted average cost of capital	r	8.68%
Equity beta	β	1.04
Net debt	D'	\$17.619B
Latest annual free cash flow	FCF_T	\$71.61B
Explicit forecast horizon	n	5 years

1.2 Theoretical Framework

1.2.1 Time Series Specification

Let $g_t = \Delta \log(\text{Revenue}_t)$ denote the log growth rate of revenue. Growth is modeled as a covariance-stationary autoregressive process of order one:

¹Additional missing data have been taken from https://www.financecharts.com/stocks/MSFT/income-statement/revenue#google_vignette

$$g_t = \mu + \phi(g_{t-1} - \mu) + \sigma\varepsilon_t, \quad \varepsilon_t \sim \mathcal{N}(0, 1)$$

This specification implies that growth fluctuates around a long-run mean μ , with persistence governed by ϕ (first-order autocovariance) and innovation volatility given by σ . The mean-reverting structure is consistent with empirical evidence that firm growth rates tend to revert over time, while allowing for temporary deviations driven by shocks.

The AR(1) representation also admits a closed-form conditional expectation:

$$\mathbb{E}[g_{T+h}] = \mu + \phi^h(g_T - \mu)$$

which plays a central role in generating forward-looking projections.

1.2.2 From Growth Dynamics to Cash Flow Projections

The starting point is the standard enterprise value DCF model. Enterprise value of a firm is defined as the present value of projected free cash flows over an explicit forecast horizon of n periods, plus the present value of a terminal value capturing all subsequent cash flows:

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

where FCF_t is the free cash flow in period t , r is the weighted average cost of capital (WACC) and TV is the terminal value. Under a perpetual constant-growth assumption, the terminal value is:

$$TV = \frac{FCF_n(1+g^*)}{r-g^*},$$

where g^* is the perpetual growth rate, which must satisfy $g^* < r$ to ensure economic consistency (according to what the Gordon growth condition predicts). We impose:

$$g^* = \min \left\{ e^{\hat{\mu}} - 1, r - 0.02 \right\}$$

In this way, we prevent eventual explosive terminal values and ensure convergence of the valuations.

Our estimated growth process is used to generate forward-looking projections of growth rates. Using the conditional expectation of the AR(1) process, we obtain a deterministic baseline projection for expected growth.

These projected growth rates are then mapped into FCF levels via exponential compounding:

$$FCF_{t+1} = FCF_t \cdot e^{g_{t+1}}$$

1.3 Estimation Methodology

1.3.1 Method of Moments Estimation

The structural model parameters $\theta = (\mu, \phi, \sigma)$ are estimated using the Simulated Method of Moments (SMM) technique.

The SMM estimator is defined as:

$$\hat{\theta} = \arg \min_{\theta} \left(m^{data} - m^{sim}(\theta) \right)' W \left(m^{data} - m^{sim}(\theta) \right)$$

where m^{data} is a vector of empirical moments computed from observed growth rates, $m^{sim}(\theta)$ is the corresponding vector obtained from simulated data under parameter θ and W is a weighting matrix. Specifically, W is a diagonal weighting matrix defined as:

$$W = \text{diag} \left(\frac{1}{m_i^2 + \epsilon} \right),$$

where ϵ is a small constant introduced to ensure numerical stability. This weighting scheme standardizes the contribution of each moment to the objective function and reduces the influence of differences in scale across moments.

Assuming regularity conditions are satisfied, it can be shown that the SMM estimator is consistent and asymptotically normal:

$$\sqrt{T}(\hat{\theta} - \theta_0) \xrightarrow{d} \mathcal{N}(0, \Sigma)$$

1.3.2 Why SMM rather than OLS?

SMM is particularly well suited for this setting because the DCF framework is inherently non-linear. Future cash flows are generated through compounding growth dynamics and discounted recursively, while terminal value calculations introduce additional non-linear sensitivity to long-run growth assumptions. In such environments, conventional estimation techniques such as Ordinary Least Squares (OLS) become less appropriate, as they are designed primarily for linear settings and large-sample asymptotic properties.

This latter point leads to an additional advantage of SMM, which is its robustness in relatively small samples. Financial time series for individual firms are often limited in length, particularly when using quarterly or annual accounting data. Because SMM relies on matching economically meaningful moments rather than exploiting strict analytical solutions, it can provide stable parameter estimates even when the available sample size is limited.

1.3.3 Simulation of Model-Implied Moments

For a given parameter vector θ , model-implied moments are approximated via Monte Carlo simulation of the AR(1) process. Each simulated path is initialized at its stationary distribution:

$$g_0 \sim \mathcal{N}\left(\mu, \frac{\sigma^2}{1 - \phi^2}\right)$$

which ensures that simulated series are consistent with the long-run properties of the process.

A large number of simulated paths are generated, and moments are computed for each path and averaged.

1.3.4 Numerical Optimization Procedure

The SMM objective function as already mentioned is defined as

$$Q(\theta) = [m - \hat{m}(\theta)]' W [m - \hat{m}(\theta)],$$

where m denotes the vector of empirical moments and $\hat{m}(\theta)$ the corresponding simulated moments implied by the parameter vector $\theta = (\mu, \phi, \sigma)$.

The objective function is minimized using the Nelder–Mead simplex algorithm (Nelder and Mead, 1965). This approach is well suited to the present setting because the objective function is simulation-based, potentially noisy and not guaranteed to be differentiable. Furthermore, the low dimensionality of the parameter space makes simplex-based optimization computationally efficient. Initial parameter values are obtained analytically from the empirical moments:

$$\mu_0 = m_1, \quad \phi_0 = \frac{m_3}{m_2}, \quad \sigma_0 = \sqrt{m_2(1 - \phi_0^2)},$$

which provides a starting point broadly consistent with the observed data and improves numerical convergence.

1.3.6 Monte Carlo Simulation

Monte Carlo simulation is a numerical method used to approximate the distribution of outcomes implied by a stochastic model. Rather than relying on analytical solutions, the method generates a large number of random realizations of the underlying process and computes the quantity of interest for each realization.

In this study, the estimated AR(1) growth process is simulated repeatedly to produce alternative future growth paths. For each simulation, the sequence of growth rates is transformed into projected free cash flows, which are then discounted to obtain an intrinsic value. Repeating this procedure many times generates an empirical distribution of valuations.

Formally, if the growth process is given by

$$g_t = \mu + \phi(g_{t-1} - \mu) + \varepsilon_t, \quad \varepsilon_t \sim N(0, \sigma^2),$$

Monte Carlo simulation consists of repeatedly drawing innovations ε_t and recursively generating future values of g_t . The resulting paths are propagated through the DCF model, yielding a distribution of firm values rather than a single point estimate.

2 Results and Interpretation

2.1 Empirical Estimation and Valuation Results

Table 2: SMM Estimates and DCF Valuation Output

Metric	Value
$\hat{\mu}$ (annual)	0.104480
$\hat{\phi}$	-0.029854
$\hat{\sigma}$	0.067100
Raw $\exp(\hat{\mu}) - 1$	11.01%
Capped perpetual growth rate (g^*)	6.68%
Base annual FCF (USD bn)	71.61
Forecast horizon (years)	5
Terminal value (USD bn)	6,435.1
PV of explicit FCFs (USD bn)	381.5
PV of terminal value (USD bn)	4,244.3
PV of Terminal Value / EV	91.8%
Enterprise value (USD bn)	4,625.8
Equity value (USD bn)	4,608.1
DCF price per share (USD)	620.57
Market price (USD)	422.79
Implied upside	46.8%

Table 3: Bootstrap SMM Inference

Parameter	Estimate	Std. Error	95% CI
μ	0.1045*	0.0163	[0.0668, 0.1308]
ϕ	-0.0299	0.2128	[-0.4761, 0.4176]
σ	0.0671*	0.0193	[0.0234, 0.0885]

Notes: Standard errors and confidence intervals are obtained using a moving-block bootstrap procedure. Reported confidence intervals correspond to the 95% bootstrap percentile intervals. Estimates marked with an asterisk have confidence intervals that exclude zero.

Table 2 reports the estimated growth parameters obtained through the SMM procedure together with the main valuation outputs implied by the DCF model. The estimated long-run growth parameter is $\hat{\mu} = 0.1045$, corresponding to an annual growth rate of approximately 11.0% (from bootstrap inference, statistically significant and precisely estimated). This suggests that Microsoft exhibited strong structural growth over the sample period.

The persistence parameter is estimated at $\hat{\phi} = -0.0299$. Combined with the bootstrap results reported, it indicates little evidence of serial dependence in growth rates as suggested by large bootstrap standard error and confidence interval spanning both positive and negative values. Growth shocks appear largely transitory and tend to revert rapidly toward the long-run mean.

The innovation volatility estimate, $\hat{\sigma} = 0.0671$, implies moderate uncertainty around the firm's expected growth path but still positively estimated and statistically significant. While growth remains strongly positive on average, temporary deviations from trend continue to play an important role in the valuation distribution.

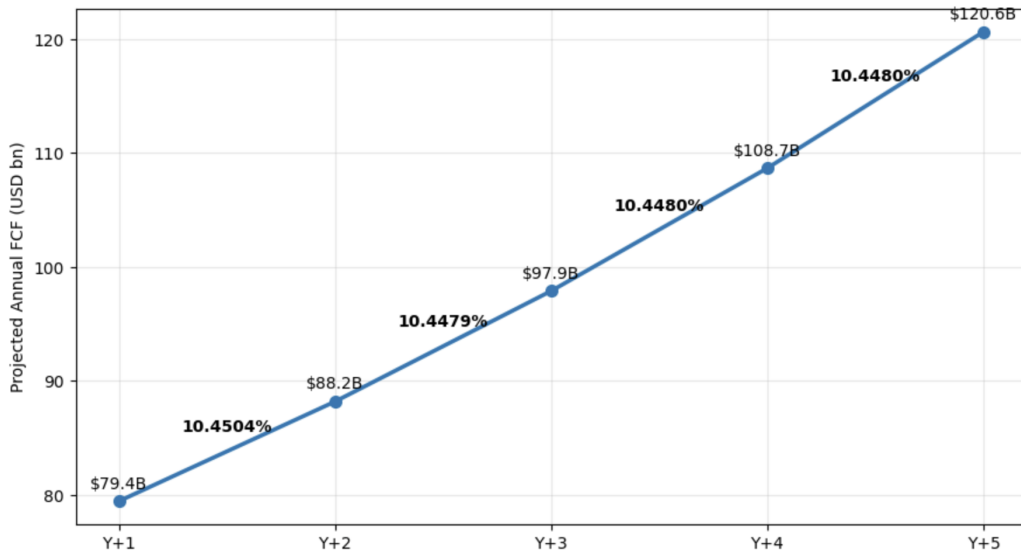


Figure 1: Projected Free Cash Flow (MSFT)-Growth in bold

Figure 1 presents the detailed DCF decomposition underlying the valuation. Projected free cash flows increase steadily over the explicit forecast horizon, reflecting the strong growth dynamics estimated by the model.

The estimated enterprise value is \$4625.8B. After subtracting net debt, the implied equity value is \$4,608.1B. Dividing by shares outstanding yields an estimated intrinsic value of \$620.57 per share, compared with a market price of \$422.79 in the model output. This corresponds to an implied upside of 46.8%. It is crucial to underline that this valuation result should not be interpreted with any trading reference, since it merely reflects the implications of applying the estimated historical growth dynamics to a DCF model under the maintained assumptions on discount rate, terminal growth and the "revenue-to-FCF" mapping.

At the same time, the terminal value is the dominant component of the valuation. Indeed, from our analysis, the present value of explicit forecast-period free cash flows equals \$381.5B, while the present value of the terminal value equals \$4244.3B. Thus, approximately 91% of enterprise value is attributable to the terminal component. This finding is important for the interpretation of the model. Although the framework estimates growth dynamics in a statistically disciplined way, the valuation remains highly dependent on long-run assumptions and on the cap imposed on g^* .

2.2 Monte Carlo Valuation Distribution

The obtained distribution of intrinsic values, rather than a single point estimate, can be observed in Figure 2, with the corresponding percentiles.

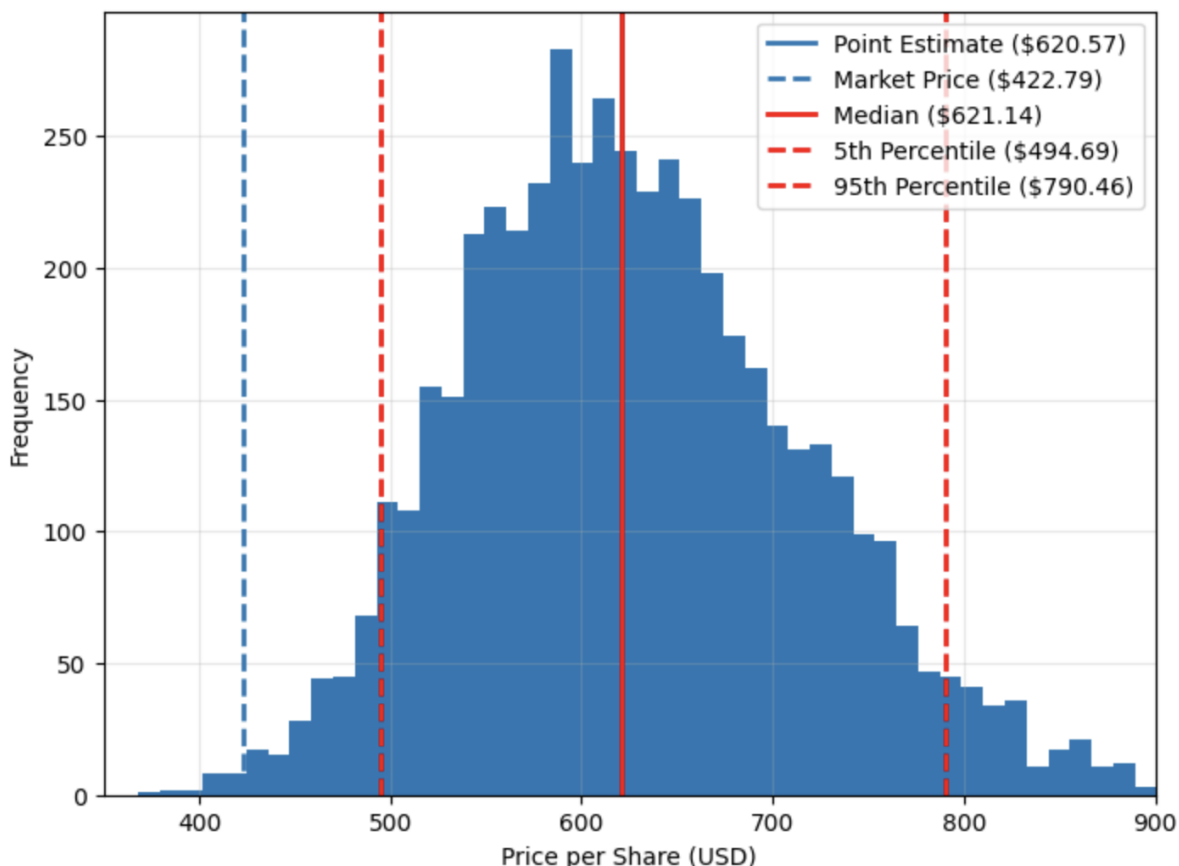


Figure 2: SMM Monte Carlo Distributions of MSFT Intrinsic Value

When interpreting the Monte Carlo distribution, it is important to note that the model produces a valuation distribution skewed toward higher intrinsic values. This outcome arises because the framework is structurally calibrated on historically strong growth dynamics. As these historically estimated growth rates are projected forward through the DCF mechanism, the compounding effect of sustained growth assumptions mechanically pushes the distribution of intrinsic values upward.

2.3 Discussion

Summarizing the several advantages the SMM model offers:

- **Data-driven estimation of growth dynamics:** We do not need to rely on ad hoc data since the model estimates the stochastic process, which determines cash flow growth, from historical data.
- **Internal consistency between projections and valuation:** All components of the valuation are derived from a unified structural model. Growth forecasts, terminal value assumptions and uncertainty are jointly determined, which ensures coherence between short-term projections and long-run observed behavior. In typical DCF approaches, there are many inconsistencies where inputs are chosen independently, which are avoided choosing this approach.
- **Formal statistical inference:** As we are working with estimated parameters, we can rely on well-defined statistical properties. This enables the construction of confidence intervals using standard errors. We do not rely anymore on a single point estimate but on a distribution which allows for a probabilistic interpretation.
- **Explicit treatment of uncertainty:** Monte Carlo simulation propagates uncertainty from estimated parameters through to firm value. This provides a full distribution of intrinsic value, offering a principled alternative to sensitivity tables and scenario analysis commonly used in practice.

3 Limitations

This article presents an alternative approach to DCF valuation. However, the proposed framework remains subject to several limitations and should be viewed as a preliminary step towards a more comprehensive valuation methodology.

Although the use of quarterly revenue data increases the number of available observations relative to annual accounting data, the estimation remains based on a relatively short time series from an econometric perspective. This may reduce the precision with which persistence and volatility parameters are identified and links the sensitivity of the results to the specific sample period considered. The issue is relevant in our setting, as we analyse large technology firms whose recent performance may reflect particular AI advancements rather than stable long-run dynamics.

In addition, the framework relies on the assumption that revenue growth follows a stationary Gaussian AR(1) process. While this specification provides an economically interpretable representation of growth dynamics, it may not capture structural changes in the firm’s underlying business model. For Microsoft specifically, as previously mentioned, AI developments and investments might lead to changes in product mix and may alter the growth process over time, challenging the stationarity assumption.

A further source of uncertainty arises from the fact that growth dynamics are estimated using revenue data but subsequently applied to free cash flow projections. This implicitly assumes that long-run free cash flow growth evolves consistently with revenue growth. In the real world, changes in operating margins, capital expenditures, or other variables, may cause cash flows to differ from revenues growth, weakening the link between the estimated process and the valuation exercise.

Last but not least, as already stated throughout this work, the estimated long-run growth parameter captures historically observed growth dynamics, however it does not necessarily correspond to an economically sustainable perpetual growth rate. As a consequence, the terminal growth assumption must be constrained exogenously, to ensure convergence of the valuation model and avoiding an overestimated growth.

Future research could address these limitations by incorporating richer growth specifications, Bayesian estimation techniques or explicit models linking revenue growth, profitability and free cash flow generation.

4 Conclusions

This study proposes a data-driven extension of the traditional Discounted Cash Flow framework by estimating firm growth dynamics through the Simulated Method of Moments. Rather than relying on exogenous or discretionary growth assumptions, the methodology derives growth projections from a stochastic process estimated directly from historical data.

The empirical results derived from a real application on Microsoft shares and financial data, show that the proposed framework is capable of generating internally consistent cash-flow projections and valuation estimates while preserving the statistical properties of the underlying growth process. By combining SMM estimation with Monte Carlo simulation, the approach extends the conventional DCF framework from a deterministic valuation exercise to a probabilistic one, allowing uncertainty in growth dynamics to be explicitly incorporated into the valuation process.

More broadly, the analysis illustrates how simulation-based econometric techniques can be integrated into corporate valuation. The methodology provides a coherent link between historical growth behaviour, future cash-flow projections and valuation outcomes, while remaining sufficiently flexible to accommodate non-linearities that are difficult to address using traditional estimation methods.

Although the framework remains subject to limitations related to sample size, model specification and terminal value assumptions, the results suggest that SMM represents a viable and statistically rigorous approach for incorporating empirically estimated growth dynamics into DCF valuation.

References

- [1] Botta, C. (2026). *DCF Valuation via Simulated Method of Moments: Structural Estimation of Cash Flow Dynamics*. SDA Bocconi School of Management, March 18, 2026.