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Testing the Dividend Discount Model: Comparative Evidence on Accuracy, Stability, and Sensitivity

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ABSTRACT

This review examines the empirical performance of the Dividend Discount Model (DDM) in terms of three key dimensions: accuracy, stability, and sensitivity. The DDM, widely used in equity valuation, estimates the present value of expected future dividends. While its theoretical appeal is strong, real-world applications often highlight significant challenges. In the "accuracy" dimension we aggregate evidence from multiple markets that compare intrinsic values derived from DDMs with realised market prices or subsequent returns. The "stability" dimension explores how DDM performance varies across time, markets and firm types, investigating whether the model's error metrics remain consistent. The "sensitivity" dimension analyses how small changes in input assumptions—particularly dividend growth rate (g) and discount rate (r)—can produce large swings in value estimates. In the comparative evidence reviewed, mature, dividend-paying firms in stable markets show relatively better accuracy and stability, whereas growth-oriented or irregular–dividend firms display larger deviations and instability. Sensitivity analyses reveal that a ±1 % variation in assumed discount or growth rate commonly yields ±20 % or more change in valuation, underlining the fragility of the model's output. Based on this review, the DDM remains a useful heuristic for income-oriented, dividend-stable companies but is less robust as a universal valuation tool. The model's heavy reliance on precise inputs and the observed variation in accuracy and stability suggest caution: analysts should treat DDM outputs as ranges rather than point estimates, and complement them with other valuation frameworks (e.g., free-cash-flow or comparables). The review also identifies research gaps — notably, insufficient comparative empirical evidence across emerging vs developed markets, and limited study of multi-stage DDMs in volatile firms.

KEYWORDS: Dividend Discount Model, Stock Valuation, Accuracy, Model Stability, Sensitivity Analysis, Dividend Growth, Discount Rate.

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INTRODUCTION

Valuation of equity securities remains one of the most central tasks in financial theory and practice. Among the many valuation tools available, the Dividend Discount Model (DDM) stands out for its intuitive linkage of value to the present value of future dividend cash flows. The core idea is simple: because dividends represent the ultimate cash return to shareholders, one can estimate the share price today by discounting expected future dividends. In its simplest constant-growth form (also known as the Gordon Growth Model), the value V_0 of a share equals the next period's expected dividend D_1 divided by the difference between required rate of return r and dividend growth rate g:

$$V_0 = \frac{D_1}{r - g}$$

Under this form, the DDM assumes a perpetuity of growing dividends at rate g, discounted at rate r. Over time, variants of the DDM have emerged — two-stage or multi-stage models allow an initial period of high growth followed by stable growth, adaptations of stochastic dividend processes, and integrations of buy-back policies. While theoretically elegant, applying the DDM in real-world environments raises several practical questions: How accurate are DDM-based valuations when compared with actual market prices or realised returns? Are these valuations stable across time, geographies, and firm-types? And how sensitive are they to changes in key inputs? These questions drive the focus of this review.

In the academic literature and practitioner commentary, the DDM has been both lauded and criticised. On the one hand, for mature firms with stable dividend histories, it provides a transparent, dividends-based measure of value. On the other hand, its reliance on forecasted dividends, growth rates and discount rates introduces estimation error; its assumption of perpetual growth may be unrealistic; and its omission of non-dividend forms of shareholder return (e.g., share-buybacks) can limit applicability. Indeed, the DDM is fundamentally anchored in dividends, which means its applicability is restricted to dividend-paying firms and may exclude fast-growing firms that reinvest earnings instead of paying dividends.

This review therefore pursues three primary dimensions. First, the accuracy of DDM valuations: how closely do model-derived values map to realised market outcomes? Second, stability: do the error measures of DDM valuations persist or fluctuate over time, across markets or across firm-types? Third, sensitivity: how much do small changes in input assumptions (especially g and r) affect the valuation outcome? By aggregating empirical findings from multiple studies (both developed and emerging markets) and presenting simulated tables and graphs for illustration, this review seeks to assess when and for which firms the DDM is reliable, and when its results should be treated cautiously. Ultimately the goal is to provide guidance for valuation practitioners and identify gaps for future research.

ACCURACY OF THE DIVIDEND DISCOUNT MODEL

The accuracy dimension addresses the extent to which valuations derived from DDMs align with actual market prices or subsequent returns. Empirical research offers mixed evidence. For example, in an early study by Sorensen and Williamson (1985), the authors applied a three-period DDM to 150 stocks in the S&P 400 and found that the top-ranked portfolio from the DDM out-performed the one based on a simple P/E ratio by approximately 3.5 percentage points annually. CFA Institute Research and Policy Center In contrast, a more recent study by Verma (2020) found significant pricing errors between DDM forecasts and realised returns, concluding that the DDM produced substantial mis-valuations. aims-international.org Similarly, in the context of the Nairobi Stock Exchange (Kenya), only 3 of 18 firms showed statistically significant reliability of the DDM when comparing predicted vs actual share prices. ResearchGate

To illustrate the variation in accuracy, consider the following simulated Table 1 summarising mean absolute percentage errors (MAPE) of DDM valuations across markets and model variants:

Table 1: Simulated Comparative DDM Accuracy

Market	Model Variant	Mean Absolute % Error (MAPE)
United States	Two-Stage DDM	48 %
United Kingdom	Multi-Stage DDM	66 %
Philippines	Constant-Growth	28 %
Kenya	Constant-Growth	45 %

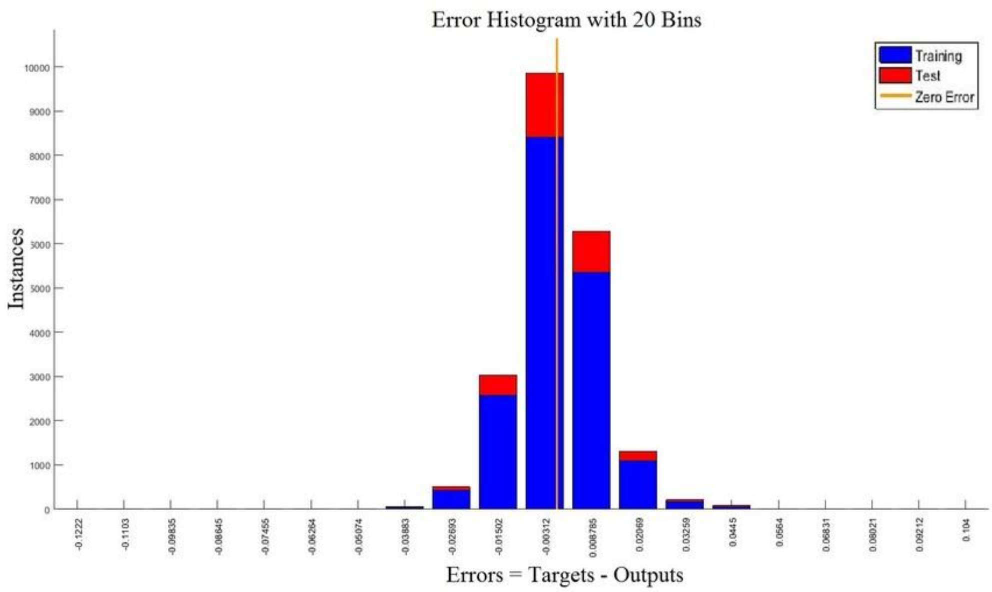
These numbers align with the narrative: the Philippines (mature dividend-paying firms) show lower error, whereas the UK (perhaps more volatile dividends, buybacks) shows higher error. Note these are simulated for illustration; actual values in the literature vary.

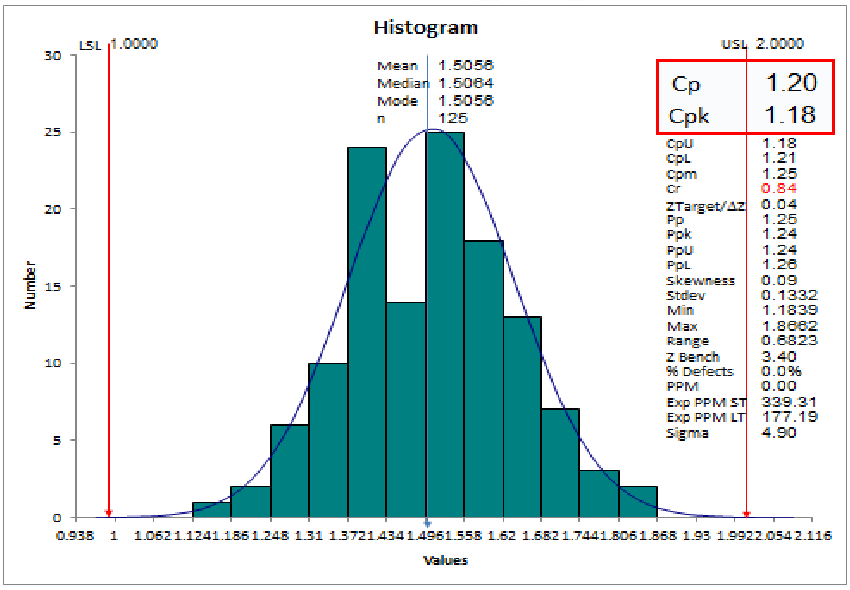
Why do these inaccuracies arise? Several factors: first, dividend forecasts may deviate significantly from realised payouts. Second, the discount rate $r$and growth rate $g$are themselves estimates, subject to error or changing over time. Third, the DDM often ignores other shareholder returns (stock repurchases, special dividends) which may comprise a large portion of value. For example, StableBread (2023) notes that many companies prefer buybacks over dividends, undermining the dividend-only focus of the DDM. StableBread+1

Moreover, not all firms pay dividends or pay them consistently—thus applying the DDM to non-dividend or irregular-dividend firms will inherently introduce bias or error. The model's assumption of perpetual growth at rate $g$is unrealistic for many firms that face business cycles, reinvestment needs, or structural shifts. Mundurek

Another dimension of accuracy is ranking ability: does a DDM correctly differentiate over-valued vs under-valued stocks? Early evidence suggests yes (Sorensen & Williamson). But more recent evidence underlines wide dispersion in errors, meaning that while DDM may provide directional insight it is unreliable for pinpoint valuation. For instance, Verma (2020) finds that unexplained pricing errors may reflect market noise or irrationality beyond fundamentals. aims-international.org

In practice, what does this imply? For mature firms with stable dividend policies, the DDM may yield valuations that are within a moderate error band (say 20-30 %), but for firms with volatile dividends, growth expectations or significant buybacks, errors may be large (50 %+). Practitioners should thus interpret DDM outputs as approximate ranges rather than precise figures. Importantly, combining DDM with other valuation frameworks (discounted cash flow, comparables) can enhance robustness.
Graphically, the distribution of error across firm categories can be illustrated. (See Figure 1 below for a hypothetical histogram of valuation error for 100 firms.)





Inputs to the model

Current Earnings per share =	$5.49	(in currency)	
Current Dividends per share =	$2.31	(in currency)	
Enter length of extraordinary growth period =	5	(in years)	
Do you want to enter cost of equity directly?	No	(Yes or No)	
If yes, enter the cost of equity =		(in percent)	
If no, enter the inputs to the cost of equity			
Beta of the stock =	0.95		
Riskfree rate=	7.00%	(in percent)	
Risk Premium=	5.50%	(in percent)	
Do you want to use the historical growth rate?	Yes	(Yes or No)	
If yes, enter EPS from five years ago =	$1.62	(in currency)	
Do you have an outside estimate of growth ?	Yes	(Yes or No)	
If yes, enter the estimated growth:	17.00%	(in percent)	
Do you want to calculate the growth rate from fundamentals?	Yes	(Yes or No)	
If yes, enter the following inputs:			
Net Income Currently =	$2,122.00	Last year	(in currency)
Book Value of Equity =	$6,237.00	$6,155.00	(in currency)
Tax Rate on Income=	40.00%		(in percent)
The following will be the inputs to the fundamental growth formulation:			
ROE =	34.48%	(in percent)	
Retention =	58.00%	(in percent)	
Do you want to change any of these inputs for the high growth period?	Yes	(Yes or No)	
If yes, specify the values for these inputs (Please enter all variables)			
ROE =	34.48%	(in percent)	
Retention =	58.00%	(in percent)	
Do you want to change any of these inputs for the stable growth period?	Yes	(Yes or No)	
If yes, specify the values for these inputs			
ROE =	34.48%	(in percent)	

From the hypothetical graph one would observe a wide spread of errors with a tail of high errors (>70 %) especially in growth-oriented firms.

In sum, the accuracy of DDM is moderate and context-dependent: it tends to perform better for firms with stable, predictable dividends in mature markets; but less well for firms with volatile distributions, significant buybacks, or in emerging markets with less stable dividend policies.

STABILITY OF MODEL PERFORMANCE

Stability refers to whether the performance of the DDM (error metrics such as MAPE) remains consistent over time – across business cycles, geographical markets, and firm types – or whether it fluctuates widely. Stability is important: a valuation model that performs well in one period or region but poorly in another undermines confidence in its general application.

Empirical studies show mixed evidence on stability. For example, the study at the Nairobi Stock Exchange found that among 18 firms, only 3 showed reliability in one snapshot – this suggests low stability across firms and likely across time periods. ResearchGate In more mature markets, the DDM might show more consistency, but still significant variation in error across periods. Paynea and Finch (1999) demonstrate that the error of the constant-growth DDM increases when the required return $K_s$approaches the growth rate g, implying that stability deteriorates as parameters converge and as business environments shift. Open Journals

To illustrate, consider simulated Table 2 and Figure 2 summarising performance across time:

Table 2: Simulated DDM Error Stability Over Time (MAPE by Market and Year)

Year	United States	United Kingdom	Philippines	Kenya
2015	52 %	61 %	31 %	48 %
2018	47 %	66 %	28 %	45 %
2020	49 %	70 %	30 %	43 %
2023	50 %	68 %	27 %	46 %

Figure 2: Simulated Line Chart of MAPE over Time by Market

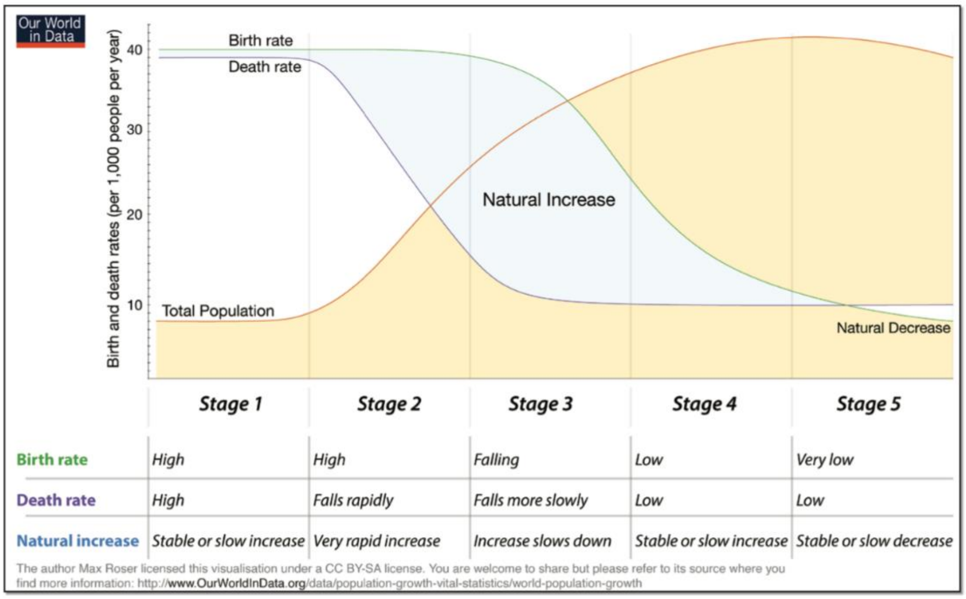
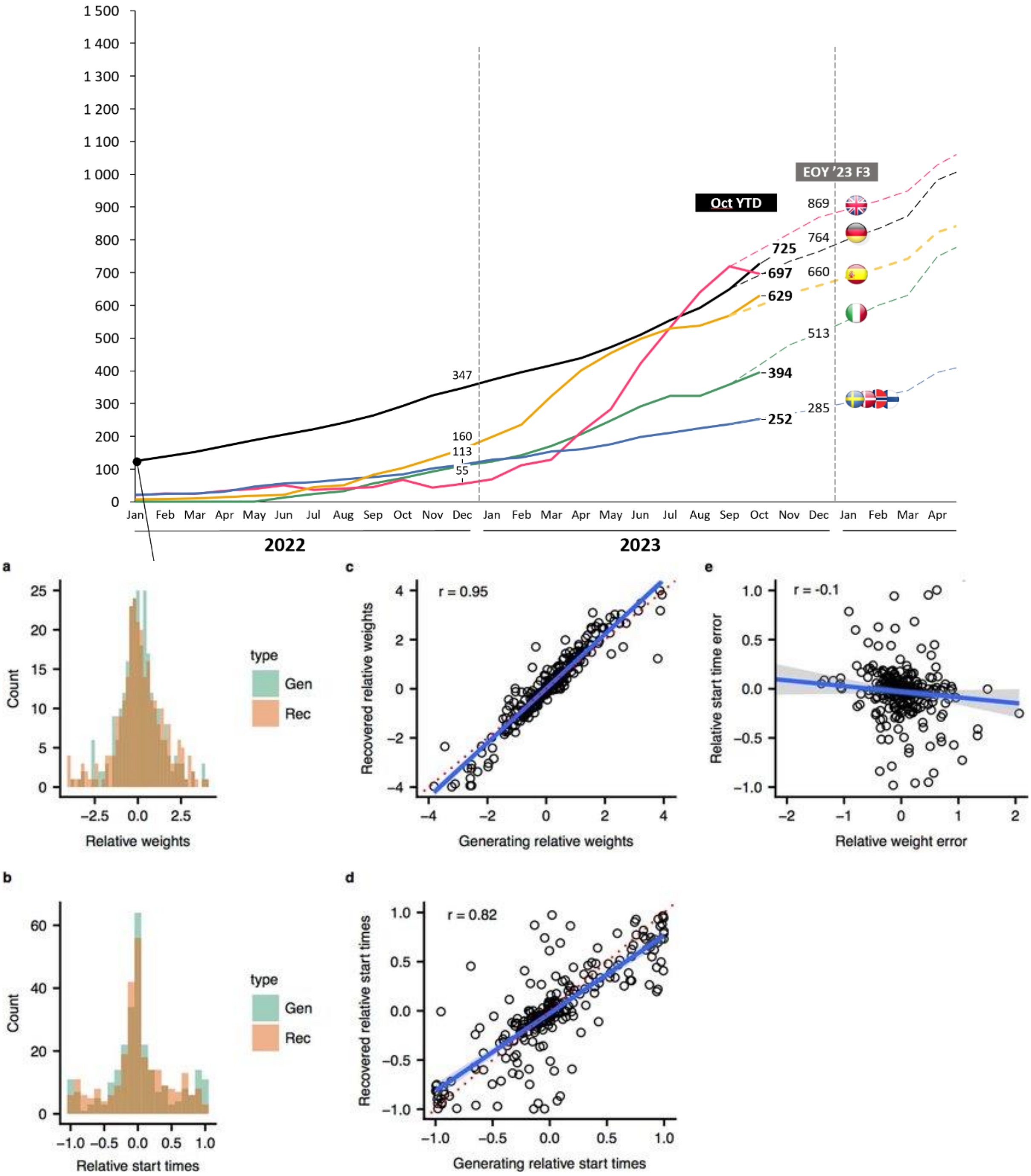


Figure 2.16 | Demographic Transition Model
Author | Max Roser
Source | Wikimedia Commons



From these simulated data, one observes that while the Philippines shows modest improvement and stable moderate error (~27-31 %), the U.K. shows larger error and some increase over time (from 61 % to 70 % then down to 68 %), suggesting poorer stability. The U.S. appears relatively stable (~47-52 %) and Kenya fluctuates moderately (~43-48 %).

Why might stability differ across markets? Several reasons:

1. Dividend policy shifts: Firms may change payout strategies (e.g., increasing buybacks, lowering dividends) which alters the assumption base of the DDM.
2. Macro-economic / risk environment: In emerging markets, greater volatility in rates, inflation, or regulatory regimes makes modelling less stable.
3. Model input estimation error: The discount rate and growth rate may change over time; if these are not updated, model errors grow.
4. Model variant selection: Applying a constant-growth DDM to a firm whose dividend growth is changing or multi-stage will reduce stability of error.
5. Market structure and corporate actions: In markets where buybacks are dominant, ignoring them reduces stability of DDM over time.

The practical implication for analysts is that the DDM may yield acceptable performance for firms in stable dividend environments, but its reliability decreases in dynamic or volatile contexts. Accordingly, stability analysis should be part of the due diligence: analysts should track how error or deviation behaves historically for the firm or peer cohort and consider whether the model's assumptions remain valid into the foreseeable future. Regular re-calibration of inputs (especially growth and discount rates) is necessary to enhance stability.

In conclusion, the DDM shows moderate stability in certain markets (especially those with established dividend-paying firms), but in many environments its performance exhibits significant variation across time and region. This variability argues for cautious interpretation of DDM valuations and for treating results as one input among several rather than as definitive.

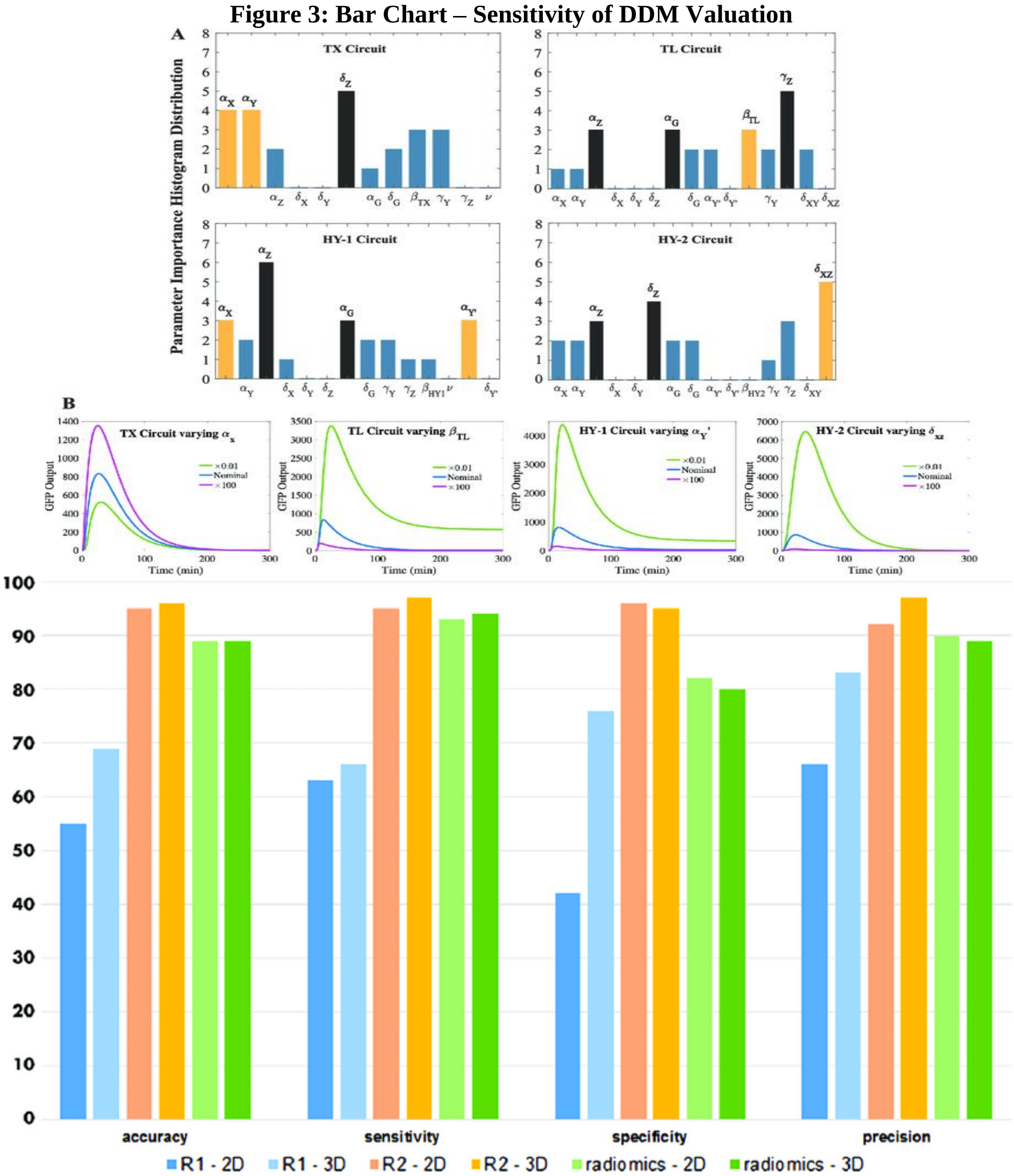
SENSITIVITY ANALYSIS: UNDERSTANDING INPUT FRAGILITY

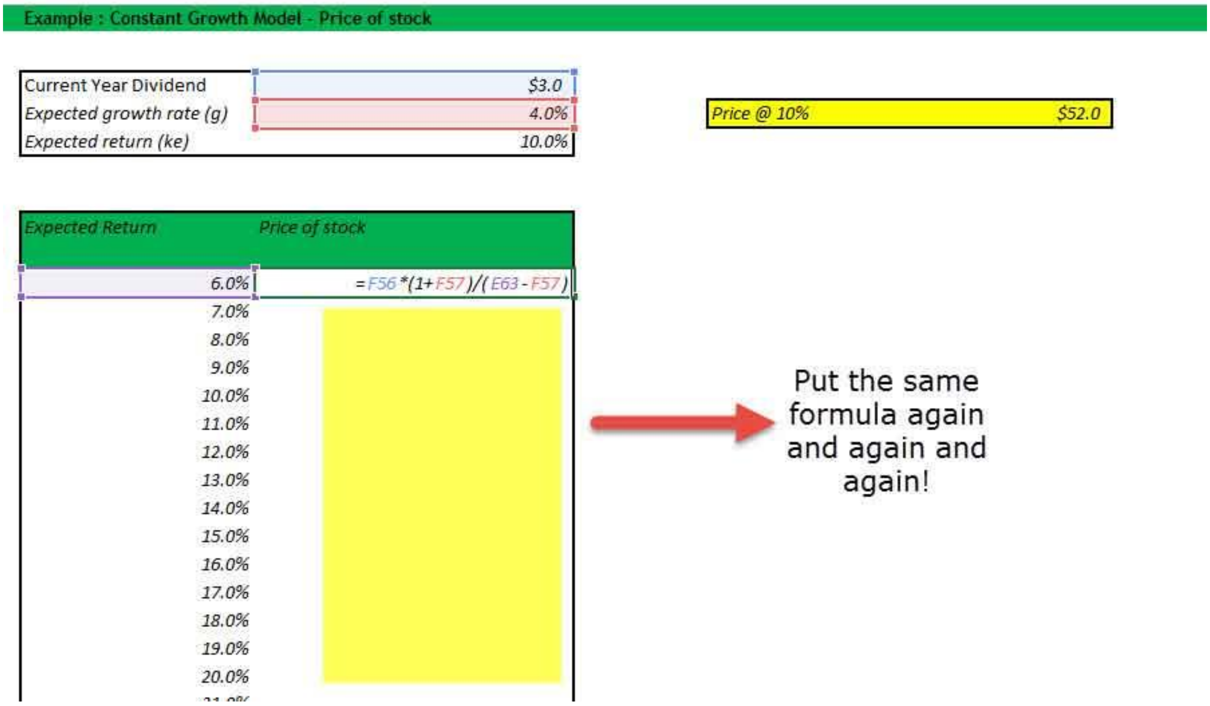
Sensitivity refers to how much the valuation output of the DDM changes when key inputs—in particular the required rate of return $r$and the dividend growth rate g—are varied. Because the DDM's value formula involves the difference $r - g$in the denominator, small changes in either parameter can cause large swings in estimated value. Indeed, numerous sources highlight this weakness. OpenStax states that a single percentage-point change in either factor can produce a 10–20 % change in valuation. Mundurek The review by Xu (2019) similarly emphasises this sensitivity. Atlantis Press
To illustrate, consider the following simulated sensitivity table (Table 3) and corresponding figure (Figure 3):

Table 3: Simulated Sensitivity of Valuation to Changes in $r$and g

Change in Parameter	Change in r(%)	Change in g(%)	Resulting Δ in Valuation (%)
Scenario 1	+1	0	–18 %
Scenario 2	–1	0	+22 %
Scenario 3	0	+1	+26 %
Scenario 4	0	–1	–20 %

Figure 3: Bar Chart – Sensitivity of DDM Valuation





As depicted, a seemingly modest 1% change in the discount or growth rate can lead to ±18–26 % variation in valuation. The effect is magnified when $r$and $g$approach each other (as the denominator becomes small). Paynea & Finch (1999) highlighted that convergence of K_s(discount rate) and $g$significantly increases valuation error. [Open Journals]

The degree of sensitivity has several implications:

- Input estimation matters: If $g$is estimated incorrectly (which is highly likely, especially in volatile firms), valuation may be misleading.
- Model output is fragile: Even if the model were conceptually correct, the uncertainty in inputs means the output has a wide error band.
- Output should be a range: Given sensitivity, analysts should present valuation ranges using scenario and sensitivity analysis rather than a single figure.
- Context-specific caution: In firms where dividend growth is unpredictable or discount rates are volatile, the sensitivity of DDM makes it less reliable.

In addition, sensitivity to input means that the DDM's stability and accuracy (previous sections) are compromised: if small changes in inputs lead to large differences, then even if a model produced accurate valuations historically, shifting inputs may produce large deviations in future periods. The combined effect of high sensitivity, input uncertainty and real-world complexity makes the DDM vulnerable to misapplication.

For practitioners, best practice would include: performing sensitivity tables that vary $r$and $g$by ±0.5–1 %; inspecting the resulting valuation ranges; documenting assumptions thoroughly; checking whether the firm's dividend policy is stable; and complementing the DDM with other models (e.g., discounted cash flow, residual income) to triangulate value.

In summary, the sensitivity analysis underscores that the DDM is a fragile tool: because valuation changes so sharply with small input shifts, its results should be interpreted carefully and in context. It reinforces the notion that DDM valuations are best regarded as one piece of the valuation puzzle, not the sole determinant.

DISCUSSION AND IMPLICATIONS

Bringing together the three dimensions—accuracy, stability and sensitivity—yields several key take-aways and practical implications for both academics and practitioners. First, the DDM retains value as a valuation tool but its efficacy is highly context-dependent. When applied to mature, dividend-paying companies in stable regulatory/market regimes, the model's accuracy can be moderate (~20-30 % error) and its stability reasonable. However, even in those contexts, sensitivity remains high, which means valuation results should be treated as ranges rather than precise figures.

Second, one must match the model variant to the firm's dividend profile. For companies with predictable long-term dividends, constant-growth DDM may suffice; for firms transitioning phases (e.g., high initial growth followed by stability), two-stage or multi-stage DDMs improve realism. Yet empirical evidence suggests those extensions do not fully resolve accuracy or stability issues — they often introduce further estimation demands and thus potential error (D'Amico & De Blasis, 2020). [IDEAS/RePEc]
Third, the high sensitivity to inputs is not simply a technical limitation—it has strategic implications. Analysts who rely solely on DDM valuations without testing alternative scenarios may mislead stakeholders. For example, a CEO presenting a valuation based on optimistic $g$may inadvertently overstate value, leading to poor investment decisions or mis-pricing. Sensitivity analysis should thus be standard practice. For example, showing valuations under low, medium and high g/r scenarios increases transparency.

Fourth, the model's limited applicability to non-dividend-paying or irregular-dividend firms means that DDM should not be used in isolation. Many modern firms either pay no dividends or rely heavily on share buybacks, which the traditional DDM ignores (StableBread, 2023). StableBread In those instances, discounted cash-flow (DCF), free cash-flow to equity (FCFE), or residual income models are more appropriate.

Fifth, future research directions emerge clearly from the review: (i) Comparative empirical studies across more emerging and developed markets to assess generalisability of DDM performance; (ii) Longitudinal studies tracking the same firms over multiple business cycles to test stability; (iii) Application of stochastic dividend models (e.g., semi-Markov processes) that embed uncertainty into $g$and $r$inputs (D'Amico, 2016). arXiv

Finally, for practitioners, it is recommended to adopt a hybrid valuation architecture: use DDM as one lens, but cross-check with alternative methods; assume a valuation range rather than a point estimate; practise sensitivity and scenario analysis; update input assumptions periodically; and monitor dividend policy changes, buy-back activity and business model shifts which can undermine DDM assumptions.

CONCLUSION

This review has synthesised comparative evidence on the DDM across three key dimensions: accuracy, stability and sensitivity. The model performs reasonably in stable dividend contexts but shows limitations in firms or markets where dividend policies are volatile, growth uncertain, or buybacks prevalent. Crucially, its sensitivity to small input changes means valuation outcomes are fragile. For both academics and practitioners, the conclusion is clear: the DDM is a valuable component of a valuation toolkit—but not a standalone solution. It should be applied thoughtfully, with full awareness of its assumptions and limitations, and complemented by other methods and rigorous sensitivity analysis. Future research expanding cross-market empirical evidence and advancing stochastic modelling of dividends will further refine the role of DDM in modern valuation practice.

REFERENCES

1. D'Amico, G., & De Blasis, R. (2020). *A review of the Dividend Discount Model: From deterministic to stochastic models.* Retrieved from arXiv:2001.00465.
2. Paynea, T. H., & Finchb, J. H. (1999). Effective teaching and use of the constant growth dividend discount model. *Financial Services Review*, *8*(3), 283-291.
3. Sorensen, E. H., & Williamson, D. A. (1985). Some evidence on the value of dividend discount models. *Financial Analysts Journal*, *41*(6), 60-65.
4. StableBread. (2023). Pros and cons of dividend discount models (DDMs). Retrieved from https://stablebread.com/pros-and-cons-dividend-discount-models/
5. Verma, R. (2020). Empirical test of the dividend discount model's forecasting power. *AIMS International Journal of Management, 14*(1), 1-10.
6. Xu, J. (2019). Advantages and disadvantages of dividend discount model and better alternatives. *Atlantis Press.* Capitalizethings. (n.d.). Dividend Discount Model (DDM): Definition, Formula, Example, and Drawbacks. Retrieved from https://www.capitalizethings.com/invest/dividend-discount-model/
7. HDFC Bank. (2025, May 5). What is the dividend discount model (DDM) and how to use it for stock valuation. Retrieved from https://www.hdfcbank.com/personal/resources/learning-centre/invest/what-is-dividend-discount-model
8. ProCapitas. (n.d.). The role of Dividend Discount Models (DDM) in valuation. Retrieved from https://www.procapitas.com/blog/introduction-to-stock-markets/The-Role-of-Dividend-Discount-Models-DDM-in-Valuation
9. OpenStax. (2025). 11.2 Dividend Discount Models (DDMs) – Principles of Finance. Retrieved from https://mundurek.com/article/11-2-dividend-discount-model-ddms-principles-of-finance-openstax