A Scenario-Dependent Dividend Discount Model: Bridging the Gap Between Top-Down Investment Information and Bottom-Up Forecasts

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Stock value is dependent on the market environment. Yet many stock valuation models have fixed, hidden biases that implicitly represent a forecast market scenario and prevent the model from being responsive to top-down investment information. The popular dividend discount model (DDM) is a case in point: The DDM provides a framework for efficient management of bottom-up investment information, but it has inherent biases that cause it consistently to favor high-yield, low price-earnings ratio stocks.

An approximate mathematical decomposition of the information coefficient of standard DDM valuations confirms the existence of the yield bias and reveals a second bias—a negative correlation between the model's forecast components—that represents an internal inconsistency and affects performance. The analysis shows, however, that the biases in the model are independent of the underlying discounted cash flow framework. This independence provides an opportunity to create a scenario-dependent dividend discount model, while maintaining reliance on near-term analysts' forecasts for relative valuation.

A scenario-dependent generalization of the DDM—the "conditional valuation" or CV-DDM—controls the observed biases. CV-DDM valuations may be explicitly conditioned to reflect an institution's investment philosophy and available top-down investment information. The enhanced technology thus eliminates self-defeating inconsistencies, providing a tool for bridging the gap between top-down investment information and bottom-up analysts' forecasts. A more realistic return structure may also lead to an increase in the level of information that can be derived from analysts' forecasts.

EVERY WELL MANAGED investment organization has an investment philosophy and employs a valuation model. When the philosophy and model are implicitly, rather than explicitly, stated, the result may be inefficiencies in the control of the investment process and the use of investment information, inconsistencies in security selection, and underperformance.

The advantages of an explicit, or quantitative, valuation model may be substantial. A quantitative model requires the definition of mutually agreed upon relevant inputs that are systematically collected and used in a timely fashion. The output of the process provides unambiguous evaluations of value. Such an investment proc-

Richard Michaud is Senior Vice President at Zacks Investment Research and a member of this journal's Editorial Board.

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ess may be characterized by a degree of control, consistency, accountability and risk-sharing not normally available in more traditional investment processes.

The standard dividend discount model (DDM) is a price-sensitive, relative valuation that generates an explicit return forecast.[1] Based on a modern, or Graham and Dodd, view of financial value, it is prospective, grounded in fundamental analysis, and intrinsically related to price. DDM return is defined as the internal rate of return that equates the discounted stream of derived forecast dividends to current price. The DDM is thus a natural generalization of the fixed-income yield-to-maturity concept applied to the valuation of equity securities. It has many attractive investment management characteristics and is part of the investment process of many major financial institutions.

Unfortunately, the standard DDM has severe limitations as a stock selection tool. Specifically, it is a "fixed bias" or "fixed scenario" valuation model. That is, it has known structural biases—not primarily the result of analysts' forecasts—that make its valuation insensitive to changes in an institution's investment philosophy or the market outlook. Such biases tend to limit any valid application of the DDM for value-oriented investors, long-term investment strategies, bear market cycles or comparisons with other stock valuation data.

A number of risk-adjustment methods may be used to eliminate biases in DDM valuation. Probably the simplest is to base security valuation on residuals, or alphas, computed from cross-sectional regressions of DDM returns against dividend yield and beta.[2] The appropriate objective, however is to control, rather than eliminate, valuation bias. A given bias is not necessarily inappropriate if the investor is aware of it and it is consistent with his investment philosophy and information. However, if a given bias is inappropriate for the stock universe being examined or the prevailing market outlook, adjustment is appropriate.

This article examines two biases inherent in the standard dividend discount model. Methods for controlling these biases are discussed and tested. The results suggest that a significantly enhanced, scenario-dependent generalization of the DDM avoids the problems of internal biases and narrow applicability suffered by models currently in widespread use in the investment community.

1. Footnotes appear at end of article.

Two Biases

Empirical tests by Michaud and Davis have indicated that the *ex ante* characteristics of the standard DDM on a period-by-period basis strongly resemble a dividend yield or low price-earnings ratio valuation.[3] This consistent tilt, or anti-growth-stock bias, statistically explained the performance of the model. Michaud and Davis showed that the yield bias was a consequence of arbitrary "default" assumptions used to complete the infinite stream of forecast dividends. By defining the default assumptions so that the valuations reflect a market or sector outlook consistent with available top-down information, the DDM can be converted from a fixed-bias model to one that is "scenario-dependent." Michaud and Davis introduced a simple and convenient scaling method—the "structured," or "conditional valuation" DDM (the CV-DDM)—to control yield bias.

This article provides a theoretical explanation for the observed yield bias. The discussion is based on an approximate mathematical "decomposition" of the cross-sectional information correlation ("information coefficient," or "IC") of DDM forecasts with *ex post* total return. The results indicate that the observed yield bias is not an artifact of the time period being examined, but a characteristic of the model itself, and that the CV-DDM scaling method provides a reliable basis for the management of the *ex post* yield-return relation in a DDM framework.

The decomposition also reveals the existence of another *ex ante* bias in the standard DDM—a large negative "component correlation" (CC) that indicates the existence of an internal inconsistency in the structure of model forecasts. The linear scale transformation used to control DDM yield bias has no effect on CC bias. A significant departure from the standard DDM format—a new method called "horizon truncation"—is introduced to manage the CC bias.[4]

Decomposing the DDM IC

The IC—the cross-sectional (simple) correlation of standard DDM return (K) with *ex post* total return (R)—is the statistic most commonly used for evaluating the level of information in return forecasts.[5] The appendix provides a derivation of an approximate DDM IC decomposition.[6] For the standard DDM, the approximation is:

$$c(K,R) \doteq -0.08 + 1.2c(g,C) + 1.2c(Y,R), \quad (1)$$

Table I Cross-Sectional Correlations (A data from 1973–81, B & C data from 1973–80)

	'73	'74	'75	'76	'77	'78	'79	'80	'81	Avg.	S.D.
c(y,R)	0.14	0.22	0.12	0.31	0.15	−0.28	−0.23	−0.35	0.38	0.05	0.27
	0.19	0.40	0.33	0.46	−0.45	−0.29	−0.29	−0.15		0.01	0.36
c(Y,R)	0.17	0.30	0.20	0.38	0.21	−0.23	−0.19	−0.29	0.38	0.10	0.27
	0.34	0.46	0.28	0.46	−0.42	−0.27	−0.24	−0.14		0.06	0.36
c(g,C)	−0.31	−0.16	0.14	0.03	0.14	0.33	0.25	0.34	−0.22	0.06	0.24
	−0.02	−0.16	0.10	0.01	0.57	0.27	0.32	0.11		0.15	0.23
c(y,g)	−0.65	−0.57	−0.06	−0.67	−0.78	−0.81	−0.78	−0.76	−0.73	−0.65	0.24
	−0.60	−0.44	−0.46	−0.57	−0.76	−0.85	−0.79	−0.74		−0.65	0.16
c(Y,C)	0.12	0.18	0.12	0.29	0.12	−0.31	−0.26	−0.36	0.27	−0.02	0.26
	0.28	0.35	0.18	0.36	−0.48	−0.34	−0.30	−0.23		−0.02	0.35
c(y,Y)	0.96	0.66	0.80	0.91	0.93	0.95	0.95	0.96	0.97	0.90	0.10
	0.86	0.93	0.88	0.91	0.93	0.89	0.94	0.97		0.91	0.04

Selected Time-Series Regressions		Abs. Value: Avg/S.D.
c(Y,R) = 0.05 + 0.99c(y,R)	r = 0.99	c(g,C) = 0.21/0.10
= 0.03 + 0.99c(y,R)	r = 0.99	= 0.20/0.19
c(Y,R) = 0.15 − 0.85c(g,C)	r = −0.76	c(Y,R) = 0.26/0.08
= 0.27 − 1.42c(g,C)	r = −0.90	= 0.33/0.11

where c(g,C) is the correlation of forecast capital appreciation (g) with actual capital appreciation (C), and c(Y,R) is the correlation of *ex post* yield (Y) with *ex post* total return (R).

Equation (1) shows that the relation of *ex post* yield to return—c(Y,R)—is as prominent a factor in explaining the performance of standard DDMs as the factor that represents the information in analysts' forecasts—c(g,C). The data in Table I, indicating that the two factors have approximately the same magnitude, suggest that the standard DDM is unlikely to show a positive relation to return unless the *ex post* yield-return relation is positive. The use of the standard DDM as a forecasting tool, in other words, represents a substantial bet on high-dividend-yield stocks.

A general approximation for the CV-DDM (derived in the appendix) is:

$$c(E,R) \doteq [x/\sqrt{(1+x^2-1.3x)}]$$
$$[-0.065 + c(g,C) + c(Y,R)/x], \quad (2)$$

where c(E,R) is the correlation of CV-DDM return (E) with *ex post* total return (R) and x is the CV-DDM scale factor defined by the forecast market line risk premium.[7]

Equation (2) describes how the CV-DDM scaling method affects the performance of the model. The multiplicative factor—the first term on the right-hand side of the equation—is approximately a constant for scale factors of interest. Thus the scale factor in effect changes the dependence of the performance of the DDM on the *ex post* yield-return relation by a factor of 1/x. The decomposition demonstrates the importance of the yield-return relation to model forecasting performance.

In the empirical studies of Michaud and Davis, a "passive," or "balanced," CV-DDM was defined in reference to a forecast 6 per cent market line risk premium, which may represent a "normal" yield-capital appreciation relation. In this case, the value of x in Equation (2) averaged about two. Consequently, a balanced CV-DDM reduces the impact of the c(Y,R) term on DDM performance by a factor of half, compared with the standard DDM.

In order to test the accuracy of Equation (1), we performed time series multiple regressions using c(K,R) as the dependent variable and c(g,C) and c(Y,R) as independent variables. The data used were the annual cross-sectional correlations observed for the A database of Michaud and Davis over the nine-year period 1973–81 and the B and C databases (considered as one database) over the eight-year period 1973–80. As a test of Equation (2), balanced CV-DDM cross-sectional correlations for the A and B&C databases were regressed against c(g,C) and c(Y,R). A scale factor of x equal to two was used to evaluate the likely values of the parameters of the decomposition Equation (2). The resulting formula (derived in the appendix) is as follows:

$$c(E',R) \doteq -0.08 + 1.3c(g,C) + 0.65c(Y,R). \quad (3)$$

Table II gives the partial regression coefficients, t-statistics and adjusted R-squares for the standard and balanced DDM IC decompositions.

Except for the value of the constant, −0.07, which is significant at the 0.1 level, the coeffi-

Table II Standard and Balanced DDM Multiple Regression Coefficients, t-Statistics and R-Squares (A data from 1973–81; B & C data from 1973–80)

c(E,R)	*a*	*c(g,C)*	*c(Y,R)*	*R-Squared*
Standard	−0.10/4.0	0.91/7.4	1.11/10	0.94
	−0.14/2.5	1.74/6.6	1.36/8.2	0.91
Balanced	−0.08/8.0	1.16/24	0.45/10	0.99
	−0.07/2.0	1.3/7.4	0.49/4.4	0.92

cients are all statistically significant at the 0.05 level and are roughly consistent with expectations. In particular, the coefficient of c(Y,R) for the balanced CV-DDM case is reduced by approximately half. The available time series data consisted of no more than nine points, the residual error may not be normally distributed, and some of the *ex post* data used to derive the approximations were not evaluated independently from the regression test data; nevertheless the value of the corrected R-squares and the level of significance of the F statistic (at the 0.1 per cent level or less) are impressive. The regression analysis suggests that approximating Equations (1) and (2) provide a reasonably reliable description of the forecasting characteristics of the DDM, under the assumptions used.

The mathematical properties of Equation (2), and tests of the accuracy of the appoximation, provide evidence that the existence of yield bias in the standard DDM and the reduction of yield bias in the balanced CV-DDM using the scaling technology are not characteristic of the time period but of the model and method. The analysis also suggests that a critical issue in the use of the DDM is control of the model's response characteristics with respect to the *ex post* yield-return relation.

A Second DDM Bias

A good mathematical model can be helpful, not only in interpreting prior data, but in revealing characteristics of a process not otherwise easily observable. The mathematical approximation of DDM IC given by Equation (2) indicates the existence of a second *ex ante* bias and internal inconsistency in the structure of DDM returns that also affects forecasting performance.

The presence of a negative constant term in Equation (2) leads to a deeper understanding of the forecasting behavior of standard DDMs. The constant term in Equation (2) (derived in the appendix) is:

$$M = c(g,y).\ \sigma_Y/\sigma_R, \qquad (4)$$

which was approximated as −0.065.

The approximation resulted, in part, from the observation that the value of the *ex ante* component correlation (CC) is of the order −0.65. This high negative correlation is significantly different from the corresponding *ex post* correlation c(Y,C), which, as the data in Table I show, has a time series average value close to zero. Although the value of the constant is not independent of the other factors, formally, it seems plausible that a DDM with a more realistic *ex ante* structure with respect to the value of the CC would have a smaller constant value in the decomposition, which would lead to improved performance.

The data in Table I show that c(Y,R) and C(Y,C) always have the same sign, while corresponding standard DDM correlations are always of opposite sign and generally much larger in magnitude. The surprising inference is that the *ex ante* structure of the standard DDM returns was not consistent with the structure of *ex post* returns over any time period. An unrealistic and financially inconsistent *ex ante* return structure may explain the difficulty many security analysts experience when using the standard model to forecast returns.

The CC bias is not equivalent to the DDM yield bias. This is evident from the fact that the CV-DDM scaling method does not alter the value of the CC. Consequently, the *ex ante* values of the CC and yield bias may be separately controllable.

The likely impact of the CC bias on the performance of the DDM can be explained with a simple principle: To the extent that the relevant structure of *ex ante* returns is consistent with *ex post* returns, DDM IC should increase. A more realistic *ex ante* return structure may also elicit input forecasts with higher levels of information, inasmuch as anecdotal evidence suggests that analysts change their input forecasts when presented with a DDM with a more realistic *ex ante* structure.

Another issue associated with the CC bias is the negative collinearity of the two explanatory factors in the approximation. The standard DDM CC value implies that half the variance of g is explainable by the variance of y (or, under the assumptions of the appendix, Y). This means that c(g,C) is negatively correlated, or collinear, with c(Y,R); linear regressions given in Table I confirm the hypothesis and the extent of the relation. Consequently, much of the value of c(g,C) is related to the factor c(Y,R). While collinearity may often affect the estimation efficiency of the regression parameters, the results in Table II do not indicate it is a problem in this instance. Collinearity may induce instability in the estimates of the coefficients, but it does not appear to affect the predictive power of the decomposition.

The CC bias in the standard DDM represents an internal inconsistency with respect to the yield bias in the model. This is because a negative *ex post* component correlation is associated with a market environment that is not yield-oriented. In contrast to a standard DDM, we will define a *yield* CV-DDM to have a "more than normal" positive correlation with yield and a positive component correlation, and a *growth* CV-DDM to have negative yield-return and component correlations. Additionally, a neutral, or *balanced*, CV-DDM will be defined in terms of a "normal" correlation with yield and a statistically insignificant (CC-neutral) component correlation.

Some Properties of CV-DDM Valuation

It is useful to begin an analysis of some general properties of the CV-DDM with an approximation of the DDM IC that assumes nothing about the characteristics of a specific DDM. This is important because alternative CC-value DDMs are unlikely to have the same *ex ante* structure as the standard DDM. Equation (5) gives such an approximation:

$$c(E,R) \doteq (x\sigma_g/\sigma_E)\,[0.1c(g,y) + c(g,C) + c(Y,R)(\sigma_y/x\sigma_g)] \qquad (5)$$

where

$$\sigma_E = \sqrt{(\sigma_y^2 + (x\,\sigma_g)^2 + 2x\sigma_y\sigma_g c(g,y))}.$$

Some interesting characteristics of CV-DDMs may be found using Equation (5) in conjunction with the correlation of E with y:

$$c(E,y) = [c(y,g) + \sigma_y/x\sigma_g]/\sqrt{[1 + \sigma_y^2/(x\sigma_g)^2 + 2\sigma_y c(g,y)/x\sigma_g]}. \qquad (6)$$

Note that a CC-neutral DDM is always positively correlated with *ex ante* dividend yield. This result demonstrates that a CV-DDM risk-adjusted return may be fundamentally different from one based on residuals, where the effect of dividend yield is removed using regression analysis.

A balanced, CC-neutral CV-DDM does not imply dividend yield neutrality, but rather some positive or normal balance between yield and capital appreciation. In this regard, the *ex ante* properties of dividend yield residual valuations make little financial sense, because a well-formed valuation model should always prefer more dividend yield to less, all other things being equal. It is when further information concerning the *ex post* characteristics of the yield-return relation can be assumed known, as may be the case when the growth CV-DDM is used, that the yield-return relation may be validly non-positive, *ex ante*.

To understand some of the properties of the CV-DDM, consider what happens as the scale parameter, x, varies. As x approaches zero ($x \rightarrow 0$), the following will occur:

$$c(E,y) \rightarrow 1,$$
$$c(E,R) \rightarrow c(Y,R).$$

A value of x less than one represents a cross-sectional underweighting of the importance of forecast capital appreciation relative to dividend yield. Consequently, at the limit, the correlation of forecast returns with yield should be one and the correlation with *ex post* returns should depend totally on the *ex post* relation of yield to return. As the results confirm, the CV-DDM has these properties.

Now consider the case where x approaches infinity ($x \rightarrow \infty$). In this case:

$$c(E,y) \rightarrow c(y,g),$$
$$c(E,R) \rightarrow 0.1c(y,g) + c(g,C).$$

A large value of x represents a cross-sectional overweighting of forecast appreciation relative to yield. Such a scenario may be appropriate if we anticipate that dividend yield will be irrelevant or negatively related to return. As this case shows, the value of the CC plays an important role in both the yield and return correlation. With a "growth scenario" outlook, if the value of the CC is negative, the correlation of the CV-DDM with yield will be negative. With respect to the DDM IC, a negative CC value has a negative impact on the value of the first term; this may be offset, however, by a positive second term because of the induced dependency caused by the collinearity with $-c(Y,R)$ and the magnitude of the anticipated negative *ex post* yield-return relation.

One final observation may be of interest. As Equation (5) shows, the ratio $\sigma_y/\,x\sigma_g$ behaves similarly to x in Equation (2) in terms of altering the importance of capital appreciation relative to yield. Because alternative CC-value DDMs re-

Table III Cross-Sectional Component Correlations for Alternative DDM Assumptions and Formats

Additive Transition Period Length (D data from 79/06)				
0	10	20		40
−0.73	−0.67	−0.63		−0.60
Additive Growth Factor (D data from 79/06)				
0	5	10		20
−0.73	−0.76	−0.77		−0.39
Truncation Period Analysis (D data average and standard deviation)				
200	*50*	*25*		*15*
−0.57	−0.42	−0.17		0.10
0.04	0.04	0.05		0.06
Final-Price Truncation Period Analysis (D data average and standard deviation)				
200	*50*	*25*	*15*	*10*
−0.57	−0.48	−0.33	−0.12	0.09
0.04	0.04	0.04	0.06	0.14

quire a different discounted cash flow framework from the standard DDM, the value of the ratio of the *ex ante* component standard deviations may be different from that of the standard model. One consequence is that the value of x associated with scenarios for the new CV-DDMs may be different.

A New Method for Controlling Bias

We examined alternative assumptions or formats of DDM return construction to find a practical method for controlling the value of the CC. The analysis is based solely on the D database of Michaud and Davis. There are six data sets in the D database, but only two have nonoverlapping annual returns. Consequently, our objective is to search for guidelines, rather than proofs of statistical significance.

The first two panels of Table III report the results of two sets of model construction experiments on the first of the six D data sets. The first set of experiments examines the effect of increasing the length of the second, or "transition," stage on the value of the CC. As the data in the first panel indicate, the CC decreases from −0.73 to −0.60 when the transition period is lengthened by 40 periods (years).

The second set of experiments (panel 2) increased the terminal, or third-stage, earnings growth assumption of 8 per cent used to complete the infinite stream of anticipated dividends, holding the payout ratio constant at 50 per cent. As indicated, raising the earnings growth rate by 20 per cent reduced the CC from −0.73 to −0.41.

Although these experiments in changing standardized assumptions in the standard DDM are far from exhaustive, they are nevertheless typical and indicate the strength of the negative CC bias in the traditional DDM framework. Unless one is willing to alter model assumptions severely—in general, far beyond plausibility—this approach seems unpromising. Substantially different forms of the basic discounted cash flow format appear to be required to control the value of the CC.

We considered two significantly different alternative DDM formats—"truncated" and "final-price" models. In the pure truncated model, the valuation is based solely on discounted forecast dividends over some prespecified finite horizon. Alternatively, a final price may be estimated for the end of a prespecified horizon and included in the computation of forecast return.

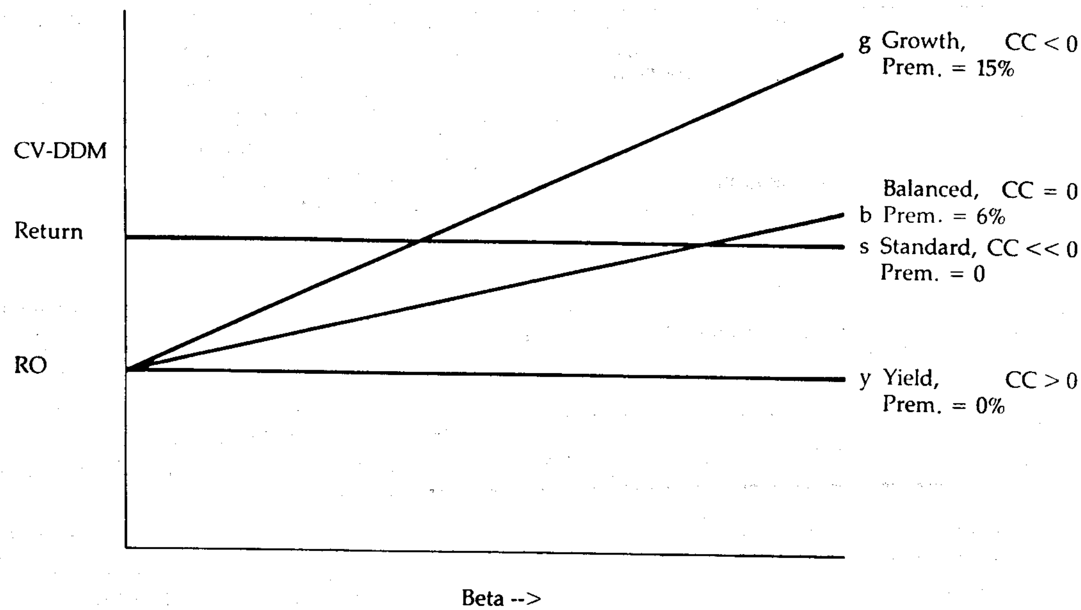
Pure truncation was used as a method of last resort in order to understand the source of the CC bias in the standard DDM. However, a truncated final-price DDM is a serious and valid alternative to the traditional process of estimating an infinite stream of future dividends. Even variable truncation, which is related to the CC value, can be given a plausible financial interpretation.

A market scenario where yield is positively related to return may be associated with economic uncertainty and preference for current over prospective return. As a consequence, the length of an investment horizon with valid forecast information is likely to be short. Alternatively, an economy where growth or capital appreciation potential is valued is likely to be one with less economic uncertainty, where the length of the investment horizon with valid forecast information is longer. Such considerations can be directly reflected in the length of the time period used in the truncation process, on a stock universe or sector basis.

The third panel of Table III gives the results from applying the pure truncation method to the DDM CC. The data refer to the time series average and standard deviation of the cross-sectional CCs for the six D databases truncated at various specified time horizons. When the model is truncated after 15 periods, the CC becomes insignificant. The truncation process appears to be a viable method for controlling the value of the CC.

The analysis of (truncated) final-price DDMs requires a method of computing final price. In

Figure A Comparisons of Forecast Market Lines, Standard vs. "Default" CV-DDMs



the fourth panel of Table III, final price (FP) is estimated by dividing forecast dividends in the final period (Dn) by "normal" dividend yield:

$$FP = Dn/(\text{normal long-term yield}). \quad (7)$$

The normal long-term yield assumed in the analysis was 5 per cent.

As the data show, final-price DDMs, truncated at the 15th or 10th year, can reduce the CC to statistical insignificance as well as change the sign of the correlation. The data imply that final price DDMs deserve consideration as a plausible and conceptually attractive alternative discounted cash flow framework that allows significant control of the CC over a wide range of values. Horizon truncation with a final price estimate represents an important new tool for conditioning the *ex ante* structure of DDMs consistent with the anticipated *ex post* structure of returns.

Figure A graphically illustrates the yield, balanced and growth CV-DDMs and compares them with the standard DDM. As indicated, the CV-DDMs are defined to reflect forecast market premiums of zero, 6 per cent and 15 per cent, an intercept that reflects the forecast risk-free rate and a CC value consistent with the structure of *ex post* returns. The three CV-DDM scenarios are designed to span a reasonable spectrum of "more than normal," "long-term average" and "less than normal" forecasts of the yield-return relation. In contrast, the standard DDM generally has a nearly zero slope, a "much more than normal" yield-return relation, an intercept equal to the average value of returns (approximately 15 per cent if standard default assumptions are used) and a large negative CC value.

Although experiments to control the value of the CC in a discounted cash flow valuation model may be of interest, it is possible that the technique is self-defeating, since g, hence forecast return, will be redefined in the process. A technique that controls the magnitude of the CC may be a necessary, but is not a sufficient, condition for reaching the potential of increased DDM performance.

Tests of the Decomposition

Table IV presents a multiple regression analysis in the same format as Table II for the untruncated (N = 200 periods, CC strongly negative) and truncated (N = 10 and 15 periods, CC neutral) final-price DDM data for the D database. Given the significant statistical limitations of the database, the t-statistics in the multiple regression analysis should not be used as valid tests of statistical significance. Nevertheless, the results are generally consistent with expectations of Equations (2) and (5). In terms of the scaling method, the results are similar to those in Table

Table IV Multiple Regression Coefficients, t-Statistics and R-Squares, Final Price DDM (D database)

c(E,R)	*a*	*c(g,C)*	*c(Y,R)*	*R-Squared*
Standard				
N = 200	−0.19/5.0	1.70/7.7	1.38/4.7	0.92
N = 15	−0.06/3.3*	1.17/11	0.99/5.8	0.96
N = 10	−0.01/0.7*	1.01/12	0.76/5.2	0.97
Yield				
N = 100	−0.19/4.3	1.79/6.0	1.34/3.3	0.87
N = 15	−0.04/2.8*	1.21/13	0.86/5.8	0.97
N = 10	0.01/0.8*	1.08/17	0.44/4.1	0.98
Balanced				
N = 200	−0.12/5.6	1.38/9.9	0.46/2.4*	0.80
N = 15	−0.03/4.1	1.12/28	0.41/6.4	0.99
N = 10	0.01/1.8*	1.04/28	0.24/3.8	0.99
Growth				
N = 200	−0.08/7.2	1.18/15	0.15/1.4*	0.98
N = 15	−0.02/5.3	1.07/46	0.22/5.7	0.99
N = 10	0.02/28*	1.03/38	0.17/3.6	0.99

* Not significant at the 0.05 level.

II. Specifically, we note the projected similarity of the importance of the factors for the standard and yield DDMs and the reduction of the influence of dividend yield on returns in the balanced and growth DDMs.

The analysis of the effect of truncation in the multiple regression is less straightforward. As projected, truncation diminishes the constant term. The regression coefficient for c(Y,R) also diminishes, because of the reduction in collinearity between the two explanatory variables.[8]

If the only effect of changing the CC value is to change the collinearity between the two explanatory variables, then the regression coefficient of c(g,C) would not change. In fact, we anticipate that the importance of c(g,C), as reflected by the magnitude of the estimated regression coefficients, changes when the truncation horizon is changed. This is what the data in Table IV show.

For these data and time periods, a reduction in the value of the regression coefficient of c(g,C) as the horizon is truncated is consistent with expectations. This is because the *ex post* yield-return relation, hence the component correlation, was negative for five of the six periods and zero for the remaining period. Truncation therefore reduces the c(g,C) regression coefficient because the *ex ante* CC is less similar to the *ex post* CC, which is consistent with the expectation that the analysts' information factor will be most important when the *ex ante* return structure is most consistent with *ex post* returns.

Different Market Environments

In Table V, the alphas (regression residuals with respect to forecast beta) of the standard DDM, *ex post* return, and yield, balanced and growth CV-DDMs are denoted AK, AR, AEY, AE, and AEG, respectively. In order to evaluate the effect of scaling and truncation on the level of the IC, we segregated time periods in terms of similar signs of the *ex post* yield-return correlation. All but one of the six time periods in the database had a negative *ex post* yield-return correlation; that one time period was omitted from the time series averages when computing the correlation differences shown in the first panel of Table V and for c(Y,R).

Table V Cross-Sectional Correlations, Final Price DDM (D database)

N =	*200*	*15*	*10*
c(AEY,AR) -c(AK,AR)*	0.01/0.01	0.02/0.002	0.04/0.004
c(AE,AR) -c(AK,AR)*	0.09/0.03	0.06/0.01	0.05/0.01
c(AEG,AR)-c(AK,AR)*	0.12/0.05	0.09/0.03	0.06/0.007
c(AK,y)	0.37/0.05	0.54/0.03	0.57/0.03
c(AE,y)	−0.09/0.08	0.22/0.04	0.30/0.04
c(g,K)	0.54/0.05	0.75/0.02	0.86/0.01
c(g,C)	0.16/0.09	0.06/0.10	−0.02/0.11
c(Y,R)*	−0.12/0.04		
c(Y,C)	−0.18/0.05		

* Omits non-negative c(Y,R) time period.

The first column of data in the first panel in Table V presents time series averages and standard deviations of differences of cross-sectional correlations for the CV-DDM truncated at the 200th forecast dividend. Each cross-sectional difference represents the increase in IC associated with the CV-DDM forecast alpha of *ex post* alpha over the standard DDM alpha. The final two columns in Table V show similar data for the final-price (CC-neutral) CV-DDM truncated at the 15th and 10th years.

Analysis of the data in Table V shows that the basic structure of the results is consistent with expectations. For this time period, the less yield-biased DDMs performed better than AK. Also, for the same reason, truncated DDMs do worse in this market environment. Reading from right to left, the IC value differences increase as the value of the CC becomes more negative. The evidence suggests that scaling may be the more effective method for controlling the IC.

Analysis also shows that truncation is associated with expected changes in other characteristics of the model, including an increase in the relation of dividend yield and forecast capital appreciation. The results, especially with re-

Table VI Comparisons of Standard with Growth and Balanced CV-DDMs: DDM IC Differences as a Function of c(Y,AR) (A and B&C databases; scaling method only)

Linear Regression Estimates				
c(AE,AR) − c(AK,AR)	*a*	+	*bc(Y,AR)*	*r*
A	0.060	−	0.70c(Y,AR)	−0.88
B&C	0.082	−	0.69c(Y,AR)	−0.90
c(AEG,AR) − c(AK,AR)				
A	0.074	−	1.01c(Y,AR)	−0.94
B&C	0.077	−	0.95c(Y,AR)	−0.95
Average Difference Estimates				
Databases	*A*	*B&C*	*A*	*B&C*
	c(Y,AR) > 0		c(Y,AR) < 0	
c(Y,AR)	0.272	0.362	−0.164	−0.126
c(AE,AR) − c(AK,AR)	−0.131	−0.167	0.174	0.169
c(AEG,AR) − C(AK,AR)	−0.201	−0.251	0.274	0.205

spect to the size of the increase in DDM IC, should be evaluated in terms of the limitations of the database and the fact that the method employed was not designed to increase the IC optimally but to determine whether projected changes in the model's response characteristics would be observed.

Table VI provides further estimates of differences in the forecasting performance of CV-DDMs in different market environments. The results are based on the A and B&C databases; the horizon truncation method is not included in the analysis. Linear regressions of year-by-year differences in either the balanced or growth CV-DDM ICs with respect to the standard DDM IC were estimated as a function of the value of the *ex post* yield-alpha correlation. The results are given in the first panel of Table VI. The high R-squares indicate the reliability of the relation. The regressions indicate the effect of the value of the *ex post* yield-alpha correlation on differences in the performance of the balanced or growth CV-DDMs with respect to the standard DDM.

The second panel in Table VI estimates the average difference in the performance of the balanced or growth CV-DDM with respect to the standard DDM assuming only the knowledge that *ex post* yield is positively or negatively related to *ex post* alpha. The estimates are derived by inputting the average value of the positive or negative *ex post* yield-alpha correlations as the independent variable into the appropriate estimated linear regression in panel 1 for the indicated database.

The data show that when c(Y,AR) is positive (negative), the balanced or growth CV-DDM IC will, on average, be roughly 0.15 to 0.25 less (greater), respectively, than the standard DDM IC. Although the standard DDM will significantly outperform both the balanced and growth CV-DDM when yield is positively related to alpha, it will significantly underperform the CV-DDM alternatives when yield is negatively related to alpha.

Conclusion

Scaling and horizon truncation change the performance of the model by changing the fit of the *ex ante* returns to *ex post* data. This change in the fit of the data, however, has financial meaning. It reflects a more realistic security valuation framework—one that liberates analysts' forecasts from financially irrelevant structural biases and constraints. The enhanced CV-DDM allows for the expanded application of DDM technology to a wide range of investment styles, market timing strategies and market cycles without altering the basic characteristics of a bottom-up, price-sensitive discounted cash flow security valuation framework.

The underlying mathematical structure of the *ex ante* biases found in the standard DDM may be intuitively described as follows. Because of the effect of arbitrary default assumptions, the scale of the *ex ante* capital appreciation of the DDM is ambiguous. There is thus a standard deviation problem of the scale of g with respect to y that results in an *ex ante* yield bias for the standard DDM and a levels problem that results in the large negative component correlation (CC). Truncation controls the CC while scaling controls the yield relation.

The CV-DDM is not a mechanical way of improving the information coefficient of dividend discount model results, but rather a tool for using available information to improve IC. An institution must be able to make simple but reliable quantitative judgments concerning the sign of the *ex post* yield-alpha relation. Although many institutions may wish to ignore such a decision, they cannot easily avoid it. The standard DDM, as well as many other valuation models, represents a significant implicit bet on the sign of the *ex post* yield-alpha relation. A decision by default may expose the institution to a significant amount of unnecessary risk.

If no reliable market or economic outlook is available, a balanced CV-DDM may be appropriate. However, many financial institutions believe they can make market environment judgments with some reliability. Indeed, a great deal of the deliberations of investment policy commitees is directed toward developing expectations concerning the likely characteristics of the *ex post* return-generating process. What has been lacking until now is a stock selection method that consistently and explicitly reflects such information.

Many issues remain for future research. In particular, the potential use of the technology may be far greater when based on a sector or industry group approach. Techniques for optimal implementation of the technology, in line with available information, remain to be worked out. Also, the management of bottom-up information from analysts' forecasts is not independent of the institution's outlook.

The evidence strongly suggests that many applications of the standard DDM—estimates of stock duration or required rates of return used in rate regulation hearings and other corporate applications—are likely to be erroneous. In particular, standard DDM changes in the estimated parameters of the market line or plane, or levels of stock universe returns, if they have any financial meaning, probably reflect changes in the default assumptions of the model or characteristics of the underlying stock universe.[9]

Perhaps the most important general conclusion to be derived from the analysis is that the standard DDM may be a case study of how all non-scenario-dependent valuation models work—i.e., "they work for a time and then stop working." Most "black box" valuation models are likely to contain hidden biases at least as severe as those found in the standard DDM. With the CV-DDM, however, the user is provided with a detailed description of the *ex ante* statistical characteristics of the valuation prior to its use and with the tools necessary to make the appropriate changes. ■

Footnotes

1. See W. Sharpe, *Investments*, 2nd ed. (Englewood Cliffs, N.J.: Prentice Hall Inc., 1981), pp. 381–382.
2. Ibid., p. 385.
3. R. Michaud and P. Davis, "Valuation Model Bias and the Scale Structure of Dividend Discount Returns," *Journal of Finance*, May 1982.
4. The data employed in the analysis are derived from the A, B, C and D DDM databases described in Michaud and Davis, *op. cit*. For the A database, 1981 data were added. The D database was used in the analysis of alternative discounted cash flow formats and tests because it was the only one with sufficient information for full reconstruction of DDM returns. The conclusions from the statistical analyses must be considered in light of the significant limitations of the data.
5. See K. Ambachtsheer and J. Farrell, "Can Active Management Add Value?" *Financial Analysts Journal*, November/December 1979.
6. Although the assumptions used—a stock universe of general institutional interest, a one-year time horizon and a standard DDM—may appear critical, they are not necessary for application of the method; the values of the coefficients and constants would probably change, however, given different assumptions.
7. This is described in Michaud and Davis, *op cit*.
8. The argument is as follows: If we perform a new multiple regression by replacing c(g,C) with a factor that is the residual of the regression of c(g,C) on c(Y,R), the R-square and the coefficient of the c(g,C) residual factor will be the same, but the coefficient of c(Y,R) will diminish. This result assumes that the original multiple regression coefficients for c(g,C) and c(Y,R) are positive and that the factors are negatively correlated.
9. See Sharpe, *Investments, op. cit.*, pp. 368–369.

Appendix

Decomposition of DDM IC

Let the standard DDM return forecast be:

$$K = y + g, \qquad \text{(A1)}$$

where

y = forecast dividend yield and
g = forecast growth, or capital appreciation.

For the conditional valuation DDM forecast, let:

$$E = y + xy + b, \qquad \text{(A2)}$$

where

x = scale factor and
b = scale constant.

Actual subsequent total return is defined as:

$$R = Y + C, \qquad \text{(A3)}$$

where

Y = actual dividend yield and
C = actual capital appreciation.

Proposition

The proposition is as follows:

$$c(E,R) \doteq [-0.065 + c(g,c) + c(Y,R/x)] \cdot [x/\sqrt{(1 + x^2 - 1.3x)}] \qquad \text{(A4)}$$

where c(u,v) denotes the correlation of u with v. Equation (A4) is the same as Equation (2) in the text.

Corollaries

A corollary is that if x equals one, E will equal K and:

$$c(K,R) \doteq -0.08 + 1.2c(g,C) + 1.2c(Y,R), \qquad (A5)$$

which is the same as Equation (1) in the text.

Another corollary is that if x equals two, then E' represents a "balanced" DDM and:

$$c(E',R) = -0.08 + 1.3c(g,C) + 0.65c(Y,R), \qquad (A6)$$

which is the same as Equation (3) in the text.

Proof

1. $c(E,R) = c(y + xg,R)$
$= cov(y + xg,R)/(\sigma_E/\sigma_R)$
$= c(y,R)\sigma_y/\sigma_E + c(g,R)(x\sigma_g/\sigma_E)$
$= (x\sigma_g/\sigma_E)\,[c(y,R)(\sigma_y/x\sigma_g) + cov\,(g,Y + C)]$
$= (x\sigma_g/\sigma_E)\,[c(y,R)(\sigma_y/x\sigma_g) + c(g,C)(\sigma_C/\sigma_R) + c(g,Y)(\sigma_Y/\sigma_R)]$,

where σ_u represents the standard deviation of u.

2. *Lemma*: If $c(y,Y) \doteq 1$, then $c(A,y) = c(A,Y)$.

Proof: If $c(y,Y) = 1$, then $y = e + fY$ and $c(A,y) = c(A,Y)$ and by continuity of $c(u,v)$.

3. *Approximations*

(i) For stock universes of general institutional interest the lemma should express a valid approximation. Applications of the lemma:

$$c(g,y) \doteq c(g,Y);\ c(Y,R) \doteq c(y,R).$$

(ii) Observations from empirical data for large stock universes of general institutional interest:

$$\sigma_C \doteq \sigma_R;\ \sigma_Y \doteq 0.1\,\sigma_R.$$

(iii) Standard DDM relations:

$$\sigma_y \doteq \sigma_g;\ c(g,y) \doteq -0.65;$$
$$\sigma_E \doteq \sigma_g\sqrt{(1 + x^2 - 1.3x)}.$$

4. *Applications of the approximations*

Application of Approximation (i):

$$c(E,R) \doteq (x\sigma_g/\sigma_E)\,[c(g,y)\,(\sigma_Y/\sigma_R) + c(g,C)\,(\sigma_C/\sigma_R) + c(Y,R)\,(\sigma_y/x\sigma_g)]. \qquad (4i)$$

Application of Approximation (ii):

$$c(E,R) \doteq (x\sigma_g/\sigma_E)\,[0.1c(g,y) + c(g,C) + c(Y,R)(\sigma_y/x\sigma_g)]. \qquad (4ii)$$

Application of Approximation (iii):

$$c(E,R) \doteq [x/\sqrt{(1 + x^2 - 1.3x)}][-0.065 + c(g,C) + c(Y,R)/x] \qquad (4iii)$$

5. *Proof of Corollaries*: Evaluate (4iii) at x = 1 or x = 2.