# THE VALUE LINE DOW JONES

# STOCK EVALUATION MODEL:

# IS IT USEFUL?

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**Abstract**: At the end of every year the Value Line (VL) Corporation publishes its forecasts of the Dow Jones Index and its probable ranges for the coming three years using a three explanatory variable multiple regression model that we call the Value Line Dow Jones (VL-DJ) model. The model is a static time series model. Therefore, forecasts of the Dow Jones Index rely on forecasts of the independent variables of the model. In this paper we examine the VL-DJ model for econometric soundness (balance, dynamic completeness, parameter stability, and economic plausibility) and examine, vis-à-vis an out-of-sample forecasting experiment, how useful it is for forecasting the Dow Jones Index from 1 – 6 years ahead when compared to a simple Box-Jenkins model of the Dow Jones Index. We find the VL-DJ model to be econometrically sound, the Transfer Function implementation of the VL-DJ model to be no more accurate than a Box-Jenkins model of the Dow Jones Series but that the "in-house" implementation of the VL-DJ model by the Value Line Corporation Staff has historically provided more accurate forecasts than those produced by the Box-Jenkins model we examined. Irrespective of forecasting accuracy, the VL-DJ model is of historical importance in explaining the movements in stock market indices like the Dow Jones Index. Earnings and dividend growth provide positive impetus to the growth in the Dow Jones Index while interest rate yields, as typified by Moody's AAA Bond Yield, inversely impact its growth.

**Keywords**: Time Series Forecast Evaluation, Transfer Function Model, Box-Jenkins Model, Out-Of-Sample Forecasting Experiment, Dow-Jones Industrial Average.

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## THE VALUE LINE DOW JONES
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### I. Introduction

Since 1982, in late December of each year, the Value Line (VL) Corporation publishes its forecasts of the Dow Jones Index and its probable ranges for the coming three years in its publication *The Value Line Investment Survey*. The model that Value Line uses to produce the forecasts is based on a static, three-variable multiple linear regression model of the following form:

$$\Delta \ln(DJ_t) = \beta_0 + \beta_1 \Delta \ln(EP_t) + \beta_2 \Delta \ln(DP_t) + \beta_3 \Delta \ln(BY_t) + \varepsilon_t \quad . \text{[1]} \qquad (1)$$

See, for example, *The Value Line Investment Survey*, December 26, 2003, part 2, p. 2568 where the model is presented mathematically in a footnote and the historical data used to build the model is reported in an insert labeled "A Long-Term Perspective, Dow Jones Industrial Average, 1920 – 2002." DJ denotes the annual average of the Dow Jones Industrial Average Index, EP denotes the annual Earnings Per Share on the Dow Jones Index, DP denotes the annual Dividends Per Share on the Dow Jones Index, and BY denotes the annual average of the Moody's AAA Corporate Bond Yield. Also ln denotes

[1] The regression formula for the Value Line Dow Jones Stock Evaluation Model is published by Value Line in the following form:

$$DJ_t = \alpha DJ_{t-1} \times \left[\frac{EP_t}{EP_{t-1}}\right]^{\beta_1} \times \left[\frac{DP_t}{DP_{t-1}}\right]^{\beta_2} \times \left[\frac{BY_t}{BY_{t-1}}\right]^{\beta_3} \qquad (1')$$

Mr. Samuel Eisenstadt, the model's creator and supervisor at the Value Line Corporation, indicated in a telephone conversation to the first author that the log transformation of equation (1') is performed and then ordinary least squares is applied in order to get the coefficient estimates of the Value Line Dow Jones model as compared to estimating the model by means of nonlinear least squares. Model (1) then follows from equation (1') after log transformation with $\beta_0 = \ln(\alpha)$.

the natural logarithmic transformation, $\Delta$ denotes the first difference operator, for example, $\Delta\ln(DJ_t) = \ln(DJ_t) - \ln(DJ_{t-1})$, $\beta_0$, $\beta_1$, $\beta_2$ and $\beta_3$ are coefficients to be estimated from the data and $\varepsilon_t$ denotes the approximation (statistical) error of the model. The Value Line Dow Jones Model (1) (hereafter referred to as the VL-DJ model) states that, apart from statistical error, the annual percentage change in the Dow Jones Index is linearly related to the annual percentage change in Earnings Per Share on the Dow Jones Index, the annual percentage change in the Dividends Per Share on the Dow Jones Index, and the annual percentage change in the Moody's AAA Corporate Bond Yield. Given that all of the variables in the regression equation have the same time subscript, the relationship is a static one in that the variables are contemporaneously related to each other as compared to being related to each other in lagging or leading ways.

This model has been in use for more than twenty years to date since its first appearance in the last issue of the 1982 *Value Line Investment Survey*.[2] Enormous numbers of subscribers and readers of the *Survey* probably have used the predictions based on this model, more or less as a guideline for their investment decision-making in the coming year. Therefore, we think it may be interesting and useful to know just how precise and reliable these forecasts are. Evidently, in December of each year, the Value Line staff takes the most recent estimates of the regression equation's coefficients based on the available historical data and then uses their best projections of the next year's percentage changes of EP, DP, and BY to produce a projection for next year's percentage change in the Dow Jones Index.[3] Likewise, two and three year ahead projections of annual percentages changes in EP, DP, and BY are used to produce the two and three-year ahead projections of the Dow Jones Index that they publish.

The purpose of this paper is two-fold. First, we would like to examine how "econometrically sound" the VL-DJ model is. Is the model **"balanced"** in the sense that the dependent variable of the model is stationary and, correspondingly, the explanatory

[2] From 1982 to 2002, only three annual *Surveys* do not report forecasts, namely for the years 1993-1995.

[3] Given that the above annual data on the explanatory variables EP, DP, and BY are not available for the current year in December, it is likely that the estimated version of the VL-DJ model used by the VL Staff in forecasting the Dow Jones Index is based on all of the available data up to and including the previous year and possibly preliminary estimates of the current end-of-year values for EP, DP, and BY.

variables are also stationary?[4] If not, the model might be representing a spurious relationship.[5] Is the VL-DJ model **"dynamically complete"** in the sense that no further lags of the dependent variable or explanatory variables are needed to make the errors $\varepsilon_t$ temporally uncorrelated with each other and homoskedastic.[6] Are the coefficients of the VL-DJ model **stable** over time or have they changed over time? If the VL-DJ model is balanced, dynamically complete, and stable, the method of ordinary least squares is appropriate for estimating the coefficients of the model and determining the statistical significances of the explanatory variables of the model. Finally, we would hope that the signs of the estimated coefficients we obtain are intuitively **plausible** in the sense that the coefficients estimates of the effects of EP and DP on the Dow Jones Index ($\beta_1$ and $\beta_2$, respectively) should be positive while the coefficient estimate of the effect of BY on the Dow Jones Index ($\beta_3$) should be negative. Naturally, for the VL-DJ model to potentially have good predictive abilities, it should be econometrically sound in the above four respects.

Second, we would like to look at the **predictive accuracy** implied by the VL-DJ model. Does the "causal" VL-DJ model produce forecasts of the Dow-Jones Index that are more accurate than those that might be provided by a purely statistical model, like the Box-Jenkins model?[7] If the VL-DJ model forecasts are not as accurate as those produced by a non-causal Box-Jenkins model, then one might want to reconsider the usefulness of the VL-DJ model forecasts that the Value Line Corporation produce.

The organization of the rest of the paper is as follows: In the next section we examine the econometric soundness of the VL-DJ model. In the subsequent section, we use an out-of-sample forecasting experiment to compare the forecasting accuracy of the VL-DJ model as implemented by a Transfer Function model approach with that of an appropriate Box-Jenkins model of the Dow-Jones Index.[8] We also look at the forecasts provided by the Value Line Corporation in their annual publication and compare their accuracy with the accuracy of the Box-Jenkins model forecasts and the Transfer Function

[4] See, for example, Enders (1995, p. 219).
[5] See, for example, Granger and Newbold (1974) and Phillips (1986).
[6] See, for example, Wooldridge (2006), Chapter 11.
[7] See, for example, Box, Jenkins, and Reinsel (1994).
[8] See, for example, Box, Jenkins, and Reinsel (1994), Chapters 10 and 11 for a discussion of the Transfer Function model approach.

implementation of the VL-DJ model in the out-of-sample period. Finally, in the final section of the paper, we discuss the conclusions we draw from our research.

Looking ahead, we find the VL-DJ model to be econometrically sound, the Transfer Function implementation of the VL-DJ model to be no more accurate than a Box-Jenkins model of the Dow Jones series but that the "in-house" implementation of the VL-DJ model by the Value Line Corporation Staff has historically provided more accurate forecasts than those produced by a Box-Jenkins model or a Transfer Function implementation of the VL-DJ model. In the case of forecasting the future of the Dow-Jones Index, the more perceptive one's predictions of the future values of the explanatory variables of the VL-DJ model, the more accurate the forecasts, especially relative to a non-causal statistical model like the Box-Jenkins model. Irrespective of forecasting accuracy, the VL-DJ model is of historical importance in explaining the movements in stock market indices like the Dow Jones Index. Earnings and dividend growth provide positive impetus to the growth in the Dow Jones Index while interest rate yields, as typified by Moody's AAA Bond Yield, inversely impact its growth.

## II. The Econometric Soundness of the VL-DJ Model [9]

For the purpose of examining the econometric soundness of the VL-DJ model we take the annual data on the four series of the model as obtained from the table labeled "A Long-Term Perspective, Dow Jones Industrial Average, 1920 – 2002" published by the Value Line Publishing Corporation in an insert to *The Value Line Investment Survey* dated December 26, 2003. From that document we obtained 83 annual observations on the four series DJ, EP, DP, and BY.[10]

The first issue we address is whether or not the VL-DJ model specification (1) represents a "balanced" time series regression in that the dependent variable, $\Delta \ln(DJ_t)$,

[9] The empirical results reported below in Tables 1-3 and Figures 1-2 were produced by means of EVIEWS 4.1, Quantitative Micro Software, Inc., Irvine, CA, 2002.

[10] All of the data is taken as is except for the 1932 observation on EPwhich is recorded as –0.5. Obviously, we cannot perform the logarithmic transformation on such a negative number so we followed the suggestion of Mr. Eisenstadt of Value Line who said they had replaced it with the small positive number of 0.5 to avoid creating a missing observation for log(EP) in that year. The data are available upon request from the authors.

should be stationary (I(0)) while the explanatory variables $\Delta\ln(EP_t)$, $\Delta\ln(DP_t)$, and $\Delta\ln(BY_t)$ should be stationary as well. That all of these variables are, in fact, stationary can be seen from the results of the Augmented Dickey-Fuller Unit Root tests reported in Table 1 below.

**Table 1**

Augmented Dickey-Fuller Tests
For Stationarity of the Variables
In the VL-DJ Model[11]
(1920 – 2002)

| Variable* | ADF t-statistic | p-value** |
|---|---|---|
| DLDJ | -6.838940 | 0.0000 |
| DLEP | -5.784701 | 0.0000 |
| DLDP | -7.124527 | 0.0000 |
| DLBY | -6.778639 | 0.0000 |

*DL denotes the difference in the logarithm of the variable

** MacKinnon (1996) one-sided p-values

Applying Ordinary Least Squares to the VL-DJ model (1) results in the estimated model reported in Table 2 below.

[11] The ADF test equation included a constant term but no trend. The number of augmenting terms for the test equation was chosen by minimizing the Schwartz Information Criterion. Unit Root tests of the levels of the logged values of DJ, EP, DP, and BY (denoted by LDJ, LEP, LDP, and LBY, respectively) were also conducted using the ADF test. It was found that LDJ and LBY have unit roots while LEP and LDP appear to be trend stationary. These results suggest that a viable alternative model might be constructed by regressing $\Delta\ln(DJ_t)$ on $\ln(EP_t)$, $\ln(DP_t)$, $\Delta\ln(BY_t)$, a constant, and a time trend to distinguish between the different stochastic natures of the individual series. We do not pursue this alternative here but instead examine the traditional VL-DJ model as used by the Value Line Corporation.

**Table 2**

Ordinary Least Squares Estimates of

The VL-DJ Model

Dependent Variable: DLDJ
Method: Least Squares

Sample(adjusted): 1921 2002
Included observations: 82 after adjusting endpoints

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| C | 0.033826 | 0.013848 | 2.442577 | 0.0168 |
| DLEP | 0.171378 | 0.037295 | 4.595196 | 0.0000 |
| DLDP | 0.346502 | 0.101546 | 3.412258 | 0.0010 |
| DLBY | -0.412907 | 0.163852 | -2.519996 | 0.0138 |

| | | | |
|---|---|---|---|
| R-squared | 0.549334 | Mean dependent var | 0.056447 |
| Adjusted R-squared | 0.532001 | S.D. dependent var | 0.177120 |
| S.E. of regression | 0.121169 | Akaike info criterion | -1.335711 |
| Sum squared resid | 1.145190 | Schwarz criterion | -1.218310 |
| Log likelihood | 58.76415 | F-statistic | 31.69237 |
| Durbin-Watson stat | 1.537558 | Prob(F-statistic) | 0.000000 |

Obviously, the coefficients on the explanatory variables of the model are statistically significant at a very high level ($p < 0.014$) and are economically plausible in that the signs of the coefficients associated with DLEP and DLDP are positive while the sign of the coefficient for DLBY is negative. Thus, in this estimated model, percentage changes in EP and DP are positively related to growth in the Dow Jones Index while percentage changes in BY are negatively related to growth in the Dow Jones Index, all as expected given economic reasoning. Moreover, the above OLS results draw support from the fact that the autocorrelations of the residuals as reported in the correlogram of the model are generally statistically insignificant at the various lags as implied the Box-Pierce (1970) Q statistics of, for example, $Q(6) = 7.96$ with $p=0.241$ and $Q(12) = 14.91$ with $p=0.246$. That is, the residuals of the model appear to be temporally uncorrelated. Inspection of the residuals of the model also indicate that heteroskedasticity does not appear to be present in the residuals.[12]

[12] An ARCH(1) test of the squared residuals of the model (see Engle (1982)) resulted in the following statistically insignificant test statistics: F-statistic = 0.8797 (p=0.351) and Chi-square statistic = 0.8921.

Of course, given the fact that the VL-DJ model has statistically significant coefficients of the appropriate signs and the residuals appear to be uncorrelated and homoskedastic, one might conclude that the VL-DJ model is dynamically complete. However, to take one more step to verify this conclusion we consider adding lagged values of the dependent variable and explanatory variables to the original VL-DJ equation to see if any of them are statistically significant. Table 3 below reports some regression specifications toward this end.

**Table 3**

Different Dynamic Variants

Of the VL-DJ Model

Version 1

Dependent Variable: DLDJ
Method: Least Squares

Sample(adjusted): 1922 2002
Included observations: 81 after adjusting endpoints

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| C | 0.020011 | 0.014692 | 1.361969 | 0.1774 |
| DLDJ(-1) | 0.208507 | 0.117243 | 1.778411 | 0.0795 |
| DLEP | 0.198107 | 0.043067 | 4.599932 | 0.0000 |
| DLEP(-1) | -0.042806 | 0.043363 | -0.987140 | 0.3268 |
| DLDP | 0.296764 | 0.123239 | 2.408032 | 0.0186 |
| DLDP(-1) | 0.050089 | 0.112935 | 0.443524 | 0.6587 |
| DLBY | -0.453204 | 0.170222 | -2.662426 | 0.0095 |
| DLBY(-1) | 0.208259 | 0.179291 | 1.161572 | 0.2492 |

Version 2

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| C | 0.025769 | 0.014181 | 1.817136 | 0.0731 |
| DLDJ(-1) | 0.140445 | 0.087109 | 1.612294 | 0.1110 |
| DLEP | 0.199868 | 0.039251 | 5.092073 | 0.0000 |
| DLDP | 0.266511 | 0.115937 | 2.298752 | 0.0243 |
| DLBY | -0.400754 | 0.162349 | -2.468468 | 0.0158 |

(p=0.350). White's (1980) test of heteroskedasticity without cross product terms produced the following statistically insignificant test statistics: F-statistic = 1.331 (p=0.254) and Chi-square statistic = 7.889 (p=0.246).

In version 1 in Table 3 we have included one lag of the dependent variable and one lag each of the explanatory variables and have estimated the resulting model using ordinary least squares. Here all of the lagged values of the variables are statistically insignificant at conventional levels except for the lag on the dependent variable which is statistically significant at the 10% level. In version 2 we have dropped all of the lagged variables except for the lagged value of the dependent variable and it is no longer significant at the 10% level. Thus, we might conclude from these over-fitting equations that the original static VL-DJ model is dynamically complete and coherent with our economic understanding of the stock market.

Next we turn to an investigation of the stability of the coefficients of the VL-DJ model (1) over time. We examine this issue by using the Cusum and Cusum of Squares tests of Brown, Durbin, and Evans (1975). We report the results of these tests in Figures 1 and 2 below.

**Figure 1**

Cusum Test of Stability of VL-DJ Model

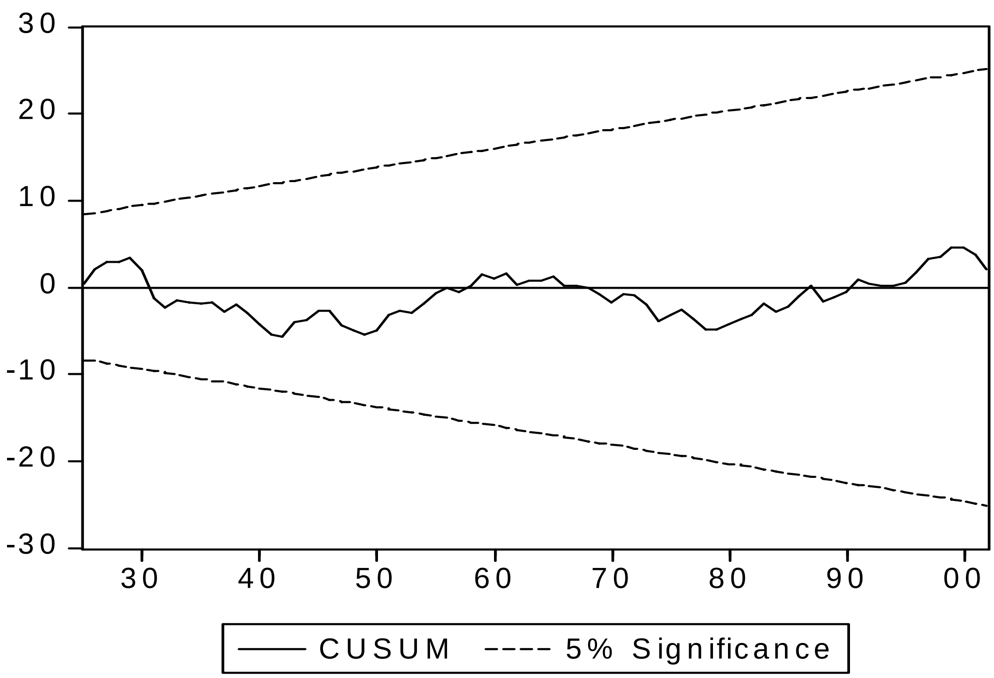
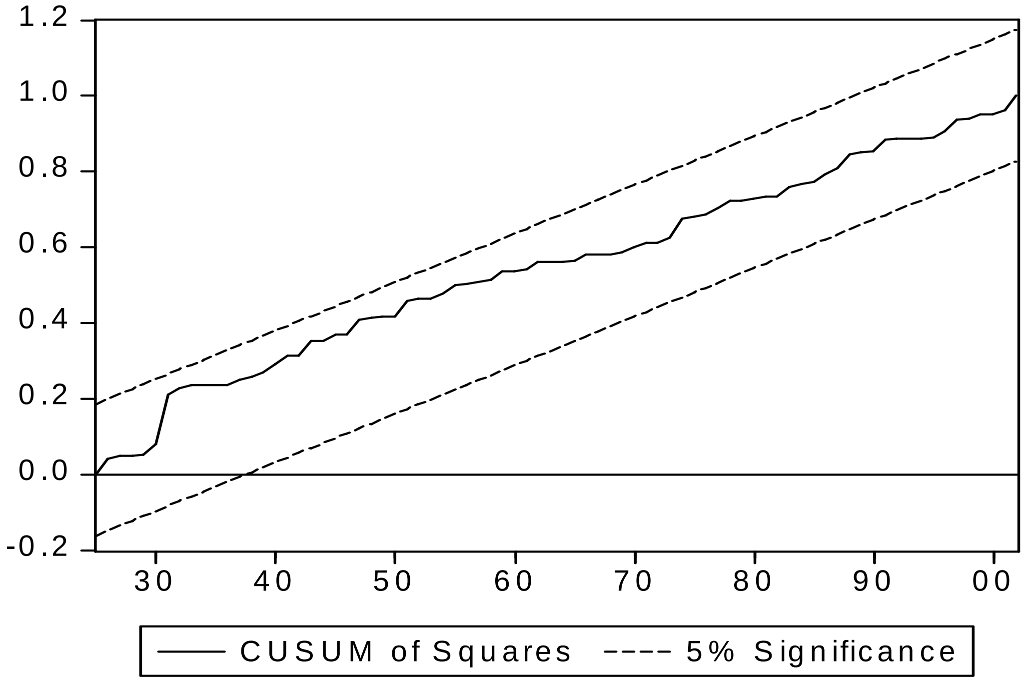


**Figure 2**

Cusum of Squares Test

Of Stability of VL-DJ Model




In both cases we can see that the corresponding recursive test statistic stays within the 95% confidence band of the statistic as we move through the data beginning with the first 5 observations of the data set. Here the null hypothesis is that the coefficients of the VL-DJ model are constant over time. A visual inspection of the recursively estimated coefficients of the model also indicates that the recursively estimated coefficients are relatively stable after the first few observations are used to estimate them.

In conclusion, it appears that the VL-DJ model has pretty solid footing in terms of econometric considerations. We next turn to judging the model based on its ability to forecast future values of the Dow Jones Index. That is the business of the next section.

## III. Comparing the VL-DJ Model with a Box-Jenkins Model for the Dow Jones Index in an Out-of-Sample Forecasting Experiment[13]

In the previous section we established that the VL-DJ model appears to be econometrically sound when considering the full sample. However, the implementation of the VL-DJ model in a forecasting context is problematic in that the explanatory variables of the model are contemporaneous with the dependent variable of the model and, in order to forecast with the model, future values of the explanatory variables must be predicted first before the model can provide the user with a prediction of the dependent variable. One way, of course, to solve this problem is to treat the VL-DJ model as a Multiple-Input Transfer Function model.[14] The Transfer Function model implementation of the VL-DJ model consists of two parts. The first part is simply equation (1) that we have previously specified to be the VL-DJ model. The second part of the Transfer Function implementation consists of treating the inputs (here $\Delta \ln(EP_t)$, $\Delta \ln(DP_t)$, and $\Delta \ln(BY_t)$) as independent Box-Jenkins processes which in turn provide the user with future values of the explanatory variables for the purpose of forecasting the dependent variable vis-à-vis equation (1).

Unfortunately, all may not be well with the practical solution offered by the Transfer function implementation of the VL-DJ model. As Ashley (1983) has shown, when forecasts of an explanatory variable are sufficiently inaccurate, their use in a multiple regression forecasting equation can lead to less precision than a simple extrapolation of the dependent variable, say, offered by a Box-Jenkins model. This is the case even if the original regression equation is, historically speaking, very data coherent with statistically significant coefficients, high coefficients of determination, and the like. In order to gauge whether this malady might apply to the Transfer Function implementation of the VL-DJ model we choose to conduct an out-of sample forecasting

[13] The empirical results reported below in Tables 4 – 8 were produced by SAS Version 8.0, The SAS Institute, Cary, NC.
[14] See footnote 8.

experiment where we compare the forecasting accuracy of the Transfer Function implementation of the VL-DJ model with the forecasting accuracy of a simple Box-Jenkins model of the Dow Jones index.

**III.1 The Design of the Out-of-Sample Forecasting Experiment**

Our out-of-sample forecasting experiment is designed as follows. We partition our data set into two parts: The first 53 observations (1920 – 1972) we take to be our in-sample data set while we take the last 30 observations (1973 – 2002) to be our out-of-sample data set. The in-sample data is then used to estimate equation (1) and separate Box-Jenkins models for the three inputs of the VL-DJ model. We then use the estimated Transfer Function implementation of the VL-DJ model to forecast the Dow Jones Index 1, 2, through 6 steps ahead (observations 54 – 59) while recording the error of each forecast. Once these forecasts are produced we go back and add one observation to our previous estimation data set and re-estimate equation (1) and the three Box-Jenkins models describing the inputs and again forecast the Dow Jones Index 1, 2, through 6 steps ahead (observations 55 – 60) and again record the error of each forecast. This process of "rolling" the Transfer Function implemented VL-DJ model through the rest of the out-of-sample data continues until we have run out of data to forecast. Notice that the number of one-step-ahead, out-of-sample forecasts will exceed the number of, say, six-step-ahead forecasts by five and similarly for the other multiple-step-ahead forecasts. In a similar manner we can use the in-sample data to fit a simple Box-Jenkins model to the Dow Jones index itself and then "roll" it through the out-of-sample data set producing 1 through 6 step-ahead forecasts while recording the errors associated with each forecast.

Now let us discuss a few more details concerning the above forecasting experiment. We did find that the VL-DJ model (1) was "econometrically sound" over the shorter in-sample data set as well. The equation remained balanced, dynamically complete, and stable over the in-sample data set with the same plausible coefficient signs implied by the full data set.[15] As far as the separate Box-Jenkins processes for the inputs of equation (1) are concerned, it was determined from the in-sample data that DLEP is well approximated by a MA(2) model, DLDP by a MA(1) model, and DLBY by an

[15] The variable DLBY has the right sign (-) but starts out statistically insignificant in the first estimation. However, it becomes statistically significant as estimation progresses through the rest of the data. These results are available from the authors upon request.

AR(1) model. As a naïve competitor it was determined from the in-sample data set that the dependent variable DLDJ could be well approximated by a MA(1) process.

In addition, since our primary interest is in comparing the forecasts of the DJ series in levels, we must convert any DLDJ forecast back into a DJ forecast. This is done in two steps:[16] the first step is to convert the predictions from differenced log form (DLDJ) to level log form (LDJ) with the following formula

$$L\hat{D}J_{t,h} = LDJ_t + D\hat{L}DJ_{t,1} + \cdots + D\hat{L}DJ_{t+h-1,1} \tag{2}$$

where $L\hat{D}J_{t,h}$ denotes the *h*-step-ahead forecast for $LDJ_{t+h}$ made at time *t*, $D\hat{L}DJ_{t,1}$ denotes the 1-step-ahead forecast for $DLDJ_{t+1}$ made at time *t*, etc., and $LDJ_t$ is the actual observation of LDJ at time *t*. The second step is to convert the predictions from the log level form (LDJ) to the anti-log level form (DJ) using with the formula

$$\hat{DJ}_{t,h} = \exp\left(L\hat{D}J_{t,h} + 0.5\hat{\sigma}_h^2\right), \tag{3}$$

where $\hat{\sigma}_h$ is the estimated standard deviation of the $h$ - step-ahead forecast error. The term involving $\hat{\sigma}_h$ is to correct the bias associated with the anti-log transformation.

Finally, we must choose some measures of forecasting accuracy in order to make comparisons between the Transfer Function implementation of the VL-DJ model and a simple Box-Jenkins model for the Dow Jones Index in the out-of-sample forecasting experiment. A forecast error is defined by the difference between the forecast value and the actual observation from the data, i.e.

$$e_{t,h} = y_{t+h} - f_{t,h} \tag{4}$$

where $f_{t,h}$ is an *h*-step-ahead forecast of $y_{t+h}$ made at time *t*. For notational simplicity, let us assume that there are J such forecast errors and let us denote them simply by $e_1, e_2, \cdots, e_J$. The Mean Absolute Forecast Error (MAFE) is defined as

$$MAFE = \frac{1}{J}\sum_{j=1}^{J} | e_j | . \tag{5}$$

The Root Mean Squared Forecast Error (RMSFE) is defined as

[16] See, for example, Pankratz (1991), p. 338.

$$RMSFE = \sqrt{\frac{1}{J}\sum_{j=1}^{J} e_j^2} \quad . \qquad (6)$$

### III.2 The Results of the Out-of-Sample Forecasting Experiment

As can be seen from the results reported in Tables 4 and 5 below, the Transfer Function implementation of the VL-DJ model performs worse than the benchmark MA(1) Box-Jenkins model at all forecast horizons for both forecasting accuracy measures, MAFE and RMSFE. As expected, the forecasting accuracies of the two methods diminish with an increasing horizon but, in all instances, the Box-Jenkins model proves to be superior.

**Table 4. Forecast Accuracy of the Transfer Function Implementation of the VL-DJ Model and the Benchmark Box-Jenkins Model At Different Forecast Horizons—MAFE**

| Forecast Horizon | MAFE | | Accuracy Ranking | |
|---|---|---|---|---|
| | TF | BJ | TF | BJ |
| Horizon1 | 378.85 | 351.91 | 2 | 1 |
| Horizon2 | 630.54 | 604.64 | 2 | 1 |
| Horizon3 | 822.84 | 764.41 | 2 | 1 |
| Horizon4 | 998.43 | 895.69 | 2 | 1 |
| Horizon5 | 1,189.42 | 1,092.55 | 2 | 1 |
| Horizon6 | 1,385.33 | 1,198.63 | 2 | 1 |
| Increase in MAFE (H6-H1)/H1 | 265.67% | 240.60% | | |

Note: "TF" denotes the Transfer Function Model Implementation of the VL-DJ Model and "BJ" denotes the MA(1) Box Jenkins Model for the Dow Jones Index.

**Table 5. Forecast Accuracy of the Transfer Function Implementation of the VL-DJ Model and the Benchmark Box-Jenkins Model At Different Forecast Horizons—RMSFE**

| Forecast Horizon | RMSFE | | Accuracy Ranking | |
|---|---|---|---|---|
| | TF | BJ | TF | BJ |
| Horizon1 | 605.30 | 528.40 | 2 | 1 |
| Horizon2 | 1,046.46 | 999.61 | 2 | 1 |
| Horizon3 | 1,405.36 | 1,355.96 | 2 | 1 |
| Horizon4 | 1,645.72 | 1,470.20 | 2 | 1 |
| Horizon5 | 1,884.64 | 1,719.23 | 2 | 1 |
| Horizon6 | 2,090.61 | 1,870.55 | 2 | 1 |
| Increase in RMSE (H6-H1)/H1 | 245.38% | 254.00% | | |

One might ask what causes this failure of the VL-DJ model to dominate the Box-Jenkins model? The answer lies in the critique offered by Ashley (1983). When forecasts of an explanatory variable are sufficiently inaccurate, their use in a multiple regression forecasting equation can lead to less precision than a simple extrapolation of the dependent variable, say, provided by a Box-Jenkins model. In fact, Ashley offers a criterion to use in judging when forecasting with multiple regression might be problematic. He states (p.211), "For a variety of types of models inclusion of an exogenous variable $x_t$ is shown to worsen the $y_t$ forecasts whenever $x_t$ must itself be forecast by $\hat{x}_t$ and MSE( $\hat{x}_t$ ) > Var( $x_t$ )." That is, when the mean squared error (variance plus $bias^2$) of the forecast of the explanatory variable is greater than the variance of the explanatory variable itself, forecasting with a multiple regression using the explanatory variable often will forecast worse than simple extrapolative models like the Box-Jenkins model. Of course, in defense of multiple regression, statistical inference can still be pursued in determining which factors are important explanatory variables of the variation in a dependent variable. However, despite good in-sample fits, multiple regression may not be that useful in a prediction context, especially if the explanatory variables are themselves difficult to predict.

To see why the Transfer Function implementation of the VL-DJ model did so poorly, we calculated the following "Ashley" ratios for the explanatory variables for the VL-DJ model at different forecast horizons. They are presented in Table 6 below. We define the "Ashley" ratio as

$$MSFE(\hat{x}_t)/Var(x_t) \tag{7}$$

where, for the one-step-ahead forecast, $MSFE(\hat{x}_t) = \frac{1}{30}\sum_{t=53}^{82}(x_{t+1} - \hat{x}_{t,1})^2$ and

$Var(x_t) = \frac{1}{30}\sum_{t=54}^{83}(x_t - \bar{x})^2$ with the sample mean $\bar{x}$ being calculated over the last 30 observations. The Ashley ratios for the other forecast horizons are similarly defined except that fewer forecasts are available to construct the MSFE of the forecast.

When the Ashley ratios are greater than one we know from Ashley's critique that the forecasts produced by the Transfer Function implementation of the VL-DJ are likely to be worse than a simple extrapolative model like the Box-Jenkins model. We can see from Table 6, that at each horizon there is at least one explanatory variable whose predictive mean square error is greater than the variance in the variable itself. In fact, at horizons two and three, the Ashley ratios for the explanatory variables are **all** greater than one. Thus, we can see that the problem with the Transfer Function implementation of the VL-DJ model lies largely with the difficulty in predicting the input variables themselves not the historical explanatory power of the VL-DJ model itself.

**Table 6. Ashley Ratios for the Explanatory Variables of the VL-DJ Model**

| Forecast Horizon | DLEP | DLDP | DLBY |
|---|---|---|---|
| Horizon1 | 0.90621 | 1.04771 | 0.95627 |
| Horizon2 | 1.06544 | 1.14441 | 1.11007 |
| Horizon3 | 1.05522 | 1.13803 | 1.03032 |
| Horizon4 | 1.02157 | 1.15946 | 0.96935 |
| Horizon5 | 1.00511 | 1.18731 | 0.97723 |
| Horizon6 | 0.96534 | 1.22971 | 1.00496 |

### III.3 The Value of Perfect Foresight With Respect to the Explanatory Variables of the VL-DJ Model and the Foresight of the Value Line Staff in the Use of Their Model

In this section of the paper we are going to 1) examine to what extent "perfect foresight" of future values of the explanatory variables would "rescue" the forecasting accuracy of the VL-DJ model relative to the Box-Jenkins type of extrapolation and 2) to what extent the Value Line Staff and the forecasts they produced are superior to those offered by the Box-Jenkins model we have used here and the VL-DJ model with and without perfect foresight on the explanatory variables.

By perfect foresight we mean using the actual future realized values of the explanatory variables when generating forecasts from the VL-DJ equation (1) as compared to forecasting the explanatory variables and then using the VL-DJ equation (1) to produce forecasts (as in the Transfer Function implementation of the VL-DJ model previously reported in Tables 4 and 5). In Table 7 below we compare the perfect foresight implementation of the VL-DJ model (referred to as the "TF-Perfect" foresight model) with the Transfer Function implementation of the VL-DJ model (referred to as the "TF-Imperfect" foresight model) and the Box-Jenkins model.

**Table 7. Forecast Accuracy Comparisons of VL-DJ Model and the Box-Jenkins Model Assuming Different Degrees of Foresight on the Explanatory Variables**

| Forecast Horizon | TF-Perfect MAFE | TF-Imperfect MAFE | TF-Imperfect Disadvantage* | BJ MAFE | BJ Disadvantage* | Accuracy Ranking TF-Perfect | Accuracy Ranking BJ |
|---|---|---|---|---|---|---|---|
| Horizon1 | 354 | 379 | 107.11% | 352 | 99.49% | 2 | 1 |
| Horizon2 | 602 | 631 | 104.74% | 605 | 100.44% | 1 | 2 |
| Horizon3 | 684 | 823 | 120.24% | 764 | 111.70% | 1 | 2 |
| Horizon4 | 772 | 998 | 129.34% | 896 | 116.03% | 1 | 2 |
| Horizon5 | 923 | 1,189 | 128.81% | 1,093 | 118.31% | 1 | 2 |
| Horizon6 | 994 | 1,385 | 139.39% | 1,199 | 120.60% | 1 | 2 |

| Forecast Horizon | TF-Perfect RMSFE | TF-Imperfect RMSFE | TF-Imperfect Disadvantage* | BJ RMSFE | BJ Disadvantage* | Accuracy Ranking TF-Perfect | Accuracy Ranking BJ |
|---|---|---|---|---|---|---|---|
| Horizon1 | 607 | 605 | 99.69% | 528 | 87.02% | 2 | 1 |
| Horizon2 | 980 | 1,046 | 106.73% | 1,000 | 101.95% | 1 | 2 |
| Horizon3 | 1,175 | 1,405 | 119.59% | 1,356 | 115.38% | 1 | 2 |
| Horizon4 | 1,295 | 1,646 | 127.04% | 1,470 | 113.49% | 1 | 2 |
| Horizon5 | 1,490 | 1,885 | 126.46% | 1,719 | 115.36% | 1 | 2 |
| Horizon6 | 1,575 | 2,091 | 132.77% | 1,871 | 118.80% | 1 | 2 |

*Disadvantage: Loss of forecast accuracy relative to TF-Perfect.

With the exception of one-step-ahead forecasting using the RMSFE measure, when the perfect foresight assumption is imposed (i.e. the TF-Perfect model), the accuracy of the VL-DJ model improves considerably when compared to the case where the explanatory variables have to be forecasted (i.e. the TF-Imperfect model). The "Disadvantage" column shows the percentage loss of forecasting accuracy of either the TF-Imperfect model or the Box-Jenkins model relative to the TF-Perfect model. For example, at forecast horizon 3, the TF-Imperfect model is 19.59% less accurate, using the RMSFE measure, than the TF-Perfect model while the Box-Jenkins model is 15.38% less accurate than the TF-Perfect model, when using the RMSFE measure. We can see that, except for one-step-ahead forecasting, perfect foresight on the explanatory variables of the VL-DJ model offers superior forecasting accuracy to the Box-Jenkins model. Obviously, with respect to the forecasting accuracy offered by the VL-DJ model, the lack of perfect foresight on the explanatory variables costs the forecaster dearly.

But how successful was the Value Line staff in using their model? Possibly they had very good foresight with respect to the future values of the explanatory variables when they used their model to generate forecasts of the Dow Jones Index. Recall from our earlier discussion that the model was first used to forecast the Dow Jones Index in 1982. The one-step-ahead Value Line forecasts of the Dow Jones Index as reported in the various end-of-year issues of their *Value Line Investment Survey* are reported in Table 8 below.

**Table 8. Value Line Forecasts vs. VL-DJ Transfer Function and Box-Jenkins Forecasts**

| Year | Actual DJ | Value Line DJ Forecast | 1-step-ahead TF | 1-step-ahead BJ | 2-step-ahead TF | 2-step-ahead BJ |
|---|---|---|---|---|---|---|
| 1983 | 1190 | 1180 | 972 | 906 | 1,020 | 1,051 |
| 1984 | 1178 | 1390 | 1,335 | 1,368 | 1,069 | 964 |
| 1985 | 1330 | 1290 | 1,230 | 1,202 | 1,414 | 1,465 |
| 1986 | 1797 | 1435 | 1,421 | 1,451 | 1,286 | 1,283 |
| 1987 | 2264 | 2035 | 2,002 | 2,034 | 1,517 | 1,550 |
| 1988 | 2062 | 2425 | 2,355 | 2,497 | 2,149 | 2,185 |
| 1989 | 2510 | 2190 | 2,107 | 2,086 | 2,455 | 2,689 |
| 1990 | 2670 | 2710 | 2,645 | 2,819 | 2,175 | 2,239 |
| 1991 | 2933 | 2940 | 2,779 | 2,817 | 2,780 | 3,035 |
| 1992 | 3282 | 3445 | 3,234 | 3,172 | 2,956 | 3,030 |
| 1993 | 3565 | N/A | 3,647 | 3,546 | 3,590 | 3,414 |
| 1994 | 3735 | N/A | 3,785 | 3,824 | 3,844 | 3,819 |
| 1995 | 4494 | N/A | 3,872 | 3,975 | 4,055 | 4,118 |
| 1996 | 5740 | 5110 | 4,674 | 4,977 | 4,029 | 4,278 |
| 1997 | 7448 | 6415 | 6,001 | 6,412 | 4,896 | 5,368 |
| 1998 | 8631 | 8400 | 7,757 | 8,368 | 6,322 | 6,935 |
| 1999 | 10482 | 9800 | 9,327 | 9,396 | 8,201 | 9,076 |
| 2000 | 10731 | 11800 | 11,056 | 11,681 | 10,022 | 10,197 |
| 2001 | 10209 | 11800 | 11,178 | 11,327 | 11,701 | 12,701 |
| 2002 | 9214 | 10900 | 11,096 | 10,700 | 11,922 | 12,297 |
| MAFE* | | 510 | 593 | 555 | 985 | 928 |
| RMSFE* | | 727 | 807 | 704 | 1,386 | 1,322 |

* The MAFE and RMSFE are computed based on years 1983-2002 except for the years 1993-1995.

Recall that, for some reason, the Value Line Corporation did not provide forecasts for the 1993-1995 years. In the above table the MAFE and RMSFE forecast accuracy measures are computed over the years 1983 – 2002, except for the years 1993-1995, for the Value Line one-step-ahead forecasts and the one and two-step-ahead forecasts of the

Imperfect Foresight Transfer Function implementation of the VL-DJ model and the Box-Jenkins model. When the Value Line Staff performs its forecasts at the end of each year (probably in late November or early December before going to press) they are probably performing somewhere between a one-step-ahead and a two-step-ahead forecast to generate the next year's forecast because they invariable only have part of the data for the current year required to update the coefficients of their model and therefore to generate the next year's forecast. Therefore, out of "fairness," we provide both the one-step-ahead and two-step-ahead forecasts of the Imperfect Forecast VL-DJ model and Box-Jenkins model with which to compare the Value Line forecasts. We can see from Table 8 that the Value Line Staff's forecasts compare quite favorably relative to the Imperfect TF implementation of the VL-DJ model and the Box-Jenkins model, especially if you consider the TF and BJ two-step-ahead forecasts which are probably more indicative of the information that the Value Line Staff had to work with when they were producing their forecasts. Evidently, over the years, the Value Line Staff has been able to generate pretty perceptive forecasts of the explanatory variables when using their model to produce forecasts of the Dow Jones Index. It just goes to show you that econometric models with explanatory variables can be pretty useful tools for forecasting when the users are quite perceptive with respect to the future values of the explanatory variables they are using.

## IV. Conclusions

In this paper we evaluated the econometric soundness and the forecasting capabilities of the Value Line Dow Jones Model that the Value Line Corporation uses in producing their Dow Jones forecasts for their end-of-year *Value Line Investment Survey*. We draw the following conclusions from our research.

- The model that the Value Line Corporation has constructed for the Dow Jones Index is econometrically sound in that it is balanced, dynamically complete, stable, and has economically plausible signs for the model's coefficients. Quite logically, the model implies that growth in the Dow Jones Index is positively related to percentage changes in earnings per share and dividends per share and negatively related to changes in interest rate yields.

- With respect to the implementation of the VL-DJ model, the lack of perfect foresight on the future values of the explanatory variables of the model is quite costly in terms of forecasting accuracy as compared to using a simple Box-Jenkins model to forecast next year's Dow Jones Index. As it turns out, the mean square errors associated with the forecasts of the explanatory variables of the model are larger than the inherent variability in the variables themselves, thus, according to the Ashley (1983) criterion, one might expect the VL-DJ model to perform poorly given a Transfer Function implementation of it.
- Evidently the Value Line Staff has been pretty perceptive with respect to its forecasts of the explanatory variables of their model because over the 1983 – 2002 period their forecasts have generally been more accurate than comparable forecasts generated by a Transfer Function implementation of the model or a simple Box-Jenkins model that ignores the explanatory variables that the Staff has proposed. Thus, a multiple regression model can be a useful prediction device in the hands of a perceptive user. As always, a multiple regression, as typified by the VJ-DJ model, can be very helpful in explaining the degree and direction of the effects that explanatory variables have on a dependent variable.
- Given this exercise, one might want to "pre-test" the difficulty of predicting future values of explanatory variables by calculating Ashley ratios before using a multiple regression or Transfer Function for prediction purposes. If the Ashley ratios exceed one for most of the explanatory variables of the model and for most of the forecast horizons, one might want to temper one's expectations about the potential forecasting accuracy of such models relative to a simple Box-Jenkins model of the dependent variable. Of course, a perceptive user of a multiple regression model can still produce good forecasts but the key is the perceptiveness of the user. False confidence can be costly. On the other hand, if one's purpose is to generate "optimistic," "average," and "pessimistic" forecasts of the future values of a dependent variable based on optimist, average, and pessimistic forecasts of explanatory variables then there is a clear preference for a coherent econometric model as compared to a simple extrapolative device like the Box-Jenkins model.

## References


Ashley, R. (1983): “On the Usefulness of Macroeconomic Forecasts as Inputs to Forecasting Models,” *Journal of Forecasting*, 2, 211-223.

Box, G. E. P., G. M. Jenkins and G. C. Reinsel (1994): *Time Series Analysis, Forecasting and Control*. 3rd ed. Prentice Hall, Englewood Cliffs, N.J.

Box, G.E.P. and D.A. Pierce (1970): “Distribution of Residual Autocorrelations in Autoregressive Integrated Moving Average Time Series Modes,” *Journal of the American Statistical Association*, 65, 1509 – 1526.

Brown, R. L., J. Durbin, and J. M. Evans (1975): "Techniques for Testing the Constancy of Regression Relationships Over Time," *Journal of the Royal Statistical Society*, Series B, 37, 149-192.

Dickey, David and Wayne A. Fuller (1979): “Distribution of the Estimates for Autoregressive Time Series with a Unit Root,” *Journal of the American Statistical Association*, 74, 427 – 431.

Eisenstadt, Samuel, Value Line Corporation. Personal communication concerning details of the estimation and specification of the VJ-DJ Model. See footnote 10.

Enders, Walter (1995): *Applied Econometric Time Series*. Wiley, New York, NY.

Engle, Robert F. (1982): “Autoregressive Conditional Heteroscedasticity with Estimates of the Variance of United Kingdom Inflation,” *Econometrica*, 50, 987 – 1007.

*EVIEWS 4.1*, Standard Edition, 2002, Quantitative Micro Software, LLC, Irvine, CA.

Granger, Clive and P. Newbold (1974): “Spurious Regression in Econometrics,” *Journal of Econometrics*, 2, 111-120.

MacKinnon, James G. (1996): “Numerical Distribution Functions for Unit Root and Cointegration Tests,” *Journal of Applied Econometrics*, 11, 601-618.

Pankratz, Alan (1991): *Forecasting with Dynamic Regression Models*. Wiley, New York, NY.

Phillips, Peter (1986): “Understanding Spurious Regressions in Econometrics,” *Journal of Econometrics*, 33, 311 – 340.

*SAS Version 8.0*, SAS Institute, Cary, NC.

*The Value Line Investment Survey*, December Issues from 1982 – 2003. Value Line Publishing Inc.

White, Halbert (1980): A Heteroskedasticity-Consistent Covariance Matrix Estimator and a Direct Test for Heteroskedasticity," *Econometrica*, 48, 817 – 838.

Wooldridge, Jeffrey M. (2006): *Introductory Econometrics*, 3rd edition. Thomson Publishing, Mason, Ohio.