COMBINING FORECASTS WITHIN THE MLTIVARIATE C_LOGISTIC: A FRESH APPROACH TO FORECASTING

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ABSTRACT

The concept of combining forecasts enables the multivariate C_logistic model to rival all time series and econometric models in computing accurate forecasts from growth data. The "C" notation signifies a multivariate logistic equation that possesses a continuous response variable. The C_logistic model is easy to understand, simple to apply, and derived from both spreadsheets and statistical software. Therefore, this model is attractive to academicians in teaching and practitioners in computing superior out-of-sample forecasts. Indeed, the structural form, innovative seasonal variable (S_j), combined forecasts, and judgmental modifications capabilities make the multivariate C_logistic model ideally suited for forecasting in today's dynamic environments.

INTRODUCTION

The multivariate C_logistic equation possesses the needed ingredients of an exceptional forecasting model: an upper asymptote, a point of inflection, event modeling, judgmental modification, and combined forecasts capabilities. There are four stages to this S-shaped growth curve: (a) slow growth, (b) growth at an increasing rate, (c) growth at a decreasing rate, and (d) saturation. A plot of the data and knowledge of the subject matter help identify the current stage of growth. The concept of combining forecasts within the multivariate C_logistic model is unique with these authors. When using growth data, the predictive capabilities of this model enable it to rival all time series (including Box-Jenkins ARIMA) and econometric models in computing accurate forecasts. Since the "C" notation signifies a continuous response variable, this equation should not be confused with the familiar logistic equations that possess a binary or nominal scaled response variable.

This article promotes the use of combined forecasts and time series components within the multivariate C_logistic model. The advantages of a single seasonal index variable (S_j) rather than multiple (11 for monthly) indicator variables have only recently been committed to writing (Landram, et al. 2004, 2008). This seasonal variable (S_j) is used as an explanatory variable in describing seasonal variation in the multivariate C_logistic. Since historical conditions of the past may not prevail in the future, structured judgmental modifications are employed thereby increasing the accuracy of future predictions. Hence, in an effort to produce superior forecasts, an innovative seasonal variable (S_j), combined forecasts, and structured judgmental modifications capabilities are used within the multivariate C_logistic model.

In an effort to eliminate any confusion of this model with the logit, probit, or single variable logistic models, the originality of the multivariate C_logistic model is reiterated below:

(a) The C_logistic equation conforms to an S-shape growth pattern as does the logistiand Gompertz equations. However, this model possesses a continuous response variable with multiple explanatory variables.
(b) Both econometric variables and time series components can be combined in the C_logistic model.
(c) In this article, the innovative least squares seasonal index variable is extended to the C_logistic model.

Equations with the above characteristics of the C_logistic equation have not appeared in the literature.

In reviewing the past 25 years of forecasting, Gooijer and Hyndman (2006) cite the need for additional research into multivariate time series forecasting. They also stress the need for deeper research in forecasting methods based on nonlinear models. These needs are addressed in describing the C_logistic model. Furthermore, many have expressed concern and disappointment over the lack of "new" methods of forecasting (Fildes, 2006). They also prefer the description of an innovative forecasting method be grounded in real data and compared to other proven alternative methods of forecasting. This article addresses all of these concerns. A major goal in forecasting is the integration of judgment and quantitative methods (Armstrong and Collopy, 1998). The judgmental selection of the asymptote enables the C_logistic to easily integrate prior knowledge into a statistical model thereby achieving this goal.

COMBINED FORECASTS

The multivariate C_logistic equation is defined as

$$\hat{Y} = \frac{K}{1 + e^{-f}} \qquad (1)$$

where K is the upper limit or asymptote and f is a function of one or more explanatory variables. Here lies the originality of this article: (a) Y is a continuous variable, (b) f is not limited to a single trend variable, and (c) multiple explanatory variables are combined within the C_logistic model. Indeed, explanatory variables such as time series, event modeling, and judgment as well as forecasts from other models are combined in this function.

Applications

Figure 1 illustrates population growth in the US using the tradition (one variable) logistic equation; where f in (1) is

$$f = b_0 + b_1X. \qquad (2)$$

Figure 2 is a multivariable fit using

$$f = b_0 + b_1X + b_2X^2 + b_3D + b_4XD; \quad (3)$$

where X and X^2 signify population growth trends, and D signifies an event modeling population growth change. The increased accuracy of the multivariate C_logistic model using (3) rather than (2) for f is evident when comparing Figures 1 and 2.

Figure 1. Logistic Equation

$f = a + bX$

US Population Growth

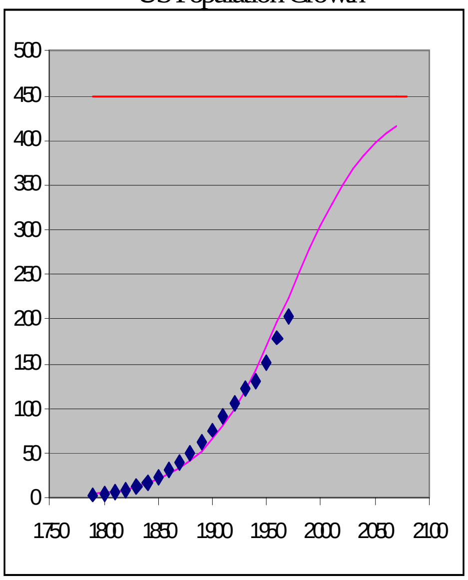
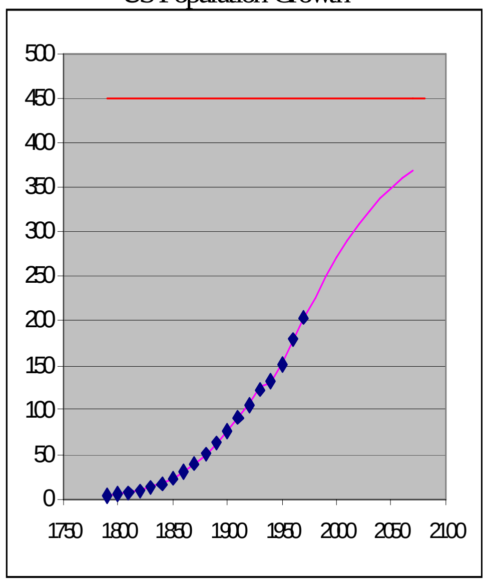


Figure 2. Logistic Equation

$f = a + b_1X + b_2X^2 + b_3D + b_4XD$

US Population Growth



Since combining forecasts within the multivariate C_logistic is a new and innovative concept, it must prove its worth—especially when limited commercial software is available. Although this model can be run from the nonlinear procedures of SAS, user friendly spreadsheet operations are provided below. The rationale and spreadsheet numerics used in deriving the multivariate C_logistic model are first described. Then, using data from SAS (1988), the multivariate C_logistic is shown to be 81.5% more accurate than the nonlinear growth model employed in the SAS example. Its forecasting capabilities are then compared to those computed from time series and econometric forecasting models.

MODEL DERIVATION AND CONCEPTS

The asymptote K in (1) may be obtained subjectively or from equations found in articles such as Nelder (1961). The subjective value assigned to the upper limit K is described in greater detail below. Given a value for K, a little algebra transforms (1) into

$$g = e^{f} = Y/(K-Y). \tag{4}$$

Let f be a traditional simple linear function; then

$$\ln g = \beta_0 + \beta_1 X = \ln[Y/(K-Y)]. \tag{5a}$$

If f is the multivariate function estimated by (3) then

$$\ln g = \beta_0 + \beta_1 X + \beta_2 X^2 + \beta_3 D + \beta_4 XD = \ln[Y/(K-Y)]. \tag{5b}$$

By regressing ln g on X, X^2, D, and XD, least squares estimates of ln g are obtained;

$$\overline{\widehat{\ln g}} = \ln[\hat{Y}/(K-\hat{Y})] = b_0 + b_1 X. + b_2 X^2 + b_3 D + b_4 XD. \tag{6}$$

Note, from (6), estimates of Y are obtained by taking the antilog of $\overline{\widehat{\ln g}}$ and solving for $\hat{Y}$;

$$\hat{Y} = K\hat{g}/(1+\hat{g}). \tag{7}$$

Hence, from (6) as X increases, both $\overline{\widehat{\ln g}}$ and $\hat{g}$ increase; (7) reveals as $\hat{g}$ increases $\hat{Y}$ approaches its upper limit K. Least squares are used to estimate ln g; then, an estimate of Y is obtained from (7). Estimates of Y are also obtained by substituting the numerical values of (3) into (1) and calculating $\hat{Y}$ directly.

Unrestricted Least Squares

Granger and Ramanathan (1984**)** argue that combined forecasts from several methods outperform forecasts from a single method. They point out that values from discarded forecasting models still contain useful information about the underlying behavior of Y. When biased forecasts are included in a least squares equation, the intercept adjusts for the bias. Hence, in the combination process, it is important to include the intercept—unrestricted least squares—and let least squares automatically assign weights to the forecasts. The authors also recommend the use of variable selection techniques concerning the inclusion of time series components and other forecasts as explanatory variables.

If the data is nonstationary or autocorrelated, there is a possibility that a combined forecast model with variables weighted other than by least squares will produce more accurate out-of-sample predictions (Aksu and Gunter, 1992). However, the authors of this paper advocate the use of unrestricted least squares and contend this inferior performance may occur when the model is misspecified. Therefore, it is necessary to analyze the adequacy of out-of-sample values from econometric and time series variables. It is possible that moving rather than constant seasonal indices may be needed, time series cyclical factors may need adjusting, and (the C_logistic's major judgment advantage) the upper asymptote may need reconfirming. The it will be possible to obtain a properly specified model by concentrating on the subject and let least squares do the weighting.

Statistical Modeling

Forecasts used as explanatory variables in a combined forecasts equation are subject to the same statistical modeling scrutiny as other variables. When two highly accurate forecasts are used as explanatory variables and combined, they may be multicollinear (redundant) with one needing deletion. The reverse is also true when two inaccurate forecasts are used as explanatory variables and the combined forecast equation produces highly accurate forecasts.

Seasonality

The above statistical modeling concept also applies to time series components. Multicollinearity is why the seasonal index variable (obtained from time series decomposition) and dummy variables used in describing seasonal variation should not be combined in the same model. However, additive and multiplicative seasonal variables may be combined:

$$\hat{Y}_t = b_0 + b_1X_t + b_2C_t + b_3S_j + b_4T_tC_tS_j ; \tag{8a}$$

where X_t, C_t and S_j represent trend, cyclical and seasonal components of a time series. The multiplicative component $T_tC_tS_j$ equals $T_t*C_t*S_j$; where $T_t = b_0 + b_1X_t$. A detailed discussion concerning the use of time series components in least squares equations is given by Landram et al (2004, 2008).

Forecasting Software

From a survey of 240 US corporations, Sanders and Manrodt (2003) found that only 11% reported using forecasting software in which 60% indicated they routinely adjusted the forecasts. Judgmental interventions are often difficult to perform with commercial software but relatively simple with spreadsheets. The above concepts along with spreadsheet simplicity are illustrated below.

WORKED EXAMPLES

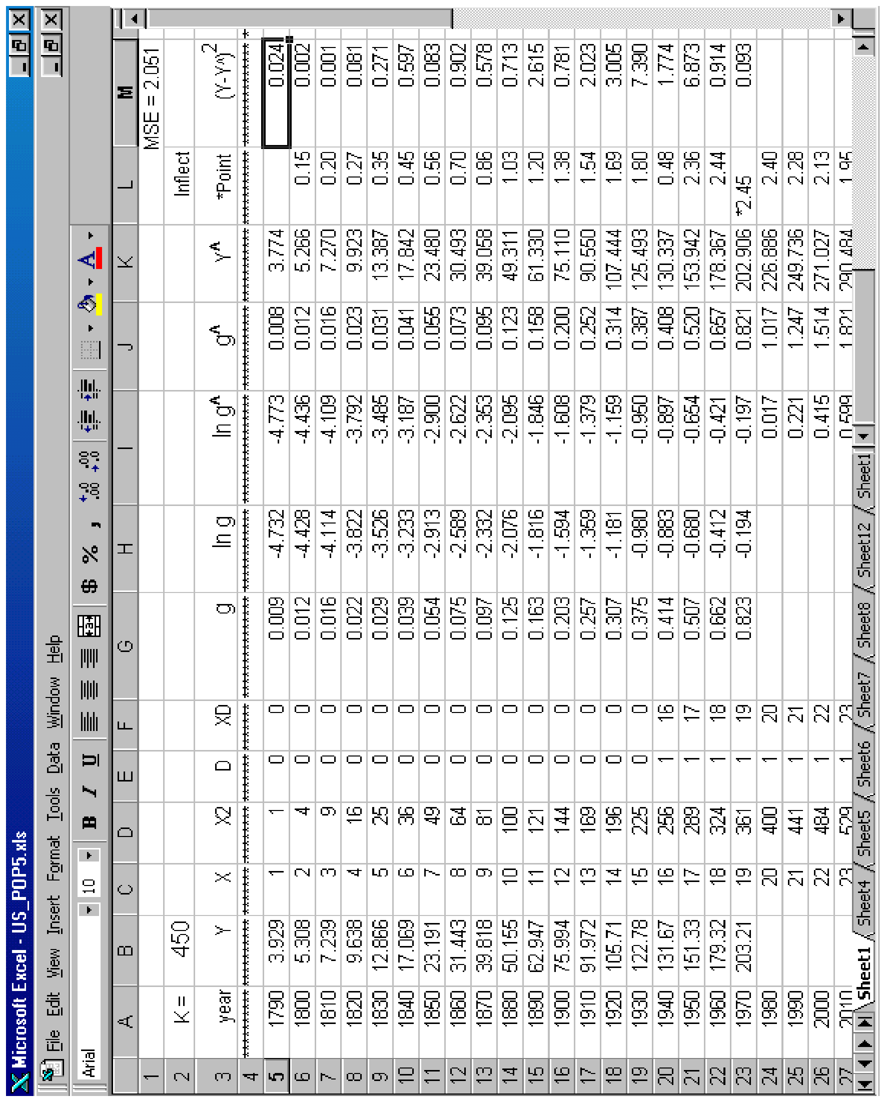
In order to fix concepts and further explore the originality and benefits of combining forecasts within the multivariate C_logistic model, two examples are given. These examples illustrate that the transformations given above are easily adaptable for spreadsheet pedagogy. They also illustrate the versatility and accuracy of the multivariate C_logistic when compared with other forecasting methods.

Example 1. United States Population Growth

Using the 1790 to 1970 US population data given in SAS (1988), the curve from the traditional logistic equation is given in Figure 1. The population values for Figure 2 are calculated in a spreadsheet using the multivariate C_logistic equation depicted in Figure 3. Observe that the asymptote K is in cell B2 as a driver and is obtained subjectively (Edmundson, 1990). After a detailed study of the population growth in the US, the asymptote K is set at 450 million. However, this upper limit changes with technology advancements and political attitudes. Hence, this value can easily be changed to simulate forecasts with various values of K given in (1). Letting (3) define function f in (1), values of Y, X, X^2, D, and XD are entered. Event modeling variable D signifies the baby boom era, also Hawaii and Alaska becoming states. Values of g = Y/(K-Y) are calculated in column G. After calculating lng, the Excel regression operations are performed. This is accomplished by clicking on **TOOLS**, then **DATA ANALYSIS**, and then **REGRESSION;**

TOOLS > DATA ANALYSIS > REGRESSION.

Figure 3
Deriving The Multivariate C_Logistic



	A	B	C	D	E	F	G	H	I	J	K	L	M
1													MSE = 2.051
2	K =	450										Inflect	
3	year	Y	X	X2	D	XD	g	ln g	ln g^	g^	Y^	*Point	(Y-Y^)^2
4	********	********	******	******	*****	*****	**********	**********	**********	**********	**********	********	**********
5	1790	3.929	1	1	0	0	0.009	-4.732	-4.773	0.008	3.774		0.024
6	1800	5.308	2	4	0	0	0.012	-4.428	-4.436	0.012	5.266	0.15	0.002
7	1810	7.239	3	9	0	0	0.016	-4.114	-4.109	0.016	7.270	0.20	0.001
8	1820	9.638	4	16	0	0	0.022	-3.822	-3.792	0.023	9.923	0.27	0.081
9	1830	12.866	5	25	0	0	0.029	-3.526	-3.485	0.031	13.387	0.35	0.271
10	1840	17.069	6	36	0	0	0.039	-3.233	-3.187	0.041	17.842	0.45	0.597
11	1850	23.191	7	49	0	0	0.054	-2.913	-2.900	0.055	23.480	0.56	0.083
12	1860	31.443	8	64	0	0	0.075	-2.589	-2.622	0.073	30.493	0.70	0.902
13	1870	39.818	9	81	0	0	0.097	-2.332	-2.353	0.095	39.058	0.86	0.578
14	1880	50.155	10	100	0	0	0.125	-2.076	-2.095	0.123	49.311	1.03	0.713
15	1890	62.947	11	121	0	0	0.163	-1.816	-1.846	0.158	61.330	1.20	2.615
16	1900	75.994	12	144	0	0	0.203	-1.594	-1.608	0.200	75.110	1.38	0.781
17	1910	91.972	13	169	0	0	0.257	-1.359	-1.379	0.252	90.550	1.54	2.023
18	1920	105.71	14	196	0	0	0.307	-1.181	-1.159	0.314	107.444	1.69	3.005
19	1930	122.78	15	225	0	0	0.375	-0.980	-0.950	0.387	125.493	1.80	7.390
20	1940	131.67	16	256	1	16	0.414	-0.883	-0.897	0.408	130.337	0.48	1.774
21	1950	151.33	17	289	1	17	0.507	-0.680	-0.654	0.520	153.942	2.36	6.873
22	1960	179.32	18	324	1	18	0.662	-0.412	-0.421	0.657	178.367	2.44	0.914
23	1970	203.21	19	361	1	19	0.823	-0.194	-0.197	0.821	202.906	*2.45	0.093
24	1980		20	400	1	20			0.017	1.017	226.886	2.40	
25	1990		21	441	1	21			0.221	1.247	249.736	2.28	
26	2000		22	484	1	22			0.415	1.514	271.027	2.13	
27	2010		23	529	1	23			0.599	1.821	290.484	1.95	

Observe from Figure 3 that ln g is the response variable located in cells H5-H23 and the explanatory variables in cells C5-F23. Estimates of ln g in (6) are computed by entering the Excel equation

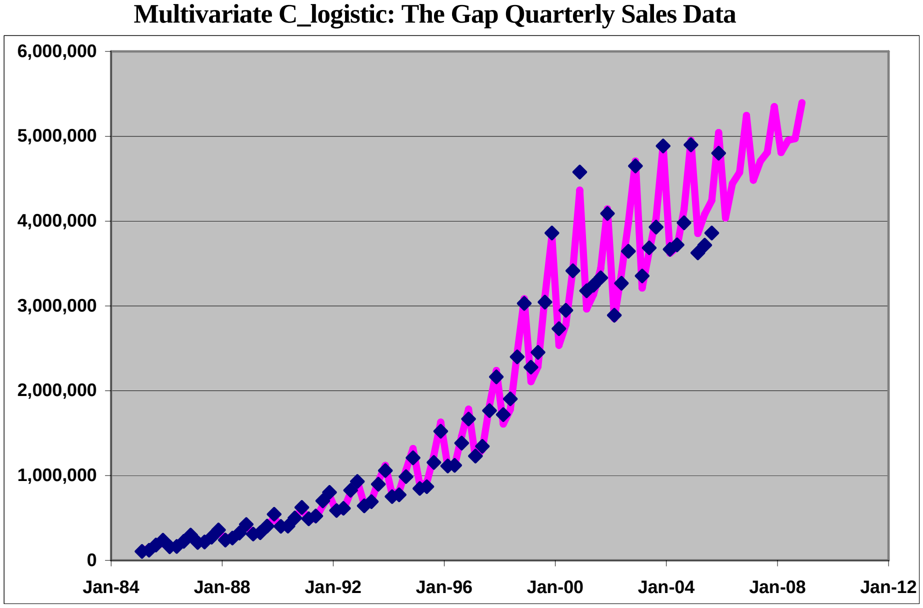
=$B$51+$B$52*C5+$B$53*D5+$B$54*E5+$B$55*F5

in cell I5. This equation is then copied in cells I6-I32, given the values of coefficients b_0, b_1, b_2, b_3, and b_4 are in cells B51, B52, B53, B54, and B55, respectively. The above Excel equation is the Excel counterpart to (3) above. In column K, $\hat{Y}$ values are obtained by employing (7) above. The mean square error (MSE = 2.051) is given in cell M1 while the point of inflection is revealed in column L.

Snedecor and Cochran (1967) comment on the striking accuracy of the traditional (one variable) logistic's U.S. population estimates for years 1790 to 1940 and failure thereafter. They also note the unrealistic value of the computed asymptote. This problem is rectified by obtaining a knowledge of the subject matter and subjectively selecting a more realistic value for K (see Figure 1). This is further evidence that a subjectively set asymptote is often more accurate than those obtained from a numerical equation. The first problem is rectified by realizing that in the 1940's the growth rate increased due to the baby boom. Also, Hawaii and Alaska became states in 1959. Therefore, an adjustment by using the dummy variable D is employed with excellent results (Figure 2). The capability of using multiple variables (qualitative and quantitative) greatly enhances the accuracy and versatility of C_logistic forecasts. In an era of turbulent conditions, qualitative variables for adjusting to events such as our post 9-11economy have proven to be extremely useful.

The MSE of 2.051 for the multivariate C_logistic is compared to MSE = 11.086 given in SAS/STAT User's Guide, 6.03 edition, page 698 using probit analysis. Probit, also logit, are nonlinear growth models closely aligned to the logistic. The SAS software uses numerical procedures to fit nonlinear regression models. These procedures are iterative methods such as the gradient, Newton, and Marquardt methods. As illustrated in Figure 3, the procedure of transforming (1) into an intrinsically linear equation decreased the MSE from 11.086 to 2.051 – a decrease of 81.5%. However, other numerical iterative procedures (including iteratively reweighted least squares) as well as segmented (piecewise) models may provide an even better fit.

Figure 4.
Multivariate C_logistic: The Gap Quarterly Sales Data



Example 2. Quarterly Sales for The Gap

The multivariate C_logistic also produces excellent results when using quarterly data given in the textbook, *Business Forecasting* by Wilson and Keating (2007). Figure 4 illustrates the accuracy of this equation when used in forecasting quarterly sales for The Gap -- a company operating over 1500 retail stores in the United States. The linear function f in (1), in the multivariate C_logistic model, is

$$f = b_0 + b_1X_t + b_2X_t^2 + b_3S_j + b_4C_t + b_5D_t + b_6T_tS_jC_t; \qquad (8b)$$

where most of the variables in (8b) were defined in (8a). Variables X_t and X_t^2 are sequential time variables; S_j is the least squares seasonal introduced by Landram, et al. (2004, 2008); C_t is a cyclical index; and D_t is an event modeling "9-11" variable. Variable $T_tS_jC_t$ is obtained from the multiplicative decomposition forecast $T_tS_jC_t = T_t{*}S_j{*}C_t$, where $T_t = b_0 + b_1X_t + b_2X_t^2$.

Table 1 reveals that forecasting method 4—Winter's exponential smoothing (Wilson and Keating 2007) forecasts combined with multiple regression forecasts—came in a distant second best with historical RMSE=105,832 and holdout RMSE=136,446. The root mean square error, RMSE = $(SSE/n)^{1/2}$, is used in comparing the various forecasting methods listed in Table 1; where SSE is the sum of squares error. A measure of goodness of fit is obtained from the historical RMSE. The historical data includes quarterly data from 1985 through 2003. A measure of goodness of prediction is obtained from the holdout RMSE. The holdout data includes quarterly data for 2004. These four quarters are not used in deriving the various models and are considered out-of-sample data. They are completely independent of the forecasting models. Again, method 1 in Table 1 reveals that combining forecasts within the multivariable C_logistic enhances the accuracy of predictions. When (8b) above is used as f in (1), the accuracy of both in-sample and out-of-sample predictions is enhanced with historical RMSE = 84,348 and holdout RMSE = 88,261.

TABLE 1
COMPARING FORECASTING METHODS:
RMSE FOR THE GAP QUARTERLY SALES

Forecasting Method	Historical RMSE	Holdout RMSE
1. C_logistic --Time Series Components	84,348	88,261
2. C_logistic -- Multiple Regression	195,695	552,605
3. Multiple Regression	262,900	729,879
4. Combined Winter's and Multiple Regression	105,832	136,446
5. Time-Series Decomposition	145,517	345,359
6. ARMA(1,0) (0,1,0)	339,476	1,152,442

Multivariate C_logistic $\quad Y = \dfrac{K}{1+e^{-f}}$

January 1, 1985 to December 31, 2003 timeline for historical RMSE.
January 1, 2004 to December 31, 2004 timeline for holdout RMSE.

$f = b_0 + b_1X + b_2X^2 + b_3S_j + b_4C_t + b_5D_t + b_6T_tS_jC_t$ (8b) used with Forecasting Method 1.

$\hat{Y} = b_0 + b_1X + b_2X^2 + b_3D_2 + b_4D_3 + b_5D_4 + b_6P;$ (9) used with Forecasting Methods 2, 3, 4

Wolson and Keating employ (9) as their multiple regression model in forecasting quarterly sales;

$$\hat{Y}_t = b_0 + b_1X_t + b_2X_t^2 + b_3D_2 + b_4D_3 + b_5D_4 + b_6P_t; \qquad (9)$$

P_t is the Standard and Poor's 500 Returns, and D_2, D_3, and D_4 are dummy variables representing quarters 2, 3, and 4, respectively. Method 3 in Table 1 shows the unsatisfactory results of this model with historical RMSE=262,900 and holdout RMSE=729,879. However, when (9) is used as f in the multivariate C_logistic model (method 2 in Table 1), the RMSE becomes smaller with historical RMSE=195,695 and holdout RMSE=552,605. The poor performance of (9) in methods 2 and 3 of Table 1 is caused by conditional error explained below. Nevertheless, the RMSE values become significantly smaller when (9) is employed as the f function in (1); method 2 compared to method 3.

DISCUSSION

The multivariate C_logistic is extremely flexible with a myriad of shapes. In addition to the trend, also included are seasonal variation and cyclical variables. Econometric variables enable the model to forecast turning points. As in the above population example, qualitative (dummy) variables enable the model to make needed adjustments. Again, the D in (8b) above represents pre- and post-9-11 economies. When variables other than the trend are included in the multivariate C_logistic model, the point of inflection is no longer at the middle of the range. In Example 2, the inflection point for The Gap data occurs when the estimates $\hat{Y}$ are at approximately 2002. The increased capabilities of the multivariate C_logistic enable it to become extremely effective in forecasting growth data.

Judgmental Modification

Judgmental Modification consists of injecting the forecaster's knowledge of the subject matter into the equation (Young, 1982). Many feel that judgmental modification is an essential ingredient in forecasting (Tsay, 2000). Bunn and Wright (1991) remind readers that model specification, variable selection, how far back to go in a time series, and special event modeling are judgmental. A subjectively set upper limit is in agreement with the structured visual aids promoted by Edmundson (1990). The idea is to obtain judgmental modification at the level of time series components. Therefore, the asymptote K of the multivariate C_logistic may be subjectively set in an effort to fine tune the predictive accuracy of the model. This is accomplished by finding a reasonable asymptotic value which produces a low holdout RMSE. Under current conditions, upper limits are moving. For example, the asymptote of K=450 for the US population growth in Figure 3 is controlled by such factors as immigration policies, life expectancy, birth control, and technological changes. Since this upper limit is constantly moving, the multivariate C_logistic model is best served by using the asymptote as a judgmental modification tool.

Conditional Error

Kennedy (2003) discusses four types of forecasting errors: (a) random, (b) sampling, (c) specification, and (d) conditional errors. Conditional error occurs when one must first predict an X value to use in predicting the desired Y value. Certainly, in Example 2, using Standard and Poor's 500 Returns (P) in (9) creates the latter error. Indeed, multiple regression methods (2), (3), and (4) in Table 1 must predict values for S&P 500 Returns before predicting quarterly sales of the future. Thus, conditional error often results in poor out-of-sample predictions. Nevertheless, using business barometers of this type sometimes enables the model to predict downturns.

CONCLUSION

Accurate forecasts are computed from econometric and time series models. However, it is a safe bet to say, "Show me a 'good' forecast and I can make it better." Note that R^2 can never decrease by including an additional variable in the model. Therefore combine the "good" forecast with time series components and other forecasts thereby increasing R^2. Overfitting is the downside of combining forecasts. Nevertheless, when forecasting growth data, it is a safe bet to combine the "good" forecast and then place it in a multivariate C_logistic model.

Although the multivariate C_logistic outperformed other forecasting methods described by Wilson and Keating (2007), each business must select the forecasting method that best helps their particular situation. Still, combined forecasts are generally superior to forecasts from a single method, and the multivariate C_logistic model rivals all time series and econometric models in forecasting growth data. Since its upper asymptote can be determined subjectively, this model possesses a unique judgmental modification capability for out-of-sample predictions. Indeed, the structural form, event modeling, judgment and combined forecasts capabilities make the multivariable C_logistic model ideally suited for forecasting in today's dynamic environments.

REFERENCES

Aksu, C., and S. Gunter. 1992. "An empirical analysis of the accuracy of SA, OLS, ERLS, and NRLS combination forecasts." *International Journal of Forecasting* 8: 27-43.

Armstrong, J., and F. Collopy. 1998. "Integration of statistical methods and judgment for time-series forecasting: Principles from empirical research." In G. Wright & P. Goodwin, *Forecasting with Judgment.* Wiley: 69-293.

Bunn, D. and G. Wright. 1991. "Interaction of Judgmental and Statistical Forecasting Methods: Issues & Analysis." *Management Science* 37: 501-518.

Edmundson, R. 1990. "Decomposition: A Strategy for Judgmental Forecasts." *Journal of Forecasting* 9:4: 305.

Fildes, R. 2006. "The forecasting journals and their contribution to forecasting research: Citation analysis and expert opinion." *International Journal of Forecasting* 22: 415-432.

De Gooijer, J. and R. Hyndman. 2006. "25 years of time series forecasting." *International Journal of Forecasting* 22: 443-473.

Granger, C. and R. Ramanathan. 1984. "Improved Methods of Combining Forecasts." *Journal of Forecasting* 3: 197-204.

Kennedy, Peter. 2003. *A Guide to Econometrics.* 4th edition, Cambridge, Mass, The MIT Press.

Landram, F., A. Abdullat, and V. Shah. 2004. "Using Seasonal and Cyclical Components in Least Squares Forecasting Models." *Southwestern Economic Review* 31: 189-196.

Landram, F., B. Alidaee, and R. Pavur. 2008. "Combining Time Series Components for Improved Forecasts." *Decision Sciences: Journal of Innovative Education* 6(2) (forthcoming).

Nelder, J.A. 1961. "The Fitting of a Generalization of the Logistic Curve." *Biometrics* 17: 89-110.

SAS/STAT User's Guide, 6.03 edition. 1988. Cary N.C., SAS Institute.

Sanders, N. R., and K. Manrodt. 2003. "The efficacy of using judgmental versus quantitative forecasting methods in practice." *Omega* 31: 511-522.

Snederoc, G., and W.G. Cochran. 1967. *Statistical Methods*, 6th ed., The Iowa State Press, Ames, Iowa.

Tsay, R. 2000. "Time series and forecasting: Brief history and future research." *Journal of the American Statistical Association* 95: 638-643.

Wilson, H.J., and B. Keating. 2007. *Business Forecasting*, 5th ed., New York, McGraw-Hill.

Young, R. 1982. "Forecasting With An Econometric Model: The Issue of Judgmental Adjustment." *Journal of Forecasting* 1: 189-204.