JUDGMENTAL MODIFICATION FOR TIME SERIES FORECASTING

Frank G. Landram, West Texas A & M University
Suzanne V. Landram, University of Northern Colorado
Francis Mendez, Texas State University
Vivek Shah, Texas State University

ABSTRACT

By combining time series components in least squares models, a method of forecasting superior to time series decomposition is obtained. The accuracy of these forecasts is further enhanced by the use of judgmental modification in the form of event modeling and moving seasonal indices. Hence, the objective is to describe time series models that rival all others in out-of-sample prediction accuracy. The use of seasonal indices as a least squares explanatory variable has only recently been committed to writing. This concept is extended with event modeling and moving (rather than constant) seasonal indices thereby injecting judgmental modification into the equation. *JEL Classification: C53*

INTRODUCTION

The recent economic decline has brought an increased recognition that forecasting is an essential activity in the profitability of most 21st century enterprises. However, since no specific method fits all situations, each business must select the forecasting methods that help their particular situation. This forecasting dilemma is further complicated by the fact that most economic conditions are constantly changing. Therefore, the practice of combining forecasts that are conducive to a variety of economic conditions has gained popularity (Fang, 2003; Batchelor and Dua 1995). This paper promotes the use of time series models that we contend will rival all other models in out-of-sample prediction accuracy. This accuracy is accomplished by combining judgmental modification in the form of moving seasonal indices along with cyclical components and event modeling variables within unrestricted least squares equations.

Combined Forecasts

Many articles have been written concerning the improved accuracy of combining forecasts (Bates and Granger,1969; Clemen, 1989). However the use of a traditional seasonal index variable rather than multiple (11 for monthly) indicator variables has only recently been committed to writing (Landram, et al. 2004, 2008a). Also, the use of moving seasonal indices and event modeling variables injects judgmental modification into the model thereby increasing the accuracy of out-of-sample predictions. This process also assists in correcting autocorrelation.

Judgmental Modification

The process of injecting the forecaster's acquired knowledge of the subject matter into the equation. Many feel judgmental modification is an essential ingredient in forecasting (De Gooijer and Hyndman, 2006; Manganelli, 2007). Thus, in an effort to produce superior forecasts, a method of combining time series decomposition variables into least squares equations is described. A major problem with all forecasting methods is their inability to determine changing conditions in advance. Forecasting methods and time series values appropriate for one period are not necessarily appropriate in another period. Therefore, human judgment is needed to help predict when these changes will occur and the effect these changes will have on the behavior of their forecasts.

Conditional Error

In using econometric models, there is a great likelihood of conditional error. As defined by Kennedy (2008), conditional error occurs when a predicted value for an explanatory variable (X_t) is used in computing a response (Y_t) value. In predicting Y_t values, projected moving seasonal indices are generally more accurate than projected values from econometric variables.

Event Modeling

The use of dummy variables to describe how a specific event influences the dependent Y variable (Wilson, et al., 2007). This form of judgmental modification often corrects the autocorrelation problem inherent in most macro-economic data. It also enhances the accuracy of out-of-sample predictions. Hence, the authors argue judgmental modification is essential to time series models.

Outline

The following areas of forecasting are addressed below. (a) First, merits of combining forecasts using unrestricted least squares are discussed. (b) Then, the innovative method of combining time series components in least squares models is explained followed by an example. (c) The example is given to fix concepts and illustrate how moving seasonal indices, cyclical factors, and event modeling variables enhance the accuracy of forecasts. Since overfitting is the downside to combining forecasts, statistical modeling is described to obtain the "best" combination of variables for out-of-sample predictions. (d) Next, a closer look is presented concerning how moving seasonal indices and event modeling variables may correct autocorrelation. (e) Finally, concluding remarks are given that reiterates the benefits of employing judgmental modification in time series forecasts.

COMBINED TIME SERIES MODELS

Consider the following time series forecasting model:

$$Y_t = \beta_0 + \beta_1 X_t + \beta_2 C_t + \beta_3 S_j + \varepsilon_t. \qquad (1)$$

where X_t are for trend values (X_t = 1, 2, ... n), S_j are the quarterly seasonal indices repeated each year, and C_t are cyclical factors. The constant seasonal indices [S_1=0.92, S_2=0.99, S_3=0.96, S_4=1.13] are used in the example given in Section 3. These seasonal indices are obtained from traditional time series decomposition methods (Kvanli, et al., 2003). Advantages of combining time series components within least squares equations are explained by Landram, et al. (2008a) and extended to moving seasonal indices below.

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. When biased forecasts are included in a least squares model, the intercept adjusts for the bias. Hence, it is important to use (unrestricted) least squares models with an intercept.

Since most economic conditions are constantly changing, 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 (Bohara et al. 1987). However, we advocate the use of unrestricted least squares and contend this inferior performance occurs when the model is misspecified. Therefore, explanatory variables that improve out-of-sample accuracy must be employed. Moving rather than constant seasonal indices may be needed, time series cyclical factors may need adjusting, and specific events may need emphasizing. Obtain a properly specified model by implementing judgmental modification variables and let unrestricted least squares do the weighting

Variable Selection

Forecasts used as explanatory variables in a combined forecasts equation are subject to the same statistical modeling scrutiny as any other variable. When two highly accurate forecasts are combined as explanatory variables, 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. Remember, combined forecasts are subject to the same bias of omission (specification error) as other regression models. Conversely, overfitting causes inflated prediction variances (Landram, et al., 2008b). Thus, when combining forecasts, statistical modeling is needed.

Time Series Components

The above statistical modeling concepts also apply to time series components. Multicollinearity is why the seasonal index variable in (1) (obtained from time series decomposition) and indicator (dummy) variables used in describing seasonal variation should not be combined in the same statistical model. However, additive and multiplicative seasonal variables may be combined:

$$\hat{Y}_t = b_0 + b_1X_t + \beta_2C_t + \beta_3S_j + b_4T_tC_tS_j + \varepsilon_t, \qquad (2)$$

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 $T_t{*}C_t{*}S_j$. In the example below $T_t = b_0 + b_1X_t + b_1X_t^2$. Notice that both additive and multiplicative time series components are combined in (2). Consequently, (2) will command more (never less) accuracy and is therefore superior to traditional time series decomposition methods ($T_t{*}C_t{*}S_j$) of forecasting. Remember, R^2 will never decrease when an additional variable is included in the model. Hence, forecasting with the traditional time series decomposition method may be abandoned in favor of (2).

Structured Judgmental Modification

While there is widespread acceptance that structured judgmental modification of statistical models improves forecasts, there are issues concerning how the process should be structured (Lawrence, Edmundson, and O'Connor 1986). 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. The use of moving seasonal indices as a vehicle for injecting judgmental modification is in agreement with the structured visual aids promoted by Edmundson (1990). The idea is to obtain judgmental modification at the explanatory variable level. Studies have shown that revising a "finished" forecast is ineffective (Blattberg and Hoch 1990). Hence, the treatment of forecasted values and time series components as explanatory variables in regression enables forecasters to employ structured judgmental modifications at effective levels.

Moving Seasonal Indices

When seasonal variations are moving, the use of moving seasonal indices becomes an excellent means of injecting structured judgmental modification. Stated differently, when using a constant seasonal index it is assumed the seasonal variation is not moving – does not possess a trend. However, if this assumption is incorrect, a moving seasonal index needs to be constructed. These indices are described in older textbooks (Croxton and Cowden, 1955) and are used when average seasonal indices do not adequately describe current seasonal variations. Hence, the accuracy of out-of-sample predictions is enhanced by combining judgmental modification variables in the form of moving seasonal indices in unrestricted least squares equations.

FORECASTING WITH JUDGMENTAL MODIFICATION

Often seasonal variations possess a trend. For example, when the first quarter seasonal variation trends upward, first quarter moving seasonal indices are needed. An extension of this trend is considerably more accurate than merely using the first quarter mean. Hence, moving seasonal indices increase the accuracy of forecasts. In an effort to fix ideas concerning how moving seasonal indices are employed in unrestricted least squares models, the following example is given. Observe how a moving seasonal index along with cyclical and event modeling variables alleviate the autocorrelation problem and enhance the accuracy of out-of-sample predictions.

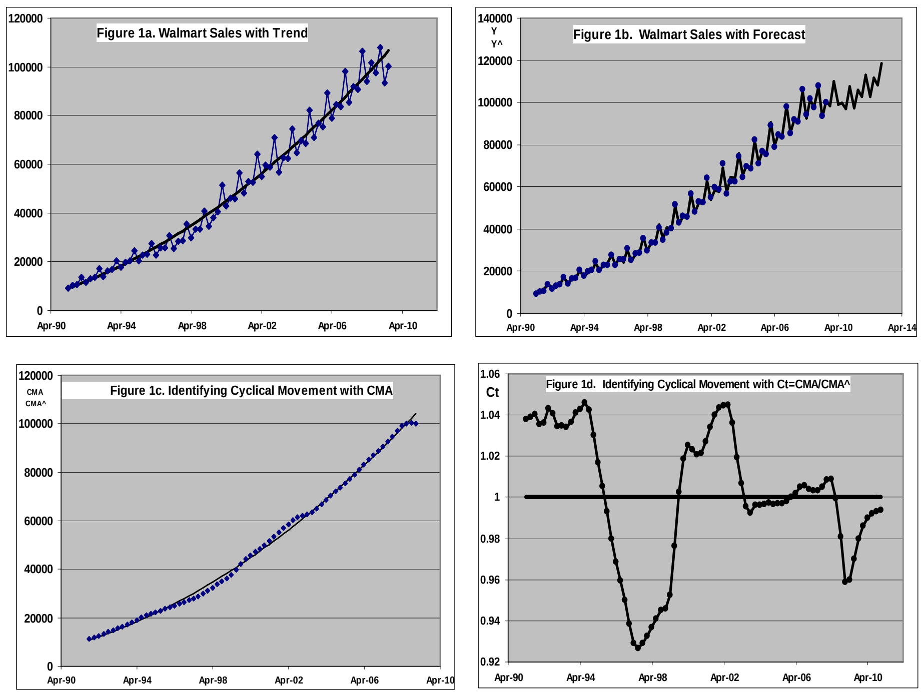
Walmart Sales Example

Figure 1a is the initial visualization of Walmart sales (1991 to quarter 3, 2009). The graph shows a curvilinear trend and seasonality. Sales for quarter 4 are seasonally above the trend line. Figure 1b shows the actual Y values and the line representing forecasted sales using the following model:

$$Y_t = \beta_0 + \beta_1 X_t + \beta_2 X_t^2 + \beta_3 S_t + \beta_4 C_t + \beta_5 TCS_t + \beta_6 V_t + \beta_7 V_t{*}TCS_t + \beta_8 W_t + \beta_9 W_t{*}TCS_t + \varepsilon_t, \quad (3a)$$

where X_t, S_t, C_t and TCS_t are defined in (1) and (2). Observe that S_t represents moving rather than constant S_j seasonal indices. The event modeling variables are defined below.

FIGURE 1
AN ANALYSIS OF WALMART QUARTERLY SALES



Model Specification

Observe from Figure 1c that a series of centered moving averages (CMA_t, see Kvanli, 2003) revolve about the trend line. This is seen more clearly in Figure 1d where the cyclical factors C_t fluctuates about 1.0:

$$C_t = CMA_t / \widehat{CMA}_t \qquad (4)$$

where $\widehat{CMA}_t = bo + b_1X_t + b_2 X_t^2$. Therefore, the event modeling variable V_t accentuates cyclical movement: $V_t = 1$ if $C_t \geq 1.0$, otherwise 0. Likewise, $W_t = 1$ if $\geq$ quarter 4, 1995, otherwise 0. This date is when Walmart began volume imports from China. Ultimately, this reversed the severe decline depicted in Figure 1d (www.wal-martchina.com). Interaction variables $V_t{*}TCS_t$ and $W_t{*}TCS_t$ are derive1d by multiplying the event modeling variables by the time series multiplicative variable TCS_t.

Statistics from (3a)--least squares model with moving seasonal index (S_t)--are given by method 4 of Table 1. Statistics from (3b) are given by method 3: The model with constant seasonal indices is

$$Y_t = \beta_0 + \beta_1X_t + \beta_2X_t^2 + \beta_3S_j + \beta_4C_t + \beta_5TCS_t + \beta_6V_t{*}TCS_t + \beta_7W_t + \beta_8W_t{*}TCS_t + \varepsilon_t. \qquad (3b)$$

The only difference between (3a) and (3b) is moving seasonal indices are represented by the moving S_t in (3a) rather than the repeating S_j in (3b) above. However, Table 1 shows that judgmental modification in the form of moving seasonal indices substantially reduces forecasting error as well as alleviates any indication of autocorrelation.

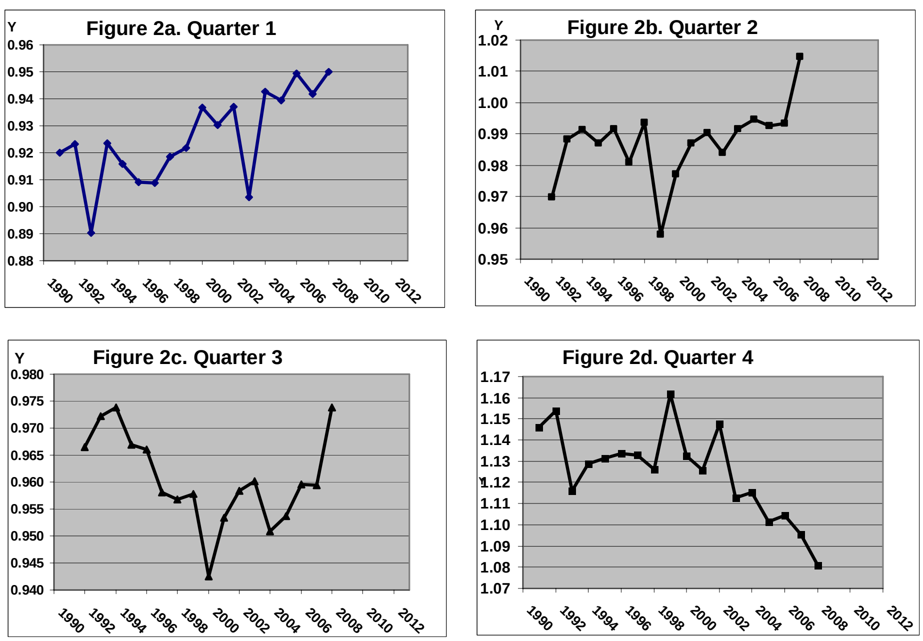
TABLE 1
COMPARING FORECASTS: WALMART SALES

Forecasting Method,	RMSE	AIC	SBC	DW
1. Time-series Decomposition	1132.58	1234.03	1234.58	0.69
2. ARIMA(0,1,0) (1,1,0)	1296.42	1272.77	1272.08	1.44
3. Combined with Constant Seasonals (3b)	796.38	1200.65	1202.96	1.47
4. Combined with Moving Seasonals (3a)	778.98	1182.17	1184.46	2.11

Combined Forecast Model: S_t is the moving seasonal indices

$$Y_t = \beta_0 + \beta_1 X_t + \beta_2 X_t^2 + \beta_3 S_t + \beta_4 C_t + \beta_5 TCS_t + \beta_6 V_t{*}TCS_t + \beta_7 W_t + \beta_8 W_t{*}TCS_t + \varepsilon_t. \qquad (3a)$$

FIGURE 2
ANALYZING MOVING SEASONAL INDICES



Statistical Measures

Table 1 reveals that the RMSE statistics for the combined forecasts models are considerably lower (better) than the time series decomposition and the Box-Jenkin models. The RMSE is the square root of the sum of squares error divided by n; RMSE = $(SSE/n)^{1/2}$. Notice also that Akaike's information criterion (AIC) and Schwartz

Bayesion criterion (SBC) agree with the RMSE statistics. The all important Durbin-Watson statistics in Table 1 indicate the presents of autocorrelation for all models except the combined forecasts model with moving seasonal indices—equation (3a). Therefore, all models possess biased statistics except (3a).

Judgmental Modification for Moving Seasonal

Figure 2a reveals the seasonal indices for quarter 1 ending in April (Walmart's fical year begins in February) are not adequately represented by their average. Therefore, values chosen subjectively are used for quarters 1, of 2009 and 2010. This subjective projection is acquired by examining Figure 2a and deciding whether future quarter 1 seasonal variations will be stronger, weaker, or equal to the previous quarter 1 variation. Other quarterly seasonal indices are created judgmentally in a similar manner. Also, remember that moving seasonal indices must sum to 4.0 for each year. Hence, the typical seasonal index is one; a seasonal index of 1.13 is 13% above typical. The cyclical movement in the data is represented by traditional cyclical factors (Kvanli et al. 2003). Predicted cyclical factors are obtained for 2009-2010 subjectively and employed within the least squares equation.

Autocorrelation

From Figure 3, the perceived accuracy indicated by R^2 = 0.9993 brings more skepticism than confidence. Quality of fit does not guarantee quality of predictions. Furthermore, influences of the past will not continue with the same intensity in the future. However, a further examination shows the out-of-sample statistics are also favorable: PRESS=59,937,207.2, P^2=1−PRESS/SST=0.9990. The Durban-Watson statistic is DW=2.11. Hence, judgmental modification in the form of moving seasonal indices and event modeling variables not only enhance the accuracy of out-of-sample predictions but also help prevent the presents of autocorrelation. Again, the event modeling variables V_t and W_t (along with their interaction) given in (3a) and (3b) significantly describe Walmart's cyclical shifts. These variables together with the moving seasonal index variable S_t in (3a) enable the model to become free of autocorrelation and possess highly accurate in-sample and out-of-sample predictions.

DISCUSSION

Time series data have historically been deseasonalized to study the behavior of variables attributed purely to economic forces. However, there is often interaction between seasonality and economic variables including time series cyclical movement. Miron and Beaulieu (1996) convincingly argue that seasonality should be included in these studies–-the data should not be deseasonalized.

Preventing Autocorrelation

In the above example, the constant quarterly seasonal indices are [S_1=0.92, S_2=0.99, S_3=0.96, S_4=1.13] while the moving quarterly seasonal indices for year 2008 are [S_1=0.95, S_2=1.01, S_3=0.97, S_4=1.07]. Notice that in 2008, the constant seasonal indices underestimate seasonal variation for quarters 1, 2, and 3 and overestimate seasonal variation for quarter 4. By employing moving seasonal indices these series of errors are corrected. This helps in preventing the problem of autocorrelation.

Figure 3
Wal-Mart Sales

Regression Statistics			
R^2 =	0.9993	AIC =	1,182.17
Adj R^2 =	0.9992	SBC =	1,184.46
P^2 =	0.9990	PRESS =	59,937,207
S =	837.6319	DW =	2.11

ANOVA	df	SS	MS	F	p-value
Reg	9	62,813,347,855.3	6,979,260,872.8	9947.25	0.0000
Error	64	44,904,136.2	701,627.1	XXX	XXX
Total	73	62,858,251,991.5	XXX	XXX	XXX

	Coef	S(b)	t Stat	p-value	Partial F
Intercept	4971.09	8869.40	0.560	0.577	0.314
X1	304.53	52.13	5.842	0.000	34.131
X2	-1.98	0.68	-2.915	0.005	8.500
Ct	-13006.21	8336.25	-1.560	0.124	2.434
St	4043.87	2450.49	1.650	0.104	2.723
TCSt	0.90	0.06	16.200	0.000	262.437
Vt	5204.32	898.56	5.792	0.000	33.546
Vt*TCSt	-0.11	0.01	-7.798	0.000	60.815
Wt	-2791.27	799.39	-3.492	0.001	12.192
Wt*TCSt	0.07	0.01	5.835	0.000	34.046

Unrestricted Least Squares Revisited

When combining forecasts, unrestricted least squares will produce the most accurate in-sample fitted values but not necessarily the most accurate out-of-sample predictions. This is true because influences of the past do not often continue at the same degree of intensity in the future. Weighting methods restrict the weighs of the variables in an effort to obtain more accurate predictions. We advocate keeping the weighs obtained from unrestricted least squares and employ judgmental interventions to acquire further out-of-sample accuracy. Moving seasonal indices, cyclical factors, and event modeling variables alter past influences to become more indicative of the future thereby providing more accurate out-of-sample predictions.

Attractive Features

The intent of this study is to promote an awareness of time series models that possess judgmental modification variables thereby increasing out-of-sample accuracy and helping correct the autocorrelation problem. Attractive features of these models are

(a) the innovative least squares seasonal indices, cyclical factors, and event modeling variables,
(b) the effective method of weighting combined forecasts using unrestricted least squares,
(c) the structured judgmental modification injected into these models, and
(d) statistical modeling to obtain the best combination of variables for out-of-sample predictions.

Observe that (2) provides a superior alternative to the traditional decomposition method of forecasting. The authors also agree with Hansen (2007), parsimonious models yield more accurate out-of-sample forecasts. Therefore, employ statistical modeling in an effort to avoid overfitting. In an article concerning the past 25 years of time series forecasting, with regard to seasonal performance, De Gooijer and Hyndman (2006) conclude there is no consensus yet as to the conditions under which each model is preferred. We contend the above combined forecast models with judgmental modification capabilities are top contenders for best performing seasonal model.

Conditional Error Revisited

The conditional error concept discussed earlier is applicable to both econometric and time series models. Both project a value for the explanatory variable to be used in the computation of a projected response (Y_t) value. However, conditional error is kept to a minimum by utilizing judgmental modification in projecting time series components. Indeed, projected trend, cyclical, and seasonal values used in predicting values of Y_t are a common practice in all time series models including the Box-Jenkin ARIMA models. When compared to econometric variables, time series judgmental variables are easier to project. This decreases the likelihood of conditional error thereby increasing the accuracy of out-of-sample predictions.

Combined Forecasts Revisited

When appropriate, derivatives of the least squares seasonal variable (such as the multiplicative T_t*C_t*S_t and/or the interaction term X_t*S_t) may also be employed. Equations (1) and (2) possess several advantages--one being superior accuracy over traditional time series decomposition forecasts. If time series decomposition forecasts (T_t*C_t*S_t) possess the approximate accuracy as (1), then combine these forecasts as shown by (2). This concept also applies to accurate econometric forecasts.

Simplicity has merit

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. Structured judgmental interventions are often difficult to perform with commercial software. However, when combining forecasts, practitioners will find the integration of unrestricted least squares and structured judgmental modifications at the explanatory variable level easy to understand and simple to apply.

CONCLUSION

The intent of this study is to describe how judgment modification in the form of moving seasonal indices, cyclical components, and event modeling variables enhance the accuracy of out-of-sample predictions. These variables also assist in correcting the problem of autocorrelation. We contend when properly specified, combined forecasts derived from unrestricted least squares challenges all other models in producing accurate predictions. Since economic conditions are constantly changing, judgmental modification is needed to obtain properly specified models. Time has revealed that no single model can claim forecasting superiority in all situations. However, with regard to the accuracy of historical fitted values, unrestricted least squares produce superior weights in combining forecasts. Furthermore, if the model is properly specified, the authors contend that unrestricted least squares rival other weighting methods in making out-of-sample predictions. We argue judgmental modification is an essential ingredient in forecasting. Moving seasonal indices with cyclical factors and event modeling variables also help insure that the model is properly specified.

By treating any suboptimum out-of-sample performance of unrestricted least squares as specification error rather than a problem in estimation or weighting, properly specified models become even more relevant. Again, forecasters should consider structured judgmental adjustments before forsaking unrestricted least squares for other weighting methods. Forecasting is a vital ingredient in all facets of business and industry. All budgeting, planning, and supply chain operations begin with assumed accurate forecasts. Therefore, knowledge of judgmental modification for time series forecasting will benefit academicians in teaching and practitioners in the workplace.

REFERENCES

Bohara, A., R. McNown and J. Batts. 1987. "A Re-evaluation of the Combination and Adjustment of Forecasts." *Applied Economics* 19: 437-455.

Batchelor, R., P. Dua. 1995. “Forecast Diversity and the Benefits of Combining Forecasts.” *Management Science* 41: 68-75.

Bates, J. and C. Granger. 1969. "The Combination of Forecasts." *Operations Research Quarterly* 20:451-469.

Blattberg, R., S. Hoch. 1990. “Database Models and Managerial Intuition: 50% Model and 50% Managers.” *Management Science* 36: 887-899.

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

Clemen, R. 1989. “Combining Forecasts: A review and Annotated Biography (with discussion).” *International Journal of Forecasting* 5: 559-583.

Croxton, Frederick E. and D. J. Cowden . 1955. *Applied General Statistics* Englewood N.J., Prentice-Hall.

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

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

Fang, Y. 2003. “Forecasting Combination and Encompassing Tests.” *International Journal of Forecasting* 19: 87-94.

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

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

Hansen, P. 2007. “Criteria-Based Shrinkage for Forecasting.” *Fifth European Central Bank Workshop on Forecasting Techniques: Forecast Uncertainty in Macroeconomics and Finance*.

Kennedy, Peter. 2008. *A Guide To Econometrics*, 5th edition, Wiley-Blackwell.

Kvanli, A., R. Pavur, and K. Keeling. 2003. *Introduction to Business Statistics, A Microsoft Excel Integrated Approach* 6th ed., Southwestern Publishing Co.

Landram,F., A. Abdullat, and V. Shah. 2004. “Using Seasonal and Cyclical Components in Least Squares Forecasting Models.” *Southwestern Economic Review* 31 (1): 189-196.

Landram,F., R. Pavur, and B. Alidaee. 2008a. “Combining Time Series Components for

Improved Forecasts."*Decision Sciences: Journal of Innovative Education* 5:2.

Landram,F., R. Pavur, and B. Alidaee. 2008b. "An Algorithm for Enhancing Spreadsheet Regression with Out-of-Sample Statistics." *Communication in Statistics: Simulation and Computation* 32: 1578-1592.

Lawrence, M. J., Edmundson, R. H. and O'Connor M. J. 1986. "The Accuracy of Combining Judgmental and Statistical Forecasts." *Management Science* 32: 1521-1532.

Manganelli, S. 2007. "Forecasting with Judgment." *Fifth European Central Bank Workshop on Forecasting Techniques: Forecast Uncertainty in Macroeconomics and Finance*.

Miron, J. and J Beaulieu. 1996. "What Have Macroeconomists Learned about Business Cycles from the Study of Seasonal Cycles?" *The Review of Economics and Statistics* 78(1): 54-66.

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

Wal-Mart data found on http://walmartstores.com\shareholdersinfo.htm.

Wilson, J., B. Keating and John Galt Solutions, Inc. 2007. *Business Forecasting* 5th ed., McGraw-Hill, N.Y.