TIME SERIES MODELS FOR FORECASTING THE DEMAND SIDE OF AN INNOVATION

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ABSTRACT

In this paper, we analyzed two sets of data (Cable television [TV] and wireless telephone) using time series and Bass diffusion models to forecast the demand side of an innovation, taking into consideration any cross correlation that may exist between supply and demand. Results show that a univariate third order autoregressive time series model was the best model for forecasting demand in the case of the wireless telephone data. This implies that the supply side in the form of the number of systems had no effect on the number of subscribers (demand side). These results are in agreement with the fact that there was no cross-correlation between supply and demand. However, in the case of cable TV, cross-correlation existed between supply and demand. In this case, a transfer function model, where supply in the form of number of systems was used as an input series, gave the best model for forecasting the number of subscribers. For both data sets, the time series models gave better forecast performance than the Bass model.

INTRODUCTION

Predicting the spread of an innovation is important in marketing and economic studies. Examples are the number of subscribers over time of innovations such as cable TV, the Internet, health clubs, telephone service, and the like. Retailers or providers make these services available to consumers at a subscription fee. Diffusion models have been used widely in marketing and economics research for forecasting the spread of an innovation. The majority of these models in marketing have focused on the demand side. On the other hand, diffusion models in economics have addressed the supply side (Stoneman & Ireland, 1983; Ireland & Stoneman, 1986). Meade and Islam (1998) considered 29 univariate models in the literature concerned with the diffusion of an innovation and used simulation to generate data from the different models for studying their forecasting performance Jones and Ritz (1991) reported on a one-way interaction between the adoption process of retailers (movie theaters) and consumers (movie viewers). Jones and Mason (1990) considered a model for the joint adoption process of retailers and consumers in the area of electronics. Dodds (1973) dealt with the diffusion of subscriber services and used the Bass (1969) model to develop a long-term forecast of cable TV in the United States. Rajkumar and Kumar (2002) used the continuous version of the Bass model and a search technique to forecast time to peak sales and future sales of cellular phone from seven western European countries.

Skiadas and Giovani (1997) introduced stochasticity into the Bass model to forecast the growth of electricity consumption in Greece. Fok and Franses (2007) used a Bass type diffusion model to forecast the diffusion of scientific publications in Econometrica and the Economics journal. A Bass diffusion model and diffusion by analogy were compared in forecasting the number of mobile service subscribers in Asia Pacific countries. The Bass model was found to perform better than modeling by analogy, which is used in practice.

Hu and Xu (2005) presented a multistage dynamic model to forecast Internet adoption. They showed that the multistage Mesak model and the Bass model are specific cases of their model. Ho, Savin, & Terwiesch (2002) extended the Bass model under a supply constraint and applied the model to determine the size of the capacity of a firm and the time to market its new product. Wang and Chang (2002) applied the Norton and Bass multigeneration diffusion model to forecast adoption of pagers and mobile phones in Taiwan. They found that the use of unequal coefficients across generations improved considerably the forecast performance of the model.

Previous research on the modeling of subscriber services using diffusion models has not considered the issue of relationship between retailers and consumers (Kim, Mahajan, & Srivastava, 1995; Mesak & Clark, 1998; Rai, Ravichandran, & Sammadar, 1998). Bronnenberg Mahajan, & Vanhanocker (2000) presented results suggesting the existence of feedback between market share and distribution in the early growth stage of the product. Hirschman and Stampfl (1980) indicated that information on the adoption process of consumers by means of sales figures is an indication of consumers' acceptance of the product, which can influence the decision making process of the retailer. Similarly, in subscriber services the level of consumer adoption may influence the number of retailers or service-providers. Allowing for a feedback or cause and effect relationship between supply and demand in a model may improve forecasting of new products or services.

In this paper, we apply and compare time series and Bass diffusion for modeling and forecasting the demand side of an innovation (exemplified by cable TV and wireless telephone) taking into consideration any cross correlation that may exist between supply and demand.

TIME SERIES MODELS

In time, series analysis situations arise where one has an input and an output series. Examples include subscribers and suppliers (for cable TV or wireless phone), where subscribers may be considered the output series and suppliers the input series. The interest is in modeling and forecasting the number of subscribers. If the input series has no effect on the output series, one may model the output series using univariate ARIMA or the Bass model. If the input series has an effect on the output series, then a transfer function model can be used. This expresses the output series (y_t) as a function of the input series (x_t). Specifically, the output and input series are related linearly as

$$y_t = v(B)x_t + n_t \qquad (1)$$

where $v(B) = \sum_{j=-\infty}^{\infty} v_j B^j$ is referred to as the transfer function and n_t is noise (Box & Jenkins, 1976).

On the other hand, if there is a feed back between the output and input series, in order to allow for this feedback, it is necessary to use a bivariate time series approach. One approach to modeling and forecasting stationary multivariate time series is the state space methodology as discussed by Akaike (1976). Any autoregressive moving average (ARMA) process has a state space representation and any state space form can be expressed as an ARMA process (Akaike, 1974). The form of the state space model is often expressed as (Wei, 1994)

$$Y_{t+1} = F_t Y_t + G e_{t+1} \qquad (2)$$

$$X_t = H Y_t, \qquad (3)$$

where Y_t is a state vector of dimension k x 1, F_t is a k x k transition matrix, G is a k x r ($r \leq k$) input matrix, e_{t+1} is an r x 1 input vector to the system, H is an r x k output or observation matrix, and X_t is the r x 1 output vector of observed variables. The input vector e_{t+1} is a sequence of independent normally distributed random vectors with mean 0 and an r x r variance –covariance matrix, $\sum_{ee}$. In the Akaike (1976) approach, Equation 2 is used to represent the state space process where the first r elements of Y_t consist of the output vector X_t and the last k-r elements consist of the forecast elements $X_{t+k|t}$. Hence,

$$X_t = [I_r, o] Y_t \qquad (4)$$

and the first r rows and columns of G consist of the identity matrix, I_r.

The canonical correlation procedure is used for the identification of the state vector (Akaike, 1976). The procedure entails fitting vector autoregressive models to the multivariate time series and choosing the model that gives the smallest Akaike information criterion (AIC). The autoregressive model of order or lag p is then used in the canonical correlation analysis. The elements of the state vector are determined through a sequence of canonical correlation analyses which correlate present and past observations of the time series with a step wise increasing number of predicted values into the future. Future predicted values that yield significant correlations are included and those that yield insignificant correlations are excluded from the state vector. Once the state vector is determined, it is fit to the data and the parameters in the F, G, and $\sum_{ee}$ matrices are estimated by maximum likelihood. After the parameters are estimated, forecasts of X_t are computed recursively from the conditional expectation of Y_t. The m step ahead forecast $Y_{t+m|t}$ is given by

$$Y_{t+m|t} = F^m Y_t = F Y_{t+m-1|t} \qquad (5)$$

DIFFUSION MODEL

An alternative approach to studying the relationship between two series is the use of diffusion models (Bass, 1969; Mesak & Darrat, 2002). In studying the nature of the relationship between retailers and consumers, exemplified by the number of firms/systems (retailers) and the number of basic subscribers (consumers), Mesak and Darrat (2002) used the following diffusion model:

$$S_t - S_{t-1} = (\alpha_0 + \alpha_1 S_{t-1})(a_0 + a_1 N_t - S_{t-1}) + e_1 \qquad (6)$$

$$N_t - N_{t-1} = (\beta_0 + \beta_1 N_{t-1})(b_1 S_t - N_{t-1}) + e_2 \qquad (7)$$

where S_t = number of cable systems or retailer outlets by end of year *t*, N_t = number of subscribers by the end of year *t*, e_1 and e_2 are random errors, and the $\alpha's, \beta's, a's$ and b_1 are parameters or constants to be estimated. This model is similar to models proposed by Jones and Masons (1990) and Jones and Ritz (1991). Equation 6 and 7 must be estimated simultaneously because of the cross dependency of S_t and N_t. In this situation, nonlinear ordinary least-squares gives inconsistent estimates of the parameters. To obtain consistent parameter estimates, one may employ two commonly used methods, the three-stage least squares, 3sls, (Gallant, 1987) or the full information maximum likelihood method, FIML, (Amemiya, 1977). The 3sls method requires specification of instrumental variables. These variables are chosen as regressors and need to be independent of the error terms. In the case of nonlinear regression, there is no standard method for choosing instrumental variables. However, for the model in Equations 6 and 7, instrumental variables are limited to lags of the endogenous variables (S_t and N_t) in the system. These lags, however, may not be adequate if there is serial correlation of the errors. The FIML estimation method does not require instrumental variables; hence, it was chosen for parameter estimation in this study. Note that once the parameters are estimated, one step ahead of forecasts are obtained by solving Equations 6 and 7 for N_t and S_t in terms of N_{t-1}, S_{t-1} and the parameter estimates.

The Bass model in discrete form (Bass, 1969) (may be viewed as a special case of Equation 7 is commonly used to study the spread or diffusion of a product or innovation. If we denote the number of subscribers at time *t* by N_t, then the Bass model in discrete form may be expressed as

$$N_t = a + (1 + b)\, N_{t-1} - cN_{t-1}^2 \qquad (8)$$

where $a = px$, $b = q-p$, and $c = q/x$. Here, *x* is the ultimate number of subscribers in the population, *p* and *q* are what is called coefficients of innovation and imitation, respectively. It is seen that Equation 8 gives rise to a Bass model with $a = 0$ when b_1 is equal to zero.

Our interest in using the Bass model is for forecasting future number of subscribers rather than estimating *p*, *q*, and *x* as such. Equation 8 is a quadratic regression equation of N_t on its lag. In fitting the model to data, we have used ordinary least squares (with and without centering the data) and auto-regression. Usually, polynomial regressions of high order may be ill conditioned because of multicollinearity. Centering the independent variable may remove this problem (Montgomery, Peck, & Vining, 2001). For time series data, autocorrelation may exist which may cause the least squares estimates to be less reliable. In this case, auto-regression using the Yule-Walker estimation technique can give estimates that are more reliable in the sense of reduced standard errors. In the present case, multicollinearity and autocorrelation did not present a serious problem and all three methods of estimation gave very similar results. Hence, we present forecast results from least squares.

DATA ANALYSIS

Time series analysis (univariate ARIMA, transfer function, and bivariate models) and Bass diffusion models were used to select the best models for forecasting the number of subscribers for two sets of data, cable TV, systems and subscribers (Figure 1) and wireless phone, systems and subscribers (Figure 2). The cable TV data were obtained from the Statistical Abstracts of the United States, in which one series (S_t) represents the number of TV systems over years and the other series (N_t) represents the number of subscribers in thousands. The data for wireless phone (Federal Communications Commission, 2001) represent the number of systems (S_t) and the number of subscribers (*Nt*) gathered every 6 months.

For these two series, the sample autocorrelation function (ACF) decayed very slowly, which indicated that the two series were not stationary and differencing, was required for the time series analysis (Wei, 1994). Hence, the analysis to choose the model and to estimate model parameters was performed on the first difference for each series. The first difference was stationary as indicated from the pattern of decay in the ACF and in the partial autocorrelation function (PACF). The software package SAS was used in the analysis of the differenced series.

For the univariate ARIMA analysis, a model was chosen based on the pattern of decay of the ACF and PACF. After an ARIMA model was identified, model parameters were estimated based on the data and forecasts were obtained from the model. For the transfer function approach where the number of systems was used as the input series and the number of subscribers as the output series, the first step was to identify a model that gave a good fit to the first differenced input series based on the decay pattern of the ACF and PACF. The second step involved computing the cross-correlation of the pre-whitened output and input series in order to identify the transfer function (Equation 1). The third step was to fit the transfer function model in Equation 1 and identify the ARIMA model for the output series from the pattern of decay of the ACF and PACF for the residuals. The fourth step was to fit and estimate the full ARIMA model.

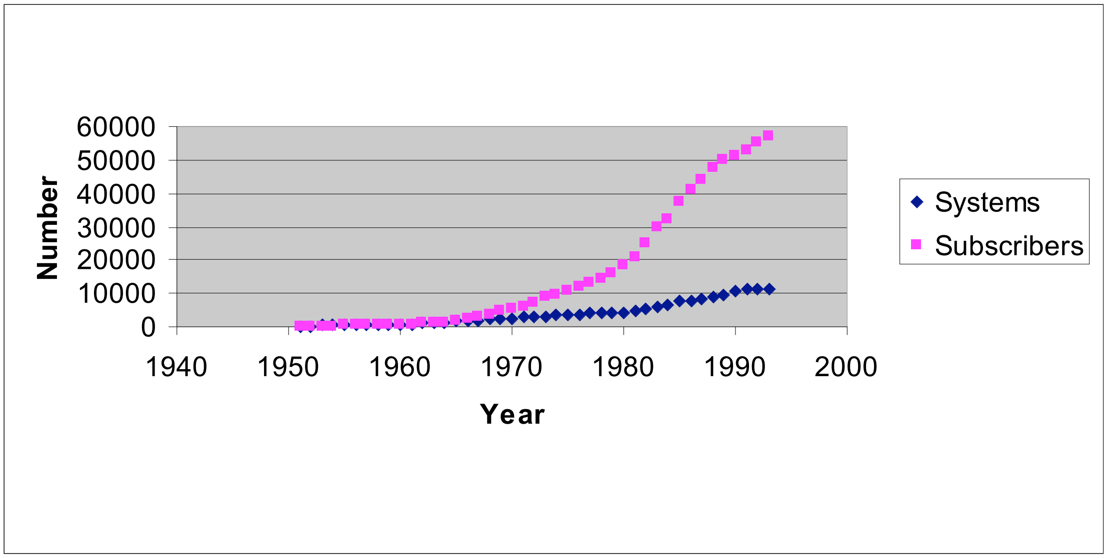

FIGURE 1. NUMBER OF SYSTEMS AND SUBSCRIBERS OVER YEARS FOR CABLE TELEVISION

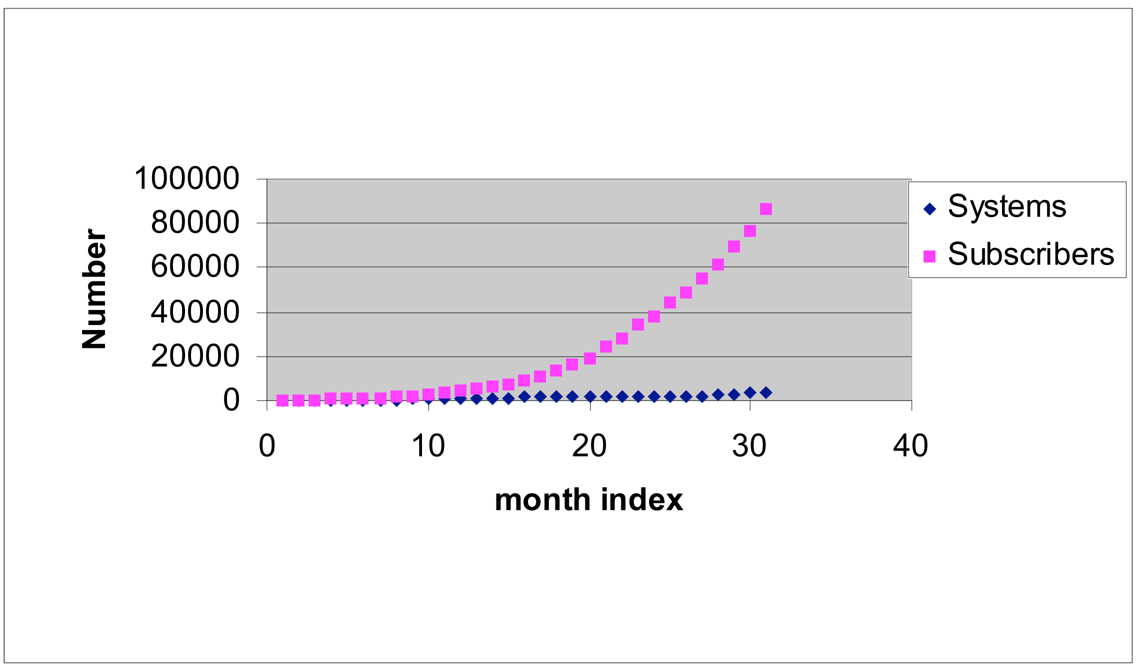

FIGURE 2. NUMBER OF SYSTEMS AND SUBSCRIBERS EVERY SIX MONTHS FROM 1984-1999 FOR WIRELESS

For the bivariate time series analysis, the Statespace procedure in SAS was used to select the model, estimate model parameters, and obtain forecasts. The FTML procedure in SAS was used to estimate model parameters for the diffusion model in Equations 6 and 7 and to obtain forecasts. For the univariate Bass model in Equation 8, the least squares regression procedure in SAS was used for parameter estimation and forecasts.

The adequacy of a chosen model was based on the autocorrelation check for residuals (a model is adequate if there is no significant autocorrelation among the residuals) and on the goodness of fit of model forecast of the last five points of each data set to their corresponding observed values.

RESULTS AND DISCUSSION

For the wireless data, the transfer function analysis indicated that the cross-correlation between the number of subscribers (as the output series) and number of systems (as the input series) was not significant. This meant that the number of systems had no effect on the number of subscribers and the best modeling strategy would be a univariate ARIMA (Wei, 1994). In fact, the best time series model in this case was an autoregressive model of order 3, AR(3),

$$N_t(1) = 0.893N_{t-1}(1) + 0.977N_{t-2}(1) - 0.865N_{t-3}(1) + a_t \qquad (9)$$

Here, $N_t(1)$ represents the first difference.

TABLE 1. OBSERVED AND FORECAST VALUES OF WIRELESS PHONE SUBSCRIBERS (IN THOUSANDS) FOR THE BASS MODEL AND FOR THE AR(3) TIME SERIES MODEL.

Year	Month	Forecast: Five steps ahead (Time series model)	Forecast: Five steps ahead (Bass model)	Observed
1997	June	54559	53479	55312
1998	December	59015	57806	60831
1998	June	64482	61588	69209
1999	December	68404	64782	76284
1999	June	73222	67400	86047

Note: SSE-Bass/SSE-time series 2.178

Year	Month	Forecast: one step ahead (Time series model)	Forecast: one step ahead (Bass model)	Observed
1997	June	54559	53479	55312
1998	December	60378	54476	60831
1998	June	68072	66063	69209
1999	December	75940	76114	76284
1999	June	85862	83188	86047

Note: SSE-Bass/SSE-time series 27.889

The diffusion analysis using Equations 6 and 7 gave a b_1 estimate that was not significantly different from zero. Replacing b_1 by zero reduces the model to the Bass univariate model. As a result, the Bass diffusion model in Equation 8 was fitted to the number of subscribers and results were compared to that of the AR(3) model. Table 1 presents the forecast values (five steps ahead and one step ahead) for the AR(3) and Bass model in Equation 8 with estimates $a = -37.41$ ($p = 0.778$), $(1+b) = 1.274$ ($p<.0001$), and $c = 0.00000359$ ($p < .0001$).

It is clear from the ratio of the sum of squares deviations (SSE) between observed and forecast values over the five years that the autoregressive model is much better than the Bass model in forecasting the number of subscribers whether the forecast is five steps or one step ahead. As expected, both models gave better forecasts for one step ahead than for five steps (SSE for five steps/SSE for one step = 11.39 for the time series model and 8.9 for the Bass model).

Analysis of the cable TV data indicated that there was a significant cross correlation for positive and negative lags between the pre-whitened output series (subscribers) and pre-whitened input series (systems). This indicated some feed back between number of subscribers and number of systems (Wei, 1994). As a result, we analyzed the bivariate time series data using statespace (Equations 2 and 3), the transfer function approach, Equation 1, and the bivariate diffusion model, Equations 6 and 7. The b_1 estimate in Equation 7 was not significantly different from zero. As a result, the univariate Bass diffusion model in Equation 8 was used instead to model the number of subscribers. The estimates for the model were $a = -24.63$ ($p=.878$), $1+b = 1.195$ ($p<.0001$), $c = 0.00000256$ ($p = .001$).

Table 2 presents the estimates of elements of the F matrix of Equation 2 from the statespace analysis. Forecasts were computed from Equation 5.
The transfer function model developed is given by

$$N_t(1-B) = W_0(1-B)S_t/(1-\delta B) + (1- \theta_1 - \theta_2 - \theta_3)a_t \qquad (10)$$

Here, B is the back shift operator ($BN_t = N_{t-1}$), $W_0 = 3.72$, $\delta = 0.44$, $\theta_1 = -.145$, $\theta_2 = -.387$, and $\theta_3 = -.527$.

TABLE 2. ESTIMATES OF THE *F* AND *G* MATRIXES FROM EQUATION 2 IN THE TEXT

Parameter	Estimate	Standard Error
F (3, 1)	-.499	.187
F (3, 2)	.179	.028
F (4, 1)	-3.568	1.097
F (4, 2)	.997	.178
F (4, 3)	2.591	.631

Table 3 presents the forecasts (one step ahead and five steps ahead) for the three models from Equations 5, 8, and 10. It is clear from the ratios of sum square deviations between observed and forecast values over the 5 years that the best model is the transfer function model and the worst model in forecasting was the Bass model. As expected, the models gave better one step ahead than five steps ahead forecasts (SSE-five steps/SSE-one step for the state space, transfer function, and Bass models were 3.98, 1.59, and 1.34, respectively).

It is interesting to see that in spite of the feed back relationship between cable TV subscribers and systems, the transfer function was a better model than the bivariate model for forecasting subscribers. The bivariate model is useful if one is interested in simultaneously forecasting supply and demand. However, as is seen from these results, if the interest is in forecasting demand only, then incorporating feedback into the model does not seem to make the forecast more accurate.

TABLE 3. OBSERVED AND FORECAST VALUES FOR CABLE TV NUMBER OF SUBSCRIBERS (IN THOUSANDS) FOR THE TIME SERIES MODELS (STATE SPACE AND TRANSFER FUNCTION) AND FOR THE BASS MODEL.

Year	Forecast: Five steps ahead - State space model	Forecast: Five steps ahead - Transfer function model	Forecast: Five steps ahead - Bass model	Observed
1989	49784	50457	47598	50800
1990	52474	52538	51053	51000
1991	54990	54303	54308	53000
1992	57121	56003	57319	55000
1993	59529	57533	60055	57000

SSE-state space/ SSE-transfer function 3.30 SSE-Bass/ SSE-transfer function 4.87

Year	Forecast: Five steps ahead - State space model	Forecast: Five steps ahead - Transfer function model	Forecast: Five steps ahead - Bass model	Observed
1989	50224	50457	47598	50800
1990	52705	52208	50558	51000
1991	52858	53326	52164	53000
1992	53929	53786	53017	55000
1993	56641	56476	54793	57000

SSE-state space/ SSE-transfer function 1.32 SSE-Bass/SSE-transfer function 5.82

CONCLUSION

This work involved using bivariate and univariate time series methodology and diffusion models to forecast the number of subscribers for cable TV and wireless phone. Both number of subscribers (demand) and number of systems (supply) were considered in developing the best models for forecasting the number of subscribers.

For the wireless phone data, there was no indication of any relationship between subscriber and system (or supply and demand) and the best model for forecasting the number of subscribers was the autoregressive model of order 3, Equation 9.

For the cable TV data, a feedback relationship existed between subscribers and systems (or between demand and supply). However, the best time series model for forecasting the number of subscribers was the transfer function model in Equation 10 that considered the effect of systems on subscribers, but not the effect of subscribers on systems. Considering feedback in a bivariate model is useful if one is interested in simultaneously forecasting supply and demand. Incorporating feedback did not seem to improve model accuracy in forecasting demand. The Bass model did not seem to forecast as accurately as either of the two time series models.

Data involving supply and demand are very difficult to obtain. Nevertheless, this modeling approach should be applied in the future to more data of this kind as they become available in order to determine the relationship between supply and demand and to develop the best model for forecasting the spread of an innovation. The emphasis in this paper was mainly on time series models. The Bass model arose as a special case of the model in Equation 7. There are several diffusion models in the literature that may be used for forecasting innovations some of which are extensions of the Bass model (Kumar & Krishnan, 2002; Ganesh, Kumar, & Subramanian, 1997; Bemmaor & Lee, 2002; Meade & Islam, 1998). Diffusion models are mechanistic in the sense that they are developed based on certain assumptions about the process. How well a diffusion model predicts a given process depends on how well these assumptions are met. On the other hand, time series models are empirical and flexible. They can be made to fit any given process. Therefore, it is important that the application of a diffusion model be gauged by comparing its performance to a time series model. Hence, future research may involve comparisons among time series and different diffusion models with regard to forecasting different innovations.

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JOURNAL OF INTERNATIONAL BUSINESS DISCIPLINES

Volume 2, Number 1 November 2007

Published By:
International Academy of Business Disciplines and Frostburg State University

ISBN 1-889754-97-8 ISSN 1934-1822
WWW.JIBD.ORG