Estimating Integrated Time Series and Other Problems in Modelling Tourism Demand

Associate Professor Clive Morley
Office of the Dean

ISSN 1038-7448
No.WP 99/3 (July 1999)
Estimating Integrated Time Series and Other Problems in Modelling Tourism Demand

Associate Professor Clive Morley
School of Management

ISSN 1038-7448
No.WP 99/3 (July 1999)

Associate Professor Clive Morley is currently Acting Associate Dean (Academic Research). He can be contacted as follows:
Phone: 9925 5607
Email: clive.morley@rmit.edu.au
Abstract

The exponential growth in tourist numbers motivates serious analysis of this phenomenon. The econometric methods commonly used do not take this central feature of demand seriously in the form and estimating of tourism demand models. Cointegration analysis has been used in recognition of the problem as a technical estimation issue. But this is unsatisfactory, due to both technical methodological concerns with the use of cointegration analysis and because it overcomes the growth issue rather than incorporating it into the model. A model form which does incorporate growth is proposed. Other, newer methods - neural networks and structural equations modelling – are sometimes applied, but these too are not unproblematic.
1. Introduction

The number of tourists is growing exponentially: the total number of international tourists worldwide at an average rate of nearly 6% per annum recently (Bar-On 1997). The picture for many regions and specific destinations is similar (Bar-On 1997 pp289-291). Tourism has become a major industry in many countries and a large part of many national economies. Modelling tourism numbers (demand) has become a significant area of study in tourism, as it seeks to understand the factors contributing to this growth and the occasional breaks in the growth, to assess the impacts of factors on tourism numbers and to generate forecasts. These are important issues in tourism, and the results of such investigations are required for policy and business decisions and tourism planning at various levels. So, not surprisingly, an extensive academic literature has developed in this area.

What is surprising is that much of this literature seems to ignore, or treat casually, the most important feature of tourism demand, namely the exponential growth observed and which motivates much of the study. At best, this feature is seen as a technical problem to be overcome.

Most studies are simple econometric models estimated using multiple least squares regression (see, for example, the reviews by Crouch 1994, Witt and Witt 1995 and Lim 1997). The common functional form for these is the log-log form. Lim (1997) criticises the concentration on estimating log-log models that neglects consideration of the appropriate functional form. Morley (1991) cites evidence that this is an important issue, in that the choice of functional form for a model can significantly affect the parameter estimates obtained.

The least squares regression estimation methodology used is appropriate for stationary time series data, but not for series that are not stationary. Tourism demand, and a number of the explanatory variables used such as Incomes and Prices, are not stationary in many cases: where tests for stationarity (unit root tests) have been conducted they have found a strong possibility of unit roots (i.e. non-stationarity) in the data (see, for example, Lathiras and Siriopoulos 1998 using data on tourism to Greece, Kulendran 1996 for tourism to Australia). Indeed, simple inspection the growth in the total number of international tourists worldwide series shows that it is not stationary (a constant mean over time is one of the requirements for stationarity), which implies that some of the components of this aggregated series, that is some of the flows into individual country destinations, are not stationary.

Estimation using standard regression techniques, which ignore the non-stationarity of the data, is flawed (Philips 1986). This is the well-known ‘spurious regression’ problem, now found in most good text books on regression. The consequence of ignoring the requirement for stationarity is that the parameter tests are unreliable and, in particular, the standard t-tests and F-tests give misleading results. All this is established, if only fairly recently in the
tourism literature. But the consequence of it, that nearly all the tourism demand studies conducted in all but the very recent past are unreliable, has not been brought home to practitioners of tourism demand analysis. For example, the meta-analysis of Lim (1999) relies very heavily on the published t- and F- values from previous studies. It could mean that the elasticities, for example, used in tourism planning are poorly estimated and not to be relied upon. The study of tourism demand needs to start again, discarding much of what has become established results, for this reason alone. There are other reasons (to be considered below).

This paper investigates further the consequences of taking the growth phenomenon of world tourism seriously. The next section looks at the technical responses to the problem of estimating non-stationary series, and their limitations. Section 3 considers broader issues raised by the data for estimation (beyond the techniques of section 2) and for the functional form.

2. Cointegration

2.1 Integration

Firstly, it should be noted that total world tourism is intergrated of order 2. That is, the series needs to be differenced twice before it becomes stationary.

Formally testing the series total number of tourists worldwide for integration confirms that it is integrated of order 2, i.e. I(2) – see Table 1. This is also clear from graphs of the differenced series, the first differences are not stationary (see Figure 1), but have an increasing trend apparent, whilst the second differences do appear to be at least mean stationary (Figure 2). The likely presence of heteroscedasticity in Figure 2 can be noted for later consideration.

Table 1. Tests for integration

<table>
<thead>
<tr>
<th>Total tourist arrivals</th>
<th>Test: Dickey-Fuller</th>
<th>Augmented Dickey-Fuller*</th>
</tr>
</thead>
<tbody>
<tr>
<td>Level</td>
<td>+11.212</td>
<td>+11.212 (0)</td>
</tr>
<tr>
<td>First difference</td>
<td>-1.623</td>
<td>+0.051 (3)</td>
</tr>
<tr>
<td>Second difference</td>
<td>-10.418</td>
<td>-5.651</td>
</tr>
</tbody>
</table>

* number of significant lags in parentheses
Data from World Tourism Organisation (annual) and Bar-On (1997)

As the total number of international tourists series is I(2), some at least of the component series of demand for individual countries must also be I(2). Tests on some individual series (eg. tourists from Malaysia, Japan, Canada and the USA to Australia) confirm this.
Figure 1. First differences of International tourism numbers worldwide

Figure 2. Second differences of International tourism numbers worldwide
2.2 Cointegration approach

The standard econometric response to the issues involved in estimating demand models from non-stationary data is to apply cointegration analysis and an error correction model (Engle and Granger 1987). But note that if there is a cointegrating relationship between the demand and explanatory variables, as has almost invariably been found in the published studies, the Ordinary Least Squares estimates are super-consistent, and in that sense the cointegration resolves the spurious regression problem and makes the situation better, not worse (Griffiths, Hill and Judge 1993 p700). The rationale for using cointegration methods then must lie in the error correction model derived, that is the relationships in the short-term departures from the long-term equilibrium. The problem of which results to follow if Ordinary Least Squares (OLS) and cointegration analysis give different results has been resolved by analysts using cointegration methods in favour of the cointegration analysis, but if OLS is super-consistent it is not clear why they should not be given greater credibility.

Cointegration techniques have begun to be applied in tourism modelling (Kulendran 1996, Kulendran and King 1997, Wong 1997, Lathiras and Siriopoulos 1998). The approach adopted has been to take the logarithm of the demand numbers and find that the resulting time series is integrated of order one. A cointegrating vector with the explanatory variables is looked for and typically a number are found. The presence of more than one cointegrating vector is considered a positive sign, indicating “that these demand systems are stationary in more than one direction and hence more stable” (Lathiras and Siriopoulos 1998, p179). One of the cointegrating relationships is singled out for further use, the one that has coefficient signs matching prior expectations from economic theory. In this approach the prior expectations of sign are used to choose the model, not to test or confirm its validity. The model is obtained via the rather dubious practice of ignoring others, just as soundly estimated, because they don’t provide reasonable results. But the question remains: what do these other cointegrating relationships mean?. This is standard practice in cointegration analysis (Muscatelli and Hurn 1992), but the reason for it does not appear to be much more than ad hoc convenience (at least a reasonable, publishable, model results) and it “seems misplaced” (Muscatelli and Hurn 1992 p29). As this is a common and central practice in cointegration modelling, there must be concerns raised about the use of this methodology for modelling.

A linear combination of stationary – I(0) – variables is also I(0), which implies that any linear combination of the cointegrating relationships is also a possible cointegrating relationship. That means that if more than one cointegrating relationship is found, the true cointegrating relationship may be some unknown linear combination of them. So the existence of two or more cointegrating relationships is not really evidence in favour of the result (contrary to the view of Lathiras and Siriopoulos quoted above), it actually casts further doubt on the reliability of the results.
2.3 Equilibrium

The resulting cointegration relationship is considered the long run (equilibrium) relationship between the demand and explanatory variables. Short term dynamic relationships accounting for departures from equilibrium are also usually estimated using an error correction model.

Not for the last time, it is important to note that it would be useful if practitioners of this methodology took seriously the fact of the impressive and continuing tourism growth. In the face of this growth, what is the relevance of an equilibrium state postulate? On what basis and to what effect is it believed that the relationship between demand and the explanatory variables (incomes, airfares, etc) is stable enough to be described as “in equilibrium”? Equilibrium means that a stable price has been reached at which the amount willingly supplied and the amount willingly demanded are equal (Samuelson 1964 p63).

There is, at equilibrium, no upward or downward pressure on prices. At what time in the past twenty years has this been a valid description of tourism prices (airfares, hotel rates, etc) for any important destination? The question is clearly rhetorical and absurd.

Tourism is not in, and probably not even approaching, an equilibrium state: that is one of its major features of interest. Estimation of a “long run equilibrium” relationship, typically on something like 20 years’ data, relies on fundamental assumptions that are obviously not valid. One such assumption is that underlying utility functions of individuals are unchanging, despite the immense social, cultural and economic changes over the relevant time period, and the fact that many more people are travelling as tourists means that many new and quite likely different utility functions are brought into consideration. Further, technology has had an enormous impact on the tourism industry over the last ten or twenty years, one of the ways this impact is likely to have been manifested is in changing the relationships between key demand variables. So equilibrium is not an appropriate concept for tourism demand analysis at this time.

2.4 Functional form

The exponential growth of tourism demand suggests most naturally a model of the form:

\[ Y_t = \exp(t).f(\beta X_t).e_t \] (1)

In this model, the demand \((Y_t)\) has a basic exponential growth as trend, with deviations about it due to explanatory variables \((X_t)\) and error \((e_t)\). Preliminary data analysis shows that in particular cases some important explanatory variables (eg. Income) are I(1) due to a strong linear trend and hence are strongly correlated with \(t\), so it makes sense to combine the non-error terms and write the model as:

\[ Y_t = \exp(\beta X_t).e_t \] (2)
The practice of taking logarithms, then differencing, does convert $Y_t$ from an I(2) to an I(0) series, as

$$\ln(Y_t) = \beta X_t + \ln(e_t)$$

So

$$\ln(Y_t) - \ln(Y_{t-1}) = \beta(X_t - X_{t-1}) + \ln(e_t) - \ln(e_{t-1})$$

Which is I(0) if the variables in $X_t$ are I(1) and the differenced error term is I(0).

The most common model is the multiplicative model

$$Y_t = \alpha X_{1t}^{\beta_1} X_{2t}^{\beta_2} \ldots X_{kt}^{\beta_k} e_t$$

(3)

which yields the log-log form after a log transformation. This has the advantage of giving a linear form after the log transformation and is therefore favoured by modellers in many fields of demand analysis. Despite this popularity in other areas of demand analysis being imported without question into tourism demand analysis, it is not the most natural model for tourism (see equations (1) and (2) above), nor is it very useful for tourism demand, as will be discussed below. The log then differencing transformation of this model does achieve stationarity, because from (3)

$$\ln(Y_t) = \beta \ln(X_t) + \ln(e_t)$$

so

$$\ln(Y_t) - \ln(Y_{t-1}) = \beta [\ln(X_t) - \ln(X_{t-1})] + \ln(e_t) - \ln(e_{t-1})$$

which will usually be I(0), again if the differenced error term is I(0), as when $X_t$ is I(1) usually $\ln(X_t)$ is I(1) also. Taking logarithms transforms an exponential series to I(1) in this case (probably a small sample consequence), but does not transform the I(1) series to I(0). This mathematical property of the log transformation is fundamental to model (3) achieving stationarity under the log then difference transformation. The fact that model (3) can be made stationary in this way is not evidence that it is a valid model of the data, as the same result can be achieved in the same way from model (2).

The log transformation is required when using the multiplicative model, to avoid the problem of demand being I(2) when the standard cointegration estimation techniques are for I(1) variables. These standard techniques, readily available for straightforward use in econometric packages now, can then be applied without much trouble or thought. The result is an analysis that appears sophisticated (due to the cointegration) but is actually not at all difficult. Thought about appropriate model functional forms and estimation techniques has been avoided whilst giving the appearance of great technical facility. This is a triumph of show over substance.
The standard log-log models that predominate cannot be correct for much tourism demand. The reason is the growth exhibited and the falseness of the equilibrium concept. Log-log models imply constant elasticities, which the argument about the inapplicability of equilibrium to tourism demand at this time shows are not a valid result (or assumption, depending on which way one works). A few empirical studies which have allowed for the possibility of changing elasticities have found evidence that they do indeed vary over time (e.g. Morley 1998, Cumpston and Bartran 1998). So log-log models are misspecified.

3. Estimation

Rather than see the level of integration as a technical, econometric problem to be overcome in order to derive valid parameter estimates, the approach argued for here is to consider the observed integration a feature of the data generating process to be incorporated into the model. This, of course, is in the tradition of Professor Hendry’s methodology (Gilbert 1986), in particular the criterion that a satisfactory model be data coherent. The argument put for data coherence is that a technical problem with estimation can often be an indicator of a flaw in the model specification. For example, observed serial correlation implies that the model used is not a valid representation of the data generating process and hence a re-specification is called for, not just correcting for the serial correlation in the estimation methodology (such as using the Cochrane-Orcutt procedure). Thus, rather than correcting in the estimation for integration (by differencing to achieve stationarity) the principle of data coherence suggests investigating what the observed level of integration can indicate about the data generating process and model.

This section discusses two aspects of the modelling strategy appropriate for a tourism demand series. One is the model functional form, and the other the estimation fit criterion. The strong growth from a low base suggests the use of diffusion models to provide the dynamic model form; this is considered immediately below. Attention then turns to the inappropriateness of the Least Squares criterion for an integrated series and the argument for a percentage error criterion instead is put.

3.1 Diffusion model

Diffusion models of the spread of an innovation are founded in consideration of the means of communication of information about the innovation. Diffusion is the process by which an innovation is transmitted to potential consumers in a society through various channels of information flow (Mahajan et al 1990). The four essential components of diffusion models are the innovation, the channels which carry information about the innovation to new potential consumers, time and the society in which the innovation spreads. Innovation is interpreted inclusively enough for diffusion models to be applied to such disparate areas as new product marketing (Mahajan et al 1990), the spread of the multi divisional organisational structure of companies (Mahajan et al 1988), technical change (Mansfield 1961) and joint venture formations in the information technology business (Venkatrama and Koh 1990).
The theory of diffusion assumes that an innovation is adopted as information of its advantages spreads through two main channels - interpersonal communication between an adopter and a non-adopter and the mass media. The model is of once for all adoption, that is, in terms of product diffusion, there are no repeat buyers and each buyer purchases just one unit of the product. The basic model developed by Bass (1969) incorporates the two channels and combines elements of other models which assume only one or other of the information flow channels. The behavioural theory of diffusion models is that non-adopters adopt the innovation when they come in contact with the relevant information of its advantages or as a consequence of contact with the information become apprised of the disadvantages of continuing non-adoption. In economic modelling the theory of utility maximising consumers can be substituted for this behavioural theory.

The diffusion model derives from a hazard function expressed in terms of the density function \( f(t) \) of time to adoption, with \( F(t) \) the cumulative density function representing the cumulative fraction of adopters in the population. The hazard function \( f(t)/(1-F(t)) \) is the conditional probability that an adoption occurs at time \( t \) given that it has not previously (the proportion of the population newly adopting at time \( t \)). The diffusion model of this conditional probability is:

\[
f(t)/(1-F(t)) = a + b.F(t) \tag{4}
\]

that is, \( f(t) = (a + b.F(t))(1 - F(t)) \)

Let \( N* = \) the total number of potential adopters in the population,
\( A_t = N*.f(t) = \) the number of new adopters at time \( t \),
\( N_t = N*.F(t) = \) the cumulative number of adopters to time \( t \),

Then

\[
A_t = N*.dF(t)/dt = a(N* - N_t) + b.N_t(N* - N_t)/N* \tag{5}
\]

a first order differential equation. Integration results in an empirically appropriate S shaped curve for \( N_t \).

In application to tourism, a population of utility maximising economic agents is posited to have a number of potential tourists for whom taking a particular tour is part of their utility maximising consumption. Not all of these have the tour in their consideration set (Woodside and Lysonski 1989) from which their choice of tour is actually made. The information flows are means by which an unevoked tour becomes a considered tour, and hence is chosen by these agents. Applying the notation of the diffusion models, there are \( N* \) potential takers of a particular tour, of whom \( N_t \) have taken the tour at time \( t \). For details of a derivation of the diffusion model specifically in the tourism situation, see Morley (1998).
Most tourism data does not allow differentiation of new and repeat visitors, so it is necessary to augment equation (5) with a term for repeat visitors. Let $Z_t$ be the number of repeat visitors at time $t$. Assuming, as a first order approximation, that a constant proportion of past visitors return at any time, then $Z_t = d.N_t$.

The number of tourists from a population taking a particular tour (or visiting a certain destination) is

$$Y_t = A_t + Z_t$$

$$= a(N^* - N_t) + b.N_t(N^* - N_t)/N^* + d.N_t$$

(6)

To be useful for econometric purposes, this model needs to incorporate explanatory variables. Explanatory variables have been introduced into diffusion models in a variety of ways, such as adding them as further terms in the specification of equation (6). A more reasoned approach, in line with standard demand model specifications, is to have such variables impact through their effects on the $N^*$ term, as outlined in the following argument.

The relationship between diffusion and economic utility can be seen in Figure 3.

![Figure 3. Diffusion and utility](image)

In a population, represented by set $P$, there are economic agents whose maximised utility includes the product at a non-zero quantity, so they would choose the product if they knew of it and included it in their utility calculus consideration; these agents make up the set $U$. There is another set of agents who know of the product, denoted by the set $D$. Those who actually consume the product are those in $U$ who know of it, the intersection $U \cap D$ (shaded
area in Figure 3). To acknowledge that these sets change with the passage of time, they can be sub-scripted with the time variable t. The diffusion model is concerned with the spread of information over time changing $D_t$ and in particular the size of this set, denoted by $|D_t|$. In the diffusion model the product’s attractions are clear and lack of information about the product is all that prevents it being adopted, so $U$ is identified with the relevant population, does not vary over time, $|U| = N^*$ and $Y_t = |U \cap D_t|$. Economic theory provides a means of relaxing this restriction on $U$, by allowing $|U_t|$ to change as a function of time varying explanatory variables such as prices and incomes. Effectively, economic theory usually assumes that $D \equiv P$ (the product is known to all potential consumers) so that

$$Y_t = |U_t|.$$  

The diffusion and utility approaches can be combined into $Y_t = |U_t \cap D_t|$, by modelling $N^*$ in the diffusion model as a function of time varying explanatory variables. The simplest and most natural way to do this is to use the equation for $Y_t$ as a quadratic function of $N_{t-1}$,

$$Y_t = aN^* + (b + d - a)N_{t-1} - (b/N^*)N_{t-1}^2$$  \hspace{1cm} (7)

derived from the discrete analogue of equation (6), as the data to be used is time discrete. Then with explanatory variables $X_1, X_2, \ldots, X_k$, the common log-linear specification is:

$$\ln(N^*_t) = b_0 + b_1 \ln(X_{1t}) + b_2 \ln(X_{2t}) + \ldots + b_k \ln(X_{kt}).$$  \hspace{1cm} (8)

The diffusion argument is then interposed between $N^*_t$ and $Y_t$ by substituting equation (8) into equation (7), yielding:

$$Y_t = a \exp[b_0 + \sum_{i=1}^{k} b_i X_{it}] + (b + d - a)N_{t-1} - bN_{t-1}^2 \frac{\exp[b_0 + \sum_{i=1}^{k} b_i X_{it}]}{\exp[b_0 + \sum_{i=1}^{k} b_i X_{it}]}$$  \hspace{1cm} (9)

In estimating equation (9) the parameters $a$ and $b$ are not fully identified due to the $\exp(b_0)$ term allowing scaling effects, which then also affect $d$ through the term $(b + d - a)$. So the model to be estimated is:

$$Y_t = \alpha \exp[\sum_{i=1}^{k} b_i X_{it}] + \beta N_{t-1} - \gamma N_{t-1}^2 \frac{\exp[\sum_{i=1}^{k} b_i X_{it}]}{\exp[\sum_{i=1}^{k} b_i X_{it}]}$$  \hspace{1cm} (10)

with $\alpha = a \exp(b_0)$, $\beta = (b + d - a)$ and $\gamma = b/\exp(b_0)$. Estimates of the parameters $a$, $b$ and $d$ cannot be recovered from the estimates of $\alpha$, $\beta$ and $\gamma$ due to the identification problem with $b_0$.  

11
Such a model is not estimable by the usual multiple regression techniques, as it is not linear in the parameters. Non-linear estimations methods must be used; these are readily available in modern statistical packages. There are subtleties and traps for the unwary in such estimation, but it is not impossibly difficult. For examples of the use of such models, see Morley (1998). A major characteristic, and advantage, of this model form is that it does not assume constant elasticities, but lets elasticities vary with the values of the explanatory variables.

3.2 Loss function

Estimation of such a model involves the specification of a loss function to be used as the goodness of fit criterion; it is not restricted to minimising the Sum of Squared Errors (SSE), which is the defining criterion of Least Squares regression. The argument for Least Squares estimators, that they have minimum variance in the class of linear unbiased estimators of the parameters of the usual linear model, is not relevant if the model is not linear, as model (2) suggests. An option is Maximum Likelihood estimation, but that cannot be considered appropriate in the tourism demand case as the distribution of the errors cannot be specified with any confidence - there is reasonable evidence that the errors may not be Normal in distribution (Morley 1996).

The choice of loss function is a matter for the subjective judgement of the analyst, taking into account the circumstances of the data. It is argued that SSE is not the most appropriate loss function due to the growth in the series. The argument has been rehearsed in Morley (1997).

Taking the total tourist numbers series as an illustration, an error of 5 million tourists in 1950 is a massive 20% error, but the same size error would be less than 1% of demand in 1995. This raises the question as to whether the same absolute size of error is of equal weight over the full data time period, as Least Squares estimation (and robust estimation based on Mean Absolute Deviations) assumes - reasonably in the case of a stationary series. The growth evident in these I(2) demand series suggest that some weighting of the errors would be appropriate. Weighting the absolute error by the inverse of the actual demand value yields the Mean Absolute Percentage Error (MAPE) loss function. Percentage errors seem more reasonable than SSE, by analogy with other situations where percentages are reported instead of absolute values to avoid a dominating size effect in comparisons.

The MAPE can be improved on by using the estimated value of the demand series from the fitted model as the weight instead of the actual value. The improvement comes from the smaller variance of the estimated values; the argument is the same as that for the use of expected values, rather than observed values, as the denominator in Pearson’s chi-squared statistic. To distinguish it (from the MAPE), this version of the loss function is called the Percentage Error Loss Function (PELF).

More formally, the specification of a multiplicative error in a model (whether of the particular form in (2) or (3) does not matter to this argument)
\[ Y_t = F(X_t) \times e_t \]

with the errors, \( e_t \), measured in percentage terms, most naturally implies \( e_t \) as a percentage of \( F(X_t) \), the expected value of \( Y_t \), and thus the PELF rather than MAPE loss function.

### 3.3 Neural network models

An alternative form of model, recently gaining some attention and favour, is the neural network. A typical use of such a model in tourism would have a single output variable (demand) and the usual input variables (incomes, prices, etc). The output variable does not depend directly on the input variables, but indirectly does so via a number of intermediary variables. Various forms of relationships (and more than one layer of intermediary variables) can be used. Figure 4 shows an example of such a formulation in diagramatic form, with lines joining variables on the right modelled as dependent on variables on the left; each line then represents at least one parameter to be estimated.

![Figure 4. A neural network model](image.png)
The simple model in Figure 4 has 20 parameters (including constants), rather than the four parameters a regression model would be expected to have. There is potential for over-parameterisation in using such models, which is hidden somewhat by the unobserved character of the intervening variables. Neural nets can seem to give excellent fits and great accuracy because of this. The model is fitted via a search procedure for parameter values that give good fit, akin to fitting a non-linear model. Such a method is not constrained by degrees of freedom considerations or the need for certain data matrices to be invertable, as methods like Ordinary Least Squares are. A neural net model such as in Figure 5 could be fitted to (say) ten data points, whilst attempting to fit a regression model with twenty parameters to ten data points would fail. Such estimation problems are not well understood by all who try to fit neural network models.

The concern that the neural network approach tackles is that of the unknown functional form. Commonsense (and/or economic theory) leads to conceiving of demand as a function of explanatory variables, i.e.

\[ Y_t = F(X_t) \]

But the form of the function F is not specified by either commonsense or economic theory. A linear (or, log linear) form for F is convenient, in terms of estimation techniques, and is a first order approximation (in Taylor series terms) to whatever the true form F takes. Neural net models are, essentially, a flexible functional form for F, as are such second order approximations as the translog form and quadratic functions of the explanatory variables. Using forms such as the translog or quadratic makes clear the parameterisation of the functional form, and hence the problem of estimating a large number of parameters from a small data set. The neural network approach hides this problem.

Further, a neural net can fit the data extremely well, and yet be completely useless. This is because it is a-theoretic and neither tests nor estimates relationships between variables, the concentration is on goodness of fit. The intermediate variables \( (Z_i) \) have no real meaning, they are a contrivance to allow good fits through building in great flexibility to the model. To estimate or test relationships, a model that specifies the relationships is necessary, such as a regression model. The results of estimating a regression model yield measures of the impacts of explanatory variables on the dependent variable (such as elasticities). In this lies their primary value, value that neural nets do not have.

### 3.4 Structural Equations Modelling

Structural Equations Modelling (SEM) is also known as LISREL (linear structural relationships) after a commonly used package, Covariance Structure models or Path Analysis. It has recently become very popular in many social sciences. What SEM involves is multiple relationships between a number of variables; some of the variables are observed (measured) and some can be latent (unobservable, a construct that is not measured directly but is represented by a number of measured variables, as in Factor analysis). Even
although they cannot be measured directly, these latent variables are important (theoretically) in our understanding of the issue being considered, so a straight multiple regression model relating only the observed variables is not appropriate. Turner, Reisinger and Witt (1998) apply SEM to tourism demand analysis, but primarily (as they acknowledge) as a simultaneous equations estimation method, not involving latent variables. Keane (1994) illustrates how SEM can be used in tourism modelling to decompose structural relationships and better (than in regression analysis) assess the correlation structure among the variables in a model, and their impacts on each other. Again, all variables in this application are measured.

A feature of SEM is that the fitting is to the observed variance-covariance matrix of the variables, not to the values of the variables themselves. A consequence is that a researcher can arrive at different significant paths for a given model, depending upon the method of estimation used (for example, maximum likelihood versus OLS). This is not usually reported in published applied studies, for obvious reasons, but, to draw out the obvious, it does raise concerns as to the robustness of this methodology.

Conclusions

Tourism worldwide is growing rapidly. This characteristic motivates the strong and growing interest in tourism as an area of study and analysis. It should also be taken seriously as central to the modelling of tourism demand.

The growth (non-stationarity) implies that it is not appropriate to rely on the usual multiple regression estimation of the impacts of explanatory variables, such as prices, fares and incomes, on the tourism series. There are two possible responses to this problem. One is to adapt the estimation methodology to what is seen as a technical problem to be overcome: this leads to cointegration modelling. But, cointegration analysis is not appropriate either, as the explanatory variables are usually integrated of order one or zero and cannot establish a cointegrating relationship. This is “fixed” by making a log transformation of the time series. The log transformation is necessary for a cointegration analysis of tourism demand when the dependent (demand) variable is I(2) and the explanatory variables are I(1). An I(2) variable cannot be a function of I(1) and stationary variables, so there is an unacknowledged problem for modelling tourism demand. Fortuitously, the log transformation generally makes both I(2) and I(1) variables into I(1) variables, and estimation can proceed. But the necessity for the log transformation does mean that the estimation technique is driving the model functional form used, which it should not. The estimation technologies exist to estimate, as efficiently as possible, the model specified, not to determine that model’s form.

There is a further problem in assuming an equilibrium specification in the cointegration approach. The error correcting specification is not attractive here as much tourism is in an initial growth phase (pre-equilibrium) of unknown duration, so an interpretation in terms of short-term movements away from long-term equilibrium is not immediately useful. The
sophistication of the cointegration method is attractive, but it is not enough to make it automatically applicable nor a guarantee that it is problem free. An alternative form of modelling the dynamics of tourism demand is called for.

The alternative proposed is the Hendry approach of taking the data characteristic seriously, as an indicator of the appropriate model’s characteristics, not an estimation problem to be overcome. The difference this makes can be appreciated by comparing the two approaches to another estimation problem: the serial autocorrelation problem indicated by a significant Durbin-Watson statistic in a regression exercise. The technical solution is to adapt the estimation procedure to overcome the problem, such as using the Cochrane-Orcutt technique. The Hendry approach is to consider what the presence of autocorrelation tells the modeller about the appropriate model for the data, perhaps leading to refinement of the model by incorporating auto-regressive terms into it. The model is changed in response to the data. Some of the ramifications of doing this in the case of tourism demand data were explored in terms of model form (using diffusion ideas) and loss function for estimation.

Neural networks offer a seemingly attractive model, and can achieve good fits to data. But they are practically useless for purposes of forecasting or estimating relationships amongst variables, and so offer little prospect of being valuable in tourism demand analysis.
References


World Tourism Organisation (annual) *Yearbook of Tourism Statistics*, World Tourism Organisation, Madrid
1992

Barrett, M., Strategic Implications of International Countertrade, WP 92/01.

Thandi, H.S., A Case for Increasing Australian Trade with Malaysia, WP 92/02.

Thandi, H.S., Some Conceptual Designs to Facilitate the Generation and Integration of International Trade Research, WP 92/03.

Thandi, H.S., Malaysian Macrolights for the Investor, WP 92/04.

Thandi, H.S., NAFTA - Boon or Bane?: Some Initial Reactions, WP 92/05.

1993

Thandi, H.S., Self Disclosure Perceptions Among Students of Management, WP 93/01.

Thandi, H.S., Competitive Directions for Australia, WP 93/02.

Thandi, H.S., Culture-Strategy Integration in the Management of Corporate Strategy, WP 93/03.


Wu, C.L., On Producer's Surplus, WP 93/05.

Jackson, M., Unauthorised Release of Government Information, WP 93/06.

Jackson, M., Incidence of Computer Misuse - Fact or Fiction?, WP 93/07.

Beaumont, N., The Use of an Automated Storage and Retrieval System (AS/RS) at the State Library of Victoria, WP 93/08.

Morley, C., An Experiment to Investigate the Effect of Prices on Tourism Demand, WP 93/09.


Morley, C., The Use of CPI for Tourism Prices in Demand Modelling, WP 93/11.


Marks, L., Marketing and the Public Sector Library: Some Unresolved Issues, WP 93/14.

Jackson, M., Protection of the Proprietary Information of Organisations in the Asia-Pacific Region, WP 93/15.

1994


Mottram, K., Management Coaching Process, WP 94/02.


Morley, C., Beyond the MBA: Professional Doctorates in Business, WP 94/04.

1995

Morley, C., Tourism Demand: Characteristics, Segmentation and Aggregation, WP 95/01.

Morley, C., Data Bias in the Estimation of Airfare Elasticities, WP 95/02.

Morley, C., Estimating Tourism Demand Models, WP 95/03.


Callaghan, B. & Jackson, M., Accounting Professionals: Current Attitudes to Banks, WP 95/05.

Jackson, M. & O'Connor, R., Research Planning and Management in Non-traditional Research Discipline Areas, WP 95/06.

Callaghan, B. & Dunwoodie, K., How Large Are Cultural Values Differences in the 90's?, WP 95/07.

Morley, C., Diffusion Models of Tourism: International Tourism to Australia, WP 95/09.

1996

Scarlett, B., An Enterprise Management Understanding of Social Differentiation, WP 96/1.

Slade, P., Technological Change in New Zealand Sawmilling, WP 96/2.


Slade, P., Employment Relations: New Paradigm or Old Ideology, WP 96/5.

1997

Jackson, M. & O’Connor, R., Staff Mobility Programs in Australian Universities, WP 97/1.

Morley, C.L., An Econometric-Product Growth Model of Tourism to Australia, WP 97/2.

Callaghan, W.M. & Dunwoodie, K., A Comparison of Decision Making Approaches used by Australian and Malaysian Managers, WP 97/3.

Martin, W.J. & Chishti, M.A., Content and Context in Information Management: The Experience of Two Melbourne-Based Organisations, WP 97/4.


Scarlett, B., Beyond Excellence: In Search of Enterprise Effectiveness, WP 97/6.

O’Neill, M., Bellamy, S., Jackson, M. and Morley, C., An Analysis of Female Participation and Progression in the Accounting Profession in Australia, WP 97/7


1998

Scarlett, B.L., Business Goals, WP 98/1.

Scarlett, B.L., A Typology of Enterprise Effectiveness Models, WP 98/2.

Lombardo, R.W., Unravelling the Mysteries of Ellwood’s Basic Mortgage Equity Capitalisation Model, WP 98/3.


1999

Scarlett, B.L., A Cross Cultural Comparison of Business Goals, WP 99/1.


Ellingworth, R., When the Will to Change is not Enough? An Action Research Case Study from the Finance Industry, WP 5/99.


