CRANFIELD INSTITUTE OF TECHNOLOGY

CENTRE FOR TRANSPORT STUDIES

PhD THESIS

Academic Year 1980-81

T. CHERIF

MULTI-EQUATION TRAVEL DEMAND MODELS

APPLICATION TO THE AIR-RAIL COMPETITION

IN

GREAT BRITAIN

SUPERVISOR: I. Black

OCTOBER 1981

SUMMARY

The main purpose of this research is to develop a set of econometric Air-Rail competition models which are sufficiently sensitive to measure the effects upon demand of policy decisions, with regard to such variables as frequency of services and fares.

Existing Modal Competition Models have, rather uncritically, applied Multiple Regression analysis in considering only one aspect of the market, namely the demand for travel, ignoring therefore the effects of the supply upon the demand. The emergence of the so called "Simultaneous Equations Bias", due to the two-way dependency between the demand and the level of service factor expressing the supply, renders the application of the OLS (Ordinary Least Squares) inappropriate, and hence, yields biased, inconsistent, and inefficient OLS coefficients.

The models, developed in this study, depart from all existing Modal Competition Models, and overcome some of their drawbacks. They are formulated as Multi-equation Supply/Demand Modal Competition Models. They introduce the frequency of services variable not only in the demand, but also in the supply equation expressing the level of supply in response to changes in other variables. In order to derive unbiased, more consistent, and more efficient coefficients, sophisticated statistical techniques, such as 2SLS and 3SLS (Two-Stage Least Squares and Three-Stage Least Squares) , are applied as a means of calibration.

The elasticities obtained are consistent with the Supply and demand Microeconomic Theory. The frequency of services appears as the most powerful explanatory variable in Air demand; whereas fare and income are the most powerful variables in Rail demand equation. This leads

to the conclusion that Air mode is mainly higher income groups and/or business oriented market; and Rail mode lower income groups and/or personal oriented market. Furthermore, Air and Rail are competing on a fare basis in short routes; while they do not show close substitutes for each other in longer ones.

The high significance of the frequency of services, in Air demand, outlines its importance as a factor influencing the demand; and therefore, provides the Airlines management with the capability of improving the demand by acting upon the endogenous factor. This is of great interest in the scheduling fleet process.

Similarly, the significance of Rail fare variable offers the Railways management the possibility of acting upon the demand through this controllable variable, for an efficient pricing policy. Rail journey time elasticities, derived from these models, are very close to the elasticities assumed by British Railways Board, in their Passenger Traffic Model, 1980.

The statistical results indicate that the elasticities derived are useful for both analysis and forecasting purposes.

AKNOWLEDGEMENTS

This work would not have been possible without the support of many individuals and organisations, and I would like to record my appreciation to them.

In particular, I am grateful to the ICAO for their financial support, and to my Supervisor Ian Black for his guidance and encouragements.

Thanks too to John Clark for his comments, and to the rest of the CTS team for their friendliness.

Last, but not least, I owe a special gratitude to Redha's Mother for her patience in typing the indecipherable drafts of this Thesis.

<u>CONTENTS</u>

INTRODUCTION			1
PART I	LITERATURE REVIEW		
	INTRODUCTION		6
	CHAPTER 1	TYPE OF DATA	
	1.1	Aggregate vs Disaggregate Models	8
	1.2	Pure Time Series vs Pure Cross-sectional Models	11
	1.2.1	Time Series Models	11
	1.2.2	Cross-sectional Models	16
	1.3	Pooled Data Models	17
	1.4	Conclusion	19
	CHAPTER 2	UNDERLYING THEORY	
	2.1	Deterministic Models	24
	2.2	Probabilistic Models	28
	2.3	Conclusion	31
	CHAPTER 3	STRUCTURAL FORMULATIONS & METHODS OF ANALYSIS	
	3.1	Structural Formulations	33
	3.1.1	Linearity vs Non Linearity	33
	3.1.2	Gravity Formulation	35
	3.1.3	Single equation vs Multi-equation Formulation	37
	3.2	Methods of Analysis	38
	3.2.1	Ordinary Least Squares Regression Analysis	38
	3.2.2	Multi-equation Techniques Analysis	39
	3.2.3	Discriminant Analysis	40
	3.3	Conclusion	41

CHAPTER 4 FACTORS EXPLAINING TRAVEL DEMAND

4.1 Air Travel Demand Factors 42
4.1.1 Non Transport Factors 42
4.1.2 Transport Factors 46
4.2 Modal Competition Factors 50
4.2.1 Mode's Characteristics 51
4.2.2 Traveler's Characteristics 52
4.3 Conclusion 53

PART II US DOMESTIC MARKET ANALYSIS

INTRODUCTION 55

CHAPTER 5 ANALYSIS OF MIT STUDY

5.1 Presentation of the Study 57
5.2 Statistical Evaluation of the Study 60
5.3 Conclusion 64

CHAPTER 6 AGGREGATION MARKETS ANALYSIS 74

CHAPTER 7 NEW MARKET DEFINITION & SPECIFICATIONS

7.1 Aggregation Business/Leisure 84
7.2 Analysis of Variables by Individual Routes 86
7.3 Simultaneous Equations Models 91
7.4 Conclusion 93

PART III UK DOMESTIC MARKET ANALYSIS

INTRODUCTION 100

CHAPTER 8 DATA CONSTRUCTION

8.1 Catchment Areas 104
8.2 Air Data 106
8.3 Rail Data 109
8.4 Income Variables 110

CHAPTER 9 TRANSPORTATION ECONOMIC ANALYSIS

9.1	Transportation Demand is a Derived Demand	114
9.2	Transportation Product is Perishable	114
9.3	Transportation Services are Regulated	115
9.3.1	Air Transportation Pricing Regulation	115
9.3.2	Rail Pricing Policy	116
9.4	Demand Function	117
9.5	Supply Function	118
9.6	Application to the Study	119
9.7	Equilibrium	123
9.8	Originilaty of the Study	125

CHAPTER 10 MODAL COMPETITION MODELS STRUCTURE

10.1	Methodology	126
10.1.1	Variables Selection	127
10.2	Simultaneous Equations Bias	135
10.3	Statistical Calibration Techniques	135

CHAPTER 11 MULTI-EQUATION MODELSBUILDING

11.1	Pooled Models	143
11.2	Pooled Models: Results & Discussion	145
11.3	Long and Short Haul Models	156
11.3.1	Air Demand Equation	156
11.3.2	Rail Demand Equation	158
11.3.3	Supply Equations	161
11.3.4	Rail Fare Variable Equation	165

CHAPTER 12 SELECTION OF THE BEST SPECIFICATION

12.1	Model Selection	175
12.2	Ranges of Income Variable	176
12.3	Statistical Evaluation of the Model	180
12.3.1	Normality of the Errors Distribution	180

12.3.2 Constant Variance 183
12.3.3 Time Dependency of the Error Terms 183
12.3.4 Multicollinearity 183
12.3.5 Goodness-of-fit: Trace Correlation 188
12.3.6 Simulation Forecast 189
12.4 Selection of the Best Calibration Technique 196
12.4.1 Coefficients Analysis 196
12.4.2 Accuracy of the Forecast 198

CHAPTER 13 ABSTRACT MODES MODELS 204

CHAPTER 14 PURE AIR DEMAND MODELS

14.1 Region-pairs Models 210
14.2 Pure Air Business Travel Demand Models 213

CHAPTER 15 APPLICATION OF THE MODELS

15.1 Scheduling Fleet Problem 216
15.2 Effect of Fare 218
15.3 Trip Time Effect 219

CONCLUSION 221

REFERENCES 245

APPENDIX 253

FIGURES

1.1	Variations in CAB Forecasts	21
1.2	Variations in Mc Donnell Douglas Forecasts	22
1.3	Example of the Variations in Forecasts Made at One Time	23
5.1	Plots of Residuals vs Computed Demand Monopolistic Market	68
5.2	Plots of Residuals vs Computed Demand Competitive Market	69
12.1	Plots of Residuals vs Air Demand (2SLS)	184
12.2	Plots of Residuals vs Air Demand (3SLS)	185
12.3	Plots of Residuals vs Rail Demand(2SLS)	186
12.4	Plots of Residuals vs Rail Demand(3SLS)	187
8.1	UK Air Passengers Demand	227
8.2	UK Air Passengers Demand	228
8.3	UK Rail Passengers Demand	229
8.4	Glasgow	230
8.5	Glasgow	231
8.6	Edinburgh	232
8.7	Edinburgh	233
8.8	Newcastle	234
8.9	Newcastle	235
8.10	Manchester	236
8.11	Manchester	237
8.12	Birmingham	238
8.13	Birmingham	239

8.14 Birmingham 240

8.15 Leeds 241

8.16 Leeds 242

8.17 Liverpool 243

8.18 Liverpool 244

I know of scarcely anything so apt to impress the imagination as the wonderful form of cosmic order expressed by the "Law of Frequency of Error". The law would have been personified by the Greeks and deified, if they had known it.

Sir Francis Galton

Public agencies are very keen on amassing statistics - they collect them, raise them to the nth power, take the cube root and prepare wonderful diagrams. But what you must never forget is that every one of those figures comes in the first instance from the village watchman, who just puts down what he damn pleases.

Sir Josiah Stamp

INTRODUCTION

Forecasting travel demand is a central task for all sections of the transportation industry, and has in recent years become an extremely complex operation. This is particularly true in Civil Aviation, where demand fluctuations are a prime source of instability; for inaccurate demand forecasting leads to capacity problems, and consequently, to revenue difficulties.

Industry analysts have recognized the sensitivity of the productivity of the Airlines and Aircraft manufacturers to their planning process which is based upon travel demand forecasts. Traditional methodologies such as trend extrapolation, were found inadequate as a result of the impact upon travel demand of recent drastic changes within the economic and operating envir-environment : high inflation rates, fuel and labor costs increases. More elaborate models, based upon advanced econometric techniques, have generally been limited either by insufficient understanding of the whole transportation system or by lack of relevant data.

Need in forecasting

Both the planner and the policy maker need to know the consequences of their plans, recommendations or decisions. In the context of a new transportation facility, they need to know who will be affected by the new facility, both beneficially and adversely; and the extent of the gains and losses. Furthermore, in justifying a new facility, they should have quantitative estimates of its effects in order to transform them into terms that can be used to compare alternative projects.

Time horizon

The length of time ahead for which the forecasts have to be made is one of the problems of the transport industry, particularly in Aviation where the lead time is a very important element. For fleet planning purpose, Airlines have to consider the time elapsing between the commitment to a firm order of an Aircraft and its delivery. Aircraft manufacturers need to consider the time it takes to develop a prototype, and then, the production run period of pay-off for the investment in the project. In the case of Airports, Roskill's forecasts for the third London Airport extend 15 years into the future, although the total construction time was estimated as 7 years.

Model validity

The validity of the model may be judged on several criteria : its predictive power, the consistency and realism of its assumptions, the extent of the information it provides, its generality, i.e, the range of cases to which it applies, and its simplicity. There is no general agreement regarding which of the above attributes is more important.

The views of the analysts range from the position that the predictive performance is the most important criteria of the model validity to the position that realism of assumptions and power of the model in explaining the behavior of the economic agents, producers and consumers, is the most important attribute of the model. Most economists take the position that what is the most relevant attribute of the model depends on its purpose, the use for which the model is built.

When the model is designed for a pure forecasting application, the predictive performance is more important. Realism of assumptions and explanatory power are, in turn, more important if the model purpose is the explanation of why a system behaves as it does. The availability of relevant data is, of course, a key element in the modeling process; and models can only be as good as the data.

Purpose of the Thesis

The purpose of this research effort is to develop a set of econometric Air-Rail competition models that are sufficiently sensitive to measure the effects upon demand of policy decisions with respect to such variables as frequency of services and fares.

Besides particular weaknesses inherent to each type of existing models, they all suffer from a common problem: by considering only one aspect of the market, the demand for travel, they therefore ignore the effects of the supply upon the demand. This may yield biased and inconsistent estimates of the parameters.

The models developed in this Thesis depart, in many ways, from all existing models, and overcome some of their drawbacks. They are formulated as Multi-equation supply/demand models, and are therefore related to both aspects of the market, the supply of and the demand for travel.

They introduce the frequency of services variable not only in the demand equation, as an important level of service factor explaining the demand, but also in the supply equation, expressing the level of supply in response to changes in other variables. By including the frequency of services as an important factor influencing the demand, these models provide the policy maker the capability of acting upon the demand through this controlable factor.

They estimate the absolute value of Air and Rail traffic demand instead of the share by each mode, as most of the modal competition models do.

Finally, the equations are simultaneously estimated rather than being independently or recursively calibrated. This calibration involves highly sophisticated techniques, such as Two-Stage Least Squares and Three-Stage Least Squares, which provide unbiased, more consistent and more efficient estimates coefficients.

As a background for this Multi-equation models building, a literature review is presented in Part I. Instead of discussing the existing models one by one, the modeling process in this review is analysed through some important characteristics for the models, such as the type of data, the underlying theory of the models, their structural formulation, and their methods of analysis.

As an illustration of this literature review, Part II provides a detailled analysis of an econometric model, developed at MIT by the Flight Transportation Laboratory in 1976. This analysis highlights the statistical problems commonly encountered in Time Series, Cross-sectional, and Pooled models. It outlines, through this model, the main weakness of Aggregate models, namely the implicit assumption of the homogeneity of the market. Finally, it illustrates the major handicap of many travel models, due to the two-way dependency between the demand and the level of service variables.

In order to overcome this statistical difficulty, a new specification of this model is attempted, by including a second equation in which the level of service variable is expressed as the dependent variable.

However, as the Surface Modes competition is completely ignored in MIT Model, a set of Modal Competition models, the aim of this research, are developed in Part III. They involve the UK Domestic Air and Rail travel markets.

It was originally intended to estimate the coefficients of these models from pure Time Series data, by conducting Region-pairs models. However, as a result of the low degrees of freedom consequent to the small sample data, and to the Multi-equation nature of these models, it became necessary to combine Cross-sectional and Time Series data, so as to derive meaningful elasticities.

Nevertheless, pure Time Series models are attempted by applying a revised Abstract Mode approach to 7 individual

London routes. This approach has the advantage of increasing the degrees of freedom by doubling the number of observations.

Finally, pure Air travel business demand models and pure Region-pairs models applied to 3 trunk routes are developed and discussed.

P A R T I

L I T E R A T U R E R E V I E W

INTRODUCTION

The literature on travel demand models is quite extensive, and it would be a difficult task to provide an exhaustive review. Models are so numerous that one may get the impression that there are as many models as modelers.

Many classifications by types of models were attempted (e.g, Andreff & Bourgogne [1] , Taneja [2]); and their multitude is only a proof of their imperfection. The following, for instance, is a partial list of typical models names : Time Series, Cross-sectional, Gravity, Abstract Modes, Non-Linear. A detailed analysis shows that the names do not represent unique models, but rather the characteristics that the author felt were more relevant. A model, for instance, may well be Time Series, or Cross-sectional, Aggregate or Disaggregate, Linear or Non-Linear, and Abstract at the same time. The name by which the model is called being its most important characteristic, whether it is the type of data (Aggregate vs Disaggregate, Time Series vs Cross-sectional, Pooled), its underlying theory(Consumer Behavior Theory, Abstract Mode, etc..), its structural formulation (Linear vs Non-Linear, Single Equation vs Multi-equation), or its method of analysis (Regression analysis, Discriminant analysis...).

For the present review, rather than discussing the models one by one which would be a great task, we discuss the modeling process through the characteristics referred to above:

1 - Types of data
2 - Underlying Theory
3 - Structural formulation & Methods of analysis

At this stage, we are not concerned with the evaluation of the models as such, but rather by the analysis of the above characteristics.

Although Logit, Probit, and Discriminant analysis are not of great relevance to the models to be developed in this study, they are presented there-in-after for completeness.

To close the literature review, an analysis of the factors explaining Air travel demand as well as those explaining the Choice Mode decision is provided.

As an illustration of this review, an Econometric Model conducted at MIT by the Flight Transportation Laboratory in 1976 is discussed in details in Part II of this study.

CHAPTER 1

TYPE OF DATA

1.1 AGGREGATE VS DISAGGREGATE MODELS

The use of "Aggregate" and "Disaggregate" as applied to the travel demand modeling is not always totally consistent and a certain amount of unjustified mystique has been created around them.

A totally Aggregate model is a model estimated with a dependent variable which represents a group of observations, whereas a totally Disaggregate model is a model estimated with a dependent variable which represents an observation of a single occurence.

In totally Aggregate models demand is normally treated in a macroeconomic context. Usually, the dependent variable is the RPM (Revenue Passengers Miles), or the number of passengers on a large scale such as the total world traffic or the total US traffic, as usually forecasted by the ICAO, IATA, the big airlines and the air manufacturers.

In totally Disaggregate models, demand is treated in a microeconomic context. Ideally, the totally Disaggregate model would be the one specifying the consumption problem for each consumer in the population i.e the number of trips that each consumer would take to a particular destination at a given time period.

The main disadvantage of totally Aggregate models is the loss of information experienced in averaging the values of the variables affecting travel demand over the group of individuals in a traffic region whose demand is being modeled. This loss occurs because no explicit account is taken of the variability of the explanatory variables with the traffic region in estimating the coefficients.

The main disadvantage of a totally Disaggregate model is the amount of data necessary for such a modeling. Because of these great difficulties, researchers have been forced to combine somehow the data in order to develop models that fall between totally Aggregate and totally Disaggregate models.

The desirable degree of aggregation depends, of course, on the purpose of the model as well as on the data. On the planning of new equipment, manufacturers develop forecasts of future world aviation activity in terms of RPM. Similarly, both the ICAO in their concern in the total amount of world traffic and the airlines for their fleet planning purpose develop total aggregate models.

However, when the purpose is to measure the effect upon demand of particular variables such as fare, income, and quality of service the models should be somehow disaggregated. The degree of such a disaggregation is closely related to the available data.

In the following are some examples of these types of models.

- Douglas Aircraft Company Model: this total Aggregate model is designed to forecast the short and long term US domestic traffic to 1983, using a Time Series data over the period 1946 - 1974. [3].
The dependent variable is the RPM and the behavioral equation is expressed as follows:

$$RPM = \beta_0 + \beta_1(PCE) + \beta_2(VEL) + \beta_3(RINT) + \beta_4(TYLD) + \beta_5(PTL) + \beta_6\ DUMMY$$

where the variables in logarithm have the following definitions:

PCE : permanent income measure of personal consumption expenditure.
VEL : velocity of money.
RINT : ratio between the long and the short term rates of interest.
TYLD : US scheduled domestic yield in current $\not{c}$.
PTL : US average on-line passenger trip/length.
DUMMY : dummy variable aimed to correct for the definitional change of domestic traffic to a 50 states basis.

The aggregative nature of this model is characterised by the measurement of the dependent variable RPM and the extent of the geographical traffic over the whole US domestic market. Notice also the PTL variable which is an average on-line passenger trip/length.

- After this illustration of total Aggregate models, it would have been also interesting to provide an empirical example of a total Disaggregate model. Unfortunately, in our knowledge, such empirical models do not exist, However, most of the models fall between total Aggregate and total Disaggregate. As an illustration of such models, we refer to Taneja [2] who provided a quite interesting review. We do not discuss these models at this stage, since the review will refer to in different sections. But, it is interesting to define here their types of aggregation.

- Aggregation by destination:
  R Gronau 19 , Columbia University [4] .
- Aggregation by incomes:
  T Blummer 1976, MIT (Massachusett Institute of Technology). [5]
- Aggregation by modes of destination:
  P Verleger 1971, MIT [6] .
- Aggregation by incomes, modes and destination:
  P Marfisi 1976, Brown University [7] .

- Aggregation by incomes, modes and destination:
  S E Eriksen 1977, MIT [8] .

In conclusion, the choice of degree of aggregation is related to the purpose of the model as well as to the type and amount of data available.

The main disadvantage of totally Aggregate models is the implicit assumption that travel demand is a homogenous unit such as RPM, and that the value of passenger traffic is related to the same parameters in all markets (for instance, London - Palma and London - New York are assumed to be characterised by the same parameters). They also ignore the segmentation by trip purpose modes, class of service, which leads to a loss in forecasting accuracy.

The non totally Aggregate models, on the other hand, are (depending on the degree of aggregation) more accurate. They, however, require more data, time and effort.

1.2 PURE TIME SERIES VS PURE CROSS-SECTIONAL MODELS

1.2.1 Time Series

They are models using a sample of data over a period of time with fixed time intervals. The main purpose of these models is the analysis of past data in order to establish a relationship between the dependent variable and a set of explanatory variables. Once this mathematical relationship, over the considered period, is established, future values of dependent variable are derived either by assuming the stability of this relationship onto the future (as most models do) or by allowing this relationship to vary over time. The main outcome of these models is the elasticities of the demand with regard to the considered variables throughout a period of time.

Pure Time Series are usually related to total Aggregate models since neither city pairs nor any travelers' characteristics are explicitly expressed. The Douglas model, referred to earlier, is a typical example of a pure Time Series model.

One major problem encountered in Time Series is the high degree of collinearity that often exists between different independent variables. The main reason for this collinearity is a tendency of economic variables to move together over time. For example, in period of booms or rapid eeconomic growth, the basic economic magnitudes grow, although some tend to lag behind others. Thus, income, consumption, savings, investments, prices, employment tend to rise in periods of economic expansion and decrease in periods of recession.

When a strong collinearity exists, the condition for the application of OLS(ordinary least squares), namely the independence between variables, breaks down and the estimated parameters, according to Koutsoyiannis [9], might be seriously imprecise and unstable.

This statistical deficiency is present in the Douglas model [3], mainly due to the large secular trends of the personal consumption expenditures variable, trip length and yield which might be one of the reasons for the high value of R^2(=.9988).

Multicollinearity is a characteristic of the data rather than an indication of incorrect specification of the model. If the purpose of the model is a measure of variables elasticities (such as price and income) multicollinearity is a serious problem because it is rather difficult to disentangle the effect of each variable. However, when forecasting is the main purpose of the model (as in Douglas model), the deficiency is not so serious; for if multicollinearity remains the same over the projected period, the coefficients' estimates have the merit of giving good forecasts. If multicollinearity is not maintained, the problem remains.

There are different techniques, described in many econometric books, of how to identify and to overcome multicollinearity:

- The first common method is to take the first differences to eliminate the time trend. An appropriate illustration of this method is given by the CAB (Civil Aeronautics Board) model [10] developed by Brown and Watkins. This model focusses on the determination of price elasticity and uses data over 1946 - 1966, incorporating three independent variables: average fares per mile, income per capita and clock time. The dependent variable is the RPM.
Multiple regression is conducted in two ways: Time Series and Cross-sectional analysis. In the Time Series analysis, the introduction of first differences is aimed to combat multicollinearity. Both fare and income variables coefficients are statistically significant (-1.307 and 1.119).

- The second method to overcome multicollinearity is conditional regression. When the explanatory variables are highly correlated, the influence of some of them could be considered as external data known from other sources with an assigned a priori elasticity. Such method is applied by Strasheim [11] .

- A third method, is constrained regression technique introduced in the North East Corridor Project to combat multicollinearity due to the large number of variables (11 variables):

- employment in cities i and j.
- cost trip by each mode (Air, Rail, Bus, Car).
- trip time by each mode.
- per capita income in city i.
- attractiveness of city j.

The method consists of assuming linear constraints on the range of values which the estimates could take up on a priori knowledge. Each elasticity is constrained to have the correct sign: a mode's own price elasticity is constrained to be negative, cross-elasticity is constrained to be positive and a maximum value is specified for each elasticity.

- A fourth technique to overcome multicollinearity consists of using detrended variables. Taneja [12] ,in his attempt to measure the impact of high inflation rates on the demand for air transportation, uses both the first and the fourth techniques. The explanatory variables selected in his model are: measure of consumer income, yield and inflation rates; and RPM is the dependent variable. The method requires three steps:
To begin with, he detrends all the variables,except the measures of inflation, by performing a regression of a trend against each variable(one by one), the residual representing the corresponding detrended variable.
Then, he runs the following regression:

$$\text{Log(RPM*)} = \text{Log(YIELD*)} + \text{Log(INC*)} + \text{Log(INFL)}$$

where each of the different measures of incomes and inflation is tested, so as to select the best measure for each factor.
Finally, after obtaining the best measures, he runs the regression using the following equation:

$$\text{Log(RPM)} = \text{Log(YIELD*)} + \text{Log(INC*)} + \text{Log(INFL)} + \text{TREND}$$

where Log(RPM) is designed to retain the secular trend for forecasting, and the Log as well as the detrended forms to remove trend and to eliminate the multicollinearity problems.

The "*" indicates the detrended variables.

Another statistical problem,often encountered in Time Series model, is Autocorrelation. It occurs when the error term is correlated with its past value(s). Most of the standard econometric textbooks deal with the simple case of autocorrelation namely the first order autoregressive relationship:

$$U_t = \rho U_{t-1} + V_t$$

The sources of autocorrelation are numerous, the most important ones being: the omission of explanatory variables, misspecificationof the true random term. Autocorrelation may be positive or negative in theory. In practice, however, it is in most cases positive.

Some rough idea of the existence and the pattern of autocorrelation may be gained by plotting the regression residuals, either against their own lagged value(s) or against time. However, there are more accurate tests for incidence of autocorrelation such as Von Newman ratio and Durbin Watson test explained in many textbooks.

As a general rule, the presence of serial correlation does not affect the unbiasedness* or consistency* of the coefficients, but does affect their efficiency*. In the case of positive serial correlation(i.e the most common case), the SE(standard errors) of the OLS(ordinary least squares) coefficients are smaller than the true SE; i.e the coefficients appear more significant than they actually are. When serial correlation is due to misspecification of the error term U, the appropriate solution is to obtain an estimate of ρ. In many cases, researchers assume ρ=1, and proceed in the estimation of the relationship expressed in the first differences of the variables.

---

* These terms will be defined later on.

1.2.2 Cross-sectional models

Contrarily to Time Series models, Cross-sectional models use observations in a particular point of time across different routes*. The main purpose is to identify the relationship between the total demand and some explanatory variables across the markets considered. Therefore, the elasticities derived are instantaneous elasticities, i.e related to the base year considered.

The CAB have most often determined elasticities by cross-sectional analysis. One of their best known model is the model developed by Brown and Watkins [10] in 1970, over the 300 most heavily travelled city pairs in the United States.

The dependent variable is the number of passengers and the independent variables are: fare per mile, time per mile, number of stops, distance, phone messages, international passengers, income and competition index.

The regression in Log linear formulation is performed first, for the year 1960 and 1964 separately and then, for both years combined. The results show a fairly high degree of explanation of the dependent variable (R^2 exceeding .80). All the coefficients are significant and bear the right signs.

However, Cross-sectional models do have some drawbacks. We recall here the potential existence of heteroscedasticity. In a city pairs model, the error of specification for one market may be quite different from the error for another market, since different factors may explain the underlying process in the two markets. One market may

---

* Other types of Cross-sections are, of course, possible such as across of ranges of incomes for instance.

be more pleasure oriented while the second may be more business oriented. A Las Vegas - San Francisco, or, a Los Angeles - San Francisco, for instance, could hardly be combined with Washington - New York, or, Chicago - Boston markets.

Heteroscedasticity arises when the variance of the random term is not constant. This can easily be understood if we take account of the factors whose influences are absorbed by the disturbance term. Notice that this term expresses the influence, on the dependent variable, of errors in its measurement and of omitted variables.
When this deficiency occurs, the OLS estimated do not have the minimum variance property in the class of unbiased estimators, i.e, they are <u>inefficient</u> (although still unbiased).
Some tests are proposed to identify the existence of heteroscedasticity, among them Goldfeld and Quandt tests. Solutions for these difficulties are described in many textbooks (e.g Pindyck [13] , Koutsoyiannis [9]). It should be remembered, however, that heteroscedasticity is less common than multicollinearity and less serious.

Another disadvantage in pure Cross-sectional models is that data taken from a specific time period may not be considered a typical base year from which to develop Cross-sectional models.

The problem of data, encountered in both pure Time Series and pure Cross-sectional models, and the statistical difficulties explained above, raise the question of whether a combination of both methods would constitute a better technique in improving the number of observations and possibly reducing the problems of multicollinearity, autocorrelation, and heteroscedasticity.

1.3 POOLED DATA MODELS

Most of travel demand models utilise combined data across city pairs and over different time periods. An example of such model is the MIT's model [14] developed by Eriksen, Scalea and Taneja in 1976. This model attempts to relate the level of air transportation activity in a number of specific markets to a set of socioeconomic and scheduling variables. Data are pooled from 58 region pairs over the period (1959 - 1974). Its formulation is as follows:

$$\text{Log } D = \beta_0 + \beta_1 \text{ Log(FARE)} + \beta_2 \text{ Log(BPI)} + \beta_3 \text{ Log(LOS)}$$

where:

D = demand between region pairs.
FARE = fare charged in region pairs.
BPI = buying power index characterising each region pair.
LOS = level of service.
β_i = coefficients to be calibrated.

As this model will be discussed, later on, in greater details we only note at this stage the existence of <u>heteroscedasticity</u> and <u>autocorrelation</u> which are the combination of both disadvantages of Time Series and Cross-sectional models.

In this type of pooling data technique, all cross-sectional and Time Series data are combined and multiple regression is performed on the entire data set. However, another pooling process exists. It consists of estimating one (or more) coefficients from the Cross-sectional data, insert them in the original function, substract from the dependent variables the terms involving the estimated parameters, and then, regress the residual value of the dependent variable on the remaining explanatory variables, obtaining estimates of the remaining coefficients from the Time Series sample.

This procedure offers many advantages. According to Koutsoyiannis [9] , the use of Cross-sectional data in combination with Time Series in the estimation of demand functions may avoid to a certain extent the problem of multicollinearity, identification*, simultaneous equation bias*. However, there are various snags which must be carefully watched, if the values of the coefficients are to be properly estimated:

- First, the Cross-section estimates are long run elasticities whereas the Time Series estimates are short run elasticities. This difference in the meaning of the estimates is due to the implicit assumption underlying the two types of estimates: is it a long run demand function or a short run relationship that is estimated from the pooling technique?

- Second, it is clear that from a Cross-section sample we obtain estimates in a particular point of time; the procedure implies that the Cross-section coefficients remain constant over the whole period of the Time Series sample, an assumption which may well be expected to be unrealistic.

Such considerations have induced various analysts to argue that functions estimated from pooling techniques are not efficient for prediction [9] .

1.4 CONCLUSION

What to conclude from this "type of data" review?

- First, the aggregation/disaggregation dilemma is primarily a question of purpose of the model. If the main reason of the model is to draw a general picture of the evolution of the traffic over the total world demand or a given domestic market, the total aggregation

(*) Identification and simultaneous equation bias will be discussed later on.

approach is reasonable. On the other hand, if the purpose is the evaluation of the demand in a particular segment of the market, such as a region pairs or a segment of the population, the corresponding aggregation is more appropriate.

- Second, the Time Series, Cross-sectional and Pooled data procedures are methods of estimating elasticities They consist of finding the mean of evaluating these elasticities (usually income and price), with regard to the potential statistical and theoretical problems inherent to each procedure:
- multicollinearity and autocorrelation, particularly common in pure Time Series.
- heteroscedasticity, usually characterising Cross-sectional models.
- finally, the combination of these problems in addition to the ambiguity longrun/short run elasticities in pooled techniques.

Once again, the availability of reliable data are the most determinative element in the selection of these procedures. Empirical travel demand mdels have invariably applied these methods with more or less success depending on the available data. However, the wide differences in the forecast values experienced particularly by the total aggregate models, raises the question of reliability of these models.

The Fig : 1.1,1.2,1.3 illustrate very well such differences. In particular, the 1968 forecast in Mc Donnell Douglas model (Fig 1.2) exceeds the 1965 forecast by more than 133% for the year 1975.

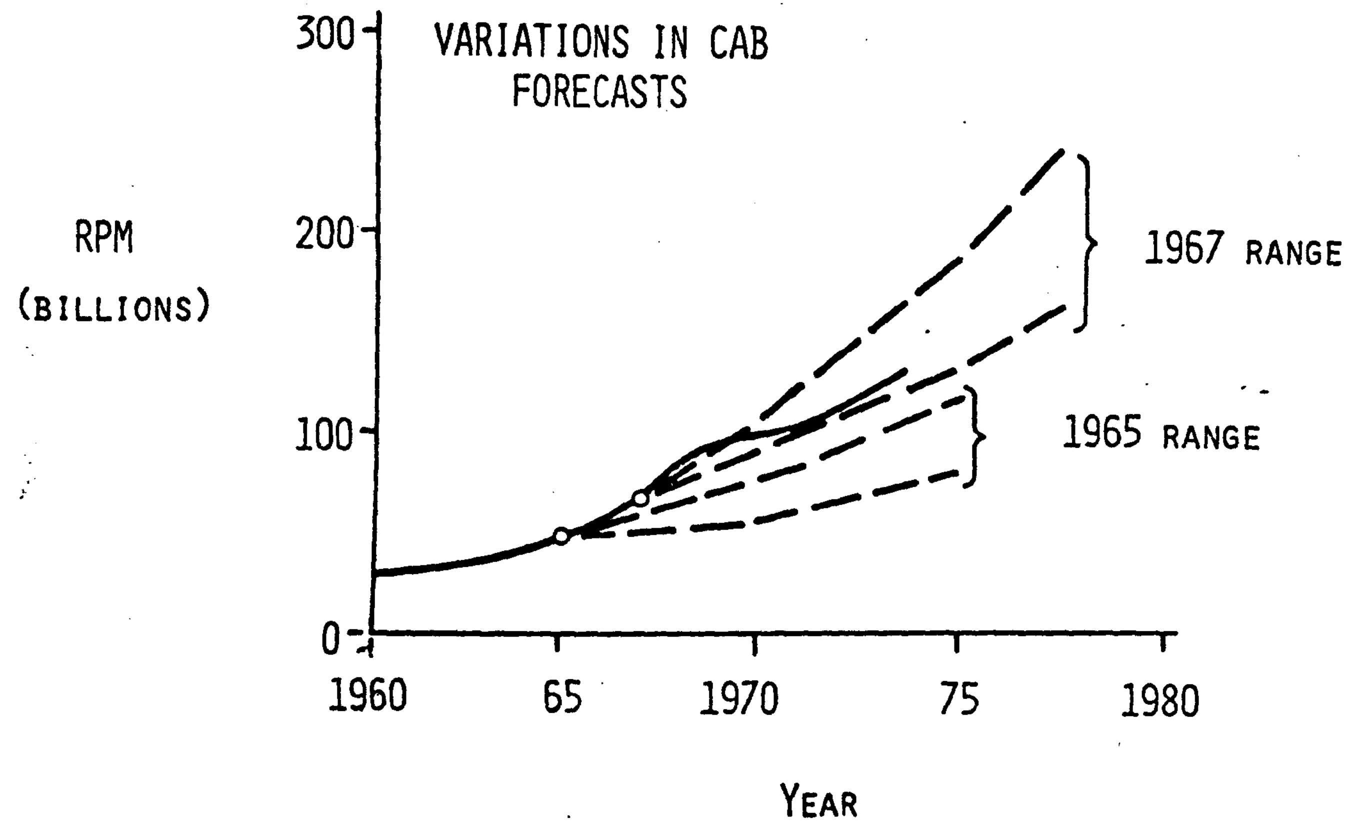

VARIATIONS IN CAB FORECASTS
RPM (BILLIONS)
300
200
100
0
1960
65
1970
75
1980
YEAR
1967 RANGE
1965 RANGE

Figure 1.1

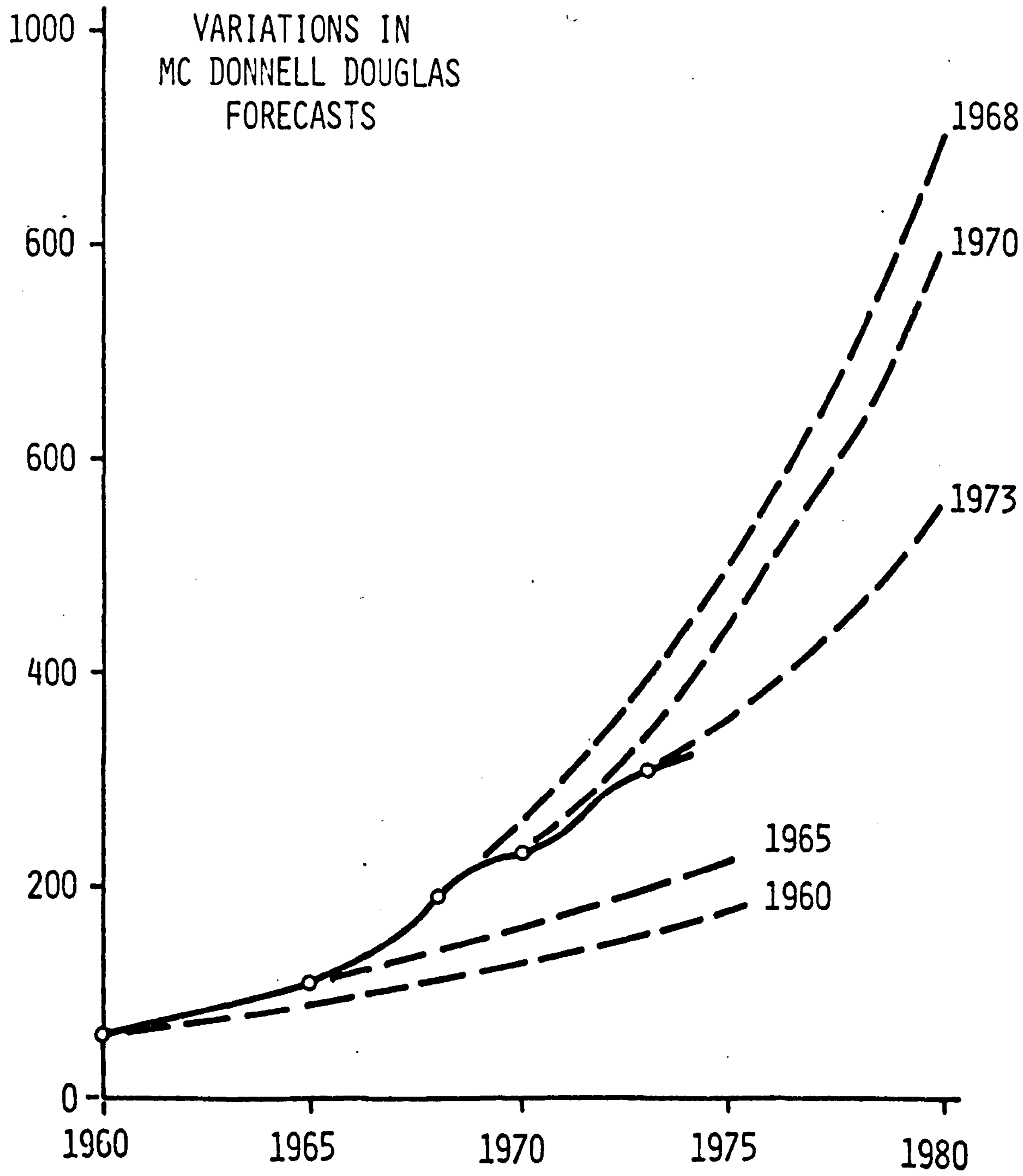
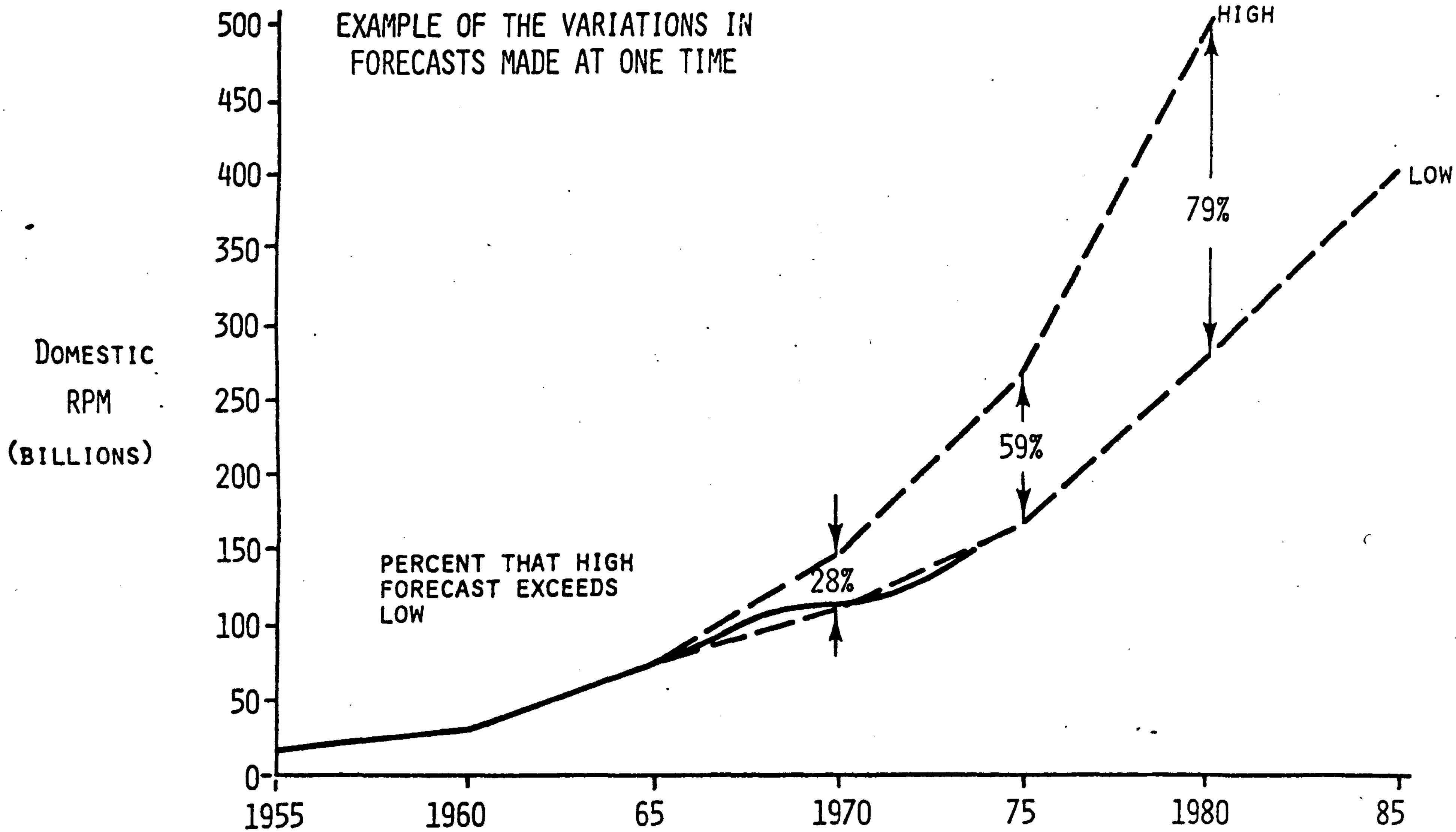

VARIATIONS IN
MC DONNELL DOUGLAS
FORECASTS
1000
600
600
400
200
0
1968
1970
1973
1965
1960
1960
1965
1970
1975
1980

Figure 1.2



SOURCES: ATA, BOEING, CAB, DOUGLAS, FAA, GE, LOCKHEED, NORTH AMERICAN

Figure 1.3

CHAPTER 2

UNDERLYING THEORY

One of the criteria by which models are usually judged is the consistency of their theoretical foundation. In this chapter, we attempt to explain how some theoretical concepts derived from economics and psychology have been applied to travel demand models.

For the clarity of the presentation, we first discuss the theory underlying the Deterministic models,i.e, the models that attempt to determine the absolute value of traffic demand, and then the theory of probabilistic models which evaluate the probability for a consumer to choose a particular alternative.

2.1 DETERMINISTIC MODELS THEORY

The stages by which the theory of travel demand has progressed from its state, some 25 years ago, to the rather more satisfactory state are complex.
The first and more important change was the recognition that travelers' decisions emerge out of the individual's optimizing behavior.

Another improvement was introduced by Y Young [15] in his PhD dissertation in the University of Washington in 1966. He suggested that the fact, that travelers were willing to pay a higher price for a faster mode of transport, revealed their consciousness of the value of time and a time constraint in their activity. He argued that neoclassical consumer choice theory was deficient and misleading in air travel market analysis, in that it ignored the time constraint and the value of time of the consumer. He, therefore, proposed a trade off between time and money, and modified the neoclassical theory by introducing a time constraint analogous to the budget constraint. He then, formulated an empirical model in which both time and fares were included as explanatory variables; and obtained estimation parameters of business and non business air travel demand functions separately. Both Time Series and Cross-sectional data were used in estimating these parameters.

The second very important element was introduced by K Lancaster [16] : a new and more fruitful theory of consumer behavior could be devised by assuming that travel services can be entirely characterised by their attributes, and that the consumer desires to maximize a utility function which has commodity attributes as its arguments rather than quantity of the various commodities consumed.

If Z is a vector of quantities of various attributes,
X a vector of quantities of various commodities,
P the vector of corresponding prices and
Y the level of income,
then the consumer desires to maximize the utility function U(Z) subject to:

$$Z = G(X)$$
$$PX \leqslant Y$$
$$X, Z \geqslant 0$$

where G(X) describes the production of attributes by commodities.

One attempt,using some of these ideas,was made by Quandt and Baumol [17] . In their original "Abstract" mode model*, designed to estimate the passengers travel volume in the North East Corridor, they used a single equation to represent the modal choices for all modes.

(*) They now prefer to call it "Attribute Mode".

The originality of the approach was that demand for travel by a mode was not dependent on the name of the mode, but on the characteristics describing the level of service offered by each mode. Every mode was characterised by several variables specifying its supply attributes. These variables were defined relatively to the level of that variable attained by the best mode. The model form was hypothesised as an adaptation of the gravity model form and different from the SARC-Kraft model [18] , the first study to estimate demand relationship for all modes. Contrarily to SARC-Kraft's model in which separate demand functions were estimated for each mode (one equation for each mode), Quandt and Baumol's model evaluated parameters by pooling data across modes. Both models, as well as their further developments, assumed constant elasticities and cross-elasticities.

The dependency on the best mode in Quandt and Baumol's model is one of the main weaknesses of this model. The empirical application of the Abstract mode has not been successful. The model was initially using observations for 16 city pairs in California across 3 modes. The estimated parameters showed higher variances when data were pooled across the modes than when models were specified for each mode.

Although widely applied, the validity of this pure Abstract mode can be questioned. It can be debated whether the resulting elasticities, since they pertain to an average of the travel market, are sufficiently representative of any individual mode.

Other disadvantage of the Abstract mode was that it could not account for certain non quantifiable but very real characteristics of each mode. Some travellers, for instance, simply do not like train while others are fearful of the air travel.

In order to surmount these weaknesses, Quandt and Young [19] incorporated dummy variables for different modes and routes which made these models less abstract.

In general, current applications of these models have not been conspicuously successful. The use of SARC-Kraft's and Quandt and Baumol's models in the North East Corridor Project yielded forecasts that were considered to be implausible.

One major theorëtical problem encountered by these models resulted from the fact that none of these models took into account the idea that travel was a <u>derived demand</u>. They all were based on the application of demand theory to travel. Thus, given an improvement in the quality of services offered by all modes, total travel demand would be expected to rise substantially without any reference to what that demand would be servicing.

Finally, the recent improvement, in the theory underlying the deterministic models, was carried out by Gronau [4] in his PhD dissertation at Columbia University later published as a book in 1970. Gronau developed Lancaster's theory by defining the utility function over an "activity" space. As an example of activity is the "visit" which constitutes a combination of transportation, accommodation, meals, travel time, Like Young [15] , he considered the time as a constraint analogous to the income constraint which not included in Lancaster's theory. Therefore, the consumer's optimizatiom problem for travel activities was written as follos:

$$\text{Max } U = U(Z_1, Z_2 \ldots\ldots\ldots Z_n)$$

subject to:

$$\sum_{i=1}^{n} P_i \; X_i = Y$$

$$\sum_{i=1}^{n} T_i = T_0$$

where:

P_i : prices of product X_i
Y : consumer's monetary travel budget
T_i : time investment for X_i
T_0 : consumer's travel time limit

The specification of Gronau's model was as follows:

$$X_{ij} = \beta_j \, \Pi_{ij}^{\beta_{1j}} \, Y_i^{\beta_{2j}} \, e^{U_{ij}}$$

where:

X_{ij} : number of trips to destination j by family in income group i
Π_{ij} : generalised trip cost = $P_j + k_i T_j$
Y_i : average income for income in group i
U_{ij} : disturbance term

However, these models suffer from a common problem. They treat only one aspect of the market, namely the demand for travel, generally ignoring the supply. This omission has two short comings:
- One is theortical, the omission of the supply restricts the scope of the analysis, since demand for and supply of goods and services are generally inter-related in real world.
- The other is statistical, the ignorance of the supply influence on the demand might yield biased coefficients due the two way causality.

2.2 PROBABILISTIC MODELS THEORY

Probabilistic choice models constitute a relatively new area of research. They find their development in the field of urban transportation planning. According to Stopher [20] , their theortical approach is founded in two disciplines dealing with behavior: the economics of consumer behavior and the psychology of choice behavior.

The psychologist view is that humain decisions are probabilistic in nature, but are based upon evaluation of utilities. These utilities provide a basis for estimating the probabilities of choice for each alternative. The individual is assumed to have an exact "measurable" utility. In this approach formulized through the application of Luce's axiom* of the independence of irrelevant alternatives, any alternative a has a utility U_{ia} comprising attributes of the alternative X_a modified by the attributes of the individual S_i such as:

$$U_{ia} = U(S_i, X_a) \qquad (1)$$

On the other hand, the economics' view is that the individual is being deterministic maximizer. In the economic theory, formulated in Mc Fadden's paper, each individual is assumed to have a utility function as follows [21] :

$$U_{ia} = V(S_i, X_a) + \mathcal{E}(S_i, X'_a) \qquad (2)$$

where:

- $V(S_i, X_a)$: the common utility of alternative a for individual i
- $\mathcal{E}(S_i, X'_a)$: the individual utility of alternative a for individual i with socioeconomic characteristics S_i

This model is termed random utility model because of the existence of a random term in contrast with the strict utility model. While in the first approach (equation 1), the individual is assumed to assess his utilities of each alternative, in the second one (equation 2) he is presumed to choose the alternative k which maximizes the utility U_{ik}.

(*) The axiom states that the relative odds of choosing one alternative over another is unaffected by the presence or absence of any additional alternative in the set.

In the psychological approach, direct correlation between probability of choice and utility is hypothesised (Luce's axiom):

$$\frac{P_a^i}{P_b^i} = \frac{U(S_i,X_a)}{U(S_i,X_b)} \qquad (3)$$

Assuming an exponential form $U(S_i,X_a) = \exp V(S_i,X_a)$ where $V(S_i,X_a)$ is linear in X_a and M available alternatives, the standard multilogit model is derived from (3):

$$P_j^i = \frac{\exp\left[V(S_i,X_j)\right]}{\sum \exp\left[V(S_i,X_k)\right]} \qquad (4)$$

In the economics approach, however, the probability that an individual drawn randomly from the population with attributes S will choose the alternatives k is:

$$P_k^i = \Pr\left\{ V(S_i,X_k) + \mathcal{E}(S_i,X_k) > V(S_i,X_j) + \mathcal{E}(S_i,X_j) \right\}_{\forall j \neq k} \qquad (5)$$

From this equation, Mc Fadden [21] derived the multilogit model form analagous to the form (4).

Therefore, as Stopher [20] points out, it may be asserted that multilogit model is an intuitively and theoretically acceptable model structure for a choice model, regardless of whether the choice model is derived from a strict utility approach or a random utility approach.

According to Horwitz [22] , however, the assumption, contained in the equation (2), that the random components of utilities are independently and identically distributed implying that individuals with identical observable characteristics have identical tastes, constitute a potentially severe restriction of the types of behavior that can be treated by the logit model.

A more general model can be obtained by assuming that the random components of utilities are <u>multivariate normally</u> distributed, producing the <u>multinomial probit model</u>. The probit model permits tests to vary among individuals with identical observable characteristics and allows effects of unobserved variables to be correlated across alternatives.

Hence, the multinomial probit model allows treatment of a considerable broader range of behavior than the multilogit model does. However, despite its generality, multinomial probit received little use in travel demand analysis, because of its computational intractability.

On the contrary, because of its relative simplicity the multilogit model has been applied successfully in a wide variety of forecasting contexts (Kanafani [23] , Benakiva & Richards [24] , Horwitz [25]).

As previously stated, "disaggregate behavioral demand models", as they came to be called, were generally applied in mode choice context though there exist other choice contexts. In a paper written in 1975 Kanafani [23] presented a multinomial choice model where the alternatives were the choice of fares types on the North Atlantic market. Again, in another short haul transportation demand, Kanafani [26] developed a model where travelers faced a choice between various routes in the California Corridor.

2.3 CONCLUSION

The theory of travel demand has progressed by several different stages in the two last decades. The first important change was the assumption that the travel choice emerges out of the individual's optimizing behavior: so, as individuals were presumed to be utility maximizers, the demand for travel ought to be positively related to incomes and negatively to prices of transportation services. The second considerable innovation was brought up by Lancaster's theory of consumer behavior. The general concept in an economic sense of the consumer choice independence from product names or labels led to the development of "Abstract modes" models mainly applied to the North East Corridor project.

These deterministic models derived their structure from the gravity models formulation, used aggregate data across city pairs and were generally calibrated by means of regression technique.

Probabilistic models, on the other hand, were founded in two disciplines dealing with behaviour, the economics of consumer behaviour and the psychology of choice behaviour. They made use of disaggregate individual data, and were calibrated by maximum likelihood. Contrarily to the above models, they did not assume the constancy of demand elasticities, but supposed a constant total traffic by all modes. Therefore, the improvement of attributes of one mode was presumed to capture traffic from all other modes.

CHAPTER 3

STRUCTURAL FORMULATIONS & METHODS OF ANALYSIS

3.1 STRUCTURAL FORMULATIONS

One of the most critical steps, in the demand modeling process, is the establishment of the functional form of the model. Three important types of structure are recorded in the literature:

- Linearity vs non Linearity formulation
- Gravity formulation
- Single equation vs Multi-equation formulation

3.1.1 Linearity vs non Linearity formulation

A model is said to be linear when the dependent variable is a linear combination of the explanatory variables; e.g:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \dots + \beta_n X_n \qquad (1)$$

Some models, however, are not linear in the variables, but can be linearized by applying appropriate transformations. Such models are termed, intrinsically, linear models. The most common forms of these models are the multiplicative or logarithm linear form, the exponential or semi logarithm form:

- Multiplicative form:

$$Y = \beta_0 X_1^{\beta_1} X_2^{\beta_2} \dots X_n^{\beta_n} \varepsilon \qquad (2)$$

This model can be transformed to:

$$\text{Log } Y = \text{Log} \beta_0 + \beta_1 \text{Log } X_1 + \beta_2 \text{Log } X_2 + \dots + \beta_n \text{Log } X_n + \text{Log} \varepsilon$$

- Exponential form:

$$Y = \exp(\beta_0 + \beta_1 X_1 + \ldots + \beta_n X_n)\mathcal{E} \qquad (3)$$

This model can be transformed to:

$$\text{Log } Y = \beta_0 + \beta_1 X_1 + \ldots + \beta_n X_n + \text{Log}\mathcal{E}$$

The choice of the general form of the demand model depends, primarily, upon such factors as historical traffic trends, data consideration, time period of forecast; and certain desired properties of the demand function, such as constant or variable elasticity of demand.

The linear additive form is more suitable if the predictor variables are expected to be independent. conversely, a multiplicative form may be justified if a strong collinearity among these variables exists. Similarly, a choice between the multiplicative and the exponential form may be determined from an analysis of the desired properties of the elasticity demand. And, while in the multiplicative form the coefficients represent partial elasticities, in the exponential form the elasticities are function of the variables themselves.

In running his first differences models, over 17 UK domestic routes for the period 1954 - 1966, Ellison [27] recorded highly instable results, many perverse signs, and bad fits. He attributed the failure of these models to the exponential growth formulation, in being an inaccurate assumption to make, concerning the behavior of the trend on domestic routes. He then, calibrated the models on a logarithm form, over the UK trunk routes, and obtained more consistent results. The fit was significant and the coefficients borne the right signs.

In the case of intrinsically non linear model(i.e, non linearizable), the use of the least squares procedure may be difficult. Under certain assumptions, non linear models can be handled using maximum likelihood technique [3] .

3.1.2 Gravity formulation

Developed by analogy with Newton's gravity equation, Gravity models constitute the striking example of the models characterised by their structural formulation. Having both a long history and continuing usefulness in forecasting trip generation and zonal interchanges, these models were the starting point for the development of intercity passenger models. The original formulation is based upon the assumption that travel demand, between two city pairs, is proportional to their populations, and inversely proportional to the distance between them:

$$T_{ij} = K^{\alpha_0} \frac{(P_i \ P_j)^{\alpha_1}}{D_{ij}^{\alpha_2}} \qquad (4)$$

From this simple formulation different and more complicated forms have emerged. Probably, the most elaborate Gravity model, yet used for an analysis of intercity passengers demand, was the Kraft-SARC's Model [18] .

In his PhD dissertation, Verleger [6] took an original step in defining the mass variable. Instead of the product of city pairs populations, this variable had the following structure:

$$M_i = \sum X_i^k \ e^{(\beta_i \ Y_i^k)} \qquad (5)$$

Where: X_i^k : group of individuals in city i

$e^{(\beta_i Y_i^k)}$: propensity to travel for individuals i

Y_i^k : average income for the group i (affecting the propensity to travel in an exponential manner by giving greater weight to higher income levels within the population).

Finally, starting from a Gravity model formulation, Blummer [5] developed his so called "Mode Sensitive Model":

$$T_{ij} = b_0 \left(\frac{M_i M_j}{D_{ij}} \right)^{b_1} I_{ij}^{b_2} f_{ij}^{b_3} \qquad (6)$$

Where:

T_{ij} : Air traffic between i and j

M_i : effective buying income in city i

M_j : effective buying income in city j

D_{ij} : distance between i and j

f_{ij} : share of Air travel

I_{ij} : total transportation inpedance

The total transportation impedance is defined as follows:

$$\frac{1}{I_{ij}^2} = \frac{1}{I_{ija}^2} + \frac{1}{I_{iju}^2} + \frac{1}{I_{ijr}^2}$$

Where I_{iju}, I_{ijr} are the impedance for Auto and Rail respectively, and I_{ija} the Air impedance, defined as follows:

$$I_{ija} = \text{block time} + \text{waiting time} + \text{fare} \times V$$

Where V = hours/dollars = 1/value of time

This approach was quite original and departed from the concept regularly used in the split models; and which consisted of estimating the total traffic, and then, the fraction of the traffic captured by a particular mode. Instead, a hybrid single equation, formulated in (6), was used in which the component $f_{ij}^{b_3}$ stood for the Air share and the remaining components stood for the total traffic. Besides, the total transportation impedance I_{ij} had several desirable properties: its structure combined the impedances of all modes into a single figure; which helped to ovoid the multicollinearity, common to the models entering each mode separately (Kraft, Young), and to prevent the consideration of the "best" mode (Abstract Mode).

3.1.3 Single equation vs Multi-equation formulation

Almost all models referred to , were constructed on a single equation formulation. There are, however, multi-equation model structures, such as the FAA (Federal Aviation Authority) macroeconomic forecasting model consisting of three equations [28] . Two of these equations were calibrated by means of ordinary least squares technique. The third equation was an identity. The three endogenous variables were:

- RPM : revenue passenger miles
- ENP : revenue passenger enplanements
- OPS : Air carrier itinerant operations

Other multi-equation structures were attempted, such as Eriksen Model [8], but were calibrated in a <u>recursive</u> manner, instead of a simultaneous one.

The models, we develop in this study, are truly simultaneous, and the multi-equation structure is their mainoutcome. We do not introduce, here, the simultaneity concept which will be widely discussed later.

Note only, that depending on the nature of the relationship, between the dependent variable and the explanatory variables, single equation formulation may not be an appropriate structure. The introduction of one or more equations may appear necessary when a two-way dependency, between the demand and any other independent variable, exists.

3.2 METHODS OF ANALYSIS

The fourth characteristic, that may distinguish between types of models, is the method of analysis applied to their calibration. These methods are:

- Ordinary least squares regression analysis (OLS)
- Simultaneous equations techniques analysis
- Discriminant analysis
- Logit and Probit analysis

Since they are explained in many textbooks, and since Logit and Probit models have already been referred to, in Chapter 2, we will briefly present the first three methods.

3.2.1 Ordinary least squares regression analysis

This method attempts to relate the variation in traffic to the variation of some logically relevant variables, such as economic variables, demographic variables, transport factors. The calibration involves the empirical manipulation of various functional relationships. The aim is to find the relationship that produces the least deviation between the computed demand and the actual observed demand. This method is the most commonly employed; and multiple regression packages are available almost everywhere. As will be explained next, other estimation procedures are more appropriate when the assumptions of OLS are violated.

3.2.2 Multi-equation techniques analysis

In the general linear model:

$$Y = \beta_0 + \beta_1 X_1 + \ldots + \beta_n X_n + \varepsilon \qquad ,$$

one major assumption of the validity of the OLS is that $COV(X_i, \varepsilon) = 0 \quad \forall i$. This means that the explanatory variable X_i must be uncorrelated with the error term. If this assumption is violated, it follows the unsatisfactory consequences:

- the estimates β_i are biased, inconsistent, and inefficient
- the estimate of the variance of ε is biased
- the usual t and F tests are not appropriate

A necessary condition for $COV(X_i, \varepsilon) = 0 \quad \forall i$ is that the variables X_i should be truly exogenous. When this is not verified, it yields what is often called "Simultaneous Equations Bias", and several problems arise:

- the problem of identification of the parameters of individual relationships
- the problem of estimation

One, therefore, should choose a Multi-equation structure for the model, and an estimation other than the OLS technique. There are several methods for this purpose; the most common are:

- The reduced form method or Indirect Least Squares
- Two-Stage Least Squares (2SLS)
- Limited Information Maximum Likelihood
- Three-Stage Least Squares (3SLS)
- Full Information Maximum Likelihood (FIML)

The first four methods are named single equation methods, because they are applied to one equation of the system at a time. The 3SLS and FIML are called <u>system methods</u>, because they are applied to all the equations of the system <u>simultaneously</u>.

Since the models developed in this study involves 2SLS and 3SLS, a general presentation of these techniques is provided in Part III. The selection between alternative multi-equation estimation techniques is not straightforward. The choice may depend, in part, upon the purpose for which the estimated system of equations is to be used. Simultaneous equations packages are not widely available and their computer costs are generally high.

3.2.3 <u>Discriminant analysis</u>

This technique is one of the earliest to be considered in the choice models calibration. It was originally developed in the field of biology [20] . It is based upon the assumption that there exists, in a population two or more distinct subgroups that can be distinguished by means of a discriminating function.

The Leeds study [29] adopted this technique, as a method of analysis, in order to isolate the factors influencing the choice of travel mode, between Air and Rail. It consists in establishing a mathematical function, in terms of travel and travelers variables, which best separates the two types of passengers.

In addition to considering each route separately, the Leeds study attempted to obtain two discriminant functions, for work and non work travels covering the 5 routes considered. The examination, of the discriminant functions obtained, suggests that the model choice decision process varies from route to route; and indicates the absence of a general law, governing a traveler's choice of mode.

3.3 CONCLUSION

The choice of the general form of a model depends, primarily, upon such factors as historical traffic trends, data consideration,and certain desired properties of the demand function. Most of travel demand models were of logarithm-linear form. This form is attractive because it is easy to conduct, and because its estimated coefficients represent elasticities.

Gravity models formulation was the starting point of the intercity passengers demand models which found their application in the North East Corridor Project. Many sophisticated forms have been developed since, from the simple original one.

Most of the travel demand models were constructed on a single equation form. Only a few were structured as Multi-equation models. Instead of being simultaneously calibrated, these models were recursively estimated.

Ordinary Least Squares are the most commonly used techniques of calibration in travel demand models. However, when a two-way causality between the dependent variable and any explanatory variable exists, the application of OLS is no longer valid. Then, the introduction of additional equation(s) may appear more appropriate. For such a Multi-equation structure, many calibration techniques are open to the modeler such as Indirect Least Squares, Instrumental variable , 2SLS, 3SLS, Limited or Full Information Maximum Likelihood. The selection between these techniques may depend upon the modeler's purpose and the nature of the data available.

Discriminant Analysis, Logit and Probit Analysis are the methods applied in Choice models. They were originally developed in the field of Biology. Empirical tests of Discriminant Analysis seem to confirm that this techni- may be inferior to Logit and Probit Analysis.

CHAPTER 4

FACTORS EXPLAINING TRAVEL DEMAND

4.1 AIR TRAVEL DEMAND FACTORS

These factors are of two types : exogenous variables which are determined independently to the transport system and upon which the Airline management has no control; endogenous variables defined within the system and which are under his control.

For the following presentation these factors will be categorized into:

- non transport factors
- transports factors

Note, however, that transport factors are not necessarily endogenous : e.g, the fare is a transport factor, but can be endogenous.

4.1.1 Non transport factors

Apart from traditional simple models such as Judgemental and Extrapolation models (based upon clock time factor only), most of the Air travel demand models are seeking to identify the causality of the demand. The original idea,underlying the development of what came to be called Econmetric models, was that socio-economic factors were the elements that generated the need for travelling. Businessmen travel by reason of developing theirown business, and because of economic expansion at home and abroad. Personal travelers make a trip either for leisure or shopping, or for VFR(visiting friends and relatives), or for satisfying intellectual curiosity needs. Therefore, modelers retained socio-economic factors as variables likely to explain the demand.

Income

Income has been recognized as the main element determining the consumption of a good or a service. Several economic factors measuring the level of income, such as GNP(Gross National Product), GDP(Gross Domestic Product), Personal Income, National Income, Personal Disposible Income, Corporate Profits before tax, Total Personal Consumption Expenditure, etc.., are generally investigated in the modelling process. Some might be more meaningful than others with regard to the purpose of the model.

- Business travel demand, for instance, is thought to be better interpreted by factors such as GNP, Export, Import, the level of investment abroad, and the balance of payments; and is considered to increase in recession situations. However, the economic factor that is generally selected is the one that provides the best fit.

- Personal travel demand is generally thought to be related to the personal income, since personal travelers unlike most businessmen have to bear the cost of their travel expenses. Some models incorporate the income distribution variable; the idea being that Air travel is a superior good, and hence, Air travelers are likely to belong to the highest income brackets. As recalled earlier, Verleger [6] disaggregated the travelling population by income, and gave greater weight to higher income groups within the population by assuming their propensity to travel as an expential factor of their income.

Many studies were carried out, providing interesting information on travel demand by tranche of incomes. The Roskill Commission [30] figures, for non business travelers, are an interesting source from which income elasticities could be derived. There is a general belief that income elasticities are not constant, neither from a range of income population to another in a given point of time, nor from one period to the other in a given range of income population. The French and UK Study [31], for instance, revealed that the higher the income, the higher the income elasticity.

Inflation

Inflation is generally considered as a factor influencing the demand. In the specification of the model structure, some questions invariably arise concerning the explanatory variables. Should permanent income rather than current income, or price expectation rather than market price, or fixed rather than current prices be used? All these questions are, in fact, related to whether to take into account the inflation or not.

According to Thompson [32] "raw data are always better than deflated data. When data are deflated there is always some loss of detail that may significantly mask the identification of underlying trends". However, most studies have taken account of the inflation. This was generally achieved by use of various deflators for price and income.

Probably the only model, that attempted to treat inflation as a separate variable, was the model developed at MIT in 1975 by Viteck and Taneja [12]. Its main purpose was to determine whether or not high inflation rates were significant factors in estimating the demand. The answer was positive and according to the authors, inflation should be included, explicitly, as a separate factor.

Occupation and social structures

Many surveys argued that the travelers' characteristics were important elements in the travel decision, and should, therefore, be retained in the modelling process. These characteristics being : occupation, education, age, life cycle, family structure. The Survey (source: The

Registrar General's Statistical Review 1972) showed that the propensity to fly was greater in the :

- 35-45 age group, for business travelers
- 50-55 age group, for holiday travelers
- 35-55 age group, for VFR travelers

It also revealed that 70% of leisure passengers, travelling from London by Air in 1972, had no children under the age of 15 in their household.

Probably the most successful model thattook into account these relevant factors was the Port of New York Authority Model [33] , known as the Cells Model. The main purpose of this model was to determine whether a person was a "flier",and if so, how many trips were taken each year. The market was divided into a large number of travel "cells", for personal and business travel. Personal travelers cells were classified by age, occupation, education, and income; and business cells by industry, occupation, and income. A total of 134 individual cells were defined.

City characteristics

Among the factors influencing the demand, the characteristics of the cities were also retained. Recreational cities are likely to attract more leisure travelers than business ones. According to Quandt [34] "cities with high concentration of financial intermediaries, educational and governmental institutions and other service industries give rise to more travel per capita than cities with predominantly manufacturing industries".

Real but not so clear is the influence of a factor that came to be called "community of interest" between cities. An original step was taken by Brown and Watkins [35] in adopting the number of long distance telephone messages and the number of international passengers between city-pairs as proxies for community of interest.

4.1.2 Transport factors

Many studies have recognized the importance of trip cost, trip time, comfort, safety, reliability, and convenience as relevant factors affecting Air travel demand. While some of these elements, such as trip cost and trip time, are relatively easy to measure; others, more qualitative than quantitative, are rather hard to evaluate.

Fare

Obviously, one of the key elements in travel demand is the price factor that responds to the simple law, making the consumer buying more at lower prices and less at higher prices. The consideration of fare variable always raises the question of which fare to choose. Should first class fare, coach fare, or discount fare be used?

Most models selected the average fare actually paid by the traveler. This average was obtained, first, by aggregating the various fares applicable to a given route; then, by taking a second average calculated on the basis of the various routes grouped together (Total Aggregate Models). According to Lippke and Stewart [36] the elasticity, calculated on the basis of an average fare, is biased and the exact value of the average price elasticity is lower than the estimated one.

Fare elasticity, particularly in Total Aggregate Models, could hardly be interpreted; since it reflects the behavior of an imaginary individual(part businessman, part tourist, etc..)paying just an imaginary fare, and therefore bears little relationship to the personal behavior.

In their Report at MIT in 1976 [14] the authors tested three types of fares for comparative purpose: standard fare, estimated fare, and actual average fare.

Their results showed no significant differences between the three types.

Since one of the main purpose in travel demand models is the estimation of fare elasticities, many studies attempted to analyse the factors influencing these elasticities.

- A well known factor is the <u>characteristics</u> of the traveler. It has always been stated, for instance, that business travelers are less fare elastic than personal travelers. This assumption has most often been supported by empirical investigations. Probably, one of the earliest studies, segmenting the travel market by trip purpose (business/personal), was conducted by Young in his PhD dissertation at the University of Washington in 1966. The results, in both Time Series and Cross-sectional analysis, corroborated the above assumption.

- Another factor, suspected to influence fare elasticity, is the trip length. It is sometimes argued that Air travel has better substitutes for short trips than for longer ones; henceforth, the sensitivity to fares should decline as the length of the journey increases. In a Paper, given at the American Statistical Association Annual Meeting at Fort Collins (Colorado) in 1971, Brown and Watkins [35] attempted to test this assumption by an empirical investigation. A Regression analysis was carried out in which the fare coefficient was made function of five dummy variables standing for the distance group of the city-pair, as follows:

$$\text{FARE}(\alpha_0 + \alpha_1 D_1 + \alpha_2 D_2 + \alpha_3 D_3 + \alpha_4 D_4 + \alpha_5 D_5)$$

Where D_1, D_2, D_3, D_4, D_5 were dummy variables corresponding to the range of distances.

The Regression used Cross-sectional data of 438 domestic city-pairs for the year 1969; and the results showed no tendency for fare elasticities to decrease numerically with the trip length. However, although the use of dummy variables seems quite reasonable, the approach is questionable. It would have been more appropriate to apply this approach to the only personal travelers market, since business travelers are less sensitive to the fare factor.

Other studies related the fare elasticities to the density of the market. In his Model Verleger [6] concluded that fare elasticities had a tendency to be more uniformely significant in high density markets, while in the low density markets few were significant. He suggested that elasticities decreased as traffic increased.

Quality of service factor

Because of the regulated nature of Air transportation services, which takes prices out of the Airline control, the market share belonging to each competing carrier is mainly determined by the quality of service provided. In his theory for Domestic Airlines Economics R Simpson [37] defined the quality of trip by a vector quantity in four major categories:

Q_1 : trip time　　Q_2 : trip reliability

Q_3 : trip comfort　　Q_4 : trip convenience

- Trip time : Probably the most important variable determining the level of service is the trip time. Many models considered the whole components of this variable (access time, waiting time, flying time, egress time). R Simpson defined the trip time as follows:

$$T = t_0 + t_1 d + \frac{t_2}{n} \qquad (1)$$

Where: t_0 : constant

t_1 : $\frac{1}{v}$ where v=speed

t_2 : constant to express average waiting time

n : frequency of services

As the speed is a technical performance, usually beyond the Airlines control, the only way to improve the quality of service is to reduce the waiting time, access and egress times through an efficient scheduling process and better facilities at the terminals.

The inequal importance, given to the travel time factor by the travlers, has raised the question of whether and to what extent this importance is related to the characteristics of the travelers. As stated earlier, the first model to analyse the concept of time on a theoretical ground was Young's Model [15] . Gronau [4],later on, estimated a monetary value of time for various income groups

From the Simpson equation (1), the <u>frequency of services</u> n becomes a quality of service variable. In this model, since the inverse of the frequency has the dimension of time, the frequency of services n was included in the trip time variable. In fact, n constitutes the effective quality of service variable under the Airlines control; since neither the flying time nor the access or egress times are truly under such a control, while the waiting time is a function of the frequency.

Contrarily to Simpson's Model, others explicitly introduced the frequency of services as a separate variable. In the MIT Report [14] , the authors tested the frequency as a factor determining the level of service. They defined this variable as the product of the number of flights offered in each direction. However, as this variable did not take account of the time departure and the number of stops in a given trip, they developed an index called LOS (Level Of Service), scaled from zero to one. This index represented the ratio of non stop jet flight time to the average total passenger trip time.

The comparison of the model containing the frequency of services variable and the one using LOS variable revealed the superiority of the second model over the first one. But with LOS Model, rather restrictive assumptions were implicitly presumed : the uniformity of the Air travel demand throughout the day and the infinite seat capacity.

- Trip reliability : is measured in terms of probability.

Q_2^1 : probability of space available, which is a function of LF (Load Factor) and the spread of the distribution of requests for the flight. Thus, considering LF linked to the quality of service through this measure Simpson defined an upper bound for LF to maintain a desired availability and named it LF_{MAX}.

Q_2^2 : probability of time departure and arrival.

Q_2^3 : probability of cancellation .

Q_2^4 : probability of injury/death (or damage/loss)

- Trip comfort : including all on board services such as meals, stewardesses, etc..

- Trip convenience : covering items such as time and cost to get reservations, to get tickets, and to pay for the trip.

These variables are kept at practically the same high level by the Airlines and, therefore, could hardly be considered as important factors in the Airlines competition. Besides, they are very difficult to measure.

4.2 MODAL COMPETITION FACTORS

The last section reviewed the factors explaining the travel demand, in a unimode context (Air mode) without reference to any mode competition. The present section discusses the common factors traditionally considered by the Choice Mode Models. These models seek to interpret the choice decision in terms of mode's attributes and user's characteristics. The mode's attributes involve variables such as time and trip costs; and the user's characteristics refer to the socio-economic features of the traveler. The earliest of these models were developed in the United Kingdom by Stopher [38], Quaramby [39], and Leake [40]; and in the United States by Lisco [41], and Warner [42].

4.2.1 Modes' characteristics

Time variable

The consideration of time variable in Modal Choice Models usually raises two questions:

- Which part of the journey time, the time variable refers to?
- What is the best relationship between the time by each mode(ratio or difference)?

With regard to the first question, Watson [43] observed "It seems reasonable to treat time spent on different activities as different, for time spent in a car seems different from time spent waiting in a line or waiting between vehicles".

Stopher and Lisco took a different view and selected total journey time; while Quaramby considered it more appropriate to separate in-vehicle time from time spent walking and waiting.

The second question concerns the expression of the relative journey time variable. Basically, it is possible to express this variable as difference or ratio of time by different modes. According to Watson, since the model is an attempt to represent actual behavior, it seems better to use differences; for the traveler is more likely to perceive relative times in terms of differences rather than in terms of ratios. A difference formulation is, therefore, based upon a subjective judgement about the way in which people think. However, Warner and Leake used time ratio whereas Quaramby and Lisco preferred time difference.

Cost variable

The cost variable raises the same questions as the time variable, referred to above. And, as in the case of time variable, it is impossible to provide a sound objective justification for the selection of any formulation of this variable. Again, Stopher adopted the cost difference whereas Quaramby took the cost ratio. In his Discriminant analysis, Leake found that the cost ratio gave more significant results than the cost difference.

4.2.2 Travelers' characteristics

Previous studies incorporated a number of variables reflecting the characteristics of the traveler. The most important are :

Income

It is generally agreed that the level of a subject's income affects his choice of travel modes. Modelers handled income variables in at least two ways :

- By stratification : Many analysts believe that each income group has a decision process that should be modeled separately, and the operational results of this point of view is that the sample is divided into income groups that are analysed as distinct samples. The Leeds Study [29] , for instance, found that the journeys for work by Air were undertaken by the highest household income levels; while non work journeys by Rail were travelled by the lowest income level groups. Medium household income levels vary from route to route. The disadvantage of this method is that a large sample is required to make such stratification possible.

- In combination with other variables : The attempt, to explain the complexities of the process by which income affects modal choice, has led some analysts to conclude that income operates through or in conjuncture with other variables, such as cost, time and comfort. In some cases, it is argued, the cost difference is important only in relation to income, so that a given cost difference will produce a different reaction in higher-income-group traveler than in a lower one [43]. A suggested solution is to combine the income and the cost variables to produce a new variable, say, the ratio of cost difference to income. In other cases, it is argued, it is the time difference that is perceived differently by different income groups. High-income-group travelers are more sensitive to this difference,because they value their time more highly (assuming that the value of time rises with income).

Age/sex

The age and sex of the traveler have been included in a number of models. But,there is no easy way of predicting their effect; and it is difficult to relate their cofficients to any specific real world interpretation. Accordingly, their inclusion is only judged on the basis of fitting consideration. The proportions of travelers, less than 25 years and above 64 years of age, were found by Leeds Study lower on Air than on Rail for both work and non work journeys. 60% of non work journeys were being made by men.

Other factors such as household size, car availability, party size, were also investigated as explanatory factors in the Choice Mode process.

4.3 CONCLUSION

The factors explaining Air travel demand are numerous. Different economic factors aimed to measure the level of income were investigated such as GNP, GDP, Personal Income,Personal Disposable Income, Personal Consumption Expenditure, etc.. The selection among these factors was generally founded on the basis of statistical fit.

Many surveys outlined the importance of the traveler's characteristics as factors explaining the decision to travel. The well known "Cells Model" of Port of NewYork Authority introduced all these relevant characteristics (business and personal characteristics, age, occupation, education, income).

The city characteristics, as well as the so called "community of interest" were also considered in Air travel demand models.

Among the transport factors, fare was recognized as one of the most important. Many empirical studies supported the assumption that business travelers were less fare elastic than non business ones. Finally, other factors more qualitative than quantitative such as comfort, reliability, convenience found little application.

The Choice Mode process is dictated by such factors as Mode's attributes and travelers' characteristics. Time and cost variables were invariably investigated in Choice Mode Models. The same questions have often raised such as : which part of the journey time or the journey cost these variables referred to; and which relative value, ratio or difference, to consider. Modelers took different views, though it is quite difficult to provide a sound objective justification for the selection of any formulation.

Travelers' characteristics such as income level group, age, sex, party size, and car availability were investigated, in many models, as factors influencing the choice mode decision.

PART II

US DOMESTIC MARKET ANALYSIS

INTRODUCTION

As an illustration of the literature review, discussed in Part I, we provide, in this Part, an analysis of an econometric model, developed at MIT by the Flight Transportation Laboratory in 1976. This analysis concentrates, essentially, on three points.

First, different statistical tests highlight the statistical deficiencies from which this model is suffering, illustrating, therefore, the common problems encountered in Time Series, Cross-Sectional, and Pooled models such as Multicollinearity, Heteroscedasticity, and Serial Correlation.

Second, this analysis outlines, through this model, the main weakness of Aggregate models, namely the implicit assumption of homogeneity of the market. Indeed,series of CHOW tests, applied to different markets, reveal the significant differences between the Aggregate models of these markets and the Region-pairs models, corresponding to their individual routes.

Third, the particular specification of the model, as a single demand equation, illustrates the major handicap of most of the models discussed, so far, in the literature review. By considering only one aspect of the market, the demand for travel, they ignore the effect of the supply onto the demand. This may lead to biased, inconsistent, and inefficient coefficients estimates.

Finally, attempts to overcome the two-way dependency supply/demand problem are achieved by the introduction of a second equation to the original model, and the application of 2SLS (Two-Stage Least Squares) as a means of calibration.

For this purpose, the analysis is conducted as follows:

Chapter 5		ANALYSIS OF THE STUDY
	5.1	Presentation of the study
	5.2	Statistical evaluation of the study
	5.3	Conclusion
Chapter 6		AGGREGATION MARKET ANALYSIS
Chapter 7		NEW MARKET DEFINITION AND SPECIFICATIONS
	7.1	Aggregation Business/Leisure
	7.2	Variables analysis by individual routes
	7.3	Simultaneous Equations Specification

CHAPTER 5

ANALYSIS OF THE STUDY

In this chapter, we analyse the study: "A methodology for determining the relationship between Air transportation demand and the level of service", conducted at MIT by Eriksen, Scalea, and Taneja.

5.1 PRESENTATION OF THE STUDY

The objective of the MIT Study is to relate the level of Air transportation activity, measured by the number of origin to destination passengers carried in a number of specified markets, to a set of economic, demographic, and scheduling variables.

-Market selection

Since an Airport generally attracts demands from a larger area than its respective city, the authors chose to define the markets as Region-pairs rather than the more traditional City-pairs. For this aim, they used a study conducted by the Bureau of Economic Analysis in 1972, in which the United States was divided into 173 regions (organised, primarly, along county lines). Of 15,000 possible Region-pairs, a 3 x 2 x 3 cross-classification sample was chosen from a matrix of market density, extent of competition (between Airlines), and length of haul.

-Market density

This factor was defined by the average number of passengers carried each way each day. Data was obtained from the 1970 CAB Origin/Destination Survey. Three classifications were retained:

Low Density : less than 50 passengers per day
Medium Density : 50 to 200 passengers per day
High Density : more than 200 passengers per day

- Competition factor

The markets were defined as monopolistic and competitive. A monopolistic market is a market in which the second most active Airline carried less than 10% of the number of passengers carried by the most active Airline (using 1970 as the base year).

- Length of haul factor

Five classifications were defined:

Ultra-short haul : routes with distances 260 km
Short haul : routes with distances 260-560 km
Medium haul : routes with distances 560-880 km
Long haul : routes with distances 880-2410km
Ultra-long haul : routes with distances 2410 km

The final sample contained data from 58 Region-pairs over a 16 year period span, 1959 - 1974.

- Variables

The variables selected are the following:

LOS : the level of service index is a dimensionless number scaled from zero to one, representing the ratio of non-stop jet flight time to the average total passenger trip time.

FARE : is the average of the standard coach fare deflated by the consumer price index.

BPI : the buying power index is an aggregation of three important socio-economic characteristics of a given area selected to reflect the level of economic activity in the specified region.

$$BPI = .5I_i + .3R_i + .2P_i$$

Where:

I_i = percentage of national income in area i

R_i = percentage of national retail in area i

P_i = percentage of national population in area i

- Model specification

The general form of the model is:

$$DMD = \beta_1 \; FARE_2^{\beta_2} \; BPI^{\beta_3} \; LOS^{\beta_4} \, \varepsilon$$

which is an intrinsically linear function that can be put into standard linear additive form by the appropriate logarithmic transformation of the data. This form of the equation can, then, be estimated using Ordinary Least Squares:

$$\text{Log DMD} = \text{Log}\,\beta_1 + \beta_2 \text{Log FARE} + \beta_3 \text{Log BPI} + \beta_4 \text{Log LOS} + \text{Log}\,\varepsilon$$

The equation estimated with the 58 Region-pairs was:

$$\text{Log DMD} = 12.2758 \underset{(.1461)}{-.4941\text{Log FARE}} \underset{(.0746)}{+.3226\text{Log BPI}} \underset{(.1707)}{+1.2672\text{Log LOS}}$$

R^2=.75

The results corresponding to the different aggregation schemes are shown in Table 5.1 .

This is the point at which the MIT Study ends. The following section begins with the next step: testing the validity of the model. The most critical part of any research modeling effort is not fitting the model, but rather testing whether the correct specification had originally been selected.

5.2 STATISTICAL EVALUATION OF THE STUDY

Although choosing to use a linear model ia a typical approach to demand analysis, Linear Regression imposes strict assumptions which must be met in order that the estimation procedure can be valid.

For the purpose of this test analysis, we concentrate on the following assumptions of OLS:

- The residuals ($e = Y - \hat{Y}$) must be random variables with a mean of zero (<u>Normality</u>)
- The variance of the error term (e) must be constant; i.e, the dispersion of e around its mean zero must not increase or decrease systematically over time or with changes in the levels of the independent variables (<u>Homoscedasticity</u>)
- The error terms, must be independent over time. Knowledge of the residual in time t, must tell nothing about its size in time t+1 (<u>No Serial Correlation</u>)
- Finally, the independent variables must not be highly correlated with each other (<u>No Collinearity</u>)

<u>Normality of the errors distribution</u>

One test for the normality of the error term distribution is the CHI-SQUARE goodness of fit test. This test determines how closely the observed frequency distribution of the error term fits the normal probability distribution, by comparing the observed to the expected frequencies.

For this purpose, a Regression analysis, over 50 Region-pairs, is run with the specification (1); and its residuals are standardized. Recall that standardizing a residual consists of dividing its value by the standard error of the estimate (i.e, standardized residual = $\frac{e_i}{SE}$).

Table 5.2 displays, in column 2, the observed frequencies of the standardized residuals corresponding to different ranges of magnitudes. The expected frequencies from the normal distribution are given in the third column. The remainder of the table is used to compute the value of the CHI-SQUARE. The further the expected value is from the observed values (the larger value of χ^2), the poorer is the fit of the hypothesized distribution.

In the present case, $\chi^2 = 19.33$. This value is greater than the critical χ^2 value: $\chi^2_{(.95,4)} = 9.49$. Therefore, we may conclude that the error terms of the model are not normally distributed. However, it is difficult to determine whether the violation of this assumption is serious, because non normality is a difficult condition to interpret. This non normality is often the results of other departures from the model; so, even though the sample size is large, it is difficult to decide whether the normality is real, or is a function of inappropriate regression formulation, or is a non constant variance.

Constant variance

A common way to check for Heteroscedasticity is to plot the residuals against the estimated $\hat{Y}$'s, and then, examine the shape. Constant variance would make the residuals appear as a solid horizontal band.

Fig 5.1 and Fig 5.2 are plot of residuals against the estimated values, for a monopolistic market and a competitive one. While Fig 5.1 corresponding to the monopolistic market does not show any serious divergence from constant variance; Fig 5.2 , however, clearly indicates the existence of specification error. Indeed, Fig 5.2 exhibits two groups of plots strikingly distinct. The first group, corresponding to the lowest values of the demand in the competitive market, reveals systematic negative residuals; that is to say, these observations are overestimated. On the contrary, the second group, corresponding to medium values of the demand, shows positive residuals; which means that their respective observations are underestimated.

Time dependency of errors terms

The lack of indepecdency of the error terms over time, Autocorrelation, can lead to the loss of the efficiency properties of the estimators. This makes the coefficients appear more significant than they really are. It does not, however, affect their unbiasedness or consistency.

The usual test, for Autocorrelation, is the Durbin - Watson test which compares the size of the difference between adjacent (in time) residuals to the absolute value of the residual itself. In order for the test to be valid, the observations must be in some meaningful order by time. This is impossible with Aggregate models, because there is more than one observation per time period: one for each individual market. As a result, the DW test on the Aggregate (50 Region-pairs) model, though very low (=.329), may not be of great signification. However, an investigation of the data, disaggregated onto individual markets, shows the existence of Serial Correlation in most routes, where the corresponding DW values are very low (see Table 5.3; 5.4; 5.5 and Table 5.6).

Multicollinearity

The problem of Multicollinearity is not so much in detecting its existence, but rather in determining its severity. The seriousness of Multicollinearity can, usually, be examined in the correlation coefficients of the explanatory variables. How high can the correlation coefficient reach before it is declared intolerable? This is a difficult question to answer, since it varies from case to case, and among different analysts.

To identify which individual variables are most affected by Collinearity, an F - distributed statistic, proposed by Farrar and Glauber [44] , tests the null hypothesis (H : variable X_j is not affected against the alternative, H_1 : variable X_j is affected).

This test is defined as follows:

$$F_{(n-p,p-1)} = (r^{*j} - 1) \left(\frac{n - p}{p - 1}\right)$$

Where. r^{*j} denotes the jth diagonal element of the inverse matrix of simple correlation coefficients. The null hypothesis H_0 is rejected if the calculated F - distributed statistic exceeds the critical $F(\alpha, n-p, p-1)$, where n is the number of independent variables including the constant.

In the present case, the correlation matrix corresponding to the Aggregate model (50 Region-pairs) computed is:

	LOS	FARE	BPI
LOS	1.000	.326	.600
FARE	.326	1.000	.334
BPI	.600	.334	1.000

The inverse matrix of the matrix above is:

$$\begin{vmatrix} 1.606 & -.227 & -.888 \\ -.227 & 1.157 & -.250 \\ -.888 & -.250 & 1.616 \end{vmatrix}$$

where:

$$r^*(LOS) = 1.606$$

$$r^*(FARE) = 1.157$$

$$r^*(BPI) = 1.616$$

Applying the test above, one gets:

$$F_{(LOS)} = (1.606 - 1)\left(\frac{800 - 4}{4 - 1}\right) = 160.8$$

$$F_{(FARE)} = (1.157 - 1)\left(\frac{800 - 4}{4 - 1}\right) = 41.7$$

$$F_{(BPI)} = (1.616 - 1)\left(\frac{800 - 4}{4 - 1}\right) = 163.4$$

All the calculated F statistics exeed the critical $F(.05, 800-4, 4-1) = 8.53$. Thus, the null hypothesis can be rejected, and the alternative that <u>all variables are significantly affected by Multicollinearity can be accepted</u>.

5.3 CONCLUSION

The analysis of the MIT Model reveals many violations of the assumptions of OLS, namely Non Normality of the error terms distribution, Heteroscedasticity (though not too serious), Serial Correlation, and Multicollinearity.

These violations have some undesirable effects on the estimators' characteristics, such as biasedness, and inefficiency. Many reasons could be suggested for these defects, in particular, the wrong specification of the model and the omission of important factors in the specification.

In fact, as will be explained in the next Chapter, one unique aggregate equation is clearly inappropriate for describing the nature of demand and predicting new demands in any individual market.

MARKETS	Cst	LOS	FARE	BPI	R^2
MONOPOLISTIC	12.133	1.264 (.078)	-.444 (.060)	.165 (.032)	.65
COMPETITIVE	12.042	1.340 (.099)	-.379 (.066)	.332 (.038)	.74
ULTRA-SHORT	6.748	.689 (.098)	.935 (.279)	.382 (.040)	.79
SHORT	15.159	1.446 (.073)	-1.208 (.334)	.105 (.034)	.76
MEDIUM	12.909	1.183 (.069)	-.667 (.368)	.272 (.063)	.76
LONG	13.440	1.258 (.086)	-.705 (.203)	.433 (.033)	.86
ULTRA-LONG	15.209	.927 (.078)	-1.338 (.183)	.633 (.040)	.82

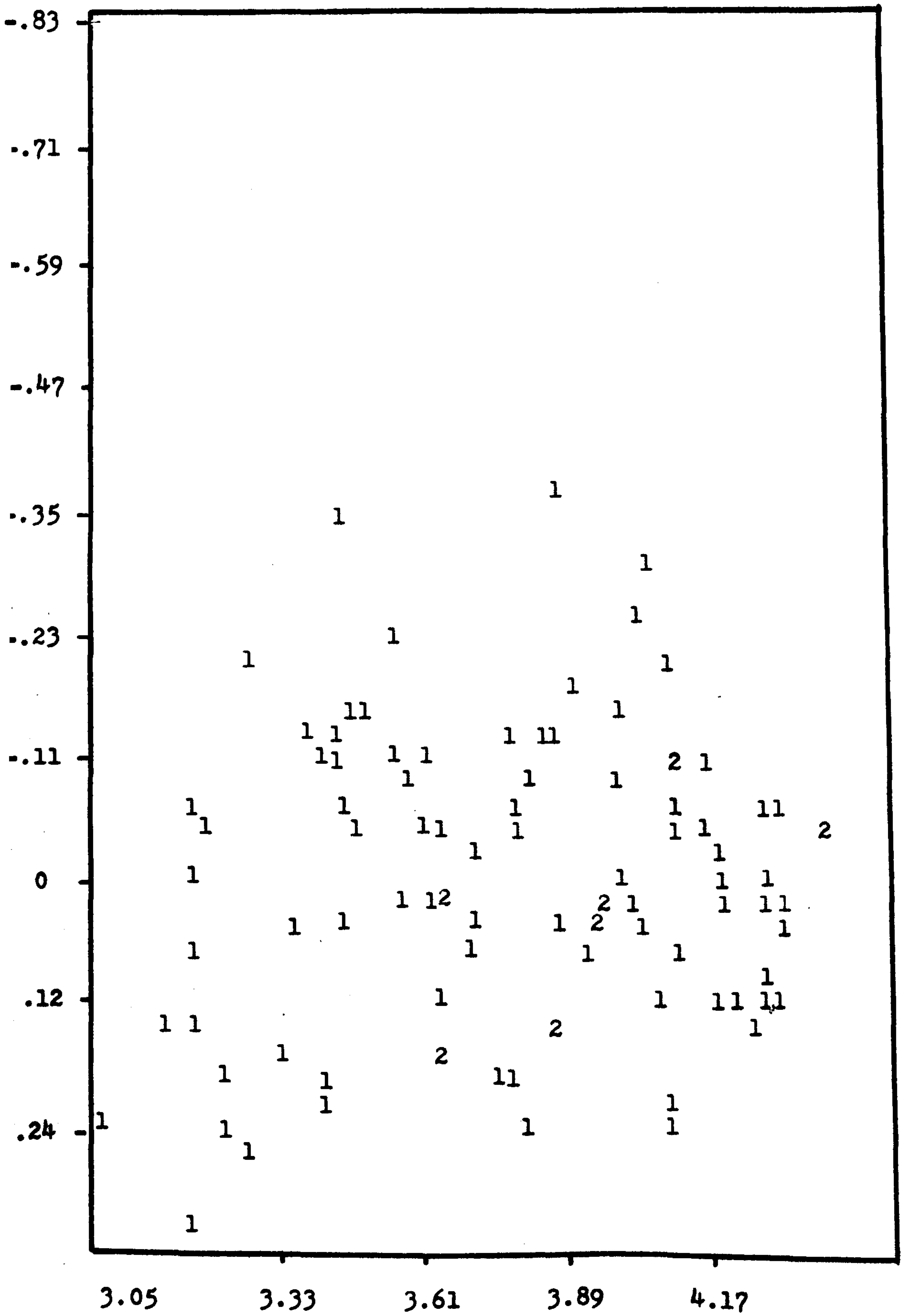
Table 5.1

MIT MODEL RESULTS

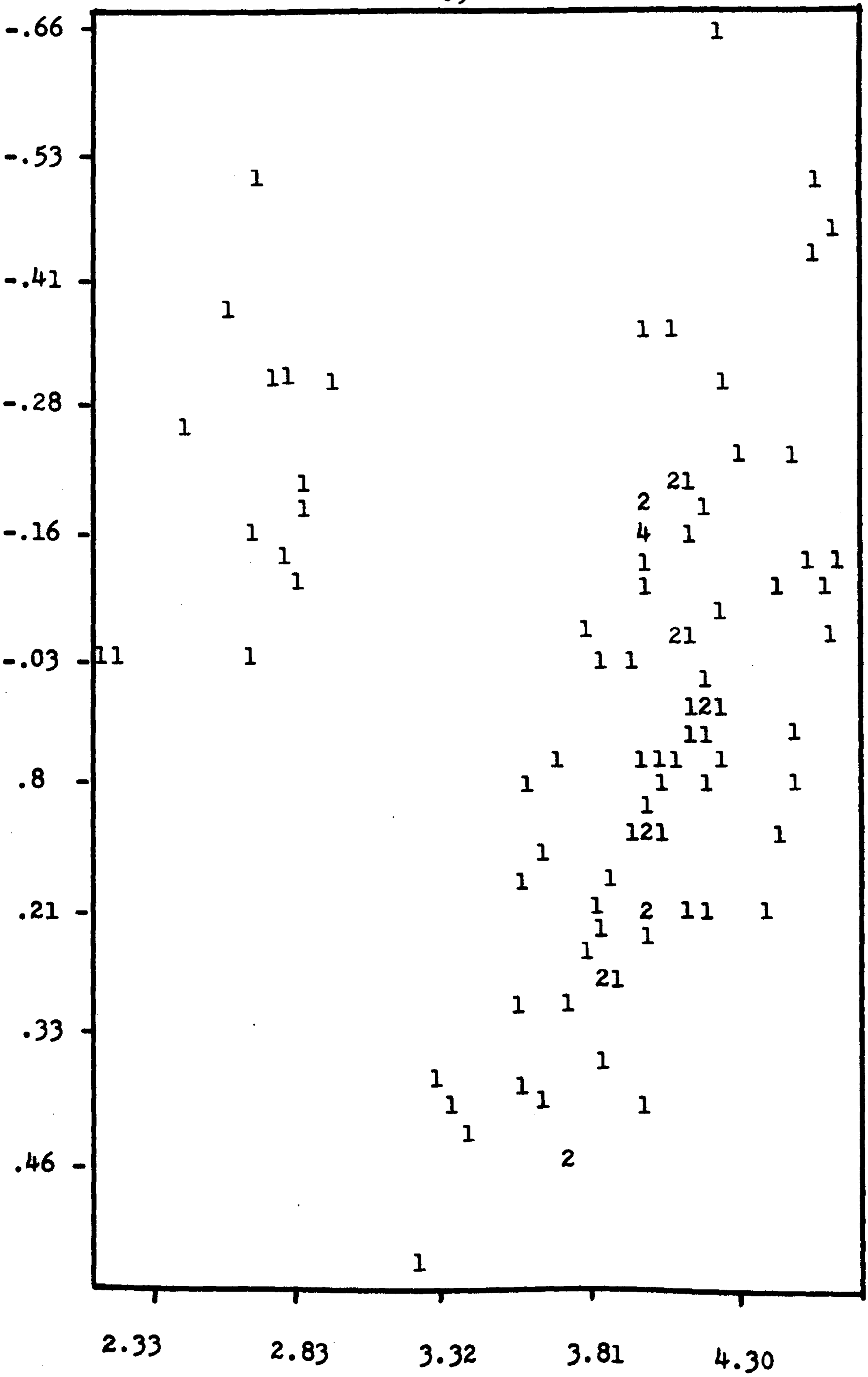
CHI-SQUARE COMPUTATION

RANGE OF STANDARDIZED residuals		O_i OBSERVED FREQUENCIES	E_i EXPECTED FREQUENCIES	$\frac{(O_i - E_i)^2}{E_i}$
-	-1	118	126.96	.632
-1	-.5	91	119.84	6.920
-.5	0	179	153.20	4.380
0	.5	183	153.20	5.840
.5	1	107	119.84	1.370
1		122	126.96	.194
TOTAL		800	800.00	19.33

Table 5.2



<u>Figure 5.1</u> PLOTS OF RESIDUALS VS COMPUTED DEMAND MONOPOLISTIC MARKET



<u>Figure 5.2</u> PLOTS OF RESIDUALS VS COMPUTED DEMAND
COMPETITIVE MARKET

RP Idx	Cst	LOS	FARE	BPI	R^2	SE	DW
1	3.32	.131 (.101)	-.667 (.526)	-.821 (.614)	.34	.087	1.01
2	5.88	-.001 (9.990)	-1.393 (1.074	3.416 (1.699)	.28	.143	.57
3	6.91	.331 (.164)	-2.110 (.577)	3.955 (.649)	.96	.043	2.48
4	8.10	.511 (.153)	-2.468 (.682)	1.339 (.370)	.99	.033	1.10
5	1.04	.868 (.180)	-4.040 (.872)	4.789 (2.236)	.85	.114	.75
6	2.35	.502 (.265)	-.080 (.288)	4.218 (1.158)	.97	.059	.60
7	8.92	.893 (.251)	-.082 (1.155)	-4.201 (2.730)	.81	.111	.77
8	2.31	.611 (.195)	1.398 (.600)	.709 (4.989)	.74	.064	1.01
9	1.41	.093 (.095)	1.993 (1.735)	4.366 (2.223)	.47	.111	.61
10	4.11	.426 (.137)	-1.175 (.527)	3.683 (.860)	.97	.063	.70
11	6.59	.478 (.134)	-.998 (.674)	2.427 (.596)	.95	.049	.53
12	5.99	1.070 (.100)	-.807 (.934)	.458 (1.885)	.91	.063	.45
13	2.41	.730 (.285)	-1.619 (.756)	-1.995 (1.999)	.78	.116	1.36
14	8.05	.965 (.180)	-1.872 (1.169)	1.789 (.829)	.91	.075	.50
15	7.11	.657 (.113)	-1.596 (.578)	1.152 (.375)	.95	.048	.76

Table 5.3 **REGION-PAIRS MODELS**

RP Idx	Cst	LOS	FARE	BPI	R^2	SE	DW
16	8.45	.342	-2.569	1.380	.94	.076	.37
		(1.459)	(1.005)	(1.124)			
17	7.44	.074	-.965	-3.501	.30	.115	.81
		(.484)	(1.120)	(1.847)			
18	6.15	.832	-2.652	-.148	.38	2.471	.95
		(.340)	(1.717)	(.779)			
19	2.92	.746	-.820	-3.618	.81	.088	2.20
		(.213)	(.597)	(2.040)			
20	4.88	.208	-.538	3.276	.99	.027	1.33
		(.087)	(.509)	(.271)			
21	7.14	.044	-2.101	2.378	.94	.046	.67
		(.123)	(.938)	(.374)			
22	8.42	.013	-1.210	3.770	.95	.048	.57
		(.543)	(.799)	(1.118)			
23	7.44	.684	-.301	-2.890	.84	.051	2.53
		(.153)	(.299)	(.438)			
24	11.82	.521	-1.897	-1.998	.88	.052	1.51
		(.128)	(.624)	(.497)			
25	15.08	.401	-6.453	2.362	.91	.077	.76
		(.184)	(.784)	(1.383)			
26	11.02	.472	-2.702	-1.516	.85	.066	1.50
		(.128)	(.846)	(1.274)			
27	8.18	.758	-2.431	-.335	.88	.060	1.61
		(.183)	(.696)	(1.247)			

Table 5.4

REGION-PAIRS MODELS

RP Idx	Cst	LOS	FARE	BPI	R^2	SE	DW
28	8.39	.381 (.106)	-1.483 (1.456)	-8.515 (2.313)	.88	.097	1.93
29	12.50	.027 (.188)	-4.666 (1.046)	.101 (.283)	.97	.074	2.11
30	1.55	.147 (.133)	1.436 (.738)	-2.899 (.653)	.93	.047	1.71
31	4.72	-.008 (.089)	-.437 (.242)	-2.663 (.327)	.96	.024	1.44
32	5.62	.492 (.083)	-1.315 (.756)	-2.638 (.402)	.96	.033	1.35
33	5.59	.351 (.217)	-1.387 (.447)	1.753 (1.470)	.46	.081	1.05
34	4.35	.219 (.080)	-.241 (.795)	2.047 (.886)	.60	.064	1.60
35	4.91	1.307 (.145)	-.079 (.177)	.300 (.838)	.92	.065	1.14
36	5.70	.505 (.078)	-1.640 (.598)	.006 (.060)	.95	.78	1.01
37	7.79	1.270 (.080)	-1.756 (.660)	.893 (.400)	.66	.289	1.31
38	5.00	.759 (.086)	-.384 (.348)	1.954 (.521)	.98	.039	2.79
39	14.58	.170 (.238)	-5.915 (.978)	-.916 (1.062)	.89	.087	.97

Table 5.5

REGION-PAIRS MODELS

RP Idx	Cst	LOS	FARE	BPI	R^2	SE	DW
40	6.52	-.038 (.179)	-1.176 (.324)	1.804 (.437)	.92	.059	1.15
41	10.17	.614 (.088)	-3.350 (.580)	4.970 (1.420)	.92	.067	1.01
42	11:20	.971 (.229)	-4.040 (1.423)	1.975 (3.260	.90	.096	.75
43	5.63	.755 (.187)	-1.146 (1.343)	-1.708 (1.054)	.88	.079	2.28
44	5.93	.605 (.134)	-.761 (.487)	-1.867 (1.020)	.90	.042	1.70
45	5.43	2.054 (.568)	-.249 (1.443)	-3.003 (1.677)	.58	.132	.84
46	9.32	.623 (.132)	-2.739 (.880)	-.090 (.120)	.79	.112	1.49
47	8.26	.447 (.189)	-2.544 (.530)	1.558 (.428)	.96	.063	1.25
48	4.06	.343 (.111)	-.002 (5.609)	1.454 (.242)	.96	.042	1.10
49	4.09	1.176 (.393)	-1.608 (.640)	2.852 (1.550)	.74	.083	1.30
50	13.01	-.093 (.167)	-4.750 (.696)	1.574 (.906)	.96	.066	2.09

Table 5.6

REGION-PAIRS MODELS

CHAPTER 6

AGGREGATION MARKETS ANALYSIS

This chapter outlines the main weakness of Aggregate models, namely the assumption of homogeneity of the market. Indeed, these models considere the travel demand as a homogeneous unit related to the same parameters in all markets. For instance, the model, analysed so far, assumes constant elasticities throughout the 50 Region-pairs, regardless of the peculiarities of each individual one.

In an attempt to aggregate the domestic US market into different homogeneous sets, the authors suggested three classifications:

DENSITY	- Low density markets - Medium density markets - High density markets
COMPETITION	- Monopolistic markets - Competitive markets
LENGTH of HAUL	- Ultra-short haul markets - Short haul markets - Medium haul markets - Long haul markets - Ultra-long haul markets

The authors, then, conducted series of Regression analysis for these markets, recorded in Table 5.1 .

In this chapter, we go one step further; we analyse the subclassifications within each of the above classifications, and test whether the former constitute homogeneous markets. For this purpose, sets of markets, randomly drawn from each subclassification, as well as the individual routes, composing these markets, were analysed. Tables 6.1 (a,b) provide the list of the Region-pairs corresponding to each set.

Regression analysis, using equation (1), were run for the selected markets above, and their individual routes. Their results are displayed in Table 6.2 .

To show whether the equation, corresponding to a given market, is truly representive of the equations of the individual routes composing this market, a CHOW test was computed for each market and its respective routes. In other words, this test examines whether the individual routes observations and the corresponding aggregate market ones belong to the same regression line.

The CHOW test formula is as follows:

$$F_{p(k-1),(n-pk)} = \frac{(SSR - \sum_{i=1}^{k} SSR_i)/p(k-1)}{\sum SSR_i/(n-pk)}$$

Where:

SSR = sum of squares of residuals of pooled market

$\sum SSR_i$ = sum of squares of residuals corresponding to each route

p = number of estimated parameters (including constant)

n = total number of observations

k = number of sub samples (i.e, number of routes)

The above ratio is an F-distributed statistic, with p(k-1) degrees of freedom at the numerator, and (n-pk) degrees of freedom at the denominator.

The results of these computations displayed in Tables: 6.3; 6.4; 6.5, show the following values of:

$$F_{(p(k-1),(n-pk))}$$

Low density	F = 23.18
Medium density	F = 23.32
High density	F = 37.71
Monopolistic market	F = 11.43
Competitive market	F = 38.34
Ultra-short market	F = 26.41
Short market	F = 9.17
Medium market	F = 65.29
Long market	F = 16.58
Ultra-long market	F = 53.49

Therefore, since the computed F values are all higher than the critical ones, we conclude that Region-pairs models equations are significantly different from their corresponding Aggregate models equations. This may well be due to the fact that these subclassifications do not take account of the particular characteristics of the Region-pairs, and the different segmentations of the markets. A current assumption in Air demand is that travelers with dissimilar ecomomic, social, and demographic characteristics have different reactions towards traveling. While leisure travelers are generally more sensitive to the trip cost and the availability of complementary activities at the destination point; business travelers are more sensitive to the level of service: time of day schedule, number of flights available, comfort, reliability, and service on board.

Since the purpose of the authors is the determination of the relationship between the demand and the <u>level of service</u>, the classification adopted ignores an important factor in this relationship, namely the segmentation business/leisure. In fact, the "competition" factor classification considers Region-pairs, such as Washington-Houston, and New Orleans-Houston, as belonging to the same competitive market; and Detroit-Atlanta or Miami-Los Angeles , as belonging to the same monopolistic market. However, although considered as "competitive", a market such as Washington-Houston is certainly not segmented in the same way as New Orleans-Houston. While the former is most likely mainly business oriented, the latter is rather more leisure oriented. Equally, Detroit-Atlanta is mainly a business oriented market, while Miami-Los Angeles is essentially a leisure oriented one. This argumentation is also true for the density and length of haul classifications where business and leisure oriented markets are, sometimes, aggregated altogether. In the next chapter, we attempt to aggregate markets across this segmentation business/leisure.

LOW DENSITY MARKET		MEDIUM DENSITY MARKET		HIGH DENSITY MARKET	
Idx	REGION-PAIRS	Idx	REGION-PAIRS	Idx	REGION-PAIRS
1	BINGHAMPTON-ALBANY	3	CINCINNATI-NASHVILLE	8	DETROIT-CLEVELAND
9	ERIE-DETROIT	17	MILWAUKEE-CHICAGO	23	NEW YORK-CHICAGO
13	LINCOLN-OMAHA	12	LUBBOCK-DALLAS	21	NEWORLEANS-HOUSTON
18	MINOT-BISMARK	19	MINNEAPOLIS-FARGO	44	ST LOUIS-KANSAS
33	RICHMOND-NORFOLK	28	NORFOLK-PHILADELPHIA	49	WASHINGTON-NEW YORK
34	RICHMOND-RALEIGH	31	PETTESBURG-CINCINNATI	40	SAN FRANCISCO-LAS VEGAS
36	SACRAMENTO-RENO	32	PETTESBURG-DAYTON	4	DALLAS-ATLANTA

MONOPOLISTIC MARKET		COMPETITIVE MARKET	
Idx	REGION-PAIRS	Idx	REGION-PAIRS
2	NEWORLEANS-LAS VEGAS	8	DETROIT-CLEVELAND
3	CINCINNATI-ATLANTA	10	HOUSTON-DETROIT
5	DENVER-CLEVELAND	13	LINCOLN-OMAHA
6	DETROIT-ATLANTA	14	MENPHIS-KNOXVILLE
9	ERIE-DETROIT	18	MINOT-BISMARK
26	NEW YORK-KANSAS	20	NEWORLEANS-HOUSTON
27	OMAHA-CHICAGO	31	PETTESBURG-CINCINNATI

<u>MARKETS and corresponding REGION-PAIRS</u> Table 6.1a

ULTRA-SHORT HAUL MARKET

Idx	RE	REGION-PAIRS
8		DETROIT-CLEVELAND
9		ERIE-DETROIT
13		LINCOLN-OMAHA
17		MILKWAUKEE-CHICAGO
18		MINOT-BISMARK
23		NEW YORK-ALBANY
33		RICHMOND-NORFOLK
34		RICHMOND-RALEIGH

SHORT HAUL MARKET

Idx	REGION-PAIRS
2	CINCINNATI-NASHVILLE
12	LUBBOCK-DALLAS
19	MINNEAPOLIS-FARGO
21	NEWORLEANS-HOUSTON
31	PETTESBURG-CINCINNATI
32	PETTESBURG-DAYTON
44	ST LOUIS-KANSAS
45	ST LOUIS-OKLAHOMA

MEDIUM HAUL MARKET

Idx	REGION-PAIRS
3	CINCINNATI-ATLANTA
11	DALLAS-JACKSON
14	MENPHIS-KNOXVILLE
20	NEWORLEANS-ATLANTA
27	OMAHA-CHICAGO
30	PETTESBURG-ALBANY
35	ROCHEST-CHICAGO
40	SAN FRANCISCO-LAS VEGAS

LONG HAUL MARKET

Idx	REGION-PAIRS
4	DALLAS-ATLANTA
5	DENVER-CLEVELAND
6	DETROIT-ATLANTA
15	MIAMI-CINCINNATI
26	NEW YORK-KANSAS
37	SAN DIEGO-DENVER
47	WASHINGTON-HOUSTON
48	WASHINGTON-MIAMI

ULTRA-LONG HAUL MARKET

Idx	REGION-PAIRS
16	MIAMI-LOS ANGELES
22	NEWORLEANS-LAS VEGAS
25	NEW YORK-DENVER
29	PORTLAND-DALLAS
41	SAN FRANCISCO-OMAHA
42	SAN FRANCISCO-ST LOUIS
46	TUSCON-CHICAGO
50	WASHINGTON-PORTLAND

MARKETS and corresponding REGION-PAIRS Table 6.1b

MARKETS	Cst	LOS	FARE	BPI	R^2	SE	DW
MONOPOLISTIC	5.54	1.185 (.095)	-.621 (.100)	.382 (.041)	.82	.168	1.31
COMPETITIVE	3.97	1.575 (.162)	.547 (.075)	.080 (.059)	.83	.253	.48
LOW DENSITY	3.50	.382 (.079)	.012 (.089)	.377 (.047)	.72	.243	.38
MED DENSITY	4.45	.996 (.094)	-.065 (.076)	-.216 (.047)	.55	.183	1.32
HIGH DENSITY	4.84	1.055 (.113)	-.131 (.058)	.048 (.057)	.48	.170	.45
ULTRA-LONG	8.768	.781 (.071)	-2.440 (.201)	.703 (.035)	.90	.177	1.57
LONG	6.927	1.107 (.119)	-1.408 (.238)	.417 (.062)	.61	.253	1.05
MEDIUM	5.380	1.212 (.082)	-.502 (.385)	.067 (.064)	.67	.218	.64
SHORT	5.557	1.398 (.051)	-.560 (.150)	.008 (.037)	.86	.140	.51
ULTRA-SHORT	2.863	.668 (.100)	.920 (.228)	.450 (.037)	.88	.253	.89
TOTAL MARKET (50RP)	4.963	1.035 (.044)	-.370 (.037)	.433 (.021)	.74	.317	.33

Table 6.2

MARKETS AGGREGATION RESULTS

LOW DENSITY MARKET		MED DENSITY MARKET		HIGH DENSITY MARKET	
SSR=6.380		SSR=3.620		SSR=3.120	
n=112 p=4 k=7		n=112 p=4 k=7		n=112 p=4 k=7	
Idx	SSR_i	Idx	SSR_i	Idx	SSR_i
1	.091	3	.022	8	.049
9	.148	17	.159	23	.031
13	.161	12	.048	21	.025
18	.238	19	.093	44	.021
33	.077	28	.113	49	.084
34	.049	31	.007	40	.042
36	.073	32	.013	4	.013
$\sum SSR_i=.837$		$\sum SSR_i=.450$		$\sum SSR_i=.265$	
F=23.18		F=23.32		F=37.71	

CHOW TEST FORMULA

$$F=\frac{(SSR-\sum SSR_i)/p(k-1)}{\sum SSR_i/(n-pk)}$$

CHOW TEST COMPUTATIONS

SSR = sum of squares of residuals of the total market
SSR_i = sum of squares of residuals of the Region-pair i
p = number of estimated parameters(including constant)
n = total number of observations
k = number of subsamples (i.e, Region-pairs)
Idx = index of the Region-pair

Table 6.3

MONOPOLISTIC MARKET

$SSR=3.050$

$n=112 \quad p=4 \quad k=7$

Idx	SSR_i
2	.245
3	.022
5	.156
6	.042
9	.148
26	.052
27	.050

$\sum SSR_i = .715$

F=11.43

COMPETITIVE MARKET

$SSR=6.910$

$n=112 \quad p=4 \quad k=7$

Idx	SSR_i
8	.049
10	.048
13	.161
14	.067
18	.238
20	.008
31	.007

$\sum SSR_i = .578$

F=38.34

CHOW TEST COMPUTATIONS

Table 6.4

ULTRA-SHORT HAUL MARKET		SHORT HAUL MARKET		MEDIUM HAUL MARKET		LONG HAUL MARKET		ULTRA-LONG HAUL MARKET	
SSR=7.937		SSR=2.470		SSR=5.890		SSR=7.937		SSR=3.885	
n=128 p=4 k=8		n=128 p=4 k=8		n=128 p=4 k=8		n=128 p=4 k=8		n=128 p=4 k=8	
Idx	SSR_i	Idx	SSR_i	Idx	SSR_i	Idx	SSR_i	Idx	SSR_i
8	.049	2	.245	3	.022	4	.013	16	.069
9	.148	12	.048	11	.029	5	.156	22	.028
13	.161	19	.093	14	.067	6	.042	25	.071
17	.159	21	.025	20	.008	15	.028	29	.066
18	.238	31	.007	27	.050	26	.052	41	.054
23	.031	32	.013	30	.026	37	1.000	42	.110
33	.077	44	.021	35	.050	47	.048	46	.150
34	.049	45	.209	40	.042	48	.021	50	.052
$\sum SSR_i$=.912		$\sum SSR_i$=.9.17		$\sum SBR_i$=.294		$\sum SSR_i$=1.360		$\sum SSR_i$=.234	
F=26.41		**F=9.17**		**F=65.29**		**F=16.58**		**F=53.49**	

CHOW TEST COMPUTATIONS

Table 6.5

CHAPTER 7

NEW MARKET DEFINITION & SPECIFICATION

7.1 BUSINESS/LEISURE AGGREGATION

By their socioeconomic, geographic, and touristic characteristics, cities have different degrees of attractiveness for travelers. While cities, like Las Vegas, Miami, New Orleans are likely to be more attractive for tourists; on the contrary, cities like Houston, Seatle, Boston are probably more attractive for business travelers.

In order to outline these different characteristics, cities were grouped into three broad categories: Industrial, trade centers, and recreational. Whereas for many cities, it is not easy to decide which category they belong to, others are easy to classify under these three headings:

Industrial	Trade Centers	Recreational
Detroit		San Francisco
Cleveland	New York	Denver
St Louis	Chicago	New Orleans
Boston	Dallas	Miami
Seattle	Washington	Las Vegas
Kansas City	Atlanta	
Houston		

Given this classification, it is not unreasonable to assume that routes between the two first groups and the third one are mostly leisure, while routes between the two first groups are mainly business travelled.

In order to test this assumption, two sets of 10 routes each were selected. The first, called BSNS, involves routes between or within the two first groups; and the second, named LESR includes routes between the third and the two first groups. The Regression analysis, applied to these sets, provides the following results:

	Ct	LOS	FARE	BPI	R^2	SE
BSNS	5.02	1.377 (.089)	-.379 (.065)	.673 (.038)	.88	.205
LESR	.65	.689 (.104)	-1.329 (.084)	.554 (.051)	.77	.229

These results are interesting:

1 - All the variables bear the correct sign, and are, according to their t ratio values, significant at more than 99% level of confidence.

2 - The LOS and FARE variables are significantly different from one model to the other.

3 - In BSNS model, not only has FARE variable coefficient the smallest magnitude compared to LOS and BPI variables coefficients; but it has also the lowest t value, i.e, the lowest significance. Since the demand appears FARE inelastic (-.379), and highly LOS elastic (1.377), we should admit that this market is most likely business oriented.

4 - On the other hand, LESR model shows the opposite pattern, since FARE variable coefficient has the highest magnitude in absolute value (1.329), and the highest t ratio value, compared to LOS and BPI variables coefficients. Besides, LOS elasticity is less than 1. Therefore, this market shows a leisure characteristic, which confirms our previous assumption.

Having established this new classification business/leisure, we may need to test the homogeneity of each market within this classification, by verifying whether each market is truly representative of its corresponding individual Region-pairs. As previously, a CHOW test was used.

Once again, the results in Table 7.1 show that the two Aggregate markets are different from their corresponding Region-pairs.

What these CHOW tests, as well as those conducted earlier, indicate more than anything else, is the fact that one Aggregate equation is clearly inappropriate for explaining the variation of demand in any individual market. These differences are outlined in the following section.

7.2 ANALYSIS OF VARIABLES BY INDIVIDUAL ROUTES

In order to get a more accurate picture of the differences that exist between behavioral equations of different routes, it is worth examining the individual Regression results of Tables: 5.3; 5.4; 5.5; 5.6 , summarized in Table 7.2 and Table 7.3 ..

The strikingly heterogeneous nature of the markets appears clearly in these results. Four markets show no significant Regression relation at all; while others express a relationship based only on one variable (19 markets), or only on two variables (20 markets). Finally, only 7 markets have equations in which all the three variables are significant.

LOS appears as the most frequently significant variable, since it is significant 36 times out of 50 (i.e, 72%); while FARE and BPI variables are only significant 24 times and 20 times respectively (i.e, 48% and 40%), and bear the counterintuitive sign 3 times and 19 times respectively (i.e, 6% and 38%).

In general, the intra-market variances are more than 14 times smaller than the variance generated by the

Aggregate equation. Indeed, the variance corresponding to the total Aggregate equation is: (.317) = .100 (see Table 6.2). The weighted variance corresponding to the intra-market is:

$$\frac{\sum_{i=1}^{i=50} (SE_i)^2}{50} = .007$$

Where SE_i is the standard error of the Regression i.

This decrease in variance (.007 vs .100) indicates the advantage in terms of minimizing error that can be gained from a Disaggregation*. However, the results obtained by this Disaggregation are still not satisfactory, as manifested by the low frequency of the significance of the variables.

The conclusion to be drawn, from these results as well as from the statistical deficiencies recalled earlier: Multicollinearity, Heteroscedasticity, Serial correlation, is that an important factor is still missing. This may be due either to omitted variables or to a wrong specification in the MIT Model.

Next section discusses the specification of this model, and suggests a new structure : a Simultaneous Equations model formulation.

---

* Such a Disaggregation, however, is not always possible; particularly, when the observations by individual routes are not large enough to conduct meaningful Regressions, because of the low degree of freedom. This is the case of the Multi-equation models to be developed in Part III with the UK Domestic Market.

BUSINESS MARKET

SSR=6.556

n=160 p=4 k=10

Idx	SSR_i
4	.156
6	.042
7	.148
8	.049
10	.048
24	.032
26	.052
44	.021
47	.048
49	.084

$\sum SSR_i = .680$

F=28.80

LEISURE MARKET

SSR=8.180

n=160 p=4 k=10

Idx	SSR_i
5	.156
15	.028
16	.069
20	.008
21	.025
22	.028
39	.091
40	.042
41	.054
42	.110

$\sum SSR_i = .611$

F=41.24

CHOW TEST COMPUTATIONS

Table 7.1

REGION-PAIR INDEX	LOS	FARE	BPI	NUMBER OF SIGNIFICANT VARIABLES
1			*	0
2			x	1
3	x	x	x	3
4	x	x	x	3
5	x	x	x	3
6	x		x	2
7	x		*	1
8	x	*		1
9		*	x	1
10	x	x	x	3
11	x		x	2
12	x			1
13	x	x	*	2
14	x		x	2
15	x	x	x	3
16		x		1
17			*	0
18	x		*	1
19	x		*	1
20	x		x	2
21		x	x	2
22			x	1
23	x		*	1
24	x	x	*	2
25	x	x		2

Table 7.2

SIGNIFICANCE OF VARIABLES BY INDIVIDUAL ROUTES

* variable with a wrong sign

x significant variable at 90% level of confidence

REGION-PAIR INDEX	LOS	FARE	BPI	NUMBER OF SIGNIFICANT VARIABLES
26	x	x	*	2
27	x	x	*	2
28	x		*	1
29		x		1
30		*	*	0
31			*	0
32	x	x	*	2
33		x		1
34	x		x	2
35	x			1
36	x	x		2
37	x			1
38	x		x	2
39		x	*	1
40		x	x	2
41	x	x	x	3
42	x	x		2
43	x		*	1
44	x		*	1
45	x		*	1
46	x	x	*	2
47	x	x	x	3
48	x		x	2
49	x	x		2
50		x	x	2

Table 7.3

SIGNIFICANCE OF VARIABLES BY INDIVIDUAL ROUTES

* variable with a wrong sign
x significant variable at 90% level of confidence

7.3 SIMULTANEOUS EQUATIONS MODEL

As stated earlier, one major assumption for the validity of OLS (Ordinary Least Squares) is that the independent variables must be uncorrelated with the error term. This means that all independent variables must be truly exogenous. Otherwise, the coefficients obtained by the OLS are biased and inconsistent.

The FARE and BPI variables are not dependent upon Air travel demand; since the first one is fixed by the CAB (Civil Aeronautics Board), and the second one is a socioeconomic characteristic of the Region-pair. The level of service LOS is, however, dependent upon Air travel demand, since carriers would increase the number of flights and the level of service, if the demand in a given market were to increase. Hence, a two-way causality exists, and LOS is no longer a truly exogenous variable. In such case, the application of the Ordinary Least Squares is not appropriate.

In order to get around this difficulty, a second equation, in which Los is the dependent variable is added to the model. The new formulation is as follows:

$$D = \beta_0 + \beta_1 \, LOS + \beta_2 \, FARE + \beta_3 \, BPI + \varepsilon_1$$

$$LOS = \alpha_0 + \alpha_1 \, D + \alpha_2 \, DIST + \varepsilon_2$$

Where the variables in logarithm have the same meaning as previously; and where DIST is the inter-distance between two regions in a Region-pair.

To solve this Simultaneous Equations Model, a technique called 2SLS (Two-Stage Least Squares) has been applied. Since this technique as well as other Multi-equation calibration techniques are fully discussed later on, we provide, there-in-after, only a brief presentation of 2SLS.

This technique works in two stages as follows:

- The first stage, consists in determining the reduced form of the model, the form in which the endogenous variables (demand and LOS) are expressed only in terms of exogenous variables, FARE, BPI, DISTANCE. Then, this reduced form is solved, using Ordinary Least Squares. For each observation, the values of exogenous variables are substituted to obtain "observed" values of D and LOS in the following equations:

$$D = \gamma_{10} + \gamma_{11}\ FARE + \gamma_{12}\ BPI + \gamma_{13}\ DIST$$

$$LOS = \gamma_{20} + \gamma_{21}\ FARE + \gamma_{22}\ BPI + \gamma_{23}\ DIST$$

- The second stage, consists in performing the Ordinary Least Squares on the modified structural form, in which D and LOS variables are replaced by their values fitted in the first stage.

<u>Statistical Results</u>

Twelve models, corresponding to the following markets, have been calibrated in the new specification:

Ultra-short	
Short	Low Density
Medium	Medium Density
Long	High Density
Ultra-long	
Competitive	BSNS
Monopolistic	LESR

The results of these models are displayed in Table 7.4 .

As a general observation LOS elasticity, assumed purged of any correlation with the error term, has systematically increased in the new formulation.

Apart from the variation in the magnitude of the coefficients, the general conclusions are almost similar to those obtained by the authors in the single equation formulation. However, the following remarks should be retained:

- LOS elasticity increases from ultra-short to long haul, and decreases in ultra-long haul market; while it starts decreasing in long haul market in the original specification.

- In Leisure Market, FARE elasticity is lower than LOS elasticity.

- Finally, the DW test reveals the existence of positive Serial Correlation in all the runs, except in Monopolistic, Medium density, Ultra-long haul and Long haul markets models. This means that important factors are still missing.

In fact, one very important factor, the surface modes competition, is completely ignored in these models. Indeed, Air mode is treated as a totally independent mode, and no other substitute is assumed. However, while there are long distances transportation situations, where the multi-modal context becomes irrelevant, and where the Aircraft becomes the only feasible mode of transport; there are in turn, situations where surface modes are strongly competitive with Air mode. The ignorance of this factor may well be one of the reasons for the failure of these models, particularly, in ultra-short, short, medium haul markets.

7.4 CONCLUSION

The analysis of the MIT Model has been conducted under different angles:

1. Validity of the statistical assumptions

The original model manifests some departures from the necessary conditions for the application of the Ordinary Least Squares, such as the non Normality of the residuals distribution, their non constant Variance, their Serial Correlation, and the Collinearity of the variables.

2. Homogeneity of the markets

A serie of CHOW tests reveals that not only does the total Aggregate Market (50 RP) not constitute a homogeneous market, but also the classifications,by market density, competition, length of haul, business/leisure, do not yield separate homogeneous markets. Moreover, the variances of the error terms are lower than those of the total Aggregate (50 RP).

Besides, the analysis of the individual Region-pairs discloses the high variations of the elasticities from one region to another.

What these findings, essentially, indicate is the fact that one Aggregate equation is clearly inappropriate for explaining the variation of the demand in any individual market.

3. Model specification

The behavioral equation of the original model suffers from a two-way causality effect, due to the dependency of LOS variable upon the demand, which engenders biased, inefficient and inconsistent coefficients. To overcome this difficulty, a second equation with the level of service as the dependent variable has been added to the model with the 2SLS technique as a means of calibration. The results, however, still show positive Serial Correlation, particularly, in medium, short, and ultra-short haul markets models. This implies that some other explanatory factor is still missing.

Indeed, one major omission is the surface modes competition which is very strong in short distances, particularly, the Air/Car competition.

The main purpose of Part III is, precisely, the calibration of competition models formulated as Multi-equation models. The market involved in this modeling process is the Domestic UK Air and Rail Markets.

MARKETS	Cst	LOS	FARE	BPI	R^2	SE	DW
MONOPOLISTIC	6.05	1.495 (.187)	-.791 (.142)	.341 (.048)	.81	.171	1.86
COMPETITIVE	-3.31	2.887 (.410)	.503 (.097)	-.288 (.124)	.71	.323	.42
LOW DENSITY	5.64	1.615 (.370)	-.554 (.227)	.289 (.080)	.72	.449	.54
MED DENSITY	5.62	3.034 (1.420)	.078 (.208)	-.627 (.305)	.69	.437	1.61
HIGH DENSITY	-5.61	-15.330 (64.400)	1.164 (5.160)	-.585 (2.630)	.73	2.490	.31
ULTRA LONG	7.74	1.637 (.155)	-1.627 (.309)	.484 (.059)	.79	.255	2.35
LONG	7.76	2.570 (.282)	-1.288 (.349)	.261 (.094)	.73	.372	1.61
MEDIUM	5.32	1.917 (.130)	-.083 (.480)	-.120 (.083)	.49	.143	.65
SHORT	5.67	1.619 (.058)	-.511 (.158)	-.029 (.041)	.84	.185	.45
ULTRA-SHORT	4.32	1.619 (.058)	-.511 (.158)	-.029 (.041)	.84	.185	.76
BUSINESS	4.52	2.231 (.159)	.385 (.652)	.921 (.098)	.80	.401	.77
LEISURE	6.98	3.315 (.529)	-.632 (.225)	-.159 (.172)	.79	.509	.65

TWO-STAGE LEAST SQUARES ESTIMATES : DEMAND EQUATIONS

Table 7.4

		DENSITY			COMPETITION		LENGTH OF HAUL					TRIP PURPOSE	
Idx	REGION-PAIRS	L	M	H	MONO	COMP	U-Sh	Sh	Md	Lg	U-Lg	BSNS	LESR
1	BINGHAMPTON-ALBANY	x			x		x						
2	CINCINNATI-NASHVILLE	x			x			x					
3	CINCINNATI-ATLANTA		x		x				x				
4	DALLAS-ATLANTA			x	x					x		x	
5	DENVER-CLEVELAND		x		x					x			x
6	DETROIT-ATLANTA		x		x					x		x	
7	DETROIT-BOSTON			x	x					x		x	
8	DETROIT-CLEVELAND			x		x	x					x	
9	ERIE-DETROIT	x			x		x						
10	HOUSTON-DETROIT			x		x				x		x	
11	DALLAS-JACKSON	x			x				x				
12	LUBBOCK-DALLAS		x			x		x					
13	LINCOLN-OMAHA	x				x	x						
14	MENPHIS-KNOXVILLE	x				x		x					
15	MIAMI-CINCINNATI		x			x				x			x
16	MIAMI-LOS ANGELES			x	x						x		x
17	MILWAUKEE-CHICAGO		x			x	x						

REGION-PAIRS and corresponding CHARACTERISTICS **Table 7.5**

		DENSITY			COMPETITION		LENGTH OF HAUL					TRIP PURPOSE	
Idx	REGION-PAIRS	L	M	H	MONO	COMP	U-Sh	Sh	Md	Lg	U-Lg	BSNS	LESR
18	MINOT-BISMARK	x				x	x						
19	MINNEAPOLIS-FARGO		x		x			x					
20	NEWORLEANS-ATLANTA		x			x			x				x
21	NEWORLEANS-HOUSTON			x		x		x					x
22	NEWORLEANS-LAS VEGAS	x				x							x
23	NEW YORK-ALBANY			x	x		x						
24	NEW YORK-CHICAGO			x		x				x		x	
25	NEW YORK-DENVER			x		x					x		
26	NEW YORK-KANSAS			x	x					x		x	
27	OMAHA-CHICAGO			x	x				x				
28	NORFOLK-PHILADELPHIA		x		x			x					
29	PORTLAND-DALLAS	x			x						x		
30	PETTESBURG-ALBANY	x				x			x				
31	PETTESBURG-CINCINNATI		x			x		x					
32	PETTESBURG-DAYTON		x			x		x					
33	RICHMOND-NORFOLK	x			x		x						
34	RICHMOND-RALEIGH	x			x		x						

<u>REGION-PAIRS and corresponding CHARACTERISTICS</u>

Table 7.6

		DENSITY			COMPETITION		LENGTH OF HAUL					TRIP PURPOSE	
Idx	REGION-PAIRS	L	M	H	MONO	COMP	U-Sh	Sh	Md	Lg	U-Lg	BSNS	LESR
35	ROCHEST-CHICAGO		x			x			x				
36	SACREMENTO-RENO	x			x		x						
37	SAN DIEGO-DENVER		x		x					x			
38	SEATLE-DENVER		x		x					x			
39	SEATLE-SAN DIEGO		x		x					x			x
40	SAN FRANCISCO-LAS VEG			x		x			x				x
41	SAN FRANCISCO-OMAHA	x			x					x			x
42	SAN FRANCISCO-ST LOUIS		x		x						x		x
43	ST LOUIS-DAYTON	x			x			x					
44	ST LOUIS-KANSAS			x	x			x				x	
45	ST LOUIS-OKLAHOMA	x				x			x				
46	TUCSON-CHICAGO		x			x				x			
47	WASHINGTON-HOUSTON		x			x				x		x	
48	WASHINGTON-MIAMI			x		x				x			
49	WASHINGTON-NEW YORK			x		x		x				x	
50	WASHINGTON-PORTLAND	x				x					x		

REGION-PAIRS and corresponding CHARACTERISTICS **Table 7.7**

PART III

UK DOMESTIC MARKET ANALYSIS

INTRODUCTION

Part II provides an analysis of the MIT Model, and suggests a Multi-equation specification structure for the original model. However, the ignorance of the Surface Modes Competition renders the short haul market results questionable. This part is aimed to bridge the gap by constructing several Modal Competition Models that estimate Air and Rail demands traffic over 7 Londoner routes.

The purpose of this modeling process is threefold :

- To establish a behavioral relationship evaluating the traffic demand by each mode.
- To relate this demand to some supply factors under the control of the carrier, so as to enable him to act upon the demand through these controllable factors.
- To derive unbiased, more consistent, and more efficient structural estimates coefficients, representing level of service, fares, and income elasticities.

Consequently, in order to meet the above objectives, the present models have the following characteristics :

- They are Modal Competition Models.
- The demand, by each mode, is partly expressed as function of the frequency of services variable which is under the carrier control.
- In order to combat the Simultaneous Equations Bias due to the two-way dependency supply/demand, the supply endogenous factors are expressed, in the supply equations, as dependent variables. 2SLS and 3SLS are applied as a means of calibration, so as to provide unbiased, more consistent,

and more efficient estimates coefficients.

The restriction of the competition to the Air and Rail modes only is essentially dictated by data consideration problems. It was originally intended to conducted this model building in a pure Time Series analysis. However, due to the low degrees of freedom, consequent to the small sample data, and to the Multi-equation structure nature of the models, it was necessary to combine Cross-sectional and Time Series data, so as to derive meaningful elasticities. In order to achieve a reasonable data combination, an aggregation by length of haul is undertaken.

Nevertheless, pure Time Series models are also estimated for the 7 individual routes under study. This has been made possible by use of the Abstract Mode approach which has the advantage of increasing substantially the degrees of freedom by aggregating data across modes for each route.

Finally, pure Air travel demand models of two types are constructed :

- Pure Air business travel demand over the UK Domestic market.
- Pure Air Time Series for 3 individual trunk routes.

This model building process is set up throughout 9 chapters summarized in the following :

- The first, Chapter 8, begins with the definition of the catchments areas of the Airports and the Rail stations, considered in this study. It reviews the sources of data, explains the methods of construction of the different variables and their underlying assumptions.
- Chapter 9 draws a brief transportation economic analysis outlining the peculiarities of the

transport product and of the transportation services industry. It lays out a theoretical demand and supply model in which the frequency of services is included, not only in the demand equation as an important level of service factor explaining the demand, but also in the supply equation as a dependent variable expressing the level of supply. Furthermore, Rail fare, recognized as an endogenous variable for both Air and Rail demands, is introduced in a fifth equation as function of these demands.

- Chapter 10 explains the step by step procedure adopted in the course of modeling, selects a set of variables choosen among many candidates ones, and discusses the Multi-equation calibration techniques to be applied in the subsequent models.

- Chapter 11 constitutes the most important part of this research. Six Aggregate Multi-equation Modal Competition Models are run over the period 1968 - 1978 on the 7 following routes.

London-Glasgow
London-Edinburgh
London-Newcastle
London- Manchester
London-Birmingham
London-Leeds
London-Liverpool

  Three structural formulations, among the six above, are selected on both theoretical consideration and statistical significance, and applied to the length of haul aggregation retained. This comes up with Long Haul and Short Haul markets models, and a detailled discussion of their results.

- Chapter 12 selects the best formulation among the remaining three, and provides a statistical evaluation of the selected model by testing the validity of the assumptions underlying the 2SLS and 3SLS. Finally, in order to measure the accuracy of the forecast, an Ex post Forecast is simulated and its "estimates" compared to the actual Air and Rail demands observations for the years 1976, 1977, 1978.

- Chapter 13 runs 7 pure Time Series models in an Abstract Mode approach.
- Chapter 14 conducts respectively a pure Air business demand model over the UK Domestic market, and three pure Air Time Series models over the period 1961 - 1978, on the following trunk routes:

London-Glasgow London-Edinburgh London-Belfast

- Chapter 15 illustrates the application of these models.

It should be emphasized at this point, that although these models are formulated as supply/demand models, our primary purpose remains the identification of the Air and Rail travel <u>demand functions</u>. The introduction of the supply and Rail fare equations is essentially aimed to reduce as much as possible the Simultaneous Equations Bias, due to the dependency of the level of service and Rail fare variables on both Air and Rail demands.

The Multi-equation structure adopted as well as the 2SLS and 3SLS techniques, by reducing to a certain extent this bias, yield less biased, more consistent, and more efficient parameters than the ones that would have been obtained by OLS.

Since these structural parameters are the ones expressing the <u>behavioral relationships</u> between the demands on one hand and the level of service, fares, and incomes on the other, we focuss our analysis on the <u>Structural Forms</u> of the models rather than on their <u>Reduced Forms</u>.

CHAPTER 8

DATA CONSTRUCTION

8.1 CATCHMENT AREAS

Recent moves, in Origin/Destination air passengers flows models, have come to consider the "Region Pairs" concept rather than the "City Pairs", because Airports are thought to attract demands from larger areas than their own cities [14] . The modeling process on a region basis, however, is highly dependent upon the quality and accuracy of the delineation of the regions themselves.

The problem is even more complicated when one comes to model the competition between Air and Rail, since the passengers flows are assumed to originate in the same region and to end in the same other one for both modes.

Although the problem is relatively simpler when the Rail stations are near to the Airports, in which case they belong to the catchment areas of their nearest Airports; there are situations where Rail stations are, somehow, equally distant from two Airports. This is, for instance, the case for Motherwell and Perth Rail stations in Scotland. In this case [(1) on table 8.1], we have assumed that half rail traffic originating (or ending) at these stations belongs to Glasgow Airport catchment area and half to Edinburgh Airport catchment area.

On the other hand, Airports that are near to each other are considered as a unique Airport. Heathrow and Gatwick,for instance, are regarded as a unique Londonian Airport. This is also the case of Leeds and Bradford Airports.

In the course of delineation of the catchment areas, we tried as much as possible to take account of existing administrative boundaries, such as standard planning

AIRPORTS	RAIL STATIONS	1977/78 - 1974/75 METROPOLITAN COUNTIES	1973/74 - 1971/72 CONNURBATIONS
London Airport (Heath + Gatw)	Central London Guildford Brighton Ashford Canterbury Chatham Croydon Woking Slowgh Southend	Greater London	Greater London
Birmingham	Birmingham Wolverhampton	West Midlands	West Midlamds
Liverpool	Liverpool Southport	Merseyside	Merseyside
Leeds (Leeds/ Bradf)	Leeds Bradford Huddersfield Wakefield	West Yorkshire	West Yorkshire
Manchester	P. Manchester Oxrd. Manch Vic. Manch	Greater Manchester	*
Newcastle	Newcastle	Tyne & Wear	Tineside
Glasgow	Glasgow (1) Motherwell (1) Perth Port William	Central Clydeside	Central Clydeside
Edinburgh	Edinburgh (1) Motherwell (1) Perth Kircaldy	Lothian	*
Aberdeen	Aberdeen	Grampian	*

* : Non available

Table 8.1

regions, counties and connurbations. The advantage is that many socio-economic data are available at these levels (Inland Revenue Personal Income Surveys, Family Expenditures, Regional Statics, Registrar General's Annual Census of Population...).

Note in passing, that regional boundaries changed over the period considered in this study which complicated the derivation of the desired data. Finally, the catchment areas for Airports and Rail stations have been defined as displayed in table 8.1 ..

The two last columns of table 8.1 , indicate the catchment areas represented by metropolitan counties in the 1974-1978 period,and by the conurbations in the 1971-1974 period. The two first columns indicate the Airports and the Rail stations corresponding to these catchment areas. For instance, any passenger originating (or ending) at either Heathrow or Gatwick Airports, or at any Rail station in the first row is considered to be originating (or ending) in Greater London area. For simplicity, Airports and Rail stations in the same catchment area will have the same name, usually, the name of the Airport like Glasgow or Edinburgh; or the name of the main Airport like Leeds (instead of Leeds/Bradford); or the group name like London Airports (or simply London) for Heathrow and Gatwick. Therefore, in this study these Airports represent the catchment area they belong to (unless the opposite is stated).

8.2 AIR DATA

These data have been obtained from disparate sources.

- Traffic passengers

The main sources of these data have been the CAA Annual Statistics [45] and Surveys [46] . The first has provided annual domestic traffic passengers between the Airports considered for the period(1968-1978). Prior to this period, data for trunk routes (London-Glasgow, London-Edinburgh, London-Manchester, London-Belfast) have been taken from Edward Reports [47].

The ratios of business traffic figures have been derived from different CAA Surveys(1970, 1971/72, 1975/76) and from British Airways Inflights Surveys (1974, 1977, 1978). These ratios, applied to the total domestic traffic have yielded the business traffic for the corresponding periods on the following routes:

London-Glasgow :	1971,	1974,	1975,	1976,	1977,	1978.
London-Edinburgh :	1971,	1974,	1975,	1976,	1977,	1978.
London-Belfast :		1974,	1975,	1976,	1977,	1978.
London-Manchester :	1971,		1975.			
London-Aberdeen :			1975.			
London-Leeds :	1971,			1976.		
London-Liverpool :	1971,			1976.		
London-Newcastle :				1976.		
Belfast-Leeds :				1976.		
Belfast-Liverpool :				1976.		
Belfast-Manchester:				1976.		
Glasgow-Manchester:	1971,			1976.		

The dependent variables corresponds to the two-way passengers traffic.

- <u>Air fares</u>

Air fare corresponds to the normal economy single fare taken from ABC Guide [48] for the period (1961-1978) for each route. In order to take account of the seasonal fare variations, the two months figures (April and October) of each year have been considered. These values have been deflated by the Consumer's Price Index (taken from National Income and Expenditures [49]), in order to eliminate the inflation effect. The base year corresponds to 1975.

- Frequency of services

The frequency of services, used in this study, corresponds to the product of the number of flights offered in each direction between two Airports. It has been shown [14] that the product form was more appropriate than the sum, as the former more accurately measures the effect of substantial imbalance in the number of flights offered in the two directions. It seems logical that a route with 3 daily flights in each direction, for instance, is better served than with 1 flight in one direction and 5 in the other. The use of the sum of flights, as proxy for the level of service, would not measure this imbalance whereas the product does (the sum being equal for the two cases, but the products are 9 for the first and 5 for the second).

Furthermore, as the number of flights a day in each direction shows some variations from one day to another, the product considered has been the product of the weekly number of flights by direction derived from ABC Guide.

- Time variable

Trip time figures for the period (1961-1978) have also been taken from ABC Guide. They correspond to the trip time in each route. As time variable is to be analysed in a competing context, it appeared more appropriate to consider not only the flying time but also the waiting, access and egress times for each mode.

For the purpose of this study, total trip time variable has been constructed by adding to the flying time the hypothetical following figures taken from Guwilliam [50]

city centre - Airport time	= 54 minutes for London
	= 30 minutes for other Airports
Loading time	= 30 minutes
Unloading time	= 15 minutes

i.e, 120 minutes for London routes and 105 minutes for other routes.

- Load factor

This variable has been constructed by taking the ratio of seat/km available and seat/km used in the "scheduled services by UK Airlines" 1965-1975 and 1967-1977 [51]. The figures prior to 1965 have been taken from Edward Report.

8.3 RAIL DATA

All Rail data, except the "electrification" variable, have been provided by British Railways:

- Traffic passengers between different Rail stations have been aggregated by catchment areas as explained earlier (two ways traffic).

- The Rail frequency of service has also been expressed by the product of the weekly numbers of trains in each direction.

- Trip time variable includes the waiting time, but does not take account of any access or egress time; the assumption being that Rail stations are usually in the city centre (or town centres).

- Fare variable corresponds to the published single economy fare in each route. Again these values have been deflated by the consumer price index.

-"Electrification" variable designed to measure the effect of the electrification is the ratio of the number of kilometres of electrified routes and the distance between them. These figures have been taken from CSO Annual Abstract of Statistics 1979. [52] .

All the above data are available for the following routes for the period (1968-1978):

London-Glsgow
London-Edinburgh
London-Manchester
London-Birmingham
London-Leeds
London-Liverpool
London-Newcastle

8.4 INCOME VARIABLES

Derived from Regional Statistics (1973 and 1979)/[53],these variables have been rather difficult to construct because of the changes in the administrative boundaries of different regions.

- Personal incomes before tax and after tax

These variables have been set up for the Airports in table 8.2 . In the first column is included the list of the Airports concerned (except Aberdeen and Edinburgh). In columns 2 and 3 are comprised the corresponding catchment areas. The income variables, for these catchment areas, are published in Regional Statistics for the two periods 1977/78-1974/75 and 1973/74-1971/72 (except for Manchester).

AIRPORTS	1977/78-1974/75 METROPOLITAN COUNTIES	1973/74-1971/72 CONURBATIONS	1970/71 - 1967/68
Newcastle	Tyne & Wear	Tyneside	*
Leeds	W Yorkshire	W Yorkshire	*
London	Greater London	Greater London	G London
Birmingham	West Midlands	West Midlands	*
Manchester	G Manchester	*	*
Liverpool	Merseyside	Merseyside	*
Glasgow	Centr Clydeside	Centr Clydeside	

* : Non available

Table 8.2

For the third period 1967/68-1970/71, the figures do not exist at Counties or Conurbations levels (apart from Greater London), but still exist at regional levels. Therefore, the figures desired have been derived by comparing the figures for both Conurbations and Regions for the period 1971/72-1973/74 and applying the ratio of these figures to the period 1970/71-1967/68. For Manchester, the figures for the second and third periods have been derived from ratios computed in the first period. The planning regions considered for deriving these figures are shown, below, with their corresponding Airports:

AIRPORTS	PLANNING REGIONS
Newcastle	North
Leeds	Yorkshire & Humberside
Birmingham	West Midlands
Manchester	North West
Liverpool	North West
Glasgow	Scotland

For Edinburgh and Aberdeen, the population figures, taken from Census Population 1971, have been compared to Glasgow population figures. Assuming that incomes are equally proportional to the populations in these three areas, income variables have been computed for Edinburgh and Aberdeen.

- <u>Gross domestic product (GDP) and GDP per capita</u>

GDP figures published in Regional Statistics (1973 and 1979) are only on a region level. The figures corresponding to the catchment areas considered earlier, have been derived by comparing the income before tax variables on a region level with those obtained on a county level, and extending the proportionality to the published GDP variable.

For Edinburgh and Aberdeen, however, the Scotland GDP by head has been multiplied by their corresponding population. The assumption being that these two areas have the same GDP per capita as Scotland has.

Finally, the GDP per head has been forthwith taken from the published data by assuming that the Counties(or Conurbations) have the same GDP per head as the standard Regions they belong to.

All incomes variables, considered so far(before tax, after tax, GDP, GDP per head),have been deflated by the Index number of GDP (income based) £1975 = 100, taken from National Income and Expenditures (1979).

- <u>Personal incomes (before tax) by ranges of incomes</u>

The process of constructing these variables has taken two steps:
First, from several personal incomes by ranges of incomes figures for standard regions displayed in Regional Statistics, the number of tax units corresponding to four ranges of incomes has been calculated:

people with incomes	$\leqslant$	£1,000	per year
people with incomes		£1,000 - £2,000	per year
people with incomes		£2,000 - £5,000	per year
people with incomes	$\geqslant$	£5,000	per year

Then, by taking the ratio of the population in the standard regions and the corresponding catchment areas, and assuming that the distribution of incomes in a catchment area is the same as the distribution of incomes in the standard regions it belongs to, the desired variable has been obtained.

Finally, once all the income variables, described earlier (before tax, after tax, GDP, GDP head, ranges of incomes), have been constructed for each catchment area, the income variables for each route are obtained by taking the product of the variables corresponding to the Origin/Destination catchment areas.

These routes are as follows:

London-Glasgow
London-Edinburgh
London-Manchester
London-Birmingham
London-Leeds
London-Liverpool
London-Newcastle
London-Belfast
London-Aberdeen

Belfast-Birmingham
Belfast-Glasgow
Belfast-Leeds
Belfast-Liverpool
Belfast-Manchester

Birmingham-Edinburgh
Birmingham-Glasgow
Glasgow-Manchester

While Air data are available for all these 17 routes, Rail data are available for the first 7 Londoner routes only. Plots of the relevant variables are displayed in the figures numbered from 8.1 to 8.18 .

CHAPTER 9

TRANSPORTATION ECONOMICS ANALYSIS

In order to better understand the process of demand modeling in commercial transportation, it is important to draw a brief analysis of the economics of this industry.

In general, the classical theories of Microeconomics are applicable to transportation economics. The law of supply and demand, and the concept of elasticity still hold. However, due to the transportation product attributes and the peculiarities of this industry, the supply and demand of transport, as will be seen in this chapter, show some differences with the classical theory.

9.1 TRANSPORTATION DEMAND IS A DERIVED DEMAND

The demand for travel is not an end in itself. Travelers are not buying any physical object which becomes their property. The product they purchase is the service of their transportation from one point to another. This service is derived from what they can achieve in being at the point of destination, either for business purpose or personal reasons. Therefore, unlike demand for traditional goods which is related to the good itself, travel demand is very sensitive to the demand for the product at the point of destination.

9.2 TRANSPORTATION PRODUCT IS PERISHABLE

The product of transportation is perishable, and in this respect is similar to a newspaper or a christmas tree. Unlike traditional goods, a seat mile available in a particular departure cannot be stocked to the next departure, if it has not been sold. It remains, however, that its cost is essentially the same for the carrier as if it has been purchased.

Industries with storable goods do not encounter this problem, and can generally gear production to a steady output, relying on a store to act as a reservoir. As transportation services do not enjoy the freedom of being able to store surplus products, they must come to some decision about the level of supply to offer on the market.

9.3 TRANSPORTATION SERVICES ARE REGULATED

In an ideal world of economists' perfect competition, there might be no need for government intervention in transportation policy. A perfectly functioning market could be left to determine the quality, the quantity and the price of transportation services, according to consumer preferences and subject to resources constraints. Such an ideal does not exist, and the control of the government takes different aspects though varying from time to time, from mode to mode, and from country to country.

9.3.1 Air transportation pricing regulation

Airline industry is subject to a great deal of regulation, and various reasons have been advanced for the degree of regulation that exists, namely the maintenance of safety standards and the maintenance of public service requirements by avoiding disruptive competition [54].

Within the United States, Air fares are fixed by the CAB (Civil Aeronautics Board) which prescribes a piecewise linear concave function of intercity distance for the standard coach fare. First class and discount fares are computed solely on the basis of the percentage of the standards fares*. Thus, Air fares at a given point of time are function only of distance and independent of absolute consumer demand in the market and fluctuations in this demand. That is why Air fare variable has always been considered by the modelers as an exogenous variable in Air demand models.

Within the United Kingdom (Domestic routes including routes to the Channels Islands), the former ATLB (Air Transport Licensing Board) which has been replaced since by the CAA, consequently to the Civil Aviation Act 1971, used to determine, after a public hearing, the tariffs to be charged.

The Civil Aviation Act 1971 declares that it should be the main objective of the CAA to secure that British Airlines provide services which satisfy public demand at the lowest charges consistent with a high standard of safety and an economic return on investment. The subsequent policy guidance, further required the CAA to secure tariffs that are rational, simple and enforceable [55].

9.3.2 Rail pricing policy

Railways in Britain, as in many other countries, have been subject to rigorous controls, both for their fare levels and the quantity, quality and nature of services provided.

(*) According to Richard A Ippolito, in 1982 Air fares will no longer be regulated.

(Journal of Transport Economics & Policy)
January 1981

During the fifties and the early sixties (1953-1961), Railways were under the authority of the Transport Tribunal which had power to set maximum fares. Under the 1962 Act, this was removed and Railways were allowed to charge fares which could cover their financial targets. The only remaining controls were over London fares.

In theory, this left the Railways free to pursue the policy of vigorous price discrimination for its services: discrimination between routes by times and by class of travel as they thought best. This evolution in Rail fares policy is of crucial importance in the analysis and the modeling of Air-Rail competition [27]. It means that since 1962, statistical estimation procedures would have to recognize that to evaluate Air demand function, with included Rail price Crosselasticities, might mean considering an unconstrained operator (Rail) and a constrained one (Air). There is, therefore, a possibility of obtaining "perverse" cross-price elasticities*, since Railways have been, theoretically, able to react promptly within the year to any price change introduced by Air.

In practice, as Gwilliam [50] pointed out, "it has taken a number of years for the steps away from a per mile fare structure to be taken". We will turn to this point when considering the Air/Rail competition.

9.4 DEMAND FUNCTION

As explained earlier, the classical demand approach ignores the characteristics or quality attributes of commodities and instead, treats them as uni-dimensional.

(*) This will be explained in section 8.6.3 of this chapter.

The most important modification, introduced by Lancaster in his Consumer Behavior Theory [16] , upon which are based our models, is that the consumer is regarded as deriving utility from characteristics or attributes.

As will be seen in the Methodology approach chapter, a set of different Air and Rail demand equations are tested in order to identify the best relationship between the demand and the most relevant factors. The structural demand equation by each mode has been of the following type:

$$D = f(NFL, FARES, INCOME)$$

where:

<u>NFL</u> : is the level of service of the mode invariably represented by the frequency of services variable.

<u>FARES</u> : is the price of the trip represented either by the <u>absolute</u> fare of the mode or by a <u>relative</u> fare(i.e, ratio of 2 fares).

<u>INCOME</u> : is a measure of an income variable characterising the region pair.

Further discussion of these variables and the structural relationship above will be provided later.

9.5 SUPPLY FUNCTION

Unlike classical economic models for goods markets, the units used to measure the quantity of demand (passengers) are different from those designed to measure the quantity of supply. Indeed, since the transport product is only sold in <u>batch</u>, the unit of output for a scheduling process is a set of vehicle departure, called a flight (or simply departure for the Rail mode).

It is generally assumed that suppliers in transportation services are seeking to maximize their profit, although this is not necessarily true in the real world. British Railways aim, for instance, "is to meet the financial obligations imposed by PSO* (Public Service Obligation) and cash limits, and broadly within that objective to maximize passenger miles. They direct their pricing policy towards achieving this objective which is somewhat different from a purely commercial maximization of revenue" [56] .

Offering the maximum level of service is not necessarily an optimum decision for a supplier. Thus, for a given demand function, there is an optimal number of flights (or departure for rail) that an operator can offer. Therefore, the supply function for any mode may have the following form:

$$NFL = f(D, VARIABLES)$$

Where:

NFL : is the level of service variable described earlier.

VARIABLES : are other variables to be explained later on.

9.6 APPLICATION TO THE STUDY

We have drawn so far a brief analysis of the transportation services economics. We have first examined the attributes of the transportation product that distinguishes it from other common goods, and then analysed

* a PSO is defined as an activity which a transport undertaking would not assume to the same extent or under the same conditions if it were considering only its own commercial interests [56] .

the demand and supply of transport and the difference they show with the traditional economic theory.

Yet, for the application to our empirical models, we have to define some restrictive assumptions, mainly dictated by the unavailability of the data.

Air mode supply function

In order to select the best variables for the equation, a step by step procedure has been conducted. This procedure is largely explained in the methodology chapter. Note at present, that it uses the stepwise regression analysis as a means of selection of the best variables among a set of canditates ones.

Earlier canditates variables to include with the demand variables in the supply equation NFL = f(D,VARIABLES) were: LF(Load factor) and capacity variables:

$$NFL = \beta_0 D^{\beta_1} \, LF^{\beta_2} \, CAPACITY^{\beta_3}$$

However, the inclusion of LF variable poses an identification problem: indeed, for a given demand and aircraft capacity the LF is closely related to the frequency of service which means that there is a two-way dependency (i.e, LF is also an endogenous variable). Therefore, a third equation with LF as the dependent variable would have been necessary to introduce. This equation, that might have been called "operational equation", would have had, for instance, the following form:

$$LF = \gamma_0 \, D^{\gamma_1} \, NFL^{\gamma_2} \, CAPACITY^{\gamma_3}$$

In order to keep the problem manageable and to ovoid any two-way dependency in the supply equation NFL = f(D,VAR), it has been decided to include the past year load factor $LF_{(-1)}$ instead of the actual year load factor. In this way, this variable is truly exogenous and no fear of bias exists. It even sounds theoretically better: it is reasonable for an operator to supply flights for a given period, according to the load factor experienced during the last period.

On the other hand, Aircraft Capacity variable, as seen from the data, shows no real variation. Therefore, it is considered constant and the definitive air supply equation is as follows:

$$NFL = \beta_0 \, D^{\beta_1} \, LF^{\beta_2}$$

where LF is the load factor of the past year (since there is no confusion, we write LF instead of $LF_{(-1)}$)

Rail mode supply function

Here again, the step by step procedure for selecting the variables has been applied. Unfortunately, since Rail data do not contain any LF or Capacity variables, other variables have been investigated. This necessarily leads to handle differently Rail and Air modes supply equations. This is not, however, of serious concern. All along this study many differences are being outlined between these modes, not only on their regulations such as their pricing policy but also on their operational nature.

Finally, by this step by step procedure the supply equation retained in the selection process is of the following type:

$$NFL = \gamma_0 \, D^{\gamma_1} \, TIME^{\gamma_2} \, ELEC^{\gamma_3}$$

Where:

- D : is the Rail demand
- Time : is the Rail trip time
- ELEC : the electrification variable explained in the data section.

Both TIME and ELEC variables are expressions of the quality of service, since the more you improve the trip time the more you improve the quality of service; and equally the more you improve the electrification of the routes the more you improve the quality of service.

Incidently, the idea of including such variables has been derived from a study conducted at MIT by Mathaisel & Taneja in 1977 [57]. The authors have developed an Air Quality of Service index through Principal Component Analysis, by considering the combination of 5 quality of service variables. However, their objective, contrarily to ours, is not to construct a <u>supply equation</u> for use in a simultaneous equation model, but rather to design <u>one factor</u> which can be used as a <u>proxy</u> for the quality of service in a single equation model. Principal Component Analysis takes the 5 variables and makes a linear combination of them in such a manner that it captures as much of the total variation as possible. This combination, or principal component, serves as a proxy for their level of service variable.

In conclusion, Air and Rail modes supply equations retained are as follows:

$$NFL_1 = \beta_0 \, DA^{\beta_1} \, LF^{\beta_2}$$

$$NFL_2 = \gamma_0 \, DR^{\gamma_1} \, TIME^{\gamma_2} \, ELEC^{\gamma_3}$$

where:

NFL_1 and NFL_2	: are respectively the Air and Rail level of service variables.
DA and DR	: respectively the Air and Rail demands.
LF	: Air load factor (past period)
TIME	: Rail trip time.
ELEC	: electrification variable.

Both TIME and ELEC variables are expressions of the quality of service, since the more you improve the trip time the more you improve the quality of service, and equally the more you improve the electrification of the routes the more you improve the quality of service.

Therefore the air and rail modes supply equations retained are as follows :

$$NFL_1 = \beta_0 \, DA^{\beta_1} \, LF^{\beta_2}$$
$$NFL_2 = \gamma_0 \, DR^{\gamma_1} \, TIME^{\gamma_2} \, ELEC^{\gamma_3}$$

where :

NFL_1 and NFL_2	: are respectively the air and rail level of service variables.
DA and DR	: respectively the air and rail demands.
LF	: air load factor (past period)
TIME	: rail trip time.
ELEC	: electrification variable.

Rail fare equation

Up till now, we have defined the demand and supply equations for both Air and Rail modes. Before introducing the fifth and last equation, let us return to the problem of "perverse" elasticity briefly mentioned when we have discussed the Railways fare policy.

We have stated that after the 1962 act, Railways have been theoretically able to react promptly within the year to any price changes introduced by Airlines.

Assume a decrease in Air fare which induces an increase in Air demand and consequently a decrease in Rail demand. Although Air and Rail are not necessarily supplying at the same price, the effect would be to force Rail down its supply curve and perhaps to lower its price in turn. The observations in the regression would show an increase in Air demand and a decrease in Rail fare, leading therefore to a negative Rail cross fare elasticity:

Air fare ↘ Air demand ↗ Rail demand ↘ Rail fare ↘

Thus:

$$\text{Rail fare} = f\ (DA, DR)$$

This means that while Air fare is still an exogenous variable for the constrained operator (Air), Rail fare appears as an endogenous variable for both Air and Rail modes. This endogenous nature will be established later on.

9.7 EQUILIBRIUM

We have, so far, defined Air and Rail demand equations, Air and Rail supply equations and Rail fare equation.

The equilibrium is, therefore, defined by the following simultaneous equations model:

1. $DA = f(NFL_1, FARES, INCOME)$

2. $DR = f(NFL_2, FARES, INCOME)$

3. $NFL_1 = f(DA, LF)$

4. $NFL_2 = f(DR, TIME_2, ELEC)$

5. $FARE_2 = f(DA, DR)$

$FARE_1 = \text{Exogenous}$

In the literature review, we have analysed the Modal Competition models and discussed the different structures proposed by the modelers.

Besides particular disadvantages characterising each type of models, they all suffer from a common problem as earlier stated: they consider only one aspect of the market, namely the demand for travel, generally ignoring the supply side.

This omission has two negative consequences:

- The first is a theoretical aspect. The omission of the supply in the analysis of the market constitutes an important restriction to the analysis. Since demand and supply of goods and services are generally inter-related in the real world, such a restriction may throw some doubts on the consistency of the analysis.

- The second is a statistical problem. The ignorance of the supply influence on the demand might yield biased coefficients due to the two-way dependency between the demand and the variable expressing the supply.

9.8 ORIGINALITY OF THE STUDY

Our model departs from all other models discussed so far, overcomes some of their drawbacks and has the following advantages:

- It is not restricted to the demand aspect only, but is also related to the supply side. This is achieved by the introduction of the frequency of services variable, not only in the demand equation as an important factor explaining the demand, but also in the service equation expressing the level of supply in response to changes in other variables.

- By including the frequency of services factor as an expression of the level of service as well as of supply, the policy maker is given the capability of acting upon the demand through this controlable factor.

- It estimates the absolute value of traffic by each mode instead of only the share by mode and does not assume the constancy of total traffic, since it also allows the growth of traffic's modes independently to each other.

- Instead of being independently (or recursively) estimated, the equations of this model are simultaneously calibrated. This simultaneity permits the feedback demand-supply, by allowing the variables to interact with each other across the equations. It also overcome the so called "Simultaneous Equations Bias", since the calibration is achieved by means of multi-equation techniques (2 stage least squares and 3 stage least squares) instead of the ordinary least squares.

- Finally, the coefficients obtained by such sophisticated techniques are less biased, more consistent and more efficient and therefore, more reliable than those obtainable by OLS regression.

CHAPTER 10

MODAL COMPETITION MODELS STRUCTURE

10.1 METHODOLOGY

A critical step in developing models is the choice of the most suitable set of independent variables to include in the model. To keep the problem manageable, only a few variables should be included. First, because a large number of variables are expensive to maintain, update and store. Second, because a small number is easier to understand, to analyse and to forecast while a large number increases the probability of multicollinearity between them.

Thus, the problem is not one of finding a set of explanatory variables that provides the utmost control for policy analysis, nor one of finding the set which best predicts the behavior of the dependent variable, but rather one of reducing the number of these variables to a minimum.

For this purpose, a step by step procedure has been applied. It consists in adopting at an early stage, Stepwise Regression Analysis as a means of investigation. First, because of its low computer cost. Second, because it has the advantage of entering the variables one by one into the regression. At each step,the added variable is the one which makes the greatest reduction in the error sum of squares. Also, at each step , it shows the improvement induced by the new variable on the overall fit of the equation. It allows the detection of any multicollinearity between the added variable and the already included ones, by comparing their standard errors; and therefore, permits the choice between the candidates variables.

Alternative model specifications have been evaluated in terms of magnitude of the estimated coefficients and their signs. Finally, after discarding options by this investigation procedure, the simultaneous estimations have been applied to the remaining specifications. The following section provides a good illustration of the first stage of this step by step approach.

10.1.1 Variables selection

- Income variable

The candidate income variables collected in the data investigation process, GDP (Gross Domestic Product), GDPHEAD (GDP per head), BFTAX (Personal Income Before Tax), AFTAX (Personal Income After Tax), cannot be , of course, included all together in the equation and a choice should be made in this preselection stage.

It could be argued, since business demand is more sensitive to the economic activity, that GDP might be a better explanatory variable when modeling the business travel demand. Similarly, Personal Income (before or after Tax) might be a more relevant variable in a personal travel model, for the propensity to travel, for personal reasons, is generally related to the household incomes.

Since data collected are not disaggregated by trip purpose, there is no a priori reason why selecting one particular variable instead of another. Therefore, the selection choice has been based upon the statistical significance of each variable in the regression and its improvement on the overall fit of the equation.

For the purpose of this selection, the following Air demand equation has been regressed on the 17 Regions-Pairs, one by one over the period (1968-1978).

For each run, one particular income variable has been used:

$$j = \alpha_0 \, NFL^{\alpha_1} \, FARE^{\alpha_2} \, FARE^{\alpha_3(time)} INCOME^{\alpha_4} \, INCOME^{\alpha_5(time)} + \varepsilon_1 \quad (1)$$

where:

- D_{ij} : demand between i and j
- NFL : frequency of services variable
- FARE : Air fare
- INCOME : income variable representing, at each run, one of the 4 income variables: GDP, GDPHEAD, BFTAX, AFTAX
- α_3(time) : α_3 Log time
- α_5(time) : α_5 Log time

where time is the clock time starting at the year zero: 1960.

The reason for the explicit inclusion of the clock time into the equation will be discussed later on.

The analysis of the results of the 68 runs (17 x 4) is summarized in Table 10.1 . For each regression and each type of income correspond three values: the Multiple Regression Coefficient R, the F test and the index of the variables selected in the regression*.

From Table 10.1 , it appears that GDP is a better explanatory variable than the other income variables. This, with regard to the R coefficient and F test that are almost higher with GDP than any other variable, except in London-Liverpool where GDPHEAD Model has a

---

(*) We retain the variables contained in the step after which one or more variables are not significant.

COMPARISON BETWEEN INCOME VARIABLES

ROUTES	BFTAX			GDPHEAD			GDP			AFTAX		
	R	F	NV	R	F	NV	R	F	NV	R	F	NV
LDN-GLS	.74	13	1	.74	14	1	.77	16	1	.83	11	2
LDN-EDB	.96	125	1	.99	20	2	.99	234	2	.96	123	1
LDN-MCH	.70	11	1	.70	11	1	.70	11	1	.70	11	1
LDN-BLF	.80	20	1	.80	20	1	.88	11	2	.86	14	2
LDN-BRM	.90	40	1	.90	40	1	.93	27	1	.90	40	1
LDN-ABR	.99	367	1	.99	352	1	.99	339	1	.98	201	1
LDN-LDS	.80	19	1	.93	18	3	.90	21	2	.86	32	1
LDN-LVP	.65	8	1	.85	8	2	.81	6	2	.65	8	1
LDN-NWC	.95	50	2	.92	60	1	.93	67	1	.96	57	2
BLF-BRM	.51	3	1	.51	3	1	.51	3	1	.64	3	2
BLF-GLS	.93	59	1	.93	29	4	.93	59	1	.93	59	1
BLF-LDS	.34	1	0	.72	2	0	.72	4	3	.23	1	0
BLF-LVP	.60	5	4	.70	4	2	.87	5	4	.59	5	1
BLF-MCH	.92	14	3	.88	31	1	.93	9	4	.93	31	2
BRM-EDB	.91	12	3	.97	19	5	.97	18	5	.97	17	5
BRM-GLS	.87	7	3	.93	6	5	.94	7	5	.96	7	3
GLS-MCH	.89	15	2	.86	27	1	.86	27	1	.90	18	2
T.O.H.V	2	7	3	6	4	5	9	8	7	7	5	5

Table 10.1

BFTAX : income before tax AFTAX : income after tax

GDP : gross domestic product GDPHEAD : GDP per head

NV : number of significant variables retained

T.O.H.V : times occurences of highest values greater R but where NFL variable has a very low t test, and in London-Newcastle where BFTAX and AFTAX Models have a greater R but a wrong sign in their NFL variable.

Table 10.1 also shows that in GDP Model the number of significant variables, retained in the regression, is higher than elswhere, particularly in the Belfast-Liverpool, Belfast-Manchester, Birmingham-Edinburgh; and Birmingham-Glasgow Models where almost all the variables are included and are very significant.

The main conclusion is that while statistical tests (R and F) are very high in almost all the routes and the variables bear nearly always the right signs, the specified variables are <u>not all together</u> included in the equation.

For the 9 first routes(i.e, Londonian routes) the only explanatory variables selected are either NFL (number of flights),or Income variable, or both; but there is no Fare variable in these models. On the contrary, for the remaining 8 routes, except Glasgow-Manchester, Fare variable is systematically included either alone or with NFL and Income variables.

Finally and curiously enough, the only selected variable in London-Aberdeen route is the $\text{INCOME}^{(\text{Log time})}$ variable with a high level of significanceand the highest R(=.99). This means that income elasticity is a logarithmical function of time. The selection of this unique variable may explain the drastic growth of Air traffic, mainly due to the important economical expansion activity in Aberdeen (North Sea oil) during this decade.

The reason for the explicit inclusion of the clock time into the equation (1) is whether or not Fare and Income elasticities vary with the time, To make it clearer, take the logarithm of the demand so as to linearize the model:

$$\text{Log } D = \alpha_0 + \alpha_1 \text{Log NFL} + \alpha_2 \text{Log FARE} + \alpha_3 \text{Log time Log FARE}$$
$$+ \alpha_4 \text{Log INCOME} + \alpha_5 \text{Log time Log INCOME}$$

where the fare and income elasticities are respectively the following:

$\alpha_2 + \alpha_3 \text{Log time}$ and $\alpha_4 + \alpha_5 \text{Log time}$

It could be argued that this functionalform of the elasticity is quite arbitrary, and there is no way, indeed, of refuting this argument on a theoretical ground. However, since it is commonly admitted, in the literature, that the variation of this elasticity is very slow the logarithm form has been retained.

Note also, that the separate inclusion in the equation of the two parts of the elasticities - constant parts α_2 and α_4, and variable parts α_2Log time and α_5Log time - allows the determination of the significance of each part onto the regression, such that each part might well be significant while the other might not(Both, of course, might or might not be simultaneously significant).

It is at this investigation stage that the stepwise regression technique is of interest, since it introduces the variables one by one and permits the analysis at each step.

- <u>Competition factors</u>

The competition between modes could take different forms: fares, frequency of services, trip time, comfort,etc.

For the purpose of this study, the variables thought to be of importance in Air-Rail modes competition are, apart from the own fares and frequencies of the modes, the following relative values:

$$\frac{FARE_1}{FARE_2}, \frac{NFL_1}{NFL_2}, \frac{TIME_1}{TIME_2}$$

where index 1 indicates Air mode, and index 2 Rail mode.

Once again, stepwise regression technique has been used to identify the best variables to be selected; and the results correspond to the following model, run for all London routes combined (except London-Belfast and London-Aberdeen, for which there exist no Rail data).

$$DA = \alpha_0 \; NFL_1^{\alpha_1} \; FARE_1^{\alpha_2} \; FARE_1^{\alpha_3 (time)} \; FARE_2^{\alpha_4} \left(\frac{FARE_1}{FARE_2}\right)^{\alpha_5} \left(\frac{TIME_1}{TIME_2}\right)^{\alpha_6} \left(\frac{NFL_1}{NFL_2}\right)^{\alpha_7} \left(INCOME\right)^{\alpha_8} \left(INCOME\right)^{\alpha_9 (time)} + \varepsilon_1 \qquad (2)$$

The results are as follows:

NFL_1 : is always very highly significant

$\frac{FARE_1}{FARE_2}$: is always significant and always more significant than $FARE_1$ and $FARE_2$

$FARE_1$ and $FARE_1^{3(time)}$: are either rejected from the equation or not significant at all if included

$FARE_2$: when included is significant

The conclusions to be drawn from these results are:

1 - The high significance of NFL variable is very important. Most of Air models have neglected this supply factor as an important factor explaining and determining travel demand.

2 - The ratio $\frac{FARE_1}{FARE_2}$ is a better explanatory variable than $FARE_1$ and $FARE_2$. This explains the importance of Air - Rail competition. It may also suggest that this relative fare is better perceived (from a traveler point of view) than the absolute fare difference.

3 - $FARE_2$ (i.e, Rail cross fare) appears to be a better explanatory variable than $FARE_1$, since $FARE_1$ has been rejected while $FARE_2$ has been included. This corrobores the idea that Air mode may not be an independent mode, but also a mode that is explained by the cost of other substitutes (e.g, Rail).

However, one should, at this stage, investigate whether or not Rail fare is fixed independently to Air fare, for if it is not, it can no longer be considered as an exogenous variable in the Air demand equation.

For the purpose of this investigation, $FARE_2$ has been regressed upon Air and Rail demands in the following model:

$$\text{Log } FARE_2 = \alpha_0 + \alpha_1 \text{Log DA} + \alpha_2 \text{Log DR} + \varepsilon$$

The results are as follows:

$$\text{Log } FARE_2 = -1.046 + \underset{(.0145)}{.258} \text{ Log DA} - \underset{(.0128)}{.231} \text{ Log DR}$$

$$R^2 = .83 \qquad SE = .06 \qquad F = 225.4$$

The coefficients DA and DR are highly significant with t values respectively equal to: 17.75 and 18.10; R^2 and F test are high.

Therefore, one should admit that $FARE_2$ is a function of

Air demand,and consequently, is an endogenous variable with regard not only to Rail demand but also to Air demand.

This constitutes a very important result, and its consequence is that the introduction of $FARE_2$ in Air demand equation might induce the so called "Simultaneous Equations Bias" due to the two-way dependency between Air demand and $FARE_2$.

Thus, a multi-equation structure is necessary; and the application of OLS (ordinary least squares) as a means of calibration is no longer valid.

- Fare and income elasticities analysis

It appears, from the results of equation (2), that income variables: AFTAX, GDP, GDPHEAD, show an acceptable significance but an independency to the clock time; while BFTAX variable shows a high significance and a dependency upon time. Its elasticity is as follows:

$$\text{ELASTICITY} = .527 \ -.05 \ \text{Log (time)}$$

The coefficient of time is so small that it will take a long time before this elasticity decreases significantly. For instance, it will take more than 128 years in order that this elasticity decreases by 20%.

On the other hand, FARE elasticity shows no dependency with time. Therefore, we will not take account of any dependency on time of income or fare variables.

In conclusion, the preselected variables in demand function at this stage of investigation are:

$$NFL_1, \ NFL_2, \ FARE_1, \ FARE_2, \ \frac{FARE_1}{FARE_2}, \ GDP$$

Since the potential explanatory variables have been selected and the necessity of a multi-equation structure has been recognized, we move to the next step: the multi-equation models. However, before doing so, we will first discuss the statistical problems brought up by such a structure.

10.2 SIMULTANEOUS EQUATIONS BIAS

It has been recorded, in chapter 4, that one major assumption of the validity of OLS is that $COV(X_i, \mathcal{E}) = 0 \quad \forall i$, which means that the explanatory variables X_i must be uncorrelated with the error term. A necessary condition, for $COV(X_i, \mathcal{E}) = 0 \quad \forall i$, is that the variables X_i should be truly exogenous. When this condition is not satisfied, it arises what is called "Simultaneous Equation Bias"; that is to say, that the equation belongs to a wider system of equations. Such system describes the relationship among all the relevant variables.

In our model the variables NFL_1, NFL_2, $FARE_2$, included in the demand equation, are endogenous. Therefore, one should estimate the coefficients by a means of multi-equation calibration techniques. For the purpose of this study, we have selected two of these techniques, namely 2SLS and 3SLS, that are briefly presented in the following section.

10.3 STATISTICAL CALIBRATION TECHNIQUES

The presentation of 2SLS and 3SLS below is taken from Koutsoyiannis [9] .

Two stages least squares

This method has been developed by Theil and independently by Basemann and aims, like other simultaneous techniques, at the elimination, as far as possible, of the

Simultaneous Equations Bias. It boils down to the application of OLS in two stages.
- In the first stage, OLS is applied to the reduced form equations to obtain an estimate of the exact and the random components of the endogenous variables.
- In the second stage, OLS is applied to the structural equations in which the endogenous variables in the right hand of the equations are replaced by their computed values found in the first stage.

<u>Assumptions of 2SLS</u>

They may be outlined as follows:

1 - The error term u of the original structural equations must satisfy the usual stochastic assumptions of zero mean, constant variance and zero covariance.

2 - The error term v of the reduced form equations must satisfy the same above assumptions and must be independent of the exogenous variables of the whole structural model.

3 - The explanatory variables are not perfectly multicollinear.

4 - The specification of the model is assumed to be correct so far as the exogenous variables are concerned(it is not necessary to know the mathematical formulation of the whole system in all its details, but the exogenous variables of the system must be all known correctly).

5 - The sample is assumed to be large.

Provided that the above assumptions are satisfied, the 2SLS are <u>unbiased</u>, <u>consistent</u> and <u>efficient</u> when the samples get large.

Three stage least squares

Developed by Zellner and Theil, 3SLS is a system method, that is, it is applied to all the equations of the model at the same time and gives estimates of all the parameters simultaneously (contrarily to the 2SLS).

It utilizes more information than the single equation techniques (such as 2SLS), that is, it takes into account the entire structure of the model with all the restrictions that this structure imposes on the values of the parameters.

In simultaneous equations models, it is almost certain that the random variable of any equation will be correlated with the random variable of other equations. This fact is ignored by single equation methods (such as 2SLS).

Of course, the computations of 3SLS are much more complicated and the data requirements are enormous. While in 2SLS we may use a small sample, since for each equation we use the same sample anew; in the 3SLS all the parameters are estimated at the same time, so that the sample must contain more observations than the total number of parameters of the entire system.

3SLS is a logical extension of Theil's 2SLS and involves the application of least squares in three stages:
- The first two stages are the same as 2SLS, except that we deal with the reduced form of all the equations of the system.
- The third stage involves the application of least squares to a set of transformed equations, in whch the transformation required is obtained from the reduced-form residuals of the previous stage.

Assumptions of 3SLS

1 - The complete specification of the entire system is

correctly known (not only should we know the variables which appear in each equation, but also its mathematical form).

2 - The random of each equation is serialy independent (no autocorrelation).

3 - The random variables of the various relations of the system are contemporaneously dependent (if they are independent, the 3SLS reduces to the 2SLS). However, as stated by Koutsoyiannis, taking account of the nature of economic phenomena and the simplifications which we adopt in specifying the econometric models, we may expect the u's to be contemporaneously correlated. That is, $E(u_i\ u_j \neq 0)$, where i refers to the ith equation and j to the jth equation.

As will be seen in our study, for various reasons, we include explicitly in the relationship only the most important explanatory variables leaving the influence of the other, less important, variables to be absorbed by the random variables of the relation. Therefore, it is inevitable that the u's of these relations are correlated and hence, the application of 3SLS is appropriate. The application of the 2SLS under these circumstances would ignore one part of the information included in the entire system, and the estimates of the parameters would be less efficient.

4 - The system is overidentified.

Inferences about structural-equation slopes

Consider the following structural equation having two or more jointly dependent variables:

$$Y_1 + \sum_2^H \beta_i Y_i + \sum_1^J \gamma_K Z_K = u \qquad (1)$$

where the Y's are jointly dependent, the Z's predetermined, u is disturbance and the β's and γ's are unknown parameters. The parameters σ^2, equal to VAR(u) is also unknown.

According to Christ [58] the following statistics (analogous to the "t" ratios in single equation) have approximately (not exactly) the normal distribution:

$$(2) \qquad \frac{\hat{\beta}_i - \beta_i}{\hat{\sigma}(\hat{\beta}_i)} \quad ; \quad \frac{\hat{\gamma}_K - \gamma_K}{\hat{\sigma}(\hat{\gamma}_K)} \qquad \begin{matrix} i = 2, H \\ K = 1, J \end{matrix}$$

where $\hat{\beta}_i$ and $\hat{\gamma}_K$ are the estimators of equation (1) calibrated with a multi-equation technique. $\hat{\beta}_i$ and $\hat{\gamma}_K$ are only approximately normal (not exactly). The $\hat{\sigma}$'s are estimators of the approximate (not the exact) standard deviations of $\hat{\beta}$'s and $\hat{\gamma}$'s and the $\hat{\sigma}^2_s$ presumably have the χ^2 distribution, only approximately at best.

According to Christ, the appropriate degree of freedom for the approximate distribution (2) is not clear. Most practitioners use the sample size diminished by the number of unknown parameters in the equation (i.e, T - H + 1 - J) in analogy to the correct number for least squares estimation of a reduced form equation.

Goodness of fit of structural equations

Consider the calculated residuals and values of Y_1 in equation (1) as follows:

$$\hat{u}_t = Y_{1t} - \hat{Y}_{1t} = Y_{1t} - \sum_2^H \hat{\beta}_i Y_{it} - \sum_1^J \hat{\gamma}_K Z_{Kt} \quad (3)$$

According to Christ, a statistic can be defined that estimates the variance of the structural disturbance by taking the mean squares of the residuals $\hat{u}_t$ form (3):

$$\hat{\sigma}^2 = \text{est.}\,\sigma^2 = \frac{1}{T-H+1-J} \sum_1^T \hat{u}_t^2$$

One might think of a statistical analogous to the R^2 and defined as:

$$1 - \frac{\sum_1^T \hat{u}_t^2}{\sum_1^T (Y_{1t} - \bar{Y}_1)^2}$$

However, whereas R^2 must lie between 0 and 1 inclusive, Basmann has pointed out that the statistic discussed here can be negative,* because u_t^2 can exceed $(Y_{1t}-\bar{Y}_1)^2$ and that can happen even when a correct model is being used.

According to Christ, a statistic called Trace correlation, has been proposed by Hooper, which measures the proportion of the total variance of the jointly dependent variables as a group that is explained by the predetermined variables as a group in a structural model.

---

* This can be seen later, on some of our empirical models.

CHAPTER 11

MULTI-EQUATION MODELS BUILDING

As stated earlier on, it was originally intended to conduct this study in a pure Time Series data. Such an analysis, by region pairs market, would indeed take account of the peculiarities of different routes. We already have outlined in Part II the disadvantages of the aggregation process, and shown that an aggregate equation was clearly inappropriate for describing the variation of demand in routes with different characteristics.

However, due to the small sample data and the multi-equation structure nature of our models,which lowers even more the degree of freedom*, it became necessary to combine Cross-sectional and Time Series data,in order to derive meaningful elasticities.

Indeed, when the degree of freedom is too low, the coefficients are not reliable, particularly with 2SLS and 3SLS, which require a large number of observations. According to Pindyck [13] , the knowledge about the properties of multi-equation estimators relates to large samples; but little is known about the small samples properties of these estimators.

In order to achieve a reasonable compromise between the usefulness of a disaggregation by region pairs, which would take account of the peculiarities of the individual routes and the imperative necessity of ensuring a

---

* The degree of freedom,in a multi-equation calibration technique, is not only dependent on the number of predetermined variables but also on the number of equations.

reasonable degree of freedom, pooling up data, by length of haul, has been retained. Various other types of aggregations have been shown in the US market (Part II); but the lack of data and the low number of routes have not allowed other aggregations.

In fact, besides its traditional use in Air travel demand analysis, the length of haul aggregation does sound reasonable in Air/Surface Modes Competition. It is commonly admitted by the analysts that such competition is stronger in short distances than in very long ones where the aircraft may become almost the only feasible means of transport.

Defining short, medium and long distances does always bear some arbitrariness. But, since the purpose of this delimitation is the analysis of the Air-Rail competition, such delimitation should be the one which best reflects the modal split.

According to a study [59] conducted by Southampton's University, the major modes of transport are Road up to 175 km, Rail between 175 km and 375 km, and Air above 375 km. Incidently, our restriction of Air/Surface Modes Competition to the Bimodes Air/Rail one, seems to derive an interesting empirical support from the Southampton's findings, since the routes considered in this analysis are all longer than 175 km. Accordingly, the main modes to consider for these routes are Air or Rail.

Finally, taking the range of 375 km as a reasonable limitation between shorter and longer routes, the 7 routes are aggregated as follows:

	London-Glasgow	548 km
<u>LONG ROUTES</u> (375 km)	London-Edinburgh	540 km
	London-Newcastle	440 km

	London-Birmingham	180 km
SHORT ROUTES	London-Manchester	260 km
(375 km)	London-Liverpool	280 km
	London-Leeds	290 km

11.1 POOLED MODELS

The starting point in the multi-equation modeling process has been the following model:

$$
\begin{aligned}
DA &= \alpha_0 + \alpha_1\, NFL_1 + \alpha_2\, FARE_1 + \alpha_3\, FARE_2 + \alpha_4\, GDP + \varepsilon_1 \\
DR &= \beta_0 + \beta_1\, NFL_2 + \beta_2\, FARE_1 + \beta_3\, FARE_2 + \beta_4\, GDP + \varepsilon_2 \\
NFL_1 &= \gamma_0 + \gamma_1\, DA + \gamma_2\, LF + \varepsilon_3 \\
NFL_2 &= \rho_0 + \rho_1\, DR + \rho_2\, TIME + \rho_3\, ELEC + \varepsilon_4 \\
FARE_2 &= \mu_0 + \mu_1\, DA + \mu_2\, DR + \varepsilon_5
\end{aligned}
$$

Where the variables in Logarithm are as previously defined. This model corresponds to the total pooled model, aggregated across the 7 routes over the period 1968 - 1978 (i.e, 11 years - 77 observations).

The initial results (not displayed) showed perverse cross-elasticities, most likely due to the collinearity between fares variables illustrated in the correlation matrix below by their mutual correlation factor. Indeed, the value (.894) of this factor is higher than the partial correlation values of both fares with both demands which may indicate the existence of a strong collinearity. When multi-collinearity is serious, it is difficult if not impossible to disentangle the separate influences of each variable. It is then impossible to estimate the separate effects of each variable.

Therefore, it appears reasonable to ovoid the inclusion of the two variables in the same equation; and the following modifications were introduced in the demand equations (ignoring the intercept and the random term in each equation, for simplicity).

$$\text{MODEL 1}\begin{cases} DA = {}_1\,NFL_1 + {}_2\,FARE_1 + {}_3\,GDP \\ DR = {}_1\,NFL_2 + {}_2\,FARE_2 + {}_3\,GDP \end{cases}$$

$$\text{MODEL 2}\begin{cases} DA = {}_1\,NFL_1 + {}_2\,FARE_1 + {}_3\,GDP \\ DR = {}_1\,NFL_2 + {}_2\,\dfrac{FARE_1}{FARE_2} + {}_3\,GDP \end{cases}$$

$$\text{MODEL 3}\begin{cases} DA = {}_1\,NFL_1 + {}_2\,\dfrac{FARE_1}{FARE_2} + {}_3\,GDP \\ DR = {}_1\,NFL_2 + {}_2\,FARE_2 + {}_3\,GDP \end{cases}$$

$$\text{MODEL 4}\begin{cases} DA = {}_1\,NFL_1 + {}_2\,\dfrac{FARE_1}{FARE_2} + {}_3\,GDP \\ DR = {}_1\,NFL_2 + {}_2\,\dfrac{FARE_1}{FARE_2} + {}_3\,GDP \end{cases}$$

$$\text{MODEL 5}\begin{cases} DA = {}_1\,NFL_1 + {}_2\,\dfrac{FARE_1}{FARE_2} + {}_3\,GDP \\ DR = {}_1\,NFL_2 + {}_2\,\dfrac{TIME_1}{TIME_2} + {}_3\,GDP \end{cases}$$

$$\text{MODEL 6}\begin{cases} DA = {}_1\,NFL_1 + {}_2\,\dfrac{TIME_1}{TIME_2} + {}_3\,GDP \\ DR = {}_1\,NFL_2 + {}_2\,\dfrac{TIME_1}{TIME_2} + {}_3\,GDP \end{cases}$$

All the other equations remained unchanged, except in Models 4 and 5 where $FARE_2$ equation is formulated as follows:

$$\frac{FARE_1}{FARE_2} = \rho_1 \, DA + \rho_2 \, DR$$

(ignoring the intercept and the random term)

Finally, in Model 6, $FARE_2$ equation is not included at all, since this variable has been removed from demand equations. The results are displayed on the tables numbered from 11.1 to 11.6.

Correlation Matrix

DA	DR	NFL_1	NFL_2	$FARE_2$	$FARE_1$	GDP
1.000	.425	.961	.230	.475	-.275	.414
	1.000	.347	.845	-.498	.646	.903
		1.000	.121	.491	.340	.356
			1.000	-.504	-.619	.316
				1.000	.894	-.449
					1.000	-.525
						1.000

11.2 POOLED MODELS: RESULTS AND DISCUSSIONS

The six pooled models have been estimated by a means of two-stage least squares (2SLS), and three-stage least squares (3SLS).

At this preselection stage of the most acceptable form, we first analyse the results in rather general terms; the main purpose being the identification of the common characteristics of these models, their overall fit, and the elimination of the less satisfactory models. Then, the remaining ones are analysed in

	2SLS Coef	2SLS Se	2SLS t	3SLS Coef	3SLS Se	3SLS t
EQ. DA						
NFL_1	.692	.035	19.770	.688	.023	29.913
$FARE_1$	-.262	.184	-1.420	-.095	.051	-1.863
GDP	.011	.063	1.746	-.026	.020	-1.300
Cst	-.109			.167		
	R^2=.92		SE=.132	R^2=.91		SE=.139
EQ. DR						
NFL_2	-.176	.171	-.029	-.498	.153	-3.255
$FARE_2$	-.951	.284	-.348	-1.479	.259	-5.714
GDP	1.366	.218	6.266	1.647	.199	8.291
Cst	-2.315			-2.701		
	R^2=.76		SE=.265	R^2=.58		SE=.270
EQ. NFL_1						
DA	1.414	.054	26.180	1.473	.044	33.477
LF	-1.660	.903	1.840	-.323	.280	-1.153
Cst	2.822			.306		
	R^2=.93		SE=.193	R^2=.92		SE=.201
EQ. NFL_2						
DR	.762	.081	9.407	.707	.080	8.837
$TIME_2$	-1.011	.222	-4.554	-1.041	.220	-4.732
ELEC	3.078	.612	5.029	3.643	.564	6.459
Cst	4.328			4.909		
	R^2=.82		SE=.276	R^2=.82		SE=.285
EQ. $FARE_2$						
DA	.264	.016	16.500	.259	.016	16.187
DR	-.254	.013	-19.540	-.259	.013	19.923
Cst	-.999			-.972		
	R^2=.81		SE=.063	R^2=.81		SE=.068

Table 11.1

POOLED MODEL 1

Se= stand. error of Coef. SE= stand. error of Equa.

	2SLS			3SLS		
	Coef	Se	t	Coef	Se	t
EQ. DA						
NFL_1	.725	.035	20.714	.734	.024	30.583
$FARE_1$	-.394	.185	-2.130	-.200	.060	-3.333
GDP	-.035	.064	-.547	-.044	.021	-2.095
Cst	-.164			.003		
	R^2=.92		SE=.137	R^2=.91		SE=.142
EQ. DR						
NFL_2	.348	.088	3.954	.383	.080	4.787
$\frac{FARE_1}{FARE_2}$	-.854	.317	-2.694	-.881	.291	-3.027
GDP	.802	.132	6.076	.741	.119	6.227
Cst	-1.003			-.916		
	R^2=.86		SE=.206	R^2=.93		SE=.208
EQ. NFL_1						
DA	1.366	.051	26.784	1.392	.049	28.408
LF	-2.106	.885	-2.380	-.604	.879	-.687
Cst	3.722			.982		
	R^2=.93		SE=.193	R^2=.93		SE=.196
EQ. NFL_2						
DR	.787	.076	10.355	.815	.068	11.985
$TIME_2$	-.961	.216	-4.449	-.896	.195	-4.595
ELEC	3.094	.612	5.055	1.871	.590	3.171
Cst	4.250			3.237		
	R^2=.82		SE=.276	R^2=.81		SE=.283
EQ. $FARE_2$						
DA	.282	.015	18.800	.285	.010	28.500
DR	-.246	.013	-18.923	-.248	.009	27.555
Cst	-1.060			3.237		
	R^2=.81		SE=.063	R^2=.81		SE=.063

Table 11.2

POOLED MODEL 2

	2SLS			3SLS		
	Coef	Se	t	Coef	Se	t
EQ. DA						
NFL_1	.583	.018	32.889	.613	.016	38.312
$\frac{FARE_1}{FARE_2}$	-.555	.172	-3.227	-.195	.090	-2.167
GDP	-.107	.047	-2.276	-.021	.024	-.875
Cst	1.022			.531		
	R^2=.96		SE=.086	R^2=.94		SE=.095
EQ. DR						
NFL_2	.107	.028	3.821	.030	.023	1.304
$FARE_2$	-.847	.070	-12.100	-1.037	.060	-17.283
GDP	.287	.037	7.757	.292	.036	8.111
Cst	.604			.662		
	R^2=.93		SE=.062	R^2=.90		SE=.071
EQ. NFL_1						
DA	1.365	.061	22.377	1.491	.054	27.611
LF	-.600	.800	-.750	-.175	.420	-.417
Cst	.562			-.257		
	R^2=.94		SE=.164	R^2=.94		SE=.164
EQ. NFL_2						
DR	-1.069	.503	-2.125	-.843	.470	-1.794
$TIME_2$	-3.103	.575	-5.397	-2.901	.543	-5.342
ELEC	2.005	.574	3.509	1.908	.534	3.558
Cst	10.080			9.230		
	R^2=.77		SE=.210	R^2=.77		SE=.210
EQ. $FARE_2$						
DA	.174	.029	6.000	.159	.028	5.678
DR	-.441	.049	-9.000	-.461	.048	-9.604
Cst	-.221			-.128		
	R^2=.90		SE=.054	R^2=.89		SE=.055

Table 11.3

POOLED MODEL 3

	2SLS			3SLS		
	Coef	Se	t	Coef	Se	t
EQ. DA						
NFL_1	.619	.032	19.344	.642	.025	25.680
$\frac{FARE_1}{FARE_2}$	-.807	.600	-1.345	-.657	.422	-1.557
GDP	.101	.035	2.886	.031	.017	1.823
Cst	.238			.365		
	R^2=.96		SE=.113	R^2=.97		SE=.119
EQ. DR						
NFL_2	-.400	.378	-1.058	-.868	.247	-3.514
$\frac{FARE_1}{FARE_2}$	4.563	2.430	1.878	9.053	1.480	6.117
GDP	1.868	.549	3.402	2.432	.388	6.268
Cst	-3.379			-4.816		
	R^2=.15		SE=.505	R^2*		SE=.852
EQ. NFL_1						
DA	1.422	.055	25.854	1.486	.048	30.958
LF	-1.581	.906	-1.745	-.064	.618	-.103
Cst	2.661			.186		
	R^2=.93		SE=.193	R^2=.92		SE=.199
EQ. NFL_2						
DR	.752	.082	9.171	.715	.081	8.827
$TIME_2$	-1.033	.224	-4.612	-1.024	.220	-4.654
ELEC	3.070	.612	5.016	3.000	.567	5.291
Cst	4.364			4.410		
	R^2=.82		SE=.276	R^2=.82		SE=.277
EQ. $\frac{FARE_1}{FARE_2}$						
DA	-.065	.014	-4.643	-.059	.013	-4.538
DR	.025	.012	2.083	.028	.011	2.545
Cst	.343			.323		
	R^2=.25		SE=.058	R^2=.22		SE=.060

Table 11.4

POOLED MODEL 4

* negative coef.

	2SLS			3SLS		
	Coef	Se	t	Coef	Se	t
EQ. DA						
NFL_1	.603	.024	25.125	.627	.020	31.350
$\frac{FARE_1}{FARE_2}$	.117	.482	.243	.232	.274	.847
GDP	-.187	.073	-2.562	-.061	.035	-1.743
Cst	1.060			.195		
	R^2=.94		SE=.090	R^2=.93		SE=.095
EQ. DR						
NFL_2	-.187	.064	-2.922	-.148	.044	-3.364
$\frac{TIME_1}{TIME_2}$	1.570	.176	8.920	1.438	.125	11.504
GDP	.197	.052	3.788	.241	.046	5.239
Cst	3.128			3.560		
	R^2=.87		SE=.080	R^2=.86		SE=.085
EQ. NFL_1						
DA	1.581	.483	3.273	1.602	.053	30.245
LF	-.480	.798	-.601	.058	.485	.119
Cst	.316			.285		
	R^2=.94		SE=.160	R^2=.93		SE=.164
EQ. NFL_2						
DR	-1.400	.542	-2.583	-1.248	.477	-2.616
$TIME_2$	-3.472	.619	-5.609	-3.282	.553	-5.935
ELEC	1.850	.608	3.043	2.863	.459	6.237
Cst	11.140			11.760		
	R^2=.74		SE=.220	R^2=.73		SE=.226
EQ. $\frac{FARE_1}{FARE_2}$						
DA	.034	.031	1.097	.016	.030	.533
DR	.230	.053	4.340	.194	.048	4.042
Cst	-.509			-.540		
	R^2=.26		SE=.060	R^2=.26		SE=.065

Table 11.5

POOLED MODEL 5

	2SLS			3SLS		
	Coef	Se	t	Coef	Se	t
EQ. DA						
NFL_1	.511	.073	7.001	.552	.041	13.463
$\frac{TIME_1}{TIME_2}$	-.728	.365	1.994	-.548	.206	2.660
GDP	.373	.148	2.520	.240	.080	3.000
Cst	-.665			-.319		
	R^2=.94		SE=.121	R^2=.93		SE=.123
EQ. DR						
NFL_2	-1.026	.446	-2.300	-1.560	.302	-5.165
$\frac{TIME_1}{TIME_2}$	2.143	.789	2.716	3.192	.570	5.600
GDP	2.128	.463	4.596	2.435	.348	6.997
Cst	.531			.472		
	R^2=.27		SE=.469	R^2*		SE=.635
EQ. NFL_1						
DA	1.424	.055	25.891	1.473	.049	30.061
LF	-1.561	.906	-1.723	-.753	.547	-1.376
Cst	2.620			1.040		
	R^2=.93		SE=.193	R^2=.93		SE=.194
EQ. NFL_2						
DR	.682	.081	8.419	.638	.079	8.076
$TIME_2$	-1.175	.222	5.293	-1.195	.217	-5.507
ELEC	3.024	.615	4.917	2.514	.483	5.205
Cst	4.600			4.355		
	R^2=.82		SE=.277	R^2=.81		SE=.279

Table 11.6

POOLED MODEL 6

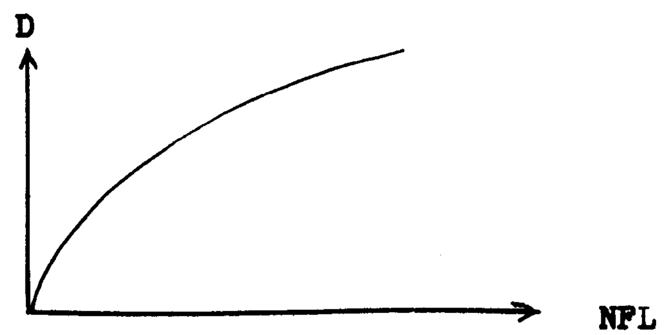
* negative coeefficient

greater details, and finally, applied to the length of haul market aggregation.

The most striking result is that Air frequency of services elasticity is highly significant, bears the correct sign, and has a rather stable and reasonable value in all the following models:

MODEL'S INDEX	1	2	3	4	5	6
2SLS	.692	.725	.583	.619	.603	.511
3SLS	.688	.734	.613	.642	.627	.552

This result is very important, since it is in accordance with the economic theory reviewed earlier. In particular, the fact that these values are <1 is interesting and shows that the demand vs frequency curve is of the following expected form:



This means that an increase in NFL induces an increase less than proportional in traffic. In other wor ds, there is a diminishing return of demand.

It is also interesting to note that fare variable, either absolute or relative, has the right sign in all Air demand equations; and is generally significant, except in Model 5 where it has neither significance nor correct sign. This result too, is consistent with the economic theory, since demand appears to be a decreasing function of fares.

In Model 6 the variable $\frac{TIME_1}{TIME_2}$, which replaces fare variable, has also the expected sign and is significant. Its negative sign means that demand increases when the relative time decreases. However, income elasticity appears very low, or rather not significant at all, in Air demand equations.

In Rail demand equations, NFL_2 bears a wrong sign in most modes, which contradicts the economic theory, whereas fare variable, absolute or relative, as well as income variable seem to behave correctly.

Finally, the supply equations appear to be reasonable; and this confirms the endogenous nature of NFL_1 and NFL_2 as well as $FARE_2$.

Now that we have commented these results in general terms, we should remove the models that show either bad overall fit or are in contradition with the economic theory.

The first two models to be removed are Model 4 and Model 6, because of their bad fit in Rail demand equations. Their R^2 coefficients are, respectively, .15 and .27 when using 2SLS; and are surprisingly negative* when using 3SLS. They also show systematic negative

---

* The possibility of negative "multiple regression coefficient" in multi-equation systems, has been discussed in Chap. 10.

NFL_2 coefficient in Rail demand equations which is in contradiction with the economic theory.

The third model to be removed is the Modle 5, because it combines two defects : it shows, like Model 4, a low fit in the fifth equation where R^2 = .26 for both 2SLS and 3SLS estimations; and a wrong sign for NFL_2 in Rail demand equations.

The remaining models are : (1), (2), and (3) . Although some of their coefficients still bear incorrect sign, they all provide good overall fits with 2SLS and 3SLS estimations.

Therefore, the analysis will focus on these models which will be applied to the length of haul markets segmentation. However, before doing so, let us return to the results of these models, on the tables above, and compare Air and Rail medes throughout these results.

The results show that Air and Rail modes are following different, if not opposite, patterns. As stated earlier, income elasticity appears very low, or rather not significant at all, in Air demand equations, while it is high and highly significant in all Rail demand equations. This elas ticity varies as follows:

	MODEL 1	MODEL 2	MODEL 3
2SLS	1.366	.802	.287
3SLS	1.647	.741	.292

On the contrary, while the frequency of services variable elasticity , in Rail equations, shows a low significance, and even a wrong sign in Model 1; it shows a high significance and rather stable values in Air demands, as indicated below:

	MODEL 1	MODEL 2	MODEL 3
2SLS	.692	.725	.583
3SLS	.688	.734	.613

Combining these results with the fact that fare elasticity, absolute or relative, is systematically lower than the Air frequency elasticity, and higher than the Rail frequency elasticity, we may conclude that Air travel is a business and/or a high incomes users oriented market, while Rail travel is a personal and/or a low incomes users oriented market.

This conclusion emerges from the utility maximization concept assumption. Travelers are assumed to choose the mode, the attributes of which maximize their utility functions. Since business travelers do not, generally have to bear the cost of their travel, they choose the mode that provides the highest level of service, caring a little about its fares. On the contrary, personal travelers attribute greater importance to the trip cost than to the level of service. Similarly, high incomes travelers, comparatively to the low incomes ones, do generally accord higher importance to the level of service and lower one to the trip cost.

Since the frequency of services, which is a measure of the level of service, is the most significant variable in the Air demand; and since fare and income are the most significant variables in Rail demand, the logical conclusion is that the Air mode is mainly selected by businessmen and/or high income users, whereas Rail mode by personal and/or low incomes travelers.

11.3 LONG AND SHORT HAUL MODELS

It is of great importance to the planner and the policy maker to appreciate the orientation of the travel market, according to the routes serviced by both Air and Rail modes, so as to achieve an efficient "fleet" scheduling, able to match the demand and ensure a profitable price differentiation.

The revenue, that a supplier is able to extract from travelers, depends upon its ability, in practice, to discriminate between them. The better he is able to discriminate, the more nearly will he be able to relate its actual revenue to what the market will bear.

Later, we will discuss the application of these models to planning purposes. Before doing so, let us analyse the coefficients, derived from the length of haul aggregation, and interpret their signification. The results, for long haul markets (Glasgow, Edingurgh, Newcastle), are displayed on the tables: 11.7, 11.8, and 11.9; and for short haul markets (Birmingham, Manchester, Liverpool, Leeds), on the tables: 11.10, 11.11, 11.12.

11.3.1 Air demand equation

Frequency of services variable

In all three models, the frequency of services is the most powerful variable, in terms of statistical significance, and bears the correct sign. It displays higher elasticity in short than in long haul markets, as shown below:

	2SLS			3SLS		
MODEL INDEX	1	2	3	1	2	3
SHORT	.766	.789	.646	.766	.788	.639
LONG	.492	.484	.492	.502	.492	.489

The fact that this elasticity is, systematically, greater in short than in long haul markets, may well be due to the high ratio of business Air travelers, in short haul, who place the level of service at a high rank in their preferences scale.

Fare variable

Trip cost has been represented by the absolute Air fare, in Model 1 and Model 2; and by the relative Air fare/ Rail fare ratio, in Model 3.

In the three models, the fare variable coefficient bears the correct sign; and is significant in short haul, but not in long haul markets (see below). Its significance, in short hauls, accounts for the travelers who may shift from one mode to the other, according to their relative fares; while its non significance, in long hauls, may suggest that little substitute to Air mode exists. This is of importance from an Airline point of view. It means that a decrease in the relative fare, in short hauls, induces an increase in demand; but an increase of it, in long hauls, may not cause a substantial decrease in the demand.

Note, however, that such an increase in Air demand does not necessarily mean, of course, an increase in the profit. One should balance the yield, induced by the additional demand against the loss experienced by lowering the fare.

	2SLS			3SLS		
MODEL INDEX	1	2	3	1	2	3
SHORT	-.685	-.763	-.971	-.205	-.606	-.443
LONG	-.032	-.006	-.098	-.010	-.005	-011

11.3.2 Rail demand equation

Frequency of services variable

Rail demand shows a quite opposite pattern to Air demand with respect to the frequency of services and fare variables.

The Rail frequency of services coefficients are found highly significant in the three long haul models, and not significant at all (with even a wrong sign) in short haul models. However, as Model 2 does not show a high goodness-of fit in the Rail demand equation; its results are less credible, and thus, the discussion will focus on the other two models.

The non significance of the frequency variable, in short hauls, outlines its low rank in the travelers'preferences scale within this market. Its magnitude , although significant in long hauls, remains low comparatively to Air frequency of services in the following markets.

	MODEL 1	MODEL 3	MODEL 1	MODEL 3
RAIL	.166	.168	.153	.163
AIR	.492	.492	.502	.489
	2SLS		3SLS	

Fare variable

Rail fare variable turns out to be the most determinative factor in Rail demand, in both short and long haul markets. Its elasticity, the highest in Rail demand equations,has the following values:

	MODEL 1	MODEL 3	MODEL 1	MODEL 3
LONG	-.959	-.927	-1.046	-.970
SHORT	-.952	-.730	-1.046	-.921
	2SLS		3SLS	

This elasticity seems to show almost the same magnitude in short and long haul markets. However, despite this similarity, the interpretation of these elasticities are quite different from one market to another.

In fact, as explained earlier, the striking superiority of Air mode over surface modes is, significantly, reduced in short distances, because of the high proportion of the time spent on the take off, landing and operations ground in these routes. The shift, of the travelers, from one mode to the other is highly related to the relative fares, since $\frac{FARE_1}{FARE_2}$, in Air demand equation, shows an elasticity of -.971 and -.443 (in 2SLS and 3SLS respectively).

On the contrary, since $\frac{FARE_1}{FARE_2}$ is not significantly different from zero in Air equation, and since Rail fare is highly significant, one should admit that Rail demand is not very sensitive to Air fare, in long haul markets.

Income variable GDP

As explained earlier, the income variable GDP (Gross Domestic Product) shows different, if not opposite, patterns in the two demand equations. In the Rail equation, this variable is highly significant, in both long and short routes, and bears the correct sign; whereas in the Air equation, this variable shows neither significance nor a correct sign.

MODEL 1

	AIR	RAIL	AIR	RAIL
SHORT	-.293	.685	-.162	.505
LONG	.002	.298	.001	.314
	2SLS		3SLS	

MODEL 3

	AIR	RAIL	AIR	RAIL
SHORT	-.048	.453	.068	.300
LONG	-.003	.294	-.003	.551
	2SLS		3SLS	

In conclusion, the analysis of these demand equations shows that:

- The frequency of services variable NFL_1 is, in terms of significance, the most important explanatory variable in Air demand, while fare and income variables are the most important ones, in Rail demand.

- Air travel demand is highly business and/or high incomes users oriented market, while Rail travel demand is highly personal and/or low incomes oriented one.

- Air and Rail modes compete on a fare basis, in short routes; but do not constitute a close substitute to each other in longer ones.

- In short haul markets, a reduction in Air fare induces a rise in Air traffic; whereas, in long haul markets, an Air fare increase does not seem to cause a substantial loss in traffic.

- An improvement of the level of service, in terms of frequencies, generates relatively more Air traffic but conversely less Rail traffic, in short than in long haul.

11.3.3 Supply equations

Air and Rail demand coefficients DA, DR

The significance of Air and Rail demand coefficients, in the supply equations NFL_1 and NFL_2 , outlines their impact on the Air and Rail supply and the existence of the two-way dependency between the demands and the frequency of services NFL_1 and NFL_2 .

However, whereas the Air demand coefficient DA is high and highly significant in all models, the Rail demand coefficient DR is significant only in short haul models, as shown next.

2SLS

	DA	DR	DA	DR	DA	DR
SHORT	1.635	1.900	1.582	1.901	1.073	1.915
LONG	2.008	-.946*	2.016	-.953*	2.000	-1.078*
	MODEL 1		MODEL 2		MODEL 3	

3SLS

	DA	DR	DA	DR	DA	DR
SHORT	1.568	2.037	1.550	2.298	1.180	2.117
LONG	1.990	-.803*	2.024	-1.118*	2.040	-.998*
	MODEL 1		MODEL 2		MODEL 3	

* coefficient not significantly different from zero

The value of DA coefficient,around 2, in long haul markets means that for a percentage increase in DA corresponds twice this percentage in the Air frequency increase. This figure is, however, lower in short haul (around 1.6).

Once again, Rail mode seems to behave inversely to Air mode. Rail frequency of services is more sensitive to the Rail demand variation, in short than in long haul markets.

Load factor

The results show no significance to the load factor variable except in Pooled Model 2. This is, probably,due to the inappropriate measurement of the LF variable, which is an average value of the LF recorded throughout all domestic routes. That is, probably, why it proves to be significant only in a pooled model.

Trip time and electrification variables

In the Rail supply equation, the LF variable has not been included because the corresponding data are not available. Instead, trip time and electrification variables are introduced to allow the frequency of services variable to pick up their effect. Indeed, it seems reasonable to expect an increase in the frequency of services in anticipation of the demand induced by the trip time and electrification improvements.

- Trip time coefficient: appears quite stable, highly significant and bears the right sign throughout the three models. It shows higher values in long than in short haul markets; which means that the variation in the frequency of services is relatively more sensitive in long routes than in short ones.

	2SLS			3SLS		
MODEL INDEX	1	2	3	1	2	3
SHORT	-.912	-.921	-.899	-.780	-.639	-.725
LONG	-4.734	-4.740	-4.850	-4.537	-4.750	-4.770

It is interesting to note that the simultaneous equations nature of these models permits the evaluation of Rail demand elasticity with respect to the trip time variable . This can be achieved by considering the Rail demand and supply equations below:

$$DR = \beta_0 + \beta_1 NFL_2 + \beta_2 FARE_2 + \beta_3 GDP + \varepsilon_3$$

$$NFL_2 = \rho_0 + \rho_1 DR + \rho_2 TIME_2 + \rho_3 ELEC + \varepsilon_4$$

where:

β_1 : is the elasticity of DR with respect to NFL_2

ρ_2 : is the elasticity of NFL_2 with respect to $TIME_2$

Therefore, the elasticity of Rail demand DR with regard to $TIME_2$ variable is given by the product : $\beta_1 \rho_2$.

The following are the derived values of $TIME_2$ elasticity corresponding to the long haul markets.

	MODEL 1	MODEL 2	MODEL 3
2SLS	.786	-1.095	-.815
3SLS	.694	-1.211	-.777

It is also interesting to note the consistency of the above elasticities with the trip time elasticities values, assumed by British Railways Board in their Traffic Passenger Model [60] . These hypothetical values are the following :

Lower	Standard	Upper
-.70	-.85	-1.0

- Electrification variable coefficient: the values of this coefficient are consistent with the previous assumption that the frequency of services may be increased in anticipation of the rise in the demand induced by the electrification improvements of the routes. The coefficient of ELEC variable is, as expected, positive and highly significant in short routes. It shows, however, a slightly high magnitude (as displayed below) and a very low, if not inexistent, significance in long routes.

	MODEL 1	MODEL 2	MODEL 3
2SLS	3.454	3.459	3.461
3SLS	3.503	2.946	3.445

Short haul markets

11.3.4 Rail fare variable equation : $FARE_2 = f(DA, DR)$

In the fifth equation, Air and Rail demands coefficients are significant in almost all models. This confirms the endogenous nature of Rail fare with regard to Rail demand and the two-way dependency between Rail fare and Air demand.

However, surprisingly enough, Rail fare seems to be independent of Rail demand in long haul models.

In his attempt to test whether Air and Rail fares were simultaneously determined, Ellison [27] posed the following reduced forms equations:

$$PA = KA + B_{11}DA + B_{12}DR + B_{13}Y \qquad (1)$$

$$PR = KR + B_{21}DR + B_{22}DA + B_{23}Y \qquad (2)$$

where:
P = price, D = number of passengers, Y = income;
A and R designating Air and Rail variables.

He ran equation (1) and (2) on the London-Newcastle and London-Glasgow routes, for the period 1963 - 1965. The data was divided up into quarters and seasonal dummies(d) were included. The results for Newcastle were as follows:

$$\text{Log } PA = .59 + \underset{(.028)}{.007}\text{Log } DA - \underset{(.20)}{.04}\text{ Log } DR - \underset{(.33)}{.05}\text{Log } Y$$

$$+ \underset{(.002)}{.06}\text{Log } d_1 + \underset{(.006)}{.08}\text{Log } d_2 + \underset{(.007)}{.03}\text{Log } d_3$$

$$R^2 = .82 \qquad DW = 1.7 \qquad (3)$$

$$\text{Log PR} = 3.07 + \underset{(.01)}{.01\text{Log DA}} - \underset{(.22)}{.65\text{Log Y}} - \underset{(.13)}{.04\text{Log DR}}$$

$$+ \underset{(.01)}{.06\text{Log } d_1} + \underset{(.04)}{.03\text{Log } d_2} + \underset{(.05)}{.01\text{Log } d_3}$$

$$R^2 = .87 \qquad DW = 1.69 \qquad (4)$$

From the above results, Ellison concluded that the simultaneity between Rail and Air fare was not shown to be significant, and therefore, Air and Rail fares could be used as exogenous variables, in the UK domestic routes, without fear of any bias. He then ran different models on 17 domestic routes using Air and Rail fares in the Air demand equation.

This methodology calls for the following comments:

- First, the formulation of the reduced form with the endogenous variables, Air and Rail demands, on the right side of the equation does not seem to be clear.

- Second, given the significant correlation that most likely exists between the demands and income variables, equation (3) and (4) could hardly provide unbiased coefficients owing to the multicollinearity between these variables. Therefore, the significance of these coefficients are questionable.

- Finally, the third and most crucial remark is that even if the test, conducted for London-Newcastle and London-Glasgow routes, were conclusive (i.e, that the simultaneity between Air and Rail fares exists), it would not necessarily mean that it should be alike for the other routes. In fact, London-Newcastle and London-Glasgow are both long routes; and the conclusions drawn from their results could hardly be extended to the short haul routes without appropriate tests.

The results obtained by Ellison, for the 7 models on the 17 domestic routes, were highly unstable and many perverse signs were recorded. Besides, the multiple regression coefficients R^2 are drastically low. Out of 106 coefficients R^2 : 67 are lower than .20, 20 are betweem .20 and .30 and 10 are between .30 and .40; while the highest R^2 among the remaining coefficients is .68.

Ellison attributed the failure of these models to the exponential growth being an inaccurate assumption to make concerning the behavior of the trend on domestic routes. Then, he cut back the number of the routes to the most important ones:

London-Glasgow
London-Manchester
London-Newcastle
London-Edinburgh

There is, however, no reason to believe that the failure of these models was due to the Simultaneous Equations Bias. Such bias, which might have been induced by the simultaneity between Air and Rail fares, could not have, in fact, existed because most evidence showed that the Railways had not taken advantage of the pricing freedom, at least before 1968 which is beyond the forecast period considered by Ellison.

With regard to these pricing policies, Gwilliam stated in "Economic and Transport Policy" 1973:
"In the sixties, the Railways management was guilty of a failure to take advantage of the pricing freedom conferred by the 1962 act. Not until after 1968 PIB Report did market pricing for passenger journeys begin. Now, the Railways have taken advantage of the freedom to price flows of traffic according to their demand elasticity".

This assertion explains why Air demand equations that include Rail fares could be considered without fear of the Simultaneous Equations Bias, when using data prior to 1968 (as in Ellison models); but would well be affected by this bias after 1968 as shown in the fifth equation of our models.

	2SLS			3SLS		
	Coef	Se	t	Coef	Se	t
EQ. DA						
NFL_1	.492	.034	14.470	.502	.017	29.529
$FARE_1$	-.032	.200	-.160	-.010	.025	-.040
GDP	.002	.049	.041	.001	.007	.143
Cst	.851			.836		
	R^2=.96		SE=.045	R^2=.96		SE=.046
EQ. DR						
NFL_2	.166	.022	7.545	.153	.022	6.954
$FARE_2$	-.959	.156	-6.147	1.046	.154	6.792
GDP	.298	.041	7.268	.314	.040	7.850
Cst	.243			.149		
	R^2=.83		SE=.043	R^2=.81		SE=.044
EQ. NFL_1						
DA	2.008	.078	25.743	1.990	.065	30.615
LF	-.474	.571	.830	-.102	.075	1.360
Cst	-.896			-1.501		
	R^2=.97		SE=.091	R^2=.96		SE=.092
EQ. NFL_2						
DR	-.946	.538	-1.758	-.803	.513	-1.565
$TIME_2$	-4.734	.586	-8.078	-4.537	.563	-8.059
ELEC	1.073	.587	1.828	.828	.555	1.492
Cst	10.280			9.572		
	R^2=.87		SE=.142	R^2=.86		SE=.138
EQ. $FARE_2$						
DA	.203	.036	5.639	.205	.036	5.694
DR	-.011	.091	-.121	.004	.091	.043
Cst	-1.484			-1.509		
	R^2=.66		SE=.037	R^2=.61		SE=.039

Table 11.7

MODEL 1 Long Haul

	2SLS			3SLS		
	Coef	Se	t	Coef	Se	t
EQ. DA						
NFL_1	.484	.033	14.667	.492	.015	32.800
$FARE_1$	.006	.195	.031	-.005	.020	-.250
GDP	.009	.048	.187	.003	.006	.500
Cst	.888			.872		
	R^2=.96		SE=.045	R^2=.96		SE=.045
EQ. DR						
NFL_2	.231	.035	6.600	.255	.032	7.969
$\frac{FARE_1}{FARE_2}$	.357	.234	1.526	.201	.175	1.148
GDP	.211	.054	3.907	.218	.050	4.360
Cst	1.160			1.086		
	R^2=.65		SE=.061	R^2=.64		SE=.062
EQ. NFL_1						
DA	2.016	.078	25.846	2.024	.062	32.645
LF	-.450	.571	-.788	-.092	.076	-1.210
Cst	-.958			-1.616		
	R^2=.96		SE=.091	R^2=.96		SE=.092
EQ. NFL_2						
DR	-.953	.523	-1.822	-1.118	.493	-2.268
$TIME_2$	-4.740	.579	-8.186	-4.750	.550	-8.636
ELEC	1.071	.587	1.824	1.242	.523	2.373
Cst	10.310			10.890		
	R^2=.85		SE=.143	R^2=.84		SE=.150
EQ. $FARE_2$						
DA	.203	.091	2.231	.200	.036	5.555
DR	-.028	.091	-.308	.016	.090	.178
Cst	-1.430			-1.550		
	R^2=.61		SE=.038	R^2=.61		SE=.038

Table 11.8

MODEL 2 Long Haul

	2SLS			3SLS		
	Coef	Se	t	Coef	Se	t
EQ. DA						
NFL_1	.492	.021	23.428	.489	.016	30.562
$\frac{FARE_1}{FARE_2}$	-.098	.153	-.640	-.011	.023	-.478
GDP	-.003	.048	-.062	-.003	.007	-.428
Cst	.916			.899		
	R^2=.96		SE=.045	R^2=.96		SE=.045
EQ. DR						
NFL_2	.168	.022	7.636	.163	.022	7.409
$FARE_2$	-.927	.157	-6.019	-.970	.154	-6.299
GDP	.294	.041	7.171	.300	.040	7.500
Cst	.279			.234		
	R^2=.83		SE=.043	R^2=.82		SE=.044
EQ. NFL_1						
DA	2.001	.079	25.316	2.030	.066	30.757
LF	-.482	.571	-.844	-.030	.090	-.333
Cst	-.875			-1.770		
	R^2=.96		SE=.091	R^2=.96		SE=.092
EQ. NFL_2						
DR	-1.078	.583	-1.849	-.998	.560	-1.782
$TIME_2$	-4.850	.628	-7.723	-4.770	.612	-7.794
ELEC	1.030	.610	1.688	.663	.590	1.124
Cst	10.710			10.150		
	R^2=.85		SE=.148	R^2=.85		SE=.146
EQ. $FARE_2$						
DA	.205	.036	5.694	.206	.036	5.722
DR	.009	.090	.100	.010	.090	.111
Cst	-1.550			-1.550		
	R^2=.61		SE=.038	R^2=.61		SE=.038

Table 11.9

MODEL 3 Long Haul

	2SLS			3SLS		
	Coef	Se	t	Coef	Se	t
EQ. DA						
NFL_1	.766	.085	9.011	.698	.058	12.034
$FARE_1$	-.685	.336	-2.039	-.205	.165	-1.242
GDP	-.293	.185	-1.584	-.162	.076	-2.131
Cst	.373			.537		
	R^2=.87		SE=.124	R^2=.87		SE=.117
EQ. DR						
NFL_2	-.141	.104	-1.356	-.138	.080	-1.725
$FARE_2$	-.952	.173	-5.503	-1.064	.134	-7.940
GDP	.685	.212	3.231	.505	.173	2.919
Cst	.015			.524		
	R^2=.66		SE=.068	R^2=.59		SE=.074
EQ. NFL_1						
DA	1.635	.109	15.165	1.568	.087	18.023
LF	.763	1.383	.055	-.309	.526	-.587
Cst	-1.985			.072		
	R^2=.92		SE=.175	R^2=.90		SE=.175
EQ. NFL_2						
DR	1.900	.299	6.354	2.037	.294	6.928
$TIME_2$	-.912	.293	-3.113	-.780	.290	-2.689
ELEC	3.454	.365	9.463	3.503	.356	9.840
Cst	.925			.482		
	R^2=.92		SE=.101	R^2=.91		SE=.103
EQ. $FARE_2$						
DA	.184	.026	7.077	.145	.023	6.304
DR	-.704	.070	-10.057	-.784	.070	-11.200
Cst	.587			.920		
	R^2=.82		SE=.049	R^2=.79		SE=.053

Table 11.10

MODEL 1 Short Haul

	2SLS			3SLS		
	Coef	Se	t	Coef	Se	t
EQ. DA						
NFL_1	.789	.086	9.174	.788	.057	13.824
$FARE_1$	-.763	.342	-2.231	-.606	.140	-4.328
GDP	-.323	.190	-1.700	-.217	.078	-2.782
Cst	.347			.107		
	R^2=.84		SE=.128	R^2=.84		SE=.130
EQ. DR						
NFL_2	.331	.062	5.339	.338	.055	6.145
$\frac{FARE_1}{FARE_2}$	-.117	.242	-.483	.142	.137	1.036
GDP	-.153	.158	-.968	-.129	.141	-.915
Cst	2.412			2.219		
	R^2=.61		SE=.073	R^2=.59		SE=.074
EQ. NFL_1						
DA	1.582	.106	14.924	1.550	.080	19.375
LF	.373	1.369	.272	.435	.489	.889
Cst	-1.178			-1.228		
	R^2=.90		SE=.174	R^2=.90		SE=.175
EQ. NFL_2						
DR	1.901	.295	6.444	2.298	.278	8.266
$TIME_2$	-.911	.290	-3.141	-.639	.277	-2.307
ELEC	3.454	.364	9.489	2.946	.338	8.716
Cst	.922			-.802		
	R^2=.92		SE=.101	R^2=.89		SE=.114
EQ. $FARE_2$						
DA	.206	.025	8.240	.220	.024	9.167
DR	-.670	.069	-9.710	-.608	.067	9.075
Cst	.429			.210		
	R^2=.81		SE=.048	R^2=.82		SE=.048

Table 11.11

MODEL 2 Short Haul

	2SLS			3SLS		
	Coef	Se	t	Coef	Se	t
EQ. DA						
NFL_1	.646	.036	17.944	.639	.033	19.364
$\frac{FARE_1}{FARE_2}$	-.971	.349	-2.782	-.443	.134	-3.306
GDP	-.048	.127	-.378	.068	.050	1.360
Cst	.746			.182		
	R^2=.91		SE=.103	R^2=.89		SE=.106
EQ. DR						
NFL_2	-.015	.082	-.183	-.109	.070	-1.557
$FARE_2$	-.730	.135	5.407	-.921	.115	8.009
GDP	.453	.169	2.680	.551	.153	3.601
Cst	.632			.414		
	R^2=.74		SE=.058	R^2=.67		SE=.066
EQ. NFL_1						
DA	1.073	.114	9.412	1.180	.090	13.111
LF	.305	1.407	.217	-.237	.510	.465
Cst	-1.038			-.081		
	R^2=.92		SE=.174	R^2=.90		SE=.175
EQ. NFL_2						
DR	1.915	.297	6.448	2.117	.292	7.250
$TIME_2$	-.899	.291	-3.089	-.725	.288	-2.517
ELEC	3.461	.365	9.482	3.445	.359	9.596
Cst	.878			.166		
	R^2=.92		SE=.101	R^2=.90		SE=.105
EQ. $FARE_2$						
DA	.193	.026	7.423	.169	.025	6.760
DR	-.674	.069	-9.768	-.738	.068	-10.853
Cst	.471			.723		
	R^2=.83		SE=.048	R^2=.81		SE=.050

Table 11.12

MODEL 3 Short Haul

CHAPTER 12

SELECTION OF THE BEST SPECIFICATION

12.1 MODEL SELECTION

Models 1, 2, 3, displayed on the tables: 11.1;11.2;11.3, are the models remaining from the step by step modeling process after different forms and variables investigations. Although they are generally providing similar conclusions with regard to the mode competition and all showing reasonable statistical tests, it is, however, necessary at this stage to select the definitive model, for forecasting and analysis purposes.

- Model 1 does not explicitly include any direct competition factor, via a comparison of cost or service performance of the two modes, though the competition may well be indirectly involved through the last equation $FARE_2 = f(DA,DR)$.

- Model 2 and Model 3 introduce explicitly a competition factor $\frac{FARE_1}{FARE_2}$ in their Air demand equation.

Model 3, however, systematically shows a better overall fit than Model 2 in all equations. So, Model 3 is preferable to Model 1 and Model 2.

The introduction of $\frac{FARE_1}{FARE_2}$ variable in Model 3 does not, comparatively to the formulation of Model 1, alter drastically the coefficients either in the demand or in the supplyequations. But, it does provide a better understanding, on a theoretical ground, than Model 1. It also improves significantly the statistical tests : R^2, SE.

The significance of $\frac{FARE_1}{FARE_2}$ variable, in Model 3 retained, confirms the previous results:

The existence of the competition in short haul, and its almost non existence in long haul.

The fact that $\frac{FARE_1}{FARE_2}$ is not significant in long haul, neither in Air (Model 3) nor in Rail (Model 2) while $FARE_2$ is highly significant only in Rail, suggests that, in long haul, both Air and Rail are independent of the fare competition. It also implies that, in long routes, Rail attracts other than potential Air travelers: either strictly potential Rail or other surface modes travelers.

However, before declaring Model 3 as a definitive selected model, we felt it reasonable to find out whether or not it could be improved by altering the income variable, since it displays a wrong sign in long haul. The following section analyses the introduction of a new variable: the range of incomes variable (RANKOM).

12.2 RANGE OF INCOMES VARIABLE

The income variable GDP, selected up till now, does not take account of the population of the region pairs and the income distribution among them. Furthermore, it has often been argued that the propensity to travel is closely related to the traveler's range of incomes, and that Air travelers belong to the highest income brackets.

In order to test the above assumptions, and thereby , to improve the selected model, the income variable GDP was replaced by socioeconomic variables that take into account the income distribution. These variables, named RANKOM have the following form:

$$RANKOM_{(i,j)} = \sum_k \left(X_{ik}^{\bar{Y}_k} \; X_{jk}^{\bar{Y}_k} \right)$$

Where:

X_{ik} = people in range income k within city i (expressed in millions)

Y_k = the weighted average income in range income k

with:

X_{i1} = people in range income $<$ £ 1,000 per year

X_{i2} = people in range income £ 1,000 - £ 2,000

X_{i3} = people in range income £ 2,000 - £ 5,000

X_{i4} = people in range income $>$ £ 5,000

Note, however, that in order to give greater weight to higher income travelers within the population, the power from has been selected instead of the multiplicative one; i.e:

$$X_{ik}^{Y_k} \quad \text{rather than} \quad X_{ik}Y_k$$

Notice also that to qvoid excessive values for these powers, the variable, representing the population number in region i within the level of income k, is expressed in millions.

Three models have been estimated with these new constructed variables:

- The first model, introducing separately the variables

$$(X_{ik}^{Y_k} \; X_{jk}^{Y_k})$$

into the demand equation, was designed to measure the individual elasticity of each variable. The results (not displayed) showed perverse signs, and no significance to the coefficients. One of the reasons of this failure, might be the inaccuracy of the measurement of the population within a given range of incomes throughout the historical period; the incomes being expressed on current values instead of constant ones.

- In order to reduce this drawback, a constant average income Y_k was used and expressed on constant £(1975).

$$Y_1 = £\ 750 \qquad Y_3 = £\ 3{,}000$$

$$Y_2 = £\ 1{,}500 \qquad Y_4 = £\ 7{,}000$$

Furthermore, to prevent any potential multicollinearity between the variables $(X_{ik}^{Y_k}\ X_{jk}^{Y_k})$

a combination of them into a single variable has been retained:

$$RANKOM_{ij} = \sum_{k=1}^{4} (X_{ik}^{Y_k}\ X_{jk}^{Y_k})$$

The results of this model (not displayed) showed no significance to this variable, neither in Air nor in Rail demands.

- In a third attempt, we considered only two ranges of incomes:

- above £ 5,000 in Air demand
- below £ 5,000 in Rail demand

This stipulation has the advantage of assigning high level incomes to Air market only, and of reducing the inaccuracy of the measurement of the population within different incomes ranges.

In the Air demand equation, the results of this model, displayed on Table 12.1 , do not manifest drastic changes or a significance to RANKOM variable.

In Rail demand equation, it renders the NFL_2 coefficient significant, but decreases the significance of $FARE_2$ without making RANKOM variable more significant than GDP.

In the third equation, the elasticities of NFL_1 remain stable; while in the fourth and fifth equations, the

	2SLS			3SLS		
	Coef	Se	t	Coef	Se	t
EQ. DA						
NFL_1	.594	.019	31.263	.619	.017	36.412
$\frac{FARE_1}{FARE_2}$	-.645	.180	-3.583	-.149	.077	-1.935
$RANKOM_1$	.026	.014	1.857	.010	.007	1.428
Cst	.613			.421		
	R^2=.95		SE=.089	R^2=.94		SE=.090
EQ. DR						
NFL_2	.176	.040	4.400	.057	.024	2.375
$FARE_2$	-.969	.101	-9.594	-1.244	.069	-18.029
$RANKOM_2$	.011	.018	.061	.055	.011	5.000
Cst	1.172			1.343		
	R^2=.86		SE=.167	R^2=.93		SE=.167
EQ. NFL_2						
DR	-1.097	.916	-1.197	-.315	.811	-.388
$TIME_2$	-3.148	1.017	-3.095	-2.323	.964	-2.410
ELEC	1.753	.795	2.205	1.710	.731	2.339
Cst	10.010			7.218		
	R^2=.78		SE=.203	R^2=.80		SE=.180
EQ. $FARE_2$						
DA	.076	.042	1.809	.016	.027	.592
DR	-.605	.074	-8.176	-.704	.051	-13.803
Cst	.500			.938		
	R^2=.89		SE=.060	R^2=.87		SE=.058
EQ. NFL_1						
DA	1.582	.054	29.296	1.592	.053	30.038
LF	-.602	.800	.752	-.598	.750	.797
Cst	-.554			-.578		
	R^2=.93		SE=.167	R^2=.93		SE=.167

Table 12.1

POOLED MODEL 3 (with RANKOM variable)

the DR coefficient becomes significant.

However, this new variable does not appear to be as significant as GDP. Moreover, when comparing the minor improvements induced by this variable with the loss of the goodness-of-fit; and the enormous difficulties of forecasting the income distribution among the populations, one should admit the superiority of GDP. Accordingly, the definitive selected model remains Model 3, estimated in the previous section.

12.3 STATISTICAL EVALUATION OF THE MODEL

Now that we have selected Model 3, we move to the next step: testing its validity.

As in the case of OLS, various assumptions, concerning the error terms and the variables, should be met in order that multi-equation calibration techniques can be applied. These assumptions concern the normality of the error terms distribution, the constancy of their variance, their independency upon time and the non correlation of the exogenous variables. Thereafter, we provide statistical tests for Model 3.

12.3.1 Normality of the errors distribution

To test the normality of the errors distribution of the structural form equations, the CHI-SQUARE goodness-of-fit test has, once again, been applied. The standardized residuals, corresponding to the Air and Rail structural form equations, have been computed and their distribution compared to the normal distribution. The results, displayed on Table 12.2 and Table 12.3, show that, for each equation, the computed CHI-SQUARE, is less than the critical $\chi^2_{(.95,4)} = 9.49$. Therefore,

NORMALITY OF RESIDUALS DISTRIBUTION

CHI-SQUARE COMPUTATION

	RANGE OF STANDARDIZED RESIDUALS		O_i OBSERVED FREQUENCIES	E_i EXPECTED FREQUENCIES	$\frac{(O_i - E_i)^2}{E_i}$
2SLS	-	-1	14	12.220	.259
	-1	-.5	8	11.535	1.083
	-.5	0	11	14.745	.951
	0	.5	19	14.745	1.231
	.5	1	12	11.535	.019
	1		13	12.220	.050
	TOTAL		77	77.000	3.693
3SLS	-	-1	12	12.220	.004
	-1	-.5	12	11.535	.019
	-.5	0	14	14.745	.037
	0	.5	15	14.745	.004
	.5	1	12	11.535	.019
	1		12	12.220	.004
	TOTAL		77	77.000	.087

Table 12.2

AIR DEMAND EQUATION

NORMALITY OF RESIDUALS DISTRIBUTION

CHI-SQUARE COMPUTATION

	RANGE OF STANDARDIZED RESIDUALS		O_i OBSERVED FREQUENCIES	E_i EXPECTED FREQUENCIES	$\frac{(O_i - E_i)^2}{E_i}$
2SLS	-	-1	14	12.220	.259
	-1	-.5	10	11.535	.203
	-.5	0	16	14.745	.108
	0	.5	13	14.745	.118
	.5	1	12	11.535	.019
	1		12	12.220	.004
	TOTAL		77	77.000	.711
3SLS	-	-1	13	12.220	.050
	-1	-.5	12	11.535	.019
	-.5	0	15	14.745	.004
	0	.5	11	14.745	.949
	.5	1	10	11.535	.203
	1		16	12.220	1.169
	TOTAL		77	77.000	2.394

Table 12.3

RAIL DEMAND EQUATION

the hypothesis that the error terms are normally distributed can be accepted.

COMPUTED CHI-SQUARE

	2SLS	3SLS
AIR DEMAND	3.693	.087
RAIL DEMAND	.711	2.394

12.3.2 Constant variance

To check up the existence of the heteroscedasticity, the above residuals are plotted against the estimated values of the dependent variable in each structural equation, as illustrated in Fig. 12.1, 12.2, 12.3, and Fig. 12.4 . These figures show no discernable patterns or concentrations. Thereupon, we may reject the hypothesis of any serious heteroscedasticity.

12.3.3 Time dependency of the error terms

The low values manifested by the computed DW tests, may suggest the existence of serial correlation. However, since the 77 observations are not ranked on a truly chronological order (aggregation of 7 region pairs), these DW values may not be of great meaning. Besides, Serial Correlation, even serious, does not affect the unbiasedness or consistency of the coefficients.

12.3.4 Multicollinearity

The correlation matrix, below, corresponding to the five exogenous variables $\frac{FARE_1}{FARE_2}$, LF, $TIME_2$, ELEC, GDP, does not show high values to their mutual correlation coefficients. Therefore, we reject the hypothesis of perfect collinearity between the exogenous variables.

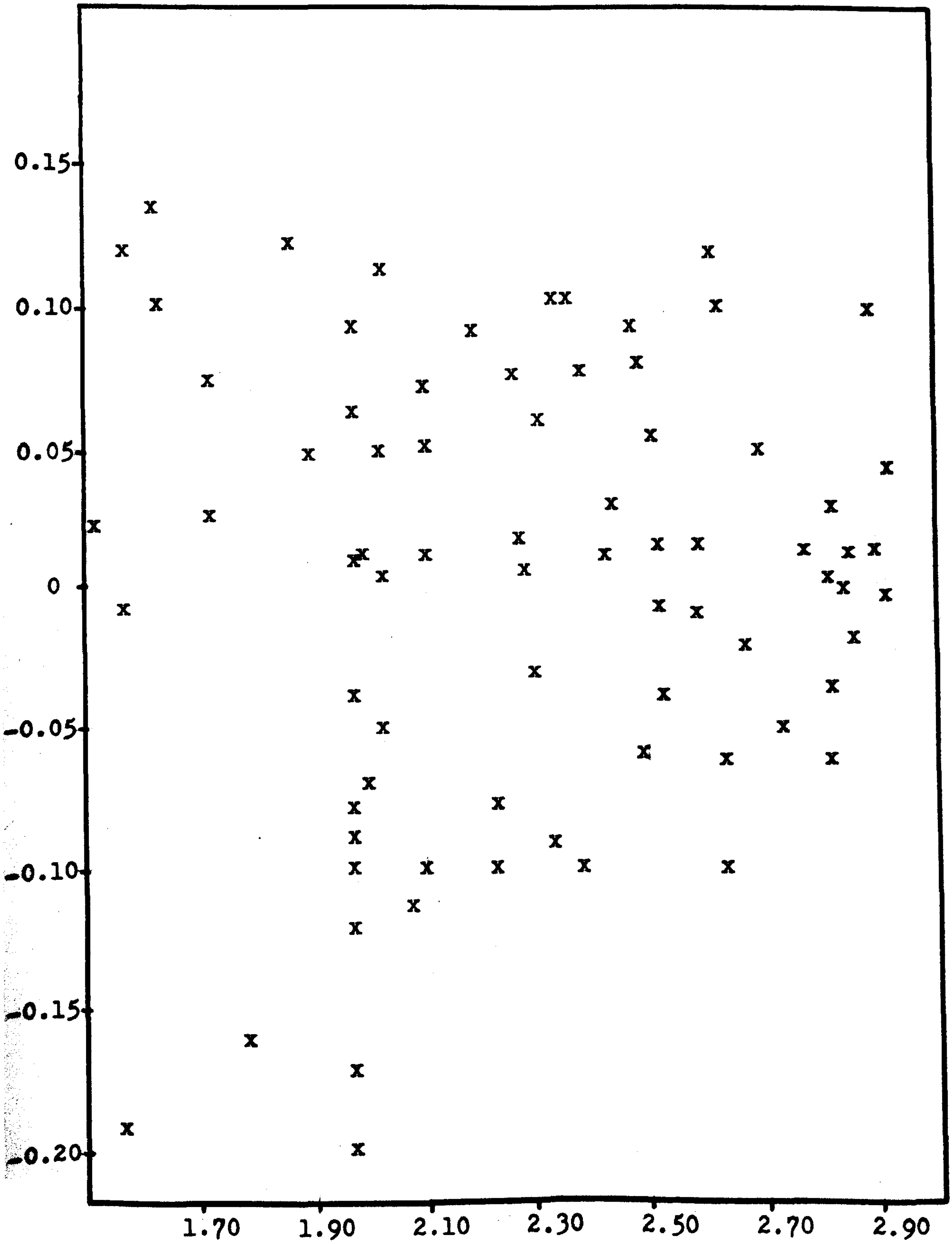


Figure 12.1 PLOTS OF RESIDUALS VS AIR DEMAND (2SLS)

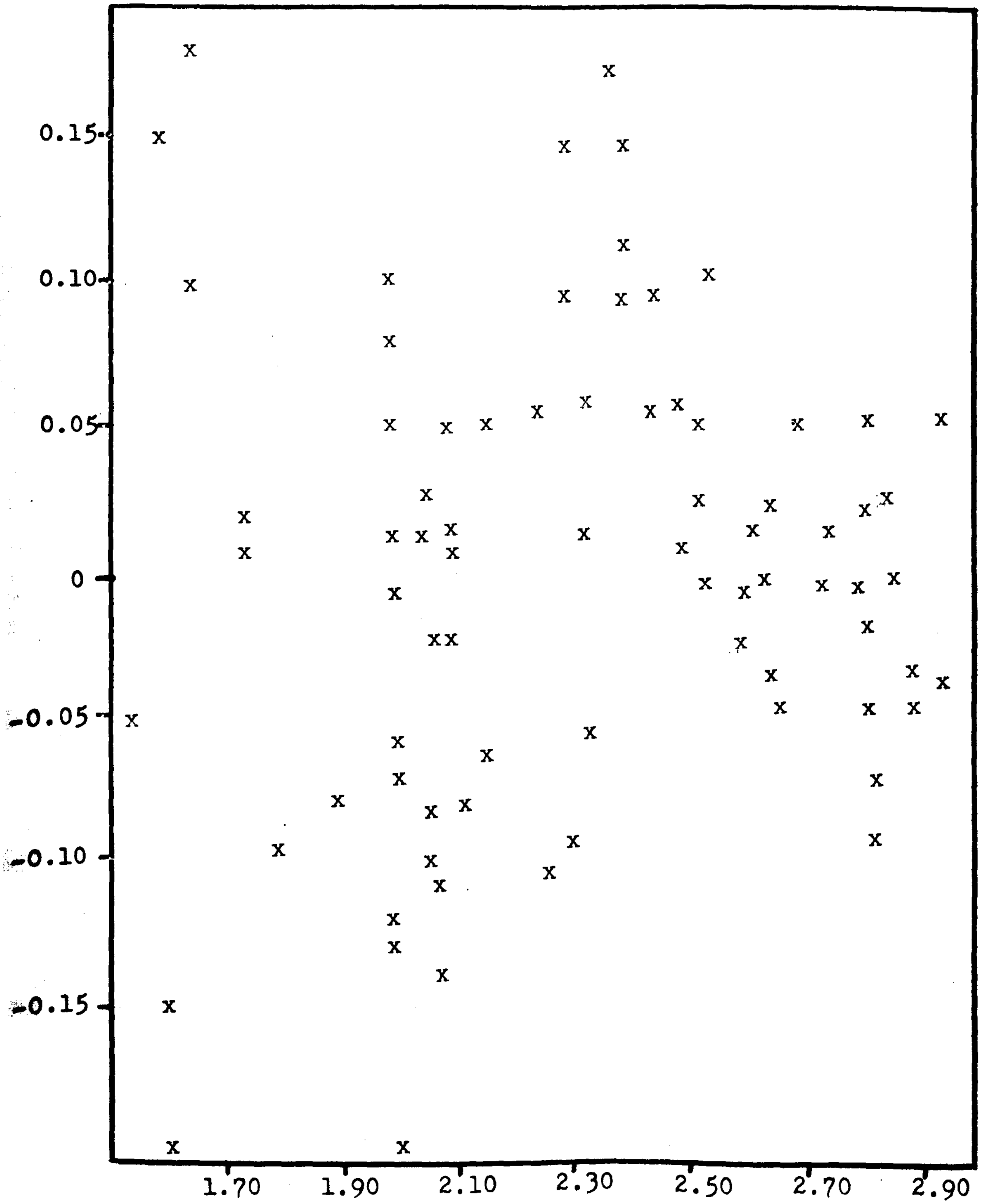


Figure 12.2 PLOTS OF RESIDUALS VS COMPUTED AIR DEMAND(3SLS)

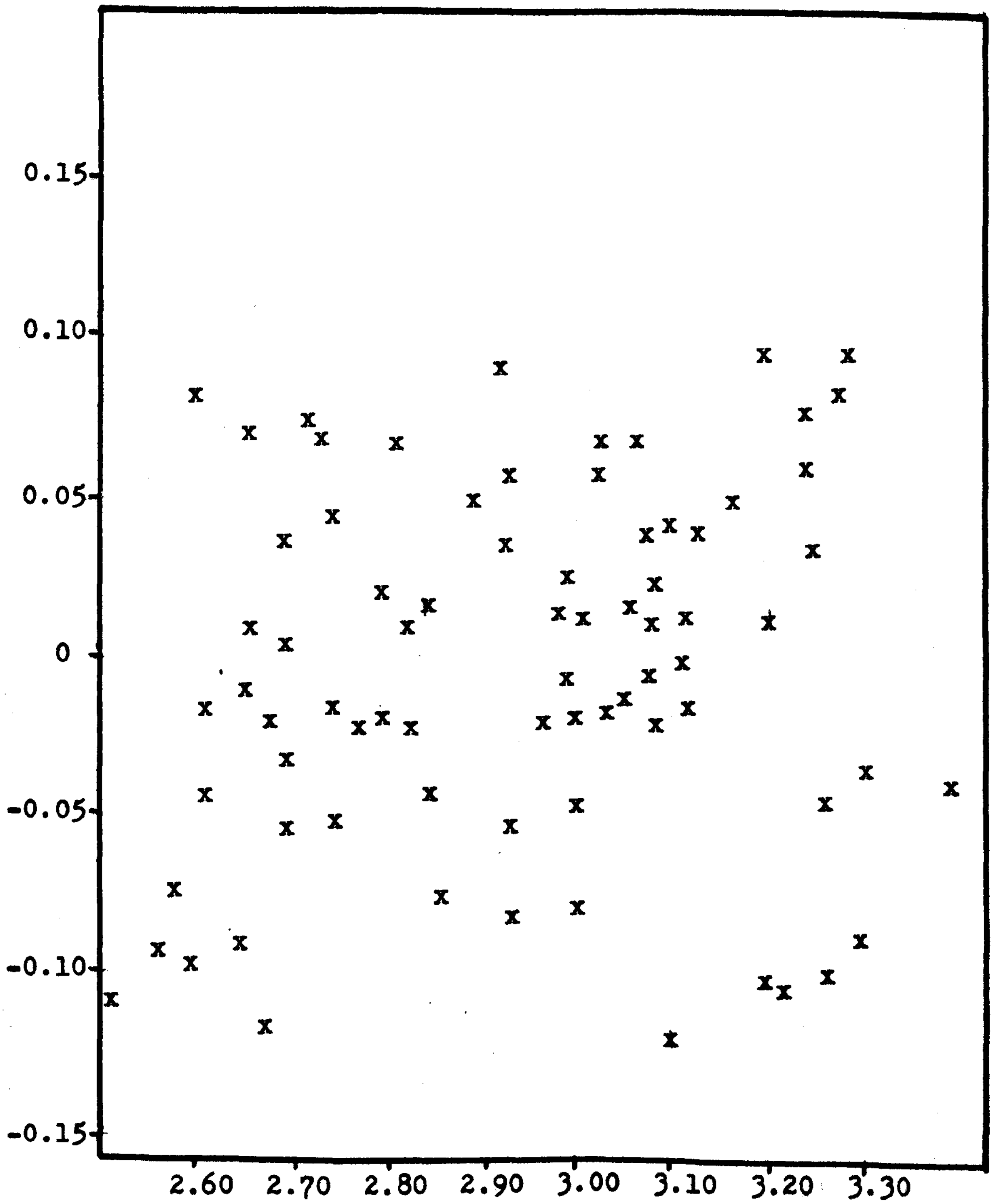
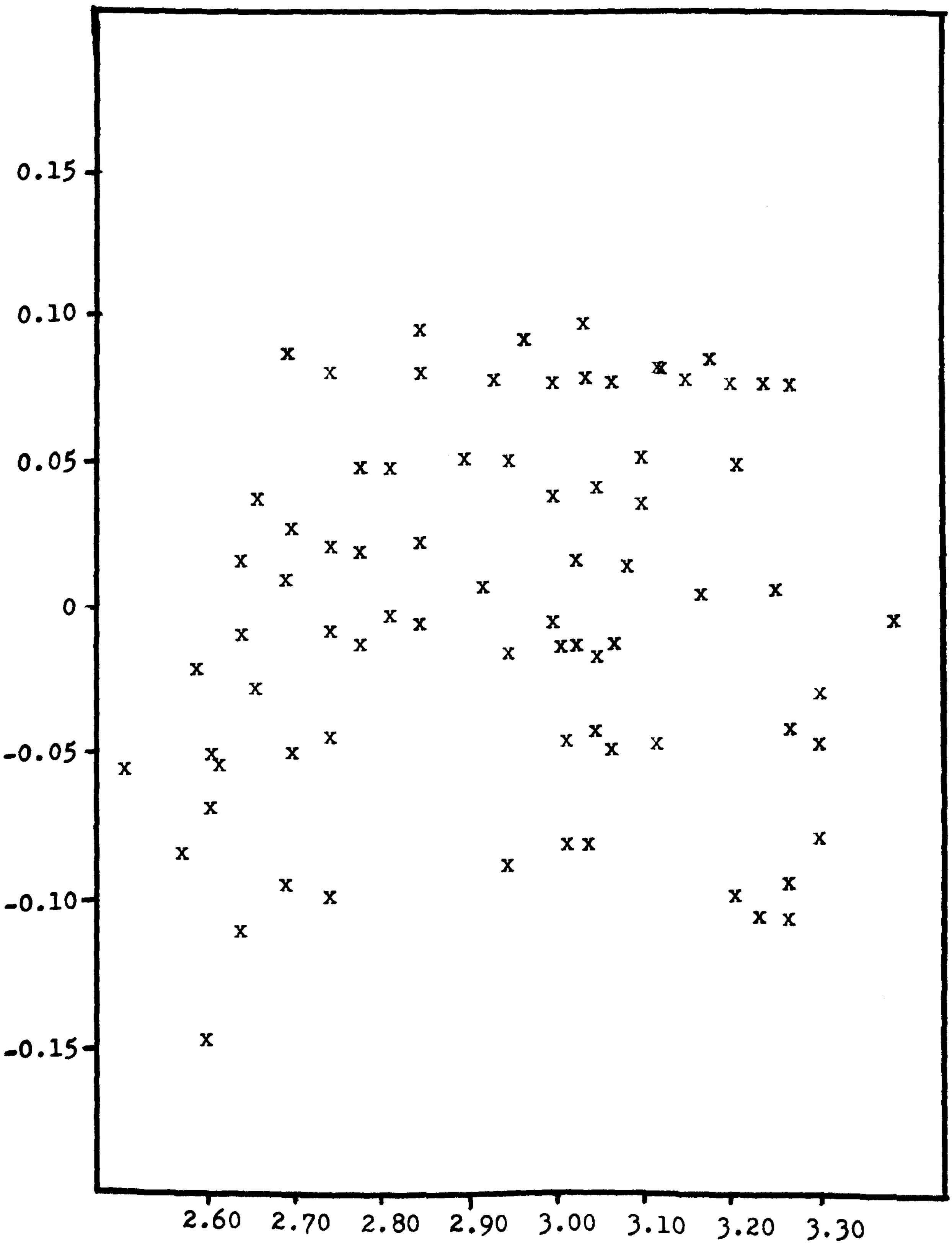


Figure 12.3 PLOTS OF RESIDUALS VS RAIL DEMAND (2SLS)



<u>Figure 12.4</u> PLOTS OF RESIDUALS VS RAIL DEMAND (3SLS)

Correlation Matrix

$\frac{FARE_1}{FARE_2}$	LF	$TIME_2$	ELEC	GDP
1.000	.007	-.284	-.129	-.037
	1.000	-.217	.087	-.128
		1.000	-.114	-.067
			1.000	.199
				1.000

12.3.5 Goodness-of-fit: TRACE CORRELATION

As stated earlier in section 10.3, a statistic called Trace correlation* has been proposed by Hooper, which measures the proportion of the total variance of the jointly dependent variables as a group that is explained by the exogenous variables as a group in a structural model

A package, providing the Trace Correlation statistic, has been run with Model 3 and the results are the following:

MODEL 3

	POOLED	LONG	SHORT
TRACE CORRELATION	.725	.717	.772

The above results show that the predetermined variables as a group explain about 72% of the variance of the

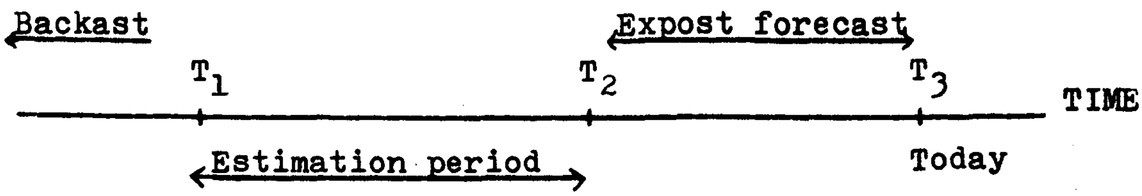
* In section 10.3, we have seen that the statistic analogous to the R^2, based on the estimate of the variance of the structural disturbance defined as:

$$1 - \sum U_t^2 / \sum (Y_t - \bar{Y})^2 \text{ can be} < 0 .$$

dependent variables as a group in pooled and long haul models. In Short Haul Model, this explanation is even higher than 77%.

12.3.6 Simulation forecast

Another criteria, for evaluating a Simultaneous Equations Model, is its ability to provide accurate "forecast" in a simulation context. It consists in estimating the model by using only part of the observations available; then, begining the forecast at the end of the estimation period and extending it to the present; and finally, comparing the results of the simulation with the actual observations not yet used. This type of simulation is called Expost Forecast*, and is often performed to test the forecasting accuracy of a model.



An expost forecast has been conducted with Air and Rail demand equations of the selected model, in order to examine how closely these demands track their corresponding historical data series. The estimated period has been restricted to the period 1968 - 1975, the three years observations 1976, 1977,1978, being retained for the comparison with the "forecast". The calibration of the model, over the 7 routes, has provided the results displayed in Table 12.4 .

* Another type of simulation called "Backast Simulation" consists of simulating a model backward in time begining at the start of the estimation period.

	2SLS			3SLS		
	Coef	Se	t	Coef	Se	t
EQ. DA						
NFL_1	.574	.017	32.707	.592	.016	36.599
$\frac{FARE_1}{FARE_2}$	-.762	.241	-3.157	-.249	.114	-2.182
GDP	-.066	.053	-1.241	-.004	.026	-.158
Cst	.969			.564		
	R^2=.96		SE=.080	R^2=.95		SE=.087
EQ. DR						
NFL_2	.126	.032	3.937	.046	.026	1.728
$FARE_2$	-.863	.091	-9.483	-1.121	.076	-14.823
GDP	.284	.041	6.927	.245	.038	6.526
Cst	.529			.668		
	R^2=.94		SE=.055	R^2=.91		SE=.068
EQ. NFL_1						
DA	1.293	.071	18.211	1.550	.058	28.619
LF	-.551	.874	-.630	-.131	.425	-.308
Cst	.297			-.525		
	R^2=.95		SE=.153	R^2=.95		SE=.155
EQ. NFL_2						
DR	-1.034	.621	-1.665	-.771	.558	-1.382
$TIME_2$	-3.155	.726	-4.346	-2.911	.662	-4.394
ELEC	2.163	.782	2.766	1.188	.661	1.798
Cst	10.126			8.482		
	R^2=.77		SE=.218	R^2=.77		SE=.214
EQ. $FARE_2$						
DA	.135	.029	4.655	.108	.027	3.992
DR	-.458	.049	-9.347	-.498	.046	-10.697
Cst	-.093			.089		
	R^2=.91		SE=.047	R^2=.91		SE=.049

Table 12.4

POOLED MODEL 3 (Historical period : 1968 - 1975)

In order to appreciate how closely Air and Rail demands fit their corresponding data, four measures have been computed.

1 - The Root Mean Square error (RMS) is defined as follows:

$$RMS = \sqrt{\frac{1}{T} \sum_{t=1}^{T} (Y_t^s - Y_t^a)^2}$$

where:

Y_t^s : the simulated value of Y_t

Y_t^a : the actual value

T : number of periods in the simulation

RMS is thus a measure of the deviation of the simulated variable from its actual time path.

2 - RMS per cent error $= \sqrt{\frac{1}{T} \sum_{t=1}^{T} \left(\frac{Y_t^s - Y_t^a}{Y_t^a} \right)^2}$

This is also a measure of the deviation of the simulated variable from its actual time path, but in percentage terms.

3 - Mean Error $= \frac{1}{T} \sum_{t=1}^{T} (Y_t^s - Y_t^a)$

4 - Mean per cent error $= \frac{1}{T} \sum_{t=1}^{T} \left(\frac{Y_t^s - Y_t^a}{Y_t^a} \right)$

The results of these computations are shown in Table 12.5, and Table 12.6 .

LONDONIAN ROUTES TO AND FROM		ACTUAL OBSERVATIONS ('000)	2SLS FORECASTS ('000)	3SLS FORECASTS ('000)
GLASGOW	1976	887	998	900
	1977	709	1023	760
	1978	903	863	903
EDINBURGH	1976	677	716	597
	1977	655	906	724
	1978	738	643	624
NEWCASTLE	1967	282	286	233
	1977	221	310	261
	1978	282	287	250
MANCHESTER	1976	456	371	410
	1977	393	391	436
	1978	534	481	527
BIRMINGHAM	1976	99	112	139
	1977	104	144	177
	1978	122	220	255
LEEDS	1976	123	118	123
	1977	129	118	135
	1978	148	127	132
LIVERPOOL	1976	119	141	146
	1977	102	140	146
	1978	138	184	180

Table 12.5

EX POST FORECASTS:Comparison with actual observations

AIR DEMAND SIMULATION

LONDONIAN ROUTES TO AND FROM		ACTUAL OBSERVATIONS ('000)	2SLS FORECASTS ('000)	3SLS FORECASTS ('000)
GLASGOW	1976	503	589	519
	1977	721	613	551
	1978	693	606	533
EDINBURGH	1976	379	442	405
	1977	493	469	481
	1978	543	484	464
NEWCASTLE	1976	570	625	549
	1977	635	637	583
	1978	614	665	596
MANCHESTER	1976	1335	1237	1065
	1977	1459	1292	1139
	1978	1616	1363	1142
BIRMINGHAM	1976	1695	2550	2468
	1977	1739	2557	2475
	1978	1718	2654	2556
LEEDS	1976	866	1070	1047
	1977	975	1138	1128
	1978	1029	1082	1057
LIVERPOOL	1976	1030	985	913
	1977	1141	1125	1076
	1978	1202	1185	982

Table 12.6

EX POST FORECASTS : Comparison with actual observations

RAIL DEMAND SIMULATION

LONDON TO AND FROM	RMS error		RMS per cent error	
	2SLS	3SLS	2SLS	3SLS
GLASGOW	193.71	30.41	26.7%	04.2%
EDINBURGH	156.57	89.73	23.6%	11.8%
NEWCASTLE	52.10	40.93	23.4%	15.9%
MANCHESTER	57.84	36.58	12.2%	08.6%
BIRMINGHAM	61.40	90.38	51.8%	74.6%
LEEDS	14.10	9.93	09.9%	06.8%
LIVERPOOL	36.54	38.28	30.6%	33.1%

MEAN error		MEAN per cent error		LONDON TO AND FROM
2SLS	3SLS	2SLS	3SLS	
128.33	21.30	17.4%	02.9%	GLASGOW
65.00	-41.67	10.4%	-00.6%	EDINBURGH
26.67	13.67	12.4%	-03.5%	NEWCASTLE
-46.67	-3.33	-09.7%	-00.1%	MANCHESTER
50.00	81.67	43.6%	72.7%	BIRMINGHAM
-12.33	-3.57	-08,9%	-02.2%	LEEDS
35.13	37.50	29.3%	32.0%	LIVERPOOL

Table 12.7

EX POST FORECASTS Period : 1968 - 1975

FORECAST YEARS : 1976, 1977, 1978

AIR DEMAND SIMULATION

LONDON TO AND FROM	RMS error		RMS per cent error	
	2SLS	3SLS	2SLS	3SLS
GLASGOW	93.9	135.0	14.9%	19.1%
EDINBURGH	51.3	48.2	11.7%	09.3%
NEWCASTLE	43.3	33.8	07.3%	05.4%
MANCHESTER	184.0	365.1	12.0%	24.1%
BIRMINGHAM	871.0	783.2	50.7%	45.7%
LEEDS	156.0	138.1	16.9%	15.2%
LIVERPOOL	29.3	148.0	02.7%	12.9%

MEAN error		MEAN per cent error		LONDON TO AND FROM
2SLS	3SLS	2SLS	3SLS	
-36.3	-104.7	-07.7%	-11.5%	GLASGOW
-20.7	-67.1	00.2%	-03.5%	EDINBURGH
36.0	-30.1	06.0%	-04.9%	NEWCASTLE
-172.7	-354.7	-11.5%	-23.8%	MANCHESTER
869.7	782.3	50.6%	45.6%	BIRMINGHAM
140.1	120.7	15.1%	13.1%	LEEDS
-26.1	-66.1	-02.4%	-11.8%	LIVERPOOL

Table 12.8

EX POST FORECASTS Period : 1968 - 1975

FORECAST YEARS : 1976, 1977, 1978

RAIL DEMAND SIMULATION

Since the results presented in Table 12.7 and Table 12.8 will be fully discussed in section12.4.2, we simply mention at this stage the low values of RMS per cent error and Mean per cent error; which indicates a good accuracy of the forecasts.

12.4 SELECTION OF THE BEST CALIBRATION TECHNIQUE

In comparing different multi-equation calibration techniques, many modelers agree that there is no general rule for selecting the best one. The answer is difficult for two reasons. First, the choice of an estimation procedure may depend,in part, upon the purpose of the model; second, most of the knowledge about the properties of estimators relates to large samples, in which case, estimators are known to be consistent, and (sometimes) asymptotically efficient. However, according to Pindyck, little is known about the small sample properties of these estimators.

In general, it remains to the modeler himself to decide which technique is best according to his purpose, the data available, the degree of accuracy desired, and the amount of time and money to spend.

In our case, since the purpose is both policy and forecast, the criteria for the selection is based upon:

- the characteristics of the coefficients (unbiasedness, consistency and efficiency), and their t values.
- the accuracy of the forecast.

12.4.1 Coefficients analysis

For the coefficients characteristics criteria, the parameters values obtained by both specifications, 2SLS and 3SLS, as well as their standard errors are displayed, for comparison in tables: 12.9 and 12.10. They correspond to the selected Model 3, applied to the following maarkets:

- Pooled markets (1968 - 1975)
- Pooled markets (1968 - 1978)
- Long haul markets (1968 - 1978)
- Short haul markets (1968 - 1978)

The standard errors of the coefficients, obtained with 3SLS are systematically lower than those estimated with 2SLS. This is not, in fact, particular to these models, but is rather a characteristic of 3SLS technique, which provides more efficient coefficients than 2SLS does.

From the t values comparison, the general remark is that 3SLS is much more superior within the length of haul aggregate models than within the pooled ones. One of the reasons might be the high sensitivity of 3SLS to specification errors or errors in data. Since the pooling process reduces the homogeneity of the observations, this loss in homogeneity is most likely to be more penalizing with 3SLS than with 2SLS; which leads to the loss in significance in 3SLS coefficients.

Nevertheless, even in the pooled models, 3SLS seems to be superior to 2SLS:

- First, the most important explanatory variables in demand equations, namely the Air frequency of services in Air demand, and Rail fare in Rail demand, have higher absolute t values in 3SLS than in 2SLS:

  NFL_1 = 38.390 and 36.599 against 33.073 and 32.707

  $FARE_2$ = -17.35 and -14.823 against -12.013 and -9.435

- Second, the GDP coefficient in Air equation, and

DR coefficient in NFL_2 equation, both having wrong signs, are not significant in 3SLS while they are in 2SLS.

- Third, the LF coefficient, not significant in both estimations, has smaller absolute value in 3SLS than in 2SLS.

- Fourth, if we except the coefficients that have either a wrong sign or no significance at all, among the remaining coefficients 5 have higher t values in 3SLS than in 2SLS, while 4 have higher t values in 2SLS than in 3SLS.

Lastly, in the length of haul aggregate models, 3SLS appears much more superior than 2SLS. Indeed, in long haul markets, 6 coefficients have higher t values in 3SLS than in 2SLS, while only 1 has greater value in 2SLS than in 3SLS. Similarly, in short haul markets, 8 coefficients have higher t values in 3SLS than in 2SLS, while only 2 have greater t values in 2SLS than in 3SLS. The coefficients with a wrong sign or no significance are not considered.

12.4.2 Accuracy of the forecast

A close examination of Table 12.7 reveals the superiority of 3SLS over 2SLS in all routes, except in Liverpool and Birmingham.

- In the RMS error figures, only 2 values are higher than 41.0 in 3SLS while 5 out of 7 are higher in 2SLS.
- For the RMS per cent error, 5 values are higher than 16% in 2SLS against only 2 in 3SLS; with 3 values even less than 10% in 3SLS.
- For the Mean error, 5 values are less than 40.0 in 3SLS against only 3 in 2SLS; with 3 even less than 15.0 in 3SLS against only 1 in 2SLS.
- Finally, for the Mean per cent error, all the values

are higher than 3.5% in 2SLS against only 1 in 3SLS.

Undoubtedly, 3SLS specification appears to be more accurate than 2SLS. In order to measure the relative accuracy of 3SLS over 2SLS, the ratio of all the 3SLS measures over the 2SLS ones are computed and displayed below:

	RMS	RMS %	MEAN	MEAN %
Glasgow	.157	.157	.166	.167
Edinburgh	.573	.500	.641	.058
Newcastle	.786	.679	.512	.282
Manchester	.632	.705	.071	.010
Birmingham	1.472	1.440	1.634	1.667
Leeds	.704	.687	.289	.247
Liverpool	1.048	1.082	1.067	1.092

The above results clearly show the gain in accuracy attached to 3SLS estimation. In Glasgow route, for instance, the values of the measurements with 3SLS are about the sixth their corresponding values with 2SLS. This ratio is, however, higher in Edinburgh route where it slightly exceeds the half for all the measures, except for the Mean per cent error for which the ratio is around the sixteenth in favour of 3SLS.

In Rail simulation, however, 3SLS does not show such a striking superiority over 2SLS **(see Table 12.8).**

In conclusion, in both estimators characteristics and forecasting accuracy criteria, 3SLS specification has shown remarkable superiority over 2SLS. On the other hand, a close examination of the residuals correlation matrix in Table 12.11, corresponding to the reduced forms, reveals substantial correlations between residuals across equations. This constitutes a violation of the 2SLS assumptions, and therefore, renders 3SLS more appropriate. Indeed, one of the assumptions of 3SLS is that random errors are contemporaneously dependent. This is, particularly, striking in short haul model correlation matrix, where the correlation between the residuals across the equations is almost perfect. All coefficients are $>$.990. According to Koutsoyiannis "taking into account the nature of economic phenomena and the simplifications which we adopt in specifying the econometric models, we may well expect the u's to be contemporaneously correlated".

As we already have pointed out, for various reasons such as multicollinearity and data availability , we have explicitly included in the equations only the most important variables, leaving the influence of the others, less important, to be absorbed by the random terms. If some variables are omitted from various equations, it is inevitable that the random terms of the equations are correlated, and hence, 3SLS is appropriate.

To summarize, all the criteria discussed so far as well as the contemporaneous dependency between random errors, are in favour of 3SLS calibration technique.

CONCLUSION

The previous chapter and the present one constitute undoubtedly the most important part of this research, and it is necessary at this point to explain their link with the following chapters.

Up to now, for data avaibility problems we have not been able to conduct our analysis on a time series basis and the only disaggregation scheme considered has been the length of haul.

The next chapters (13 and 14) explain how and why the following disaggregations can also be attempted :

- Disaggregation by routes
- Disaggregation by trip purpose.

COEFFICIENT	POOLED MODEL 1968 - 1978				POOLED MODEL 1968 - 1975			
	Std error		t Ratio		Std error		t Ratio	
	2SLS	3SLS	2SLS	3SLS	2SLS	3SLS	2SLS	3SLS
NFL_1	.018	.016	33.073	38.390	.017	.016	32.707	36.599
$\frac{FARE_1}{FARE_2}$	.172	.090	-3.220	-2.169	.241	.114	-3.157	-2.182
GDP	.047	.024	-2.302	-.883	.053	.026	-1.241	-.158
NFL_2	.028	.023	3.782	1.312	.032	.026	3.891	1.728
$FARE_2$	.070	.060	-12.013	-17.350	.091	.076	-9.435	-14.823
GDP	.037	.034	7.725	8.503	.041	.038	6.925	6.526
DA	.061	.054	22.378	27.611	.071	.058	18.162	26.672
LF	.800	.400	-.750	-.418	.874	.425	-.630	-.308
DR	.503	.470	-2.124	-1.792	.621	.558	-1.664	-1.382
$TIME_2$	.575	.543	-5.393	-5.342	.726	.662	-4.347	-4.394
ELEC	.573	.534	3.494	3.574	.782	.661	2.765	1.798
DA	.029	.028	5.892	5.640	.029	.027	4.656	3.992
DR	.049	.048	-8.905	-9.648	.049	.047	-9.289	-10.697

STANDARD ERRORS and t VALUES COMPARISON between 2SLS and 3SLS Table 12.9

COEFFICIENT	LONG HAUL MODEL 1968 - 1978				SHORT HAUL MODEL 1968 - 1978			
	Std error		t Ratio		Std error		t Ratio	
	2SLS	3SLS	2SLS	3SLS	2SLS	3SLS	2SLS	3SLS
NFL_1	.021	.016	23.081	29.696	.036	.033	17.694	19.106
$\frac{FARE_1}{FARE_2}$	.153	.023	-.642	-.459	.349	.134	-2.778	-3.308
GDP	.048	.007	-.057	-.041	.127	.050	-.381	1.373
NFL_2	.022	.022	7.600	7.443	.082	.072	-.183	-1.516
$FARE_2$	.157	.154	-5.907	-6.284	.136	.115	-5.384	-7.981
GDP	.041	.040	7.165	7.435	.170	.154	2.676	3.588
DA	.079	.066	25.475	30.763	.114	.090	9.412	13.111
LF	.571	.090	-.845	-.337	1.407	.509	.217	-.466
DR	.583	.560	-1.850	-1.783	.297	.292	6.447	7.253
$TIME_2$	.629	.612	-7.727	-7.792	.292	.288	-3.082	-2.512
ELEC	.611	.593	1.695	1.117	.365	.359	9.479	9.603
DA	.036	.036	5.630	5.648	.026	.025	7.466	6.784
DR	.092	.092	.100	.106	.069	.065	-9.791	-11.398

STANDARD ERRORS and t VALUES COMPARISON between 2SLS and 3SLS Table 12.10

RESIDUALS CORRELATION MATRIX

Reduced forms

EQUATION 1	EQUATION 2	EQUATION 3	EQUATION 4	EQUATION 5
1.000				
-.772	1.000			
.988	-.801	1.000		
.465	-.246	.434	1.000	
.889	-.873	.892	.470	1.000

POOLED MODEL

1.000				
-.741	1.000			
.995	-.794	1.000		
.613	-.317	.592	1.000	
.927	-.842	.924	.673	1.000

LONG HAUL MODEL

1.000				
-.991	1.000			
.999	-.991	1.000		
-.990	.997	-.990	1.000	
.996	-.997	.996	-.996	1.000

SHORT HAUL MODEL

Table 12.11

CHAPTER 13

ABSTRACT MODES MODELS

The low degree of freedom, consequent to the small number of observations and the multi-equation structure nature of our models that reduces further more the degree of freedom, has not allowed a Pure Time Series analysis, i.e, Region Pairs models.

In order to overcome this data problem, an abstract mode approach is conducted for the 7 individual routes. This approach has the advantage of increasing the degrees of freedom by aggregating data across modes.:

Here also, the Stepwise Regression analysis is applied, so as to select the most powerful explanatory variables and to detect any multicollinearity.

The Regression analysis is, first, applied to the following traditional abstract modes formulation:

$$D = \alpha_0 + \alpha_1 \frac{NFL}{NFL_B} + \alpha_2 \frac{FARE}{FARE_B} + \alpha_3 \frac{TIME}{TIME_B} + \alpha_4 NFL_B$$
$$+ \alpha_5 FARE_B + \alpha_6 TIME_B + \alpha_7 GDP + \varepsilon$$

Where the variables are in logarithm and index B relates to the best mode.

This single equation model is run on the two most important routes: London-Glasgow and London-Manchester.

In the London-Glasgow run, the Stepwise Regression has selected $\frac{NFL}{NFL_B}$ as the most explanatory variable in the first step, and entered GDP variable in the second. The variables introduced in further steps are not significant.

While in this run, no serious collinearity shows between $\frac{NLF}{NFL_B}$ and GDP variables; in London-Manchester results, a collinearity appears between $\frac{FARE}{FARE_B}$ (the first variable to enter) and $\frac{NFL}{NFL_B}$. This can be observed in the two following first steps of the regression.

	R^2	F	$\frac{NFL}{NFL_B}$	$\frac{FARE}{FARE_B}$
Step 1	.96	539		- .205 (.088)
Step 2	.98	385	.278 (.098)	-1.556 (.179)

London-Manchester Model

This collinearity is illustrated by the drastic varition of $\frac{FARE}{FARE_B}$ variable coefficient and its standard error. This coefficient and its SE have respectively varied from -.205 and .088, in the first step, to -1.556 and .179, in the second step.

The conclusion to be drawn is that while in London-Glasgow, $\frac{NFL}{NFL_B}$ is, in terms of statistical significance and increase in R^2, the most important variable; in London-Manchester, $\frac{FARE}{FARE_B}$ variable is the most important one. The variables other than GDP show no significance, in both models.

This conclusion suggests that long haul markets to which London-Glasgow belongs, and short haul markets to which London-Manchester belongs , may well be respectively estimated by the following models:

Long Haul
MODEL 1

$$\begin{cases} D = \alpha_0 + \alpha_1 \frac{NFL}{NFL_B} + \alpha_2 \, GDP + \varepsilon_1 \\ \frac{NFL}{NFL_B} = \beta_0 + \beta_1 D + \beta_2 \frac{TIME}{TIME_B} + \varepsilon_2 \end{cases}$$

Short Haul
MODEL 2

$$\begin{cases} D = \alpha_0 + \alpha_1 \frac{FARE}{FARE_B} + \alpha_2 \, GDP + \varepsilon_1 \\ \frac{FARE}{FARE_B} = \beta_0 + \beta_1 D + \beta_2 \frac{TIME}{TIME_B} + \varepsilon_2 \end{cases}$$

This structural form departs from the traditional abstract modes formulation, since it introduces a second equation. This is, in fact, dictated by the necessity of identification. Indeed, the variables NFL and NFL_B in Model 1, and $FARE_B$ (i.e, Rail fare) in Model 2 are endogenous. Hence, any effect on NFL_B and $FARE_B$, induced by the demand variation, might well be transmitted to $\frac{NFL}{NFL_B}$ and $\frac{FARE}{FARE_B}$. Therefore, the two latter variables are plausibly endogenous, and their inclusion, in the second equation, is appropriate.

The results, displayed in Table 13.1, are interesting. First, the statistical tests R^2 and SE are very good; the DW test shows no serial correlation. Second, the magnitude of the demand equations coefficients are significantly different with regard to the length of haul; which means that the method of competition is highly correlated with this factor.

The most powerful explanatory variables, $\frac{NFL}{NFL_B}$ for the long haul and $\frac{FARE}{FARE_B}$ for the short haul, are highly significant, even at 99% level of confidence; and bear the right sign.

1st equation	GLASGOW	EDINBURGH	NEWCASTLE
$\frac{NFL}{NFL_B}$ coef	.167 (.018	.248 (.045)	.508 (.024)

Long Haul

1st equation	MANCHESTER	BIRMINGHAM	LEEDS	LIVERPOOL
$\frac{FARE}{FARE_B}$ coef	-2.138 (.094)	-5.781 (.585)	-3.087 (.128)	-3.766 (151)

Short Haul

In long routes, GDP variable is highly significant, though in Newcastle its significance is only at 90%; whereas, in short routes, it shows no significance at all.

In the second equations, the most important coefficients, namely Air and Rail demands, bear the right sign and are significant at 99%, except for Glasgow where the significance is at 80%.

2nd equation	GLASGOW	EDINBURGH	NEWCASTLE
D coef	.642 (.330)	1.290 (.520)	3.114 (1.180)

Long Haul

2nd equation	MANCHESTER	BIRMINGHAM	LEEDS	LIVERPOOL
D coef	-.520 (.070)	-.575 (.177)	-.284 (.054)	-.248 (.078)

Short Haul

Finally, in long haul, except in Newcastle, $\frac{TIME}{TIME_B}$ shows a significance at 99% level of confidence; whereas, in short haul, except in Birmingham, it shows no significance.

It could be argued, however, that the "supply" equations, defined by $\frac{NFL}{NFL_B}$ and $\frac{FARE}{FARE_B}$, have no real economic meanings; which is quite true. In fact, the introduction of $\frac{NFL}{NFL_B}$ and $\frac{FARE}{FARE_B}$ is a pure statistical device designed to purge these endogenous variables from their correlations with the error terms, in the demand equations, and thereby, to prevent the Simultaneous Equations Bias. In this sens, these variables constitute a technical expression rather than a "supply" one.

Furthermore, since our primary purpose is the derivation of the demand elasticities, the inclusion of truly supply equations is not of a vital necessity to our analysis, as long as the coefficients in the demand equations are being purged from any bias. Therefore, the "supply" equations results could well have been ignored and not displayed at all.

	FIRST EQUATION						SECOND EQUATION					
LONG HAUL	$\frac{NFL}{NFL_B}$	GDP	Cst	R^2	SE	DW	D	$\frac{TIME}{TIME_B}$	Cst	R^2	SE	DW
LOND-GLAS	.167 (.018)	.274 (.094)	-2.23	.83	.038	1.83	.642 (.434)	-2.675 (.242)	1.85	.98	.054	2.19
LOND-EDINB	.248 (.045	.413 (.129)	-1.76	.69	.050	2.62	1.290 (.529)	-1.070 (.282)	3.55	.75	.121	2.61
LOND-NEWCAS	.508 (.024)	.174 (.123)	-3.27	.95	.053	1.66	3.114 (1.180)	-3.620 (3.740)	8.32	.90	.152	1.63
SHORT HAUL	$\frac{FARE}{FARE_B}$	GDP	Cst	R^2	SE	DW	D	$\frac{TIME}{TIME_B}$	Cst	R^2	SE	DW
LOND-MANCH	-2.136 (.094)	.122 (.171)	-3.50	.95	.060	2.02	-.520 (.070)	1.875 (2.670)	-1.64	.96	.029	2.03
LOND-BIRM	-5.781 (.585)	1.743 (.984)	3.19	.78	.37	1.84	-.575 (.117)	.271 (.119)	-1.90	.89	.050	1.87
LOND-LEEDS	-3.087 (.128)	.194 (.239)	-2.56	.98	.084	2.26	-.284 (.054)	-.894 (1.173)	-.89	.97	.030	2.26
LOND-LIVERP	-3.766 (.151)	.061 (.266)	-2.84	.98	.09	1.86	-.248 (.078)	-.016 .071)	-.76	.97	.020	1.86

Table 13.1

ABSTRACT MODES MODELS

CHAPTER 14

PURE AIR DEMAND MODELS

14.1 REGION-PAIRS MODELS

In this section, we attempt to conduct three pure Time Series models on the following trunk routes:

London-Glasgow London-Edinburgh London-Belfast

The restriction to these only Region-pairs is dictated by the reasons below:

- These routes are the only ones for which a large number of Air observations are available, since the historical period span has been extended: 1961 - 1978 instead of 1968 - 1978 .

- These routes pertain to the long haul markets and are highly business oriented. Therefore, it is not unreasonable to conduct pure Air demand models on a Region-pair basis.

$$DA = \alpha_0 + \alpha_1 \, NFL_1 + \alpha_2 \, FARE_2 + \varepsilon_1$$

$$NFL_1 = \beta_0 + \beta_1 \, DA + \beta_2 \, LF + \varepsilon_2$$

Where the variables in logarithm are as previously defined. The reasons for this structure are straightforward:

- In the demand equation, only Air fare is considered, since the available data do not cover the whole period.

- As the income variable GDP does not manifest any significance in the long haul models, conducted so far, it has been removed from the demand equation above.

	LONDON-GLASGOW	LONDON-EDINBURGH	LONDON-BELFAST
DA			
NFL_1	.672 (.092)	.545 (.110)	.397 (.053)
$FARE_1$	-.006 (.091)	.123 (.150)	-.004 (.056)
Cst	.138	.556	1.240
	R^2=.92 SE=.040 DW=1.92	R^2=.89 SE=.060 DW=1.60	R^2=.92 SE=.039 DW=1.97
NFL_1			
DA	1.511 (.243)	1.456 (.229)	2.585 (.630)
LF	.044 (.673)	-.665 (.853)	.114 (1.465)
Cst	-.343	.931	-3.480
	R^2=.91 SE=.060 DW=1.92	R^2=.89 SE=.098 DW=1.60	R^2=.88 SE=.099 DW=1.98

Pure Air Models (1961 - 1978)

The results of the three runs above show the very good overall fit of the demand equation, the absence of serial correlations, the high significance of the frequency of services variable, and the non significance ofthe fare. In the second equation, the demand coefficients are all significant; but LF coefficients are not. Statistical fits are very good.

These results are consistent with those obtained so far; and, once again, the preponderance of the frequency of services, as the most powerful explanatory variable, is confirmed. This can be observed in the Stepwise Regression technique results. The first step of this technique shows the contribution of NFL_1 variable on the explanation of the demand. This contribution is as follows:

	LONDON-GLASGOW	LONDON-EDINBURGH	LONDON-BELFAST
R^2 =	.92	.88	.89
SE =	.042	.066	.041
F =	193.1	113.7	131.2

The above values of R^2 indicate that the frequency of services variable, alone, explains more than 88% of the demand variation. The significance of NFL_1 as an important factor explaining the demand, and the non significance of FARE confirms, once again, the business characteristics of these trunk routes.

The above results are obtained by 2SLS and are identical to the 3SLS estimation results, since the Model is exactly identified. This can be easily verified when considering the order condition for identification, below:

$$G - 1 \leqslant K$$

Where:

G : is the number of endogenous variables included in the equation

K : is the number of exogenous variables excluded from the equation

When the model is identified, and the order condition*

---

* Note that the order condition is a necessary condition for identification, but not a sufficient one.

above, is, for each equation, an <u>equality</u> rather than an <u>inequality</u>, the model is <u>exactly identified</u>. In such a case, all Multi-equation techniques provide the same estimators. This is the case of our models.

14.2 PURE AIR BUSINESS TRAVEL DEMAND MODELS

Since all along this study, Air mode has shown some business oriented characteristics, it appears reasonable to estimate pure Air business travel demand models.

Data were collected from various CAA surveys conducted at different periods, in different Airports. One of the characteristics of these surveys was the information concerning the value of business traffic. As explained in the data chapter, the business travelers' figures have been derived from the surveys undertaken in 1970, 1971, 1972, and 1975/76, involving the following routes:

London-Glasgow	London-Aberdeen
London-Edinburgh	London-Leeds
London-Belfast	London-Liverpool
London-Manchester	Glasgow-Manchester

The two following models have been run:

$$DA = \alpha_0 + \alpha_1 NFL + \alpha_2 FARE + \alpha_3 GDP + \varepsilon_1$$
$$NFL = \beta_0 + \beta_1 DA + \beta_2 DIST + \varepsilon_2$$

$$DA = \alpha_0 + \alpha_1 NFL + \alpha_2 GDP + \varepsilon_1$$
$$NFL = \beta_0 + \beta_1 DA + \beta_2 DIST + \varepsilon_2$$

Where the variables in logarithm are:

DA = business demand
DIST= distance between Airport pairs
NFL, FARE, GDP : as previously defined.

AIR BUSINESS MODELS

	Equation DA				Equation NFL		
	NFL	FARE	GDP	Cst	DA	DIST	Cst
2SLS	.577 (.048)	-.034 (.315)	.228 (.387)	-.219	1.609 (186)	.247 (.517)	.449
	R^2=.94		SE=.107	DW=1.75	R^2=.94	SE=.107	DW=1.70
3SLS	.590 (.032)	-.109 (.236)	.130 (.279)	-.199	1.509 (.186)	.207 (.510)	-.401
	R^2=.94		SE=.106	DW=1.75	R^2=.94	SE=.106	DW=1.70

	Equation DA			Equation NFL		
	NFL	GDP	Cst	DA	DIST	Cst
2SLS and 3SLS	.573 (.046)	.238 (.401)	-.203	1.561 (.226)	.363 (.605)	-.391
	R^2=.93	SE=.106	DW=1.66	R^2=.94	SE=1.77	DW=1.65

The above results show very good statistical fits and reasonable DW test values. Once again, and as expected, the frequency of services variable NFL is highly significant in both models (even at 99%); while FARE variable is not significant at all. This confirms the business characteristics of these markets.

In both models, GDP and DIST variables are not significant. The non significance of GDP may well be explained by its inappropriate ability to reflect the income of the highest group of the population to which these travelers generally pertain.

However, in the second equation, surprisingly enough, the frequency of services elasticity appears to be independent of the length of haul. This seems to suggest that business travelers respond in a similar manner to the frequency of services, whether in short or long haul .

It is interesting to compare the elasticity of the frequency of services variable, in these two models, with its corresponding value recorded in Pooled Model 3, selected in Chapter 12.

	Pooled Business MODEL 1	Pooled Business MODEL 2	Pooled Air/RAIL MODEL 3
2SLS	.577	.573	.583
3SLS	.590	.573*	.613

<u>NFL Coefficient</u>

* 2SLS and 3SLS values are identical, the model being <u>exactly identified</u>.

The comparison above shows that although the samples, considered for the business models and the competition model, are completely different, the frequency of services elasticity still has the same magnitude, around .60. This confirms our previous results with regard to the business characteristics orientation of the Air mode; and provides additional confidence to their consistency.

CHAPTER 15

APPLICATION OF THE MODELS

As stated at the begining, the purpose of this research is to develop models that are sufficiently sensitive, so as to quantify the variation of the traffic demand consequent to any changes in the explanatory variables. These models are also responsive, in the sense that they enable the policy maker to estimate the impact of alternative policies.

These models can be applied in forecasting; Chapter 12 has provided measures of their forecasting accuracy. In this section, we give examples of how these models could be applied to the analysis of the demand variation , due to changes in the frequency of services, trip time and fares. These changes may well be due to technological improvements in Air or Rail services, or implementation of managerial strategies within the existing framework.

15.1 SCHEDULING FLEET PROBLEM

One of the most complex and critical tasks, facing the management, is the scheduling fleet problem, because it involves a balancing of conflicting objectives, such as public requirements, economic efficiency, and operational feasibility.

One of the most important inputs to the development of the schedule is the level of demand, in a given region-pair, since the main purpose of any scheduler is to attempt to match the volume of supply to the amount of the services demanded.

The public requirements provide an essential input to the scheduling process, which has to be balanced against the economic considerations on one hand, and the operational feasibility on the other. Since the unit of supply is the flight, it becomes necessary to consider the cost as well as the potential revenue of each flight.

The scheduler looks at the profitability of a flight, in terms of aircraft utilization and load factor which are not independent of one another. One facet of utilization is related to the length of haul. With short hauls, a high utilization is difficult to achieve , because a higher percentage of the total block to block time is spent on ground,and in the take off and landing.

In the final analysis, economic efficiency would necessitate some trade-off between utilization, load factor, and frequency. The weight attached to each of these factors would vary according to the market.

In general, suppliers are assumed to be seeking to maximize their profit; that is to say, to maximize the difference between the revenues and the cost: $P = R - C$, subject to the maximum load factor constraint, and the availability of the fleet.

In considering our models, we notice that Air demand equations are characterised by the important role played by the Air frequency of services as the most determinative factor explaining the demand. Moreover, this factor is the only one that is truly under the Airline control, since Air fares are subject to government regulations. Our models enable the planner to assess different values of the objective function P , corresponding to different values of the frequency; thereafter, it only remains to choose the frequency that maximizes this function, with regard to the maximum LF constraint, and the fleet availability.

15.2 EFFECT OF FARE

One of the common purposes of the econometric models is the determination of the demand elasticity, with respect to some traditional variables such as fare and income. One advantage, particularly appreciated in Log-linear models formulation, is that the estimated coefficients represent the elasticities.

Since Air fare is not strictly an endogenous variable, the capability of the Airlines to improve the demand by acting upon this variable is rather restricted. However, the elasticities derived from these models allow the planner to estimate different levels of demand, corresponding to hypothetical variations in both Air and Rail fares.

Table 15.1 displays the following hypothetical reductions in Air fare: 5%, 10%, 15%, 20%, 25%. For every reduction correspond four hypothetical ones, in Rail fare: 5%, 10%, 15%, 20%. The fare elasticities applied are those of Model 3 (short haul), selected in Chapter 12.

Table 15.1 shows that Air demand may decrease, even if Air fare decreases, because Air demand does not respond to the absolute fare reduction, but rather to the relative one.

- In particular, when Air fare decreases by 5% and when Rail fare, respectively, decreases by 10%, 15%, and 20%, accordingly, Air demand decreases by 2.4%, 5.2%, 8.3%.

- Equally, when Air fare decreases by 10% and when Rail fare, respectively decreases by 15%, and 20%, Air demand decreases by 2.6%, and 5.5%.

- Finally, when Air fare decreases by 15% and when Rail fare decreases by 20%, Air demand decreases by 2.7%.

On the contrary, Rail demand is related to its absolute fare, which is under the Railways control. From Model 3 results, the following variations in Rail demand, consequent to different reductions in Rail fare, can be estimated.

RAIL FARE REDUCTION	RAIL DEMAND INCREASE	
	Short Haul	Long Haul
5%	4.8%	4.6%
10%	9.7%	9.2%
15%	14.5%	13.8%
20%	19.4%	18.4%

15.3 TRIP TIME EFFECT

Instead of deriving the Rail trip time elasticity from the Rail demand equation, these Air-Rail models enable us, as explained earlier, to derive it indirectly through the fourth equation. This elasticity is measured by the product $\beta_1 \rho_2$; where:

β_1 : is the elasticity of the Rail demand with regard to the Rail frequency of services

ρ_2 : is the elasticity of the Rail frequency of services with regard to the trip time

In the following are displayed Rail demand variations, corresponding to hypothetical decreases in Rail trip time.

% $TIME_2$	5%	10%	15%	20%	25%	30%
% DR	3.9%	7.8%	11.7%	15.6%	19.5%	23.4%

Long Haul Markets

The derivation of trip time elasticities is important to the Rail management. It permits to assess the effect upon demand of improvements in journey time; such improvements being the resultsof technological developments, and efficient scheduling.

FARE$_1$ %	FARE$_2$ %	FARE$_1$/FARE$_2$ %	AIR DMD %	RAIL DMD %	
			Short	Long	Short
5%	5%	0%	0%	4.6%	4.8%
	10%	5.5%	-2.4%	9.2%	9.7%
	15%	11.8%	-5.2%	13.8%	14.5%
	20%	18.7%	-8.3%	18.4%	19.4%
10%	5%	-5.3%	2.3%	4.6%	4.8%
	10%	0%	0%	9.2%	9.7%
	15%	5.9%	-2.6%	13.8%	14.5%
	20%	12.5%	-5.5%	18.4%	19.4%
15%	5%	-10.5%	4.6%	4.6%	4.8%
	10%	-5.5%	2.4%	9.2%	9.7%
	15%	0%	0%	13.8%	14.5%
	20%	6.2%	-2.7%	18.4%	19.4%
20%	5%	-15.8%	7.0%	4.6%	4.8%
	10%	11.1%	4.9%	9.2%	9.7%
	15%	-5.9%	2.6%	13.8%	14.5%
	20%	0%	0%	18.4%	19.4%
25%	5%	-21.0%	9.3%	4.6%	4.8%
	10%	-16.7%	7.4%	9.2%	9.7%
	15%	-11.8%	5.2%	13.8%	14.5%
	20%	-6.2%	2.7%	18.4%	19.4%

Table 15.1

AIR & RAIL DEMANDS VARIATIONS

corresponding to

HYPOTHETICAL REDUCTIONS IN AIR & RAIL FARES

CONCLUSION

Model building is a hazardous process in transportation industry, and in recent years, has become more complex. The high level of investment characterising the Civil Aviation industry, and the high susceptibility of this industry to political, economic, and other trends, renders the forecasting process a useful and indispensable tool in planning for the future to face the changing circumstances.

Model building is an amalgam of Science and Art; and as such, it involves Social Sciences, Econmic Theories, Mathematical techniques, experiences, and educated guess of the modelers in choosing variables, methodologies, a and specific relations.

The stage by which the study of the demand for travel has progressed from its state, some twenty years ago, to the rather more satisfactory state are complex. The first and more crucial change was the recognition that travel decision emerge out of the individual's optimizing behavior. So as individuals are assumed to be utility maximers, the demand for travel ought to be positively related to Disposable Incomes and negatively to prices of travel.

The second important element was that a new and more fruitful theory of Consumer Behavior could be devised by assuming that travel services can be entirely characterised by their attributes; and that the consumer desires to maximize a utility function which has commodities attributes as its arguments rather than quantities of the various commodities consumed.

Despite their apparent diversity, Econometric Models are little more than variants of the oldest formulations based essentially on price and income elasticities.

Besides particular disadvantages of each type of models, they suffer from a common problem : by considering only one aspect of the market, the demand for travel, they ignore the effects of supply upon the demand, which creates the Simultaneous Equations Bias.

The models developed in this thesis overcome this drawback by introducing the supply equations and applying 2SLS and 3SLS to derive unbiased, more consistent, and more efficient coefficients. They are formulated as Multi-equation supply/demand Modal Competition Models, expressing the demand by each mode as function of the level of service of the mode, the fare - absolute or relative - and GDP variables.

The results obtained are consistent with the supply and demand Microeconomic Theory. The most powerful explanatory variables in terms of statistical significance, in both Air and Rail demand functions, bear the correct sign and show reasonable magnitude. These variables are the frequency of services in Air demand equation, and the Rail fare and GDP in Rail demand equation.

The Air frequency of services coefficients are interesting and worthy of discussion. First, their values lower than 1, as it is expected, outlines the diminishing return characteristics of the demand for travel. Second, its high significance, even at 99% level of confidence, and the very low or rather non existent significance of the relative fares and GDP variables underline the business and/or the higher income groups orientation of Air travel market.

The high significanee of Rail fare and GDP variables (99%) and the very low if not inexistent significance of Rail frequency of services illustrate the orientation of

Rail travel market involving, mainly, low income groups and/or personal travelers.

The Aggregation by length of haul is found appropriate and shows a strong fare competition over the Londonian routes to and from Birmingham, Manchester, Leeds and Liverpool. In longer routes, Glasgow, Edinburgh, Newcastle, Air and Rail modes do not appear close substitutes for each other.

The statistical significance of most coefficients, in Air and Rail supply equations, as well as the goodness of fit of these equations justify the Multi-equation structure of these models. They also confirm the interrelations between the supply of and the demand for travel through the frequency of services variables, as well as the endogenous nature of Rail fare with respect to both Air and Rail modes.

The potential existence of the Simultaneous Equations Bias, due to the two-way dependency supply/demand, has necessitated the calibration of the coefficients by means of Multi-equation techniques. While there is no general agreement between modelers regarding the best technique to apply, 3SLS has shown remarkable superiority over 2SLS, in our models. This superiority being based upon both coefficients characteristics and forecasting accuracy criteria.

The high significance of the Air frequency of services illustrates its importance as a decisive factor influencing the demand. This provides the Airlines management the capability of improving the demand by acting upon this controlable factor. This is of great importande in the fleet scheduling process, where the scheduler is faced with the critical task of supplying the optimum number of flights that best take into account the conflicting objectives, such as public requirements, economic efficiency, and operational feasibility.

With the high significance of Rail fare, these models also provide the Railways management with useful measures of the effect upon demand of different ranges of fares. This may be of interest for an efficient pricing policy, since the Railways, contrarily to the Airlines, have mo more freedom to set up their tariffs.

Rail journey time elasticities appear very close to the values assumed by British Railways Board in their Passengers Traffic Model(1980). These elasticities as well as those of the electrification variable provide measures of the impact upon the demand of the time and the electrification improvement ; the effect of the time factor being either the result of technological developments, such as further routes electrification or speeder trains introduction; or the results of efficient schedules reducing the waiting time at the connections.

The simulation forecasts,tested by the Root-mean-square error, the Root-mean-square per cent error, the Mean error, the Mean per cent error measures, illustrate the forecast accuracy of these models.

The estimation of pure Time Series models has necessitated the use of a revised Abstract Mode approach. The revision of this approach has consisted in introducing "supply" equations designed to eliminate the potential existence of the Simultaneous Equations Bias.

The results of this approach confirm the usefulness of distinguishing between long and short routes. In the short routes, the relative fare is the most powerful variable, and its high elasticity, in absolute value, illustrates the existence of a strong Air-Rail competition in these markets. In longer routes, the relative frequency of services variable appears as the most powerful explanatory factor. Its low elasticity values, however, except in London-Newcastle, shows the low competition in these routes.

The pure Air business demand models, and the pure Air Region-pairs models confirm the previous results, that is to say, the high explanatory power of the Air frequency of services variable and the predominance of business travelers and/or higher income groups in the UK Domestic Air travel market.

As stated earlier, the models developed in this study depart in many ways from the existence Modal Competition models. They constitute the first attempt of an integrated supply/demand model in the field of the travel competition modeling. However, their complex structures and the sophisticated nature of their calibration techniques may raise the question of whether such models are worth conducting, since their computational cost may be high enough to outweigh the efficiency gain. A clear answer, in favour of such modeling, may be found in a further improvements of these models by investigating more relevant data and increasing the sample size.

Indeed, the supply equations need more elaborate formulations. In fact, they are more "services equations" than truly supply ones. This made us, in the introduction of Part III, put an emphasis on the identification of the demand functions as our primary purpose, the supply equations being essentially designed to combat the Simultaneous Equations Bias.

The introduction of operating costs variables, particularly in Air supply equation, would be of great usefulness. The Aggregation by trip purpose, business/leisure for both modes, would likely provide meaningful insights, since the trip purpose along with the length of haul factor are very important elements in the Choice Mode Decision.

In conclusion, model building is a very complex process that involves numerous aspects with various alternatives: data investigation, variables and structural forms selection, Theories application, choice of techniques calibration. It is very much an Art, and part of this Art is learning to trade off alternative aspects in different ways.

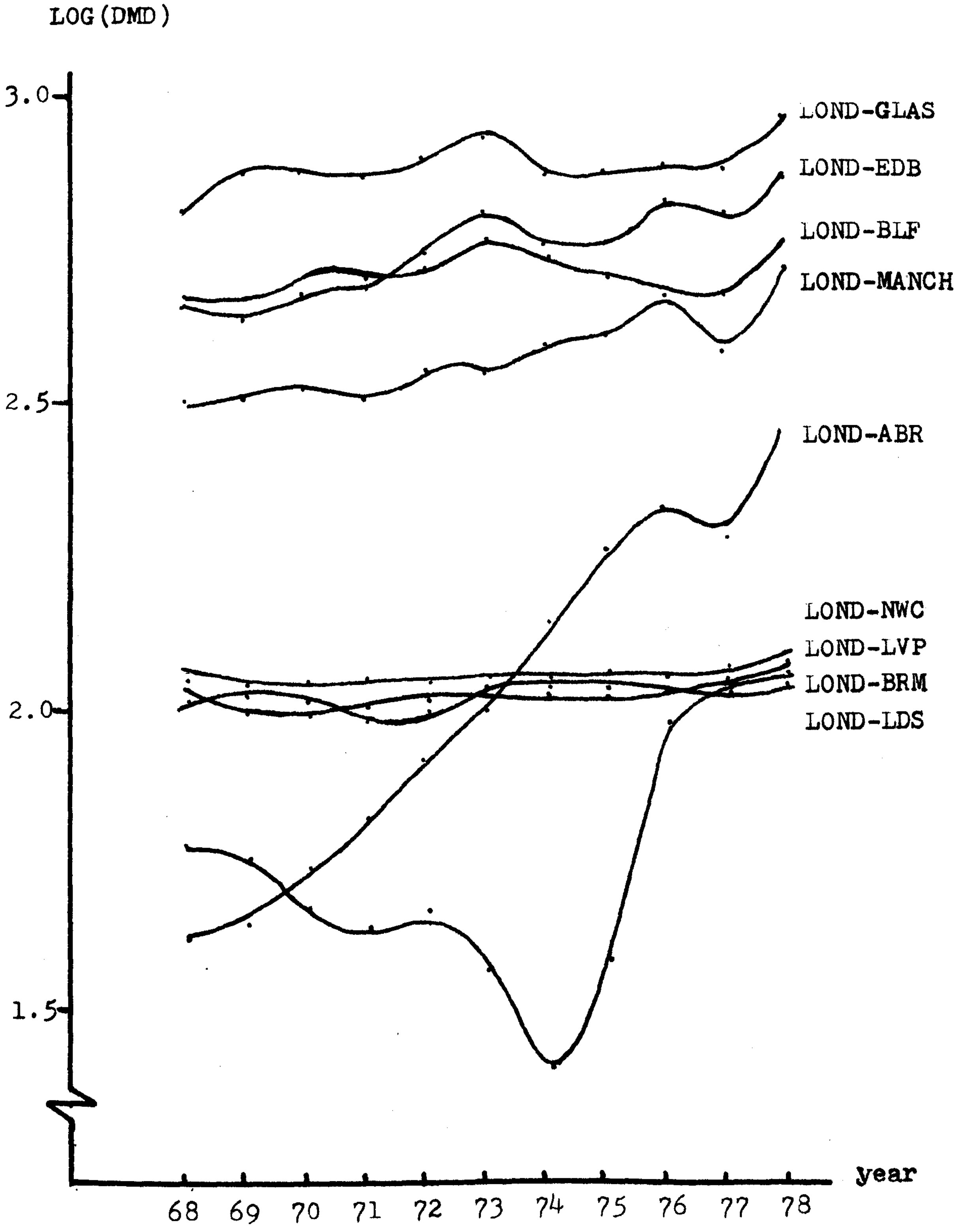


Figure 8.1 UK Air Passengers Demand

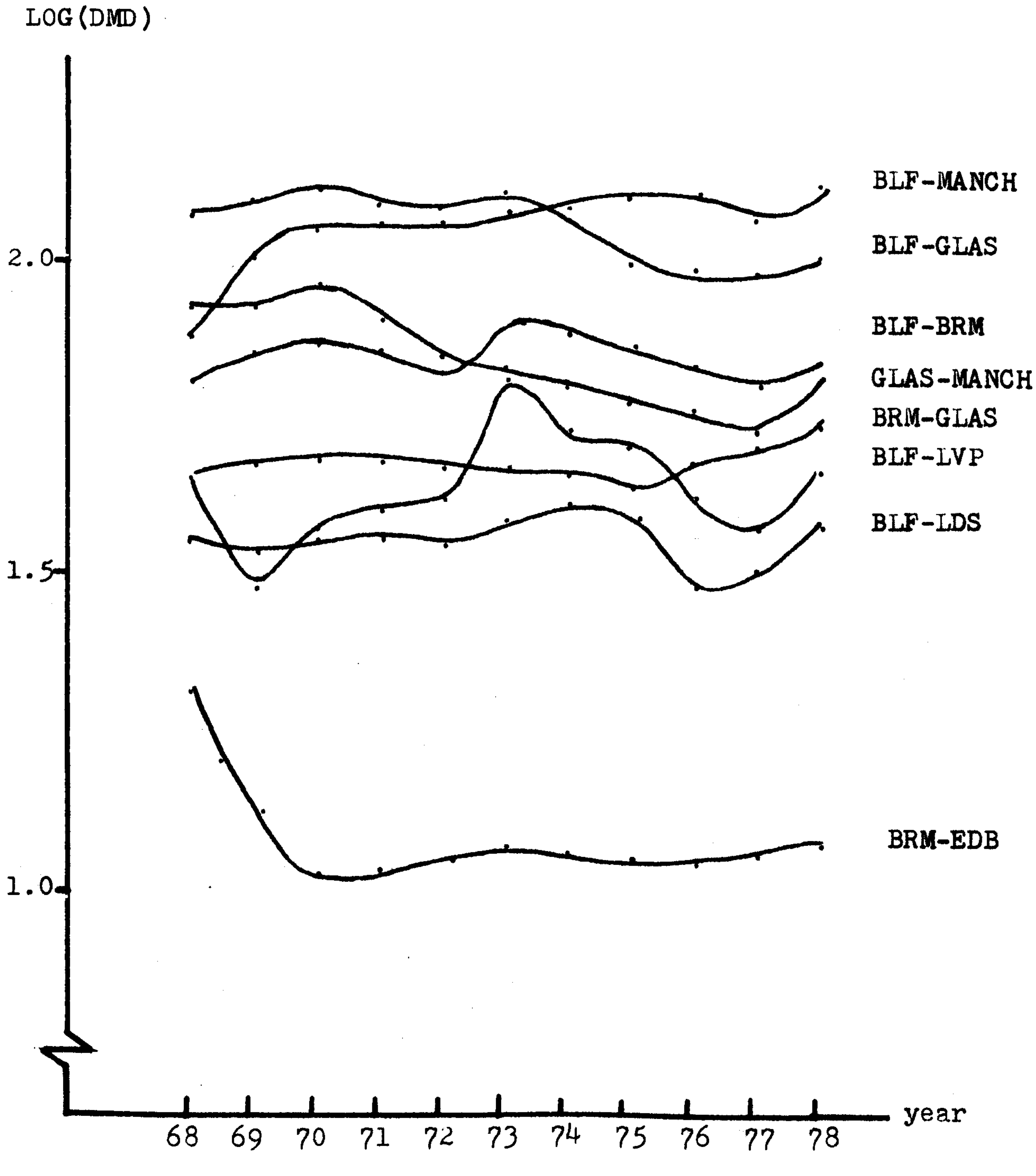


Figure 8.2 UK Air Passengers Demand

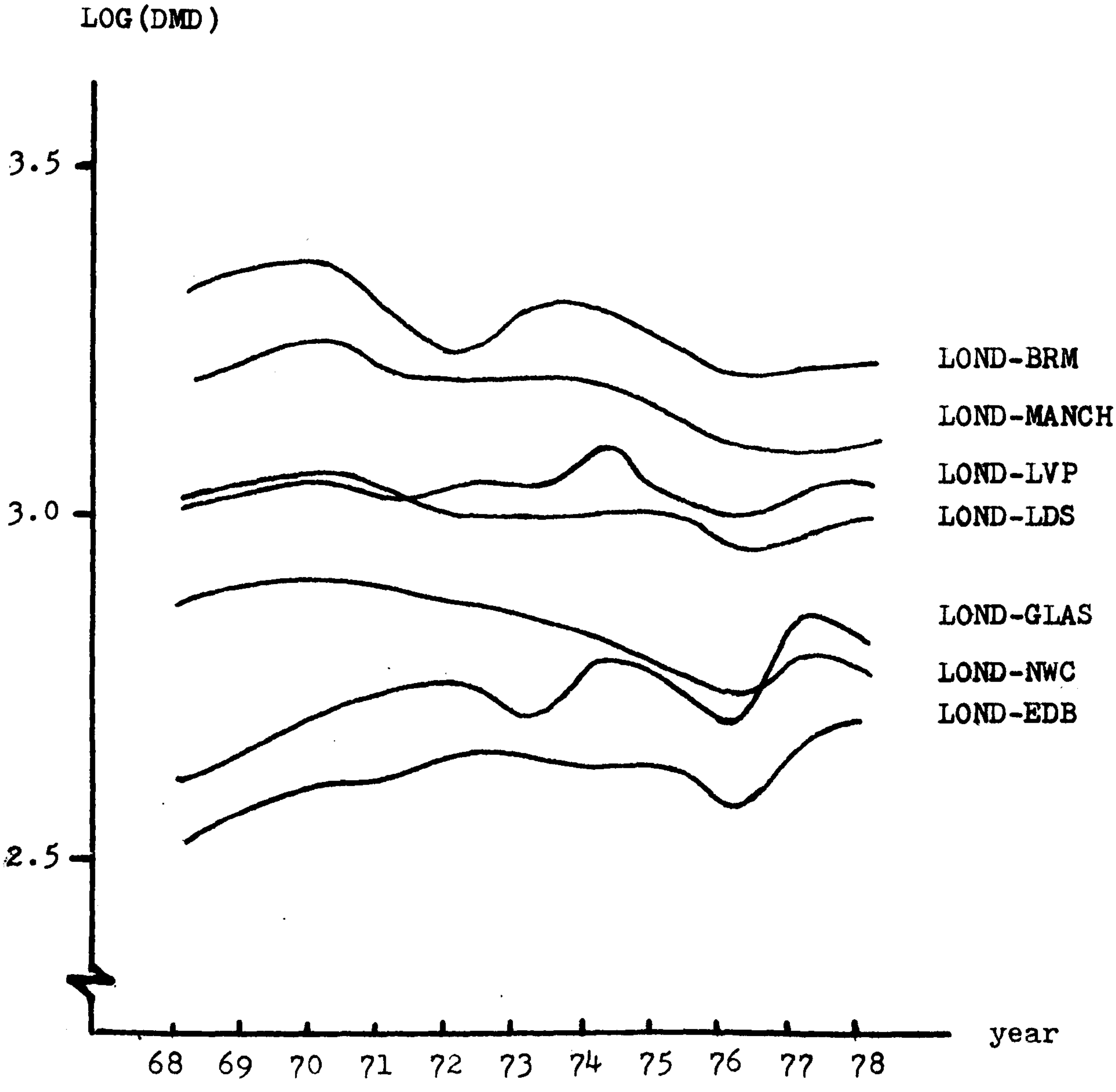


Figure 8.3 UK Rail Passengers Demand

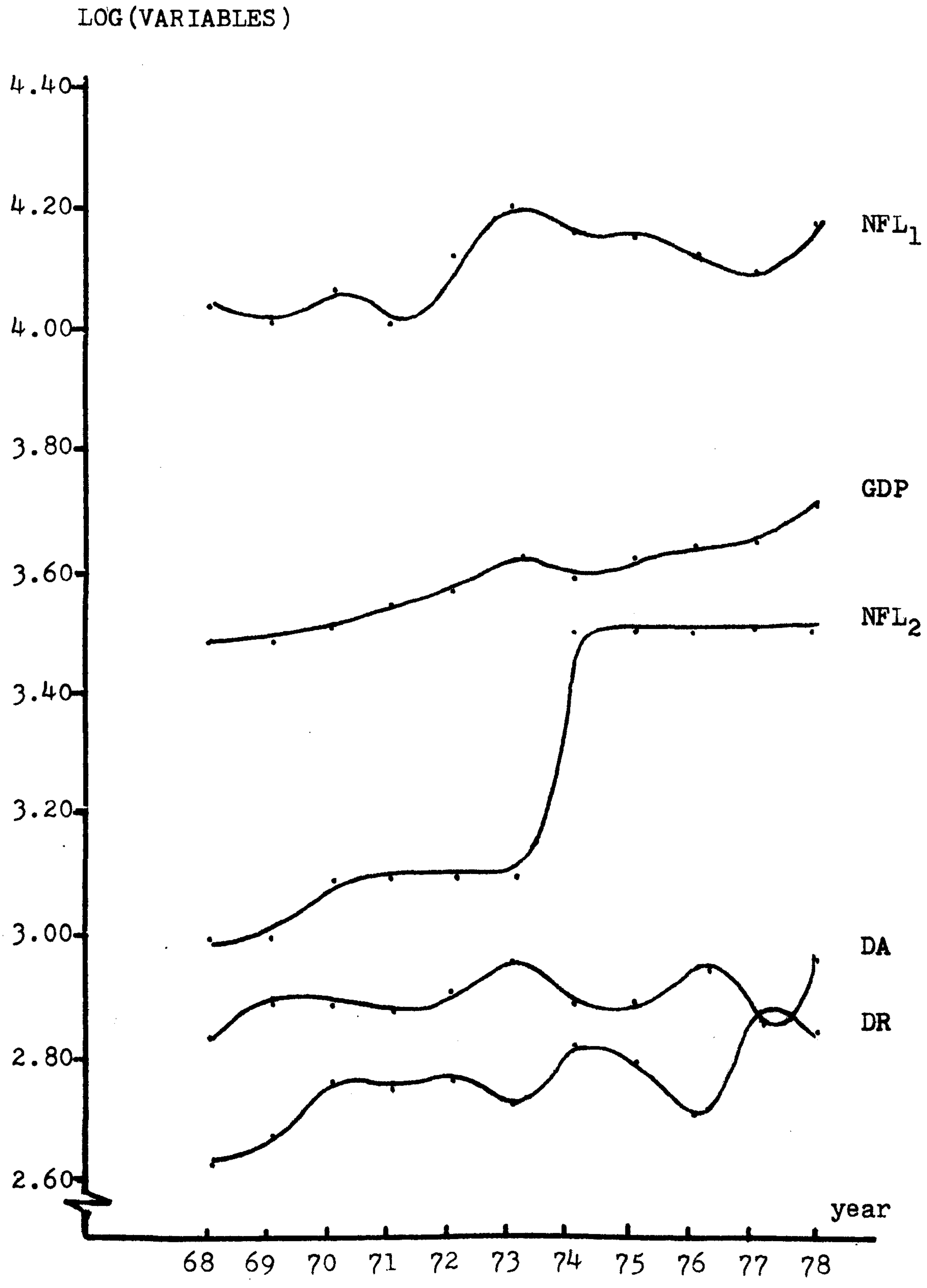


Figure 8.4 GLASGOW

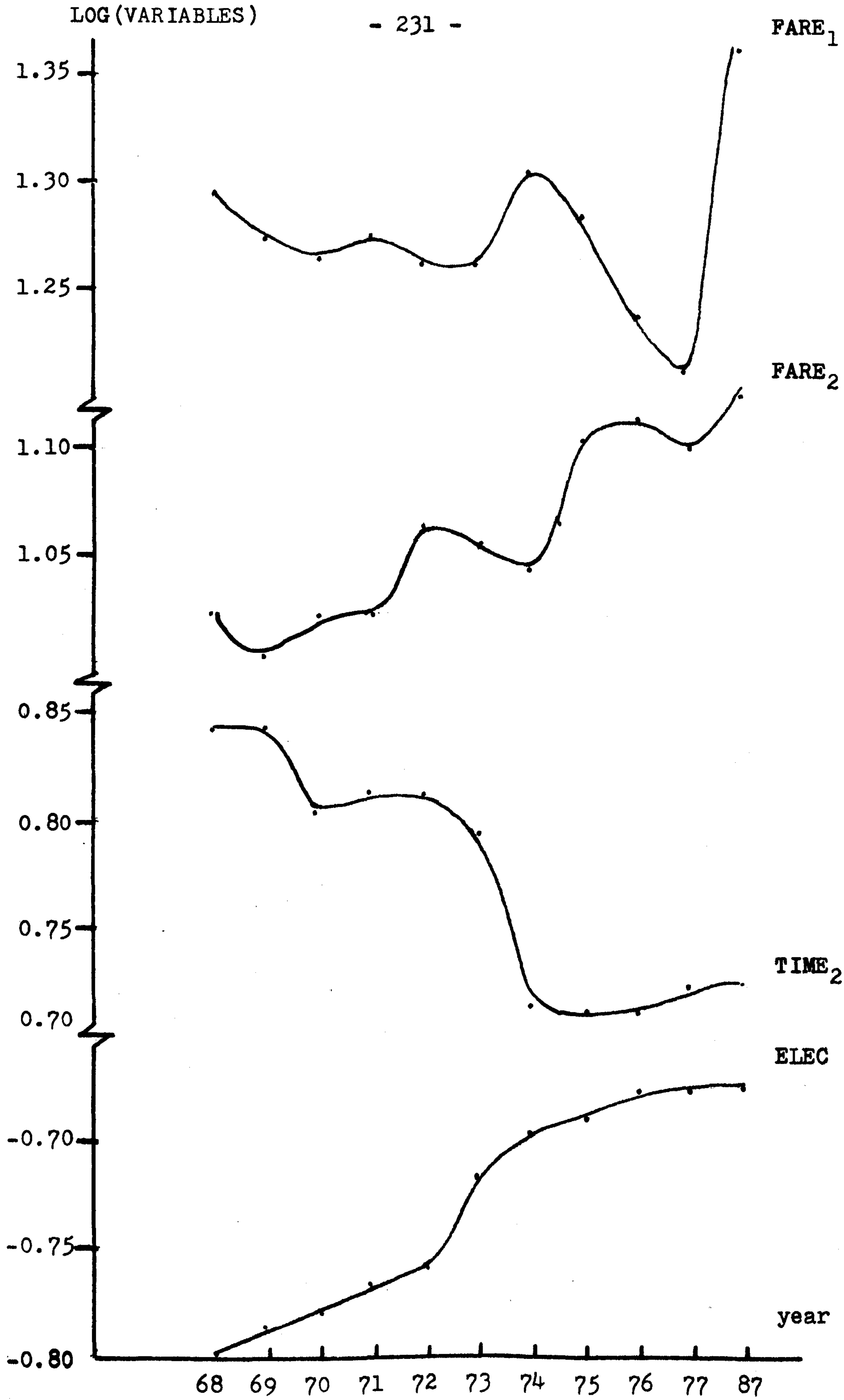


Figure 8.5 GLASGOW

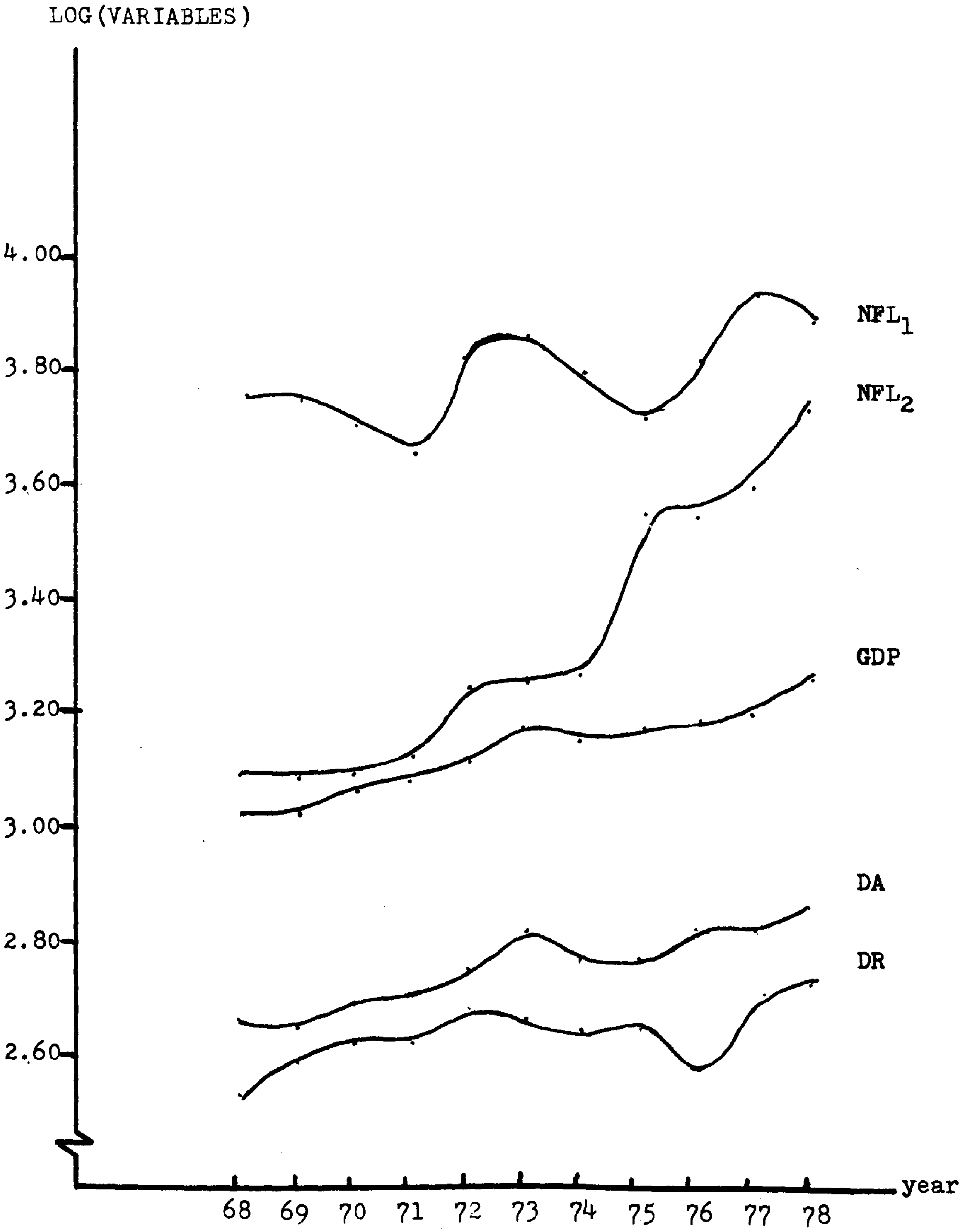


Figure 8.6 EDINBURGH

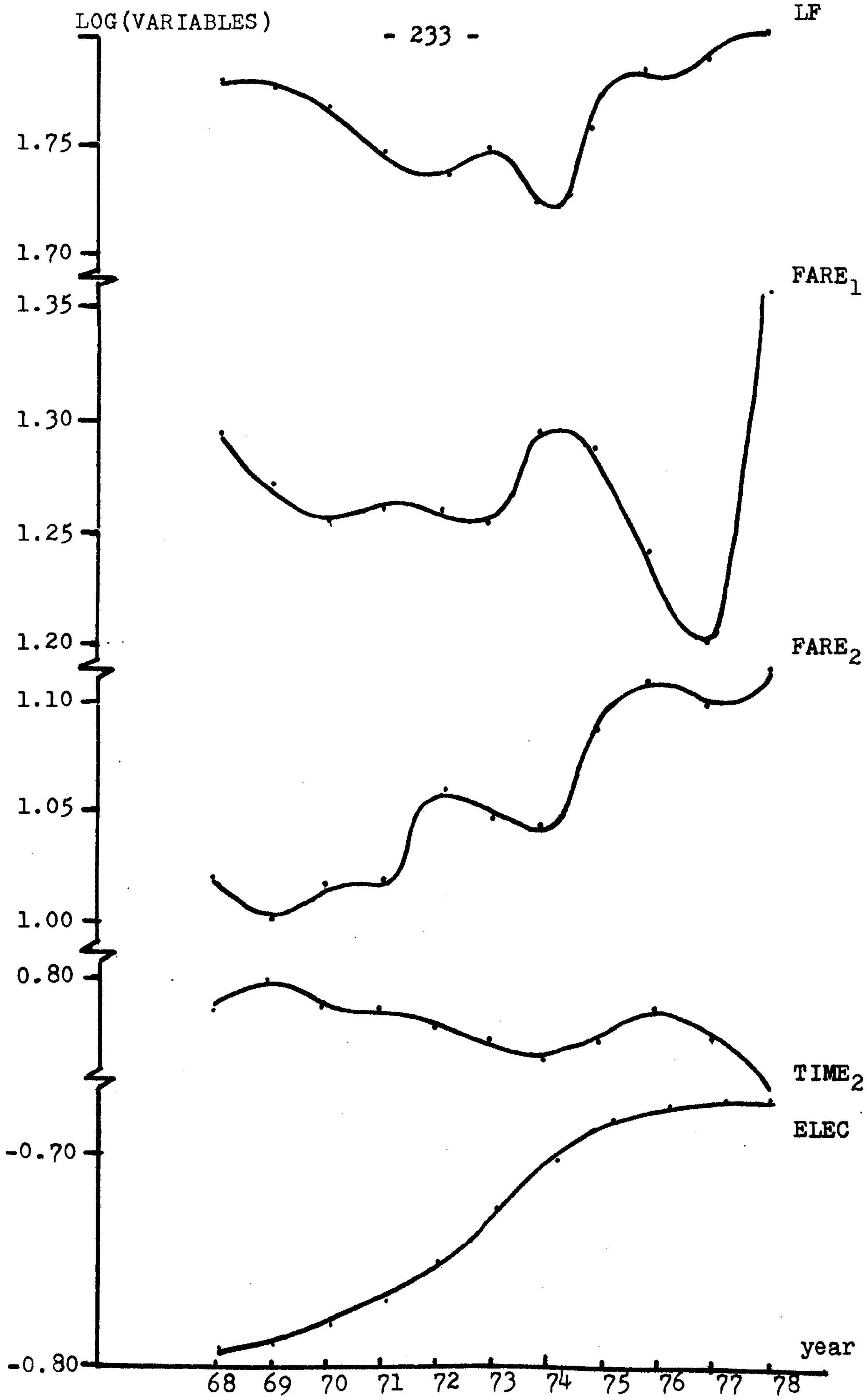


Figure 8.7 EDINBURGH

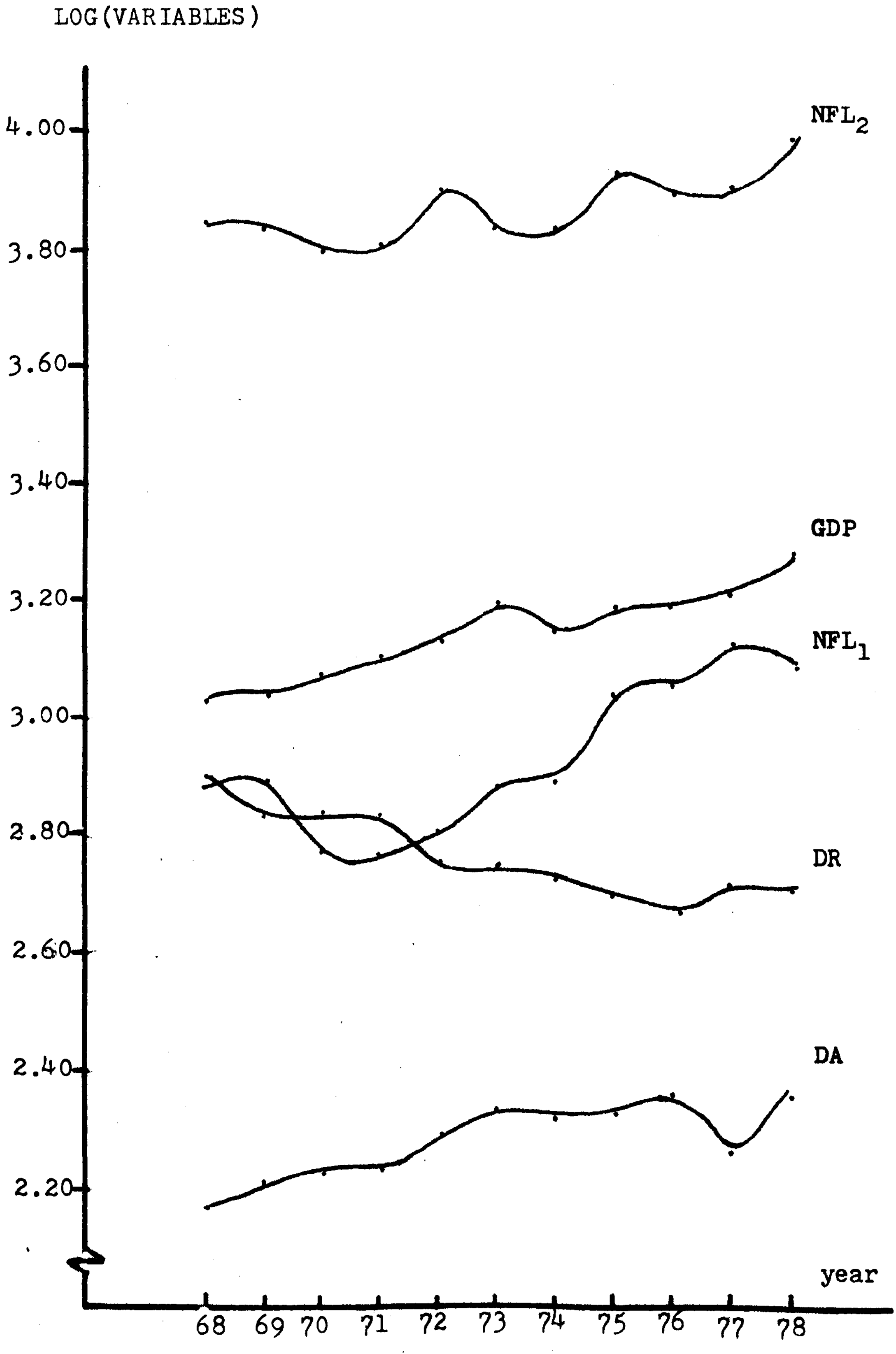


Figure 8.8 NEWCASTLE

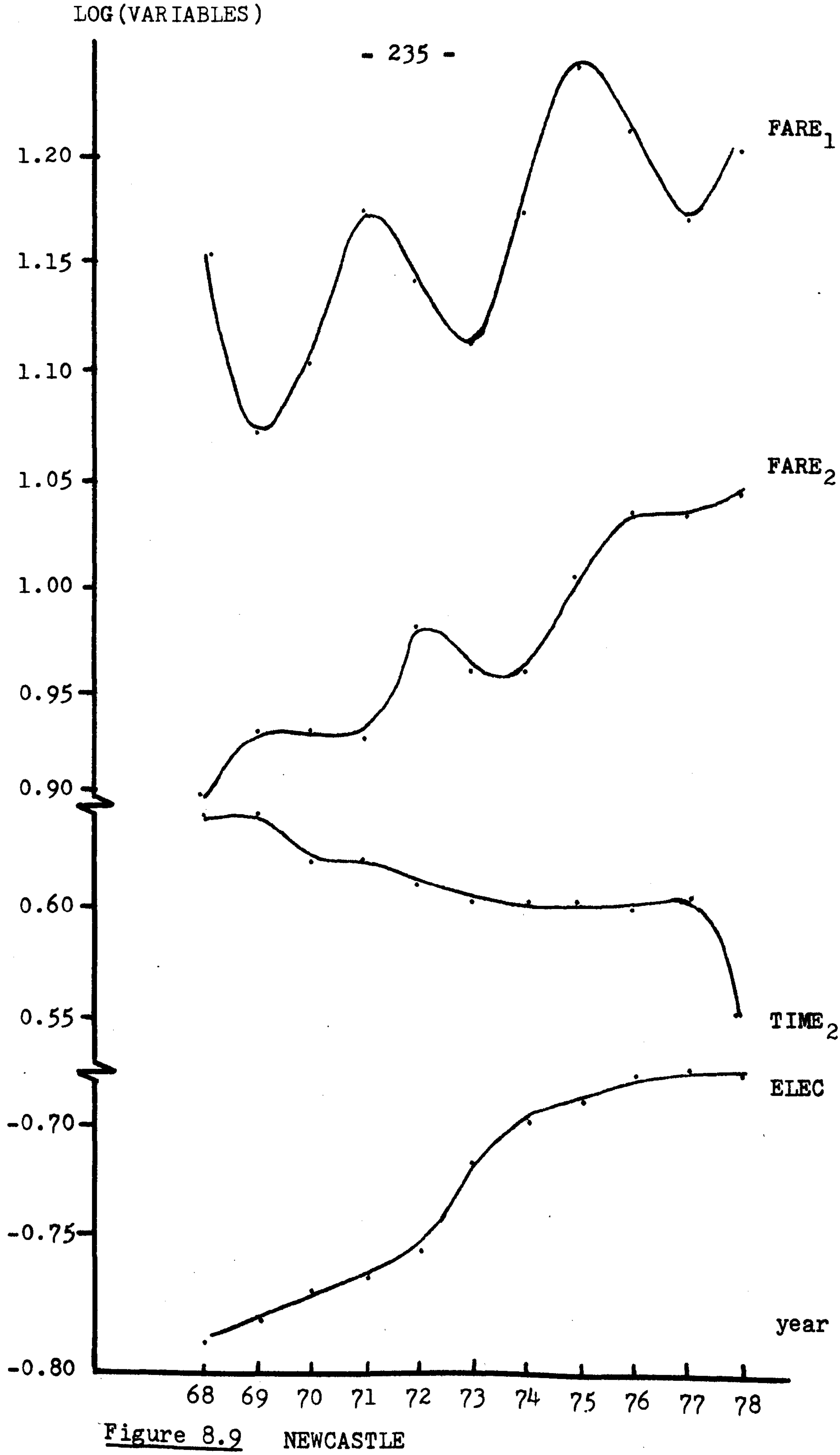


Figure 8.9 NEWCASTLE

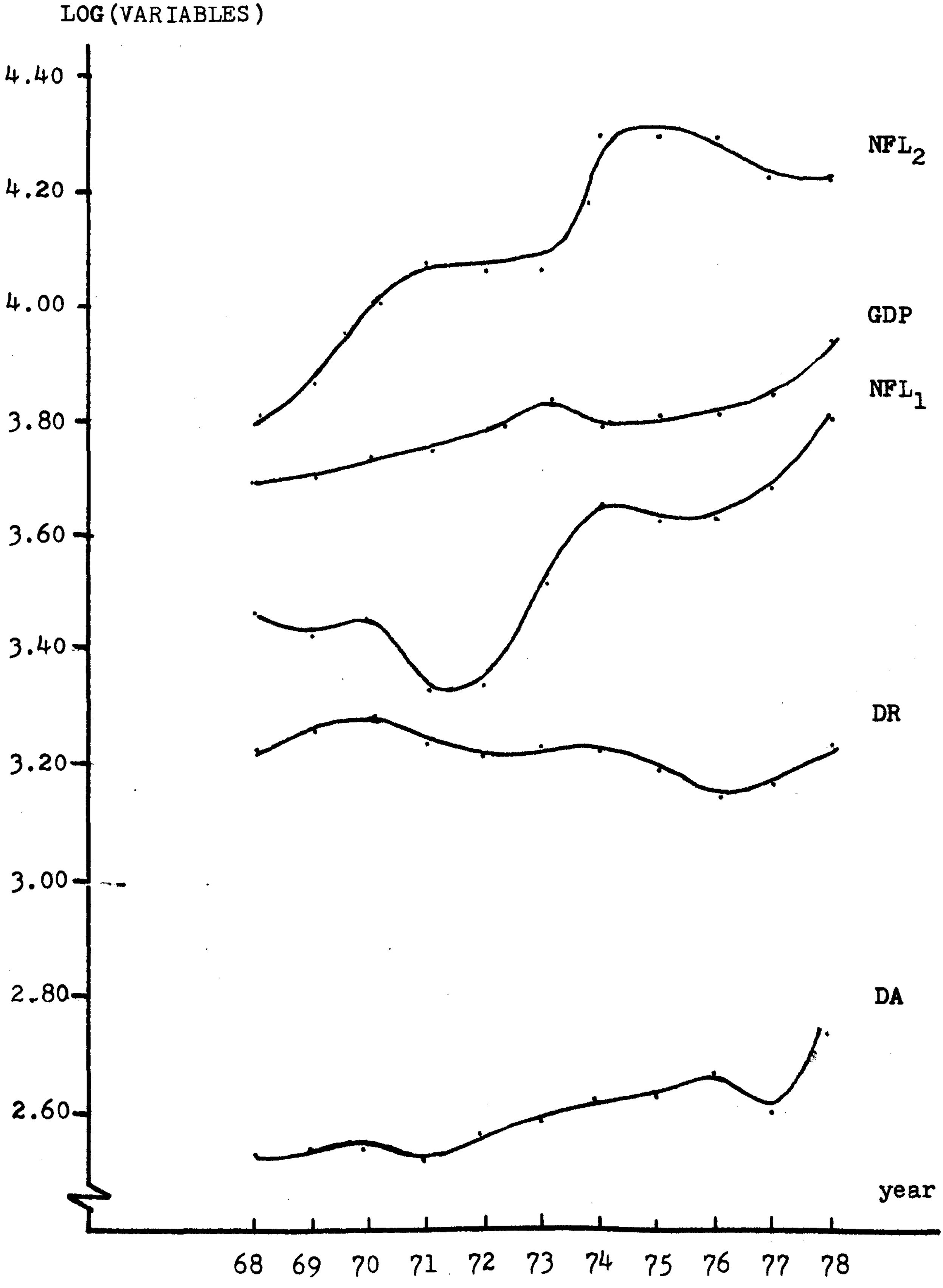


Figure 8.10 MANCHESTER

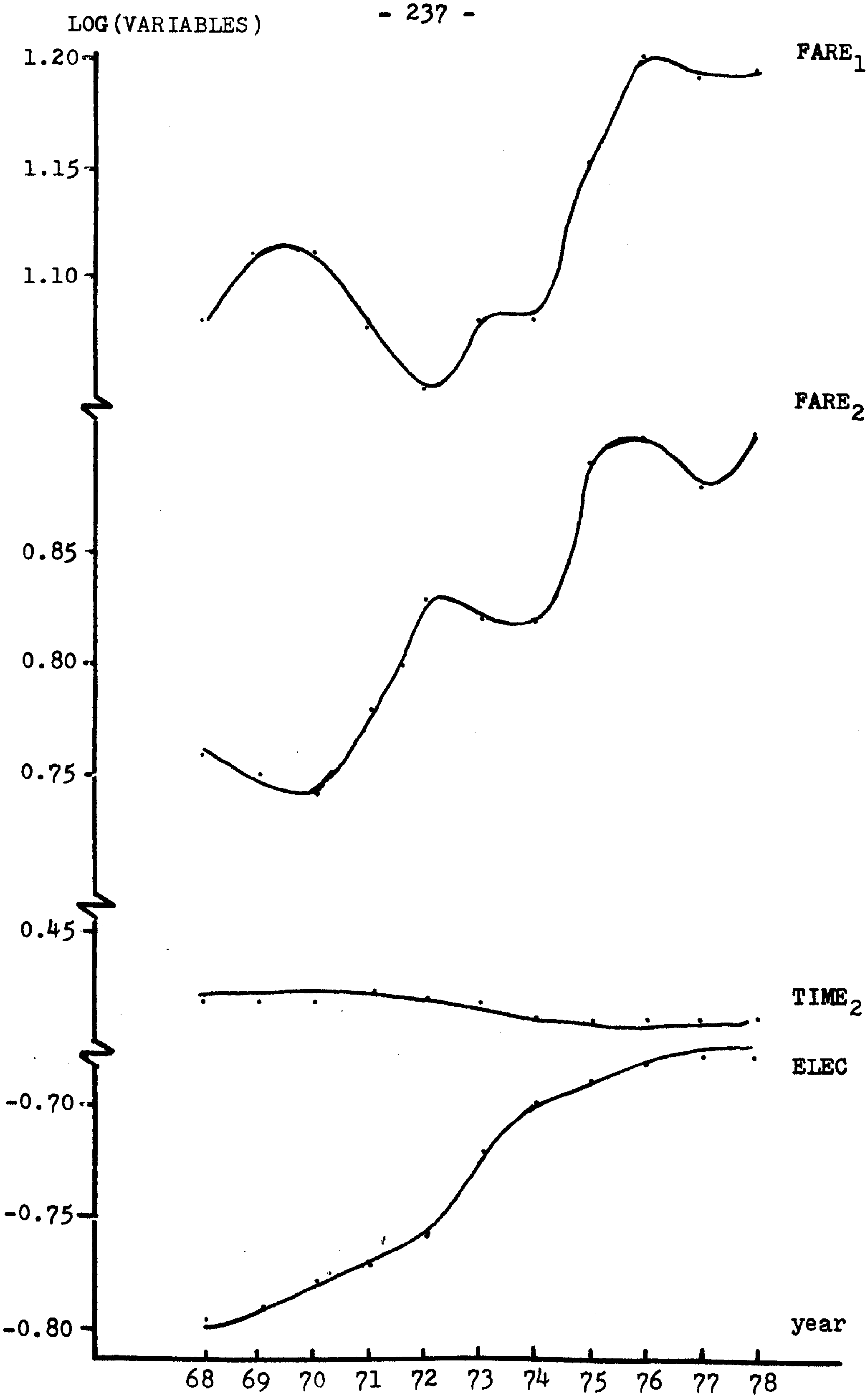


Figure 8.11 MANCHESTER

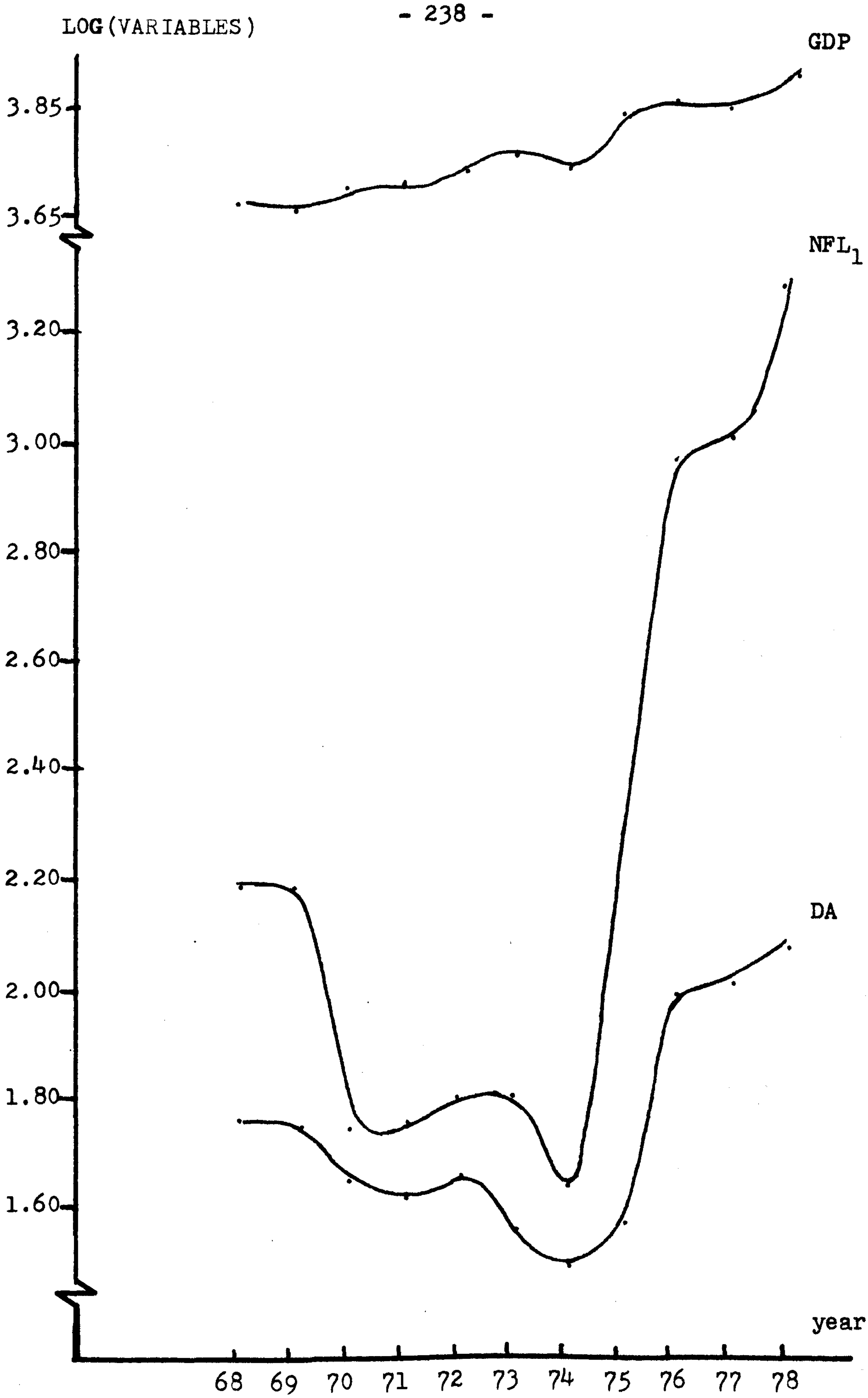


Figure 8.12 BIRMINGHAM

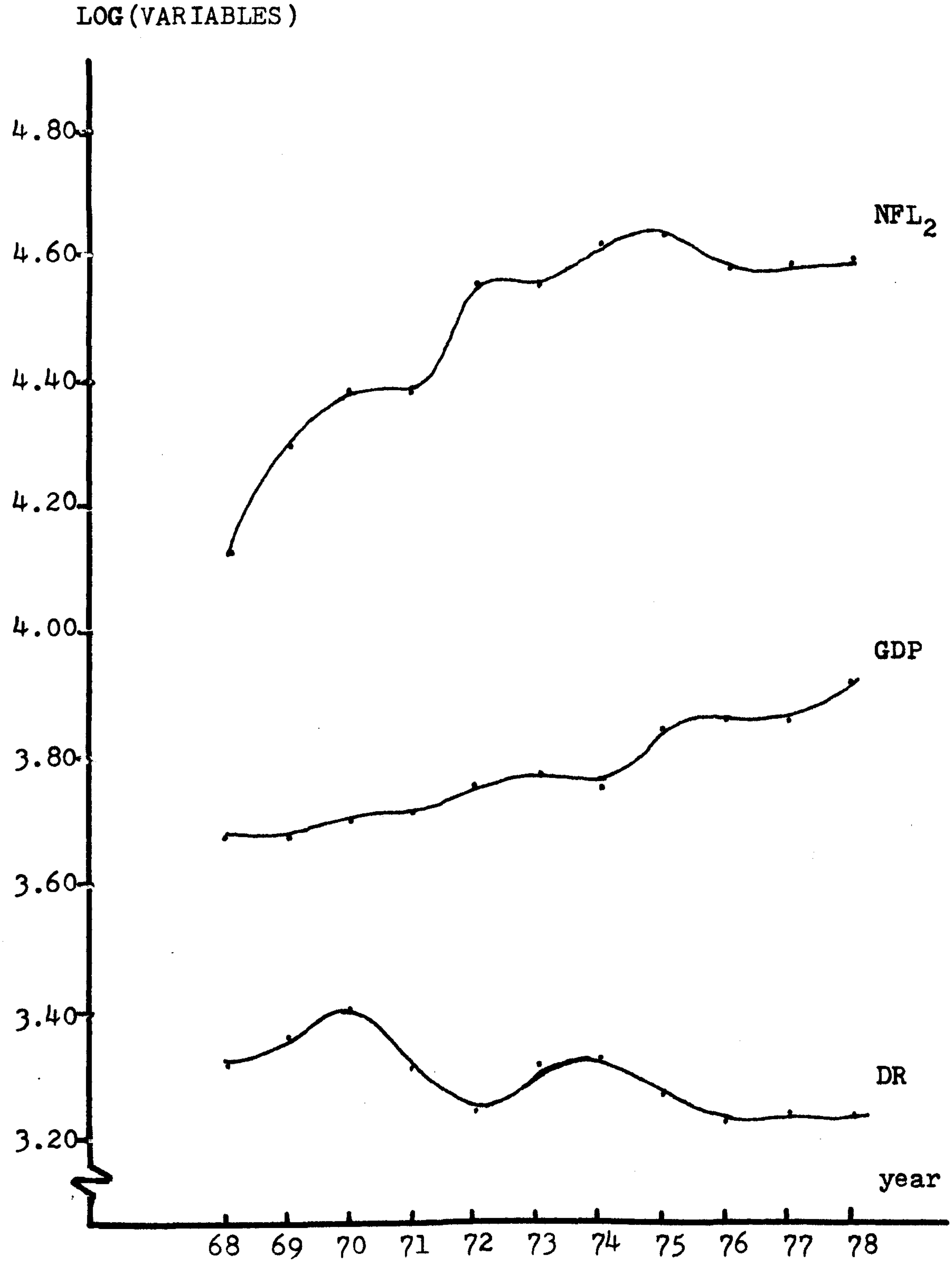


Figure 8.13 BIRMINGHAM

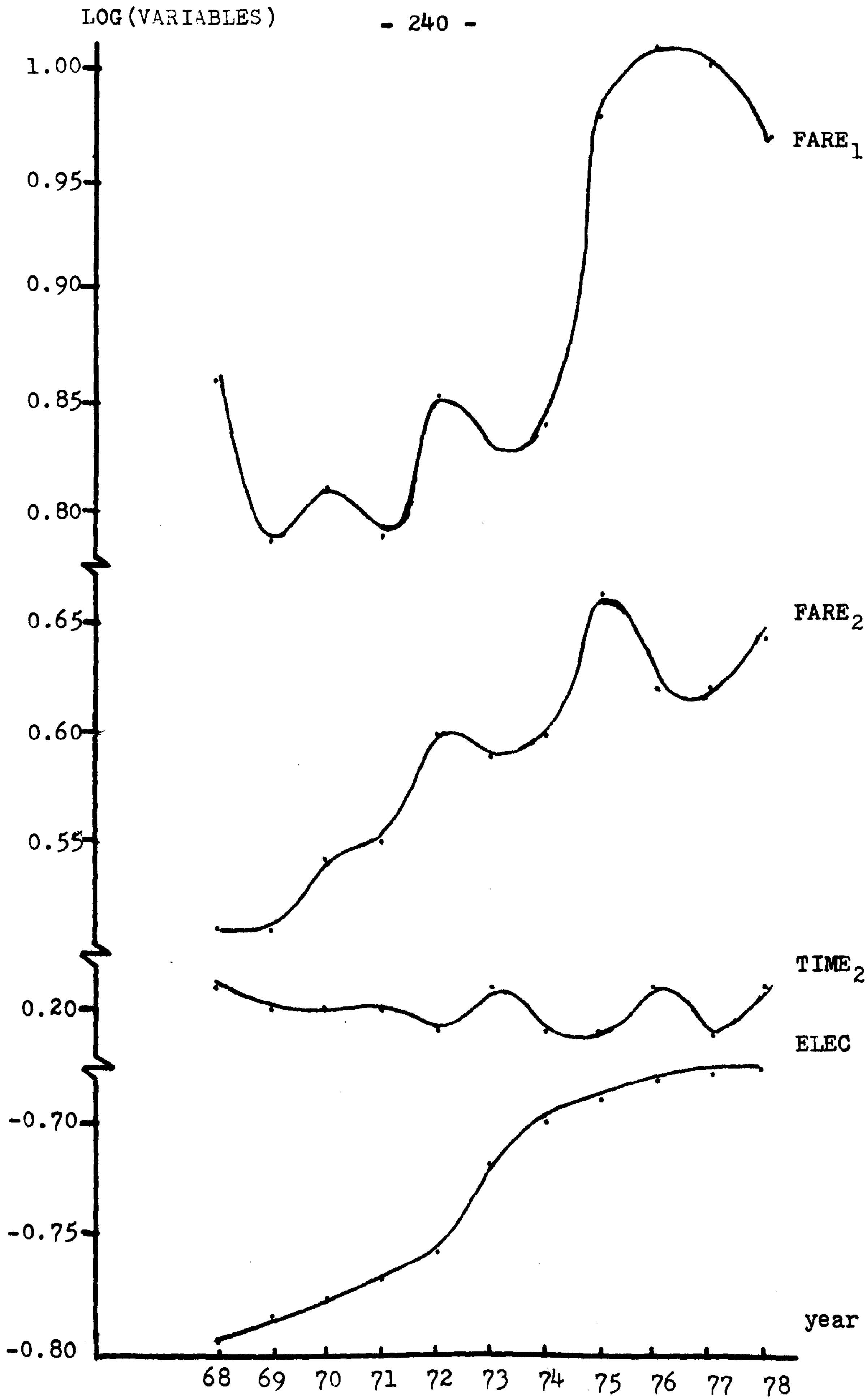


Figure 8.14 BIRMINGHAM

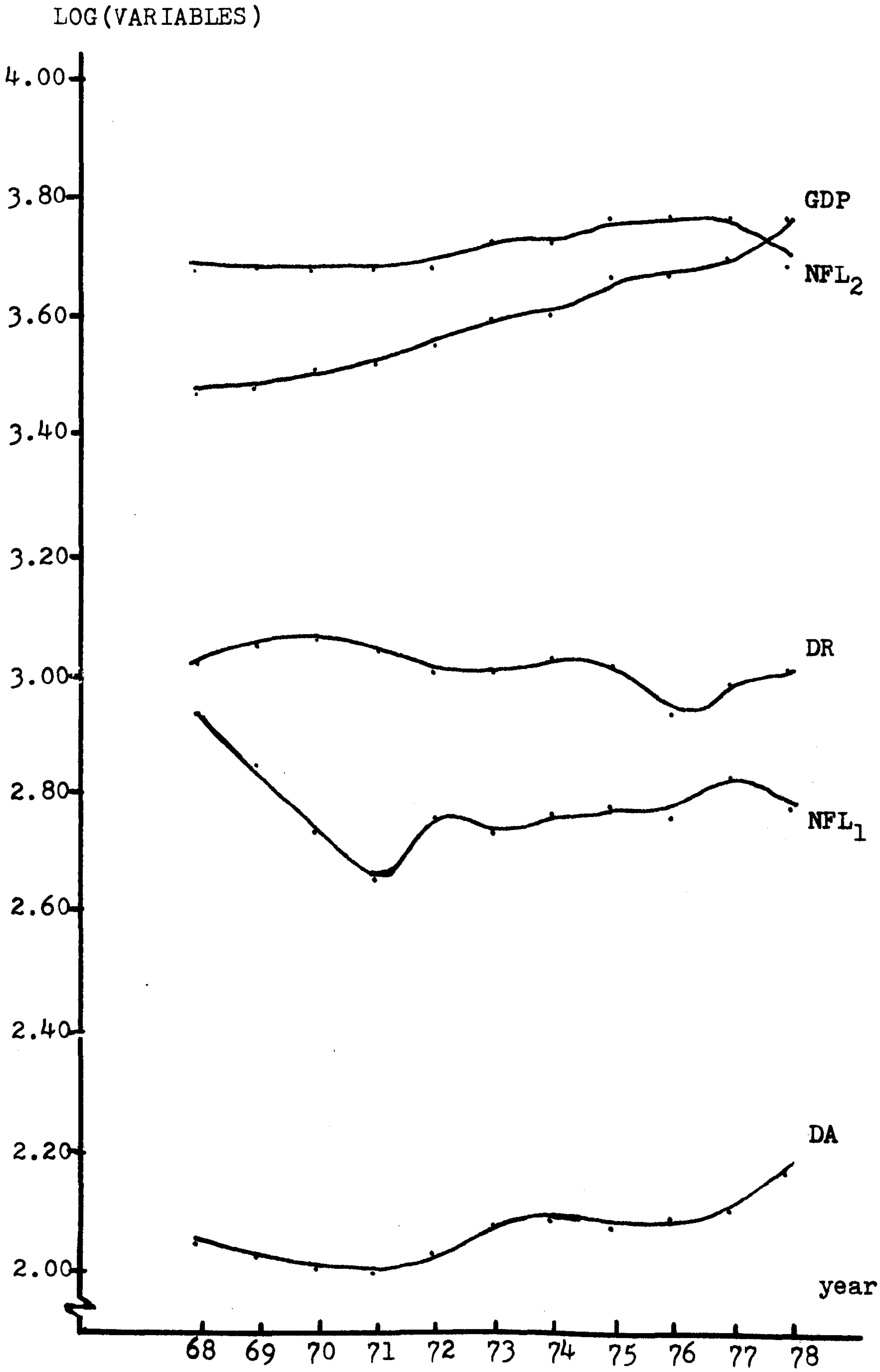


Figure 8.15 LEEDS

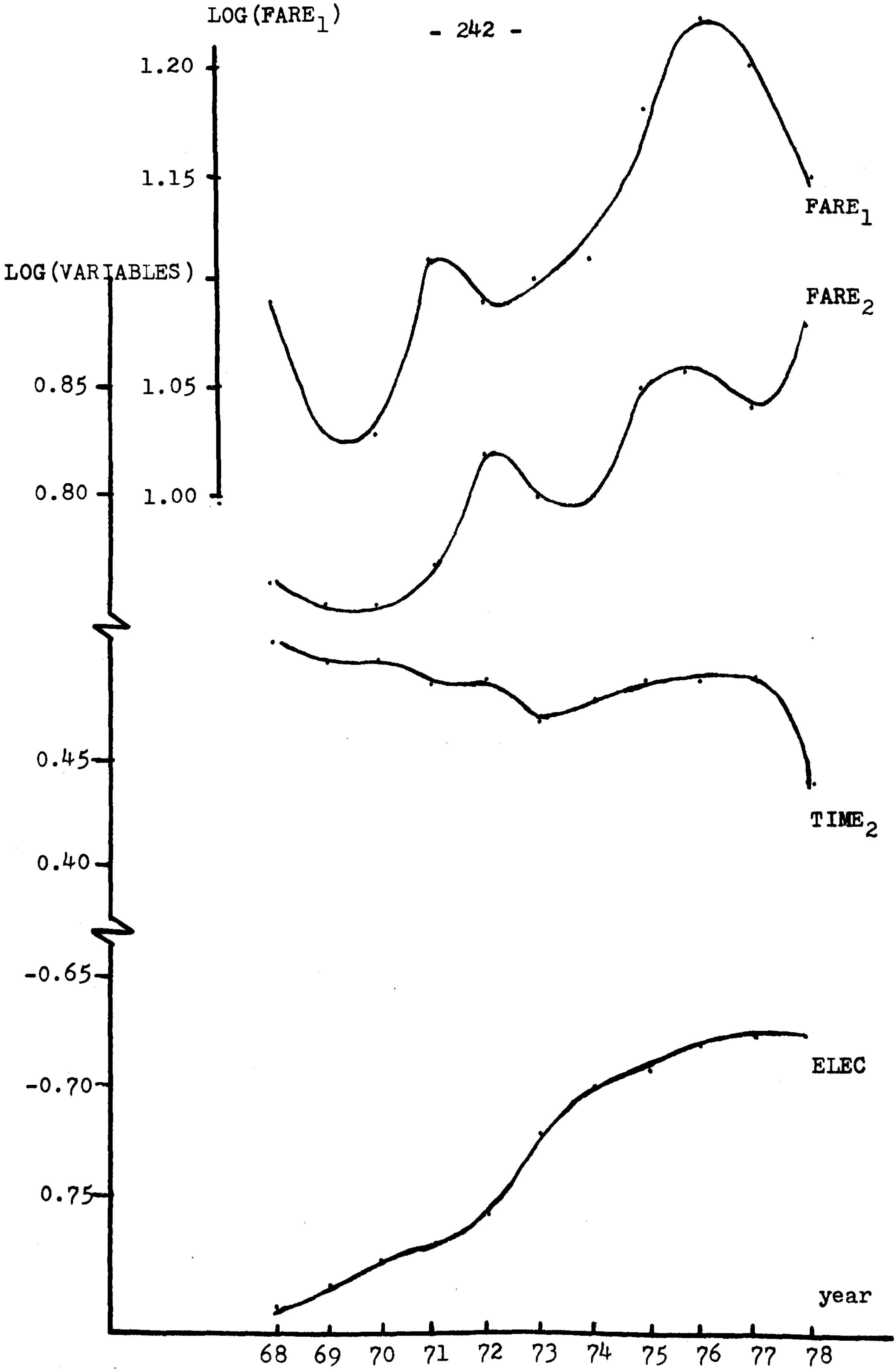


Figure 8.16 LEEDS

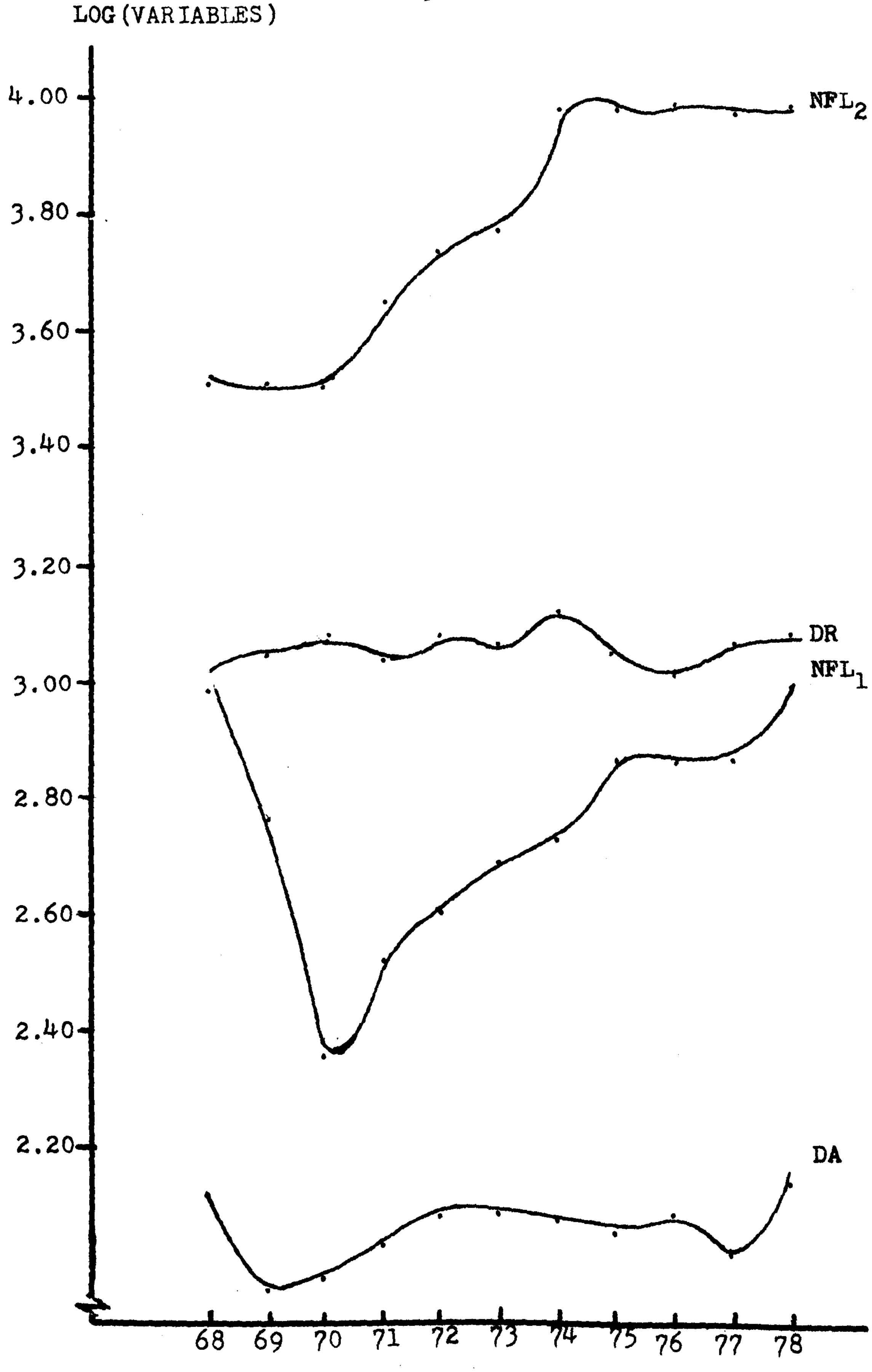


Figure 8.17 LIVERPOOL

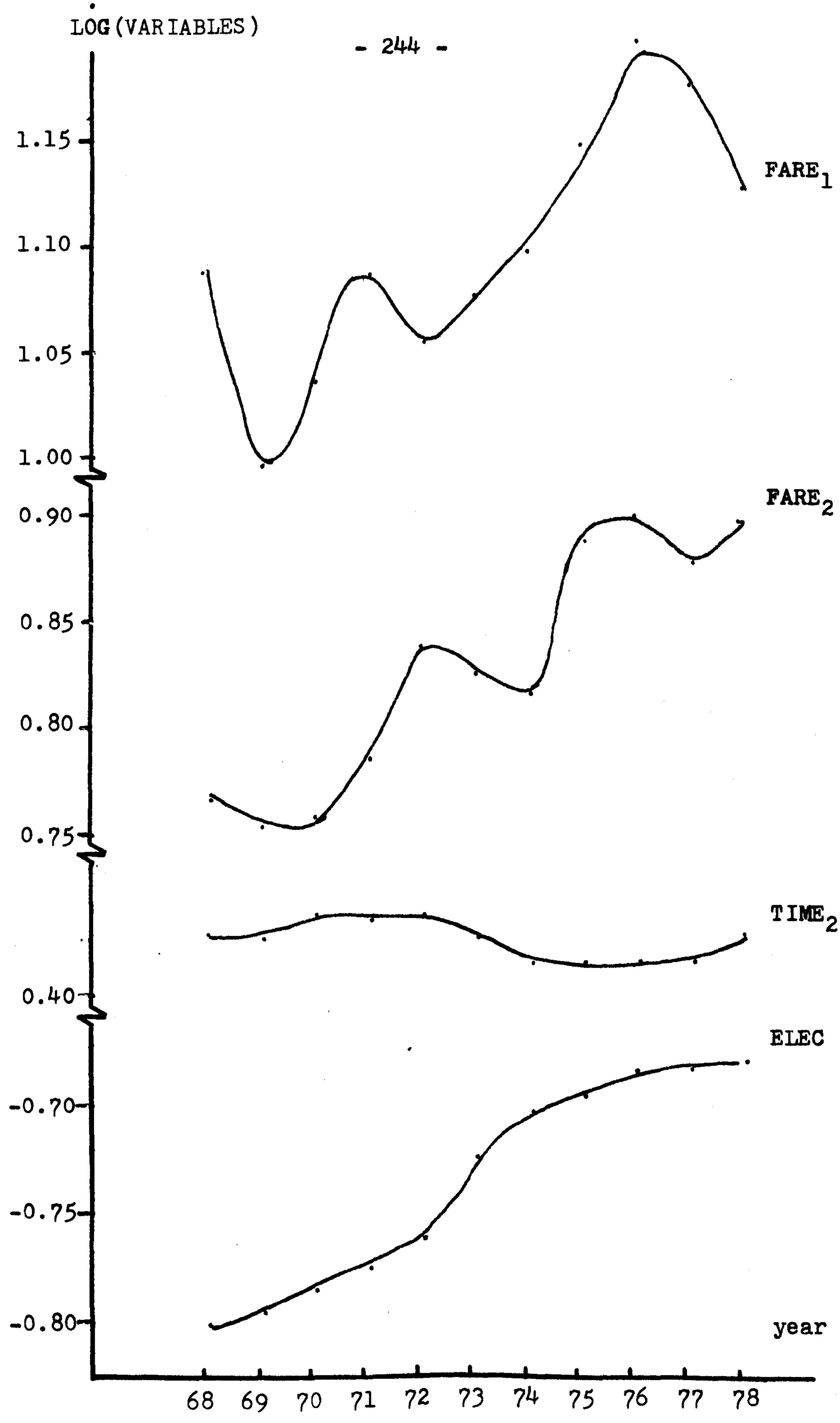


Figure 8.18 LIVERPOOL

REFERENCES

1 Andreff & Bourgogne — Models and their methodology : Application to the Study of Flows and Resources in Air Transport. ITA Study 1972

2 Taneja N K — Airline Traffic Forecasting A Regression Analysis Approach Lexington Books 1978

3 Aureille & Norris — Short and Long term Forecasting Models of the US Domestic and International Traffic and Forecast to 1983. 4th Edition 1975 Douglas Aircraft Company

4 Gronau R — The Value ot Time in Passenger Transportation: the Demand for Air Transport Unpublished PhD Thesis Columbia University 1967

5 Blummer T P — A Short Haul Passenger Demand Model for Air Transportation Unpublished Master's Thesis MIT 1976

6 Verleger P — A Point to Point Model of the Demand for Air Transportation Unpublished PhD Thesis MIT 1971

7 Marfissi P E — Theory and Evidence on the Behavior of Airline Firms facing Uncertain Demand
Unpublished PhD Thesis
Brown University 1976

8 Ericksen S E — Policy Oriented Multi-equation Models of US Domestic Air Passenger Markets
Unpublished PhD Thesis
MIT 1977

9 Koutsoyiannis A — Theory of Econometrics
2nd Edition
Mc Millan Press LTD 1977

10 Brown S L & Watkins W S — The Demand for Air Travel : A Regression Study of Time Series and Cross-sectional Data in the US Domestic Market
Highway Research Record
No 213 1968

11 Strasheim M R — The International Airline Industry
Brookings Institute 1969

12 Viteck & Taneja — The Impact of High Inflation Rates on the Demand for Air Passenger Transportation
R 75-6 MIT May 1975

13 Pindyck R S & Rubinfeld D L — Econometric Models and Econometric Forecasts
New York: Mc Graw-Hill 1976

14	Taneja N K	A Methodology for determming the Relationship between Air Transportation Demand and the Level of Service MIT 1976
15	Youn, Y.P	The demand for Air Travel unpublished PhD thesis University of Washington 1966
16	Lancaster K	A New Approach to Consumer Theory Journal of Political Economy Vol LXXXIV 1966
17	Quandt R E & Baumel W J	The Demand for Abstract Modes : Theory and Measurement Journal of Regional Science Vol 6 No 2 1966
18	SARC-Kraft	Demand for Intercity Passengers Travel in the Washington-Boston Corridor Cambridge : SARC 1963
19	Quandt R E & Young	Cross-sectional Demand Model : Estimates and Tests Journal of Regional Science Vol 9 No.2 1969
20	Stopher P & Meyburg A	Urban Transportation Modeling and Planning Lexington Books 1975
21	Mc Fadden	Conditional Logit Analysis of Qualitative Choice Behavior Frontier of Econometric New York 1973
22	Horwitz	Transportation Research Vol 14B No.4 Dec 1980

23	Kanafani A & Sadoulet E	The Partitioning of Long Haul Air Traffic A Study in Multinomial Choice Institute of Transportation and Traffic Engineering University of California Berkeley 1975
24	Benakiva & Richards	Disaggregate Multi-modal Model For Work Trips in the Netherlands Transportation Research Record No 569 (pp 107-123) 1976
25	Horwitz	Disaggregate Demand Model for Non Work Travel Transportation Research Record No 673 (pp 65-71) 1978
26	Kanafani A Gosling G & Taghavi S	Studies in the Demand for Short Haul Air Transportation Institute of Transportation and Traffic Engineering University of California Berkeley 1975
27	Ellison A P & Stafford E M	The Dynamics of the Civil Aviation Industry Saxon House/Lexington Books 1974
28	FAA	Aviation Forecasts Fiscal Year 1976-1987 FAA Technical Report FAA-AVP-75-7 Washington DC Federal Aviation Administration 1975
29	CTS University of Leeds	Intercity Modal Split in Great Britain Air vs Rail Centre for Transport Studies University of Leeds Leeds,2 June 1971

30	Roskill Commission	Commission on the Third London Airport The Roskill Report Papers and Proceedings Vol VII 1970
31	Societe d'Etudes Technique et Economiques	Characteristics and Forecasts of Demand in Europe Aeroport de Paris Societe d'Etudes Techniques et Economiques Paris 1968
32	Thompson	Transport Demand at a Provintial Airport J T E P January 1974
33	Port of New York Authority	Forecast of the US Domestic Air Passenger Market 1965-1975 The Port of New York Authority 1960
34	Quandt R E	The Demand for Travel: Theory and Measurement Heath Lexington 1970
35	Brown S L & Watkins W S	Measuring Elasticities of Air Travel from New Cross-sectional Data Annual American Statistical Association Meeting 1971
36	Lippke & Stewart	Economic Impact on Domestic Air Traffic An Econometric Approach Boeing Company 1969
37	Simpson R W	Theory for Domestic Airline Economics MIT FTL 1974
38	Stopher P.	Journey to Work PhD thesis, University College London 1967

39	Quarmby D A	Choice of Travel Mode for the Journey to Work J T E P 1967
40	Leake G & Underwood J	Comparison of Intercity Bimodal Split Models Transportation Planning and Technology Vol 5 No 1 1978
41	Lisco T E	The Value of Commuters Travel Time A Study in Urban Transportation Unpublished PhD Thesis University of Chicago 1967
42	Warner S L	Stochastic Choice of Mode in Urban Travel: A Study in Binary Choice Northwestern University Press Evanston 1962
43	Watson P	The Value of Time Behavioral Models of Modal Choice Lexington Books 1974
44	Farrar & Glauber	Multicollinearity in Regression Analysis: The Problem revisited Review of Economics & Statistics Vol 49 (pp 92-107) 1967
45	CAA Annual Statistics	CAA Annual Statistics From 1971 to 1978
46	CAA Survey	CAP 363 Origin Destination of Passengers at UK Airports CAA 1975

47	Edward Report	British Air Transport in the Seventies Report of the Committee of Transport into Civil Air Transport Cmnd 4018 May 1969
48	ABC Guide	ABC World Airways Guide From 1961 to 1978
49	National Income and Expenditure	CSO National Income and Expenditure 1979 HMSO
50	Gwilliam K M & Mackie P J	Economics and Transport Policy George Allen & Unwin 1975
51	CAA Statistics	CAA Annual Statistics CAP 375 1973
52	Annual Abstract of Statistics	CSO Annual Abstract of Statistics 1976 HMSO
53	Regional Statistics	CSO Regional Statistics Year 1973 and Year 1979 HMSO
54	Stubbs P & Tyson W	Transport Economics Charles Carter 1980
55	Future Civil Aviation Policy	Department of Trade Presented to Parliament by the Secretary of State for Trade by Command of Her Majesty 1976
56	Increases in Passenger Fares	British Railways Board Presented to Parliament in Pursuance of Section 6(a) of the Price Commission Act 1977

57 Mathaisel D F & Taneja N K — An Application of Advanced Statistical Techniques to Forecast the demand for Air Transportation
MIT FTL Report No R77-3
August 1977

58 Christ C — Economics Model and Methods
Wiley 1966

59 University of Southampton — Intercity VTOL
University of Southampton 1973

60 British Railways Board — Review of Main line electrification.
Final Report
BRB Department of Transport 1981

APPENDIX

STATISTICAL PROPERTIES OF ESTIMATORS*

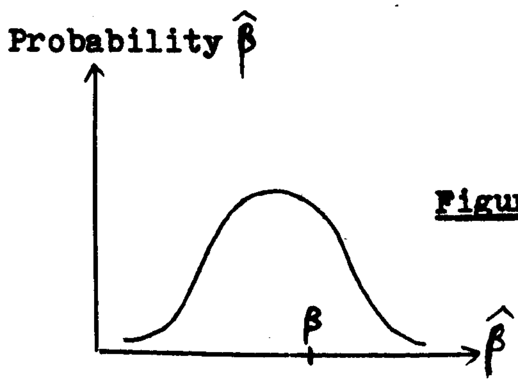
The goal in a Linear Regression model is to fit an estimated regression line $\hat{Y} = \alpha + \hat{\beta} X$ which is in some sens close to the true regression line. To test how the estimated line differs from the true regression line, some useful statistical properties are desirable for any set of estimated parameters.

Unbiasedness

An estimator $\hat{\beta}$ is unbiased when the mean or expected value of $\hat{\beta}$ is equal to the true value β ; that is : $E[\hat{\beta}] = \beta$. The bias is defined as follows:

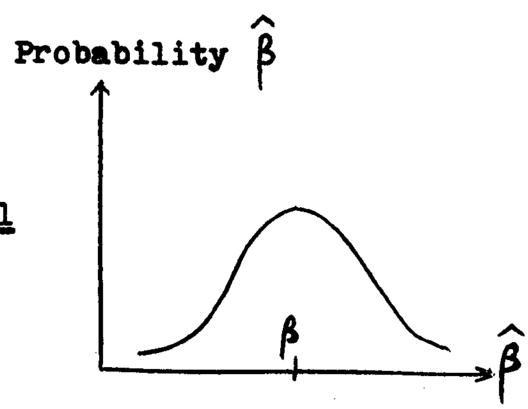
$$\text{Bias} = E(\hat{\beta}) - \beta$$

Figure 1 illustrates the difference between a biased and an unbiased estimator . While lack of bias in an estimator is a desirable property, it implies, however, nothing about the dispersion of the estimator about the true parameter. In general, one would like the estimator to be unbiased and also to have a very small dispersion about the Mean. One, therefore, should define a second criteria that allows to choose among alternative unbiased estimators.



BIASED ESTIMATOR

Figure 1

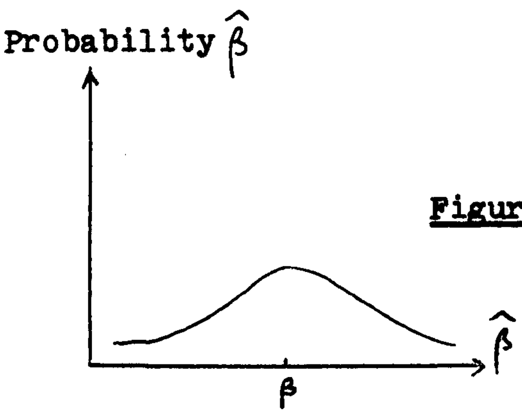


UNBIASED ESTIMATOR

* The material in this appendix has been extracted from Pindyck [13] .

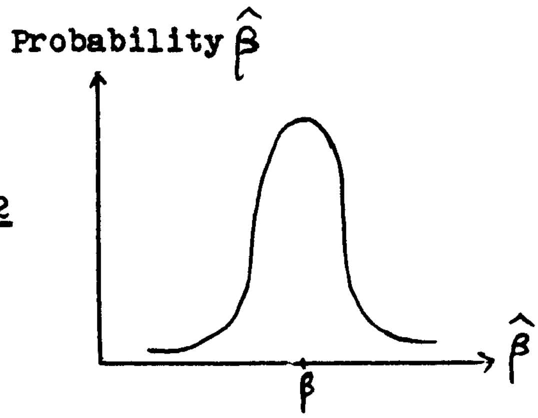
Efficiency

$\hat{\beta}$ is an efficient unbiased estimator when the variance of $\hat{\beta}$ is smaller than the variance of any other unbiased estimator. In practice, it is sometimes difficult to tell whether an estimator is efficient, so that it is natural to describe estimators in terms of their relative efficiency. One estimator is more efficient than another if it has smaller variance. This is graphically shown in Figure 2 below:



INEFFICIENT ESTIMATOR

Figure 2



EFFICIENT ESTIMATOR

Consistency

$\hat{\beta}$ is a consistent estimator of β if the probability limit of $\hat{\beta}$ is β ; i.e, if the probability that $|\beta - \hat{\beta}|$ will be less than any arbitrary small positive number will approach 1 when the sample size gets infinity. In other words, an estimator is consistent if the probability distribution of the estimator collapses to a single point, the true parameter, as the sample size gets large. This is illustrated in Figure 3 below:

Figure 3

ESTIMATOR CONSISTENCY