NOTICE

The quality of this microform is heavily dependent upon the quality of the original thesis submitted for microfilming. Every effort has been made to ensure the highest quality of reproduction possible.

If pages are missing, contact the university which granted the degree.

Some pages may have indistinct print especially if the original pages were typed with a poor typewriter ribbon or if the university sent us an inferior photocopy.

AVIS

La qualité de cette microforme dépend grandement de la qualité de la thèse soumise au microfilmage. Nous avons tout fait pour assurer une qualité supérieure de reproduction.

S'il manque des pages, veuillez communiquer avec l'université qui a conféré le grade.

La qualité d'impression de certaines pages peut laisser à désirer, surtout si les pages originales ont été dactylographiées à l'aide d'un ruban usé ou si l'université nous a fait parvenir une photocopie de qualité inférieure.

COMPARISON OF AGGREGATE AND DISAGGREGATE MODELS IN PREDICTING SHOPPING CENTRE PATRONAGE

by

Daljit S. Sandhu

B.B.A. Simon Fraser University 1983

THESIS SUBMITTED IN PARTIAL FULFILLMENT OF

THE REQUIREMENTS FOR THE DEGREE OF

MASTER OF BUSINESS ADMINISTRATION

in the Faculty

of

Business Administration

SIMON FRASER UNIVERSITY

December 1989

ISBN 0-315-66221-2

APPROVAL

Name: Daljit S. Sandhu

Degree: Master of Business Administration

Title of Thesis: Comparison of Aggregate and Disaggregate Models in Predicting Shopping Centre Patronage.

Examining Committee:

Chairman: Dr. Richard Holmes

Dr. Bert Schoner, Professor
Senior Supervisor

Dr. Ernie Love, Associate Professor

Dr. Eng Choo, Associate Professor
Division Management Science
External Examiner

Date Approved: December 11, 1989

PARTIAL COPYRIGHT LICENSE

Title of Thesis/~~Project~~/~~Extended Essay~~

COMPARISON OF AGGREGATE AND DISAGGREGATE MODELS IN

PREDICTING SHOPPING CENTRE PATRONAGE

Author: ____________________

(signature)

Daljit S. Sandhu

(name)

December 11, 1989

(date)

ABSTRACT

The increasing rate of construction and expansion of shopping centres, and the emergence of integrated downtown shopping cores, has fostered research designed to explain and predict consumer patronage for these retail centres. Hüff's model of retail gravitation has been used in this regard for well over two decades. In 1975, Nakanishi and Yamanaka extended this model by incorporating information on specific merchandise categories and the 'generalized' attraction that retail space in these specific categories possess. The model was tested at the aggregate level, with consumers grouped in order to estimate the probability of patronage for each shopping centre.

Ward, in 1985, replicated the Nakanishi and Yamanaka study in a Canadian setting, specifically in Surrey, British Columbia. Ward, too, found that the addition of merchandise category information and the generalized attraction measure does indeed increase the overall accuracy of the model's ability to predict shopping centre patronage. Ward also added a third component to the model, the image of the shopping centre, but only found marginal contributions from this construct.

This present study analyzed the same data set that was used by Ward, but at the disaggregate level, using McFadden's conditional logit model. In theory disaggregation should make much more efficient use of the data since each response is a data point, while in the aggregate approach a group of responses represents a data point. While the overall results generated by this approach were similar to that of Ward's work, the size of all significant coefficients was much more pronounced in predicting the choice of shopping centres. Also, the image construct variables in this study made a significant contribution in predicting shopping centre patronage. This effect was lost as a consequence of the aggregation employed in Ward's study.

The results strongly underline the usefulness of a disaggregate level of analysis in both predicting consumer choice and in providing diagnostic information for 'actionable' marketing strategies. It is this information that is sacrificed by employing an aggregate model.

DEDICATED TO MY MENTORS:–

Dr. Ken W. Kendall;
Dr. Gary A. Mauser;
Dr. Bertram Schoner.

ACKNOWLEDGEMENTS

The completion of this thesis is made possible with assistance, guidance and encouragement from many people. I would first like to thank Dr. Bert Schoner for the kindness he bestowed on me over the past several years as I sporadically attempted to tame this beast. Words alone cannot fully express my gratitude and appreciation to him. Throughout this thesis, he demonstrated the highest qualities of supervision and concern. Professor Bert Schoner is very much a friend and a counsellor. His constant care, words of wisdom and guidance reflect the hallmarks of a great scholar and a gentleman. To him, I owe a big "thank you!!"

To Professor Ernie Love I am indebted not only for his contributions as a member of the supervisory committee but also for the invaluable assistance he provided to me during his tenure as the Director of the MBA programs. This assistance is indeed very much appreciated.

Professors Richard Holmes and Eng Choo have my sincere thanks for their time and contributions as members of my supervisory committee. Reo Audette's contributions and patience in working with me to solve the technical maze of Troll documentation is highly appreciated.

The occasional "harrassment" from Dean Stan Shapiro and professors Barrie Gibbs, Irene Gordon, Gary Mauser, Lindsay Meredith, Drew Parker, and Judy Zaichkowsky enabled me to finally "do it!" To all of them my heart felt thanks.

I am also indebted, and forever will be, to the Faculty of Business Administration for providing the opportunity to me to learn, teach and represent the faculty in the business community. The entire faculty has my sincerest gratitude.

Mary Lou performed the Herculean task of operating the word processor for this thesis. Her diligence, patience and superb quality of work are indeed recognized and appreciated!

Finally, my friends and family deserve much credit for their encouragement and support for bringing this thesis to fruition.

TABLE OF CONTENTS

LIST OF TABLES

CHAPTER 1

INTRODUCTION

Since the emergence of shopping centres in the 1950's and 1960's, retail sales have been shifting increasingly toward such centres. Estimates indicate that shopping centres will account for 50 percent of all retail sales by 1990 (Dickinson, 1981, p.57).[1] In a study by Prestwick (1980), 53 percent of the sampled shoppers in a major shopping mall reported that they came to the centre because of a particular store or stores. What is interesting to note is that the remaining 47 percent reported that they were there because of the mall itself. Thus almost half of the shoppers did not make their shopping location choice because of the attraction of specific store(s), but instead were attracted by some aspect of the mall and its complex of units.

The Marketer's Perspective

In general, retail establishments tend to cluster together or locate in close proximity to one another largely because of zoning requirements which regulate such business operations, the limited availability of ideal free-standing retail sites, and the possibility of synergistic effects when many retail stores are located in a compact area. This clustering may be planned and formalized as a shopping centre or mall, usually run by a professional management team responsible for the promotion and maintenance of the centre. On the other hand, the clustering may be unplanned, as in downtown shopping areas where traditionally little efforts have been made to market these areas as entities.

---

[1] A study by International Council of Shopping Centres reported that in 1988 shopping centres in B.C. accounted for 58% of total retail sales in the province (The Vancouver Sun, 1989).

The evolution of planned and organized shopping areas such as shopping centres has several implications. To the consumer, the evolution represents another level of patronage decision in the form of increased choices between different shopping areas. To the marketer, it means an increasing need to attract the consumer to the shopping area, and not just to a particular store. The importance of promoting the whole shopping area thus takes on more significance than promoting a particular store.

Clearly, there is a need to not only be able to predict shopping centre patronage but also to acquire diagnostic information that will assist in uniquely marketing and positioning shopping centres. Given the intense competition in the market place, this requirement of information is crucial if long-term prosperity of shopping centres is to be ensured.

The Researcher's Perspective

Many marketing models have been developed to predict and explain consumer patronage for shopping (retail) areas (Huff, 1962; Nakanishi & Cooper, 1974; Nakanishi & Yamanaka, 1975).[2] Huff's (1962) gravitational model views patronage as a function of store size and distance from the consumer. In the models of Nakanishi and Cooper (1974) and Nakanishi and Yamanaka (1975), other store attributes are considered along with size as determinants of stores' attractiveness (e.g. space allocated to various merchandise categories). Ward (1985) replicated Nakanishi and Yamanaka's (1975) study in a Canadian setting, specifically in Surrey, B.C., and his findings were generally in agreement with those of Nakanishi and Yamanaka

---

[2] Other contributions are discussed in Chapter 2, which covers the literature review. Also, for a comprehensive discussion of various models, the reader is referred to Craig, Ghosh and McLafferty (1984).

(1975). Ward (1985) also added a third component to the model, the image of the shopping centre, but only found marginal contributions from this construct.

All of the above models are calibrated at an aggregate level (i.e., consumers are grouped in order to estimate the probability of patronage for a retail outlet) and use the MCI (Multiplicative Competitive Interaction) estimation procedure to determine store patronage. An alternative modelling approach is to calibrate the model at the disaggregate level (i.e., at the individual level, where each response is a data point, whereas in the aggregate approach a group of responses represents a data point). This approach has been suggested and empirically tested by Miller and Lerman (1981), Eagle (1984), Weisbrod, Parcells and Kern (1984), and Gensch (1985). The proposed benefits of such a modelling approach are that it should not only provide better predictions but also give more diagnostic information for managers to act on. The next step, then, is to estimate the probability of patronage for each of the stores.

Since the problem on hand is that of estimating the likelihood of an individual choosing from a set of available alternatives, the appropriate statistical model to employ is LOGIT (McFadden, 1974; Gensch & Recker, 1979; Flath & Leonard, 1979; Currim, 1982; Weisbrod et al., 1984; Eagle, 1984; Gensch, 1985).

To the author's knowledge, however, no work has been done that employs a disaggregate level of analysis and uses McFadden's conditional logit to determine the capability of modifying Huff's gravitational model (i.e., modified to include store specific attributes and the image construct) to determine shopping centre patronage.

Purpose of the Study

The purpose of this study is to re-analyze the data that were collected by Ward (1985). Even though Ward (1985) gathered data on ten product categories, this study will only re-analyze the data for three product categories; namely, ladies clothing, furniture, and greeting cards and wrapping paper. The rationale for using these three merchandise categories is that one would expect people to be less sensitive to travel time while shopping for furniture, more sensitive to travel time for greeting cards and wrapping paper, and sensitivity to travel for ladies clothing should be between that of furniture and greeting cards. For each of the three product categories, the following issues will be addressed:

1. Will McFadden's conditional logit analysis provide better predictions and diagnostic information than the MCI model (disaggregate vs aggregate)?
2. Will the image construct variables along with other variables (e.g. size of shopping centre and square footage allocated to specific merchandise categories) make a significant contribution in predicting shopping centre patronage?

Contributions of the Study

This study is expected to have implications for managers, consumer behavior and retailing research. All three are briefly discussed in the following two sections.

Managerial Implications

The research model to be tested contains variables that hold significant implications for managers. Image, product and store variables are to a considerable extent controllable by the manager. An understanding of the effect of image can help the manager to develop appropriate promotional strategies. The product and store variables can impact on the product policy and tenant mix of shopping centres. Taken together, they can enable the manager to develop better marketing and positioning strategies. Similarly, while Huff's size/distance construct may not be specifically controllable, it holds significance for site location decision-making. In addition, the size/distance construct will also help provide some useful insights into understanding and determining the size of the trading area for a mall.

The results will give managers of shopping areas indications as to the main factors that draw consumers and the order of importance or effects of such factors.

Store positioning has traditionally been considered an important aspect of retail strategy. It is conceivable that with the increasing development of shopping centres, it may also be possible to position retail shopping centres. This study will hopefully provide some insights into this managerial challenge.

Contributions to Retail Literature

The research will attempt to provide a better understanding of the image construct in relation to shopping centres. Also, this research hopes to provide a better understanding of patronage behavior toward shopping centres by incorporating the three sets of factors as they pertain to the three types or levels of decision-making – that of product, store and shopping area (represented by Huff's size/distance construct) – with that of shopping area image. The objective is to provide a model that has both predictive and diagnostic capabilities.

CHAPTER 2

LITERATURE REVIEW

Three main areas of literature are relevant for this study. Critical to the development of the theoretical framework of the study is the literature that involves gravitational models, especially Huff's probabilistic model of retail gravitation. The second pertinent area of literature is that of image research. The third is disaggregate level of analysis compared to the aggregate level. All three areas will be examined in this chapter.

Retail Gravitational Models

Historical Development of Retail Gravity Models

William A. Reilly (1929) was the first person to apply the Newtonian concept of gravity in physics to retail trade area analysis. The mathematical expression of Reilly's model is as follows:

$$\frac{B_a}{B_b} = \left[\frac{P_a}{P_b}\right] \left[\frac{D_b}{D_a}\right]^2 \qquad (2.1)$$

where:

B_a = the proportion of the trade from the intermediate town attracted by City A.

B_b = the proportion of the trade from the intermediate town attracted by City B.

P_a = the population of City A.

P_b = the population of City B.

D_a = the distance from the intermediate town to City A.

D_b = the distance from the intermediate town to City B.

Basically, the model suggests that two cities (A and B) attract retail trade from an intermediate town (or city) in direct proportion to the population of the two cities and in inverse proportion to the square of the distances from the intermediate town to each of the cities. It is important to recognize that Reilly's model was directed toward determining the relative retail pulling power of two competing cities on a third town or city. Therefore, Reilly's model is an intercity model and is not meant for predicting retail trade movements within a city. As an example of how the model works, if $P_a=200000$, $P_b=300000$, $D_a=10$, $D_b=20$, then

$$\frac{B_a}{B_b} = \left(\frac{200000}{300000}\right)\left(\frac{20}{10}\right)^2 = 2.67 \qquad (2.2)$$

This means that City A attracts 2.67 times as much trade as City B. In relative percentages, we would expect 72.8 percent of the intermediate town population to be attracted to City A and the remaining 27.2 percent to be attracted to City B.

Reilly's Law of Retail Gravitation, as it became commonly known, was reformulated by Converse (1949) to determine the "breaking point" between the trading area of any two centres of trade. This mathematical model can be expressed as follows:

$$B_b = \frac{D_{ab}}{1 + \sqrt{\frac{P_a}{P_b}}} \qquad (2.3)$$

where:

B_b = the breaking point between City A and City B in miles from B,

D_{ab} = the distance separating City A from City B,

P_a = the population of City A, and

P_b = the population of City B.

This modification made it possible to calculate the approximate point between two competing cities where the trading influence of each was equal. This modified model of Reilly's Law had also been used extensively to estimate trading areas of proposed shopping centres within cities. Generally, the square footage of each retail centre was substituted for population and the travel time between retail centres was substituted for physical distance (Ellwood, 1954).

Limitations of Reilly's Model

The contributions made by Reilly's model to retail trade area analysis were commendable. In particular, the model worked well in rural areas where distance to be travelled to a community has a major impact on the choice of a retail centre. However, the model has several conceptual and operational limitations, as pointed out by Huff (1963, 1964). First, the calculation of breaking points to delimit a retail trade area conveys an impression that a trading area is a fixed boundary circumscribing the market potential of a retail facility. Thus it is incapable of providing graduated estimates above or below the break-even position between two competing centres, and it becomes impossible to calculate objectively the total demand for the product(s) or service(s) of a particular retail centre.

Second, the exponent value of 2.0 which Reilly has originally estimated for inter–city movements was assumed to be the same within urban areas. This may not necessarily be true, as argued by Huff (1963).

Third, the model cannot account for overlapping trade boundaries of competing retail centres. In addition, when there are multi–trading areas, using the breaking point formula may result in regions that do not fall within the confines of any shopping area's influence.

Finally, the model is applicable only to total city trading areas that are of similar size. Within an intra–urban area, consumers typically have a number of choices available to them within maximum distance limits they are willing to travel. Reilly's model, therefore, does not relate well to observed consumer shopping behaviour; for example, it reveals little about the effect of distance to a centre on trip frequency.

Huff's Probabilistic Model of Retail Gravitation

In an attempt to overcome the limitations of Reilly's model, David L. Huff (1962, 1963, 1964, 1981) proposed a probabilistic model that is based on Luce's choice axiom (Luce, 1959). In the words of Huff (1963, p.85):

> The analysis will utilize the conceptual properties of the gravity model but its focus will be on the consumer rather than on the retail firm per se. Since the consumer is really the primary object of any trade area analysis, an explicit understanding is needed not only of the factors affecting his choice of a shopping centre but also of the choice process itself which gives rise to observable spatial behavior.

Huff developed his model as a result of observing important empirical regularities that have been shown to exist as a result of trading area studies. These include (Huff, 1964, p.34):

1. The proportion of consumers patronizing a given shopping area varies with distance from the shopping area.

2. The proportion of consumers patronizing various shopping areas varies with the breadth and depth of merchandise offered by each shopping area.

3. The distances that consumers travel to various shopping areas vary for different types of product purchases.

4. The "pull" of any given shopping area is influenced by the proximity of competing shopping areas.

The mathematical formulation of Huff's model is expressed as follows:

$$P_{ij} = \frac{S_j}{T_{ij}^{\lambda}} \Bigg/ \sum_{j=1}^{n} \frac{S_j}{T_{ij}^{\lambda}} \qquad (2.4)$$

where:

P_{ij} = the probability of a consumer at a given point of origin i travelling to a given shopping centre j;

S_j = the square footage of selling space devoted to the sale of a particular class of goods by shopping centre j;

T_{ij} = the travel time or distance or costs involved in getting from a consumer's travel base to shopping centre j;

λ = a parameter which is to be estimated empirically to reflect the effect of travel time on various kinds of shopping trips.

Huff's model is premised on the assumption that the greater the number of items carried by a shopping centre, the greater the consumer's expectation that his shopping trip to that centre will be successful. Thus, it is thought that consumers are willing to travel increasingly greater distances as additional goods and services are made available at various shopping centres. In the absence of better measures of the different types of goods and services, Huff used the square footage of selling space as a proxy for the "attractiveness" or utility of the centre, and distance or travelling time as a proxy for the effort and expense involved in getting in the centre. In his words (Huff, 1963, p.85):

> The utility of a shopping centre to a consumer is based upon a host of different factors. Any attempt to measure the relative intensity or weight of all of these factors would be doomed to failure. Furthermore, the difficulty would become compounded if an attempt was made to ascertain the variations among such weights that would inevitably exist from consumer to consumer. Consequently, what is desired in this study is to discover and specify only a few relevant variables that will enable predictions to be made reasonably well and consistently.

In essence, the model states that the probability of any shopper choosing a particular retail centre is equal to the ratio of the utility of that centre to the sum of utilities of <u>all</u> potential competing centres in the system (Huff, 1964, p.37). Specifically, the utility or attractiveness of a centre is directly related to the size of the centre and inversely related to the distance separating consumers from the centre.

Of particular interest in Huff's model is the exponent value (lambda) which is used to reflect the effect of travel time or distance on various kinds of shopping trips. In general, the larger the lambda, the more restrictive will be the scope of the trading area. Theoretically, if the lambda value approaches infinity, there will be impenetrable barriers; that is, each shopping centre will have its own unique and exclusive clientele. If there is substantial overlapping of the clientele, the lambda value would be very small. As the lambda value approaches zero, the model states that patronage is wholly a function of store size. In practical terms, we would expect the lambda value to be large if the model is used to predict inter-city retail centres' competition. Within a city itself where there are several competing retail centres, the lambda value will be small as trading areas and clientele are bound to overlap.

Huff's model is probably the most parsimonious specification of modern theory-based approaches to the study of consumer spatial behaviour. Earlier gravity models (Reilly 1929; Converse, 1949) were specified at an aggregate level and were deterministic in nature. In contrast, Huff's model is specified at a disaggregate level and is probabilistic. Huff specified a multiplicative utility function with two variables, selling space and travel time. These two variables clearly act as proxies for the principal constructs of Central Place Theory (Christaller, 1933; Losch, 1954) – importance of a centre and economic distance. Thus the theoretical justification for Huff's gravitational model can be found in Central Place Theory, as strongly articulated in his appropriately titled 1981 article, "Retail Location Theory" (Huff, 1981).

Since its formulation, Huff's model has been subjected to much empirical testing (Huff, 1962; Bucklin, 1967a, 1971a,b; Brunner & Mason, 1968; Turner & Cole, 1980; Gautschi, 1981). In addition, several variations and extensions of Huff's model have been suggested and tested.

Studies by urban geographers have shown that the three assumed determinants – the attraction of centres, the disincentive associated with distance, and the competitive influence of alternative centres – all appear to exert a strong influence on shopping behaviour (Lakshmanan & Hansen, 1965; Thomas, 1976). Pacione (1974) and Lieber (1977) also found support in their studies where behavioral variation was associated with the size of the centre and distance travelled.

In the marketing area, Huff's model has also been found to be a good predictor of intra-urban shopping behaviour (Bucklin, 1967a,b; Stanley & Sewall, 1976; Nevin & Houston, 1980; Gautschi, 1981). It is also interesting to note that in a recent study, Turner and Cole (1980) found that among various shopping models - including Central Place Theory and the Entropy Model - gravity models give better performances and yield better fits. Thus the use of gravity models like Huff's to predict shopping behaviour has received considerable theoretical and empirical support.

Limitations and Extensions of Huff's Model

Exponential Value

Huff's model is not without limitations. In fact, one of the biggest criticisms of the model has been the use of the exponent value (lambda) to define the distance-disincentive function. Lakshmanan and Hansen (1965), for example, calculated the lambda using known frequency of visits to centres from an origin-destination survey of flows of consumers to centres. Jensen-Butler (1972) argued that without actual trip information, the derivation of the exponent value had no theoretical justification. This view was shared by Openshaw (1973). Indeed, many researchers have examined the calibration issue for years, and have suggested and used a computer program developed by Huff and Blue (1966), Konig numbers (Higgs et al., 1976), distance decay functions (Young, 1975), the entropy-maximizing approach (Wilson, 1970, 1971, 1974), the least-square method (Cesario, 1973, 1975; Nakanishi & Cooper, 1974), and the maximum-likelihood estimation (Batty, 1971; Mackie, 1972; Haines, Simon & Alexis, 1972). Recently, the odds ratio (Gray & Sen, 1983) has also been suggested as a method for estimating the exponent value. Perhaps the controversy surrounding the calibration method was most aptly summarized as follows:

> ...the accuracy of the model is usually a result of calibrating the model to fit particular situations; that is the distance exponent is adjusted to the data being analyzed.... Unfortunately, no independent method of estimating the distance exponent for particular situations has been developed (Simons, 1973-74).
>
> The point here is that the choice of calibration method is usually arbitrary and based on the preference of the person using the model. Essentially, therefore, the choice of calibration routine embodies a value judgement about the relative importance of the interests of different groups of shoppers (Turner & Cole, 1980).

However, except for the calibration issues, the exponent value has been empirically verified in several studies. Carrothers (1956) found that lambda ranges from 1.5 to 3.0 depending on the type of trip and the geographical setting involved. Huff (1962) estimated that the lambda values for clothing and furniture shopping trips were 3.191 and 2.723 respectively. Forbes (1968) also experimented with values of lambda in his study of consumer patronage behaviour. He stated that a value of 5.0 was characteristic of a supermarket and a value of 2.0 was characteristic of a regional shopping centre. Bucklin (1971a) argued that for grocery and ordinary household goods shopping, an exponent value of 2.0 would be appropriate and characteristic. These values were confirmed in a different study (Bucklin, 1971b). Using maximum-likelihood estimation, Haines et al., (1972) in a study of geographic shopping patterns for food purchases in two inner–city neighbourhoods and two central–city neighbourhoods found that the lambda values for major stores ranged from about 0.2 to 1.1, and in general, tended to be smaller when compared to the lambda values of smaller stores. In another study, Young (1975) investigated the relationship of distance decay functions to shopping behaviour in the suburbs of Philadelphia for trips to community and regional shopping centres. He concluded that a distance decay function of 2.0 was appropriate for trips to community centres, while 1.0 was more appropriate for regional centres. Using least–square estimates, Stanley and Sewall (1976) found that the lambda values for grocery shopping at chain supermarkets ranged from 0.85 to 4.1.

Several observations about the value of lambda from the various empirical studies cited should be noted. First, the findings tend to support the theoretical foundations of Huff's model. When a retail centre is considered in isolation, the value of lambda tends to be larger for smaller centres, suggesting that there is less overlap of clientele or a smaller trading area. For the larger centres, the value of lambda tends to be smaller, suggesting that there is greater overlapping of clientele that comes about because of a larger trading area. Second, for normal household shopping trips and for those to large shopping areas such as community or regional centres within an intra–urban area, the empirical results tend to support a lambda value of around 2.0. Finally, it is very interesting to note that the various empirical lambda values are very close to Reilly's original formulation where he advocated a theoretical exponent value of 2.0 for intra–urban movements.

Behaviouristic Assumption

The behaviouristic assumptions of Huff's model have also been questioned (Mason & Moore, 1970; Nevin & Houston, 1980). For example, the model assumes that consumers with comparable socio-economic characteristics will exhibit similar retail centre patronage and that there are no internal differences of significance within the area of analysis.

Various efforts have been made to improve on Huff's model and to overcome its behavioral limitations. For example, Stanley and Sewall (1976) used a multidimensional procedure to measure store image, and added this construct to Huff's model. Their results show that adding the image construct significantly increased the model's ability to explain variations in retail food store patronage. On the other hand, Nevin and Houston (1980) found that while image was an important determinant of preference for a particular shopping area, inclusion of this variable did not substantially improve the model's ability to predict retail patronage. In their study, they also found that the special store variable is very important in affecting choice of shopping areas. Their results indicate that the special store variable even dominates Huff's mass/distance construct in that it explains a higher proportion of the variance in shopping behaviour. The contradictory findings between these two studies in relation to image can be attributed to the fact that Stanley and Sewall's study focused on the store image, while Nevin and Houston's study concentrated on shopping area image.

In another study, Gautschi (1981) found that using additional measures of distance and attractiveness improved the model's predictive performance. Gautschi also commented that in the context of competing planned and unplanned retail centres, the two-variable specification of Huff is probably too parsimonious for policy purposes such as for shopping centre management and city planning. But perhaps the last words should be reserved for Huff and Blue (1966, p.3), who explicitly recognized the limitations of Huff's model:

> A word of caution, however, should be noted in conjunction with the use of the model. Mathematical models are not infallible. They are, by necessity, simplified constructs of some aspects of reality. It is impossible for such constructs to include all the possible factors that may have a bearing on a particular problem. Therefore, decision makers should be aware that there are variables other than those specified in the model that affect the sales of a retail firm. The reputation of the firm, the newness of the store, the merchandise it carries, the services it offers are but a few examples of additional variables. As a consequence, human judgement should also play an important role in decisions of this type.

In summary, Huff's model was never intended to be comprehensive. Rather it was meant to provide understanding of a very complex behavioral phenomenon in a parsimonious way. Its strength as a predictive tool has been well acknowledged. However, a good model should not only predict, but also explain the phenomenon under study. Thus any attempt to refine the model so that it can be used both as a predictive and explanatory tool will certainly enhance the respectability of the model.

Implications and Opportunities for Further Research on Huff's Model

Huff's model indeed has very intuitive appeal, both from a practical and a theoretical point of view. In a review of urban consumer behaviour, Shepherd and Thomas (1980, p.27) commented:

> ...given the potential practical value of the model, it is rather surprising that little research effort has gone into attempts to refine the original formulation in the practical context of retail planning within the city. Perhaps this represents a worthwhile direction for further research effort.

Indeed, there are several opportunities for further research. Huff's model as originally formulated, was meant for understanding the patronage patterns of consumers toward <u>shopping centres</u> and not individual stores. The strength of the model is, therefore, in explaining drawing power of shopping centres. This strength apparently was recognized by two prominent marketing researchers who wrote:

> Mass retains its overall significance as a factor in determining the attraction of a centre, but it appears that adjustment of gravity models to fit differential consumer perceptions of mass would improve predictability (Bucklin, 1967).

> Short of including additional variables, it is felt by many analysts that Huff's equation is of limited value in estimating sales potential for single stores. Individual store size per se has not been found to have the great influence claimed on drawing power. Size appears to be more of a factor in explaining drawing power differences of shopping centres and here is where Huff's model may be most effective (Kotler, 1971, p.319).

In a more recent study, Turner and Cole (1980) found that gravitational models are better in explaining shopping patterns for large and medium-size centres (in terms of floor space) than for small centres. In view of the increasing retail sales in shopping centres, which one source puts at 50 percent of all retail sales by 1990 (Dickinson, 1981, p.57), and the emergence of organized downtown shopping areas, there is definitely an increasing need to understand consumer patronage patterns toward shopping areas. Huff's model provides a very useful start for building shopping area patronage models.

It is interesting to note that Huff's competitive system includes all potential retail centres in that system (Huff, 1964, p.37). In other words, the basic set of shopping area choice alternatives is assumed to be spatially accessible to all consumers without taking into account other possible factors that might affect the choice of shopping areas. Thus the use of the basic set in the model is similar to what urban geographers labelled as "store opportunity set" in store choice behaviour (Marble & Bowlby, 1968) and what marketers labelled as "awareness set" in brand choice behaviour (Campbell, 1973; Narayana & Markin, 1975; Hawkins et al., 1980). Subsequent studies have tended to apply the model in the same way.

While this approach may be appealing when there are only a few recognizable shopping centres within the city, the situation becomes obscured when there are many shopping centres within the city. Should all the centres be included? Are they all competitors in the eyes of a consumer? What criteria should be used for inclusion/exclusion of shopping centres in the competitive system? Clearly, if all centres are assumed to be the basic set of alternatives, the model may not give meaningful predictions and explanations if consumers patronize different subsets of shopping areas within the basic set or if consumers patronize shopping areas that are not within that basic set.

As argued earlier, using an *a priori* assumption that the same basic set of area choice alternatives applies to all consumers may be necessary if one is attempting to use the model in relation to predicting patronage behaviour or estimating the size of trading area for a new centre. The same assumption becomes highly questionable when one wishes to explain patronage behaviour among an existing set of shopping areas.

The problem of specification of what centres are to be included in the set is also strongly stated by Gautschi (1981):

> In addition to the potential bias resulting from omitted variables, bias may stem from an improperly specified choice set....

This problem is further compounded by socio-demographic factors. Mobile shoppers, for example, may visit many centres within the city, or take advantage of car-oriented out-of-town centres if available, whereas other shoppers who are relatively confined spatially are more dependent on local shopping facilities.

One way of overcoming this problem is to allow the consumers to specify their choice set of shopping centres, as opposed to an arbitrary imposed set from the retailer's point of view. The choice set could be defined as those centres that the consumers choose to patronize over a certain period of time. Thus it would resemble the evoked set concept that is used in brand choice research (Campbell, 1973; Hawkins et al., 1980, pp.413–4).

The use of a choice set has intuitive appeal. Conceivably, it may act as a surrogate measure for socio-economic, mobility and psychographic factors. As shown by Goldman (1976), the lower income consumers may have a more restricted shopping scope. Huff's model can be expected to yield better explanation of patronage behaviour when the concept of choice set is used.

Huff's disincentive measure is expressed as the distance (or travelling time) in getting from a consumer's travel base to a shopping area. The travel base has been typically represented by the home. Thus the disincentive measure in the model is the distance from the consumer's home to the shopping area. Obviously such a measure has flaws. It assumes that all trips are initiated from the home. In reality, for a person who is working, a trip to a shopping area may occur while she is on the way from home to her place of work, or vice versa, in between working hours, and while going to and from other places. Ideally, the point-of-origin should be taken into account when measuring distance. Thus, it may be possible to improve the measure of distance or travelling time by taking into account where the trip actually originates and ends, instead of assuming a common travel base such as the home.

As correctly pointed out by Gautschi (1981), Huff's model is probably too parsimonious for policy purposes in the context of competing planned and unplanned retail centres. The works of Gautschi (1981), Nevin and Houston (1980), Stanley and Sewall (1976) are steps in the right direction. Perhaps more refinement to their works may result in a better model. The choice of a shopping centre may also largely depend on the drawing power of anchor store(s) and the type of product or service that the consumer is seeking (Dickinson, 1981, p.26; Hawkins et al., 1980, ch.18; Prasad, 1975). Nevin and Houston's study only included the effect of individual store attraction as a dichotomous variable. To the author's knowledge the effects of product attraction have only been considered in relation to Huff's model by Nakanishi and Yamanaka (1975) and Ward (1985).[1]

[1] Both of these studies are unpublished; the former is a working paper and the latter an MBA graduating project.

Image Research

Pierre Martineau (1958) was the first person who popularized the concept that retail institutions possess unique images. Later George Fisk (1961–62) provided a major impetus for research into the nature and meaning of store image through his article "A Conceptual Model for Studying Customer Image." However, most researchers have concentrated on store image.

Over the past 25 years, research on store image has taken three main directions. Each of these will be reviewed, and their implications for shopping area image will be discussed.

Meaning and Dimensions of Image

One of the most striking phenomena in store image research has been the lack of consensus on what exactly store image means. The following are some examples of the widely differing definitions:

> ...a subjective phenomenon that results from the acquisition of knowledge about the store as it is perceived relative to other stores and in accordance with the consumer's unique cognitive framework (Hirschman, 1981a);
>
> ...[given that] retail store attributes are also influential in a consumer's decision to shop at a given store when making a particular purchase, a given consumer's or target market's perception of all these attributes (Hawkins et al., 1980);
>
> ...the subjective attitude the consumer takes toward the business institution as a functioning entity (Walters, 1978);
>
> ...a combination of tangible or functional factors and intangible or psychological factors that a consumer perceives to be present (Lindquist, 1974–75);

> ...the total conceptualized or expected reinforcement that a person associates with shopping at a particular store (Kunkel & Berry, 1968);
>
> ...a complex of meanings and relationships serving to characterize the store for people (Arons, 1961);
>
> ...the way in which a store is defined in the shopper's mind, partly by its functional qualities and partly by an aura of psychological attributes (Martineau, 1957).

These varied definitions have resulted in different approaches and attempts by researchers in conducting store image research. Some attempts have been made, however, to study the concept of store image as consisting of distinct dimensions, components or attributes. The works of Martineau (1958), Fisk (1961–62), Kelly and Stephenson (1967), Kunkel and Berry (1968), Berry (1969), and Marks (1976) are examples of attempts to conceptualize the construct of store image. Perhaps the most distinctive attempt was that of Lindquist (1974–75), who reviewed the published results of some 19 studies and synthesized them into nine dimensions of the store-image construct. These nine dimensions are: merchandise, service, clientele, physical facilities, convenience, promotion, store atmosphere, institutional factors and post–transactional satisfaction. In general, however, no consensus on the specific components of image has emerged from the literature, and the number of dimensions has ranged from 3 to 12, making attempts to define image by its components very difficult (Berkowitz, Deutscher & Hansen, 1978).

Measurement of Store Image

A whole range of approaches has been used to measure store image. The typical approach is the use of semantic differential scales, which has, however, certain weaknesses. First, people are asked to respond to characteristics that do not necessarily comprise the image they have of the store being studied. At the same time, characteristics that a consumer considers important may not be in the scale. Second, a person's position on the scale may not be comparable to others. For example, one person's "1" on a 7-point scale may be another's "3", thus making summarized measures of the distribution of responses difficult to interpret.[2]

In attempts to overcome the problems of using semantic differential techniques, researchers have used other techniques such as non-metric multidimensional scaling (Singson, 1975; Jain & Etgar, 1976-77; Blommestein, Nijkamp & Veenendaal, 1980; Neidell & Teach, 1974; Whipple & Neidell, 1971-72), and factor analytic techniques (Egan, 1971; Perry & Norton, 1970). The usefulness of such techniques is well recognized by Berkowitz et al. (1978):

> Scaling algorithms have the advantage of not pre-specifying dimensions for respondents. Yet the problems of identifying dimensions, interpretability of multiple dimensions, and the stability of a store's position in a perceptual space over time have not been addressed. This uncertainty about the exact components of a store's image has contributed to the appeal of factor analysis in attempting to measure this construct. While this approach is a useful data reduction technique, often the data bases employed were gathered with semantic differentials, with little mention of the reason for particular attributes being rated.

Another approach that has been used to measure store image is the multi-attribute attitude model (Doyle & Fenwick, 1974-75; James et al.,

---

[2] A simple way to alleviate this problem is to standardize the individual's ratings. Details are discussed in Chapter Four.

1976). The problems with this approach are the lack of a conceptual framework, the non-identification of salient dimensions, and its limited usefulness in dealing with heterogeneous populations (Berkowitz et al., 1978).

Several other approaches have been used to measure store image. These include the open-end technique (McDougall & Fry, 1974-75), the Stapel scale (Hawkins et al., 1974, 1976-77), the Likert scale (Menezes & Elbert, 1979), multiple discriminant analysis (Ring, 1979), and joint-space analysis (Pessemier, 1980).

Several observations about the use of scales to measure store image are worth noting. Hawkins et al. (1974) showed that there were no significant differences in store image when the semantic differential and Stapel scale were used. Menezes and Elbert (1979) concluded that there were no overall differences in results whether semantic differential, Stapel or Likert scale formats were employed. However, to improve understanding for respondents, the Likert scale format was preferred. The findings tend to support an earlier study by Kassarjian and Nakanishi (1967) in which they concluded that Likert and other types of scales, such as the semantic differential scale formats, may be treated as functionally equivalent.

Overall, the various studies cited seem to indicate that the use of scaling techniques per se is not as serious a problem as that of identifying the appropriate dimensions that form the image construct.

Image and Patronage Behaviour

Ultimately, the usefulness of any store image research must be its relevance to marketing or retailing management in such areas as market segmentation and positioning so as to achieve better patronage results. Towards this end, research has focused on identifying and assessing the importance of store image dimensions that consumers use to evaluate similar types of retailers, such as women's clothing stores (Perry & Norton, 1970; Mason & Mayer, 1973; Marks, 1976), department stores (Egan, 1971; Hansen & Deutscher, 1977), drug stores (Nickel & Wertheimer, 1979), men's clothing stores (James et al., 1976), banks (Brown et al., 1977), restaurants (Swinyard, 1977), and supermarkets (Anderson & Scott, 1970; Hansen & Deutscher, 1977–78). Studies have also shown that store images vary between different types of stores (Cardozo, 1974–75; Singson, 1975; Jain & Etgar, 1976–77; Reich et al., 1977; Schiffman et al., 1977).

The role of store image in determining store loyalty and choice has been shown in studies by Anderson and Scott (1970), Lessig (1973), Doyle and Fenwick (1974–75), Schiffman et al. (1977), and Acito and Anderson (1979). The possible relationships between consumer self–image and retail store images have also been investigated by Mason and Mayer (1970), Dornoff and Tatham (1972), Pathak et al. (1974–75), Bellenger et al. (1976), and Stern et al. (1977). In the Bellenger et al. study, they found that "...those whose views of self and store image...are congruent tend to be more loyal" (p.18). Similarly, Arnold and Tigert (1973–74) tracked image changes and patronage changes in the grocery retail business in Toronto and found close associations between the two variables.

The evidence so far seems to indicate that store image variables as variously defined and operationalized do have some effects on patronage behaviour (Stephenson, 1969; Monroe & Guiltinan, 1975). Several studies even show that the store image variables account for 15 to 20 percent of the variance in patronage decisions (Bellenger et al., 1976; Stanley & Sewall, 1976; Schiffman et al., 1977; Nickel & Wertheimer, 1979).

In summary, the relevance and importance of store image to retail marketing management cannot be denied. Ring (1979) examined the application of the retail store image concept to strategic positioning, and King and Ring (1980) stated:

> To establish a market position, the retailer strives to develop a unique store personality or image built around the retailer's produce/service delivery capabilities (p.37).

Similar views are presented in King et al. (1979, 1980) and May (1974–75, 1983).

Relevance and Implications of Store Image Research to Shopping Area Image

What has made store image research practical, acceptable and useful is that the image research findings have been applied to the analysis of individual and chain store positionings and the development of marketing strategies. There is no theoretical reason why such research cannot be extended and applied to the shopping area level. In fact, the importance and relevance of image research to shopping area patronage was recognized 20 years ago by Moore and Mason (1969):

> Socio–economic variables do not satisfactorily explain the retail centre patronage decisions of the residents of the study area. It may be inferred that psychological or attitudinal differences of the residents are perhaps of more importance.

With the development of shopping centres, studies have begun to focus on image–like variables of shopping areas (Frederick et al., 1975; Carter, 1978, 1981; Hauser & Koppelman, 1979; O'Neill & Hawkins, 1980; Berman, 1983). Studies by Bellenger, Robertson and Greenberg (1977), and Gentry and Burns (1977) have confirmed the importance of image-like variables in shopping centre patronage. Nevin and Houston (1980) extended the concept of image to that of a shopping area that includes both downtown and suburban shopping centres.

In a recent study of the downtown area and four shopping centres on 16 image items, Houston and Nevin (1980) used factor analysis to identify three major dimensions or factors of shopping area image. The first factor consisted of six items – quality of stores, variety of stores, merchandise quality, product selection, special sales/promotion, and great place to spend a few hours – which were related to the assortment of benefits offered by the area. The second factor (6 items) consisted of features that helped to ease the shopping effort – parking facilities, availability of lunch/refreshment, comfort areas, easy to take children, layout of area, and special events/exhibits – and was named the facilitative nature of the area. The third factor (four items) – general price level, atmosphere, store personnel, and conservatism – were associated with positioning of the area as an integrated complex of stores, and was named "market posture". Using factor congruency tests, they found that the first two factors were quite stable across all five areas, while the third factor exhibited stability across the four shopping centres but was not stable in comparison between downtown and each centre. They thus concluded that downtown areas may be deficient in promoting themselves as integrated shopping units.

Acito and Anderson (1979) found that image was more differentiated, better articulated and of higher dimensionality for recent shoppers compared with non-recent shoppers of a retail store. In the words of Hirschman (1981b):

> One would anticipate that long-term rather than short-term shoppers (or heavy versus light shoppers) would have more finely developed images of a given store.... The basic idea is: that which we know best, we see more clearly and in greater detail.

These comments have a very interesting implication. Image research that is based on ratings by consumers without taking into account the extent of their familiarity with the stores or areas is <u>not</u> likely to provide meaningful results that managers can act on. For example, can one rely on the ratings of consumers, whether favourable or unfavourable, if they have never been to particular shopping areas, or have only been there once or twice in a year? When one considers that respondents are typically asked to react to some 15 to 20 items on the image scale, the problem is further compounded. Furthermore, it can be argued that the image of a shopping area may be more complex than that of a single store, since a shopping area is a conglomerate of different kinds of stores that offer a wide variety of products and services. Thus the need for the consumer to be familiar with the shopping area is crucial to any assessment of its image. It is in this light that the two 1980 studies by Nevin and Houston are questioned. How reliable are consumers' ratings on 16 preselected items of image scale across 5 different shopping areas?

Another concern involves the appropriateness of applying the items drawn from the store image literature to that of shopping area research. Houston and Nevin (1980) developed their scale from the review of earlier store image research and discussions with shopping centre managers. Whether the items were appropriate, especially in the eyes of the consumers, was not considered. Thus, as pointed out by Howell and Rogers (1980), the appropriateness of store image items to shopping area image is a question that begs further research. To begin with, it may be more appropriate to sample a wider domain of items, especially at such an exploratory level, in order to have a better understanding of the underlying dimensions of shopping area image. It may be the inappropriateness of items and the familiarity issue that have accounted for the inability of Nevin and Houston's (1980) study to demonstrate substantial relationships between shopping area image and shopping behaviour.

Effects of Products/Services and Stores

Most theories and models of patronage behaviour explicitly recognize the role of products/services in affecting the choice of retail outlets (Nakanishi & Yamanaka, 1975; Darden, 1980; Hawkins et al., 1980; Dickinson, 1981; Sheth, 1983; Ward, 1985). To quote Hawkins et al. (1980, p.466):

> ...consumers must select both specific items (brands) and specific outlets to resolve problems. There are three ways these two decisions can be made: (1) simultaneously; (2) item first, outlet second; or (3) outlet first, item second.

With the increasing emergence and prominence of shopping areas, a third level of decision – shopping area choice – is added for the consumer besides brand and store decisions (May, 1983, p.153). Conceivably, specific stores, products and services may have an effect on the consumer's choice of a particular shopping area. Prestwick's (1980) study showed that 53 percent of sampled shoppers in a major shopping mall reported that they definitely planned to visit a particular store or stores when they came to the centre that day, and 60 percent of those stores were anchor stores. The study, however, was only an on-site survey of a single visit and it did not distinguish whether the shoppers were attracted by the name of the store or the kinds of products it carried.

In another study, Nevin and Houston (1980) found that the specific store variable exhibited the strongest influence on behavioral intentions and actual behaviour in that the variable entered each of the regression equations first, and accounted for an explained R-square of 0.18 to 0.36. However, it is important to note that the specific store variable was measured by asking respondents to indicate whether or not there was a store that attracted them to each shopping area. The variable was then coded as a dummy variable, indicating the absence or presence of such a store in each area.

This method of store variable measurement suffers from at least two serious shortcomings. First, the variable as measured does not differentiate between the effects of products or services and the effects of the store itself. For example, are consumers attracted to a particular store because of the kind of merchandise it carries, or because of the name of the store? Would consumer patronage behaviour in the area be affected if that specific store were replaced by a similar store carrying the same type of merchandise (for example, replacing Eatons with Sears)? The measure used by Nevin and Houston apparently reflects <u>both</u> the effects of products/services and store.

Second, when analyzing the variable in a dichotomous way in regression analysis, and when product vectors are not included in the combined analysis, the separate regression equations for the groups under consideration are assumed to differ only in their intercepts. In other words, separate regression equations with identical regression coefficients but with different intercepts are fitted when product terms are not included in the combined regression analysis (Pedhazur, 1982, p.474).

In summary, it is questionable that the effects of the specific store variable have been established in Nevin and Houston's study. The need for further research, especially to determine the separate effects of store and products or services on shopping area patronage, definitely exists. It is this problem that has been recognized and addressed by Nakanishi and Cooper (1974, 1982), Nakanishi and Yamanaka (1975), and Ward (1985). These studies will be discussed in some detail in Chapter Three as they form the basis of this present study.

Aggregate vs. Disaggregate Level of Analysis

In developing a behavioural model of consumer choice, it is pertinent that one begin with consideration of the individual (disaggregate level). Although one is concerned with aggregates of people to identify segments, the choice behaviour can best be understood by considering the behaviour of individual choice decisions. The importance and benefits of such an approach have been reported by McFadden (1974), Domencich and McFadden (1975), Gensch and Recker (1979), Henscher and Johnson (1981), Currim (1982), Weisbrod et al. (1984), Gensch (1985), and Dunn and Wrigley (1985). In essence, the issue on hand is to model the choice(s) an individual will make when confronted with a set of alternatives in a "real" situation and the factors which influence the decision to choose among available alternatives.

There are other very important reasons which make disaggregate level of analysis attractive. These typically concern the composition and, ultimately, the size of sample used to calibrate the model. When developing a model of consumer choice, one is attempting to explain the differences in observed choice behaviour. The more differences one is able to examine and explain, the more confidence one can have in the results; it is primarily for this reason that large samples are desired. However, when observations are aggregated into groups, as is the customary process, the number of observations available to be analyzed and the variability within the sample are seriously reduced. This use of aggregation has been the norm in the marketing discipline. The recent studies that have employed this methodology in predicting consumer choice are Houston and Nevin (1980), Nakanishi and Cooper (1982), Malhotra (1984), and Ward (1985). It is apparent that by undertaking such an approach one is most likely sacrificing crucial information that may assist in understanding and explaining consumer choice behaviour.

Analysis at the aggregate level is not necessary because once the model has been calibrated on the individual (disaggregate) observations, the computation for aggregate demand/choice(s) can be accomplished by direct aggregation over values of independent variables for a representative sample. For example, if the modal split between shopping centre A and shopping centre B is found to be a function of the relative travel time, then summing the modal split frequencies over a representative sample of travel time differences provides an aggregate modal split measure. Alternatively, other statistical procedures may be used to carry out the aggregation process. For a more comprehensive discussion of the issues regarding aggregation and disaggregation, the reader is referred to McFadden and Reid (1975).

CHAPTER 3

MODELING MULTIPLICATIVE COMPETITIVE INTERACTION

In this chapter, the following are discussed: modeling multiplicative competitive interaction; Nakanishi and Yamanaka's work; Ward's study; and, McFadden's conditional logit, all of these form the basis of this current study.

As discussed and presented in chapter two (equation 2.4), Huff's (1962) gravitational model, in essence, is a special case of the Luce (1959) choice axiom. As a result, Huff's model has been extended to analyze competitive market behaviour (Kotler, 1972; Lambin, 1972; Nakanishi, 1972; Urban, 1969; Nakanishi & Cooper, 1974). This extended form of the model is stated as:

$$\pi_{ij} = \prod_{h=1}^{H} X_{hij}^{\beta_h} \Big/ \left(\sum_{j=1}^{m} \prod_{h=1}^{H} X_{hij}^{\beta_h} \right) \qquad (3.1)$$

where:

π_{ij}	=	the probability that a consumer in the i^{th} choice situation selects the j^{th} object;
X_{hij}	=	the h^{th} variable describing object j in choice situation i;
β_h	=	the parameter for sensitivity of π_{ij} with respect to variable h.

Given the above model, Kotler (1972), argued that since a firm's marketing effectiveness is contingent on what its competitors do, the model in (3.1) captures the essentials of competitive interaction. It is precisely for this reason that the model above came to be known as the Multiplicative Competitive Interaction model, or the MCI model for short.

Nakanishi and Cooper (1974) recognized the apparent marketing applications of the MCI model. They also recognized that as the model stood (equation 3.1), it was a nonlinear model and parameter estimation would be difficult given the multivariate statistical tools available. In order to develop the generalized least squares estimation techniques for the MCI model, the model in equation (3.1) was redefined to include a disturbance term (δ_{ij}). Therefore now the model in (3.1) is commonly stated as:

$$\pi_{ij} = \left[\prod_{h=1}^{H} X_{hij}^{\beta h}\right] \delta_{ij} \Big/ \left[\sum_{j=1}^{m_i}\left(\prod_{h=1}^{H} X_{hij}^{\beta h}\right)\delta_{ij}\right] \qquad (3.2)$$

where:

π_{ij} = the probability that a consumer in the i^{th} choice situation (period and/or area) selects the j^{th} object ($i=1,2...,I$; $j=1,2,...m_i$);

X_{hij} = the value of the h^{th} variable for object j in choice situation i ($X_{hij} \geq 0$, $h=1,2...,H$);

β_h = the parameter for sensitivity of π_{ij} with respect to variable h;

δ_{ij} = an independently and log-normally distributed, specification error.

Nakanishi and Cooper (1974) argue that this model produces consistent market share estimates in that the market share estimates are all non-negative and sum to unity over the available choice set.

The model in (3.2) is then transformed into a linear form by employing the following transformation to π_{ij}.

$$\log(\pi_{ij}/\tilde{\pi}_{i.}) = \sum_{h=1}^{H} \beta h \log(X_{hij}/\tilde{X}_{hi.}) + \log(\delta_{ij}/\tilde{\delta}_{i.}) \qquad (3.3)$$

where $\tilde{\pi}_{i.}$, $\tilde{X}_{hi.}$ and $\tilde{\delta}_i$ are the geometric means of π_{ij}, X_{ij} and δ_{ij} across j in choice situation i, respectively. This above transformation is referred to as "log-centering" by Nakanishi and Cooper (1974).

Since the model in equation (3.3) is linear, multiple regression analysis can be used to estimate the β_hs. However, because the true probabilities, π_{ij}, are not observable, the observed proportions (P_{ij}) in the sample are used as the dependent variable. It is this necessity that dictates an analysis using aggregation of observations to calculate proportions.

Equation in (3.3) then takes on the following form:

$$\log(P_{ij}/\tilde{P}_{i.}) = \sum_{h=1}^{H} \beta_h \log(X_{hij}/\tilde{X}_{hi.}) + \varepsilon_{ij} \qquad (3.4)$$

where:

P_{ij} = an estimate of π_{ij} ($P_{ij}>0$);

$\tilde{p}_{i.}$ = the geometric mean of P_{ij} over j in situation i;

ε_{ij} = the stochastic disturbance term, which is the function of specification errors, δ_{ij}.

Generalized least squares estimates are now used to estimate the βhs.

Subsequently, Nakanishi and Cooper (1982) suggested that the MCI model parameter estimation can be simplified by using the ordinary least squares approach and the intercept term can be suppressed as it does not change over j (the object) in a given choice situation. Hence the log-centering (equation 3.3) is not necessary and the model can be specified by using the following dummy variable regression model:

$$\log P_{ij} = \alpha_i D_i + \sum_{h=1}^{H} \beta_h \log X_{hij} + \varepsilon_{ij} \qquad (3.5)$$

where:

D_i = a dummy variable which is equal to 1 if i = 1 and 0 otherwise;

α_i = the regression coefficient for D_i.

In summary, the models in equations (3.1) through (3.5) linearize what are essentially nonlinear models of consumer choice (via modification, redefinition, and transformation).

Nakanishi and Yamanaka's (1975) Study

Nakanishi and Yamanaka (1975), using the MCI model, measure the drawing power of retail centres by examining the factors that they identified as being pertinent in predicting consumer patronage. In essence, they extended Huff's (1962) model by defining the attraction of a shopping centre as being decomposable into two components; one representing the attraction specific to a given merchandise category, and the other representing the "generalized" attraction that is common for all merchandise categories. Merchandise-specific attraction was determined by the floor space allocated to the respective category (though Nakanishi and Yamanaka actually used number of employees as a surrogate measure for merchandise and store attractiveness).

The generalized attraction factor was identified as being the overall image of the shopping centre that is characterized by the "offerings" at the retail centre. Even though this aspect of retail centres was identified by Nakanishi and Yamanaka (1975) as being crucial in predicting and explaining shopping centre patronage, they did not include it in their model.

The secondary purpose of Nakanishi and Yamanaka's study was to examine the variability of the parameter values across merchandise categories. For instance, given the parameter for shopper sensitivity towards travel time, λ, one would expect the value of λ to depend on the type of merchandise category being shopped for (e.g. greeting cards vs. furniture). The shopper should be less sensitive to travel time when shopping for furniture, implying a small value of λ.

Nakanishi and Yamanaka collected the data by a door–to–door survey of housewives in Fukuoka, Japan, in December of 1965. For the respective retail centres the respondents were asked to indicate: (1) where the last purchase was made for the specific merchandise categories, and (2) where the store(s) at which they usually shopped were located. The ten merchandise categories on which the data were sought were: kimonos, men's clothing, women's and children's clothing, perishable foods, other food, furniture, hardware, home appliances, cosmetics, and shoes. Estimated travel time from respondent's residence to the destination (retail centre) was also measured.[1]

The results showed (using generalized least squares estimation procedures) that each centre did possess a generalized attraction, but the hypothesis that it is a function of gross centre size was rejected. The generalized attraction was the strongest for centrally located centres and the weakest for neighbourhood centres. Also the parameter of shopper sensitivity toward shopping centre size between merchandise categories showed much variation. Particularly the parameter for convenience goods (food, cosmetics and hardware) was statistically insignificant.

[1] The details of the specific models used to model the MCI are discussed in the next section of this chapter, which discusses Ward's (1985) work. Ward replicated the Nakanishi and Yamanaka study in a Canadian setting in Surrey, B.C.

Ward's (1985) Study

Since the data for Nakanishi and Yamanaka's (1975) study was collected in the mid sixties, Ward (1985) essentially replicated Nakanishi and Yamanaka's study, albeit in a Canadian setting, specifically in Surrey, British Columbia. The purpose of the study was to see if the same conclusions would hold for modern shopping centres in the eighties' environment. Ward also added the image construct to the model to measure contribution of unique characteristics of the shopping centres to predict and explain consumer patronage. Also, Ward used actual gross leasable floor space of the shopping centres and the square footage allotted to the merchandise categories at the specific centres as measures of attractiveness. Nakanishi and Yamanaka (1975) had operationalized this by using a surrogate measure, the number of employees.

The area selected for Ward's study was the municipality of Surrey, B.C. This particular municipality was chosen because of the following:

1) Surrey is bounded on two sides by natural barriers, these being the Fraser River to the North and Boundary Bay and the Canada/U.S. border to the South. It was assumed by Ward that these "restrictions" may promote a sense of municipal loyalty in shopping behaviour; and,

2) Surrey housed two large shopping centres (Guildford – 836,000 sq.ft. gross leasable area, and Surrey Place – 534,000 sq.ft. gross leasable area), and two smaller centres in the neighbouring municipality of Delta (Scottsdale Mall – 168,000 sq.ft., and Kennedy Heights – 206,000 sq.ft.).

The data were collected by administering a telephone survey to the wife in the household. The household was identified by a phone number which was randomly selected.[2] The housewife was chosen in order to be consistent with Nakanishi and Yamanaka's (1975) study (Ward, 1985). Similar to Nakanishi and Yamanaka's study, the respondents were asked to state where they last and normally purchased the respective merchandise categories. The ten merchandise categories used by Ward (1985) were: ladies clothing, furniture, drugs and cosmetics, ladies shoes, food, jewellery, children's clothing, and greeting cards–gift wrap.[3] Perceived travel time was also measured from each of the four origin zones (geographic area of residence – Whalley, Port Mann, South New Westminster and Newton) to each of the four destinations (Guildford, Surrey Place, Scottsdale and Kennedy Heights).

To capture the respondents' perceptions of the image for each of the four shopping centres, Ward (1985) relied on the extensive work done by Nevin and Houston (1980). Hence, the eight image variables that were used by Ward were: quality of stores, variety of stores, parking facilities, layout of shopping centre, general price level, store personnel, atmosphere, and promotions and sales.[4]

The modified Huff model (2.4) becomes:

$$P_{ijk} = \frac{A_{jk}\, T_{ij}^{-\lambda_k}\, S_{ijk}}{\sum_{j=1}^{m} A_{jk}\, T_{ij}^{-\lambda_k}\, S_{ijk}} \qquad (3.6)$$

---

[2] For details on the sampling methodology, the reader is referred to Ward (1985). The sample size was 462.

[3] For square footage allocated to the respective merchandise categories at each of the four shopping centres, please refer to Appendix 1.

[4] A copy of the questionnaire used by Ward can be referred to in Appendix 2.

where:

P_{ijk} = probability that a shopper at origin i goes to shop for an item in the k^{th} product category at centre j;

A_{jk} = index of attraction of centre j for the k^{th} product category;

T_{ij} = travel time (or distance) between origin i and retail centre j;

λ_k = parameter of shopper sensitivity toward travel time for product category k;

ξ_{ijk} = stochastic specification error term.

Finally, the seven models used by Ward (1985) are various formulations of the index of attraction, A_{jk} (the distance variable $T_{ij}^{-\lambda_k}$ remains unchanged in the total equation) are as follows and are directly taken from Ward (1985, pp.28–32). P_{ij} was estimated for each origin–destination and the d_{ij} (distance) actually used was from the centre of the origin to the shopping centre.

1. Gross Centre Size (GS) Model[5]

$$A_{jk} = GS_j^{\beta o} \tag{3.7}$$

This model assumes that the attraction of a shopping centre is a function of its gross size (GS_j), which is the gross leasable area of the shopping centre, and is independent of the size of each merchandise category.

[5] Same as Nakanishi and Yamanaka's (1975) model.

2. Individual Category Size (IS) Model[6]

$$A_{jk} = IS_{jk}^{\beta} \qquad (3.8)$$

Here it is assumed that the attraction of a retail centre for the k^{th} merchandise category is a function of the retail area (space) allotted in the centre for that individual category, IS_{jk}.

3. Gross Centre Size – Individual Category Size (GS–IS) Model[7]

$$A_{jk} = GS_j^{\beta o} \; IS_{jk}^{\beta k} \qquad (3.9)$$

This model assumes that A_{jk} term is decomposable into two parts; one representing the generalized attraction of the gross size of the centre as in the GS model, and the other representing the merchandise category specific attraction as in (3.7) above.

4. Individual Category Size – Image Measure (IS–IM) Model

$$A_{jk} = IS_{jk}^{\beta k} \; IM_j^{\o l} \qquad (3.10)$$

This model's assumption is that the generalized attraction of a retail centre is not a function of the centre's overall gross size, but the product of the merchandise category size IS_{jk} and some combination of various characteristics which are unique to the centre (e.g. accessibility, price level, atmosphere, quality of stores, etc.), and are included in some measure of the centre's image (IM_j). This latter item was not explicitly taken into account in the Nakanashi and

[6] Same as Nakanishi and Yamanaka's (1975) model.

[7] Same as Nakanishi and Yamanaka's (1975) model.

Yamanaka (1975) study, which used $e^{\alpha j}$, instead of the currently proposed image measure IMj, and estimated the parameter αj's using a dummy variable for each retail centre.

5. Gross Centre Size – Image Measure (GS–IM) Model

$$A_{jk} = GS_j^{\beta o} \, IM_j^{\phi 1} \qquad (3.11)$$

This model, which is similar to the GS–IS model outlined previously, assumes that the second part of the decomposable model is represented by the new image measure rather than the merchandise category size.

6. Gross Centre Size – Individual Category Size – Image Measure (GS–IS–IM) Model

$$A_{jk} = GS_j^{\beta o} \, IS_{jk}^{\beta k} \, IM_j^{\phi 1} \qquad (3.12)$$

Here it is assumed that the attraction of a shopping centre is best described by including all three of the components discussed so far, that is, the centre's gross size, the size of the individual merchandise category, and the image measure of the centre.

7. Image Measure (IM) Model

$$A_{jk} = IM_j^{\phi 1} \qquad (3.13)$$

This last model assumes that the attraction of a retail centre for any merchandise is dependent solely on the image of that centre and not on its gross size or the size of individual merchandise categories.

The model represented by equation (3.6) can be transformed into a linear form by taking logs, and introducing dummy variables as suggested by

Nakaniski and Cooper (1982) in equation (3.5). This transformation yields the following model:

$$\log P_{ijk} = \alpha_i D_i + \sum_{j=1}^{m} - \lambda_k \log A_{jk} T_{ij} + \varepsilon_{ijk} \tag{3.14}$$

where:

D_i = a dummy variable which is equal to 1 if i = 1 and 0 otherwise;

α_i = the regression coefficient for D_i.

Nakanishi and Cooper (1982) point out that while equation (3.14) makes the estimation of multiplicative competitive interaction (MCI) models easy, because it is an ordinary least squares procedure, it does not produce minimum variance estimates.

Following the same procedure as in equations (3.5) and (3.14), the overall model becomes:

$$\log P_{ijk} = \gamma_{ik} - \sum_{k'=1}^{K} d_{k'} \lambda_k \log D_{ij} + \beta_0 \log GS_j + \sum_{l=1}^{L} \phi_l \log IM_{ijl} + \sum_{k'=1}^{K} d_{k'} \beta_k \log IS_{jk} \tag{3.15}$$

where:

P_{ijk} = observed proportion of shoppers at origin zone i making a purchase of an item in the k^{th} product category at shopping centre j;

D_{ij} = distance (in kilometres) between origin zone i and shopping centre j;

GS_j = gross size (in square feet) of shopping centre j;

IM_{ijl} = mean value of image measure l for shopping centre j as perceived by all shoppers surveyed in origin zone i;

IS_{jk} = size of merchandise category k (in square feet) at shopping centre j;

λ_k = parameter of shopper sensitivity towards travel time for merchandise category k;

β_o = parameter of shopper sensitivity towards gross size;

ϕ_l = parameter of shopper sensitivity towards image measure l;

β_k = parameter of shopper sensitivity towards the size of the individual merchandise category k;

d_k' = dummy variable for merchandise category k (i.e., $d_k'=1$ if $k'=k$; $dk'=0$ otherwise);

ψ_{ik} = parameter of shoppers' loyalty;

I = number of household areas or origin zones included in the study;

J = number of shopping centres included in the study;

K = number of merchandise categories in the study;

L = number of image measures.

The overall results of Ward's study, which used the OLS analysis, were in general agreement with Nakanishi and Yamanaka's (1975) study. That is, the addition of merchandise category information and the generalized attraction, to Huff's (1962) model, did indeed increase the overall accuracy of the model's ability to predict shopping centre patronage; though, the contributions from the image construct were only found to be marginal. The details of the findings are presented and discussed in the next chapter.

In summary, by examining equation (3.15) one very quickly realizes the information that is being sacrificed by employing an aggregate level of analysis. Specifically, to obtain P_{ijk} one must group consumers and this grouping significantly reduces the number of responses to be analyzed and the variability in the sample. This approach also sacrifices individual disparity on variables that measure the image construct of objects in the choice set. Such information is crucial in attempting to explain and understand consumer behaviour.

All of the concerns addressed above raise two pertinent questions: Is a disaggregate level of analysis appropriate in estimating consumer choice? and Is there an alternate model that can explain and predict consumer choice at the disaggregate level in a nonlinear form without sacrificing any information? The answer to these two questions is, yes! The last and the next section of this chapter addresses this.

McFadden's Conditional Logit

Marketing managers are typically more interested in statistics reflecting group tendencies or preferences than in sets of unique statistics for each individual. This desire can be appreciated because of the need to target market. Hence, this implies a cross-sectional rather than an individual level of analysis. Such an analysis is acceptable when the managers' concerns are to predict the choice distribution of a population as a whole or when their interests are in diagnostic information regarding an attribute's relative influence on preference for the total population. However, as has been discussed in chapter two, such an analysis is inappropriate because crucial information is sacrificed when employing such an analysis to determine consumer choice. A more appropriate form of analysis in situations like this is at the disaggregate level. Using this approach in predicting and explaining consumer choice behaviour has been empirically tested and deemed to be superior (McFadden, 1974; Domencich &

McFadden, 1975; Gensch & Recker, 1979; Henscher & Johnson, 1981; Currim, 1982; Weisbrod et al., 1984; Gensch, 1985; Dunn & Wrigley, 1985).

The purpose of this section is to outline the usefulness of the multinomial logit, and more specifically McFadden's conditional logit, in situations where consumers are faced with choice decisions. It is easy to conceive an individual who faces a choice set of alternatives from which he or she will make a choice; also, each of the considered alternatives can have a different set of determinant (relevant) attributes. Since the logit model is derived from an underlying behavioral model of choice, it is the appropriate model to use in analyzing choice situations (McFadden, 1974; Gensch & Recker, 1979; Currim, 1982; Maddala, 1983; Gensch, 1985). The use of such models has increased rapidly in psychology (choice theory), civil engineering (transportation planning), and geography (choice of migration destination) (Currim, 1982). Analysis of such situations presents problems for other covariance techniques such as regression and multiple discriminant analysis (MDA), which are often used in choice modeling (Gensch & Recker, 1979).

A discussion of why discriminant analysis is not appropriate is warranted since this model is frequently used to model choice decisions because the technique allows the dependent variable to be dichotomous or polychotomous and choices by nature are discrete. The reason why MDA is inappropriate in modeling choices is because the model is fundamentally different. It is essentially a <u>classification</u> rather than a <u>choice</u> model. Given someone's classification group (which is pre-determined), the important (significant) independent variables (measured on ratio or interval scale and nominal variables are used as dummies) are identified that best discriminate between the individuals or objects in the pre-determined groups. Whereas in the MNL (multinomial logit) model, maximum-likelihood methods are used to determine the likelihood of someone making a particular choice, given the observations on the independent variables. The independent variables can be measured on metric or nonmetric scales.

If the independent variables are normally distributed, the discriminant-analysis estimator, as stated by Maddala (1983), is the true maximum-likelihood estimator and therefore is asymptotically more efficient than the MNL estimator. But, if the independent variables are not normally distributed, the MDA estimator is not consistent, whereas the MNL estimator is and therefore is more robust.[8]

Typically, when categorical variables are used as independent predictors in covariance models and the MNL model, they are treated as dummy variables. Since it has been established that the MNL is the appropriate model to use in modeling choice behaviour, the discussion regarding dummy variables will be confined to this model only. In essence, when one is employing dummy variables as predictors, one is just measuring the impact of presence or absence of a particular characteristic, trait, or attribute on the choice decision. This type of analysis creates no problems when one is actually dealing with variables that measure the yes/no scenario. An example would be, either store A sells product X or it does not. However, when the scenario is that, given a consumer has to choose from three objects (dependent variable) having differing values[9] on an independent variable, and dummy variables are used to reflect this, one is sacrificing the ratio scale property of this variable. To date a vast

---

[8] For a detailed discussion of relationship between MDA and MNL, the reader is referred to McFadden (1976a).

[9] For example, price levels of the three objects in the choice set are A=$1,000, B=$910, and C=$875.

majority of the studies employ ratio–scaled variables when measuring attributes of individuals making the choice but dummy variables for measurement of choice objects. Ideally, one should be analyzing such properties of a variable simultaneously to determine the impact, if any, on the choice decision of an individual. To the author's knowledge, the only model that enables one to perform such an analysis is McFadden's conditional logit (McFadden, 1974; Maddala, 1983). The condition is that an individual's choice is contingent on how the alternatives in the choice set "measure up" on the determinant attributes. In essence, it makes intuitive sense that these contingencies be analyzed simultaneously, and McFadden's conditional logit does just that. The regular MNL model only allows one to incorporate individual specific data (e.g. demographics, psychographics, etc.), and alternative specific data that are measured on ratio scale are treated as dummy variables. McFadden's conditional logit permits one to incorporate both, alternative and individual specific data (Maddala, 1983).[10] To the author's knowledge, this is the only model that permits such calibration to predict and explain consumer choice behaviour.

The mathematical equivalent of the MCI model (3.1) in conditional logit form, as it relates to modeling shopping centre choice, at the disaggregate level is presented below:

$$L = \prod_{i=1}^{I} \frac{\prod_{h=1}^{m} e^{X_{hi*}\,\beta_{hi*}}}{\sum_{k=1}^{n} \prod_{h=1}^{m} e^{X_{hik}\,\beta_{hik}}} \tag{3.16}$$

[10] The mathematics for McFadden's conditional logit and MNL are the same. For technical details, refer to McFadden (1974) and Maddala (1983).

where I is the number of trips in the sample and * denotes the alternative that was selected for each trip. Given observations on the X attributes and the choice decisions, the estimated β coefficients can be selected to maximize the likelihood of the observed sample. Since this procedure relies on the observed X's and not on the unobserved choice probabilities, the estimation of the β's are done without any prior estimates of these probabilities.

In this study an individual had to choose from the four shopping centres available in the choice set. The alternatives in the choice set were characterized by attributes such as:– gross leasable area of the shopping centre; square footage allotted to individual merchandise category; four image measures and perceived travel time to the shopping centres from place of residence. The individual charactertistics (demographics) used were the presence or absence of children under the age of 12 and the age of the respondent. These were the only demographic variables on which data were collected in Ward's (1985) study and were not used in Ward's model due to aggregation of data by origin zone.

The model in equation (3.16) is used to compare the results of OLS approach used by Ward (1985).

CHAPTER 4

ANALYSIS AND FINDINGS

This final chapter covers the following: factor analysis of the image variables; results including a comparison to Ward's (1985) study; and finally, the implications and conclusions of this study and the implications for future research.

Factor Analysis of Image Variables

As discussed in the literature review in Chapter Two, there are certain weaknesses in using semantic differential scales to measure the image construct. One of them is that a person's position on the scale may not be comparable to others. For instance, one person's "2" on a seven-point scale may be another's "3" or a "1", thus making summarized measures of the distribution of responses difficult to interpret. This problem is rectified by standardizing the ratings of an individual. For example, to measure the "Quality of Stores" at each of the four shopping centres (Guildford, Surrey Place, Scottsdale and Kennedy Heights) Ward (1985) had individuals rate (on a five-point scale) the quality of stores at each of the four centres. Thus to standardize a person's evaluation of quality of stores at a shopping centre, the following can be done:

[1]$X_1' = (X_1 - \text{Mean}\ (X_1, X_2, X_3, X_4))/\text{Sd}(X_1, X_2, X_3, X_4)$

where:

X_1' = the standardized score for quality of stores at Centre 1;

---

[1] X_1' now has a mean of 0 and a standard deviation of 1.

X_1 = original rating for quality of stores at Centre 1;

X_2 = original rating for quality of stores at Centre 2;

X_3 = original rating for quality of stores at Centre 3;

X_4 = original rating for quality of stores at Centre 4;

Mean = Arithmetic average;

Sd = Standard deviation.

Similarly one can compute standardized scores, X'_2, X'_3, X'_4, for the quality of stores at Centre 2, Centre 3, and Centre 4. This process can be repeated for other variables that measure the image of each of the four shopping centres.

The above standardization[2] process was used in this study to transform the image construct variables before factor analysis was performed. This was not accomplished in Ward's (1985) study.

Table 1
Rotated Factor Matrices

	Factor 1	Factor 2	Factor 3	Factor 4	Communalities
Quality of Stores	.87(.88)[3]	.07(.19)	.09(.11)	.09(.07)	.75(.83)
Variety of Stores	.86(.89)	-.02(.16)	.10(.14)	-.03(.06)	.76(.83)
Parking Facilities	.04(.17)	-.11(.10)	.91(.95)	-.01(.07)	.84(.94)
Layout of Shopping Centre	.34(.50)	.24(.36)	.54(.44)	.02(.06)	.49(.58)
General Price Levels	-.02(.07)	.05(.12)	.01(.07)	.98(.98)	.96(.99)
Store Personnel	-.08(.11)	.81(.87)	.05(.11)	-.01(.02)	.66(.77)
Atmosphere	.54(.57)	.31(.50)	.19(.23)	-.23(.01)	.48(.63)
Promotion and Sales	.24(.32)	.65(.69)	-.03(.06)	.06(.19)	.49(.62)
Eigenvalues	1.96(2.28)	1.25(1.69)	1.19(1.20)	1.02(1.02)	
Total Variance Explained	68% (77%)				

[2] For the variables that had missing values, the mean value of 0 was assigned to these variables.

[3] The values enclosed in brackets are from Ward's (1985) study. Note: these values were generated using unstandardized variables as input to the factor analysis procedure.

The standardized variables were factor analyzed using the principal components[4] analysis and varimax rotation. Since the data for the eight image variables for each of the four shopping centres were a row vector of length thirty two, factor analyzing this vector across the sample would confuse image variables and object (shopping centre) information. Thus, before conducting factor analysis, the row vector for each individual was transformed into a matrix of 4X8 (4 shopping centres by 8 variables) in order to capture object specific information. This process is referred to as "stacking".[5] For examination of a stacked standardized data file, please refer to Appendix 3.

In order to be consistent with Ward's (1985) study, four factors were extracted and factor scores were generated for each factor. These factor scores were then "unstacked" and Appendix 4 contains a copy of this.

Table 1 presents the results of the rotated factor matrices derived from Ward's study and this study. This table compares the factors, factor loadings, eigenvalues, communalities, and total variance explained. By examining the information in Table 1, it is observed that the factors generated by standardizing the variables are similar to but more clear than those of Ward's study. For instance, the variable "layout of shopping centre" loads heavily on Factor 1 and Factor 3, and "atmosphere" loads heavily on Factor 1 and Factor 2 in Ward's study. Such cases are not found in the factor solution of this study. In fact, in the present study's factor solution, the variables "layout of

---

[4] Since the purpose of factor analysis in this study was to employ the technique for data reduction, principal components analysis was used as opposed to common factoring, which is used and recommended when the objective is to identify underlying structure in the data (Nie et al., 1975).

[5] To the author's knowledge, this term was created by Dr. Bertram Schoner, of the Faculty of Business Administration at Simon Fraser University, B.C.

shopping centre" and "atmosphere" are grouped under the factors where one would intuitively expect them to appear. That is, "layout..." is grouped with "parking facilities", and "atmosphere" with "quality and variety of stores". Now the question remains, will these so-called clean factors possess better predictive power in explaining and predicting shopping centre patronage?

To perform McFadden's Conditional Logit (MCL) analysis the TROLL statistical package on the mainframe at Simon Fraser University was used. A copy of the data file, after elimination of missing cases, input to TROLL for the merchandise category of ladies clothing is contained in Appendix 5. Appendix 6 contains how data were organized within Troll before the MCL model was executed.

In this study, the dependent variable was one of the four shopping centres an individual chose to normally shop for a merchandise category.[6] The "alternative attribute" independent variables for each of the alternatives in the choice set were: gross leasable area (ratio scale), perceived driving time (ratio scale), and four image factors (ratio scale). The independent variables for "individual attributes" were: the presence or absence of children under 12 years of age (categorical scale, 1,0), and age of the respondent (ratio scale). Ward (1985) did not use the demographic variables in his analyses as the data were aggregated by respondent's area of residence.

The above model was run on the three merchandise categories (ladies clothing, furniture, and greeting cards & wrapping paper). The reasons for using these three product categories were outlined in Chapter One. When Ward

---

[6] Ward (1985) in his study had used the dependent variable where the last purchase was made for a merchandise category. Cross-tabulations were performed to measure the association of normal purchase with last purchase and only minor differences between the two were observed (Sig = .0000).

(1985) ran his final model, he incorporated all product categories into the various models simultaneously (see equation 3.15 in Chapter Three). In this study the models for each product category were run separately to investigate the stability of the gross centre size effect on drawing power across merchandise categories, as Nakanishi and Yamanaka (1975) implied in their models.

Results, Comparisons and Implications

The results generated from the MCL model are presented in Tables 2 through 9 for each of the merchandise categories. A sample of the output from the MCL model is contained in Appendix 7 for examination.

The first item that is worthy of comment is that Ward's model had generated R^2 of value 0.83 or higher. These values are exceptionally high when compared with empirical studies that analyzed data using the regression model. But, such high values are to be expected since Ward (1985) was using aggregated data and had suppressed the intercept. Morrison (1973) states that one should expect the R^2 values to be inflated when the intercept is suppressed, and these values would be considerably lower when disaggregation is used and when the intercept is not suppressed. In this study the comparable index is the P^2.[7] According to Domencich and McFadden (1975, p.124), any values of P^2 that fall between 0.2 and 0.4 reflect an excellent fit of the data to the model. By looking at the P^2 values in Table 2, one observes that nineteen of the twenty-four values for P^2 are 0.4 or greater and the remaining values are greater than or equal to 0.36. Hence 79% of the P^2 values represent more

---

[7] See Appendix 8 for a graphic relationship between R^2 and P^2.

than an excellent fit and the remaining 21% are considered to be excellent. These results can be deemed to be exceptional since the model was calibrated at the disaggregate level.

By further examining Table 2 one observes that all the travel time coefficients for the eight models run are significant, which was not the case in Ward's (1985) study, for the three product categories studied. This implies that travel time does indeed play a prominent role in the drawing power of shopping centres and this prominence varies by merchandise category. Also, it is interesting to note that the lambda coefficients for the three merchandise categories turned out as was hypothesized. That is, one had expected people to be most sensitive to travel time when shopping for greeting cards (high lambda), least sensitive to travel time while shopping for furniture (low lambda), and the lambda value for ladies clothing was expected to be between the lambdas for furniture and greeting cards. This holds true for all eight models analyzed in this study and was also the same in Ward's (1985) study.

In this study the image construct variables were significant in predicting consumer choice. Such was not the case in Ward's (1985) study. Also, Ward (1985) was unable to use the image factor that measured the dimension of "variety and quality of merchandise" along with gross leasable area in predicting consumer choice (the two had correlations of 0.90). There were no such problems in using the two simulanteously in this study. One can attribute the above observation to the fact that individual data were used for the factor analysis procedure instead of aggregate data. And it is this process that generates factors and factor scores that have significant explanatory and predictive ability. As discussed in the literature review, many empirical studies have recognized the importance of the image construct variables for the general

TABLE 2

TRAVEL TIME (TT) LAMBDAS AND THEIR RESPECTIVE RATIOS ACROSS ALL MODELS

Note: All λ are significant

Model	Merchandise Categories: Ladies Clothing	Merchandise Categories: Furniture	Merchandise Categories: Greeting Cards Wrapping Paper	Coefficient Ratios: Ladies Clothing	Coefficient Ratios: Furniture	Coefficient Ratios: Cards/Paper
1. Gross Size - TT. Model	-1.76[1]** .41[2] 1.27[3]**	-1.21[1] .41[2] 0.76[3]	-2.24[1] .36[2] 1.65[3]	-9.04	-6.16	-10.53
2. Individual Size - TT. Model	-1.62[1] .43[2] 1.22[3]	-1.11[1] .37[2] 0.75[3]	-2.16[1] .36[2] 1.72[3]	-8.62	-6.35	-10.70
3. Gross Size - Ind. Size - TT. Model	-1.76[1] .43[2] 1.21[3]	-1.20[1] .41[2] 0.74[3]	-2.28[1] .37[2] 1.71[3]	-8.71	-5.77	-10.41
4. Individual Size - TT - Image Model	-1.63[1] .52[2] 0.50[3]	-1.08[1] .55[2] 0.00*	-2.21[1] .46[2] 0.97[3]	-7.96	-5.79	-10.24
5. Gross Size - TT - Image Model	-1.66[1] .49[2] 0.98[3]	-1.15[1] .53[2] 0.47[3]	-2.25[1] .47[2] 1.36[3]	-8.25	-5.60	-10.08
6. Gross Size - Ind. Size - TT.-Image Model	-1.61[1] .48[2] 0.95[3]	-1.09[1] .52[2] 0.46[3]	-2.28[1] .47[2] 1.42[3]	-7.52	-5.00	-9.89
7. Image - Travel Time Model	-1.23[1] .57[2] 0.38[3]	-0.84[1] .39[2] -0.13*	-2.10[1] .46[2] 0.75[3]	-8.46	-5.57	-10.59
8. All, plus child, Age Model	-1.57[1] .53[2] NA[4]	-1.09[1] .52[2] NA	-2.26[1] .53[2] NA	-7.34	-4.89	-9.54

[1] Lambdas generated by MCL model in this study.

[2] The P^2 Value is an index like the R^2 from LSE. The higher the value, the better the fit. These values should not be compared directly to R^2, as Values (of P^2) between .2 and .4 represent an excellent fit (Domencich and McFadden, 1975, p.124).

[3] Lambdas reported by Ward (1985) for respective categories across all models.

[4] Not analysed in Ward's study.

* Not reported as being significant.

**The signs of the lambdas in this study and of those reported by Ward are in opposite directions because the λ appears in the numerator in this study and was in the denominator for Ward's study.

Note: Any coefficient ratio that is $\geq$ 2.0 is significant. One needs to look at the absolute value only.

"appeal" of a retail outlet. But, to the author's knowledge, no studies have reported the image variables as being significant in predicting consumer choice when used in conjunction with other outlet specific variables.

Next, the findings from each of the eight models run for the three merchandise categories are discussed. The βs from the MCL model are not directly comparable to the LSE βs generated by Ward (1985). For this reason no direct comparisons of the βs were made between the two studies.

Gross Size – Travel Time Model[8] (Table 3)

In this model gross leasable area was used by itself to predict consumer choice; the βs for the three product categories were significant. The implications for all three merchandise categories are that leasable area (size) of the shopping centre is an excellent predictor of consumer patronage (the P^2 for ladies clothing and furniture was .41 and for greeting cards it was .36). Overall, the βs were stable across the three product classes.

Individual Category Size – Travel Time Model (Table 4)

Here the square footage allotted to each of the three product categories was used to predict shopping centre choice. Once again, all three βs were stable and significant. The implications for individual category size are the same as those for gross size model (all P^2 were greater than .36).

[8] The λs for travel time will not be discussed here as they have already been discussed in the section that addresses the information in Table 2. Note: All λs are significant and appear in all the models.

TABLE 3
GROSS SIZE - TRAVEL TIME MODEL

	Coefficient	Ratio
Ladies Clothing: (P^2=.41)		
Gross Size	4.69	13.58
Travel Time	–1.76	–9.04
Furniture: (P^2=.41)		
Gross Size	4.49	12.30
Travel Time	–1.21	–6.16
Greeting Cards/Wrapping Paper: (P^2=.36)		
Gross Size	3.16	9.56
Travel Time	–2.24	–10.53

TABLE 4
INDIVIDUAL CATEGORY SIZE - TRAVEL TIME MODEL

	Coefficient	Ratio
Ladies Clothing: (P^2=.43)		
Individual Category Size	3.94	12.62
Travel Time	–1.62	–8.62
Furniture: (P^2=.37)		
Individual Category Size	4.71	12.86
Travel Time	–1.11	–6.35
Greeting Cards/Wrapping Paper: (P^2=.36)		
Individual Category Size	3.07	9.58
Travel Time	–2.16	–10.70

Gross Size – Individual Size – Travel Time Model (Table 5)

In this model, gross size and individual category size were analyzed simultaneously to determine their impact on predicting consumer choice. Though the β coefficients were all significant, except for greeting cards – individual category size, the results were confounded. For ladies clothing the βs were plausible: both βs were positive and less than their stand–alone values. The βs for gross size for furniture and greeting cards, however, dominated the β for individual category size for furniture which was negative, and the β for greeting cards was negative and insignificant. The reason for this confounding lies in the colinearity of the two sizes (see Appendix 1). Due to this inherent bias in estimates it would be improper to draw any implications even though the βs for gross size for furniture and greeting cards were significant.

TABLE 5
GROSS SIZE – INDIVIDUAL SIZE – TRAVEL TIME MODEL

	Coefficient	Ratio
Ladies Clothing: (P^2=.43)		
Gross Size	1.57	2.34
Individual Category Size	2.83	5.13
Travel Time	–1.76	–8.71
Furniture: (P^2=.41)		
Gross Size	9.51	5.42
Individual Category Size	–5.57	–3.01
Travel Time	–1.20	–5.77
Greeting Cards/Wrapping Paper: (P^2=.37)		
Gross Size	6.22	3.21
Individual Category Size	–3.12	–1.61
Travel Time	–2.28	–10.41

Travel Time – Image Model (Table 6)

The purpose of this model was to see if the image construct variables were of assistance by themselves in predicting consumer choice. For ladies clothing all four image construct variables were significant in predicting consumer patronage. The β for the "quality, variety and atmosphere" factor was the largest, whereas the β for the "price levels" factor was the lowest and negative; the negative sign implying consumers' adversity to higher price levels. The factor measuring "parking facilities" and "layout of stores" had the only insignificant β for the furniture product category. From this, two different implications flow: the first is that since the data were collected on shopping trips to shopping centres, people might have taken "parking and layout" for granted for this merchandise category. The second, is that if one were to believe that "parking and layout of stores" does not influence consumer choice, then the marketers of shopping centres need not promote their furniture departments by using this in their communication campaigns.

The β for the "price levels" factor for greeting cards and wrapping paper was the only one that was insignificant for this product category. This is not unexpected, given that this merchandise category is a relatively inexpensive good and hence one would not expect it to be a significant predictor of centre choice. Overall the image construct variables were more than excellent predictors of consumer patronage (respective P^2 were .57, .39, and .46) for shopping centres. Such relationships have not been observed in any empirical work conducted to date.

TABLE 6
TRAVEL TIME - IMAGE MODEL

	Coefficient	Ratio
Ladies Clothing: (P^2=.57)		
A. Travel Time	-1.23	-8.46
B. Quality/Variety/Atmosphere	12.03	13.16
C. Personnel/Promotions & Sales	5.08	5.00
D. Parking/Layout of Stores	3.86	4.29
E. Price Levels	-3.13	-3.47
Furniture: (P^2=.39)		
A. Travel Time	-0.84	-5.57
B. Quality/Variety/Atmosphere	12.23	11.45
C. Personnel/Promotions & Sales	3.33	3.02
D. Parking/Layout of Stores	1.90	1.86
E. Price Levels	-2.20	-2.24
Greeting Cards/Wrapping Paper: (P^2=.46)		
A. Travel Time	-2.10	-10.59
B. Quality/Variety/Atmosphere	8.09	9.27
C. Personnel/Promotions & Sales	7.36	6.35
D. Parking/Layout of Stores	3.82	4.22
E. Price Levels	-1.61	-1.57

Gross Size – Travel Time – Image Model (Table 7)

Under this scenario, gross size was included with the image construct variables to determine the predictive power of the model. In the ladies clothing category all βs were significant except the one for the "price levels" factor. The attraction for the gross size of shopping centre overrides the one for the "price levels", which was significant in the image only model, suggesting colinearity between the variables. The predominant predictors for this category were "quality...", and "personnel..." factors and the gross size of the shopping centre. For the furniture product category, the same as above was true except that the βs for the factors "parking..." and "price levels" were insignificant. When gross size was introduced to the greeting cards model, the results were similar to the image only model for this product category. Gross size was a significant predictor of choice but had a low β coefficient (1.6), compared to the βs of ladies clothing (3.25) and furniture (3.45). This implies that gross size is a better predictor of consumer choice for ladies clothing and furniture than it is for greeting cards and wrapping paper. The respective P^2 values were .49 (ladies clothing), .53 (furniture), and .47 (greeting cards); once again, a phenomenal fit was observed.

TABLE 7
GROSS SIZE - TRAVEL TIME - IMAGE MODEL

	Coefficient	Ratio
Ladies Clothing: (P^2=.49)		
A. Gross Size	3.25	7.57
B. Travel Time	−1.66	−8.25
C. Quality/Variety/Atmosphere	6.34	5.98
D. Personnel/Promotions & Sales	6.10	5.56
E. Parking/Layout of Stores	1.99	2.07
F. Price Levels	−1.44	−1.52
Furniture: (P^2=.53)		
A. Gross Size	3.41	7.24
B. Travel Time	−1.15	−5.60
C. Quality/Variety/Atmosphere	5.73	4.65
D. Personnel/Promotions & Sales	4.43	3.73
E. Parking/Layout of Stores	−0.23	−0.20
F. Price Levels	0.32	0.30
Greeting Cards/Wrapping Paper: (P^2=.47)		
A. Gross Size	1.60	3.48
B. Travel Time	−2.25	−10.08
C. Quality/Variety/Atmosphere	5.30	4.68
D. Personnel/Promotions & Sales	7.45	6.32
E. Parking/Layout of Stores	2.96	3.16
F. Price Levels	−0.66	−0.62

Individual Category Size – Travel Time – Image Model (Table 8)

In this model the results for the ladies clothing category were generally the same as in the previous model and the "parking..." factor, which was barely significant in the gross size–image model was insignificant in this model. For the furniture and greeting cards categories the results and implications are exactly the same as for the gross size–image model discussed earlier. Overall, here too, the β coefficient was the best predictor for the furniture product category, the second best for ladies clothing, and the third best for greeting cards and wrapping paper. The P^2 values of .52, .55, and .46 respectively indicating beyond an excellent fit for all product categories.

Gross Size – Individual Category Size – Travel Time – Image Model (Table 9)

This model, in essence, was the same as the gross size–individual category size model, with the exception that image construct variables were not included in the previous model. As it may be recalled that in the gross size – individual category size model, the results were confounded because of the associations between the gross leasable area and the space allotted to the merchandise categories. The same case holds in this model and the results were still confounded by these associations; hence no implications were inferred from the significant β coefficients of gross and individual category size for the three merchandise classes. The image variables, "quality..." and "personnel..." were significant predictors of consumer choice in all three product categories. In spite of the confounding, the P^2 coefficients were superb (.48, .52, and .47).

TABLE 8
INDIVIDUAL CATEGORY SIZE - TRAVEL TIME - IMAGE MODEL

	Coefficient	Ratio
Ladies Clothing: (P^2=.52)		
A. Individual Category Size	2.89	8.27
B. Travel Time	-1.63	-7.96
C. Quality/Variety/Atmosphere	6.60	6.56
D. Personnel/Promotions & Sales	6.18	5.44
E. Parking/Layout of Stores	1.62	1.61
F. Price Levels	-1.53	-1.57
Furniture: (P^2=.55)		
A. Individual Category Size	3.28	6.62
B. Travel Time	-1.08	-5.79
C. Quality/Variety/Atmosphere	6.56	5.26
D. Personnel/Promotions & Sales	4.28	3.70
E. Parking/Layout of Stores	0.16	0.14
F. Price Levels	-0.07	-0.07
Greeting Cards/Wrapping Paper: (P^2=.46)		
A. Individual Category Size	1.39	3.01
B. Travel Time	-2.21	-10.24
C. Quality/Variety/Atmosphere	5.68	4.96
D. Personnel/Promotions & Sales	7.44	6.34
E. Parking/Layout of Stores	3.06	3.27
F. Price Levels	-0.79	-0.74

TABLE 9
GROSS SIZE - INDIVIDUAL CATEGORY SIZE - TRAVEL TIME - IMAGE - MODEL

	Coefficient	Ratio
Ladies Clothing: (P^2=.48)		
A. Gross Size	-0.267	-0.33
B. Individual Category Size	3.06	5.03
C. Travel Time	-1.61	-7.52
D. Quality/Variety/Atmosphere	6.73	6.20
E. Personnel/Promotions & Sales	6.16	5.41
F. Parking/Layout of Stores	1.64	1.62
G. Price Levels	-1.58	-1.59
Furniture: (P^2=.52)		
A. Gross Size	8.85	4.80
B. Individual Category Size	-6.17	-3.13
C. Travel Time	-1.09	-5.00
D. Quality/Variety/Atmosphere	6.05	4.84
E. Personnel/Promotions & Sales	4.34	3.53
F. Parking/Layout of Stores	-0.38	-0.33
G. Price Levels	0.30	0.28
Greeting Cards/Wrapping Paper: (P^2=.47)		
A. Gross Size	5.71	2.74
B. Individual Category Size	-4.29	-2.02
C. Travel Time	-2.28	-9.89
D. Quality/Variety/Atmosphere	5.52	4.83
E. Personnel/Promotions & Sales	7.44	6.27
F. Parking/Layout of Stores	3.06	3.24
G. Price Levels	-0.76	-0.70

All, Plus Child, Age Model (Table 10)

This last model contained all the variables plus the child and age variables. The Child variable measured the presence or absence of children in the household who were under the age of 12, and Age measured the age of the respondent. The βs for the child variable were insignificant for all choice sets across all three merchandise categories, whereas the βs for age were only insignificant for ladies clothing and furniture. The other βs that were significant for the three product categories were the two image variables ("quality..." and "personnel..."). Once again the image variables stood out in predicting shopping centre patronage. The respective P^2 coefficients were .53, .52, and .53; all of these values reflect more than an excellent fit.

The overall results from the models were logically consistent and turned out as expected, except in the situations where gross size and individual category size were included simulanteously in the model to predict shopping centre choice. Also, while these results were generally similar to those of Ward's (1985), the size of all significant coefficients was much more pronounced in predicting the patronage of shopping centres. In addition, the image construct variables in this study made a very significant contribution in predicting the choice of shopping centres. It was this effect of the image variables that was not captured in Ward's (1985) study.

To validate the results of the models, the greeting cards and wrapping paper product category was chosen as it had the lowest P^2 value for the gross size and the travel time model. The rationale for choosing this model was that if the validation for this model was at an acceptable level then it could be safely assumed that the validation would be acceptable for models that had higher P^2 values.

TABLE 10
ALL, PLUS CHILD, AGE MODEL

Ladies Clothing: (P^2=.53)

	Coefficient	Ratio
A. Gross Size	2.36	0.68
B. Individual Category Size	1.12	0.37
C. Travel Time	−1.57	−7.34
D. Quality/Variety/Atmosphere	7.01	6.21
E. Personnel/Promotions & Sales	5.66	4.97
F. Parking/Layout of Stores	0.89	0.85
G. Price Levels	−1.64	−1.64
H. Child – Guildford	0.83	0.09
I. Child – Surrey Place	8.84	0.91
J. Child – Scottsdale	12.42	1.37
K. Age – Guildford	2.02	0.74
L. Age – Surrey Place	2.33	0.81
M. Age – Scottsdale	2.09	1.35

Furniture: (P^2=.52)

	Coefficient	Ratio
A. Gross Size	9.04	0.94
B. Individual Category Size	−6.32	−0.63
C. Travel Time	−1.09	−4.89
D. Quality/Variety/Atmosphere	6.21	4.87
E. Personnel/Promotions & Sales	4.16	3.34
F. Parking/Layout of Stores	−0.48	−0.40
G. Price Levels	0.23	0.21
H. Child – Guildford	1.10	0.14
I. Child – Surrey Place	1.20	0.15
J. Child – Scottsdale	14.33	1.62
K. Age – Guildford	−0.21	−0.08
L. Age – Surrey Place	−0.15	−0.06
M. Age – Scottsdale	−2.19	−1.19

Greeting Cards/Wrapping Paper: (P^2=.53)

	Coefficient	Ratio
A. Gross Size	−7.41	−0.77
B. Individual Category Size	6.57	0.67
C. Travel Time	−2.26	−9.54
D. Quality/Variety/Atmosphere	7.11	5.66
E. Personnel/Promotions & Sales	7.45	6.00
F. Parking/Layout of Stores	1.13	1.11
G. Price Levels	−0.71	−0.62
H. Child – Guildford	−8.90	−1.08
I. Child – Surrey Place	−4.53	−0.56
J. Child – Scottsdale	−1.55	−0.20
K. Age – Guildford	9.94	3.43
L. Age – Surrey Place	9.50	3.54
M. Age – Scottsdale	6.00	2.90

Table 11 shows that the classifications made by the model are far better than those one would achieve by a chance or a random process and the validity of these classifications is supported by the predictions made by using the coefficients from Model 2 on the hold out sample in Model 3. For details on calculations and program runs refer to Appendix 9.

TABLE 11
GREETING CARDS AND WRAPPING PAPER

Model 1 GROSS SIZE – TT MODEL (P^2 = .36)
n=344

% Correct: 59
% By Chance: 36.5

S_1 = 76% S_2 = 51% S_3 = 30% S_4 = 29%[9]

Model 2 GROSS SIZE – TT MODEL (P^2 = .34)
n=172

% Correct: 63
% By Chance: 37

S_1 = 78% S_2 = 45% S_3 = 60% S_4 = 40%

Model 3 GROSS SIZE – TT MODEL (P^2 = .40)
n=172

	Own Coefficients	*Coefficients from Model #2*
% Correct:	62	58
% By Chance:	40	40

Own:	S_1 = 74%	S_2 = 61%	S_3 = 23%	S_4 = 0%
Model #2:	S_1 = 73%	S_2 = 42%	S_3 = 55%	S_4 = 0%

[9] S_1=Guildford S_2=Surrey Place S_3=Scottsdale S_4=Kennedy Heights

Summary and Conclusions

The purpose of this study was to re–analyze the data that were collected by Ward (1985) for the three product categories of ladies clothing, furniture, and greeting cards and wrapping paper.

The rationale for using these three merchandise classes was that one had expected individuals to be least sensitive to travel time while shopping for furniture, most sensitive to travel time for greeting cards and wrapping paper, and sensitivity to travel for ladies clothing was expected to be between that of furniture and greeting cards. For each of the three product classes, there were two primary issues addressed: The first, was McFadden's conditional logit going to provide better predictions and diagnostic information than the MCI model? In essence, it was a comparison between disaggregate and aggregate levels of analysis. The second, were the image construct variables along with other variables (size of shopping centre and square footage allocated to specific merchandise categories) capable of making a significant contribution towards predicting shopping centre patronage? These two objectives were achieved by comparing the results provided by McFadden's conditional logit to those generated by the MCI model in Ward's study.

The dependent variable used in this research study was the shopping centre that was chosen by an individual to normally purchase the given product category (0,1 variable), whereas in Ward's study it was the proportion of individuals that chose a particular shopping centre from any given origin.

Independent variables used in this study were:– gross leasable area of a shopping centre; square footage allotted to a product class; four image variables; perceived travel time from origin to destination; the number of children in the house under 12 years of age; and age of the respondent. While the same independent variables were used by Ward, except for the variables that measured children and the age of respondent, ratio scale properties of the variables were sacrificed by using dummy variables and by employing aggregation.

The analysis of data, across the three product categories, by using McFadden's conditional logit (disaggregate) did yield excellent to good predictions of consumer patronage for shopping centres. However, these results were not directly comparable to those of the MCI model because of the inherent differences between the two models. But, the conditional logit certainly provided more diagnostic information than the MCI model as the former model was calibrated at the individual level and the latter at the aggregate level.

The image construct variables, after standardization at the individual level and before performing factor analysis, provided not only more interpretive factor solutions but were also the most significant predictors of consumer patronage for shopping centres.

Several managerial implications flow from the results of this study. Since the information generated on choice behaviour is person specific, managers will be in position to know exactly what combination of factors (product specific and/or individual specific) influences an individual's choice of a shopping centre. The aggregation of this individual specific information by demographic, lifestyle and/or regional variables can be used to generate target markets. Such information will assist managers in formulating product positioning, image enhancement, and/or communication strategies.

It is also felt that the findings have made a significant contribution to the literature in retailing. The image construct variables that were deemed to have no predictive power in determining shopping centre patronage were found to be the most significant predictors when appropriate analyses were performed.

As in any study, this one too was not free of limitations. The intention of this work was to replicate Ward's (1985) study across the entire ten product categories, but in actuality only three merchandise categories were analyzed for the reasons already expressed in Chapter One and at the beginning of this section. For a fair comparison between the results of McFadden's conditional logit and the MCI model used by Ward, the data for all ten product categories should have been analyzed and all models should have been validated by hold out samples.

Finally, the implications for future research are to repeat the method of analysis used in this study across comparable choice sets and see if the results generated do provide more diagnostic and explanatory information. The challenge in using this type of analysis is the ability to identify key product attributes and individual characteristics that influence consumers' choices. Future research should focus on identifying techniques that would assist in this process; perhaps management scientists can be of assistance here with their goal programming type of algorithms which have very recently been used by Bean et al. (1988) in determining optimal "tenant mix" for shopping centres.

APPENDICES

AREA BY MERCHANDISE CATEGORY FOR EACH SHOPPING CENTRE
(Square Feet)

Appendix 1

Merchandise Category	Guildford		Surrey Place		Scottsdale		Kennedy Heights	
Ladies Clothing	100,620	(12.0)	82,990	(15.5)	15,040	(8.9)	9,840	(4.8)
Furniture	56,810	(6.8)	23,840	(4.5)	4,080	(2.4)	4,720	(2.3)
Drugs/Cosmetics	28,120	(3.4)	16,190	(3.0)	6,070	(3.6)	6,630	(3.2)
Ladies Shoes	22,670	(2.7)	10,450	(2.0)	2,580	(1.5)	1,670	(0.9)
Food	50,940	(6.1)	45,090	(8.4)	20,890	(12.4)	42,950	(20.8)
Jewellery	16,800	(2.0)	10,110	(1.9)	1,670	(1.0)	1,020	(0.5)
Books	14,420	(1.7)	8,230	(1.5)	1,050	(0.6)	1,620	(0.8)
Kitchenware	18,830	(2.3)	11,810	(2.2)	5,740	(3.4)	1,600	(0.8)
Childrens Clothing	19,750	(2.4)	20,830	(3.9)	10,990	(6.5)	580	(0.3)
Greeting Cards/Wrapping	7,830	(0.9)	4,380	(0.8)	1,590	(0.9)	1,820	(0.9)
TOTAL GLA	836,535		533,929		168,299		206,387	

Appendix 2

PART A

First, I would like to know what you think of a number of factors that contribute to a shopping centre's overall image. For each of the factors that I will read out, please tell me how important they are to you when deciding where to shop, rating them on a scale of 1 to 5 with 1 being very unimportant and 5 being very important. Starting then with quality of stores (remember 1 is very unimportant and 5 is very important).

			Coding
1.	Quality of Stores	____	11
2.	Variety of Stores	____	12
3.	Parking Facilities	____	13
4.	Layout of Shopping Centre	____	14
5.	General Price Level	____	15
6.	Store Personnel	____	16
7.	Atmosphere	____	17
8.	Promotions & Sales	____	18

PART B

In this next section, I would like to find out what you think of four major shopping centres. I will read out each of the same factors and I would like you to tell me how each of the shopping centres rate, once again on a scale of 1 to 5. Starting then with quality of stores, how would you rate ______________?

		Guildford Mall	Surrey Place	Scotts-dale	Kennedy Heights	Coding
1.	Quality of Stores (1 = low, 5 = high)	____	____	____	____	22-25
2.	Variety of Stores (1 = poor, 5 = excellent)	____	____	____	____	27-30
3.	Parking Facilities (1 = inadequate, 5 = adequate)	____	____	____	____	32-35
4.	Layout of Shopping Centre (1 = inconvenient, 5 = convenient)	____	____	____	____	37-40
5.	General Price Level (1 = very high, 5 = very low)	____	____	____	____	42-45
6.	Store Personnel (1 = not helpful, 5 = helpful)	____	____	____	____	47-50
7.	Atmosphere (1 = unpleasant, 5 = pleasant)	____	____	____	____	52-55
8.	Promotions & Sales (1 = not worthwhile, 5 = worthwhile)	____	____	____	____	57-60

PART C

Next, I am going to read to you a list of ten different categories of items you are likely to have purchased recently. For each category, please tell me the shopping centre or shop and location, if not at a shopping centre, at which you made your last purchase:

			Coding
1.	Ladies Clothing	______________	65
2.	Furniture	______________	66
3.	Drugs/Cosmetics	______________	67
4.	Ladies Shoes	______________	68
5.	Food	______________	69
6.	Jewellery	______________	70
7.	Books	______________	71
8.	Kitchenware	______________	72
9.	Childrens Clothing	______________	73
10.	Greeting Cards and/or Wrapping	______________	74

PART D

Coding
ID# 1-3
Card 3

For each of the same merchandise categories, would you now please tell me where you made the last five purchases. Firstly, of the last five items of ladies clothing, how many were bought at ______________?

		Guildford Mall	Surrey Place	Scotts-dale	Kennedy Heights	Elsewhere	Coding
1.	Ladies Clothing	____	____	____	____	____	11-15
2.	Furniture	____	____	____	____	____	17-21
3.	Drugs/Cosmetics	____	____	____	____	____	23-27
4.	Ladies Shoes	____	____	____	____	____	29-33
5.	Food	____	____	____	____	____	35-39
6.	Jewellery	____	____	____	____	____	41-45
7.	Books	____	____	____	____	____	47-51
8.	Kitchenware	____	____	____	____	____	53-57
9.	Childrens Clothing	____	____	____	____	____	59-63
10.	Greeting Cards and/or Wrapping	____	____	____	____	____	65-69

PART E

Now could you please tell me how many minutes it takes to drive from your residence to:

			Coding
1.	Guildford Mall	____ mins	71-2
2.	Scottsdale	____ mins	72-4
3.	Surrey Place	____ mins	73-6
4.	Kennedy Heights	____ mins	74-8

In ending this interview, I would very much appreciate two pieces of basic household data to assist us in interpreting the results.

Firstly, how many children under 12 live in your residence: ______; and lastly, which of the following categories best represents your age: [79]

1. 20 or under
2. 21 - 30
3. 31 - 40 ______ [80]
4. 41 - 50
5. over 50

That is all. Thank you very much for your help.

SURVEY QUESTIONNAIRE

Appendix 3

Listing of DJ.STN.DAT2 at 12:50:39 on NOV 29, 1989 for CCid=MBBA on MTSG

1	118	4	1.78	1.78	1.78	.76	-.25	.76	.76	.76 *
2	118	4	-.25	.76	.76	.76	-1.27	-1.27	.76	-.25
3	118	4	-1.27	-.25	-.25	-.25	.76	-1.27	-.25	-.25
4	118	4	-.25	-.25	-2.29	-.25	.76	-1.27	-1.27	-.25
5	120	4	.88	.88	.88	.88	-1.60	-.36	.88	.88
6	120	4	-.36	-.36	.88	.88	-1.60	-.35	.88	.88
7	120	4	-1.60	-.36	.88	.88	-1.60	-.36	-1.60	-.36
8	120	4	.00	.00	.00	.00	.00	.00	.00	.00
9	125	4	2.04	1.08	1.08	1.08	-.84	.12	2.04	.12
10	125	4	.12	-.84	.12	1.08	.12	.12	.12	.12
11	125	4	-.84	-1.80	-.84	.12	1.08	.12	-.84	.12
12	125	4	-.84	-1.80	-1.80	-.84	1.08	.12	-.84	.12
13	128	4	.79	1.52	.79	.79	.07	.07	1.52	.79
14	128	4	.07	.79	.79	.79	.07	.07	1.52	1.52
15	128	4	-1.39	-1.39	.07	-.66	.79	-.66	-.66	-.66
16	128	4	-1.39	-1.39	-1.39	-1.39	.79	-.66	-.66	-1.39
17	129	4	1.24	1.24	-.48	-.48	.38	2.10	2.10	1.24
18	129	4	-.48	.38	.38	-.48	-.48	-.48	.38	1.24
19	129	4	-1.34	-.48	1.24	1.24	-1.34	-.48	-.48	-.48
20	129	4	-1.34	-1.34	-.48	-1.34	-.48	.38	-.48	-.48
21	132	4	.00	.00	.00	.00	.00	.00	.00	.00
22	132	4	-.35	1.06	1.06	1.06	-.35	-.35	-.35	-1.77
23	132	4	.00	.00	.00	.00	.00	.00	.00	.00
24	132	4	.00	.00	.00	.00	.00	.00	.00	.00
25	160	4	1.09	1.09	1.09	1.09	.26	-.57	1.09	-.57
26	160	4	-.57	1.09	-.57	.26	.26	.26	1.09	.26
27	160	4	.26	.26	-2.23	-.57	-.57	1.09	.26	-1.40
28	160	4	1.09	.26	-2.23	-1.40	-.57	1.09	-1.40	-.57
29	721	3	1.32	1.32	1.32	1.32	-2.52	.04	.04	.04
30	721	3	1.32	1.32	1.32	1.32	-1.24	.04	.04	.04
31	721	3	-1.24	.04	.04	.04	-1.24	.04	.04	-1.24
32	721	3	.04	-1.24	-1.24	.04	-1.24	.04	.04	.04
33	749	4	1.59	1.59	1.59	.18	1.59	.18	.18	.18
34	749	4	-1.24	.18	.18	-1.24	1.59	.18	-1.24	-1.24
35	749	4	.18	.18	1.59	.18	.18	.18	.18	.18
36	749	4	-1.24	-1.24	-1.24	-1.24	-1.24	.18	-1.24	.18
37	121	4	1.58	1.58	-.47	1.58	-.47	.55	1.58	.55
38	121	4	-1.49	-.47	-.47	-.47	-.47	.55	-.47	.55
39	121	4	-1.49	-1.49	.55	-.47	-.47	.55	-1.49	.55
40	121	4	.00	.00	.00	.00	.00	.00	.00	.00
41	714	3	-.45	1.95	-.45	.75	.75	.75	-.45	.75
42	714	3	-.45	.75	-.45	.75	.75	-.45	-.45	-.45
43	714	3	-1.65	-1.65	.75	1.95	-.45	-.45	.75	-.45
44	714	3	-.45	-1.65	1.95	.75	-.45	-.45	-.45	-1.65
45	633	2	-.54	.69	.69	.69	-.54	.69	.69	-1.77
46	633	2	-.54	.69	.69	.69	-1.77	.69	.69	-1.77
47	633	2	.00	.00	.00	.00	.00	.00	.00	.00
48	633	2	.00	.00	.00	.00	.00	.00	.00	.00
49	630	2	.81	.81	1.88	-1.34	-.27	.81	.81	-.27
50	630	2	-1.34	-.27	-1.34	-1.34	-.27	.81	.81	-.27
51	630	2	.00	.00	.00	.00	.00	.00	.00	.00
52	630	2	.00	.00	.00	.00	.00	.00	.00	.00
53	641	2	.90	.90	.90	.90	.05	.05	.90	.05
54	641	2	-1.64	.90	.90	.05	-.79	-1.64	-.79	-1.64
55	641	2	.00	.00	.00	.00	.00	.00	.00	.00
56	641	2	.00	.00	.00	.00	.00	.00	.00	.00
57	648	2	1.20	.33	1.20	.33	-.54	1.20	1.20	1.20
58	648	2	-.54	-.54	-.54	-.54	-.54	-2.29	-.54	-.54

* THE FIRST FOUR RECORDS ARE TO BE READ AS FOLLOWS:

EIGHT IMAGE VARIABLES

GUILFORD 1.78 76

SURREY PLACE – .25 .

SCOTTSDALE –1.27 .

KENNEDY HEIGHTS – .25 . . . . . . –.25

Listing of DJ.STN.DAT2 at 12:50:39 on NOV 29, 1989 for CCid=MBBA on MTSG

59	648	2	.00	.00	.00	.00	.00	.00	.00	.00
60	648	2	.00	.00	.00	.00	.00	.00	.00	.00
61	606	1	.87	.87	-.52	.87	-1.91	-.52	.87	.87
62	606	1	-.52	-.52	-1.91	.87	-.52	-.52	.87	.87
63	606	1	.00	.00	.00	.00	.00	.00	.00	.00
64	606	1	.00	.00	.00	.00	.00	.00	.00	.00
65	708	3	.97	.97	.97	.97	-2.12	.97	.97	.19
66	708	3	.19	.97	.19	-.58	-.58	.97	.97	.19
67	708	3	-.58	.19	-.58	-2.12	.97	-.58	.97	.19
68	708	3	-.58	-.58	-2.12	-1.35	-1.35	.19	.97	.19
69	685	3	.24	.24	1.34	.24	-.86	-.86	.24	-1.97
70	685	3	1.34	1.34	.24	.24	-.86	.24	.24	.24
71	685	3	.24	.24	1.34	-.86	-.86	-.86	.24	1.34
72	685	3	1.34	.24	-1.97	-1.97	-.86	1.34	.24	-.86
73	724	3	.79	.79	.79	.79	-1.50	-.36	-.36	-.36
74	724	3	-.36	.79	.79	.79	-2.65	-.36	-.36	.79
75	724	3	.00	.00	.00	.00	.00	.00	.00	.00
76	724	3	.00	.00	.00	.00	.00	.00	.00	.00
77	722	3	.79	.79	-.79	.79	-.79	.79	.79	.79
78	722	3	-.79	-2.37	.79	.79	-.79	-.79	-.79	.79
79	722	3	.00	.00	.00	.00	.00	.00	.00	.00
80	722	3	.00	.00	.00	.00	.00	.00	.00	.00
81	167	4	1.31	1.31	1.31	1.31	-.37	.47	1.31	1.31
82	167	4	-.37	-.37	1.31	1.31	-.37	.47	-.37	1.31
83	167	4	-1.21	-1.21	1.31	-.37	-1.21	-.37	-1.21	-.37
84	167	4	-1.21	-1.21	-.37	-.37	-1.21	-.37	-1.21	-.37
85	103	4	.95	.95	.95	.95	.95	.95	.95	.95
86	103	4	-.50	-.50	-.50	-.50	-1.22	-.50	-.50	-.50
87	103	4	.95	.23	.95	.95	.95	.95	.95	.95
88	103	4	-1.22	-1.95	-.50	-1.95	-1.22	-.50	-1.22	-1.22
89	106	4	-.25	-.25	-2.05	-.25	-2.05	.65	-1.15	-2.05
90	106	4	.65	-.25	-1.15	.65	.65	.65	-.25	-.25
91	106	4	1.54	-.25	.65	1.54	1.54	-.25	.65	1.54
92	106	4	.65	-1.15	.65	-.25	-.25	-.25	.65	-.25
93	111	4	1.20	1.20	.00	-2.40	-1.20	.00	1.20	-1.20
94	111	4	.00	1.20	-1.20	.00	.00	.00	1.20	.00
95	111	4	-1.20	-1.20	1.20	1.20	.00	.00	.00	.00
96	111	4	.00	.00	.00	.00	.00	.00	.00	.00
97	652	2	.85	.85	.85	.85	-1.10	.85	.85	-1.10
98	652	2	-1.10	.85	.85	.85	-1.10	-1.10	-1.10	-1.10
99	652	2	.00	.00	.00	.00	.00	.00	.00	.00
100	652	2	.00	.00	.00	.00	.00	.00	.00	.00
101	737	3	.50	1.83	1.83	.50	-.83	-.83	.50	.50
102	737	3	.50	1.83	1.83	.50	-.83	-.83	.50	.50
103	737	3	-.83	.50	.50	-.83	-.83	-.83	.50	-.83
104	737	3	-.83	-.83	.50	-.83	-.83	-.83	.50	-2.16
105	713	3	2.29	1.36	1.36	.44	-.49	-.49	-1.42	.44
106	713	3	1.36	.44	1.36	1.36	.44	-.49	-.49	-.49
107	713	3	-.49	-1.42	.44	-.49	.44	.44	.44	-1.42
108	713	3	-.49	-1.42	-.49	-1.42	.44	-.49	.44	-1.42
109	678	2	1.54	.76	-.03	-.03	-.03	-1.61	1.54	-.03
110	678	2	.76	.76	-.03	-.03	-.03	-1.61	1.54	-.82
111	678	2	.00	.00	.00	.00	.00	.00	.00	.00
112	678	2	-.03	-.03	-.03	-.82	-.03	-1.61	1.54	-1.61
113	734	3	.70	.70	.70	-3.03	-1.16	.70	.70	-.23
114	734	3	.70	.70	-1.16	.70	-1.16	.70	.70	-.23
115	734	3	.00	.00	.00	.00	.00	.00	.00	.00
116	734	3	.70	.70	-1.16	.70	-1.16	.70	-.23	-.23

Appendix 4

* The Six Records Per Person
Are As Follows:

Record 1 4 Factor Scores For Guildford
" 2 " " " " Surrey Place
" 3 " " " " Scottsdale
" 4 " " " " Kennedy
" 5 Original Data Set Record 1
" 6 " " " " 2

```
Listing of DJ.NEW.DAT at 12:54:03 on NOV 29, 1989 for CCid=MBBA on MTSG

*  1      118 4  1.708175   .705795  -.513666   .107032
   2              .875191 -1.236122 -1.193192 -1.243467
   3             1.389202   .728713  -.502990 -2.601865
   4              .220201 -1.194361  1.217011  1.621265
   4.1    11814  34243344   5323 5433 5431 4433 3244 4222 4432 4333    1141125511
   4.2    1 5 4 4 5 2 1 1 121       300202102000005      20 51510       1 2 118 2
   5      120 4  1.224104  -.107724 -1.570887   .014285
   6              .255690   .575452  -.671547   .068397
   7              .677136   .962180  1.123860  -.265422
   8            -1.418490 -1.588550 -1.135102   .417082
   8.1    12014  55534554   5430 5440 5550 5550 3330 4440 5530 5540    3312555535
   8.2    1 5 5 1 5 125 5 3 5       00005120020005       15 51510       1 3 120 2
   9      125 4  2.101663  -.329126 -1.498171 -1.371375
  10              .376494   .584269   .602690   .571019
  11             1.029108   .488442  -.714634 -2.113739
  12             -.787847   .575221  1.763217  1.718904
  12.1   12514  42442433   5322 4211 4321 4432 2344 3333 5322 3333    2555505005
  12.2   1 5 5 1 5 0 1 1 0 5        020032000300005      25 71010       0 4 125 2
  13      128 4  1.629072   .896922 -1.576363 -1.392860
  14              .688224  1.342622  -.876660 -1.269770
  15              .621538   .696846  -.201822 -1.860204
  16              .268301   .217296  1.274556  1.187618
  16.1   12814  55345435   4311 5411 4431 4421 3344 3322 5522 4521    2222512135
  16.2   2 1 2 125 1 2 122 2        050000500000005      20101515       2 3 128 2
  17      129 4  1.562475   .176090 -1.190874 -1.681688
  18             3.013153   .328599  -.592946   .189006
  19            -1.113600  -.324924  1.709269 -1.057060
  20              .392901  -.209287 -1.105799  -.283519
  20.1   12914  53523435   4211 4321 2342 2241 3212 5223 5322 4422    2552501111
  20.2   5 5 5 5 5 0 5 5 1 1        000050000500005      20 51510       1 2 129 2
  21      132 4   .014285   .130705   .014285   .014285
  22              .068397 -1.596454   .068397   .068397
  23             -.265422  1.369970  -.265422  -.265422
  24              .417082   .026992   .417082   .417082
  24.1   13214  52325121   0400 0500 0500 0500 0400 0400 0400 0300    2055522522
  24.2   2 2 2 5 5 2 2 2 2 2        050000000500005      10 3 510       0 5 132 2
  25      160 4  1.473776   .687625   .368124   .338114
  26             -.830076   .724811   .394417   .333642
  27             1.172472  -.657388 -2.461666 -3.191904
  28              .596169   .351268  -.450677   .145916
  28.1   16014  12435415   5345 5544 5311 5432 4433 3455 5542 3423    5055501033
  28.2   141 5 2 5 3 1 2 2 3        000051200200005      20 51510       0 4 160 2
  29      721 3  1.222484  1.242322  -.728098  -.420809
  30             -.211603  -.183179  -.599134   .491488
  31             1.274139  1.315328   .059101 -1.319049
  32            -2.224224  -.765017 -1.250412 -1.017785
  32.1   72113  55555444   5534 5543 5543 5544 2333 4444 4444 4434    2052500025
  32.2   2 0 5 125 0 0 0 2 5        000050500000005      10 510 5       3 3 721 2
  33      749 4  1.482045 -1.108595  -.054225 -1.569288
  34             -.162097  -.951084   .170193   .323710
  35             1.008568  -.460119  1.287318 -1.908187
  36             2.419503  2.281195   .618721  -.872145
  36.1   74914  45554545   5343 5443 5453 4343 5543 4444 4343 4344    5031555305
  36.2   3 5 6 125 3 5 3 0 5        005002120000500      20 71015       0 3 749 2
  37      121 4  2.223574 -1.224228 -2.259338   .014285
  38             1.213694  1.023984   .825842   .068397
  39             -.202892  -.788672   .221518  -.265422
  40             -.277357  -.195267   .091880   .417082
```

```
Listing of DJ.NEW.DAT at 12:54:03 on NOV 29, 1989 for CCid=MBBA on MTSG

  40.1   12114, 53534553   5220 5320 3340 5330 3330 4440 5320 4440    1111111111
  40.2   1 1 1 1 1 1 1 1 1 1        500005000050000      20 71010       0 4 121 2
  41      714 3   .682884   .268493 -1.496460 -1.563149
  42             1.075532  -.633563   .163810 -1.347226
  43             -.496759  -.306247  1.879892  2.320977
  44             1.393093  1.361763  -.460451  -.083102
  44.1   71413  43233445   3323 5422 3345 4454 4433 4333 3343 4332    2152525005
  44.2   5 1 15125 1 5 1 0 1        000053200000005      201012 5       0 5 714 2
  45      633 2  -.091062  -.110125   .014285   .014285
  46             -.306177  -.333490   .068397   .068397
  47             1.026183   .986603  -.265422  -.265422
  48             -.573933 -1.976140   .417082   .417082
  48.1   63312  13414523   4400 5500 5500 5500 4300 5500 5500 3300    2025511202
  48.2   1 5 121 5 1 1 2 0 5        000050000500005      510 510        0 5 633 2
  49      630 2   .476492  -.664888   .014285   .014285
  50              .160209   .967340   .068397   .068397
  51              .753150 -1.893965  -.265422  -.265422
  52             -.099986  -.411624   .417082   .417082
  52.1   63012  44513552   4200 4300 5200 2200 3300 4400 4400 3300    2052505502
  52.2   0 5 5 5 5 0 5 2 0 1        000050000500005      510 510        0 5 630 2
  53      641 2  1.115232  -.459048   .014285   .014285
  54              .151831 -2.856440   .068397   .068397
  55              .890535   .717272  -.265422  -.265422
  56              .387310  -.492683   .417082   .417082
  56.1   64112  45514531   5200 5500 5500 5400 4300 4200 5300 4200    1111111151
  56.2   1 1 1 1 1 1 1 1 5 1        500005000000005      210 610        0 4 641 2
  57      648 2   .737116  -.101580   .014285   .014285
  58             1.971194 -2.471644   .068397   .068397
  59              .843773 -1.081410  -.265422  -.265422
  60             -.331782  -.075659   .417082   .417082
  60.1   64812  45315551   5300 4300 5300 4300 3300 5100 5300 5300    5555505555
  60.2   5 5 5 5 5 0 5 0 5 5        000050000500005      5201020        1 4 648 2
  61      606 1  1.502258   .285366   .014285   .014285
  62              .276648   .852606   .068397   .068397
  63             -.662242 -1.603766  -.265422  -.265422
  64            -1.774543  -.390916   .417082   .417082
  64.1   60611  55515334   5400 5400 4300 5500 3400 4400 5500 5500    2222122122
  64.2   2 5 2 2 1 1 2 2 2 2        000050500000005      1025 520       1 3 606 2
  65      708 3   .938660   .610047   .265377  -.064832
  66             1.069609  1.019436  -.376281   .770417
  67              .962290  -.429366 -1.838891 -2.819739
  68            -2.126573  -.538509  1.128937 -1.538207
  68.1   70813  55554555   5433 5543 5431 5312 1352 5534 5555 4444    4434240205
  68.2   4 4 5 4 5 4 0 2 0 5        000050005000005      151010 5       0 5 708 2
  69      685 3   .192513  1.431570   .347573   .773995
  70            -2.177122   .148485  -.243394   .604122
  71             1.230497  -.249450   .246776 -3.130398
  72             -.667893  -.431208  -.493713  -.663371
  72.1   68513  44242545   4545 4544 5452 4432 3333 3435 4444 2453    2552525225
  72.2   2 5 5 2 5 2 5 2 2 5        000050500000005      1010 5 5       2 2 685 2
  73      724 3   .700579   .142470   .014285   .014285
  74             -.797792   .015880   .068397   .068397
  75              .653202   .611585  -.265422  -.265422
  76            -1.054005 -2.439683   .417082   .417082
  76.1   72413  54555554   5400 5500 5500 5500 3200 4400 4400 4500    2005100005
  76.2   2 0 0 5 1 0 0 0 0 5               0000550000      201010 5       0 5 724 2
  77      722 3  1.111462 -1.779865   .014285   .014285
  78             1.523213   .118978   .068397   .068397
```

Appendix 5

```
Listing of LC.LOGIT.DA2 at 12:56:09 on NOV 29, 1989 for CCid=MBBA on MTSG

TROLL_MACRO_INPUT
TROLL_MACRO_INPUT
TROLL_MACRO_INPUT
 118 4 1 0 0 0 836.5 533.9 168.3 206.4 100.6 83.0 15.0 9.8 20 15  5 10 1 25
  1.708175   .705795  -.513666   .107032   .875191 -1.236122 -1.193192 -1.243467
  1.389202   .728713  -.502990 -2.601865   .220201 -1.194361  1.217011  1.621265
 120 4 1 0 0 0 836.5 533.9 168.3 206.4 100.6 83.0 15.0 9.8 15 15  5 10 1 35
  1.224104  -.107724 -1.570887   .014285   .255890   .575452  -.671547   .068397
   .677136   .962180  1.123860  -.265422 -1.418490 -1.588550 -1.135102   .417082
 125 4 1 0 0 0 836.5 533.9 168.3 206.4 100.6 83.0 15.0 9.8 25 10  7 10 0 45
  2.101663  -.329128 -1.498171 -1.371375   .376494   .584269   .602690   .571019
  1.029108   .488442  -.714634 -2.113739  -.787847   .575221  1.763217  1.718904
 128 4 0 1 0 0 836.5 533.9 168.3 206.4 100.6 83.0 15.0 9.8 20 15 10 15 1 35
  1.629072   .896922 -1.576363 -1.392860   .688224  1.342622  -.878660 -1.269770
   .621538   .696846  -.201822 -1.860204   .268301   .217296  1.274556  1.187618
 132 4 0 1 0 0 836.5 533.9 168.3 206.4 100.6 83.0 15.0 9.8 10  5  3 10 0 60
   .014285   .130705   .014285   .014285   .068397 -1.596454   .068397   .068397
  -.265422  1.369970  -.265422  -.265422   .417082   .026992   .417082   .417082
 160 4 1 0 0 0 836.5 533.9 168.3 206.4 100.6 83.0 15.0 9.8 20 15  5 10 0 45
  1.473776   .687625   .368124   .338114  -.830076   .724811   .394417   .333642
  1.172472  -.657388 -2.461666 -3.191904   .596169   .351268  -.450677   .145916
 721 3 0 1 0 0 836.5 533.9 168.3 206.4 100.6 83.0 15.0 9.8 10 10  5  5 1 35
  1.222484  1.242322  -.728098  -.420809  -.211603  -.183179  -.599134   .491488
  1.274139  1.315328   .059101 -1.319049 -2.224224  -.765017 -1.250412 -1.017785
 749 4 0 0 1 0 836.5 533.9 168.3 206.4 100.6 83.0 15.0 9.8 20 10  7 15 0 35
  1.482045 -1.108595  -.054225 -1.569288  -.162097  -.951084   .170193   .323710
  1.008568  -.460119  1.287318 -1.908187  2.419503  2.281195   .618721  -.872145
 121 4 1 0 0 0 836.5 533.9 168.3 206.4 100.6 83.0 15.0 9.8 20 10  7 10 0 45
  2.223574 -1.224228 -2.259338   .014285  1.213694  1.023984   .825842   .068397
  -.202892  -.788672   .221518  -.265422  -.277357  -.195267   .091880   .417082
 633 2 1 0 0 0 836.5 533.9 168.3 206.4 100.6 83.0 15.0 9.8  5  5 10 10 0 60
  -.091062  -.110125   .014285   .014285  -.306177  -.333490   .068397   .068397
  1.026183   .986603  -.265422  -.265422  -.573933 -1.976140   .417082   .417082
 641 2 1 0 0 0 836.5 533.9 168.3 206.4 100.6 83.0 15.0 9.8  2  6 10 10 0 45
  1.115232  -.459048   .014285   .014285   .151831 -2.856440   .068397   .068397
   .890535   .717272  -.265422  -.265422   .387310  -.492683   .417082   .417082
 606 1 0 1 0 0 836.5 533.9 168.3 206.4 100.6 83.0 15.0 9.8 10  5 25 20 1 35
  1.502258   .285366   .014285   .014285   .276648   .852606   .068397   .068397
  -.662242 -1.603766  -.265422  -.265422 -1.774543  -.390916   .417082   .417082
 708 3 0 0 0 1 836.5 533.9 168.3 206.4 100.6 83.0 15.0 9.8 15 10 10  5 0 60
   .938860   .610047   .265377  -.064832  1.069609  1.019436  -.376281   .770417
   .962290  -.429366 -1.838891 -2.819739 -2.126573  -.538509  1.128937 -1.538207
 685 3 0 1 0 0 836.5 533.9 168.3 206.4 100.6 83.0 15.0 9.8 10  5 10  5 1 25
   .192513  1.431570   .347573   .773995 -2.177122   .148485  -.243394   .604122
  1.230497  -.249450   .246776 -3.130398  -.667893  -.431208  -.493713  -.663371
 724 3 0 1 0 0 836.5 533.9 168.3 206.4 100.6 83.0 15.0 9.8 20 10 10  5 0 60
   .700579   .142470   .014285   .014285  -.797792   .015880   .068397   .068397
   .653202   .611585  -.265422  -.265422 -1.054005 -2.439683   .417082   .417082
 722 3 1 0 0 0 836.5 533.9 168.3 206.4 100.6 83.0 15.0 9.8 20 10 10  5 0 35
  1.111462 -1.779865   .014285   .014285  1.523213   .118978   .068397   .068397
  -.799103  1.010207  -.265422  -.265422  -.556989  -.256037   .417082   .417082
 167 4 1 0 0 0 836.5 533.9 168.3 206.4 100.6 83.0 15.0 9.8 15 10  5 10 1 35
  1.586001  -.707758 -1.843059 -1.535459  1.349881  1.400237  -.749103  -.523513
  1.278010  1.567000   .961227  -.616981  -.068312   .173022  -.800250  -.812757
 103 4 1 0 0 0 836.5 533.9 168.3 206.4 100.6 83.0 15.0 9.8 15 10  4  6 0 35
  1.015240  -.523693   .626124 -2.021163  1.604918  -.756287  1.725822 -1.315319
   .938827  -.922407  1.017185 -1.380157  1.425885  -.934670  1.421043  -.939439
 106 4 0 0 1 0 836.5 533.9 168.3 206.4 100.6 83.0 15.0 9.8 20 15  5 10 1 35
```

* THERE ARE 3 RECORDS PER PERSON. RECORD 1 CONTAINS THE FOLLOWING DATA: ID; ZONE; CENTRE CHOSEN; GROSS LEASEABLE AREA; MERCHANDISE CATEGORY AREA; PERCEIVED TRAVEL TIME; CHILDREN; AGE OF RESPONDENT.

RECORDS 2 AND 3 CONTAIN THE DATA ON THE FOUR IMAGE FACTORS FOR EACH OF THE FOUR CENTRES.

```
Listing of LC.LOGIT.DA2 at 12:56:09 on NOV 29, 1989 for CCid=MBBA on MTSG

  -.557463   .222755  1.036673  -.157903  -.633825   .731609  1.071694  -.181519
 -2.090551  -.973974   .859496   .304215 -1.820458  1.281640  2.366178   .016917
 111 4 0 1 0 0 836.5 533.9 168.3 206.4 100.6 83.0 15.0 9.8 15 10  5 10 1 25
 -1.435087  1.232060 -1.433076   .014285 -1.163423   .301506   .417433   .068397
 -1.603574 -1.453881  1.759308  -.265422 -1.294908   .079263   .307900   .417082
 652 2 1 0 0 0 836.5 533.9 168.3 206.4 100.6 83.0 15.0 9.8  5  5 15 10 0 45
   .755245  -.348413   .014285   .014285   .152275 -1.973849   .068397   .068397
   .993172   .969898  -.265422  -.265422 -1.031017  -.647879   .417082   .417082
 737 3 0 1 0 0 836.5 533.9 168.3 206.4 100.6 83.0 15.0 9.8 15 10 10  5 1 25
  1.340115  1.340115   .002434  -.801205  -.821024  -.821024 -1.372860 -2.000453
  1.330352  1.330352  -.135936   .175130  -.488011  -.488011  -.818907  -.914951
 713 3 1 0 0 0 836.5 533.9 168.3 206.4 100.6 83.0 15.0 9.8 10  5  3  2 1 19
  1.478430   .757866 -1.189708  -.826084  -.994634  -.965016  -.169545 -1.085932
   .625131  1.514412   .358199 -1.067049   .643585  1.289885   .592704   .592653
 678 2 1 0 0 0 836.5 533.9 168.3 206.4 100.6 83.0 15.0 9.8  3 10 25 20 0 60
  2.113789  1.647167   .014285   .707959 -1.400950 -1.836228   .068397 -2.270092
  -.607329  -.414120  -.265422  -.542940   .227293   .073829   .417082  -.116837
 734 3 1 0 0 0 836.5 533.9 168.3 206.4 100.6 83.0 15.0 9.8 15 10 10 10 0 60
   .473380  1.004228   .014285   .733339  -.059663   .814018   .068397   .602072
 -1.253742 -1.068934  -.265422 -1.122741 -1.165311 -1.034750   .417082  -.773609
 148 4 0 1 0 0 836.5 533.9 168.3 206.4 100.6 83.0 15.0 9.8 10 10  3 10 1 25
   .669038   .283798 -2.249547   .014285  -.697671   .984045  -.449301   .068397
   .897743  -.893853  1.591979  -.265422  1.677751   .475162  -.699383   .417082
 692 3 0 0 1 0 836.5 533.9 168.3 206.4 100.6 83.0 15.0 9.8 20 10 15  5 1 25
  1.361494   .635059 -1.324760 -1.983806   .375081   .341465  -.268047 -1.103994
   .772493   .846498  1.109771 -2.218375   .593190  1.851718   .883870  1.121580
 135 4 0 0 1 0 836.5 533.9 168.3 206.4 100.6 83.0 15.0 9.8 15 10  4 12 1 25
  1.624258   .919121 -1.982991 -1.846673  -.862100   .405377   .101706 -1.227314
  1.171906   .358918  1.333807   .723552  -.015707  -.138463  -.861150   .473769
 651 2 1 0 0 0 836.5 533.9 168.3 206.4 100.6 83.0 15.0 9.8  5  8 15 10 0 45
   .861976  -.125384 -2.130351 -1.996692  1.639661  2.006485 -1.029844  -.931819
  1.102766   .758915   .753881   .068112   .030926   .155336   .465679   .460244
 614 1 1 0 0 0 836.5 533.9 168.3 206.4 100.6 83.0 15.0 9.8  5  2  8  6 0 45
  2.314933  -.562010   .014285   .014285  -.614824 -1.393619   .068397   .068397
  -.454814 -1.046182  -.265422  -.265422  1.462349   .059980   .417082   .417082
 671 2 1 0 0 0 836.5 533.9 168.3 206.4 100.6 83.0 15.0 9.8  7  7 15 15 0 60
   .361428   .433871   .014285   .014285   .479460   .716984   .068397   .068397
  -.534601 [illegible]  -.265422  -.265422 -2.408273 -2.353297   .417082   .417082
 639 2 1 0 0 0 836.5 533.9 168.3 206.4 100.6 83.0 15.0 9.8 10 10 20 20 0 45
   .993678  -.071765   .014285 -1.911482  1.309860  1.742069   .068397 -1.028973
  1.296093  -.391554  -.265422 -1.609766   .030161  -.131769   .417082   .834502
 675 2 1 0 0 0 836.5 533.9 168.3 206.4 100.6 83.0 15.0 9.8  5 10 20 15 1 25
  1.022542   .247469   .014285   .014285 -1.827481  -.933084   .068397   .068397
   .314346   .888689  -.265422  -.265422 -2.377604   .626259   .417082   .417082
 131 4 0 0 1 0 836.5 533.9 168.3 206.4 100.6 83.0 15.0 9.8 15 15  5 15 1 25
  1.712897   .207290 -1.482667 -1.739475  1.212313  1.595269  1.222410  -.220375
   .236129 -1.326095   .670970 -1.070139  -.484707  -.487710   .573339   .690314
 156 4 1 0 0 0 836.5 533.9 168.3 206.4 100.6 83.0 15.0 9.8 15 10  5 15 0 25
  -.127196  -.127196 -1.965184 -1.965184  1.326491  1.326491   .706874   .706874
   .778559   .778559  1.352334  1.352334  -.887059  -.887059 -1.214022 -1.214022
 136 4 0 1 0 0 836.5 533.9 168.3 206.4 100.6 83.0 15.0 9.8 20 15  5 15 0 45
   .834853   .149459 -1.327202  -.942547  1.602085  1.840728   .395300 -1.573665
  1.415899   .520892   .682470 -2.622667  -.108183   .679977  -.206223 -1.511958
 124 4 1 0 0 0 836.5 533.9 168.3 206.4 100.6 83.0 15.0 9.8 20 10  5 15 1 35
  -.906632  -.506421  -.908968  -.937444  1.481269  1.413806  1.481585  1.785216
   .894577   .803793   .590332 -1.854179 -2.584351 -2.486535   .933145   .881779
 123 4 1 0 0 0 836.5 533.9 168.3 206.4 100.6 83.0 15.0 9.8 30 20 10 15 1 35
  1.011626  -.261625  -.560763  -.478889  1.761736   .494934   .818203 -1.590974
```

Appendix 6

```
$Log Output:                          st=MTSG, 15:20:06 Wed Nov 08/89
#run *troll par=1000k
#Execution begins   15:20:15

MTS/TROLL Version 12.1

Time:  15:20:15  .....  Date:  NOV  8, 1989.
Program parameters in effect:   1000K SYSIN110
ACCESSed users: TROLLSYS SYSLIB
TROLL: Copyright (C) 1978, 1982, 1986  Massachusetts Institute of Technology

HELLO MBBA !

& TROLL COMMAND:
do y=colcomb(m1_c3,m1_c4,m1_c5,m1_c6);   *
& DO COMMAND:
prtdata y
& NAME:
;

Y  -   DATE REVISED: 11/08/89
   408 BY 4 MATRIX

  Y = COLCOMB(M1_C3,M1_C4,M1_C5,M1_C6)
```

1	1	1.	0.	0.	0.
2	1	1.	0.	0.	0.
3	1	1.	0.	0.	0.
4	1	0.	1.	0.	0.
5	1	0.	1.	0.	0.
6	1	1.	0.	0.	0.
7	1	0.	1.	0.	0.
8	1	0.	0.	1.	0.
9	1	1.	0.	0.	0.
10	1	1.	0.	0.	0.
11	1	1.	0.	0.	0.
12	1	0.	1.	0.	0.
13	1	0.	0.	0.	1.
14	1	0.	1.	0.	0.
15	1	0.	1.	0.	0.
16	1	1.	0.	0.	0.
17	1	1.	0.	0.	0.
18	1	1.	0.	0.	0.
19	1	0.	0.	1.	0.
20	1	0.	1.	0.	0.
21	1	1.	0.	0.	0.
22	1	0.	1.	0.	0.
23	1	1.	0.	0.	0.
24	1	1.	0.	0.	0.
25	1	1.	0.	0.	0.
26	1	0.	1.	0.	0.
27	1	0.	0.	1.	0.
28	1	0.	0.	1.	0.
29	1	1.	0.	0.	0.
30	1	1.	0.	0.	0.
31	1	1.	0.	0.	0.
32	1	1.	0.	0.	0.
33	1	1.	0.	0.	0.
34	1	0.	0.	1.	0.
35	1	1.	0.	0.	0.
36	1	0.	1.	0.	0.
37	1	1.	0.	0.	0.
38	1	1.	0.	0.	0.
39	1	0.	1.	0.	0.
40	1	0.	1.	0.	0.
41	1	0.	0.	1.	0.
42	1	1.	0.	0.	0.
43	1	0.	1.	0.	0.
44	1	1.	0.	0.	0.
45	1	0.	1.	0.	0.
46	1	0.	1.	0.	0.
47	1	1.	0.	0.	0.
48	1	1.	0.	0.	0.
49	1	0.	1.	0.	0.
50	1	0.	1.	0.	0.
51	1	1.	0.	0.	0.
52	1	1.	0.	0.	0.
53	1	1.	0.	0.	0.
54	1	1.	0.	0.	0.
55	1	1.	0.	0.	0.
56	1	1.	0.	0.	0.
57	1	1.	0.	0.	0.
58	1	0.	1.	0.	0.
59	1	0.	1.	0.	0.
60	1	0.	1.	0.	0.
61	1	0.	1.	0.	0.
62	1	1.	0.	0.	0.
63	1	0.	1.	0.	0.
64	1	1.	0.	0.	0.
65	1	1.	0.	0.	0.
66	1	0.	0.	1.	0.
67	1	1.	0.	0.	0.
68	1	1.	0.	0.	0.
69	1	1.	0.	0.	0.
70	1	1.	0.	0.	0.
71	1	1.	0.	0.	0.
72	1	1.	0.	0.	0.
73	1	1.	0.	0.	0.
74	1	0.	1.	0.	0.
75	1	1.	0.	0.	0.
76	1	1.	0.	0.	0.
77	1	0.	1.	0.	0.
78	1	1.	0.	0.	0.
79	1	1.	0.	0.	0.
80	1	0.	1.	0.	0.
81	1	0.	1.	0.	0.
82	1	0.	1.	0.	0.
83	1	0.	0.	1.	0.
84	1	1.	0.	0.	0.
85	1	0.	1.	0.	0.
86	1	1.	0.	0.	0.
87	1	1.	0.	0.	0.
88	1	0.	1.	0.	0.
89	1	0.	1.	0.	0.
90	1	1.	0.	0.	0.
91	1	0.	1.	0.	0.

* COMBINES THE 4 COLUMNS OF THE DEPENDENT VARIABLE TO BE READ A 408 BY 4 MATRIX.

NOTE:- SIMILAR 'COLCOMB' WERE CONDUCTED FOR THE INDEPENDENT VARIABLES THAT MEASURED THE ATTRIBUTES OF THE CENTRES. FOR EXAMPLE GROSS LEASEABLE AREA FOR EACH OF THE FOUR CENTRES.

92	1	1.	0.	0.	0.
93	1	1.	0.	0.	0.
94	1	0.	1.	0.	0.
95	1	1.	0.	0.	0.
96	1	1.	0.	0.	0.
97	1	0.	1.	0.	0.
98	1	0.	1.	0.	0.
99	1	0.	1.	0.	0.
100	1	1.	0.	0.	0.
101	1	1.	0.	0.	0.
102	1	1.	0.	0.	0.
103	1	0.	1.	0.	0.
104	1	1.	0.	0.	0.
105	1	0.	1.	0.	0.
106	1	0.	1.	0.	0.
107	1	1.	0.	0.	0.
108	1	1.	0.	0.	0.
109	1	1.	0.	0.	0.
110	1	1.	0.	0.	0.
111	1	1.	0.	0.	0.
112	1	1.	0.	0.	0.
113	1	0.	1.	0.	0.
114	1	0.	1.	0.	0.
115	1	1.	0.	0.	0.
116	1	0.	0.	1.	0.
117	1	0.	1.	0.	0.
118	1	0.	1.	0.	0.
119	1	1.	0.	0.	0.
120	1	1.	0.	0.	0.
121	1	1.	0.	0.	0.
122	1	1.	0.	0.	0.
123	1	0.	0.	1.	0.
124	1	0.	1.	0.	0.
125	1	1.	0.	0.	0.
126	1	0.	0.	1.	0.
127	1	1.	0.	0.	0.
128	1	1.	0.	0.	0.
129	1	0.	1.	0.	0.
130	1	0.	1.	0.	0.
131	1	1.	0.	0.	0.
132	1	1.	0.	0.	0.
133	1	1.	0.	0.	0.
134	1	0.	1.	0.	0.
135	1	0.	0.	1.	0.
136	1	1.	0.	0.	0.
137	1	0.	0.	1.	0.
138	1	0.	1.	0.	0.
139	1	1.	0.	0.	0.
140	1	1.	0.	0.	0.
141	1	1.	0.	0.	0.
142	1	1.	0.	0.	0.
143	1	0.	1.	0.	0.
144	1	1.	0.	0.	0.
145	1	0.	1.	0.	0.
146	1	0.	0.	1.	0.
147	1	0.	1.	0.	0.
148	1	1.	0.	0.	0.
149	1	0.	1.	0.	0.
150	1	0.	0.	1.	0.
151	1	0.	0.	1.	0.
152	1	0.	1.	0.	0.
153	1	1.	0.	0.	0.
154	1	0.	1.	0.	0.
155	1	1.	0.	0.	0.
156	1	1.	0.	0.	0.
157	1	1.	0.	0.	0.
158	1	1.	0.	0.	0.
159	1	0.	0.	1.	0.
160	1	1.	0.	0.	0.
161	1	1.	0.	0.	0.
162	1	0.	0.	1.	0.
163	1	1.	0.	0.	0.
164	1	0.	0.	1.	0.
165	1	0.	1.	0.	0.
166	1	0.	0.	1.	0.
167	1	1.	0.	0.	0.
168	1	1.	0.	0.	0.
169	1	1.	0.	0.	0.
170	1	1.	0.	0.	0.
171	1	1.	0.	0.	0.
172	1	1.	0.	0.	0.
173	1	0.	1.	0.	0.
174	1	0.	0.	0.	1.
175	1	0.	1.	0.	0.
176	1	1.	0.	0.	0.
177	1	1.	0.	0.	0.
178	1	0.	1.	0.	0.
179	1	1.	0.	0.	0.
180	1	1.	0.	0.	0.
181	1	1.	0.	0.	0.
182	1	0.	1.	0.	0.
183	1	1.	0.	0.	0.
184	1	0.	1.	0.	0.
185	1	0.	1.	0.	0.
186	1	1.	0.	0.	0.
187	1	1.	0.	0.	0.
188	1	0.	1.	0.	0.
189	1	1.	0.	0.	0.
190	1	0.	1.	0.	0.
191	1	1.	0.	0.	0.
192	1	1.	0.	0.	0.
193	1	0.	1.	0.	0.
194	1	1.	0.	0.	0.
195	1	0.	1.	0.	0.
196	1	0.	0.	0.	1.
197	1	1.	0.	0.	0.
198	1	1.	0.	0.	0.
199	1	1.	0.	0.	0.
200	1	1.	0.	0.	0.
201	1	1.	0.	0.	0.
202	1	1.	0.	0.	0.
203	1	1.	0.	0.	0.
204	1	1.	0.	0.	0.
205	1	1.	0.	0.	0.
206	1	1.	0.	0.	0.
207	1	1.	0.	0.	0.
208	1	1.	0.	0.	0.
209	1	1.	0.	0.	0.
210	1	1.	0.	0.	0.
211	1	1.	0.	0.	0.

212	1	1.	0.	0.	0.
213	1	1.	0.	0.	0.
214	1	1.	0.	0.	0.
215	1	1.	0.	0.	0.
216	1	1.	0.	0.	0.
217	1	1.	0.	0.	0.
218	1	0.	J.	0.	0.
219	1	1.	0.	0.	0.
220	1	1.	0.	0.	0.
221	1	0.	1.	0.	0.
222	1	1.	0.	0.	0.
223	1	1.	0.	0.	0.
224	1	1.	0.	0.	0.
225	1	1.	0.	0.	0.
226	1	1.	0.	0.	0.
227	1	1.	0.	0.	0.
228	1	0.	1.	0.	0.
229	1	1.	0.	0.	0.
230	1	1.	0.	0.	0.
231	1	1.	0.	0.	0.
232	1	1.	0.	0.	0.
233	1	1.	0.	0.	0.
234	1	1.	0.	0.	0.
235	1	1.	0.	0.	0.
236	1	1.	0.	0.	0.
237	1	0.	1.	0.	0.
238	1	0.	1.	0.	0.
239	1	1.	0.	0.	0.
240	1	1.	0.	0.	0.
241	1	0.	1.	0.	0.
242	1	1.	0.	0.	0.
243	1	1.	0.	0.	0.
244	1	0.	1.	0.	0.
245	1	0.	1.	0.	0.
246	1	1.	0.	0.	0.
247	1	1.	0.	0.	0.
248	1	0.	1.	0.	0.
249	1	1.	0.	0.	0.
250	1	0.	1.	0.	0.
251	1	1.	0.	0.	0.
252	1	1.	0.	0.	0.
253	1	1.	0.	0.	0.
254	1	1.	0.	0.	0.
255	1	0.	1.	0.	0.
256	1	1.	0.	0.	0.
257	1	0.	1.	0.	0.
258	1	0.	1.	0.	0.
259	1	0.	1.	0.	0.
260	1	0.	1.	0.	0.
261	1	1.	0.	0.	0.
262	1	0.	1.	0.	0.
263	1	0.	1.	0.	0.
264	1	0.	1.	0.	0.
265	1	1.	0.	0.	0.
266	1	0.	1.	0.	0.
267	1	0.	1.	0.	0.
268	1	1.	0.	0.	0.
269	1	1.	0.	0.	0.
270	1	1.	0.	0.	0.
271	1	0.	1.	0.	0.

272	1	0.	1.	0.	0.
273	1	1.	0.	0.	0.
274	1	0.	1.	0.	0.
275	1	0.	1.	0.	0.
276	1	0.	1.	0.	0.
277	1	0.	1.	0.	0.
278	1	0.	1.	0.	0.
279	1	0.	1.	0.	0.
280	1	0.	1.	0.	0.
281	1	0.	1.	0.	0.
282	1	1.	0.	0.	0.
283	1	0.	1.	0.	0.
284	1	0.	0.	1.	0.
285	1	1.	0.	0.	0.
286	1	0.	0.	1.	0.
287	1	1.	0.	0.	0.
288	1	0.	1.	0.	0.
289	1	1.	0.	0.	0.
290	1	0.	0.	1.	0.
291	1	1.	0.	0.	0.
292	1	0.	1.	0.	0.
293	1	0.	0.	1.	0.
294	1	0.	1.	0.	0.
295	1	0.	1.	0.	0.
296	1	1.	0.	0.	0.
297	1	1.	0.	0.	0.
298	1	1.	0.	0.	0.
299	1	0.	1.	0.	0.
300	1	0.	1.	0.	0.
301	1	1.	0.	0.	0.
302	1	0.	1.	0.	0.
303	1	1.	0.	0.	0.
304	1	1.	0.	0.	0.
305	1	1.	0.	0.	0.
306	1	0.	1.	0.	0.
307	1	0.	1.	0.	0.
308	1	1.	0.	0.	0.
309	1	1.	0.	0.	0.
310	1	0.	1.	0.	0.
311	1	0.	1.	0.	0.
312	1	0.	1.	0.	0.
313	1	1.	0.	0.	0.
314	1	1.	0.	0.	0.
315	1	0.	1.	0.	0.
316	1	0.	1.	0.	0.
317	1	0.	1.	0.	0.
318	1	0.	1.	0.	0.
319	1	0.	1.	0.	0.
320	1	1.	0.	0.	0.
321	1	0.	1.	0.	0.
322	1	1.	0.	0.	0.
323	1	1.	0.	0.	0.
324	1	1.	0.	0.	0.
325	1	1.	0.	0.	0.
326	1	1.	0.	0.	0.
327	1	1.	0.	0.	0.
328	1	1.	0.	0.	0.
329	1	0.	1.	0.	0.
330	1	1.	0.	0.	0.
331	1	0.	1.	0.	0.

332	1	1.	0.	0.	0.
333	1	0.	1.	0.	0.
334	1	1.	0.	0.	0.
335	1	0.	0.	0.	1.
336	1	0.	1.	0.	0.
337	1	1.	0.	0.	0.
338	1	0.	1.	0.	0.
339	1	1.	0.	0.	0.
340	1	1.	0.	0.	0.
341	1	1.	0.	0.	0.
342	1	1.	0.	0.	0.
343	1	1.	0.	0.	0.
344	1	1.	0.	0.	0.
345	1	0.	1.	0.	0.
346	1	1.	0.	0.	0.
347	1	1.	0.	0.	0.
348	1	1.	0.	0.	0.
349	1	1.	0.	0.	0.
350	1	1.	0.	0.	0.
351	1	1.	0.	0.	0.
352	1	1.	0.	0.	0.
353	1	1.	0.	0.	0.
354	1	1.	0.	0.	0.
355	1	0.	1.	0.	0.
356	1	1.	0.	0.	0.
357	1	1.	0.	0.	0.
358	1	1.	0.	0.	0.
359	1	1.	0.	0.	0.
360	1	1.	0.	0.	0.
361	1	1.	0.	0.	0.
362	1	1.	0.	0.	0.
363	1	0.	0.	1.	0.
364	1	1.	0.	0.	0.
365	1	1.	0.	0.	0.
366	1	1.	0.	0.	0.
367	1	1.	0.	0.	0.
368	1	1.	0.	0.	0.
369	1	1.	0.	0.	0.
370	1	1.	0.	0.	0.
371	1	1.	0.	0.	0.
372	1	1.	0.	0.	0.
373	1	0.	1.	0.	0.
374	1	0.	1.	0.	0.
375	1	1.	0.	0.	0.
376	1	1.	0.	0.	0.
377	1	0.	1.	0.	0.
378	1	0.	1.	0.	0.
379	1	0.	1.	0.	0.
380	1	0.	1.	0.	0.
381	1	0.	1.	0.	0.
382	1	0.	0.	0.	1.
383	1	1.	0.	0.	0.
384	1	0.	1.	0.	0.
385	1	1.	0.	0.	0.
386	1	0.	1.	0.	0.
387	1	0.	1.	0.	0.
388	1	0.	1.	0.	0.
389	1	0.	1.	0.	0.
390	1	0.	1.	0.	0.
391	1	0.	1.	0.	0.

```
File "-OUT" has been emptied.
#r *troll par=5000k
#Execution begins   08:43:44

MTS/TROLL Version 12.1

Time:  08:43:44  .....  Date:  DEC 14, 1989.
Program parameters in effect:   5000K SYSINI10
ACCESSed users: TROLLSYS SYSLIB
TROLL: Copyright (C) 1978, 1982, 1986  Massachusetts Institute of Technology

HELLO MBBA !

& TROLL COMMAND:
 &logit ttgstt;

MULTINOMIAL LOGIT ANALYSIS---VER. 2.4 5/18/78

SEARCH LIST

DATA_TTGSTT  W
MBBA  (W)
DATA

NEW MODEL: TTGSTT
& DEPENDENT VARIABLE:
 Y;
& LOGIT COMMAND:
 addvar alt x1 x3;
& LOGIT COMMAND:
 mlest;
```

MODELS FOR LADIES CLOTHING

```
ITERATION 0,     1 F AND G EVALUATIONS,      1 H EVALUATIONS

-LN LKLHD =    565.608   ,  CONDITION NUMBER =          45.36
```

GROSS SIZE - TRAVEL TIME (TT) MODEL

```
CONVERGENCE ACHIEVED AT
ITERATION 5,     5 F AND G EVALUATIONS,      5 H EVALUATIONS

-LN LKLHD =    335.904   ,  CONDITION NUMBER =          76.75

ML.ESTIM
```

	COEF.ESTIMATE	ST.ERROR	RATIO	GRADIENT
-LN LKLHD	335.904	NA	NA	NA
X1 G.S.	0.004685	0.000344	13.6227	-64.2939
X3 TT	-0.175612	0.019367	-9.06781	1.1755

```
& LOGIT COMMAND:
 quit;
& DO COMMAND:
```

```
&logit ttistt;

MULTINOMIAL LOGIT ANALYSIS---VER. 2.4 5/18/78

SEARCH LIST

DATA_TTISTT  W
MBBA  (W)
DATA

NEW MODEL: TTISTT
& DEPENDENT VARIABLE:
 Y;
& LOGIT COMMAND:
 addvar alt x2 x3;
& LOGIT COMMAND:
 mlest;

ITERATION 0,     1 F AND G EVALUATIONS,      1 H EVALUATIONS

-LN LKLHD =    565.608   ,  CONDITION NUMBER =          6.64

CONVERGENCE ACHIEVED AT
ITERATION 6,     6 F AND G EVALUATIONS,      6 H EVALUATIONS

-LN LKLHD =    324.884   ,  CONDITION NUMBER =          7.22
```

INDIVIDUAL SIZE - TT MODEL

```
ML.ESTIM
```

	COEF.ESTIMATE	ST.ERROR	RATIO	GRADIENT
-LN LKLHD	324.884	NA	NA	NA
X2 I.S.	0.039394	0.003121	12.6212	-0.194505
X3 TT	-0.162335	0.018835	-8.61888	0.013009

```
& LOGIT COMMAND:
 quit;
& DO COMMAND:
 &logit ttgit;

MULTINOMIAL LOGIT ANALYSIS---VER. 2.4 5/18/78

SEARCH LIST

DATA_TTGIT  W
MBBA  (W)
DATA

& LOGIT COMMAND:
 Y;
INVALID LOGIT COMMAND--Y
  TYPE 'HELP' FOR LIST OF VALID COMMANDS
& LOGIT COMMAND:
```

```
quit;
& DO COMMAND:
 &logit dtgit;

MULTINOMIAL LOGIT ANALYSIS——VER. 2.4 5/18/78

SEARCH LIST

DATA_DTGIT  W
MBBA  (W)
DATA

NEW MODEL: DTGIT
& DEPENDENT VARIABLE:
 y;
& LOGIT COMMAND:
 addvar alt x1 x2 x3;
& LOGIT COMMAND:
 mlest;


ITERATION 0,      1 F AND G EVALUATIONS,      1 H EVALUATIONS
-LN LKLHD =     565.608    , CONDITION NUMBER =          43.30


CONVERGENCE ACHIEVED AT
ITERATION 6,      6 F AND G EVALUATIONS,      6 H EVALUATIONS
-LN LKLHD =     322.075    , CONDITION NUMBER =          70.17

ML.ESTIM
```

G.S.-I.S.-TT MODEL

	COEF.ESTIMATE	ST.ERROR	RATIO	GRADIENT
-LN LKLHD	322.075	NA	NA	NA
X1 G.S	0.001585	0.000669	2.33959	-1.0943
X2 I.S	0.02833	0.005537	5.11661	-0.153024
X3 TT	-0.176274	0.020321	-8.67449	0.013682

```
& LOGIT COMMAND:
 quit;
& DO COMMAND:
 &logit ttimt;

MULTINOMIAL LOGIT ANALYSIS——VER. 2.4 5/18/78

SEARCH LIST

DATA_TTIMT  W
MBBA  (W)
DATA

NEW MODEL: TTIMT
& DEPENDENT VARIABLE:
 y;
& LOGIT COMMAND:
 addvar alt x2 x3 x4 x5 x6 x7;
& LOGIT COMMAND:
 mlest;


ITERATION 0,      1 F AND G EVALUATIONS,      1 H EVALUATIONS
-LN LKLHD =     565.608    , CONDITION NUMBER =          61.75


CONVERGENCE ACHIEVED AT
ITERATION 6,      6 F AND G EVALUATIONS,      6 H EVALUATIONS
-LN LKLHD =     273.865    , CONDITION NUMBER =          40.32

ML.ESTIM
```

I.S.-IMAGE(IM)-TT MODEL

	COEF.ESTIMATE	ST.ERROR	RATIO	GRADIENT
-LN LKLHD	273.865	NA	NA	NA
X2 I.S	0.028945	0.003502	8.26589	-0.378529
X3 TT	-0.163143	0.020493	-7.9609	0.03846
X4 IMAGE FACTORS	0.659608	0.100571	6.5586	-0.005771
X5	0.618324	0.113682	5.43907	0.000439
X6	0.162257	0.100909	1.60795	-0.002826
X7	-0.153477	0.097809	-1.56915	0.002291

```
& LOGIT COMMAND:
 quit;
& DO COMMAND:
 &logit ttgmt;

MULTINOMIAL LOGIT ANALYSIS——VER. 2.4 5/18/78

SEARCH LIST

DATA_TTGMT  W
MBBA  (W)
DATA

NEW MODEL: TTGMT
& DEPENDENT VARIABLE:
 y;
& LOGIT COMMAND:
 addvar alt x1 x3 x4 x5 x6 x7;
& LOGIT COMMAND:
 mlest;


ITERATION 0,      1 F AND G EVALUATIONS,      1 H EVALUATIONS
-LN LKLHD =     565.608    , CONDITION NUMBER =         431.86
```

```
CONVERGENCE ACHIEVED AT
ITERATION 6,     6 F AND G EVALUATIONS,     6 H EVALUATIONS

-LN LKLHD =     287.183    , CONDITION NUMBER =          387.20

ML.ESTIM
```

G.S.-IM-TT MODEL 86

	COEF.ESTIMATE	ST.ERROR	RATIO	GRADIENT
-LN LKLHD	287.183	NA	NA	NA
X1	0.003253	0.000429	7.57322	-0.468097
X3	-0.166002	0.020121	-8.25016	0.009415
X4	0.634385	0.106162	5.97563	0.001003
X5	0.610034	0.109648	5.56357	0.000128
X6	0.199088	0.095983	2.0742	-0.00037
X7	-0.143631	0.094344	-1.52241	0.000398

```
& LOGIT COMMAND:
 quit;
& DO COMMAND:
 &logit ttgimt;

MULTINOMIAL LOGIT ANALYSIS---VER. 2.4 5/18/78

SEARCH LIST

DATA_TTGIMT  W
MBBA  (W)
DATA

NEW MODEL: TTGIMT
& DEPENDENT VARIABLE:
 y;
& LOGIT COMMAND:
 addvar alt x1 x2 x3 x4 x5 x6 x7;
& LOGIT COMMAND:
 mlest;

ITERATION 0,     1 F AND G EVALUATIONS,     1 H EVALUATIONS

-LN LKLHD =     565.608    , CONDITION NUMBER =          436.45

CONVERGENCE ACHIEVED AT
ITERATION 6,     6 F AND G EVALUATIONS,     6 H EVALUATIONS

-LN LKLHD =     273.81     , CONDITION NUMBER =          370.05

ML.ESTIM
```

	COEF.ESTIMATE	ST.ERROR	RATIO	GRADIENT
-LN LKLHD	273.81	NA	NA	NA
X1	-0.000267	0.000804	-0.332384	-2.03434
X2	0.030594	0.006084	5.02876	-0.292675
X3	-0.160983	0.021413	-7.51782	0.033917
X4	0.672968	0.108543	6.19999	-0.004438
X5	0.616438	0.113943	5.41004	0.000287
X6	0.164267	0.101269	1.62209	-0.002155
X7	-0.157511	0.098768	-1.59476	0.001771

GS-IS-IM-TT MODEL

```
& LOGIT COMMAND:
 quit;
& DO COMMAND:
 &logit ttimtt;

MULTINOMIAL LOGIT ANALYSIS---VER. 2.4 5/18/78

SEARCH LIST

DATA_TTIMTT  W
MBBA  (W)
DATA

NEW MODEL: TTIMTT
& DEPENDENT VARIABLE:
 y;
& LOGIT COMMAND:
 addvar x3 x4 x5 x6 x7;
 INVALID TYPE--MUST BE 'ALT', 'IND' OR 'INT'
& VARIABLE TYPE OR ';':
 alt;
& LOGIT COMMAND:
 mlest;
 WARNING 6234
 FILE CONTAINED ALL NAS
 COMBINE(NA,NA,NA)

 ERROR 6655
 LGTMLA REQUIRES BETWEEN 2 AND 50 COEFFICIENTS

& LOGIT COMMAND:
 addvar alt x3 x4 x5 x6 x7;
& LOGIT COMMAND:
 mlest'
 INVALID LOGIT COMMAND--MLEST'
   TYPE 'HELP' FOR LIST OF VALID COMMANDS
& LOGIT COMMAND:
 mlest;

ITERATION 0,     1 F AND G EVALUATIONS,     1 H EVALUATIONS

-LN LKLHD =     565.608    , CONDITION NUMBER =          8.22
```

IM-TT-MODEL

```
CONVERGENCE ACHIEVED AT
ITERATION 5,        5 F AND G EVALUATIONS,       5 H EVALUATIONS

-LN LKLHD =      321.162    ,  CONDITION NUMBER =           6.92

ML:ESTIM
```

	COEF.ESTIMATE	ST.ERROR	RATIO	GRADIENT
-LN LKLHD	321.162	NA	NA	NA
X3	-0.122512	0.014487	-8.45657	0.077923
X4	1.2027	0.091409	13.1574	-0.014385
X5	0.508119	0.101555	5.00337	-0.00683
X6	0.386138	0.089904	4.29498	-0.007364
X7	-0.313033	0.090128	-3.47322	0.000604

```
& LOGIT COMMAND:
 quit;
& DO COMMAND:
 &logit ttgimtca;

MULTINOMIAL LOGIT ANALYSIS---VER. 2.4 5/18/78

SEARCH LIST

DATA_TTGIMTCA  W
MBBA  (W)
DATA

NEW MODEL: TTGIMTCA
& DEPENDENT VARIABLE:
 y;
& LOGIT COMMAND:
 addvar alt x1 x2 x3 x4 x5 x6 x7,ind m1_c19 m1_c20;
& LOGIT COMMAND:
 mlest;


ITERATION 0,       1 F AND G EVALUATIONS,       1 H EVALUATIONS

-LN LKLHD =      565.608    ,  CONDITION NUMBER =        2355.82


CONVERGENCE ACHIEVED AT
ITERATION 7,        7 F AND G EVALUATIONS,       7 H EVALUATIONS

-LN LKLHD =      264.977    ,  CONDITION NUMBER =        5016.08

ML.ESTIM
```

	COEF.ESTIMATE	ST.ERROR	RATIO	GRADIENT
-LN LKLHD	264.977	NA	NA	NA
X1	0.002355	0.003441	0.684426	-0.005133
X2	0.011182	0.03025	0.36898	-0.000912
X3	-0.156689	0.021335	-7.34423	-2.558994E-05
X4	0.701329	0.112922	6.21075	-8.092169E-06
X5	0.565888	0.113778	4.97362	1.590987E-06
X6	0.088696	0.104587	0.848058	-1.264812E-05
X7	-0.164302	0.100416	-1.63622	4.156961E-07
M1_C19_ALT1	0.082632	0.956387	0.0864	-4.151800E-06
M1_C19_ALT2	0.883773	0.971201	0.90998	-5.438949E-06
M1_C19_ALT3	1.24247	0.905664	1.37188	-1.583588E-06
M1_C20_ALT1	0.020225	0.027333	0.739953	-0.000175
M1_C20_ALT2	0.023251	0.028548	0.814446	-0.000199
M1_C20_ALT3	0.020856	0.015454	1.34956	-4.852972E-05

ALL-MODEL

```
& LOGIT COMMAND:
 filecoef;prob;prtresult fit;

PREDICTD_CLASSIF
```

ROW	PREDICTED	ACTUAL	0=CORRECT
1	1.	1.	0.
2	1.	1.	0.
3	1.	1.	0.
4	2.	2.	0.
5	1.	2.	1.
6	2.	1.	1.
7	1.	2.	1.
8	1.	3.	1.
9	1.	1.	0.
10	1.	1.	0.
11	1.	1.	0.
12	1.	2.	1.
13	1.	4.	1.
14	2.	2.	0.
15	2.	2.	0.
16	1.	1.	0.
17	1.	1.	0.
18	1.	1.	0.
19	3.	3.	0.
20	2.	2.	0.
21	1.	1.	0.
22	2.	2.	0.
23	2.	1.	1.
24	1.	1.	0.
25	2.	1.	1.
26	2.	2.	0.
27	2.	3.	1.
28	2.	3.	1.
29	1.	1.	0.
30	1.	1.	0.
31	1.	1.	0.
32	1.	1.	0.
33	1.	1.	0.
34	1.	3.	1.
35	1.	1.	0.
36	1.	2.	1.

37	2.	1.	1.
38	3.	1.	1.
39	3.	2.	1.
40	1.	2.	1.
41	3.	3.	0.
42	2.	1.	1.
43	2.	2.	0.
44	2.	1.	1.
45	1.	2.	1.
46	2.	2.	0.
47	2.	1.	1.
48	1.	1.	0.
49	1.	2.	1.
50	2.	2.	0.
51	1.	1.	0.
52	2.	1.	1.
53	1.	1.	0.
54	1.	1.	0.
55	2.	1.	1.
56	1.	1.	0.
57	1.	1.	0.
58	2.	2.	0.
59	1.	2.	1.
60	2.	2.	0.
61	1.	2.	1.
62	1.	1.	0.
63	3.	2.	1.
64	1.	1.	0.
65	1.	1.	0.
66	2.	3.	1.
67	1.	1.	0.
68	1.	1.	0.
69	1.	1.	0.
70	1.	1.	0.
71	1.	1.	0.
72	1.	1.	0.
73	1.	1.	0.
74	2.	2.	0.
75	1.	1.	0.
76	1.	1.	0.
77	2.	2.	0.
78	1.	1.	0.
79	1.	1.	0.
80	2.	2.	0.
81	2.	2.	0.
82	2.	2.	0.
83	2.	3.	1.
84	2.	1.	1.
85	2.	2.	0.
86	2.	1.	1.
87	1.	1.	0.
88	2.	2.	0.
89	2.	2.	0.
90	1.	1.	0.
91	2.	2.	0.
92	1.	1.	0.
93	2.	1.	1.
94	2.	2.	0.
95	1.	1.	0.
96	2.	1.	1.

97	2.	2.	0.
98	2.	2.	0.
99	2.	2.	0.
100	1.	1.	0.
101	1.	1.	0.
102	1.	1.	0.
103	1.	2.	1.
104	1.	1.	0.
105	1.	2.	1.
106	1.	2.	1.
107	2.	1.	1.
108	1.	1.	0.
109	1.	1.	0.
110	1.	1.	0.
111	1.	1.	0.
112	1.	1.	0.
113	2.	2.	0.
114	1.	2.	1.
115	1.	1.	0.
116	2.	3.	1.
117	2.	2.	0.
118	2.	2.	0.
119	1.	1.	0.
120	2.	1.	1.
121	1.	1.	0.
122	2.	1.	1.
123	1.	3.	1.
124	2.	2.	0.
125	2.	1.	1.
126	3.	3.	0.
127	2.	1.	1.
128	1.	1.	0.
129	2.	2.	0.
130	2.	2.	0.
131	1.	1.	0.
132	1.	1.	0.
133	1.	1.	0.
134	2.	2.	0.
135	1.	3.	1.
136	2.	1.	1.
137	2.	3.	1.
138	1.	2.	1.
139	1.	1.	0.
140	1.	1.	0.
141	2.	1.	1.
142	1.	1.	0.
143	3.	2.	1.
144	1.	1.	0.
145	2.	2.	0.
146	2.	3.	1.
147	1.	2.	1.
148	1.	1.	0.
149	1.	2.	1.
150	1.	3.	1.
151	3.	3.	0.
152	2.	2.	0.
153	1.	1.	0.
154	2.	2.	0.
155	3.	1.	1.
156	1.	1.	0.

157	1.	1.	0.
158	1.	1.	0.
159	2.	3.	1.
160	1.	1.	0.
161	1.	1.	0.
162	2.	3.	1.
163	1.	1.	0.
164	3.	3.	0.
165	1.	2.	1.
166	1.	3.	1.
167	1.	1.	0.
168	1.	1.	0.
169	1.	1.	0.
170	1.	1.	0.
171	1.	1.	0.
172	1.	1.	0.
173	1.	2.	1.
174	1.	4.	1.
175	2.	2.	0.
176	1.	1.	0.
177	2.	1.	1.
178	2.	2.	0.
179	2.	1.	1.
180	2.	1.	1.
181	1.	1.	0.
182	2.	2.	0.
183	1.	1.	0.
184	2.	2.	0.
185	2.	2.	0.
186	2.	1.	1.
187	1.	1.	0.
188	2.	2.	0.
189	1.	1.	0.
190	2.	2.	0.
191	2.	1.	1.
192	2.	1.	1.
193	1.	2.	1.
194	1.	1.	0.
195	1.	2.	1.
196	1.	4.	1.
197	1.	1.	0.
198	1.	1.	0.
199	2.	1.	1.
200	1.	1.	0.
201	1.	1.	0.
202	1.	1.	0.
203	1.	1.	0.
204	1.	1.	0.
205	1.	1.	0.
206	1.	1.	0.
207	1.	1.	0.
208	1.	1.	0.
209	1.	1.	0.
210	1.	1.	0.
211	1.	1.	0.
212	1.	1.	0.
213	1.	1.	0.
214	1.	1.	0.
215	1.	1.	0.
216	1.	1.	0.

217	1.	1.	0.
218	2.	2.	0.
219	1.	1.	0.
220	1.	1.	0.
221	1.	2.	1.
222	1.	1.	0.
223	1.	1.	0.
224	1.	1.	0.
225	1.	1.	0.
226	1.	1.	0.
227	1.	1.	0.
228	1.	2.	1.
229	1.	1.	0.
230	1.	1.	0.
231	1.	1.	0.
232	1.	1.	0.
233	1.	1.	0.
234	1.	1.	0.
235	1.	1.	0.
236	1.	1.	0.
237	2.	2.	0.
238	1.	2.	1.
239	1.	1.	0.
240	1.	1.	0.
241	1.	2.	1.
242	1.	1.	0.
243	1.	1.	0.
244	1.	2.	1.
245	2.	2.	0.
246	1.	1.	0.
247	1.	1.	0.
248	2.	2.	0.
249	1.	1.	0.
250	1.	2.	1.
251	1.	1.	0.
252	1.	1.	0.
253	1.	1.	0.
254	1.	1.	0.
255	2.	2.	0.
256	1.	1.	0.
257	2.	2.	0.
258	2.	2.	0.
259	2.	2.	0.
260	1.	2.	1.
261	1.	1.	0.
262	1.	2.	1.
263	2.	2.	0.
264	1.	2.	1.
265	1.	1.	0.
266	2.	2.	0.
267	2.	2.	0.
268	1.	1.	0.
269	1.	1.	0.
270	1.	1.	0.
271	1.	2.	1.
272	1.	2.	1.
273	1.	1.	0.
274	2.	2.	0.
275	2.	2.	0.
276	2.	2.	0.

277	1.	2.	1.
278	2.	2.	0.
279	2.	2.	0.
280	2.	2.	0.
281	1.	2.	1.
282	1.	1.	0.
283	2.	2.	0.
284	2.	3.	1.
285	1.	1.	0.
286	3.	3.	0.
287	1.	1.	0.
288	3.	2.	1.
289	3.	1.	1.
290	1.	3.	1.
291	2.	1.	1.
292	2.	2.	0.
293	3.	3.	0.
294	1.	2.	1.
295	2.	2.	0.
296	1.	1.	0.
297	1.	1.	0.
298	1.	1.	0.
299	2.	2.	0.
300	2.	2.	0.
301	1.	1.	0.
302	1.	2.	1.
303	1.	1.	0.
304	1.	1.	0.
305	1.	1.	0.
306	1.	2.	1.
307	1.	2.	1.
308	1.	1.	0.
309	1.	1.	0.
310	2.	2.	0.
311	1.	2.	1.
312	2.	2.	0.
313	1.	1.	0.
314	2.	1.	1.
315	2.	2.	0.
316	2.	2.	0.
317	2.	2.	0.
318	2.	2.	0.
319	1.	2.	1.
320	1.	1.	0.
321	1.	2.	1.
322	1.	1.	0.
323	1.	1.	0.
324	1.	1.	0.
325	1.	1.	0.
326	1.	1.	0.
327	1.	1.	0.
328	1.	1.	0.
329	1.	2.	1.
330	2.	1.	1.
331	2.	2.	0.
332	1.	1.	0.
333	2.	2.	0.
334	1.	1.	0.
335	1.	4.	1.
336	2.	2.	0.
337	2.	1.	1.
338	1.	2.	1.
339	1.	1.	0.
340	1.	1.	0.
341	1.	1.	0.
342	1.	1.	0.
343	1.	1.	0.
344	1.	1.	0.
345	1.	2.	1.
346	1.	1.	0.
347	1.	1.	0.
348	1.	1.	0.
349	1.	1.	0.
350	1.	1.	0.
351	1.	1.	0.
352	1.	1.	0.
353	1.	1.	0.
354	1.	1.	0.
355	1.	2.	1.
356	1.	1.	0.
357	1.	1.	0.
358	1.	1.	0.
359	1.	1.	0.
360	1.	1.	0.
361	1.	1.	0.
362	1.	1.	0.
363	3.	3.	0.
364	1.	1.	0.
365	1.	1.	0.
366	1.	1.	0.
367	1.	1.	0.
368	1.	1.	0.
369	1.	1.	0.
370	1.	1.	0.
371	1.	1.	0.
372	1.	1.	0.
373	2.	2.	0.
374	2.	2.	0.
375	1.	1.	0.
376	1.	1.	0.
377	1.	2.	1.
378	2.	2.	0.
379	2.	2.	0.
380	2.	2.	0.
381	1.	2.	1.
382	1.	4.	1.
383	2.	1.	1.
384	2.	2.	0.
385	2.	1.	1.
386	2.	2.	0.
387	2.	2.	0.
388	1.	2.	1.
389	2.	2.	0.
390	2.	2.	0.
391	1.	2.	1.
392	1.	1.	0.
393	2.	2.	0.
394	2.	2.	0.
395	1.	1.	0.
396	2.	2.	0.

397	2.	2.	0.
398	2.	2.	0.
399	1.	2.	1.
400	2.	2.	0.
401	1.	1.	0.
402	2.	1.	1.
403	2.	2.	0.
404	2.	2.	0.
405	1.	2.	1.
406	1.	1.	0.
407	1.	1.	0.
408	2.	2.	0.

CROSSTAB_ACTUAL_VS_PREDICT

	PRED.—TOTAL	ALT.1	ALT.2	ALT.3	ALT.4
ACTUAL-TOTAL	408.	258.	135.	15.	0.
ALT.1	233.	196.	34.	3.	0.
ALT.2	145.	50.	91.	4.	0.
ALT.3	25.	7.	10.	8.	0.
ALT.4	5.	5.	0.	0.	0.

```
& LOGIT COMMAND:
 quit;
& DO COMMAND:
 mts;
#con *print* onesided package=loose
#*PRINT* assigned job number 85482
#*PRINT* RM085482 held
#copy -out *print*
```

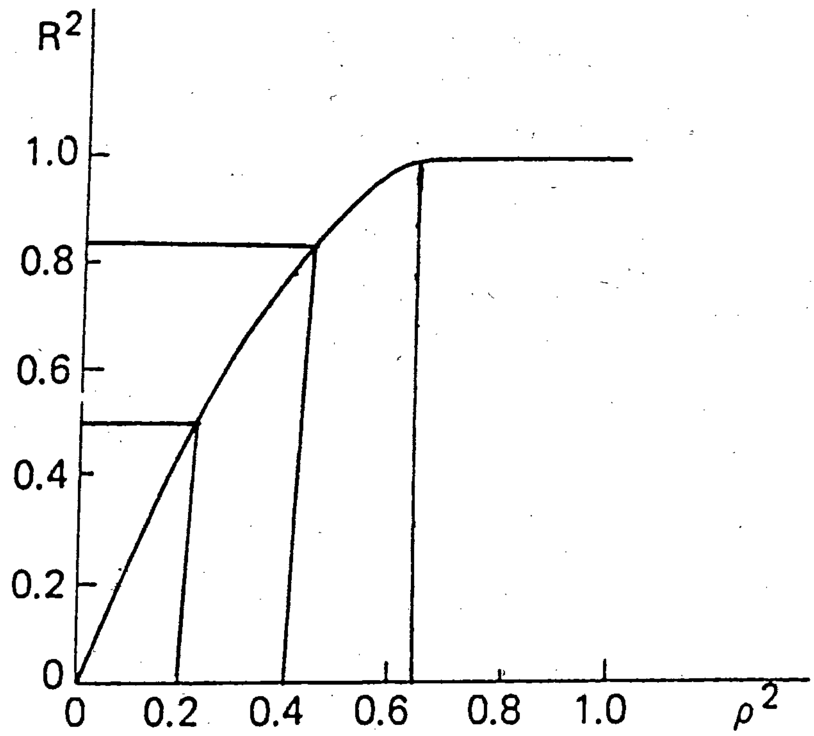
$$\% \text{ CORRECT} = \frac{196}{408} + \frac{91}{408} + \frac{8}{408} + \frac{0}{408} = 72.39\%$$

$$\% \text{ BY CHANCE} = \left(\frac{233}{408}\right)^2 + \left(\frac{145}{408}\right)^2 + \left(\frac{25}{408}\right)^2 + \left(\frac{5}{408}\right)^2$$

$$= .33 + .13 + .003 + .000 = 46\%$$

% CORRECT FOR EACH SHOPPING CENTRE $= S_1 = 84;\ S_2 = 63;\ S_3 = 32;\ S_4 = 0$

Appendix 8



SOURCE: DOMENCICH AND McFADDEN (1975)

$$\rho^2 = 1 - \frac{(\text{Ln LIKELIHOOD AT MAX. LIKELIHOOD VALUES OF } \beta)}{(\text{Ln LIKELIHOOD AT } \beta = 0)}$$

```
$Log Output: DJ Sandhu, MBBA, Job#=3450, Host=MTSG, 16:23:01 Fri Dec 08/89
#r *troll par=5000k
#Execution begins   16:23:19

 MTS/TROLL Version 12.1

 Time:  16:23:20  .....  Date:  DEC  8, 1989.
 Program parameters in effect:   5000K SYSINI10
 ACCESSed users: TROLLSYS SYSLIB
 TROLL: Copyright (C) 1978, 1982, 1986  Massachusetts Institute of Technology

 HELLO MBBA !

& TROLL COMMAND:
 &logit reoall;

 MULTINOMIAL LOGIT ANALYSIS---VER. 2.4 5/18/78

 SEARCH LIST

 DATA_REOALL  W
 MBBA  (W)
 DATA

 NEW MODEL: REOALL
& DEPENDENT VARIABLE:
 gy;
& LOGIT COMMAND:
 addvar alt gx1 gx3;
& LOGIT COMMAND:
 mlest;


 ITERATION 0,      1 F AND G EVALUATIONS,      1 H EVALUATIONS

 -LN LKLHD =     476.885   ,  CONDITION NUMBER =          44.82


 CONVERGENCE ACHIEVED AT
 ITERATION 5,      5 F AND G EVALUATIONS,      5 H EVALUATIONS

 -LN LKLHD =     303.222   ,  CONDITION NUMBER =          78.50

 ML.ESTIM
```

	COEF.ESTIMATE	ST.ERROR	RATIO	GRADIENT
-LN LKLHD	303.222	NA	NA	NA
GX1	0.003159	0.00033	9.58098	-53.8098
GX3	-0.224315	0.021247	-10.5577	1.25266

```
& LOGIT COMMAND:
 filecoef;prob;prtresult fit;
```

PREDICTD_CLASSIF

ROW	PREDICTED	ACTUAL	0=CORRECT
1	3.	1.	1.
2	2.	2.	0.
3	3.	1.	1.
4	2.	2.	0.
5	3.	3.	0.
6	2.	1.	1.
7	4.	1.	1.
8	1.	1.	0.
9	1.	1.	0.
10	2.	2.	0.
11	4.	1.	1.
12	2.	1.	1.
13	3.	3.	0.
14	2.	3.	1.
15	1.	1.	0.
16	2.	2.	0.
17	1.	1.	0.
18	2.	1.	1.
19	1.	2.	1.
20	3.	2.	1.
21	1.	1.	0.
22	1.	2.	1.
23	1.	1.	0.
24	1.	1.	0.
25	3.	3.	0.
26	3.	2.	1.
27	2.	4.	1.
28	3.	3.	0.
29	2.	2.	0.
30	3.	3.	0.
31	2.	2.	0.
32	2.	2.	0.
33	2.	3.	1.
34	2.	2.	0.
35	2.	3.	1.
36	2.	2.	0.
37	1.	1.	0.
38	1.	1.	0.
39	2.	3.	1.
40	3.	1.	1.
41	1.	2.	1.
42	1.	1.	0.
43	1.	2.	1.
44	1.	2.	1.
45	1.	1.	0.
46	2.	2.	0.
47	1.	1.	0.
48	2.	1.	1.
49	1.	1.	0.
50	2.	2.	0.
51	1.	1.	0.
52	1.	1.	0.
53	2.	2.	0.
54	2.	2.	0.

55	4.	3.	1.
56	1.	2.	1.
57	4.	2.	1.
58	2.	4.	1.
59	1.	1.	0.
60	1.	2.	1.
61	2.	3.	1.
62	1.	2.	1.
63	2.	3.	1.
64	2.	2.	0.
65	2.	3.	1.
66	1.	1.	0.
67	1.	1.	0.
68	1.	1.	0.
69	1.	2.	1.
70	1.	1.	0.
71	1.	1.	0.
72	1.	2.	1.
73	1.	1.	0.
74	1.	1.	0.
75	1.	1.	0.
76	1.	1.	0.
77	1.	1.	0.
78	1.	1.	0.
79	2.	1.	1.
80	4.	2.	1.
81	2.	2.	0.
82	4.	3.	1.
83	2.	2.	0.
84	4.	2.	1.
85	1.	3.	1.
86	2.	1.	1.
87	2.	3.	1.
88	1.	2.	1.
89	3.	3.	0.
90	2.	2.	0.
91	3.	2.	1.
92	1.	1.	0.
93	1.	3.	1.
94	1.	1.	0.
95	3.	3.	0.
96	2.	1.	1.
97	1.	3.	1.
98	1.	3.	1.
99	1.	3.	1.
100	1.	1.	0.
101	1.	2.	1.
102	1.	1.	0.
103	2.	3.	1.
104	2.	2.	0.
105	1.	3.	1.
106	1.	1.	0.
107	2.	3.	1.
108	2.	3.	1.
109	3.	2.	1.
110	2.	3.	1.
111	2.	3.	1.
112	1.	3.	1.
113	2.	3.	1.
114	4.	3.	1.

115	1.	3.	1.
116	1.	2.	1.
117	1.	1.	0.
118	1.	3.	1.
119	1.	3.	1.
120	1.	1.	0.
121	4.	3.	1.
122	1.	3.	1.
123	2.	3.	1.
124	4.	3.	1.
125	3.	3.	0.
126	2.	3.	1.
127	1.	3.	1.
128	3.	1.	1.
129	4.	3.	1.
130	2.	1.	1.
131	2.	2.	0.
132	1.	4.	1.
133	2.	2.	0.
134	2.	1.	1.
135	1.	2.	1.
136	2.	2.	0.
137	2.	2.	0.
138	2.	1.	1.
139	2.	2.	0.
140	2.	1.	1.
141	2.	1.	1.
142	2.	2.	0.
143	2.	2.	0.
144	2.	1.	1.
145	2.	1.	1.
146	2.	2.	0.
147	2.	4.	1.
148	2.	2.	0.
149	1.	2.	1.
150	4.	1.	1.
151	4.	4.	0.
152	1.	1.	0.
153	1.	1.	0.
154	1.	1.	0.
155	1.	1.	0.
156	1.	1.	0.
157	1.	1.	0.
158	1.	2.	1.
159	1.	1.	0.
160	1.	1.	0.
161	1.	1.	0.
162	1.	1.	0.
163	1.	1.	0.
164	1.	1.	0.
165	1.	1.	0.
166	1.	1.	0.
167	1.	1.	0.
168	1.	1.	0.
169	1.	1.	0.
170	1.	1.	0.
171	1.	1.	0.
172	1.	1.	0.
173	1.	2.	1.
174	1.	1.	0.

175	1.	1.	0.
176	1.	1.	0.
177	1.	1.	0.
178	1.	1.	0.
179	1.	2.	1.
180	1.	2.	1.
181	1.	1.	0.
182	1.	1.	0.
183	1.	1.	0.
184	2.	1.	1.
185	2.	2.	0.
186	2.	2.	0.
187	1.	1.	0.
188	1.	1.	0.
189	1.	1.	0.
190	2.	1.	1.
191	1.	2.	1.
192	2.	2.	0.
193	1.	1.	0.
194	2.	2.	0.
195	1.	1.	0.
196	2.	2.	0.
197	1.	1.	0.
198	2.	2.	0.
199	1.	1.	0.
200	1.	1.	0.
201	1.	2.	1.
202	1.	1.	0.
203	1.	1.	0.
204	1.	1.	0.
205	2.	2.	0.
206	2.	2.	0.
207	2.	2.	0.
208	1.	2.	1.
209	1.	2.	1.
210	1.	2.	1.
211	2.	2.	0.
212	1.	1.	0.
213	1.	1.	0.
214	2.	2.	0.
215	1.	2.	1.
216	2.	1.	1.
217	2.	1.	1.
218	2.	2.	0.
219	2.	2.	0.
220	2.	2.	0.
221	2.	2.	0.
222	4.	2.	1.
223	1.	3.	1.
224	2.	2.	0.
225	1.	2.	1.
226	2.	2.	0.
227	1.	2.	1.
228	4.	3.	1.
229	3.	2.	1.
230	2.	3.	1.
231	3.	3.	0.
232	3.	3.	0.
233	3.	4.	1.
234	2.	2.	0.
235	3.	1.	1.
236	3.	3.	0.
237	3.	3.	0.
238	3.	2.	1.
239	3.	3.	0.
240	3.	3.	0.
241	3.	2.	1.
242	3.	1.	1.
243	1.	1.	0.
244	1.	2.	1.
245	2.	2.	0.
246	3.	3.	0.
247	2.	1.	1.
248	2.	1.	1.
249	2.	1.	1.
250	1.	1.	0.
251	1.	2.	1.
252	1.	1.	0.
253	1.	1.	0.
254	2.	2.	0.
255	1.	1.	0.
256	1.	2.	1.
257	1.	2.	1.
258	1.	1.	0.
259	2.	2.	0.
260	2.	2.	0.
261	4.	3.	1.
262	4.	2.	1.
263	4.	4.	0.
264	1.	2.	1.
265	1.	1.	0.
266	1.	1.	0.
267	1.	1.	0.
268	1.	1.	0.
269	1.	1.	0.
270	1.	1.	0.
271	1.	1.	0.
272	1.	1.	0.
273	4.	2.	1.
274	4.	2.	1.
275	2.	1.	1.
276	4.	2.	1.
277	4.	1.	1.
278	4.	2.	1.
279	1.	1.	0.
280	1.	1.	0.
281	1.	1.	0.
282	1.	1.	0.
283	1.	1.	0.
284	1.	1.	0.
285	1.	1.	0.
286	1.	1.	0.
287	1.	2.	1.
288	1.	1.	0.
289	1.	1.	0.
290	1.	1.	0.
291	1.	1.	0.
292	1.	1.	0.
293	1.	1.	0.
294	1.	1.	0.

295	1.	1.	0.
296	1.	1.	0.
297	1.	1.	0.
298	1.	1.	0.
299	1.	1.	0.
300	1.	1.	0.
301	1.	1.	0.
302	1.	1.	0.
303	1.	1.	0.
304	3.	3.	0.
305	3.	3.	0.
306	2.	3.	1.
307	1.	1.	0.
308	1.	1.	0.
309	1.	1.	0.
310	1.	1.	0.
311	1.	2.	1.
312	1.	1.	0.
313	1.	1.	0.
314	1.	1.	0.
315	4.	2.	1.
316	4.	2.	1.
317	1.	1.	0.
318	2.	2.	0.
319	2.	2.	0.
320	4.	2.	1.
321	2.	2.	0.
322	4.	1.	1.
323	2.	2.	0.
324	1.	2.	1.
325	2.	2.	0.
326	2.	2.	0.
327	1.	1.	0.
328	2.	2.	0.
329	1.	2.	1.
330	1.	1.	0.
331	2.	1.	1.
332	1.	2.	1.
333	2.	1.	1.
334	1.	2.	1.
335	2.	2.	0.
336	1.	2.	1.
337	2.	2.	0.
338	2.	1.	1.
339	2.	2.	0.
340	2.	2.	0.
341	2.	2.	0.
342	4.	1.	1.
343	2.	1.	1.
344	4.	3.	1.

CROSSTAB_ACTUAL_VS_PREDICT

	PRED.—TOTAL	ALT.1	ALT.2	ALT.3	ALT.4
ACTUAL-TOTAL	344.	176.	108.	31.	29.
ALT.1	161.	123.	26.	6.	6.
ALT.2	119.	39.	61.	7.	12.
ALT.3	57.	13.	18.	17.	9.
ALT.4	7.	1.	3.	1.	2.

MODEL I

* % CORRECT = 59%

% BY CHANCE = 36.5%

% CORRECT FOR EACH CENTRE = $S_1 = 76$; $S_2 = 51$; $S_3 = 30$; $S_4 = 29$

```
& LOGIT COMMAND:
quit;
& DO COMMAND:
&logit reosub;

MULTINOMIAL LOGIT ANALYSIS---VER. 2.4 5/18/78

SEARCH LIST

DATA_REOSUB  W
MBBA  (W)
DATA

NEW MODEL: REOSUB
& DEPENDENT VARIABLE:
yy1;
& LOGIT COMMAND:
addvar alt ex1 ex3;
& LOGIT COMMAND:
mlest;


ITERATION 0,      1 F AND G EVALUATIONS,      1 H EVALUATIONS
-LN LKLHD =    238.443   , CONDITION NUMBER =        42.81


CONVERGENCE ACHIEVED AT
ITERATION 5,      5 F AND G EVALUATIONS,      5 H EVALUATIONS
-LN LKLHD =    157.634   , CONDITION NUMBER =        69.73
```

ML.ESTIM

	COEF.ESTIMATE	ST.ERROR	RATIO	GRADIENT
-LN LKLHD	157.634	NA	NA	NA
EX1	0.002449	0.000422	5.80917	-13.5046
EX3	-0.205755	0.026478	-7.7708	0.34118

```
& LOGIT COMMAND:
 savecoef mycoef;
& LOGIT COMMAND:
 filecoef;prob;prtresult fit;
```

PREDICTD_CLASSIF

ROW	PREDICTED	ACTUAL	0=CORRECT
1	3.	1.	1.
2	3.	1.	1.
3	3.	3.	0.
4	4.	1.	1.
5	1.	1.	0.
6	4.	1.	1.
7	3.	3.	0.
8	1.	1.	0.
9	1.	1.	0.
10	1.	2.	1.
11	1.	1.	0.
12	1.	1.	0.
13	3.	3.	0.
14	3.	4.	1.
15	3.	2.	1.
16	3.	2.	1.
17	3.	3.	0.
18	3.	3.	0.
19	1.	1.	0.
20	3.	3.	0.
21	1.	2.	1.
22	1.	2.	1.
23	1.	1.	0.
24	1.	1.	0.
25	1.	1.	0.
26	1.	1.	0.
27	2.	2.	0.
28	4.	3.	1.
29	4.	2.	1.
30	1.	1.	0.
31	3.	3.	0.
32	3.	3.	0.
33	3.	3.	0.
34	1.	1.	0.
35	1.	2.	1.
36	1.	1.	0.
37	2.	1.	1.
38	1.	1.	0.
39	1.	1.	0.
40	2.	1.	1.
41	2.	2.	0.
42	2.	2.	0.
43	1.	3.	1.
44	2.	3.	1.
45	3.	3.	0.
46	3.	2.	1.
47	3.	3.	0.
48	3.	3.	0.
49	1.	3.	1.
50	1.	3.	1.
51	1.	2.	1.
52	3.	3.	0.
53	1.	3.	1.
54	3.	3.	0.
55	3.	2.	1.
56	3.	3.	0.
57	2.	3.	1.
58	3.	3.	0.
59	1.	1.	0.
60	1.	3.	1.
61	4.	3.	1.
62	2.	3.	1.
63	3.	3.	0.
64	1.	3.	1.
65	4.	3.	1.
66	2.	2.	0.
67	2.	2.	0.
68	1.	2.	1.
69	2.	2.	0.
70	2.	2.	0.
71	2.	1.	1.
72	2.	2.	0.
73	2.	1.	1.
74	2.	4.	1.
75	1.	2.	1.
76	4.	4.	0.
77	1.	1.	0.
78	1.	1.	0.
79	1.	1.	0.
80	1.	1.	0.
81	1.	1.	0.
82	1.	1.	0.
83	1.	1.	0.
84	1.	1.	0.
85	1.	1.	0.
86	1.	1.	0.
87	1.	2.	1.
88	1.	1.	0.
89	1.	1.	0.
90	1.	2.	1.
91	1.	1.	0.
92	1.	1.	0.
93	2.	2.	0.
94	1.	1.	0.
95	1.	1.	0.
96	1.	2.	1.
97	1.	1.	0.
98	1.	1.	0.
99	1.	1.	0.
100	1.	1.	0.
101	1.	2.	1.
102	1.	1.	0.
103	2.	2.	0.
104	2.	2.	0.
105	1.	2.	1.
106	2.	2.	0.
107	1.	1.	0.
108	1.	2.	1.

109	2.	1.	1.
110	2.	2.	0.
111	2.	2.	0.
112	1.	3.	1.
113	1.	2.	1.
114	1.	2.	1.
115	3.	2.	1.
116	3.	3.	0.
117	3.	4.	1.
118	3.	1.	1.
119	3.	3.	0.
120	3.	3.	0.
121	3.	2.	1.
122	1.	1.	0.
123	2.	2.	0.
124	2.	1.	1.
125	2.	1.	1.
126	1.	2.	1.
127	1.	1.	0.
128	1.	1.	0.
129	1.	2.	1.
130	2.	2.	0.
131	4.	3.	1.
132	4.	4.	0.
133	1.	1.	0.
134	1.	1.	0.
135	1.	1.	0.
136	1.	1.	0.
137	4.	2.	1.
138	2.	1.	1.
139	4.	1.	1.
140	1.	1.	0.
141	1.	1.	0.
142	1.	1.	0.
143	1.	1.	0.
144	1.	2.	1.
145	1.	1.	0.
146	1.	1.	0.
147	1.	1.	0.
148	1.	1.	0.
149	1.	1.	0.
150	1.	1.	0.
151	1.	1.	0.
152	1.	1.	0.
153	3.	3.	0.
154	1.	1.	0.
155	1.	1.	0.
156	1.	2.	1.
157	1.	1.	0.
158	4.	2.	1.
159	1.	1.	0.
160	2.	2.	0.
161	2.	2.	0.
162	2.	2.	0.
163	2.	2.	0.
164	1.	1.	0.
165	1.	2.	1.
166	2.	1.	1.
167	2.	1.	1.
168	2.	2.	0.

169	2.	2.	0.
170	2.	2.	0.
171	2.	2.	0.
172	2.	1.	1.

CROSSTAB_ACTUAL_VS_PREDICT

MODEL 2

	PRED.—TOTAL	ALT.1	ALT.2	ALT.3	ALT.4
ACTUAL-TOTAL	172.	89.	39.	32.	12.
ALT.1	79.	62.	11.	3.	3.
ALT.2	53.	20.	24.	6.	3.
ALT.3	35.	7.	3.	21.	4.
ALT.4	5.	0.	1.	2.	2.

*

% CORRECT = 63%

% BY CHANCE = 37%

% CORRECT FOR EACH CENTRE = $S_1 = 78$; $S_2 = 45$; $S_3 = 60$; $S_4 = 40$.

```
& LOGIT COMMAND:
 quit;
& DO COMMAND:
 &logit reoxval;

 MULTINOMIAL LOGIT ANALYSIS---VER. 2.4 5/18/78

 SEARCH LIST

 DATA_REOXVAL  W
 MBBA  (W)
 DATA

 NEW MODEL: REOXVAL
& DEPENDENT VARIABLE:
 yy2;
& LOGIT COMMAND:
 addvar alt ex21 ex23;
& LOGIT COMMAND:
 setcoef use mycoef;
& LOGIT COMMAND:
 filecoef;
 ERROR 6013
 LABEL FILE NOT FOUND:
 REOXVAL_ML.ESTIM

& LOGIT COMMAND:
 prob;
& LOGIT COMMAND:
 prtresult fit;
```

NOTE:- NO INFORMATION IS MISSING HERE. ITS JUST A BLANK PAGE — SO NO NEED TO PANIC!

```
& LOGIT COMMAND:
 mlest;

 ITERATION 0,       1 F AND G EVALUATIONS,       1 H EVALUATIONS
 -LN LKLHD =     238.443    ,  CONDITION NUMBER =          47.20

 CONVERGENCE ACHIEVED AT
 ITERATION 6,       6 F AND G EVALUATIONS,       6 H EVALUATIONS
 -LN LKLHD =     142.738  , ,  CONDITION NUMBER =          92.46

 ML.ESTIM
```

	COEF.ESTIMATE	ST.ERROR	RATIO	GRADIENT
-LN LKLHD	142.738	NA	NA	NA
EX21	0.004059	0.000549	7.38791	-0.570757
EX23	-0.258812	0.036212	-7.14711	0.011638

```
& LOGIT COMMAND:
 filecoef;prob;prtresult fit;

 PREDICTD_CLASSIF
```

ROW	PREDICTED	ACTUAL	0=CORRECT

1	3.	1.	1.
2	3.	1.	1.
3	3.	3.	0.
4	4.	1.	1.
5	1.	1.	0.
6	4.	1.	1.
7	3.	3.	0.
8	1.	1.	0.
9	1.	1.	0.
10	1.	2.	1.
11	1.	1.	0.
12	1.	1.	0.
13	3.	3.	0.
14	3.	4.	1.
15	3.	2.	1.
16	3.	2.	1.
17	3.	3.	0.
18	3.	3.	0.
19	1.	1.	0.
20	3.	3.	0.
21	1.	2.	1.
22	1.	2.	1.
23	1.	1.	0.
24	1.	1.	0.
25	1.	1.	0.
26	1.	1.	0.
27	2.	2.	0.
28	4.	3.	1.
29	4.	2.	1.
30	1.	1.	0.
31	3.	3.	0.
32	3.	3.	0.
33	3.	3.	0.
34	1.	1.	0.
35	1.	2.	1.
36	1.	1.	0.
37	2.	1.	1.
38	1.	1.	0.
39	1.	1.	0.
40	2.	1.	1.
41	2.	2.	0.
42	2.	2.	0.
43	1.	3.	1.
44	2.	3.	1.
45	3.	3.	0.
46	3.	2.	1.
47	3.	3.	0.
48	3.	3.	0.
49	1.	3.	1.
50	1.	3.	1.
51	1.	2.	1.
52	3.	3.	0.
53	1.	3.	1.
54	3.	3.	0.
55	3.	2.	1.
56	3.	3.	0.
57	2.	3.	1.
58	3.	3.	0.
59	1.	1.	0.
60	1.	3.	1.
61	4.	3.	1.
62	2.	3.	1.
63	3.	3.	0.
64	1.	3.	1.
65	4.	3.	1.
66	2.	2.	0.
67	2.	2.	0.
68	1.	2.	1.
69	2.	2.	0.
70	2.	2.	0.
71	2.	1.	1.
72	2.	2.	0.
73	2.	1.	1.
74	2.	4.	1.
75	1.	2.	1.
76	4.	4.	0.
77	1.	1.	0.
78	1.	1.	0.
79	1.	1.	0.
80	1.	1.	0.
81	1.	1.	0.
82	1.	1.	0.
83	1.	1.	0.
84	1.	1.	0.
85	1.	1.	0.
86	1.	1.	0.
87	1.	2.	1.
88	1.	1.	0.
89	1.	1.	0.
90	1.	2.	1.
91	1.	1.	0.
92	1.	1.	0.
93	2.	2.	0.
94	1.	1.	0.
95	1.	1.	0.
96	1.	2.	1.
97	1.	1.	0.
98	1.	1.	0.
99	1.	1.	0.
100	1.	1.	0.
101	1.	2.	1.
102	1.	1.	0.
103	2.	2.	0.
104	2.	2.	0.
105	1.	2.	1.
106	2.	2.	0.
107	1.	1.	0.
108	1.	2.	1.
109	2.	1.	1.
110	2.	2.	0.
111	2.	2.	0.
112	1.	3.	1.
113	1.	2.	1.
114	1.	2.	1.
115	3.	2.	1.
116	3.	3.	0.
117	3.	4.	1.
118	3.	1.	1.
119	3.	3.	0.
120	3.	3.	0.

121	3.	2.	1.
122	1.	1.	0.
123	2.	2.	0.
124	2.	1.	1.
125	2.	1.	1.
126	1.	2.	1.
127	1.	1.	0.
128	1.	1.	0.
129	1.	2.	1.
130	2.	2.	0.
131	4.	3.	1.
132	4.	4.	0.
133	1.	1.	0.
134	1.	1.	0.
135	1.	1.	0.
136	1.	1.	0.
137	4.	2.	1.
138	2.	1.	1.
139	4.	1.	1.
140	1.	1.	0.
141	1.	1.	0.
142	1.	1.	0.
143	1.	1.	0.
144	1.	2.	1.
145	1.	1.	0.
146	1.	1.	0.
147	1.	1.	0.
148	1.	1.	0.
149	1.	1.	0.
150	1.	1.	0.
151	1.	1.	0.
152	1.	1.	0.
153	3.	3.	0.
154	1.	1.	0.
155	1.	1.	0.
156	1.	2.	1.
157	1.	1.	0.
158	4.	2.	1.
159	1.	1.	0.
160	2.	2.	0.
161	2.	2.	0.
162	2.	2.	0.
163	2.	2.	0.
164	1.	1.	0.
165	1.	2.	1.
166	2.	1.	1.
167	2.	1.	1.
168	2.	2.	0.
169	2.	2.	0.
170	2.	2.	0.
171	2.	2.	0.
172	2.	1.	1.

CROSSTAB_ACTUAL_VS_PREDICT

	PRED.—TOTAL	ALT.1	ALT.2	ALT.3	ALT.4
ACTUAL-TOTAL	172.	89.	39.	32.	12.
ALT.1	79.	62.	11.	3.	3.
ALT.2	53.	20.	24.	6.	3.
ALT.3	35.	7.	3.	21.	4.
ALT.4	5.	0.	1.	2.	2.

* MODEL 3 USING ITS OWN COEFS

% CORRECT = 62

% BY CHANCE = 40

% CORRECT FOR EACH CENTRE = $S_1 = 74$; $S_2 = 61$; $S_3 = 23$

$S_4 = 0$.

```
& LOGIT COMMAND:
 quit;
& DO COMMAND:
 prtdata mycoef;


 MYCOEF   -    DATE REVISED: 12/09/89
   3 BY 1 MATRIX

   COEF = MATREP(COEF,NEWVAL,SUBROW,1)
```

1	0.	0.002449	-0.205756

```
& TROLL COMMAND:
 &logit reoval;

 MULTINOMIAL LOGIT ANALYSIS---VER. 2.4 5/18/78

 SEARCH LIST

 DATA_REOVAL  W
 MBBA   (W)
 DATA
 DATA

 NEW MODEL: REOVAL
& DEPENDENT VARIABLE:
 yy2;
& LOGIT COMMAND:
 addvar alt ex21 ex23;
& LOGIT COMMAND:
 prtmod all;

 DATA_REOVAL_PARAM
```

	NO.

ALTERNATIVES	4.
ALT. ATTRIB.	2.
IND. ATTRIB.	0.
INTERACTION	0.
FIXED VAR.	0.

DATA_REOVAL_VLIST

	TYPE
YY2	0.
EX21	1.
EX23	1.

DATA_REOVAL_COEF

	VALUES
	0.
EX21	0.
EX23	0.

```
& LOGIT COMMAND:
 setcoef use mycoef;
& LOGIT COMMAND:
 prtmod all;
```

DATA_REOVAL_PARAM

	NO.
ALTERNATIVES	4.
ALT. ATTRIB.	2.
IND. ATTRIB.	0.
INTERACTION	0.
FIXED VAR.	0.

DATA_REOVAL_VLIST

	TYPE
YY2	0.
EX21	1.
EX23	1.

DATA_REOVAL_COEF

	VALUES
	0.
EX21	0.
EX23	0.

```
& LOGIT COMMAND:
 setcoef all 1 1;
& LOGIT COMMAND:
 prtmod all;
```

DATA_REOVAL_PARAM

	NO.
ALTERNATIVES	4.
ALT. ATTRIB.	2.
IND. ATTRIB.	0.
INTERACTION	0.
FIXED VAR.	0.

DATA_REOVAL_VLIST

	TYPE
YY2	0.
EX21	1.
EX23	1.

DATA_REOVAL_COEF

	VALUES
	0.
EX21	1.
EX23	1.

```
& LOGIT COMMAND:
 setcoef all .002449 -.205755;
& LOGIT COMMAND:
 prtmod all;
```

DATA_REOVAL_PARAM

	NO.
ALTERNATIVES	4.
ALT. ATTRIB.	2.
IND. ATTRIB.	0.
INTERACTION	0.
FIXED VAR.	0.

DATA_REOVAL_VLIST

	TYPE
YY2	0.
EX21	1.
EX23	1.

DATA_REOVAL_COEF

	VALUES
	0.
EX21	0.002449
EX23	-0.205755

```
& LOGIT COMMAND:
 prob;prtresult fit;
```

PREDICTD_CLASSIF

ROW	PREDICTED	ACTUAL	0=CORRECT
1	3.	2.	1.
2	2.	2.	0.
3	2.	1.	1.
4	1.	1.	0.
5	2.	2.	0.
6	3.	1.	1.
7	3.	3.	0.
8	2.	2.	0.
9	2.	1.	1.
10	3.	2.	1.
11	1.	2.	1.
12	1.	1.	0.
13	3.	2.	1.
14	3.	3.	0.
15	3.	3.	0.
16	3.	2.	1.
17	3.	2.	1.
18	2.	2.	0.
19	1.	1.	0.
20	3.	1.	1.
21	1.	1.	0.
22	1.	2.	1.
23	2.	2.	0.
24	2.	1.	1.
25	2.	2.	0.
26	1.	1.	0.
27	2.	2.	0.
28	1.	2.	1.
29	2.	4.	1.
30	1.	2.	1.
31	1.	2.	1.
32	3.	2.	1.
33	1.	1.	0.
34	1.	1.	0.
35	1.	1.	0.
36	1.	2.	1.
37	1.	1.	0.
38	1.	1.	0.
39	1.	1.	0.
40	4.	2.	1.
41	4.	3.	1.
42	4.	2.	1.
43	2.	1.	1.
44	1.	2.	1.
45	3.	2.	1.
46	1.	1.	0.
47	1.	1.	0.
48	3.	1.	1.
49	1.	3.	1.
50	1.	1.	0.
51	1.	1.	0.
52	3.	2.	1.
53	1.	1.	0.
54	2.	3.	1.
55	3.	3.	0.
56	3.	3.	0.
57	4.	3.	1.
58	1.	2.	1.
59	4.	3.	1.
60	1.	1.	0.
61	4.	3.	1.
62	4.	3.	1.
63	3.	3.	0.
64	3.	1.	1.
65	4.	1.	1.
66	2.	4.	1.
67	2.	1.	1.
68	2.	2.	0.
69	2.	1.	1.
70	2.	1.	1.
71	2.	2.	0.
72	2.	1.	1.
73	2.	2.	0.
74	2.	2.	0.

75	4.	1.	1.
76	1.	1.	0.
77	1.	1.	0.
78	1.	1.	0.
79	1.	2.	1.
80	1.	1.	0.
81	1.	1.	0.
82	1.	1.	0.
83	1.	1.	0.
84	1.	1.	0.
85	1.	1.	0.
86	1.	1.	0.
87	1.	1.	0.
88	1.	1.	0.
89	1.	1.	0.
90	1.	2.	1.
91	1.	1.	0.
92	2.	1.	1.
93	2.	2.	0.
94	1.	1.	0.
95	2.	1.	1.
96	2.	2.	0.
97	2.	2.	0.
98	2.	2.	0.
99	2.	2.	0.
100	1.	1.	0.
101	1.	1.	0.
102	1.	1.	0.
103	2.	2.	0.
104	1.	2.	1.
105	1.	2.	1.
106	1.	1.	0.
107	2.	2.	0.
108	2.	1.	1.
109	2.	2.	0.
110	2.	2.	0.
111	4.	2.	1.
112	2.	2.	0.
113	2.	2.	0.
114	4.	3.	1.
115	2.	3.	1.
116	3.	3.	0.
117	3.	2.	1.
118	3.	3.	0.
119	3.	2.	1.
120	3.	3.	0.
121	3.	1.	1.
122	1.	2.	1.
123	3.	3.	0.
124	2.	1.	1.
125	1.	1.	0.
126	1.	1.	0.
127	2.	2.	0.
128	1.	2.	1.
129	1.	1.	0.
130	2.	2.	0.
131	4.	2.	1.
132	1.	2.	1.
133	1.	1.	0.
134	1.	1.	0.
135	1.	1.	0.
136	1.	1.	0.
137	4.	2.	1.
138	4.	2.	1.
139	4.	2.	1.
140	1.	1.	0.
141	1.	1.	0.
142	1.	1.	0.
143	1.	1.	0.
144	1.	1.	0.
145	1.	1.	0.
146	1.	1.	0.
147	1.	1.	0.
148	1.	1.	0.
149	1.	1.	0.
150	1.	1.	0.
151	1.	1.	0.
152	3.	3.	0.
153	3.	3.	0.
154	1.	1.	0.
155	1.	1.	0.
156	1.	1.	0.
157	1.	1.	0.
158	4.	2.	1.
159	2.	2.	0.
160	4.	2.	1.
161	4.	1.	1.
162	1.	2.	1.
163	2.	2.	0.
164	2.	2.	0.
165	1.	1.	0.
166	1.	2.	1.
167	1.	2.	1.
168	1.	2.	1.
169	2.	1.	1.
170	2.	2.	0.
171	4.	1.	1.
172	4.	3.	1.

MODEL 3 - USING MODEL 2 COEFS

CROSSTAB_ACTUAL_VS_PREDICT

	PRED.—TOTAL	ALT.1	ALT.2	ALT.3
ACTUAL-TOTAL	172.	80.	45.	27.
ALT.1	82.	60.	13.	5.
ALT.2	66.	19.	28.	10.
ALT.3	22.	1.	2.	12.
ALT.4	2.	0.	2.	0.

	ALT.4
ACTUAL-TOTAL	20.
ALT.1	4.
ALT.2	9.

% CORRECT = 58

% BY CHANCE = 40

% CORRECT FOR EACH CENTRE = $S_1 = 73$; $S_2 = 42$; $S_3 = 55$; $S_4 = 0$.

ALT.3	7.
ALT.4	0.


```
& LOGIT COMMAND:
 mts;
#logoff
#Invalid MTS command
#copy -out *print*
>*PRINT* assigned job number 75166
```

BIBLIOGRAPHY

Acito, F., & Anderson, R.D. (1979). "The influence of learning on store image differentiation: An empirical demonstration." In N. Beckwich et al. (Eds.) Educators' proceedings. Chicago, IL: American Marketing Association, 500–503.

Anderson, C.R., & Scott, R.A. (1970). "Supermarkets: Are they really alike?" Journal of Retailing, 46(Fall), 16–24.

Arons, L. (1961). "Does television viewing influence store image and shopping frequency?" Journal of Retailing, 37(Fall), 1–13.

Arnold, S.J., & Tigert, D.J. (1973–74). "Market monitoring through attitude research." Journal of Retailing, 49(Winter), 3–22.

Batty, M. (1971). "Exploratory calibration of a retail location model using search by golden section." Environment and Planning, 3, 411–32.

Bean, James C., Noon, Charles E., Ryan, Sarah M., & Salton, Gary J. (1988). "Selecting tenants in a shopping mall." Interfaces, 18 (March–April), 1–9.

Bellenger, D.N., Robertson, D.H., & Greenberg, B.A. (1977). "Shopping center patronage motives." Journal of Retailing, 53(Summer), 29–38.

Bellenger, D.N., Steinberg, E., & Stanton, W.W. (1976). "The congruence of store image and self-image." Journal of Retailing, 52(Spring), 17–32.

Berkowitz, E.N., Deutscher, T., & Hansen, R.A. (1978). "Retail image research: A case of significant unrealized potential." In Subhash C. Jain (Ed.) Educators' proceedings. Chicago, IL: American Marketing Association, 62–66.

Berman, B. (1983). "Shopper and retailer perceptions of the relative strengths and weaknesses of sixteen business districts." Spring Conference (April 16), Presentation to the American Collegiate Retailing Association.

Blommestein, H., Nijkamp, P., & Veenendaal, W. (1980). "Shopping perceptions and preferences: A multidimensional attractiveness analysis of consumer and entrepreneurial attitudes." Economic Geography, 56(4), 155–74.

Brown, S., Smith, R., & Zurowski, G. (1977). "The appropriateness and applicability of image research to banking." Journal of Bank Research, 8(Summer), 94-100.

Brunner, J.A., & Mason, J.L. (1968). "The influence of driving time upon shopping center performance." Journal of Marketing, 32(4), 57-61.

Bucklin, L.P. (1967a). "The concept of mass in intra-urban shopping." Journal of Marketing, 31(10), 37-42.

Bucklin, L.P. (1967b). Shopping patterns in an urban area. Berkeley, CA: Institute of Business and Economic Research, University of California.

Bucklin, L.P. (1971a). "Retail gravity models and consumer choice: A theoretical and empirical critique." Economic Geography, 47(10), 489-497.

Bucklin, L.P. (1971b). "Trade area boundaries: Some issues in theory and methodology." Journal of Marketing Research, 8(2), 30-37.

Campbell, B. (1973). "The existence of evoked set and determinants of its magnitude in brade choice behaviour." In J. Howard and L. Ostlund (Eds.) Buyer behaviour: Theoretical and empirical foundations. New York, NY: Alfred A. Knopf Inc., 243-244.

Cardozo, R.N. (1974-75). "How images vary by product class." Journal of Retailing, 50(Winter), 85-98.

Carrothers, G.A.P. (1956). "A historical review of gravity and potential models of human interaction." Journal of the American Institutes of Planners, 22(2).

Carter, C. (1978). "Why they shop some centers." Chain Store Age Executive, (5), 31-35.

Carter, C. (1981). "Why they shop some centers." Chain Store Age Executive, (9), 57-59.

Cesario, F.J. (1973). "Parameter estimation in spatial interaction modeling." Environment and Planning, 5, 503-18.

Cesario, F.J. (1973). "Linear and nonlinear regression models of spatial interaction." Economic Geography, 51(1), 70-77.

Christaller, W. (1933). Central places in southern Germany. Translated by C.W. Baskin, 1966. Englewood Cliffs, NJ: Prentice Hall.

Converse, P.D. (1949). "New laws of retail gravitation." Journal of Marketing, 14(1), 379-384.

Craig, C.S., Ghosh, A., & McLafferty, S. (1984). "Models of the retail location process: A review." Journal of Retailing, 60(Spring), 5-36.

Currim, I.S. (1982). "Predictive testing of consumer choice models not subject to independence of irrelevant alternatives." Journal of Marketing Research, 19, 208-222.

Darden, W.R. (1980). "A patronage model of consumer behaviour." In R.W. Stampfl and E.C. Hirschman (Eds.) Competitive structure in retail markets: The department store perspective. Chicago, IL: American Marketing Association, 43-52.

Dickinson, R.A. (1981). Retail management. Austin, TX: Austin Press.

Domencich, Thomas A., & McFadden, Daniel. (1975). Urban travel demand. New York, NY: American Elsevier Publishing Company, 165-183.

Dornoff, R.J., & Tatham, R.C. (1972). "Congruence between personal image and store image." Journal of the Market Research Society, 14(4), 45-52.

Doyle, P., & Fenwick, I. (1974-75). "How store image affects shopping habits in grocery chains." Journal of Retailing, 50(Winter), 39-52.

Dunn, Richard, & Wrigley, Neil. (1985). "Beta-logistic models of urban shopping centre choice." Geographical Analysis, 17(2), 95-113.

Eagle, Thomas C. (1984). "Parameter stability in disaggregate retail choice models: Experimental evidence." Journal of Retailing, 60, 101-23.

Egan, D. (1971). "Evaluation bias, customer attitudes and department store image." Southern Journal of Business, 6(11), 73-81.

Ellwood, L.W. (1954). "Estimating potential volume of proposed shopping centres." The Appraisal Journal, 10, 581-89.

Fisk, G.I. (1961-62). "A conceptual model for studying customer image." Journal of Retailing, 37(Winter), 1-8,54.

Flath, D., & Leonard, E.W. (1979). "A comparison of two logit models in the analysis of qualitative marketing data." Journal of Marketing Research, 16, 533–538.

Forbes, J.D. (1968). "Consumer patronage behavior." In R.L. Kind (Ed.) Marketing and the new science of planning. Chicago, IL: American Marketing Association, 381–385.

Frederick, C., Norton, D., & Shannon, M.L. (1975). "Tuscaloosa CBD redevelopment feasibility study." Unpublished report, University of Alabama. Reported in J.B. Mason and M.L. Mayer (1978) Modern retailing: Theory and practice. Dallas, TX: Business Publications Inc., 103.

Gautschi, D.A. (1981). "Specification of patronage models of retail center choice." Journal of Marketing Research, 18, 162–174.

Gensch, Dennis H. (1985). "Empirically testing a disaggregate choice model for segments." Journal of Marketing Research, 22(1), 462–67.

Gensch, Dennis H., & Recker, Wildred W. (1979). "The multinomial, multiattribute logit choice model." Journal of Marketing Research, 16(2), 124–132.

Gentry, James W., & Burns, A.C. (1977). "How important are evaluation criteria in shopping center patronage?" Journal of Retailing, 53(Winter), 73–78.

Goldman, A. (1976). "Do lower–income consumers have a more restrictive shopping scope?" Journal of Marketing, 40(1), 46–54.

Gray, R.H. & Sen, A.K. (1983). "Estimating gravity model parameters: A simplified approach based on the odds ratio." Transportation Research, 17B, 117–31.

Haines, G.H., Simon, L.S., & Alexis, M. (1972). "Maximum likelihood estimation of central city food trading areas." Journal of Marketing Research, 9, 154–159.

Hansen, R.A., & Deutscher, T. (1977). "An empirical investigation of attribute importance in retail store location." Journal of Retailing, 53(Winter), 59–72.

Hauser, J., & Koppelman, F.S. (1979). "Alternative perceptual mapping techniques: Relative accuracy and usefulness." Journal of Marketing Research, 16(11), 495–506.

Hawkins, D.I., Albaum, G., & Best, R. (1974). "Stapel scale or semantic differential in marketing research?" Journal of Marketing Research, 11(August), 318–22.

Hawkins, D.I., Albaum, G., & Best, R. (1976–77). "Reliability of retail store images as measured by the stapel scale." Journal of Retailing, 52(Winter), 31–38,92.

Hawkins, D.I., Coney, K.A., & Best, R.J. (1980). Consumer behaviour: Implications for marketing strategy. Dallas, TX: Business Publications.

Henscher, D.A., & Johnson, L.W. (1981). Applied discrete choice modeling. New York, NY: John Wiley & Sons.

Higgs, G.K., Ludwig, A.K., Hinton, D.W., & Moss, T.C. (1976). "Konig numbers as a measure of intra-urban accessibility." Proceedings of the Association of American Geographers, 8, 89–91.

Hirschman, E.C. (1981a). "An exploratory comparison of decision criteria used by retailers." In R.F. Lusch and W.R. Darden (Eds.) Retail patronage theory. Norman, OK: Center for Economic and Management Research, School of Business Administration, University of Oklahoma, 1–5.

Hirschman, E.C. (1981b). "Retail research and theory." In B. Enis and K. Roering (Eds.) Review of Marketing. Chicago, IL: American Marketing Association, 120–33.

Howell, R.D., & Rogers, J.D. (1980). "Research into shopping mall choice behaviour." In Kent B. Monroe (Ed.) Advances in consumer research Vol.8. Ann Arbor, MI: Association for Consumer Research, 671–76.

Huff, D.L. (1962). "Determination of intra-urban retail trade area." Real Estate Research Program. Los Angeles, CA: University of California.

Huff, D.L. (1963). "A probabilistic analysis of shopping center trade areas." Land Economics, 39, 81–90.

Huff, D.L. (1964). "Defining and estimating a trade area." Journal of Marketing, 28, 34–38.

Huff, D.L. (1981). "Retail location theory." In R. Stampfl and E. Hirschman (Eds.) Theory in retailing; Traditional and non traditional sources. Chicago, IL: American Marketing Association.

Huff, D.L., & Blue, L. (1966). "A programmed solution for estimating retail sales potential." Lawrence, KS: Centre for Regional Studies.

Jain, A.K., & Etgar, M. (1976-77). "Measuring store image through multidimensional scaling of free response data." Journal of Retailing, 52(Winter), 61-70.

James, D.L., Durand, R.M., & Dreves, R.A. (1976). "The use of a multi-attribute attitude model in a store image study." Journal of Retailing, 52(Summer), 23-32.

Jensen-Butler, C. (1972). "Gravity models as planning tools: A review of theoretical and operational problems." Geografiska Annaler, 54B, 68-78.

Kassarjian, H.H., & Nakanishi, M. (1967). "A study of selected opinion measurement techniques." Journal of Marketing Research, 4(5), 148-53.

Kelly, R.F., & Stephenson, P.R. (1967). "The semantic differential: An information source for designing retail patronage appeals." Journal of Marketing, 31(10), 43-47.

King, C.W., Tigert, D.J., & Ring, L.J. (1979). "Pragmatic applications of consumer research in retailing." In William Wilkie (Ed.) Advances in consumer research, Vol.6. Ann Arbor, MI: Association for Consumer Research, 20-26.

King, C.W., & Ring, L.J. (1980). "Market positioning across retail fashion institutions: A comparative analysis of store types." Journal of Retailing, 56(Spring), 37-55.

King, C.W., Tigert, D.J., & Ring, L.J. (1980). "Fashion involvement and retail shopping behaviour." In R.W. Stampfl and E.C. Hirschman (Eds.) Competitive structure in retail markets: The department store perspective. Chicago, IL: American Marketing Association, 88-97.

Kotler, P. (1971). Marketing decision making: A model building approach. New York, NY: Holt, Rinehart and Winston.

Kotler, P. (1972). Marketing management analysis, planning and control. Englewood Cliffs, NJ: Prentice-Hall.

Kunkel, S.H., & Berry, L.L. (1968). "A behavior concept of retail images." Journal of Marketing, 32, 21–27.

Lakshmanan, T.R., & Hansen, W.A. (1965). "A retail market potential model." Journal of American Institute of Planners, 31, 134–143.

Lambin, Jean–Jacques. (1972). "A computer on–line marketing mix model." Journal of Marketing Research, 119–126.

Leonard, L. Berry. (1969). "The components of department store image: A theoretical and emp;irical analysis." Journal of Retailing, 45(Spring), 3–20.

Lessig, V.P. (1973). "Consumer store images and store loyalties." Journal of Marketing, 38(10), 72–74.

Lieber, S.R. (1977). "Attitudes and revealed behaviour: A case study." Professional Geographer, 29, 53–58.

Lindquist, J. (1974). "Meaning of image." Journal of Retailing, 50(Winter), 29–38.

Losch, A. (1954). The economics of location. New Haven, CT: Yale University Press.

Luce, R. (1959). Individual choice behavior. New York, NY: John Wiley & Sons.

Mackie, S. (1972). "The calibration of spatial interaction models." Geographical Papers, Vol.14. Reading, MA: Reading University.

Maddala, G.S. (1983). Limited dependent and qualitative variables in econometrics. Port Chester, NY: Cambridge University Press.

Malhotra, Naresh K. (1984). "The use of linear logit models in marketing research." Journal of Marketing Research, 21(2), 20–32.

Marble, D.F., & Bowlby, S.R. (1968). "Shopping alternatives and recurrent travel patterns." In F.G. Horton (Ed.) Geographic studies of urban transportation and network analysis. Evanston, IL: Department of Geography, Northwestern University, 42–75.

Martineau, P. (1957). Motivation in advertising. New York, NY: McGraw–Hill Book Company, Inc.

Marks, R.B. (1976). "Operationalizing the concept of store image." Journal of Retailing, 52(Fall), 37-46.

Mason, J., & Moore, C. (1970). "An empirical reappraisal of behaviouristic assumptions in trading area studies." Journal of Retailing, 46(Winter), 31-7.

Mason, J., & Mayer, M.L. (1970). "The problem of the self concept in store image studies." Journal of Marketing, 34(4), 67-69.

May, E.G. (1974-75). "Practical applications of recent retail image research." Journal of Retailing, 50(Winter), 15-20.

May, E.G. (1983). "Product positioning and segmentation strategy: Adaptable to retail stores?" In R.W. Stampfl and E.C. Hirschman (Eds.) Theory in retailing: Traditional and nontraditional sources. Chicago, IL: American Marketing Association, 88-97.

McDougall, G.H.G., & Fry, J.N. (1974-75). "Combining two methods of image measurement." Journal of Retailing, 50(Winter), 53-61.

McFadden, Daniel (1974). "Conditional logit analysis of qualitative choice behavior." In P. Zarembka (Ed.) Frontiers in econometrics. New York, NY: Academic Press.

McFadden, D. (1976a). "A comment on discriminant analysis 'versus' logit analysis." Annals of Economics and Social Measurement, 511-523.

McFadden, D., & Reid, F. (1975). "Aggregate travel demand forecasting from disaggregated behavioral models." Transportation Research Board Record, No.534.

Menezes, D., & Elbert, N.F. (1979). "Alternative semantic scaling formats for measuring store image: An evaluation." Journal of Marketing Research, 16(2), 80-87.

Miller, E., & Lerman, S. (1981). "Disaggregate modeling and decision of retail firms: A case study of clothing retailers." Environment and Planning A, 13, 729-746.

Monroe, Kent B., & Guiltman, Joseph H. (1975). "A path-analytic exploration of retail patronage influences." Journal of Consumer Research, 2(6), 19-28.

Morrison, D.G. (1973). "Evaluating market segmentation studies: The properties of R^2." Management Science, 19, 1213–1221.

Nakanishi, M., & Cooper, L.G. (1974). "Parameter estimate for multiplicative interactive choice model: Least squares approach." Journal of Marketing Research, 11, 303–311.

Nakanishi, M., & Cooper, L.G. (1982). "Simplified estimation procedures for MCI models." Marketing Science, 1, 314–322.

Nakanishi, M., & Yamanaka, Hitoshi. (1975). "Measurement of drawing power of retail centers: Regression analysis." Working paper No.30 Center for Marketing Studies, Los Angeles, CA: University of California.

Narayana, C.L., & Markin, R.J. (1975). "Consumer behaviour and product performance: An alternative conceptualization." Journal of Marketing, 39(10), 1–6.

Neidell, L., & Teach, R. (1974). "Measuring bank images: A comparison of two approaches." Journal of the Academy of Marketing Science, 2(Spring), 374–90.

Nelson, F., Hill, R., Gelfand, M., & Wilk, R. (1976). Troll experimental programs: Qualitative and limited dependent variable models. Cambridge, MA: National Bureau of Economic Research, Inc.

Nevin, J.R., & Houston, M.J. (1980). "Image as a component of attractiveness to intra-urban shopping areas." Journal of Retailing, 56(Spring), 77–93.

Nickel, P., & Wertheimer, A.I. (1979). "Factors affecting consumers' image and choices of drugstores." Journal of Retailing, 55(Summer), 71–78.

Nie, N.H., Hull, C. Hadlai, Jenkins, Jean G., Steinbrenner, Karin, & Bent, Dale H. (1975). Statistical package for the social sciences, Second Edition. New York, NY: McGraw–Hill Book Company.

O'Neill, M.F., & Hawkins, D.I. (1980). "Managerial bias in anticipated images in competing shopping areas." Journal of Business Research, 8, 419–28.

Openshaw, S. (1973). "Insoluble problems in shopping model calibration when the trip pattern is not known." Regional Studies, 7, 367–71.

Pacione, M. (1974). "Measures of the attraction factor: A possible alternative." Area, 6, 279–282.

Pathak, D.S., Crissy, W.J.E., & Sweitzer, R.W. (1974–75). "Customer image versus the retailer's anticipated image." Journal of Retailing, 50(Winter), 21–28,116.

Pedhazur, E.J. (1982). Multiple regression in behavioural research: Explanation and prediction. 2nd Edition. New York, NY: Holt, Rinehart and Winston.

Perry, M., & Norton, N. (1970). "Dimensions of store image." Southern Journal of Business, 5(April), 1–7.

Pessemio, Edgar A. (1980). "Store image and positioning." Journal of Retailing, 56(Spring), 96–106.

Prasad, Kanti V. (1975). "Unplanned buying in two retail settings." Journal of Retailing, 51(Fall), 3–12.

Prestwick, L. (1980). "The competitive position of a small local shopping centre." Presentation to American Collegiate Retail Association (April 12). Quoted in E. G. May (1983) Product positioning and segmentation strategy: Adaptable to retail stores?

Reich, J.W., Ferguson, J.M., & Weinberger, M.G. (1977). "An information intregration analysis of retail store image." Journal of Applied Psychology, 62, 609–14.

Reilly, W.J. (1929). Methods for the study of retail relationships. Austin, TX: Bureau of Business Research Studies in Marketing, No.4.

Ring, L.J. (1979). "Retail positioning: A multiple discriminant analysis approach." Journal of Retailing, 55(Spring), 25–36.

Schiffman, L.G., Dash, J.F., & Dillon, W.R. (1977). "The contribution of store-image characteristics to store-type choice." Journal of Retailing, 53, 3–14.

Shepherd, I.D.H., & Thomas, C.J. (1980). "Urban consumer behaviour." In J.A. Dawson (Ed.) Retail geography. New York, NY: Wiley, 18–94.

Sheth, Jagdish. (1983). "Emerging trends of the retailing industry." Journal of Retailing, 59(Fall), 6–18.

Simons, P. (1973–74). "The shape of suburban retail market areas: Implications from a literature review." Journal of Retailing, 49(Winter), 65–78.

Singson, R.L. (1975). "Multidimensional scaling analysis of store image and shopping behaviour." Journal of Retailing, 51(Summer), 39–52,93.

Stanley, T.J., & Sewall, M.A. (1976). "Image inputs to a probabilistic model: Predicting retail potential." Journal of Marketing, 40, 48–53.

Stern, B.L., Bush, R.F., & Hair, J.F. Jr. (1977). "The self–image/store image matching process: An empirical test." Journal of Business, 50(1), 63–69.

Stephenson, P. Ronald. (1969). "Identifying determinants of retail patronage." Journal of Marketing, 33(3), 57–61.

Swinyard, William R. (1977). "Market segmentation in retail service industries: A multiattribute approach." Journal of Retailing, 53(Spring), 27–34,92–93.

Thomas, C.J. (1976). "Sociospatial differentiation and the use of services." In D.T. Herbert and R.J. Johnston (Eds.) Social areas in cities. London, UK: Wiley.

Turner, R., & Cole, H.S.D. (1980). "An investigation into the estimation and reliability of urban shopping models." Urban Studies, 17(6), 139–157.

Urban, Glen L. (1969). "Mathematical modeling approach to product line decisions." Journal of Marketing Research, 40–47.

Vancouver Sun, The, November 1989.

Walters, C.G. (1978). Consumer behaviour: Theory and practice. Homewood, IL: Richard D. Irwin.

Ward, Trevor J. (1985). "The effect of individual merchandise category size and image on the drawing power of shopping centres." Unpublished MBA Research Project, Burnaby, BC: Simon Fraser University.

Weisbrod, G.E., Parcells, Robert J., & Kern, Clifford. (1984). "A disaggregate model for predicting shopping area market attraction." Journal of Retailing, 60, 65–83.

Whipple, T.W., & Neidell, L.A. (1971–72). "Black and white perceptions of competing stores: An application of nonmetric multidimensional scaling." Journal of Retailing, 47(Winter), 5–20.

Wilson, A.G. (1970). Entropy in urban and regional modelling. London, UK: Pion.

Wilson, A.G. (1971). "A family of spatial interaction models and associated development." Environment and Planning, 3, 1–32.

Wilson, A.G. (1974). Urban and regional models in geography and planning. London, UK: Wiley.

Young, W.J. (1975). "Distance decay values and shopping centre size." Profressional Geographer, 27, 304–309.