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ABSTRACT

Much past research on the nature of demand for recreation or cultural activities has been either economic models based on unrealistic assumptions about willingness-to-pay or sociological models that fail to provide an in-depth analysis of the forces actually affecting the decision to participate. This paper presents an attempt to combine some of the strengths of the traditional economic and sociological methods, while avoiding some of their weaknesses. The method developed produces an index called a 'cultural elasticity' that quantitatively indicates how rates of participation may be expected to change when certain economic and sociological characteristics in the population change. A numerical example is provided using a recent Canadian national survey on performing arts audiences. Strengths and limitations in the approach are also identified.

THE CHANGING DEMAND FOR CULTURE: ESTIMATION OF 'CULTURAL ELASTICITIES'

BACKGROUND

Many current methods for the analysis of the demand for cultural, leisure, and recreational activities have been adapted from market place econometrics originally designed for analyzing the production and consumption of food, fibre, and industrial goods. Some notable successes have been achieved with these methods, but there are also some shortcomings in them that might be overcome by developing supplementary methods to account for the effects of non-economic variables on the demand for culture, leisure and related goods.

The primary measure of cultural and leisure demand is the potential customer's willingness-to-pay. Willingness-to-pay may be measured by several different methods such as inferences from actual expenditures, deductions from expressions of willingness-to-pay when faced with various hypothetical price changes, and deviations from surrogate measures for price such as distance travelled.

A few researchers working during the emergence of recreation economics, such as Seckler (1) and Hammond (2), criticized willingness- to-pay methods as inappropriate for many leisure activities. Their concern was not directed at the market place approach in general, but at the assumption that the willingness-to-pay variable can be interpreted as a measure of the personal utility of participation. Simply put, Seckler and Hammond argued that most attempts to measure willingness-to-pay actually measure only the ability to pay, variations in the utility of participation among consumers as imputed from demand schedules, and more probably variations in the unility of income among those consumers. Both researchers concluded that variations in the unility of income among those consumers. Both researchers concluded that some other demand analysis techniques should be developed, but they were not able to suggest any workable alternatives.

Perhaps because of their failure to develop alternatives, criticisms by these two had little effect on the development of demand analysis methods in the last decade and a half. Dominant methods of market analysis, represented by the work of Clawson and Knetsch (3), Kalter (4), Smith (5), Cicchetti and Smith (6), and Martin and Gum (7), still centre on market place forces. Despite the prevalence of limited economic models, some work has been undertaken to include non-economic variables. The Canadian Outdoor Recreation Demand (CORD) Study (8) made a number of significant contributions to the analysis of individual participation patterns, especially by developing several models that incorporated "demand shifters" in forecasting models. Demand shifters include education, age, family structure, and other personal, demographic, and social variables that influence the amount of a good a person is willing to consume at any given price. Unfortunately, the CORD models are "ad hoc" in that they are primarily multiple regression equations calibrated with historical data and applied to fore-casting future trends. This is a disadvantage because multiple regression necessarily assumes that the independent variables combine linearly to explain (or predict) the dependent variable. Many demand shifters are not linearly related to expected participation and, as a result, most CORD models do not explain even a third of the total variance in participation. Some explain less than 10 percent.

The inadequacy of limited economic models and of linear socio-economic regression models has been recognized for several years. Most attempts to produce new models, however, have remained theoretical. For example, Driver and Brown (9) argued for a social-psychological demand analysis, but their proposed method has apparently not been operationalized for applied economic forecasting because of difficulty in acquiring objective data and in developing a mathematical version of their model. Ontario's ambitious Tourism and Outdoor Recreation Plan (10)--a very large systems model--has been operationalized in the sense that all components and relationships have been mathematically defined and extensive data have been collected through the 1973 Ontario Recreation Survey. However, the actual model has never been used because the CPU requirements exceed the limits of available computer systems. Further, the data required for the model are so out of date it is unlikely the model will ever be utilized.

On a more modest and successful level, Kinsley and Cheney (11) in Canada and Marcin and Lime (12) in the United States have shown how changes in the age structure of North American society might be used to predict changes in the demand for different types of cultural and recreational activities. Kinsley and Cheney conclude with some specific forecasts based on the assumption that only changes in age and education affect cultural participation. Marcin and Lime conclude with some rather vague and qualitative forecasts expressed in terms such as "extractive-symbolic activity."

A different approach to understanding variations and changes in the patterns of leisure activities has been through the development of leisure typologies. Activities are grouped together on the basis of participation patterns exhibited by a group of people. These groups are then distinguished from each other by reference to socio-economic characteristics of people who frequently participate in the activities contained within each cluster. Examples of this approach include the works of McKechnie (13), Ditton, Goodale, and Johnson (14), and Yu (15). An advantage of this approach is its ability to assign an individual to a leisure type according to objective socio-economic attributes. In theory, therefore, a planner could predict patterns of participation by examining projections in the relevant socio-economic characteristics of a population. This breaks down in practice, however, because of the omission of potentially important economic variables and market place forces, as well as inconsistencies among the various leisure typologies. Chase, Kasulis, and Lusch (16) have drawn attention to the potential variability among leisure types across a single population, between sexes, and over time. Their own examination of the stability of leisure types is limited by their examination of only a small number of activities, and their use of the simple incidence (yes/no) of participation rather than frequency of participation.

For all of these reasons, the sociological models just described are rarely used for prediction. They are used instead to describe the nature of participation rather than to identify the forces affecting its occurrence.

After reviewing the progress to date in forecasting models of leisure demand and participation, it appears that the next step to be taken is the development of a model that will combine the advantages of quantitative trend and demand analysis as developed in economic models with the understanding gained from the study of demand shifters, leisure typologies and activity clustering.

The purpose of this project, therefore, is to develop a method for estimating changes in participation in selected activities (five cultural activities) that combines some of the strengths of previous forecasting methods, yet moves a bit closer to the complexity of reality. The method developed is essentially one for estimating changes expected in attendance at selected activities by specific social groups given a one percent change in the size of those social groups. The expected change is expressed in a percentage, and is a homology to the concept of price elasticity from economics. For this reason, we call the derived measure a "cultural elasticity." The formal definition of a cultural elasticity will become clearer after the discussion of calculations.

PROCEDURE

Because the purpose of this project is to develop a method for calculating cultural elasticities, the most relevant results of the project are not estimates of elasticities, per se, but the method by which these may be derived. The numerical analysis described below helps to illustrate both the types of answers one might expect and the methods that one employs to obtain those answers.

Cultural elasticities are calculated from patterns of past participation of certain groups in selected activities. Before these calculations can be done, however, one must empirically define the groups of participants. And before defining those groups, one must be able to specify the characteristis that are to be used in defining the groups. The following discussion presents methods of accomplishing each of these steps: (1) Identification of Group Characteristics, (2) Identification of Groups, and 3) Calculation of Cultural Elasticities.

Data were obtained from a nationwide survey of non-institutionalized Canadian adults, "1978 Survey of Canadians and the Arts." The survey was based on a clustered random sample of 13,400 respondents drawn from 18 urban areas.

Identification of Group Characteristics

A great many social, personal, demographic, attitudinal, and economic variables can be used to describe the preferences for and participation in cultural activities. It is desirable for a researcher to have a theoretical basis for specifiying a precise and relatively short list of variables for which data should be obtained. However, theory is not yet available to do this for forecasting cultural participation. Further, one is usually limited, for practical reasons, to working with secondary data. When using secondary data, one is not only constrained to the variables included in the original survey, but one must find some way to choose among the many related variables to find those most useful for the task at hand. One way to do this, occasionally employed, is to arbitrarily (or on the basis of previous experience) select the most "interesting" or potentially meaningful variables. This method, of course, is not very valid or reliable. And it can result in the loss of potentially important information. A better tactic would be to try to combine as many of the original variables as possible into a small number of new characteristics. This allows a compromise between reducing the number of variables and maintaining maximum information.

The method chosen to achieve this compromise was a form of factor analysis called principal components analysis (PCA). PCA begins with the construction of a correlation matrix in which the answers of these respondents to each question on the survey are compared to their answers to every other question. The form of the matrix is a square with the rows and columns representing individual variables (the questions in the survey). The correlations between variables range between 1.0 (perfect positive correlation) and -1.0 (perfect inverse correlation). Most values are not very close to these extremes, indicating some degree of imperfect correlation. Usually the diagonal of a correlation matrix is composed of 1.0's, because each variable is perfectly correlated with itself. For PCA, however this diagonal is replaced by an estimate of the correlation between each individual variable and all other variables. This estimate is called a "commonality." Variables with high commonalities are desired. Variables with low commonalities do not contribute much to the results of a PCA and are therefore frequently discarded from further analysis. In this project, 0.4 was used as the commonality threshold for retaining a variable in the PCA.

After the correlation matrix is computed, PCA examines the pattern of correlations to try to find the best combination of variables that will summarize that pattern. A new set of variables, "components," are defined. Each component is a set of the original variables, each mutliplied by a weight (called a "loading") that summarizes as much of the correlation matrix as possible. There are as many components produced by PCA as there are original variables, but only a small number of these are meaningful. Because there is no particular number of components expected in this particular project, some objective guide should be used to guide the selection of the "proper" number of components. A common guide is the use of "eigenvalues." An eigenvalue is a measure of the variance explained by a particular component. The first component produced usually explains the most variance, with subsequent components explaining successively less variance. Similarly, the first component has an eigenvalue well above 1.0; successive components have eigenvalues successively smaller, until they drop below 1.0. It is at this point that one might stop producing components. Eigenvalues greater than 1.0 indicate that the component explains more than the "average" original variable, and thus contains much useful information; eigenvalues below 1.0 indicate the components contain less information than the original variables, and thus can be ignored. This procedure was used to select the number of components produced by PCA.

After the number of components has been selected, one can try to simplify the interpretation of the components by rotating them. The original components are orthogonal, or independent of each other. It is possible to rotate them mathematically to change the loadings of different variables on each component without altering the basic component structure or affecting the information explained by the original components. Varimax rotation, the most common method, was used to perform this operation. Varimax rotation seeks a component solution that makes the loadings as close to ±1.0 or 0.0 as possible on each component. Because the interpretation of a component is based on which of the original variables load highly on it (i.e., close to ±1.0) varimax rotation makes the interpretation simpler.

Table is a summary of the results of the principal components analysis. Twelve components were identified. Only those variables with relatively high loadings are shown.

Identification of Groups

Groups of relatively similar respondents are defined on the basis of their observed characteristics. The basic purpose is to derive a relatively small number of groups containing individuals who are very similar to each other and very different from individual groups.

The first task is to calculate the scores of each respondent on each of the 12 components. 'Component scores' are the values each respondent has on each of the components. They are calculated in the following manner.

Recall that each component is made up of a series of weights or loadings associated with each of the original variables. To calculate a respondent's score on one of the components, the loading of a variable from that component is multiplied by the respondent's original value associated with that original variable. Thus, if the loading of 'Number of times attending classical music in the last 12 months' was 0.9, and the respondent's answer to that question was '5 times' his score would be (0.9) x (4) = 4.5. This is repeated for all variables on the component and the individual scores are totaled for that component. Scores are then computed for all other components for that respondent. Next, the whole process is repeated for all other respondents. Finally, the scores are converted to standardized scores (mean of 0, standard deviation of 1). The result is a matrix of 12 components by N respondents.

Because the components are independent of each other, they can be interpreted as defining a 12-dimensional mathematical space. The set of 12 component scores locates each respondent in that space, just as a set of latitude and longitude 'scores' can locate a person in geographical space. The scores are also a measure of 'similarity.' The more similar two respondents are on one component, the more similar their component scores will be. Groups may be defined by locating 'clusters' of respondents in the 12 dimensional space. The method chosen to do this is 'Ward's Method' (16).

Ward's Method is based on a generalization of the Pythagorean theorem. The role of the Pythagorean theorem is to measure the distance between any two points. This distance can then be compared to the distances between all other pairs of points. The algorithm that operationalizes Ward's Method involves the following tasks:

1. Calculate distances between all pairs of points.

2. Identify the smallest distance.

3. Replace the pair of points associated with the smallest

distance by a new point midway between them.

4. Re-calculate distances between all remaining pairs of

points, including the new point.

5. Continue the process to some cut-off point.

For the 13,400 respondents to the '1978 Canadians and the Arts' survey, this process would begin with 13,400 groups of one respondent each and end with one group of 13,400 respondents. The initial solution has perfect homogeneity in each group, but too many groups. The ultimate solution has a minimum number of groups, 1, but maximum heterogeneity. A compromise is needed. The tactic chosen to find the compromise in this project was to plot an 'information statistic' that can be provided by Ward's Method--a measure of the increase in heterogeneity as the membership in the various groups increases. The plot was examined to find some point in the clustering process that shows a marked increase in the loss of information caused by the combining of two relatively disparate groups. This is indicated by a relatively large jump in the size of the information statistic. A jump in the statistic between 12- and 11-cluster solutions was observed, so it was decided to terminate the clustering at the 12- cluster solution.

Once the clusters are formed, it is necessary to characterize each cluster. This is done by first identifying each respondent in each cluster by means of an identification number attached to the responses from each individual. It is then possible to examine the individual's component scores in detail in each cluster. This analysis consists of the following issues:

1. The number of individuals in each cluster who have component scores greater than ±1.0 (representing a component score more than 1 standard deviation from the mean) for each component are tabulated. If a cluster has many people with such extreme component scores on a particular component, this can be interpreted as evidence that component is important in both creating and in identifying the cluster.

2. F-ratios and t-tests are computed for each component in each cluster. The F-ratio expresses the degree of variance in each component; one hopes to find several components with a small degree of variance in each cluster. These indicate those respondent characteristics that are relatively similar among respondents in that particular cluster. T-tests compare means between the mean of component scores of cluster individuals and all other individuals; one hopes to find several pairs of components within each cluster whose t-tests indicate a fairly great difference between average component scores. To interpret each cluster, one looks for those components whose F-ratios are small, indicating homogenity in that cluster and whose t-tests are large, indicating significant characteristics for that cluster. Tables 2 and 3 summarize this phase of the analysis. On the basis of this examination, cluster descriptions in Table 4 were derived.

It should be mentioned that because of technical limitations in the programme used to form these clusters, only 500 respondents could be used for this stage of the analysis. Caution should be exercised in generalizing from these groups to the entire Canadian population. Groups 11 and 12, especially, are based on very small absolute samples. Component scores for the subsample of 500 were compared to the component scores for the entire sample. No signficant differences were found. We concluded that the clusters based on the 500 respondents are adequately reliable for the purposes of this project.

Calculation of Elasticities

Once clusters of similar respondents are identified, it is possible to calculate cultural elasticities. The procedure for doing this is based on a technique employed by Gum and Martin (17). It is presented in a step-by-step fashion here for the sake of clarity.

1. Select those activities for which cultural elasticities are desired. In this study, five were chosen: (1) Attendance at Live Theatre, (2) Attendance at Classical Music/Ballet/Opera/Modern Dance, (3) Attendance at Folk/Rock/Popular/Country and Western Music, (4) Attendance at "Other Music," and (5) Visits to Art Galleries.

The number of "attendances" at each activity by the individuals in each cluster is obtained. "Attendance" is defined as self-reported attendance in the 12 months preceding the time of the survey. The number of attendances for each activity is then summed across all groups to get the total number of attendances by the sample respondents.

2. Divide the number of attendances at a given activity by the individuals in each cluster by the total attendances to obtain the percentage of attendances generated by each cluster. Table 5 is a summary of the numerical results of Steps 1 through 3. The summation at the bottom of each of the activity columns represents the number of self-reported attendances at each activity by the 500 respondents on which the clusters are based. For example, those 500 people reported a total of 171 attendances at live theatre in the 12 months preceding the survey. The figures within the activity columns represent the percentage distribution of the total attendance across all clusters. In the case of live theatre, again, 1.2 percent of 171 trips to live theatre are associated with Cluster 1.

3. Finally, cultural elasticities may be computed by dividing the percentages in Table 5 by 100. Thus, the cultural elasticity of Cluster 1 for live theatre is 1.2/100 0.012. Cultural elasticities for all clusters and all activities are presented in Table 6.

INTERPRETATION OF ELASTICITIES

An illustration of the use of cultural elasticities may help to clarify their interpretation and to highlight some of the potential uses of the elasticities.

Kinsley (18) in Arts and Culture Monograph IV, "Cultural Participation" forecasts a change in the number of people 65 years of age and older from about 9 percent currently to about 11 percent in the year 2000. This change represents a relative increase of 22 percent. Based on the clusters defined previously, it can be assumed that the majority of this group belong to Cluster 9, older, predominantly married people with average cultural interests, plus a few in Cluster 12, a small, highly diverse group of predominantly retirees. Let us further assume that the relative proportions between Cluster 9 and 12 will remain the same until at least the year 2000. Finally, let us assume that the percentages and relationships represented by this small sample of 500 respondents are truly representative of the entire national population. Thus, the 171 theatre visits registered by the 500 respondents of a total population of about 23,000,000 represents a total of about 7,800,000 theatre visits for the country's population in the year prior to the survey. With these assumptions and data, one can forecast changes in theatre attendance to be expected from a shift in the age distribution as forecast by Kinsley.

If both Cluster 9 and 12 increase at the same percentage rate, 22 percent, they will represent about 7.8 percent and 1.2 percent of the population respectively in 2000. The cultural elasticity for live theatre for Cluster 9 is 0.053. An increase of 22 percent in the size of Cluster 9 will thus translate into a (0.53 x 22) = 1.166 percent increase in theatre visits. Cluster 9 people were responsible for 5.3 percent of the 7,800,000 theatre visits, or about 400,000 theatre visits. A 1.166 percent increase in this figure is equal to approximately 4,700 theatre visits.

Cluster 12 has a cultural elasticity for theatre trips of 0.117. A 22 percent increase in the size of Cluster 12 will cause a (0.117 x 22) = 2.574 percent increase in total theatre trips. Cluster 12 generate 11.7 percent of the 7,800,000 theatre trips reported or about 858,000 trips. A 2.574 percent increase in that number is approximately equal to an increase of 22,000 theatre trips.

The increase in the number of people over 65, indicated by increases in Clusters 9 and 12, necessarily means that some people have "left" other clusters. To simplify the analysis of this effect, let us make the unrealistic assumption that all the increases in Clusters 9 and 12 came at the expense of Cluster 4, the most average group of people. In real life, of course, increases in any cluster would be supported by "transfers" from several clusters, and these clusters would be affected by still other "transfers".

The 22 percent increase in Cluster 9 and 12 represent an absolute increase of about 374,000 people. If all these came from Cluster 4, originally 3,800,000 people, Cluster 4 decreases by about 374,000 or about 9.8 percent.

The cultural elasticity of Cluster 4 for live theatre is .146. A 9.8 percent decrease means theatre visits will drop by (0.146 x 9.8) = 1.43 percent. Since 14.6 percent of all theatre visits or 1,100,000 trips, were made by Cluster 4 people, a 1.43 percent decline represents an absolute decline of about 14,700 visits.

The net effect of a change in the age structure on theatre attendance can thus be estimated by examining changes associated with increases in older age groups adjusted for decreases in younger age groups. Increases in Cluster 9 and 12 procuded a total of 26,700 additional theatre visits; decreases in Cluster 4 created a loss of 15,700 visits for a net increase of 11,000 visits.

Advantages of Elasticities

The calculation of cultural elasticities offers several advantages over other forecasting techniques. First, because they are based on a rather complex way of combining different variables, their development can reveal new and unexpected aspects of the structure of demand for cultural activities. Elasticities are thus constructs of potentially major theoretical interest.

Elasticities assist a forecaster or planner in estimating changes in likely future participation with greater validity than has previously been possible. Because these measures are based on more realistic assumptions about relationships among variables, and permit including of more different variables, the forecasts based on them will tend to be more valid and accurate than if those relationships and variables are ignored. Forecasts can now be made for a single group, or for several groups simultaneously. This feature is especially desirable because a single variable does not usually effect different people in the same way. As we saw in the simple numerical illustration of the use of elasticities above, the single phenomenon, aging, was responsible for two different rates of increase in participation in two different groups, and a decrease in participation in a third group.

Because the elasticities can be constructed to take account of attitudinal and opinion variables, it is possible to use them to assess the effects of government sponsored educational and promotional programmes to change various opinions about cultural activities. If clusters can be defined on the basis, at least partially, of opinion variables, it would be possible to develop forecast changes in participation resulting from shifts in opinions as reflected through shifts in cluster membership. It is conceivable (although this is still a matter of speculation) that the development of cultural elasticities from opinion-related data would help identify which items of opinion are the most influential in affecting participation rates. Basically, those opinion variables that showed up in various clusters with high t-test values and low F-ratios would be the most important opinion-related variables to influence.

The cultural elasticity model also helps to identify those groups most important in generating business for different cultural facilities and organizations, as well as those who are least sympathetic to or least uninterested in cultural programmes. Cultural elasticities are, in other words, a means for market segmentation. For example, in the case of live theatre, Cluster 12 people are responsible for about 11 percent of total theatre visits, although they make up only 1 percent of the percent of the population. This group represents one of the most important markets for live theatre and one of the greatest potential sources of support for public programmes to further live theatre. On the other hand, Cluster 6 people represent 15 percent of the population, but produce only 5 percent of all theatre visits. Better understanding of members of this group and their apparent dislike for live theatre may yield potentially fruitful information for cultural policy and cultural promotion.

Limitations to Elasticities

Several assumptions underlying the calculation and use of cultural elasticities have already been discussed. Some of these bear repeating and a few other limitations should be mentioned.

1. The calculation of elasticities depends greatly on the variables available for analysis. Ideally, information should be available regarding social, economic, attitudinal, demographic and participation characteristics of the population.

2. The elasticities are also strongly influenced by the statistical methods employed, especially PCA. Stability of the components defined over time as well as the reliability of the component structure estimated through PCA needs to be tested more.

3. Before one can use the elasticities to forecast change, one must have access to other forecasts about changes in the sizes of the clusters. These clusters will frequently not match up with the usual age cohort or other socio-economic or geographic clusters for which forecasts are usually made. This might be interpreted as evidence that the use of forecasts for traditional age cohorts or other social groups is actually inappropriate. However, the fact remains that additional work will need to be done to develop forecasts for groups that are meaningful in the context of cultural elasticity clusters.

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Table 1: Detailed Definition of 12 Components

1
"Reading"

How often read science fiction
How often read mysteries
How often read romances
How often read westerns
How often read classics
How often read other novels
How often read drama, short stories
How often read poetry
How often read biography
How often read philosophy
How often read how-to-do-it
How often read other non-fiction

2
"Attendance"

Times attended cinema
Times attended theatre
Times attended classical music
Times attended popular music
Times attended cultural festivals
Times attended arts and crafts
Times attended museums
Times attended art galleries

3
"Educational T.V."

How often watch TV interviews
How often watch TV newscasts
How often watch TV public affairs
How often watch TV plays
How often watch TV classical music
How often watch TV instructional shows

4
"Popular Records"

How often listen to records at home
How often listen to popular, folk, rock records
How often listen to jazz, blues records

5
"Popular T.V."

How often watch TV variety
How often watch TV soap operas
How often watch TV movies
How often watch TV game shows
How often watch TV police shows

6
"Life Cycles I"

Retired or not
Age
Number in household
Married or not

7
"Popular Radio"

How often listen to radio at home
How often listen to radio popular music
How often listen to radio local news
How often listen to radio national news
How often listen to radio interviews

8
"Classical Music"

How often listen to radio classical music
How often listen to opera on records
How often listen to classical records

9 "Sport Viewing"	10 "Life Cycle II"
Times attended sports How often watch TV sports How often listen to radio sports Sex	Student or not Homemaker or not Number of school age children at home Single or not

11 "Education"	12 "Sport Participation"
Level of education Professional or not	Number of years playing sports Money spent on sports

Table 2: Summary of Component Scores by Cluster for Each Component

	Component											
Cluster	1	2	3	4	5	6	7	8	9	10	11	12
1			+	-	+					-		
2											+	
3								-				
4												
5			+				-					+
6				+					-			
7										+		
8				+	-							
9			-	+		+						
10							+					
11	-		+					+	+			
12		+							+			

(+) = majority of respondents in group had a component score + 1.0.

(-) = majority of respondents in group had a component score - 1.0.

Table 3: F-ratios and t-values for 12 Clusters

Key: t-value
(F-ratio)

Components

Clusters	1	2	3	4	5	6
1	0.2901	-0.2970	1.4691	-0.7159	1.6423	-0.3048
	(0.4423)	(0.3012)	(0.0329)	(1.6705)	(0.0835)	(1.2228)
2	-0.1267	0.3985	0.1543	-0.0536	0.4695	0.0288
	(0.6486)	(0.7950)	(0.9951)	(0.6861)	(0.7600)	(0.6020)
3	-0.4705	0.5094	-0.3346	-0.4049	0.4992	-0.4255
	(0.3938)	(0.7659)	(0.8713)	(0.8180)	(0.4547)	(0.4444)
4	0.0259	0.0162	0.1352	-0.5539	-0.6459	-0.9113
	(0.7262)	(0.2909)	(0.7794)	(0.4316)	(0.5936)	(0.2941)
5	-0.2262	-0.3303	0.6514	-0.2022	0.4681	0.1233
	(0.5445)	(0.3444)	(1.0768)	(0.9095)	(0.6085)	(1.0838)
6	0.1229	-0.3837	0.0548	0.6999	0.4901	0.2544
	(0.6114)	(0.2474)	(0.5453)	(0.6419)	(0.6517)	(0.6256)
7	0.7445	0.3844	-0.4215	-0.8458	-0.4432	-0.0051
	(0.1867)	(1.2095)	(0.7812)	(0.5857)	(0.6123)	(0.4564)
8	0.0757	-0.3198	-0.2422	0.5409	-0.7994	-0.2528
	(0.8381)	(0.2051)	(0.6429)	(0.8262)	(0.5699)	(0.4173)
9	-0.0079	-0.0554	-0.8247	0.7555	-0.3579	1.7519
	(0.6441)	(0.5619)	(0.5957)	(0.6101)	(0.7333)	(0.3332)
10	0.3066	-0.3443	-0.3691	0.0330	-0.0229	0.4595
	(0.3983)	(0.2960)	(1.1981)	(0.8743)	(0.9264)	(1.2982)
11	-6.5097	-0.9148	0.9539	-0.1678	-0.1199	0.5861
	(1.3674)	(0.1785)	(0.7840)	(1.2911)	(0.6115)	(0.2334)
12	-0.7823	6.3807	0.7887	0.6401	-0.0310	0.8736
	(0.2676)	(4.0691)	(2.1607)	(0.9220)	(1.9380)	(0.3296)

Table 3: F-ratios and t-values for 12 Clusters

Components

7	8	9	10	11	12
0.8902 (0.6710)	0.1931 (0.1989)	0.5753 (0.4442)	-0.7089 (0.9051)	-0.4919 (0.0701)	-0.2276 (0.4990)
0.0080 (0.5625)	-0.2761 (1.4568)	0.2574 (0.6708)	-0.0267 (0.6550)	2.3743 (0.1147)	0.1522 (0.9502)
0.3259 (1.1217)	-1.5755 (1.6961)	0.3747 (0.3288)	0.1101 (0.9016)	-0.6680 (0.1580)	-0.1662 (0.8151)
0.1147 (0.7097)	0.1758 (0.4966)	-0.2500 (0.8504)	-1.0542 (0.3910)	-0.2075 (0.1102)	0.1476 (0.6469)
-0.7990 (0.2603)	0.1314 (0.7200)	0.6695 (0.4079)	0.2249 (0.6540)	-0.3558 (0.2468)	0.5392 (1.6742)
-0.3994 (0.3784)	0.1734 (0.4138)	-0.9859 (1.0537)	-0.0286 (0.3988)	-0.3033 (0.1856)	0.1635 (0.7878)
-0.6112 (0.4248)	-0.0706 (1.7230)	-0.6565 (0.9279)	0.7963 (0.9605)	-0.2763 (0.1898)	0.2069 (1.4410)
-0.3261 (0.5455)	0.2383 (0.4070)	0.3250 (0.6471)	0.5096 (0.6281)	-0.3372 (0.0574)	0.6515 (0.4909)
-0.5319 (0.3500)	0.2716 (0.3248)	0.5474 (0.5323)	-0.4757 (0.3083)	-0.3993 (0.0981)	-0.4915 (0.5130)
1.7341 (0.3352)	0.2065 (0.5063)	0.2839 (0.5389)	0.8049 (1.0785)	-0.2682 (0.3495)	0.0564 (1.0061)
0.4005 (1.7806)	1.5489 (0.3904)	-0.7496 (1.4253)	1.0190 (1.1473)	-1.0268 (0.0952)	0.5025 (1.7966)
0.5704 (2.3808)	-0.5052 (3.7702)	1.0398 (0.3239)	0.4659 (1.3566)	-0.0762 (3.9954)	-0.4691 (5.1580)

Table 4: Identification of 12 Clusters

CLUSTER	NUMBER OF RESPONDENTS	% OF SAMPLE	DESCRIPTION
1	18	3.6	Prominantly singles and students who watch a lot of television. Some tend to listen to a lot of popular radio. They are average in the amount of reading for pleasure, their attendance at performing arts, and in the frequency of listening to classical music at home.
2	62	12.4	Educated professionals, primarily. Their cultural interests and activities are relatively homogeneous with the rest of the population.
3	34	6.8	Average socio-economic group, with typical family structures and cultural interests and rates of participation except for an apparent above-average dislike of classical music.
4	82	16.4	Perhaps the most typical group. Average and relatively uniform cultural interests and rates of participation. Slightly more smaller families and two-income families than in most other groups.
5	41	8.2	A diverse group of respondents in terms of age, marital status, and household size. They are alike in a shared interest in playing sports, watching television frequently and an apparent lack of interest in popular radio.
6	76	15.2	Another group of average individuals. These are distinguished by an apparent dislike for televised sports and by a strong preference for listening to music on records and tapes.
7	37	7.4	Homemakers and non-professional heads of households. They read more than average. They are quite diverse in terms of interests in listening to classical music and in attending performing arts.
8	62	12.4	A generally average, and uniform set of respondents who are unusual only in that they report watching very little, if any, television.

9	32	6.4	Older, married people with average cultural interests, except for below average viewing of educational television. A few also report frequently listening to records and tapes.
10	47	9.4	A diverse group socially, who are alike in that they listen to the radio more than they do anything else.
11	4	0.8	A small group of primarily homemakers and non-professional workers, with below average educations, who do not read much, but spend a lot of time watching educational television and listening to classical music.
12	5	1.0	A small, highly diverse group. They tend to be older, retired people. They generally read little, but go to performing arts frequently and watch televised sports regularly.

Table 5: Distribution of "Attendances" at Each Cultural Activity by Cluster

% Cluster	% Theatre	% Classical Music	% Popular Music	% Other Music	% Art Galleries
1	1.2	3.0	4.7	0.0	0.6
2	21.1	25.8	18.3	21.1	20.5
3	15.8	16.7	9.9	9.9	20.5
4	14.6	12.9	16.0	23.9	4.6
5	4.1	6.1	4.7	4.2	4.6
6	5.3	4.5	4.2	7.0	3.4
7	5.8	8.3	19.2	9.9	8.6
8	8.2	3.8	6.1	7.0	8.0
9	5.3	3.8	3.8	5.6	2.3
10	6.4	3.0	2.8	7.0	8.0
11	0.6	0.0	0.0	2.8	0.6
12	11.7	12.1	8.9	1.4	18.3
	100%	100%	100%	100%	100%
Total Actual Attendances	171	132	213	71	175

Table 6: Cultural Elasticities

Cluster	Theatre	Classical Music	Popular Music	Other Music	Art Galleries
1	.012	.030	.047	.000	.006
2	.211	.258	.183	.211	.205
3	.158	.167	.099	.099	.205
4	.146	.129	.160	.239	.046
5	.041	.061	.047	.042	.046
6	.053	.045	.042	.070	.034
7	.058	.083	.192	.099	.086
8	.082	.038	.061	.070	.080
9	.053	.038	.038	.056	.023
10	.064	.030	.028	.070	.080
11	.006	.000	.000	.028	.183
12	.117	.121	.089	.014	.183