An Empirical Analysis of Cultural Demand and the Structure of Household Expenditure

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Abstract

In many empirical studies pertaining to cultural demand, various demand functions are specified and are thus estimated for cultural goods and services. In most cases, cultural demand or cultural expenditure, as dependent variables, can be explained by income, price, and other effective household and social variables. However, cultural demand is usually assumed to be determined either by stage of consumption or independently. The purpose of this work of research was to explore the relationship between cultural and other expenditure and to establish the structure of household expenditure, using Bayesian networks on a dataset drawn from the Family Income and Expenditure Survey in Japan. We compared results for workers' and two-or-more-person households and obtained relatively stable results for each of the two types. A close relationship was observed between cultural expenditures, some of which were located close to end or independent nodes. These results imply that cultural demand has the characteristics of a luxury good although the structure of household expenditure is complicated.

Keywords: cultural demand, causal structure, Bayesian networks, Family Income and Expenditure Survey

JEL classification: C11·D10·Z11

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1 Introduction

The purpose of this paper is to explore the relationship between cultural and other expenditure and to establish the network structure of household expenditure, using Bayesian networks on a dataset drawn from the Family Income and Expenditure Survey in Japan.

In previous studies, estimating a demand function that includes cultural demand has required a certain causal relationship to be assumed for various types of equations from which models are composed. The models are usually derived from a certain type of economic theory. Moreover, in estimating specific expenditures by allocating income to many items of expenditure, it is sometimes assumed that the decision is made in multiple stages. For example, in the first stage, a household allocates income between consumption and saving; in the second stage, given the decision in the first stage, consumption expenditures as a whole are allocated among a major group of items (e.g., food, housing, clothing and footwear, education, etc.); in the third stage, expenditures for major items are allocated among detailed categories of commodities (e.g., allocating expenditure for food among cereals, fish, meat, vegetables, etc.), and so on.

Such assumptions impose impractical restrictions on the form of the demand functions and parameters in models. Practically, people do not always make decisions by allocating their income or expenditures according to the aforementioned stages.

One of the reasons for assuming such restrictive behavior is to provide the possibility of estimation. Although researchers try to use many items of expenditure in the model, the sample size is not always enough for estimating parameters that increase in accordance with the number of items used. Such a problem in the relationship between the number of parameters and the sample size is serious, given the existence of structural changes and seasonality.

The objective of the estimation of specific demand functions is to clarify how households make their expenditure decisions, given their budget constraints, meaning that information regarding the relationship between the items of expenditure considered, other expenditures, income, and prices is needed. Although the relationship is sometimes derived from a utility function and economic theory, this paper empirically explores the structures among expenditures, which are classified by a certain number of items, including cultural expenditures, by using Bayesian networks. Hashimoto and Araki (2013) utilized a similar methodology in their consideration of a major group of household expenditures, with some categories in culture and recreation. This paper develops their work into more detailed categories of cultural expenditures.

The remainder of the paper is organized as follows. Section 2 briefly reviews previous empirical work on the analysis of cultural demand. Section 3 outlines the Bayesian networks used in this paper. Section 4 presents the dataset and its basic properties. Section 5 provides results of expenditure structures and how cultural expenditures are affected by other expenditures. The final section presents a brief conclusion.

2 Previous Work on Cultural Demand

Previous empirical studies of cultural demand mainly focused on the estimation of demand functions, which are mainly modeled on the relationship between cultural demand and its determinants, such as income, price, and population. Contemporary demand analyses for culture are closely related to Baumol and Bowen (1966). Income/price elasticity of cultural demand or participation has been discussed in relation to many countries, periods, items of cultural demand, models, etc. Moore (1966); Houthakker and Taylor (1970); Withers (1980); and Gapinski (1986) are typical examples of the earliest works. Seaman (2006) provided an excellent survey of this field by summarizing the quantitative results of elasticity.

It is well established that numerous factors influence cultural demand: demographics (i.e., age, gender, and cohort); social factors (i.e., region, education, and family); economic factors (i.e., income and price); and supply factors (i.e., number of concerts or theaters), among others. If cultural demand is measured by participation in cultural activities, attendance functions are estimated to assess the factors mainly by using cross-section data. This type of study employs binary regression models for its estimation. See Abbé-Decarroux and Grin (1992); Lévy-Garboua and Montmarquette (1996); Gray (1998); Prieto-Rodríguez and Fernández-Blanco (2000); Borgonovi (2004); Ateca-Amestoy (2008); and Katsuura (2008).

For details of demand theory for cultural activities underlying empirical analysis, see Stigler and Becker (1997); Becker and Murphy (1988); Abbé-Decarroux and Grin (1992); Throsby (1994); Lévy-Garboua and Montmarquette (1996, 2003); and Ateca-Amestoy (2007).

The works that estimate the system of demand functions for cultural expenditures on the basis of the Almost Ideal Demand System (AI Demand System or AIDS), developed by Deaton and Muellbauer (1980), are Pommerhene and Kirchgassner (1987), Prieto-Rodríguez, et al. (2005), and Katsuura (2014). This “almost ideal” system is derived from the cost function using duality and assumes multi-stage decision-making with respect to expenditures as described above.

This paper is not based on economic theory but rather explores expenditure structure simply from the dataset. In doing so, the theory of demand is not ignored; rather, information about how cultural expenditures relate to other items is clarified. This effort may provide basic information that allows us to consider economic theory and empirical analysis in light of cultural demand.

3 Bayesian Networks

Bayesian networks (BNs), a type of probabilistic graphical model, can be used to build causal models from data and then be referred to as causal networks. The networks are expressed by a directed graph and the direction of the arrows can be interpreted as causal relationship showing information flows. Therefore, a Bayesian network provides a method that can intuitively reveal insights into the objective's underlying causal structure. This section outlines the basic idea of Bayesian networks by following Pearl (2000), Pourret, et al. (2008), and Scutari (2010).

3.1 The Basic Idea

Bayesian networks are graphical models where "nodes" represent random variables and "edges (arrows)" represent directed links or probabilistic dependencies between them. The graphical structure of a Bayesian network is a pair *G*=(*V*, *E*), where $V = \{v_1, v_2, \cdots, v_d\}$ is a node set and *E* is a directed edge set. A Bayesian network is called a Directed Acyclic Graph (DAG) if it has no directed cycles.

Some basic terminology used in Bayesian networks is as follows:

The edge is directed when $(v_i, v_j) \in E \; and \; (v_j, v_i) \notin E$, which is expressed as $v_i \to v_j$. v_i is a "parent" node and v_j is a "child" node. A node *v* in a directed graph is called a "root" if no edges are directed into *v*, and a node *v* is called a "sink" if *v* does not have a child. *d*-separation is an important concept; two nodes in the network are said to be *d*-separated if the information is blocked between the two nodes by a node in the middle. See Pearl (2000) and Pourret, et al. (2008) for details.

The nodes $V = \{v_1, v_2, \cdots, v_d\}$ correspond to random variables $X = \{X_1, X_2, \cdots, X_d\}$. The DAG defines a factorization of the joint distribution $P(X)$ of $X = \{X_1, X_2, \cdots, X_d\}$ into a set of local distributions, one for each variable. Let whole parent nodes of X_i be $\Pi_{X_i} = \{X_j : X_j \to X_i\}$. If every random variable X_i directly depends only on its parents Π_{X_i} and $P(X)$ is represented as follows:

$$P(X) = \prod_{i=1}^{d} P(X_i | \Pi_{X_i}),$$

where $P(X_i | \Pi_{X_i})$ is a conditional distribution of X_i, given Π_{X_i}, then *G* = (*V*, *E*) has Markov property and (*G, P*) is called a Bayesian network.

3.2 Estimation

Bayesian networks consist of pairs of graphical structure and conditional distribution. Therefore, to estimate a Bayesian network, learning the graphical structure and estimating its parameters in the distribution are required. The resulting models are often interpreted as causal models even when learned from observational data[1].

The algorithms for a Bayesian network can be classified into three categories:

1. Score-based methods

[1] Scutari (2010).

2. Constrained-based methods
3. Hybrid methods

Score-based methods are algorithms that assign a score to each candidate Bayesian network and try to maximize it with some heuristic search algorithm. Hill-climbing search and Tabu search are commonly used. Constrained-based methods are algorithms that learn the network structure by analyzing the probabilistic relations entailed in the Markov property of a Bayesian network by means of conditional independence tests and then by constructing a graph that satisfies the corresponding *d*-separation statements. Grow-Shrink algorithm is a commonly chosen method. Hybrid methods use both elements. Learning the graphical structure is efficiently accomplished by constraint-based methods, which are, in turn, refined into learning by score-based methods. A max-min hill-climbing search is commonly used and is used in the empirical results section.

4 Data and Their Properties

This paper analyzes selected series from the Family Income and Expenditure Survey (hereafter FIES) conducted monthly by the Statistics Bureau, Ministry of Internal Affairs and Communications, Japan. The FIES aims at providing comprehensive data on income and expenditure of households in Japan.[2] The survey unit is the household in the entire area of Japan and about 9,000 households are randomly selected from appropriate households for the survey. The sample households are selected on the basis of a three-stage stratified sampling method. The sampling units at three stages are as follows: first, the municipality; second, the survey unit area; and, third, the household. The sample includes both two-or-more-person and one-person households; however, our analysis concentrates only on two-or-more-person households. We can use both workers' households in two-or-more-person households (hereafter workers' households) and two-or-more-person households as a whole. Two-or-more-person households include households of individual proprietors and corporate executives, no-occupation households, and workers' households.

In the FIES, the detailed commodity classification of expenditures is aggregated into 10 major groups as follows:

1. Food
2. Housing
3. Fuel, light & water charges
4. Furniture & household utensils
5. Clothing & footwear

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[2] *Annual Report on the Family Income and Expenditure Survey 2016* (Statistics Bureau, Ministry of Internal Affairs and Communications, Japan).

6. Medical care
7. Transportation & communication
8. Education
9. Culture & recreation
10. Other consumption expenditures

The detailed classification relating to cultural expenditures is included in "9. culture and recreation" as shown in Table 1. We are interested in the relationship between cultural expenditures and others and in how other expenditures affect cultural ones. In the following analysis, all consumption expenditures are classified into the 19 items shown in Table 2. Detailed categories used as cultural expenditures by households, such as "admission fees for movies, plays, etc. (AFMP, code 882)"; "admission fees for cultural establishments (AFCE, code 884)"; "admission fees for amusement parks (AFAP, code 886)"; and "admission fees for sports (AFS, code 883)." AFMP includes admission to movies, theaters, concerts, comic storytelling, dinner shows, and kabuki; AFAP consists of admission to art galleries, museums, zoos, temples and shrines, and other cultural facilities such as safari parks, aquariums, and botanical gardens, as well as to exhibitions of insects, dinosaurs, etc.; AFAP includes ride charges, which are limited to those within an amusement park, theme park admission, attraction charge, etc.; and AFS consists of admission to venues for baseball, soccer, circuit race, golf, and sumo wrestling, etc.

Table 1. Structure of Culture and Recreation Classification

Code	item
9	Culture & recreation
9.1	Recreational durable goods
9.2	Recreational goods
9.3	Books & other reading materials
9.4	Recreational services
9.4.1	Accommodation services
9.4.2	Package tours
9.4.3	Lesson fees
9.4.4	Other recreational services
880・88A ・88B	Charges for TV licence
877,878,881-886	Admission fees & game charges
882	Admission fees for movies, plays, etc.
884	Admission fees for cultural establishments
886	Admission fees for amusement parks
883	Admission fees for sports
878	Rental fees for sports facilities
885	Other admission fees & game charges
888	Membership dues
887	Photo processing charges
88X	Hire of recreational goods
89Y	Internet connection charges
889	Others

Source: Statistics Bureau of Japan, Family Income and Expenditure Survey
(the same source for the following tables and figures)

Table 2. Variables Used in Estimation

Code	item
1	Food
2	Housing
3	Fuel, light & water charges
4	Furniture & household utensils
5	Clothing & footwear
6	Medical care
7	Transportation & communication
8	Education
9.1	Recreational durable goods
9.2	Recreational goods
9.3	Books & other reading materials
9.4.1-2	Accommodation services and package tours
9.4.3	Lesson fees
882	Admission fees for movies, plays, etc.
884	Admission fees for cultural establishments
886	Admission fees for amusement parks
883	Admission fees for sports
9.4-AF	Other recreational services
10	Other consumption expenditures

Note: 9.4.1-2=9.4.1+9.4.2 in Table 1.
9.4-AF=9.4-(882+883+884+886) in Table 1.

Hashimoto and Araki (2013) examine differences in results by numbers of categories when estimating Bayesian networks; they compare 10, 13, and 16 items by two types of households. The results for these numbers of items are similar, and they conclude that the results are robust for the number of items used in Bayesian network analysis. Furthermore, they conclude that the results of workers' households and two-or-more-person households are similar on the whole.

Figure 1 shows the time-series fluctuation in 19 variables in Table 2. These are seasonally adjusted for workers' households. Table 3 provide basic statistics for all variables in Table 2.

We used monthly data, and the sample period is from January 2000 to February 2018. Therefore, there remains the problem of seasonal adjustment. Unfortunately, Statistics Bureau Japan does not provide seasonally adjusted series for the FIES. Thus, two options are available for our analysis: creating a seasonally adjusted series or using the rate of change compared with the same month of the prior year. The former method was mainly used because the correlation among expenditures was higher than that of the results by rate of change. Seasonal adjustment is conducted using R[3] function "decompose," and then trend plus random factors are used as the seasonally adjusted series.

[3] R Core Team (2018).

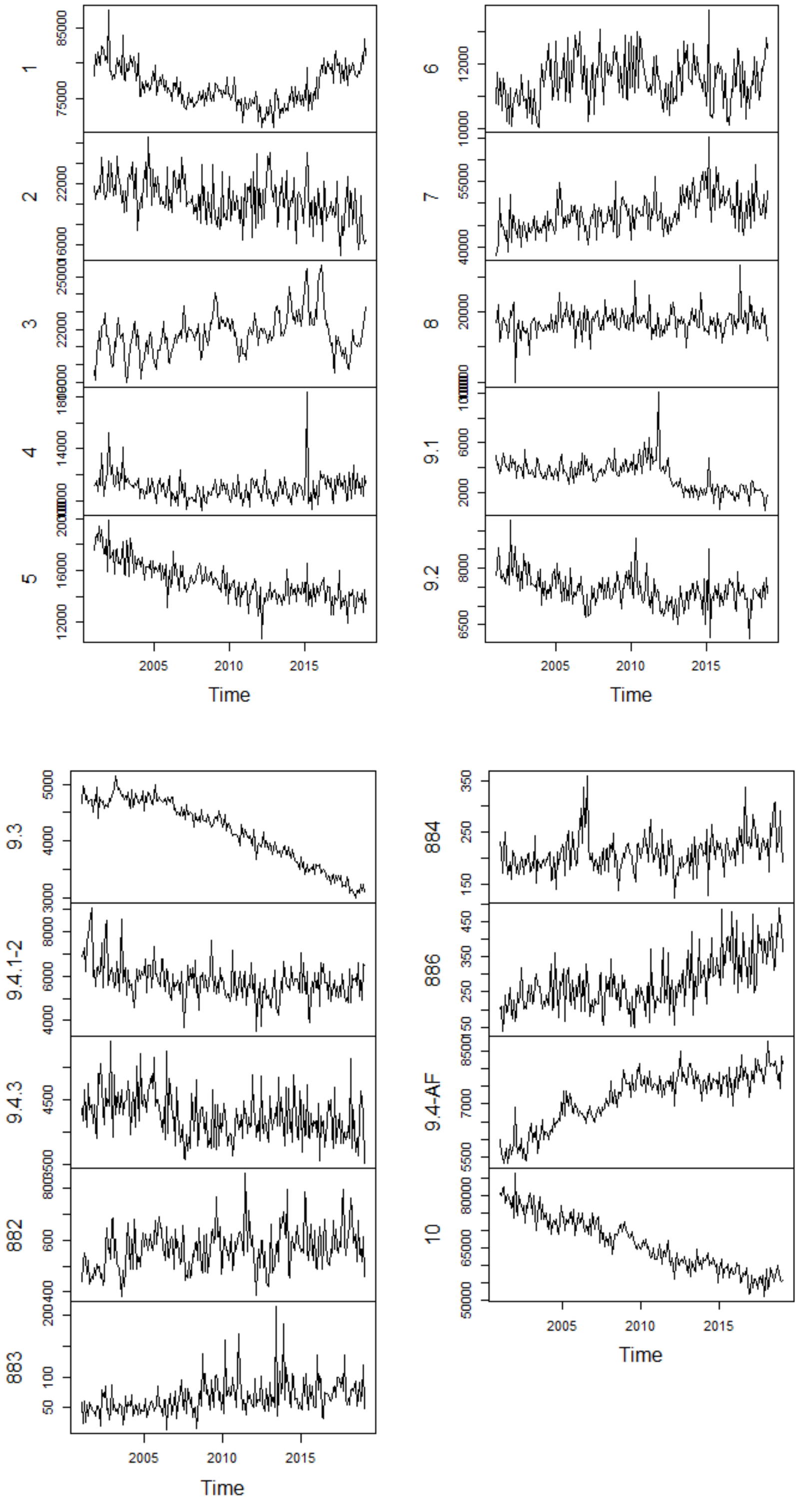


Figure 1. Fluctuation of Expenditures for 19 Items (Original Series)

Table 3. Basic Statistics of Variables (January 2000 to February 2018)

Code	item	mean	standard dev.	median	min	max
1	Food	76708.49	2660.40	76129.71	70857.15	87493.38
2	Housing	20467.41	2110.18	20599.53	14943.82	26525.11
3	Fuel, light & water charges	21756.26	1184.00	21701.24	18947.45	25667.45
4	Furniture & household utensils	10998.92	981.16	10892.66	9225.10	18347.10
5	Clothing & footwear	15132.99	1482.53	15006.58	10767.58	19899.36
6	Medical care	11487.98	714.36	11487.35	10003.97	13667.00
7	Transportation & communication	47721.93	4183.13	47212.58	38025.49	65130.77
8	Education	18549.44	1713.72	18509.39	9849.62	26730.62
9.1	Recreational durable goods	3413.00	1200.94	3529.12	569.82	10048.05
9.2	Recreational goods	7426.22	430.32	7395.02	6148.54	9275.54
9.3	Books & other reading materials	4161.76	556.05	4292.07	2993.93	5147.12
9.4.1-2	Accommodation services and package tours	5772.25	813.06	5679.27	3525.32	9026.77
9.4.3	Lesson fees	4247.43	355.71	4233.86	3513.92	5401.27
882	Admission fees for movies, plays, etc.	568.73	80.68	565.90	382.53	856.18
884	Admission fees for cultural establishments	66.05	27.31	61.05	14.96	214.96
886	Admission fees for amusement parks	210.67	34.79	208.74	122.17	359.37
883	Admission fees for sports	276.58	73.74	267.66	138.47	486.60
9.4-AF	Other recreational services	7171.75	760.11	7391.39	5312.88	8771.50
10	Other consumption expenditures	66107.10	7710.27	65525.27	51046.09	86233.09

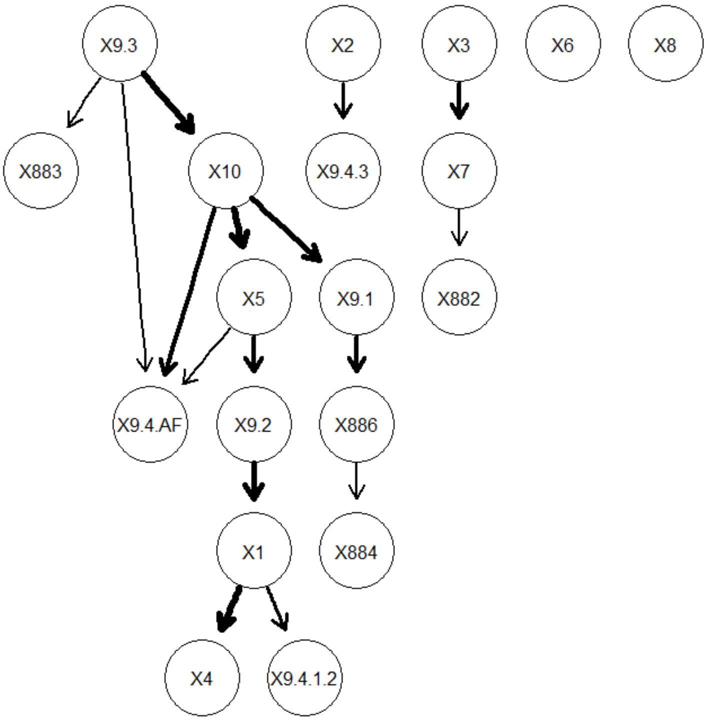
5 Empirical Results

In this paper, we use a package called "bnlearn," which implements algorithms for learning the structure of Bayesian networks in R, which then refer to a function "mmhc" (max-min hill-climbing) as a hybrid algorithm for estimation. As parameters in this function, the significance level for tests of independence is set to 0.05, and other parameters are set to their default values. The sample period spanned January 2000 to February 2018 (T = 218) for 19 variables shown in Table 2. Nonparamormal transformation was applied to all variables.[4]

5.1 Result for Worker's Household

Figure 2 represents causal structures of expenditures for workers' households, using seasonal adjusted series. In Figure 2, medical care (X6) and education (X8) are separate nodes. Housing (X2); fuel, light and water charges (X3); and books and other reading materials (X9.3) are not affected by other items, i.e., root nodes. Admission fees for sports (X883, AFS); other recreational services (X9.4-AF); furniture and household utensils (X4); accommodation services and package tours (X9.4.1-2); admission fees for cultural establishments (X884, AFCE); lesson fees (X9.4.3); and admission fees for movies, plays, etc. (882, AFMP) are nodes that do not influence other items, viz. sink nodes.

[4] See Liu *et al*. (2009).



Note: *X* reprents a node (item) and the figures followed by X correspond to the code in Table 2.

Figure 2. Expenditure Structure of 19 Items for Workers' Household by Bayesian Networks

We can see three causal processes, descendants, which start from housing (X2); fuel, light and water charges (X3); and books and other reading materials (X9.3). Lesson fees (X9.4.3) is affected by housing (X2). AFMP is affected by fuel, light and water charges (X3) via transportation and communication (X7). This means that the activity of watching a movie or a play is closely related to communication. As one might imagine, a lot of information on cultural activities is obtained by mobile phones and computers, and using these instruments, one can also make bookings for cinemas and theaters. To examine this effect more thoroughly, however, transportation and communication (X7) should be divided into more detailed categories.

Observing the causal relationship starting with books and other reading materials (X9.3), we can tell that cultural expenditures are located near the end nodes (sinks), except for books and other reading materials (X9.3). Books and other reading materials (X9.3) have many descendants, affecting via various items, including food (X1), clothing and footwear (X5), other consumption expenditures (X10) and etc. This suggests that books and other reading materials have properties of necessary goods. Declining trends and lower levels of recent expenditures for books and other reading materials are shown in Figure 1, which is related to this type of property. Of course, this is caused by the development of ICT.

Admission fees for sports (X883, AFS) is directly affected by books and other reading materials (X9.3), a root node. This outcome suggests that sport watching is an activity that is relatively independent from others. Accommodation services and package tours (X9.4.1-2) is a child node of food (X1) and is indirectly affected by four items. This suggests that traveling is a luxury good and expenditure for it is determined after other necessary goods are purchased.

Admission fees for amusement parks (X886, AFAP) and admission fees for cultural establishments (X884, AFCE) seem to have characteristics similar to those of traveling. In particular, AFCE is the endpoint that is directly affected by AFAP; this means that visiting cultural establishments such as art galleries and museums is decided after visiting amusement parks. The route to such cultural expenditures is directed via other consumption expenditures (X10) and recreational durable goods (X9.1).

5.2 Result for Two-or-more-person Households

Figure 3 represents causal structures for two-or-more-person households. Two-or-more-person households consist of workers' households and other households. The latter includes individual proprietors' households, which refer to households the heads of which are merchants, artisans, or administrators of unincorporated enterprises.

The results of Figures 2 and 3 are, in part, similar. Medical care (X6) is a separate node; books and other reading materials (X9.3) affect a number of items as a root node; and the location and role of other consumption expenditures (X10) is almost the same. Admission fees for amusement parks (X886, AFAP) is affected by the same three items as those in Figure 2, except for education (X8), but it becomes a sink node.

Among the cultural expenditures, the causal structure in Figure 3 is different than those found in Figure 2. Cultural expenditures as a whole seem to be relatively independent. Accommodation services and package tours (X9.4.1-2) and admission fees for cultural establishments (X884, AFCE) are independent nodes. Admission fees for movies, plays, etc. (882, AFMP) is a child node, with their sole parent being admission fees for sports (X883, AFS); these two items constitute an independent group. Therefore, these four cultural expenditures are decided independently from other expenditures by households.

Such differences between workers' and two-or-more-person households might be caused by differences in income levels and ages. Income levels of workers' households tend to be lower than those of two-or-more-person households because the latter include individual proprietors' households, corporate executives, and so on. While cultural expenditures are decided after other necessary goods in workers' households are purchased, cultural expenditures in non-workers' households are decided relatively freely, irrespective of other necessities. Furthermore, two-or-more-person households include no-occupation households, mainly those of aged people; the result in Figure 3 is supposed to partly reflect the behavior of aged people. Cultural expenditures for aged people are characterized as being close to necessity goods or that they would determine the amount of cultural expenditures in earlier stages of consumption.

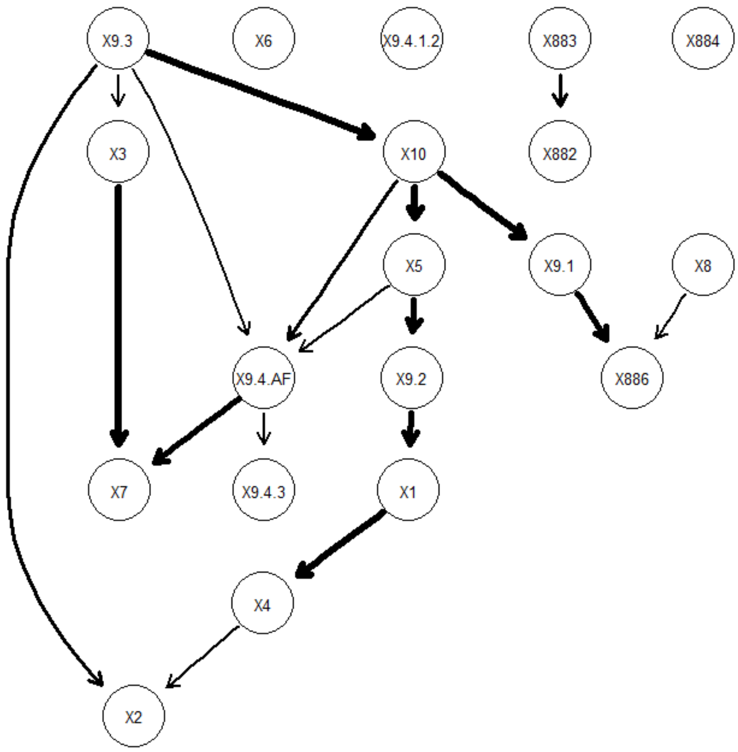


Figure 3. Expenditure Structure of 19 Items for Two-or-more-person Households by Bayesian Networks

5.3 Results Based on Percentage Changes

Figures 4 and 5 represent causal structures based on the transformed data into percentage changes year-on-year for the original series (seasonally unadjusted). In these cases, the expenditure structures seem to be very simple, and each item is only related to one or two others; they are sometimes independent, in particular those seen in Figure 5. This is because the correlation among percentage changes is lower than that found in the case of level data.

Food (X1) becomes a root node and affects more items than those found in Figures 2 and 3. Even in Figure 4 and 5, nodes of cultural expenditures are located near the end (sink) nodes. In Figure 4, admission fees for cultural establishments (X884, AFCE) is affected by food (X1), medical care (X6), and accommodation services and package tours (X9.4.1-2) and does not influence other items (i.e., it is a sink node). Admission fees for movies, plays, etc. (882, AFMP) is affected by transportation and communication (X7), which is similar to the result as noted in Figure 2, forming an independent group under two nodes. Admission fees for amusement parks (X886, AFAP) is an independent node.

In Figure 5, admission fees for cultural establishments (X884, AFCE) is not affected by food (X1) but still affect accommodation services and package tours (X9.4.1-2) and transportation and communication (X7) via fuel, light and water charges (X3). It is difficult to interpret this result. Admission fees for movies, plays, etc. (882, AFMP) and admission fees for sports (X883, AFS) belong to the same group as in Figure 3.

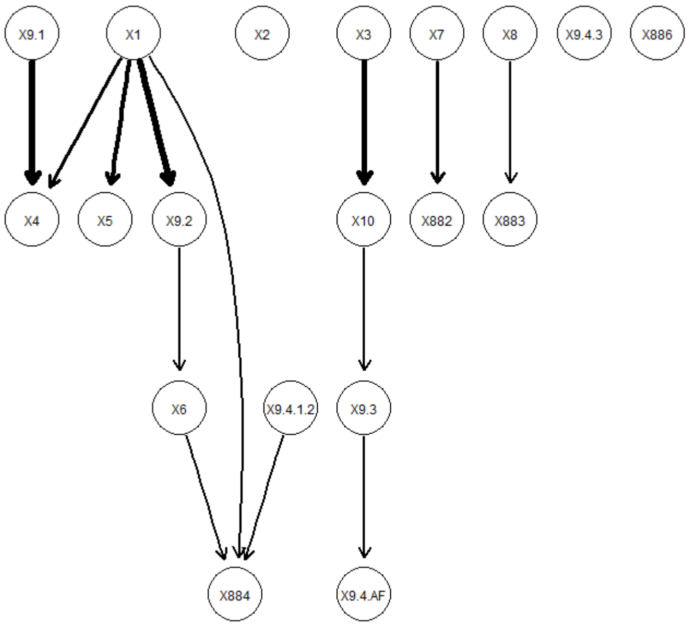


Figure 4. Expenditure Structure of 19 Items for Workers' Households by Bayesian Networks: Based on Percentage Change

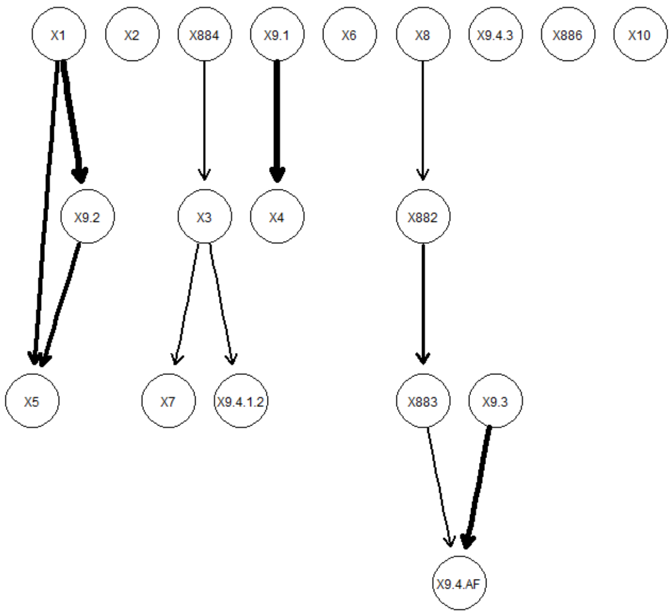


Figure 5. Expenditure Structure of 19 Items for Two-or-more-person Households by Bayesian Networks: Based on Percentage Change

6 Concluding Remarks

This paper explores causal structures among categories in the FIES by applying Bayesian networks with cultural expenditures as the focus. Valid results are obtained by this method and can be interpreted appropriately according to the implications gleaned from the results. In workers' households, cultural expenditures tend to be affected by some items and unaffected by some others. Furthermore, some cultural expenditures influence other cultural expenditures. This outcome suggests that cultural expenditures are not necessary but luxury goods. In two-or-more-person households, we get similar results; however, cultural expenditures are relatively independent, and their relationship with other items is weak. These results suggest that cultural expenditures have higher income elasticities than do other categories of expenditure. Of course, the results would depend on the attributes of households, such as age, region, household size, etc.

When conducting such an analysis, it is difficult to decide how many expenditure items should be used. In this paper, only culture and recreation (code 9 in Table 1) in 10 major groups, which include culture-related items, were divided into detailed categories, and nine other major groups were used simply without categorizing. It is desirable that Bayesian networks be applied to detailed categories for all major groups. However, to do so, a sufficient (usually larger) sample size is required for estimation. The more detailed the categories, the more unstable the result. This is one of the reasons for focusing uniquely on cultural expenditure.

This sort of exploratory analysis forms the preliminary analysis for modeling a demand function or demand system. It is expected that the estimated causal structure of expenditure will be utilized for extensive research. Moreover, our results have a close relationship with elasticities of income and prices. Those analyses remain for future study.

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