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HEALTH AS AN UNOBSERVABLE: A MIMIC MODEL OF DEMAND FOR HEALTH CARE

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A MIMIC Model of Demand for Health Care

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ABSTRACT

This paper develops a model to analyze the demand for health care. It differs from current practice in that (1) it deals explicitly with the complex relation between income, health, health insurance, and the demand for health care; and (2) "health" is treated as an unobservable variable.

We prove the identification of a 10-equation, simultaneous, multiple indicator, multiple causes (MIMIC) model, containing two simultaneously determined unobservables and, in total, 8 "indicators."

We present the ML-estimates of the structural parameters of different versions of the model, using data from a health-care survey among 8000 households in The Netherlands.

The results show, among other things, that health and permanent income have mutual, positive impacts. Both age and education have important direct and indirect (via permanent income) effects on health. A variable representing the percentage of unemployment in an individual's region shows a significantly negative influence on health. The estimated impact of the availability of health care on demand confirms similar results based on aggregated data.

The health index derived from this model can be used to measure, e.g., the difference in "health status" among socioeconomic groups and between regions or countries. In a more elaborated version of the model, this health index may be used to compare the effectiveness of different kinds of input in the production function of health.

Health as an Unobservable: A MIMIC Model of Demand for Health Care

1. INTRODUCTION

This paper analyzes the demand for health care, defined in terms of number of doctor-patient visits, expenditures for drugs, hospital admissions, etc. Our approach is in the spirit of Andersen (1968) (see also Andersen et al., 1975), and draws on recent developments in the theory of health economics (Grossman, 1972; Newhouse, 1978a, b). It differs from the current approach, however, in at least two important ways:

First, in our model, we deal explicitly with the complex relationships among health, income, health insurance, and demand for health care. Health and income are determined simultaneously; next, health insurance is considered, as a function of income, among other things. Finally, the demand for health care is specified as a function of all three--income, health, and health insurance.

Secondly, we treat health as an unobservable variable. Since the model we develop is fully identified, estimation of the structural coefficients enables us to calculate a "health index" for each individual. This index can be used to compare, for example, the health status of different socioeconomic groups and the health status of inhabitants of different areas. By treating health as a latent variable (compare Robinson and Ferrara, 1977) we are able to specify and esimate a system of structural equations instead of the partially reduced-form equations usually encountered in research on the economics of health care.

In section 2 we develop the general model. In section 3, we present and discuss the ML-estimates of the model, using data from a health-care survey among 8000 households in The Netherlands. In section 4, we examine in detail the concept of "permanent" health and illustrate the usefulness of the estimated health index. Section 5 assesses the fit of the model.

2. THE GENERAL MODEL

2.1 Health

In presenting a general framework to study the demand for health care, Andersen et al. (1975) distinguished among three types of variables: need, enabling variables, and predisposing variables.

For the measurement of need, ad hoc variables are often used, such as "presence of an important disease," "work days lost because of illness," etc.

Enabling variables include income measures, insurance variables, prices, the available of care, etc.

Our measure of health is closely related to the set of predisposing variables. Certain demographic and socioeconomic variables are considered to be present at the onset of specific episodes of illness. They are labeled "predisposing" variables in that they show a clear relationship to health-care utilitization, although they are themselves no reason for seeking health care. For instance, health-care utilization rates are known to vary considerably with age and sex, but "age" and "sex" themselves are no reason to seek medical assistance. In our model we will define a single predisposing factor, η_1, which is a linear function of age, sex, permanent income, education, etc. This predisposing factor (or index of "permanent health") enters in the equations explaining permanent income and health-care demand. It is conceptually equal to Andersen's set of predisposing variables, but we will, as noted above, treat it as a single unobservable variable in our model. This will appear to have a number of important advantages.

Our data are taken from a health-care survey of 8000 households in The Netherlands.[1] The variables that we shall use in the following equations are tabulated and defined in Table 1, below.

Formally, we can write the permanent health equation of our model as

$$\eta_1 = \beta_1\eta_2 + \gamma_1'\xi_1 + \varepsilon_1 \tag{1}$$

where η_1 is the unobservable predisposing factor, permanent health (PH),

η_2 is permanent family income (PINC), defined in section 2.2,

ξ_1 is a vector of five exogenous variables, FS, UNEMPL, AGE, SEX, EDUC,

β_1 and the vector γ_1 (to be discussed below; see also Table 1) are parameters to be estimated, and

ε_1 is a disturbance term.

Of the exogenous variables, AGE and SEX are self-explanatory. From the percentage unemployed in a region, (UMEMPL) we expect a negative (stress-related) effect on an individual's health.

Though it is well known that large families show relatively low figures for per capita medical consumption, that does not imply that we

Table 1

Description of the Variables

Predisposing variables	
PH	unobservable predisposing factor, permanent health
PINC	permanent family income (logarithmic)
FS	logarithm of family size
UNEMPL	percentage of unemployment in the region (here, per province in The Netherlands)
AGE	age in years
AGEH	age of the family head (in years)
SEX	dummy variable 1/0 (female/male)
EDUC	number of years of education
EDUCH	number of years of education of the family head
Enabling variables	
FINC	logarithm of family-income
INS1	dummy variable, indicating yes/no (1/0) insurance (with a coinsurance rate of .20) for GP-visits and prescribed medicine
TIME	total time needed for a visit to the GP
DIST	distance (in km) to the nearest general or university hospital
FULLT	dummy, equals 1 if working in full-time paid job; 0 else
Income-determining variables	
PH	unobservable predisposing factor "permanent" health
AGEH	age of head of the family (in years)
EDUCH	number of years education of family head
EMPL	number of employed family members
INCRS	number of different family income sources (e.g., labor; wealth; pension; Social Security benefits; grant; alimentation).
EARN	a dummy variable that equals 1 if earned income (labor) constitutes the main source of family income, 0 otherwise.
Health-services utilization	
SELF	money value of nonprescribed self-medication during six months
GPCON	number of general practitioner consultations during six months
GPMED	money value of medicine prescribed by the GP during six months
SPCON	number of specialist (outpatient) consultations during six months
SPMED	money value of medicine prescribed by a specialist during six months
HOSP	number of days spent in general or university hospital during one year
Supply variables	
SPEC	number of specialists per 1000 population in the region (15 regions)
BED	number of beds in general or university hospitals per 1000 population in the region (123 regions around hospitals)
Other variables	
INS2	a dummy variable where 2 = complete hospital insurance, highest class 1 = " " ", medium class 0 = " " ", lowest class categories of "luxury" treatment in the hospital
CONST	constant (=1)
Need variable(s)	
ILL	number of days being ill (during a half year) as reported by the respondent

expect family size (FS) to exert a positive influence on permanent health, since FS will also appear in the equation explaining permanent income. The same complication holds for the number of years of education (EDUC).

We should realize here that the variable "permanent health" includes at least two components. We would like to capture someone's "basic," "permanent," or "expected" health status--that is, his health status given his age, sex, etc. But since we will use data on the utilization of health care as indicators for this latent variable, our measure of permanent health also captures an individual's attitude toward health distortions, as revealed by his use of health-care facilities. In other words, data from two groups of individuals that are equally healthy or unhealthy will give different results if one group uses health-care facilities and services more extensively than the other group.

We will suggest some ways to disentangle those two components in section 4.

2.2 Observed Income and "Permanent Income"

It will be clear that since our main purpose is to estimate an index of permanent health, permanent income (PINC), not observed income, is the appropriate variable that should enter equation (1).

Permanent income is used here as a proxy for someone's "life style" or "quality of life" (quality of food, recreation, housing, etc.). It is by no means clear that the relationship between permanent health and permanent income should be positive. Unhealthy habits such as overeating might increase with income. A nonlinear relationship might be more likely, but in the model presented here PINC enters equation (1) in a linear form.

In order to estimate permanent income, we will estimate a family's earnings function, relating a number of exogenous variables to total family income. Permanent income is the expected value of this function. Observed income is equal to permanent income plus a disturbance term ("transitory income"). Of special interest here is that we will also include permanent health as an explanatory variable in this function. Health, as one of the human capital variables, may raise market productivity and increase income (compare Luft, 1978).

Thus, the "income-module" of our model can be written as follows:[2]

$$\eta_2 = \beta_2\eta_1 + \gamma_2{}' \xi_2 \qquad (2)$$

$$\eta_3 = 1.\eta_2 + \varepsilon_3 \qquad (3)$$

where η_1 and η_2 are the unobservable variables permanent health and permanent family income,

η_3 is observed family income

ξ_2 is a vector of six exogenous variables, FS, AGEH, EDUCH, EMPL, INCRS, and EARN (see Table 1 for definitions),

β_2 and the vector γ_2 are parameters to be estimated, and

ε_3 is a disturbance term.

A constant term is added to equation (3).

The earnings equation conforms to conventional human capital theory, though the number of variables we included is restricted by the availability of data.

2.3 Health Insurance

In the full model that we have in mind, the demand for health insurance will be endogenous, following the analyses of Phelps (1973, 1976), Keeler et al. (1977), Newhouse (1978a), Van de Ven and Van Praag (1979), and others.

All respondents in our survey are fully insured against the cost of hospital and specialist treatment. About 40% of them are also covered for treatment by a general practitioner and for the cost of prescribed medicine, (with a 20% coinsurance rate). Lack of data prevent us from estimating an equation explaining the demand for insurance for general care.[3] This variable (INS1) will, of course, enter the model as an explanatory variable for health-care demand.

The demand for one type of health insurance, however, will be included in our model as endogenous. Over and above the insurance against "normal" hospital costs, there is available coverage for "luxury" hospital treatment--e.g., single instead of double or triple rooms.

We expect that the demand for this type of insurance will be dependent on observed family income[4] and on two "taste" variables: age and education.

The equation to be estimated is as follows:

$$\eta_4 = \beta_4 \eta_3 + \gamma_4' \xi_4 + \varepsilon_4 \qquad (4)$$

where η_4 is a dummy variable for insurance against the cost of "luxury" treatment (INS2),

η_3 is observed family income

ξ_4 is a vector of the exogenous variables, AGEH and EDUCH (see Table 1),

β_4 and the vector γ_4 are parameters to be estimated, and

ε_4 is a disturbance term.

A constant term is added to this equation.

2.4 Health-Care Demand

Given the distinctions we have just made among the three sets of variables influencing health-care demand, specification of the equations explaining the demand for different types of health care (e.g., inpatient and outpatient care, or drugs) is straightforward.

We will use the number of sick days reported as a proxy for an individual's need for medical care.

As enabling variables we use observed family income[5], η_3, a set of (exogenous) insurance variables, and measures for the availability of outpatient and inpatient care.

The set of predisposing factors is reduced to one health-status variable, η_1, as defined in Section 2.1.

In a general form, this part of our model reads:

$$B_5\eta_5 = \bar{\beta}_5\eta_1 + \bar{\bar{\beta}}_5\eta_3 + \Gamma_5\xi_5 + \varepsilon_5 \tag{5}$$

where η_5 is a vector of six health-care demand variables, SELF, GPCON, GPMED, SPCON, SPMED, HOSP (see Table 1),

ξ_5 is a vector of exogenous variables,

the vectors $\bar{\beta}_5$, $\bar{\bar{\beta}}_5$ and the matrices β_5 and Γ_5 are parameters to be estimated, and

ε_5 is a disturbance vector.

In all equations explaining the above variables, permanent health (PH) is entered on the right-hand side except in the equation for self-medication (SELF). Because PH includes an additudinal component that we expect to be different for self-medication than for professional medical treatment, we have entered the set of all predisposing variables in the equation for SELF, instead of including PH.

Family income (FINC) enters all equations as an enabling variable except those representing medical care where all costs are fully insured for everyone (SPCON and HOSP).

"Medical need" is in all equations represented by the number of days of illness, as reported by the respondent (ILL).

Since prescribed medicine can only be bought after a visit to a physician, GPCON and SPCON respectively enter in the equations explaining GPMED and SPMED.

Before hospital admission, an individual has to see a specialist in an outpatient clinic; HOSP, therefore, depends on SPCON.

In the equation explaining the use of prescribed medicine GPMED and SPMED and in the equation explaining SPCON, the insurance variable INS1, equal to one if the individual is fully insured for those types of care, and zero otherwise, is included.

We also included a set of variables representing the time needed to "consume" medical care (e.g., TIME, the total time needed to visit a general practitioner, and DIST, the distance to the nearest hospital). We will discuss these variables more fully when discussing the estimation results.

To the equation explaining SPCON, we have added availability of specialist care (SPEC) to represent the notion that the availability of care increases its use. SPEC is measured as the number of specialists per 1000 population.

In the same way, the availability of hospital care (BED) is measured by the number of hospital beds per 1000 population, and added to the equation explaining HOSP.

Finally, since the general practitioner is the first one to be seen if medical care is needed, we added a dummy variable to the equation for GPCON, representing someone's opportunity cost of time. This dummy variable (FULLT) equals 1 if the individual is working full-time and zero elsewhere.

To all equations a constant term is added. In the next subsection, we summarize the complete model and discuss the stochastic specification and the estimation procedure used.

2.5 The General Model

The model developed in the subsections 2.1-2.4 can be summarized as follows [6]:

$$PH^* = \beta_1 PINC^* + \gamma_{11} FS + \gamma_{12} UNEMPL + \gamma_{13} AGEH + \gamma_{14} EDUCH + \varepsilon_1 \qquad (1a)$$

$$PINC^* = c_2 + \beta_2 PH^* + \gamma_{21} FS + \gamma_{22} AGEH + \gamma_{23} EDUCH + \gamma_{24} EMPL + \gamma_{25} INCRS + \gamma_{26} EARN \qquad (2a)$$

$$FINC = 1.\ PINC^* + \varepsilon_3 \qquad (3a)$$

$$INS2 = c_4 + \beta_4 FINC + \gamma_{41} AGEH + \gamma_{42} EDUCH + \varepsilon_4 \tag{4a}$$

$$SELF = c_5 + \beta_5 FINC + \gamma_{51} FS + \gamma_{52} UNEMPL + \gamma_{53} AGEH + \gamma_{54} EDUCH + \gamma_{55} ILL + \gamma_{56} TIME + \varepsilon_5 \tag{5a-1}$$

$$GPCON = c_6 - 1.0\ PH^* + \beta_6 FINC + \gamma_{61} ILL + \gamma_{62} INS1 + \gamma_{63} TIME + \gamma_{64} DIST + \gamma_{65} FULLT + \varepsilon_6 \tag{5a-2}$$

$$GPMED = c_7 + \beta_{71} PH^* + \beta_{72} FINC + \beta_{73} GPCON + \gamma_{71} ILL + \gamma_{72} INS1 + \gamma_{73} TIME + \varepsilon_7 \tag{5a-3}$$

$$SPCON = c_8 + \beta_{81} PH^* + \beta_{82} GPCON + \gamma_{81} ILL + \gamma_{82} DIST + \gamma_{83} SPEC + \varepsilon_8 \tag{5a-4}$$

$$SPMED = c_9 + \beta_{91} PH^* + \beta_{92} FINC + \beta_{93} SPCON + \gamma_{91} ILL + \gamma_{92} INS1 + \varepsilon_9 \tag{5a-5}$$

$$HOSP = c_{10} + \beta_{10,1} PH^* + \beta_{10,2} SPCON + \gamma_{10,1} ILL + \gamma_{10,2} DIST + \gamma_{10,3} BED + \varepsilon_{10} \tag{5a-6}$$

The c's represent the constant terms. The variables marked with an asterisk (*) are unobservables.

In equation (5a-2) we standardized the variable PH* in such a way that the coefficient of permanent health on the number of general practitioner visits is -1.0, thus making sure that we are dealing with "good health" and not with "poor health."

In a more formal way, we can rewrite the model as:

$$B\eta = \Gamma\xi + \varepsilon \tag{6}$$

where η is a vector of ten endogenous variables (PH*, PINC*, FINC, INS2, SELF, GPCON, GPMED, SPCON, SPMED, HOSP),

ξ is a vector of 15 exogenous variables, including the constant term (FS, UNEMPL, AGEH, EDUCH, ILL, INS1, TIME, DIST, FULLT, SPEC, BED, EMPL, INCRS, EARN, 1.0), and

ε is a vector of disturbances, ε_1, 0, ε_3, ε_4, ε_5, ε_6, ε_7, ε_8, ε_9, ε_{10}.

The matrices B and Γ contain the parameters to be estimated (see Appendix 3). We define $\Phi = E\xi\xi'$ and $\Psi = E\varepsilon\varepsilon'$; we assume $E\varepsilon = 0$ and $E\xi\varepsilon' = 0$. Furthermore we assume $E\varepsilon_{1i}\varepsilon_j = 0$ if $i \neq j$, so Ψ is a diagonal matrix. We define the vector y of observable endogenous variables

$$y = \Lambda_1\eta \quad \text{with } \Lambda_1 = \begin{bmatrix} 0 & 0 & 1 & 0 & . & . & 0 \\ 0 & 0 & 0 & 1 & 0 & . & \\ . & . & . & 0 & 1 & 0 & \\ & & & & & & \\ 0 & 0 & & & & & 1 \end{bmatrix}_{(8x10)} \tag{7}$$

It follows that the covariance matrix Σ of the observable endogenous and the exogenous variables equals

$$\Sigma = \begin{bmatrix} \Lambda B^{-1}(\Gamma\Phi\Gamma' + \Psi)B^{-1'}\Lambda' & \Lambda B^{-1}\Gamma\Phi \\ & \\ \Phi\Gamma' B^{-1'}\Lambda' & \Phi \end{bmatrix} \tag{8}$$

Maximum likelihood estimates of the structural parameters of the Multiple Indicator and Multiple Causes (MIMIC) model (Jöreskog and Goldberger, 1975) thus defined can be obtained using the computer program LISREL (Jöreskog, 1977, and Jöreskog and Sörbom, 1978).

We will assume ξ to be nonrandom, i.e., we consider the conditional distribution of y for given ξ. The matrix Φ is then fixed, and equals the covariance matrix computed from the observed values of ξ. We also make the usual assumption that ε is distributed normally, so ε is $N(0, \Psi)$. This implies that y is also normally distributed.[7]

As far as we know, there is no generally applicable rule for testing the identifiability of a simultaneous equation system with latent variables. This "open territory for econometric theorists" (Goldberger, 1972a) has been explored among others by Wiley (1973) and Robinson (1974). The latter deals with the identification of a nonsimultaneous model with several unobservables. We did rewrite our model in the form used by Robinson (1974). As is shown in Appendix 2, however, our model is a degenerated case of Robinson's general model, so that his criteria are not applicable to our model.

Geraci (1976) discusses a simultaneous equation system with measurement errors. From this study it is clear that not only the number, but also the location of the measurement errors plays a crucial role for the identification problem. Though Geraci's study is very instructive, we cannot apply his device for identification because the latent variables in our model have multiple indicators and multiple causes, while Geraci deals with unobservables with one indicator and no causes.

In Appendix 2 we prove that all parameters in our model are identified.

3. ESTIMATION RESULTS

This section presents estimation results based on individual data from a health-care survey (1976) in The Netherlands among 8000 privately insured households, nearly all belonging to the highest income groups. Emphasis will be put on the simultaneous relation between health and income. Therefore we first restrict our analysis to male heads of families (N = 3636).[8]

The estimation results are given in Table 2. All equations are estimated simultaneously, using a full information, maximum likelihood estimation method. The estimation results based on data for all adults (18 years and older) are given in Table A2 (Appendix 1).

3.1 Permanent Health

In Table 2 we see that an individual's age and the percentage of unemployment in the region have a negative influence on health. Permanent income, reflecting "life-style," has a positive influence on health.

Looking at the influence of education on health, we see a negative coefficient, but we should realize that besides this direct effect there is also an indirect effect of education (via permanent income) on health; the latter completely offsets the former, resulting on balance in a positive but slight effect. In interpreting these coefficients, we should be very careful, however, and should bear in mind, as noted earlier, that our measure of permanent health covers at least two components; "health" and "attitudes towards health distortions" (see section 4).

Table 2

Full Information, Maximum Likelihood Estimates for All Male Family Heads

Variable	PH	PINC	INS2	SELF	GPCON	GPMED	SPCON	SPMED	HOSP
PH		-0.053 (1.07)			-1.0 (-)	-21.004 (5.41)	-0.979 (4.90)	-20.737 (4.77)	-1.266 (3.95)
PINC	0.627 (1.83)								
FINC			0.345 (14.8)	-0.661 (1.08)	0.044 (0.27)	4.209 (1.11)		-1.416 (0.34)	
GPCON						10.796 (20.5)	0.197 (7.05)		
SPCON								4.548 (11.1)	0.228 (6.87)
FS	0.036 (0.44)	0.149 (11.1)		-1.264 (2.75)					
UNEMPL	-0.066 (1.81)			-0.373 (1.36)					
AGEH	-0.026 (6.66)	0.0034 (2.68)	0.015 (26.0)	0.061 (3.93)					
EDUCH	-0.019 (1.39)	0.039 (25.5)	0.023 (9.65)	0.271 (4.55)					
ILL				0.020 (2.17)	0.041 (21.5)	0.113 (2.16)	0.047 (16.4)	0.580 (9.45)	0.130 (25.4)
INS1					0.417 (5.06)	4.522 (2.19)		4.605 (1.88)	
TIME				0.018 (2.20)	-0.0020 (1.20)	-0.021 (0.51)			
DIST					0.0090 (0.97)		0.0079 (0.63)		0.0284 (1.21)
FULLT					-0.122 (0.75)				
SPEC							0.700 (1.56)		
BED									0.204 (1.81)
EMPL		0.068 (3.63)							
INCRS		0.055 (4.39)							
EARN		0.219 (9.14)							
CONST		9.406 (33.1)	-4.258 (18.1)	7.293 (1.19)	5.377 (1.66)	67.601 (1.01)	4.835 (1.56)	122.303 (1.77)	5.183 (1.25)

N = 3636; t-values in parentheses.

3.2 Income

All but one of the estimated coefficients (Table 2) in the income equation are significant and with signs as expected. The positive coefficient of age indicates that the expected income increases with years of experience. One additional year of schooling completed gives a 3.9% increase in expected income; one additionally employed family member raises expected income by 6.8%, while one additional source of income causes a 5.5% increase in permanent income. Where earned income is the main source of family income, that income is on average 21.9% higher than when nonearned income is the main source of income. This finding quite agrees with the level of social security benefits for retirement or disability pensions or for unemployment insurance; these generally equal 70-80% of previous income.

The family size elasticity of income (0.15) that has been estimated while controlling for the number of employed family members may be partly explained by children's allowances. The relation between permanent income and permanent health will be discussed in detail in section 4.

3.3 Health Insurance

In section 2.3 we hypothesized that INS2 would be influenced by age and education of the family head. Indeed, we find two significantly positive coefficients. The income elasticity (+1.23) indicates that, as expected, we are dealing with a luxury good.

3.4 Health-Care Demand

We will first pay attention to the fact that some types of health-care consumption are conditional upon the consumption of other types.

The effect of an additional visit to the general practitioner and specialist on other kinds of health-care utilization is given in Table 3, which illustrates the function of the general practitioner as the entry point into the medical system. The effect of GPCON on SPCON, presented as an elasticity, is 0.242 (for male family heads). For SPCON we find 0.268 with respect to SPMED.[10]

These results illustrate that, though a patient-doctor contact itself adds to the cost of health care, an important amount of additional costs is generated by such a contact.[11]

We shall now take a look at the effect of insurance (INS1) on health care utilization. All persons in the survey are fully insured for SPCON and HOSP, but only 40% are insured for GPCON, GPMED, and SPMED, with a coinsurance rate of 0.20. In Table 2 we see that an individual who is insured for GPCON is expected to have 0.417 more consultations with a general practitioner than someone who is not insured.[12] The direct and indirect (via GPCON) effects of being insured for GPCON, GPMED and SPMED on different kinds of health-care utilization are presented in Table 4.

Another important enabling variable is travel and waiting time, functioning as a time-price (Acton, 1973, 1976). The variable TIME equals total time needed for one visit to the GP. We find a significant positive cross-TIME-elasticity for SELF (+0.162) and a negative own-TIME-elasticity for GPCON (-0.067).

Table 3

Elasticities of Health-Care Utilization With Respect to the Number of Physician Consultations

	Male Family Heads		All Adults (18 yrs and older)	
Variable	GPCON Elasticity	SPCON Elasticity	GPCON Elasticity	SPCON Elasticity
GPMED	0.545	--	0.491	--
SPCON	0.242	--	0.237	--
SPMED	0.065[a]	0.268	0.075[a]	0.316

[a]Indirect effect through SPCON.

Table 4

Direct and Indirect Effects of Insurance[a] for GPCON, GPMED, and SPMED on Health-Care Utilization

Variable	Direct Effect	Indirect Effect (via GPCON)	Total Effect	Mean Value (Insured Plus Noninsured)
GPCON	0.417	--	0.417	1.276
GPMED	4.52	4.50	9.02	25.27
SPCON	--	0.082	0.082	1.038
SPMED	4.61	0.37	4.98	17.65

[a]Coinsurance rate of 0.20.

Table 5

Income Elasticities of Expected Value of Dependent Variable, Evaluated at the Mean

	Male Family Heads		All Adults (18 Yrs. and Over	
Variable	Elasticity	t-value	Elasticity	t-value
SELF	-0.143	(1.07)	0.170	(1.92)
GPCON	+0.035	(0.27)	0.085	(1.45)
GPMED	+0.166	(1.11)	0.139	(1.62)
SPMED	-0.080	(0.34)	0.05	(0.35)

The direct effect of TIME on GPMED equals the indirect effect (via GPCON), resulting in a reduced form elasticity of -0.072. Increasing the mean value of TIME by its standard deviation causes a 3.8% and 4.1% reduction, respectively, in expected value of GPCON and GPMED.

Distance (DIST) to the hospital where the specialist works functions as a cross-price to GPCON, giving a small elasticity of 0.037 (cf. Acton, 1975, who found an elasticity of about 0.07). The effect of DIST on SPCON is expected to be negative. In the estimation based on all adults (Table A2), this coefficient is indeed negative, but for male family heads we estimated a positive, though not significant, coefficient. Because of the generally better means of conveyance for the latter, DIST might be an inappropriate measure, and (travel) time should perform better.

DIST has a positive effect on the expected number of hospital-days (HOSP) (elasticity 0.125; cf. Acton, 1975, who gives 0.18). Possibly laboratory testing and other preoperative research that require the patient to come several times to the hospital are, where long distances are involved, replaced by clinical research.

The negative coefficient of FULLT in the GPCON-equation indicates that people with a full-time, paid job are less willing to contact the general practitioner than people with a part-time or unpaid job, due to higher time-prices.

We used measured income instead of permanent income as an explanatory variable for health-care utilization, for reasons given in the INS1-equation.[13]

The income elasticity of GPCON (Table 5) is rather small (0.04 - 0.08),[14] while the elasticity of GPMED equals a value (0.14 - 0.17) that has also been found by others.[15]

From Table 5 we have no clear picture of the effect of income. This may be due to the facts, first, that we are not able to separate earned income from unearned income, and secondly, that we are dealing only with the upper 30% of income classes; this reduced variation in income and the truncated sample may bias our estimations (see Hausman and Wise, 1977).

Many studies have already indicated the large influence on utilization of health care of supply variables such as the number of hospital beds and the number of physicians per capita. Most of these studies are based on aggregated data, but May (1975), as far as we know the only study using individual data, also concluded that even after taking into account demographic, social, and illness factors, the availability of resources appeared to influence utilization significantly.

In our model we hypothesized that the number of specialist consultations would be influenced by the number of specialists per capita (SPEC), and the number of hospital-days by the bed-population ratio (BED). The estimated SPEC elasticity of SPCON equals 0.356 (0.162 for all adults). Comparable results are found in macrostudies: 0.39 by Fuchs and Kramer (1972), 0.36 by Van der Gaag (1978) and 0.22 by Rutten (1978).[16]

The influence of BED-availability is even more dramatic: after controlling for predisposing variables, need, distance to hospital, and number of specialist outpatient contacts, the estimated BED elasticity of hospital days equals 0.843 (0.551 for all adults). Compare e.g. [Van der Gaag (1978) and] Rutten (1978), who gives 0.85; Van der Gaag (1978), 0.60; and Feldstein (1967, 1970, 1971, 1977) who found elasticities ranging from 0.70 to 0.90.

The estimated coefficients of permanent health are all negative and significant. ILL, the number of days ill, which partly represents "transitory" health, has a positive and highly significant influence on all kinds of health-care utilization.

Looking at the predisposing variables in the SELF-equation, we note a negative coefficient for family size and a positive coefficient for years of schooling completed by the family head. As already pointed out, attitudinal variables may strongly influence the amount of self-medication. Therefore, we will not draw the conclusion that members of large families and less-educated people are "healthy," but we will take into account the possibility that members of large families are less inclined to self-medication, and that level of education has a positive influence on the demand for health.

4. HEALTH INDEX

The unobservable variable, permanent health, is fully characterized by its causes and indicators. Causes are the predisposing variables which indicate characteristics existing prior to the onset of a specific illness but which are, per se, no reason for seeking health care (Andersen, 1968); as indicators, we use different kinds of realized medical consumption.

Interpretation of the predisposing variables may be ambiguous. First, they may stand for some "expected" level of health. Second, they may indicate attitude or belief. One way to remove the attitudinal or belief aspects from the unobservable is to exclude all individuals who have a zero value for all five health-care utilization variables. In this way we are left only with patients who had already entered the medical system and who were (or had been) under medical treatment. In analyzing this subsample, we are explaining differences in health-care utilization that are conditional upon an already expressed decision for medical services, while in the previous section we also analyzed the decision of the patient whether or not to go to the doctor. Assuming that the physician's decision about how much care the patient needs is primarily influenced by the patient's health status, the content of our variable "permanent health" is now indeed closer to "health" than in the previous section.

In this way we can construct a health index equal to the expected value of η_1 : $E(\eta_1|\xi) = \beta_1 E(\eta_2|\xi) + \gamma_1' \xi_1$ (cf. Robinson and Ferrara, 1977).

In Table 6 we see a positive influence of health on income (and vice versa). Luft (1975) and Bartel and Taubman (1979) estimated a reduction in yearly earnings caused by poor health that ranged from 20% to 40%; they specified health as an exogenous variable. Grossman and Benham (1974) and Grossman (1975) treated health as an endogenous variable and also found that health, as one component of human capital, raised market productivity and the wage rate significantly.

A positive coefficient for the effect of income on health status was also found by Grossman (1975, p. 196), who analyzed a high-earnings, highly educated sample like ours. He suspected the major source of this finding to be a factor that he termed "the inconvenience costs of illness": "The complexity of a particular job and the amount of responsibility it entails are certainly positively correlated with the wage.

Table 6

Coefficients for the Simultaneous Structural Relation Between the Unobservables Permanent Health and Permanent Income, Estimated from a 10-Equation Model[a]

Equation	PH	PINC	FS	UNEMPL	AGEH	EDUCH	EMPL	INCRS	EARN	CONST
Permanent health equation		0.3152 (0.81)	0.0922 (0.90)	−0.0913 (1.95)	−0.0262 (4.75)	0.0070 (0.44)				
Permanent income equation	0.1797 (1.45)		0.1268 (4.95)		0.0099 (3.23)	0.0352 (10.8)	0.0668 (6.24)	0.0503 (3.55)	0.2037 (6.79)	8.6094 (12.6)

Note: t-values in parentheses.

[a]The estimation results of the full 10-equation model are given in Table A3 in Appendix 1. Because the coefficients of the other equations resemble those analyzed in the previous section, we will not discuss them in detail.

Thus, when an individual with a high wage becomes ill, tasks that only he can perform accumulate. These increase the intensity of his work load and give him an incentive to avoid illness by demanding more health capital." Phelps (1975) found similar results, concluding "that higher income may lead to a life-style that helps to avoid hospital stays".

In the previous section, we estimated a significantly positive coefficient of EDUCH in the SELF-equation and a negative effect of EDUCH in the permanent health equation; we may now conclude, from the positive effect of EDUCH on health in Table 6, that highly educated people have a high demand for good health (patient-initiated demand) but also have a high health status (as derived from the analysis of physicians' decisions).

The effect of education on health is quite interesting: besides the positive direct effect we mentioned, more education leads to a higher income, which in turn leads to a better health status. The direct and indirect effect of education on health and income are presented in Table 7, together with comparable results found by Grossman (1975).

Though Grossman's results are based on direct "health status" measures, there are two striking similarities to our results: first, the indirect effect of education (via income) on health exceeds the direct effect; secondly, in both studies the indirect effect of education on earnings is only a small fraction (3.5 to 5.5%) of the total effect. A positive effect of education on health, suggesting that health should rise with years of schooling completed, has also been found by Grossman and Benham (1974) and Edwards and Grossman (1978), among others.

Family size has a positive influence on health (cf. Kasper, 1975) and on income. Besides the arguments used in section 3 for the influence of

Table 7

Direct, Indirect, and Total Effects of Education on Health and Income (or Wage Rate)

	Estimates of Grossman (1975, p.198)		Our Estimates	
Effect	Health Effects	Wage Effects	Health Effects	Income Effects
Direct	.014	0.052	.0074	.0373
Indirect	.016	0.003	.0118	.0013
Total (Reduced form parameter)	.030	0.055	.0192	.0386

Table 8

Direct, Indirect, and Total Effects of Family Size and Age of Family Head on Health and Income

	Effect of Family Size on		Effect of Age of Family Head on	
Effect	Health	Income	Health	Income
Direct	.0977	.1344	-.0278	.0105
Indirect	.0424	.0176	.0033	-.0050
Total (Reduced form parameter)	.1401	.1520	-.0245	.0055

family size on income, one could state that increasing family size leads to a more efficient production of health and income (e.g., the time-gain of a married individual with respect to an unmarried one, or the health-experience gain of a large family with respect to a small family).

The effect of age on income is as expected: the more years of experience one has, the higher the income. This direct effect is, however, halved by the indirect effect of worsening health with increasing age.

Finally, the negative influence of the percentage of unemployment in the region on health may be explained by the stress that fear of losing one's job generates, or indirectly by the stress experienced by unemployed friends and family members.[17]

Table 9 illustrates the use of the health index $E(\eta_1 | \xi) = \delta' \xi$ with δ a vector of reduced-form parameters. Losing his job (EARN: $1 \to 0$) makes a man about three years older (with respect to his health status). Increasing family size, from one to two[18] equals the effect of a 1% reduction of the percentage unemployment in the region (e.g., from 4% to 3%) or of five additional years of schooling. The small indirect effect of an additionally employed family member equals the impact of an additional source of family income.

Of course, the illustration of the health index that results from our model should only be considered as a tentative result. Improving our specification of the model will yield more reliable results.

5. FIT OF THE MODEL

Our model contains 8 observable endogenous and 15 (observable) exogenous variables. We assumed the exogenous variables to be fixed,

Table 9

Total Effects[a] of Exogenous Variables on the Health Index

	FS	UNEMPL	AGEH	EDUCH	EMPL	INCRS	EARN
Effect	0.140	-0.097	-0.024	0.019	0.022	0.017	0.068

[a]Calculated reduced from parameters.

Table 10

Calculated Ratio of the Estimated Residual Variance (in the Structural Equation) to the Total Variance of the Observable Endogenous Variables

	FINC	INS2	SELF	GPCON	GPMED	SPCON	SPMED	HOSP
All family heads N = 3636	0.255	0.211	0.017	0.186	0.257	0.171	0.140	0.231
Family heads with medical consumption N = 2281	0.261	0.235	0.013	0.115	0.182	0.121	0.103	0.212

so we were left with $\frac{1}{2}(8+15)(8+15+1) - \frac{1}{2}.15.16 = 156$ covariances that could consistently be estimated. Because we specify 66 "free" parameters in our model, we can apply the χ^2-test[19] for goodness of fit of the model with 90 degrees of freedom. In this way we test the null-hypothesis that all parameters we specified to be zero do indeed equal zero, i.e., the null-hypothesis is rejected as soon as at least one of these parameters differs from zero. We would be surprised if this null-hypothesis could not be rejected, and indeed χ^2_{90} equals 280, indicating a very small probability that the null-hypothesis is true. Which parameter(s) should be estimated freely in addition to the 66 we estimated, is not indicated by the test. We hold the view that the χ^2-test for goodness of fit of the model, though it may be useful in small models, is not appropriate for large models.

In testing whether one of the estimated parameters differs significantly from zero, we used the t-values as presented in the tables giving the estimation results.

Finally, as an illustration, we calculated the ratio of the estimated residual variance (in the structural equation) to the total variance of the observable endogenous variables (Table 10). These figures quite agree with the value of the R^2 in the corresponding OLS regression equation after we substitute for the unobservables.

6. DISCUSSION AND CONCLUSION

In this paper we developed and estimated a 10-equation structural-equation model for health-care demand. We explicitly dealt with the complex relation between health, income, health insurance, and demand for health care, using two unobservable variables. Our results, based on a health-care survey among 8000 families, indicate a mutually positive influence of health and income. Education and age appeared to have interesting direct and indirect (via income) effects on health. In explaining the health-care demand, we found that the estimated effect of supply variables quite resemble the results found in macro-studies.

Specifying health as an unobservable, we were able to construct and illustrate a health index that may be used to compare individuals or regions. We are now estimating our model using another data base.[20] Interesting differences are the use of both permanent income and its squared value in explaining health, thus allowing us to test the hypothesis that there may exist an optimal income with respect to health. Further, we treat health insurance endogenously and we can make a distinction between earned and nonearned income.

Although the model we have developed is already quite comprehensive, the number of variables used to explain health is relatively small. It would be quite realistic to model explicitly the effect of health-care utilization on health.[21] Moreover, variables describing, e.g., environmental hygiene, welfare work, or sporting facilities may also enter the health equation. In that case the health index can, in principle, be used to compare the marginal increase in health that would arise from expenditure of extra dollars on different kinds of health care, on education, income improvement, environmental protection, etc. Such comparisons can be useful in the allocation of health-care resources or in assigning budgets to regions, and can help the search for a more effective health-care system.

APPENDIX 1. TABLES

Table A1. Mean Values and Standard Deviations

Variables	All adults (18 years and older) N = 6882		Male family heads N = 3636		Male family heads with medical consumption; N = 2281	
Health-services	Mean	S.D.	Mean	S.D.	Mean	S.D.
utilization						
SELF	5.165	12.836	4.612	11.756	5.444	13.198
GPCON	1.614	2.831	1.276	2.623	2.035	3.070
GPMED	29.657	68.851	25.273	69.043	40.286	83.635
SPCON	1.170	3.847	1.038	3.581	1.654	4.408
SPMED	17.328	75.383	17.649	77.330	28.133	96.118
HOSP	1.311	7.532	1.203	6.910	1.918	8.646
Predisposing variables						
FS	1.122	0.493	1.147	0.452	1.121	0.463
UNEMPL	4.022	0.698	4.028	0.710	4.032	0.725
AGE	43.020	14.619	-	-	-	-
AGEH	45.599	13.673	44.621	13.452	46.192	13.903
SEX	0.437	0.496	-	-	-	-
EDUC	12.122	3.692	-	-	-	-
EDUCH	12.934	3.661	12.966	3.634	13.030	3.646
Need variables						
ILL	4.913	19.359	5.513	21.092	8.427	25.882
Enabling variables						
FINC	10.305	0.376	10.322	0.350	10.331	0.352
INS1	0.409	0.492	0.421	0.494	0.445	0.497
TIME	43.932	26.063	42.757	24.501	46.192	13.903
DIST	5.190	4.357	5.294	4.371	5.242	4.334
FULLT	0.539	0.499	0.862	0.345	0.825	0.380
Supply variables						
SPEC	0.529	0.126	0.528	0.127	0.529	0.128
BED	4.969	0.913	4.966	0.907	5.004	0.913
Income-determining variables						
AGEH	45.599	13.673	44.621	13.452	46.192	13.903
EDUCH	12.934	3.661	12.966	3.634	13.030	3.646
EMPL	1.309	0.823	1.338	0.785	1.294	0.794
INCRS	1.210	0.471	1.188	0.447	1.209	0.470
EARN	0.874	0.332	0.895	0.307	0.865	0.341
Other variables						
INS2	0.305	0.536	0.280	0.518	0.322	0.553

Table A2. Full Information, Maximum Likelihood Estimates for All Adults (18 Years and Older)

Variables	PH	PINC	INS2	SELF	GPCON	GPMED	SPCON	SPMED	HOSP
PH		0.098 (2.99)			-1.0 (-)	-46.806 (6.45)	-1.069 (4.70)	-29.865 (5.44)	-1.333 (3.51)
PINC	0.144 (1.36)								
FINC			0.310 (18.7)	0.878 (1.92)	0.137 (1.45)	4.116 (1.62)		0.886 (0.35)	
GPCON						9.024 (27.6)	0.172 (10.4)		
SPCON								4.675 (18.7)	0.299 (12.8)
FS	0.089 (2.30)	0.182 (17.5)		-1.010 (2.80)					
UNEMPL	-0.025 (1.47)			-0.275 (1.25)					
AGE	-0.014 (6.84)			0.061 (5.15)					
AGEH		0.0064 (12.8)	0.016 (35.6)						
SEX	-0.168 (4.84)			1.93 (5.94)					
EDUC	0.0013 (0.29)			0.188 (3.99)					
EDUCH		0.040 (34.8)	0.026 (14.6)						
ILL				0.031 (3.87)	0.043 (26.2)	0.143 (3.50)	0.061 (26.1)	0.493 (10.4)	0.122 (26.5)
INS1					0.574 (8.78)	6.832 (4.43)		2.872 (1.64)	
TIME				0.016 (2.64)	0.0001 (0.06)	-0.011 (0.39)			
DIST					0.0054 (0.74)		-0.017 (1.76)		0.0069 (0.36)
FULLT					-0.616 (8.77)				
SPEC							0.358 (1.03)		
BED									0.145 (1.58)
EMPL		0.055 (10.3)							
INCRS		0.046 (5.43)							
EARN		0.219 (13.5)							
CONST		8.887 (88.9)	-3.931 (23.6)	-8.222 (1.79)	0.874 (0.70)	7.787 (0.17)	1.365 (1.23)	23.458 (0.67)	0.690 (0.47)

N = 6882; t-values in parentheses.

Table A3. Full Information, Maximum Likelihood Estimates for all Male Family Heads with Medical Consumption

	PH	PINC	INS2	SELF	GPCON	GPMED	SPCON	SPMED	HOSP
PH		0.180 (1.45)			-1.0 (-)	-27.514 (4.09)	-1.122 (3.62)	-25.161 (3.67)	-1.383 (2.88)
PINC	0.315 (0.80)								
FINC			0.410 (13.3)	0.207 (0.24)	-0.094 (0.41)	6.636 (1.10)		-2.459 (0.37)	
GPCON						10.698 (17.8)	0.185 (5.85)		
SPCON								4.761 (9.94)	0.249 (6.32)
FS	0.092 (0.90)	0.127 (4.95)		1.096 (1.70)					
UNEMPL	-0.091 (1.95)			-0.183 (0.48)					
AGEH	-0.026 (4.75)	0.010 (3.23)	0.016 (21.5)	0.064 (2.98)					
EDUCH	0.0070 (0.44)	0.035 (10.7)	0.023 (7.61)	0.209 (2.47)					
ILL				0.013 (1.20)	0.035 (15.0)	0.045 (0.68)	0.045 (12.6)	0.513 (6.57)	0.130 (19.8)
INS1					0.460 (3.74)	5.718 (1.77)		5.502 (1.42)	
TIME				0.026 (2.16)	-0.0015 (0.57)	-0.024 (0.36)			
DIST					0.014 (0.98)		0.011 (0.55)		0.042 (1.11)
FULLT					0.012 (0.06)				
SPEC							1.035 (1.46)		
BED									0.320 (1.79)
EMPL		0.067 (6.25)							
INCRS		0.050 (3.55)							
EARN		0.204 (6.79)							
CONST		8.609 (12.6)	-4.968 (16.0)	-1.582 (0.18)	4.352 (1.14)	-0.432 (0.00)	2.399 (0.58)	85.969 (0.86)	1.175 (0.23)

N = 2281; t-values in parentheses.

Appendix 2. Identification of the model

In this appendix we will prove the identification of the model as presented in Section 2.5. This model has been specified as follows:

$$B\eta = \Gamma\xi + \varepsilon \tag{6}$$

with

η a (10x1)- vector of observable and unobservable endogenous variables

ξ a (15x1)- vector of exogenous variables

ε a (10x1)- vector of disturbances

B a nonsingular (10x10)-matrix of parameters to be estimated

Γ a (10x15)- matrix of parameters to be estimated.

We assume

$E\xi\varepsilon' = 0$ and $\varepsilon \sim N(0,\Psi)$ with $\Psi_{i,j} = 0$ for $i \neq j$.

The matrices B and Γ are given on page 12. For convenience we shall write out all 10 equations:

$$\eta_1 = \beta_1\eta_2 + \gamma_{1,1}\xi_1 + \gamma_{1,2}\xi_2 + \gamma_{1,3}\xi_3 + \gamma_{1,4}\xi_4 + \varepsilon_1 \tag{A1}$$

$$\eta_2 = \beta_2\eta_1 + \gamma_{2,1}\xi_1 + \gamma_{2,2}\xi_3 + \gamma_{2,3}\xi_4 + \gamma_{2,4}\xi_{12} + \gamma_{2,5}\xi_{13} + \gamma_{2,6}\xi_{14} + c_2 + \varepsilon_2^{1} \tag{A2}$$

$$\eta_3 = 1.\eta_2 + \varepsilon_3 \tag{A3}$$

$$\eta_4 = \beta_4\eta_3 + \gamma_{4,1}\xi_3 + \gamma_{4,2}\xi_4 + c_4 + \varepsilon_4 \tag{A4}$$

$$\eta_5 = \beta_5\eta_3 + \gamma_{5,1}\xi_1 + \gamma_{5,2}\xi_2 + \gamma_{5,3}\xi_3 + \gamma_{5,4}\xi_4 + \gamma_{5,5}\xi_5 + \gamma_{5,6}\xi_7 + c_5 + \varepsilon_5 \tag{A5}$$

---

[1] For reasons given in footnote 2, page 6, we fixed $\varepsilon_2 = 0$ in estimating the model. Nevertheless we shall prove the identification of the model as it was originally specified, i.e. with $\varepsilon_2 \sim N(0,\Psi_{2,2})$ and $\Psi_{2,2} \neq 0$. Identification of the estimated model, with $\varepsilon_2 = 0$, is easily obtained by putting $\Psi_{2,2} = 0$ in all formulas that will follow.

$$\eta_6 = -1.\eta_1 + \beta_6\eta_3 + \gamma_{6,1}\xi_5 + \gamma_{6,2}\xi_6 + \gamma_{6,3}\xi_7 + \gamma_{6,4}\xi_8 + \gamma_{6,5}\xi_9 + c_6 + \varepsilon_6$$

$$\eta_7 = \beta_{7,1}\eta_1 + \beta_{7,2}\eta_3 + \beta_{7,3}\eta_6 + \gamma_{7,1}\xi_5 + \gamma_{7,2}\xi_6 + \gamma_{7,3}\xi_7 + c_7 + \varepsilon_7$$

$$\eta_8 = \beta_{8,1}\eta_1 + \beta_{8,2}\eta_6 + \gamma_{8,1}\xi_5 + \gamma_{8,2}\xi_8 + \gamma_{8,3}\xi_{10} + c_8 + \varepsilon_8$$

$$\eta_9 = \beta_{9,1}\eta_1 + \beta_{9,2}\eta_3 + \beta_{9,3}\eta_8 + \gamma_{9,1}\xi_5 + \gamma_{9,2}\xi_6 + c_9 + \varepsilon_9$$

$$\eta_{10} = \beta_{10,1}\eta_1 + \beta_{10,2}\eta_8 + \gamma_{10,1}\xi_5 + \gamma_{10,2}\xi_8 + \gamma_{10,3}\xi_{11} + c_{10} + \varepsilon_{10}.$$

According to the notation of the general LISREL-model we will use the symbols y and x for the observable endogenous and observable exogenous variables respectively; further we will use y^* for the unobservable endogenous variables.

In our model we have no unobservable exogenous and two unobservable endogenous variables (η_1 and η_2), so we define y, y^* and x as follows:

$$y = \Lambda_1\eta \quad , \quad y^* = \Lambda_2\eta \quad \text{and} \quad x = \xi$$

with

y a (8x1)- vector of observable endogenous variables
y^* a (2x1)- vector of unobservable endogenous variables
x a (15x1)- vector of (observable) exogenous variables

$$\Lambda_1 = \begin{bmatrix} 0&0&1&0&0&0&0&0&0&0 \\ 0&0&0&1&0&0&0&0&0&0 \\ 0&0&0&0&1&0&0&0&0&0 \\ 0&0&0&0&0&1&0&0&0&0 \\ 0&0&0&0&0&0&1&0&0&0 \\ 0&0&0&0&0&0&0&1&0&0 \\ 0&0&0&0&0&0&0&0&1&0 \\ 0&0&0&0&0&0&0&0&0&1 \end{bmatrix} \text{ and } \Lambda_2 = \begin{bmatrix} 1&0&0&0&0&0&0&0&0&0 \\ 0&1&0&0&0&0&0&0&0&0 \end{bmatrix}$$

According to the partition of η in y^* and y, we partition B and Γ as follows:

$$B = \begin{array}{cc} \begin{array}{cc} 2 & 8 \end{array} & \\ \left[\begin{array}{c|c} B_1 & B_2 \\ \hline B_3 & B_4 \end{array}\right] & \begin{array}{c} 2 \\ 8 \end{array} \end{array} \quad \text{and } \Gamma = \begin{array}{cc} 15 & \\ \left[\begin{array}{c} \Gamma_1 \\ \hline \Gamma_2 \end{array}\right] & \begin{array}{c} 2 \\ 8 \end{array} \end{array}$$

with the following dimension:

B : (10x10)	Γ : (10x15)
B_1: (2x2)	Γ_1: (2x15)
B_2: (2x8)	Γ_2: (8x15)
B_3: (8x2)	
B_4: (8x8)	

and we partion

$\varepsilon = (\varepsilon^*, \hat{\varepsilon})$, with ε^* a (2x1) vector and $\hat{\varepsilon}$ a (8x1) vector.

Now we can write equation (6) as follows:

$$\text{(A11a)} \quad B_1 y^* + B_2 y = \Gamma_1 x + \varepsilon^*$$

$$\text{(A11b)} \quad B_3 y^* + B_4 y = \Gamma_2 x + \hat{\varepsilon}$$

Because B_2 consists of all zero's and B_1 and B_4 are nonsingular, we have

$$\text{(A12a)} \quad y^* = B_1^{-1} \Gamma_1 x + B_1^{-1} \varepsilon^*$$

$$\text{(A12b)} \quad y = - B_4^{-1} B_3 y^* + B_4^{-1} \Gamma_2 x + B_4^{-1} \hat{\varepsilon}$$

Thus we have written our model according to the general model for which Robinson (1974), has developed some criteria for identification. However, Robinson discounts some degenerate cases and unfortunately our model appears to be such a case.[2] Because, as far as we know, there exists no generally applicable criterion for proving the identification of our model, we shall give a straightforward proof of it.[3]

Substituting y^* in (A12) yields the reduced form model,

$$y = \Pi x + v \tag{A13}$$

with

$$\Pi = B_4^{-1}(-B_3B_1^{-1}\Gamma_1 + \Gamma_2), \text{ the reduced form coefficient matrix, and}$$

$$v = B_4^{-1}(-B_3B_1^{-1}\varepsilon^* + \hat{\varepsilon}), \text{ the reduced form error.}$$

----

[2]This can be seen as follows: Robinson distinguishes three categories of x-variables: those appearing only in the y*-equations, those appearing only in the y-equations and those appearing in both equations. He assumes the submatrix of $B_1^{-1}\Gamma_1$ corresponding to the first category of x-variables (in our case: x_{12}, x_{13} and x_{14}) to be of full rank (p. 682). In our case this submatrix of $B_1^{-1}\Gamma_1$ ("B_{01}" in Robinson's-notation) consists of the 12, 13 and 14th column of $B_1^{-1}\Gamma_1$:

$$\begin{bmatrix} \frac{\beta_1\gamma_{2,4}}{1-\beta_1\beta_2} & \frac{\beta_1\gamma_{2,5}}{1-\beta_1\beta_2} & \frac{\beta_1\gamma_{2,6}}{1-\beta_1\beta_2} \\ \frac{\gamma_{2,4}}{1-\beta_1\beta_2} & \frac{\gamma_{2,5}}{1-\beta_1\beta_2} & \frac{\gamma_{2,6}}{1-\beta_1\beta_2} \end{bmatrix}$$

and this matrix has ranked 1, which is less than full rank (=2).

[3]The LISREL IV computer program we used makes a numerical estimate of the information matrix of the parameters. If this matrix is positive definite, it is almost certain that the model is identified (see e.g. Silvey, 1970, chapter 4). Besides this "almost certain" identification we will give a full proof of identification.

Defining the sample covariance-matrices $S_{yx'}$ and $S_{xx'}$, which are consistent estimates of Eyx' and Exx' respectively, we have $P = S_{xx'}^{-1} S_{yx'}$ as a consistent estimate of Π. Identification of the model will be given in three stages: first, we will write out equations (A12a) and (A11b); then we will present the reduced-form coefficients as a function of the structural coefficients (see Table A4) and finally we will give the structural parameters as a function of the reduced form parameters.

Equations (A12a) and (A11b) can be written as follows:[4]

$$y_1^* = \alpha_1 x_1 + \delta\gamma_{1,2}x_2 + \alpha_2 x_3 + \alpha_3 x_4 + \beta_1\delta\gamma_{2,4}x_{12} + \beta_1\delta\gamma_{2,5}x_{13} + \beta_1\delta\gamma_{2,6}x_{14} + \beta_1\delta c_2 + \delta(\varepsilon_1 + \beta_1\varepsilon_2) \quad \text{(A 1a)}$$

$$y_2^* = \alpha_4 x_1 + \beta_2\delta\gamma_{1,2}x_2 + \alpha_5 x_3 + \alpha_6 x_4 + \delta\gamma_{2,4}x_{12} + \delta\gamma_{2,5}x_{13} + \delta\gamma_{2,6}x_{14} + \delta c_2 + \delta(\varepsilon_2 + \beta_2\varepsilon_1) \quad \text{(A 2a)}$$

$$y_1 = 1.y_2^* + \varepsilon_3 \quad \text{(A 3a)}$$

$$y_2 = \beta_4 y_1 + y_{4,1}x_3 + \gamma_{4,2}x_4 + c_4 + \varepsilon_4 \quad \text{(A 4a)}$$

$$y_3 = \beta_5 y_1 + \gamma_{5,1}x_1 + \gamma_{5,2}x_2 + \gamma_{5,3}x_3 + \gamma_{5,4}x_4 + \gamma_{5,5}x_5 + \gamma_{5,6}x_7 + c_5 + \varepsilon_5 \quad \text{(A 5a)}$$

$$y_4 = -1.y_1^* + \beta_6 y_1 + \gamma_{6,1}x_5 + \gamma_{6,2}x_6 + \gamma_{6,3}x_7 + \gamma_{6,4}x_8 + \gamma_{6,5}x_9 + c_6 + \varepsilon_6 \quad \text{(A 6a)}$$

$$y_5 = \beta_{7,1}y_1^* + \beta_{7,2}y_1 + \beta_{7,3}y_4 + \gamma_{7,1}x_5 + \gamma_{7,2}x_6 + \gamma_{7,3}x_7 + c_7 + \varepsilon_7 \quad \text{(A 7a)}$$

$$y_6 = \beta_{8,1}y_1^* + \beta_{8,2}y_4 + \gamma_{8,1}x_5 + \gamma_{8,2}x_8 + \gamma_{8,3}x_{10} + c_8 + \varepsilon_8 \quad \text{(A 8a)}$$

---

[4]For convenience we will write $\beta_{i,j}$ for $-\beta_{i,j}$.

$$y_7 = \beta_{9,1}y_1^* + \beta_{9,2}y_1 + \beta_{9,3}y_6 + \gamma_{9,1}x_5 + \gamma_{9,2}x_6 + c_9 + \varepsilon_9 \qquad \text{(A9a)}$$

$$y_8 = \beta_{10,1}y_1^* + \beta_{10,2}y_6 + \gamma_{10,1}x_5 + \gamma_{10,2}x_8 + \gamma_{10,3}x_{11} + c_{10} + \varepsilon_{10} \qquad \text{(A10a)}$$

with

$$\delta = \frac{1}{1-\beta_1\beta_2}, \quad \alpha_1 = \delta(\gamma_{1,1}+\beta_1\gamma_{2,1}), \quad \alpha_4 = \delta(\gamma_{2,1}+\beta_2\gamma_{1,1})$$

$$\alpha_2 = \delta(\gamma_{1,3}+\beta_1\gamma_{2,2}), \quad \alpha_5 = \delta(\gamma_{2,2}+\beta_2\gamma_{1,3})$$

$$\alpha_3 = \delta(\gamma_{1,4}+\beta_1\gamma_{2,3}), \quad \alpha_6 = \delta(\gamma_{2,3}+\beta_2\gamma_{1,4})$$

For notational covenience we will prove that all coefficients in (A1a) - (A10a) are identified. The coefficients in equations (A1) - (A10) can then be derived as follows:

$$\gamma_{1,1} = \alpha_1 - \beta_1\alpha_4 \qquad \gamma_{2,1} = \alpha_4 - \beta_2\alpha_1$$

$$\gamma_{1,3} = \alpha_2 - \beta_1\alpha_5 \qquad \gamma_{2,2} = \alpha_5 - \beta_2\alpha_2$$

$$\gamma_{1,4} = \alpha_3 - \beta_1\alpha_6 \qquad \gamma_{2,3} = \alpha_6 - \beta_2\alpha_3$$

Table A4 presents the reduced-form coefficient matrix Π expressed in the structural coefficients; the (i,j)-element of Π is denoted by $\pi_{i,j}$.
We shall demonstrate that every structural coefficient can be written as a function of the π_{ij}'s.

The elements α_4, α_5, α_6, $\gamma_{5,5}$, $\gamma_{5,6}$, $\gamma_{6,1}$ $-\gamma_{6,5}$, $\gamma_{8,3}$ and $\gamma_{10,3}$ are directly identified (e.g. $\alpha_4 = \pi_{1,1}$, etc.).

Furthermore we have[5]

$$\beta_4 = \frac{\pi_{2,1}}{\pi_{1,1}}, \quad \beta_5 = \frac{\pi_{3,12}}{\pi_{1,12}}, \quad \beta_{7,3} = \frac{\pi_{5,8}}{\pi_{4,8}}$$

$$\beta_{8,2} = \frac{\pi_{6,7}}{\pi_{4,7}}, \quad \beta_{9,3} = \frac{\pi_{7,7}}{\pi_{6,7}}, \quad \beta_{10,2} = \frac{\pi_{8,10}}{\pi_{6,10}}$$

---

[5]Most coefficients are overidentified; we will indicate just one way to identify the structural coefficients.

Table A4. The reduced form coefficient-matrix Π expressed in the structural coefficients; the (i,j)-element of Π is denoted by $\Pi_{i,j}$

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1	α_4	$\beta_2\delta\gamma_{1,2}$	α_5	α_6								$\delta\gamma_{2,4}$	$\delta\gamma_{2,5}$	$\delta\gamma_{2,6}$	δc_2
2	$\beta_4\Pi_{1,1}$	$\beta_4\Pi_{1,2}$	$\beta_4\Pi_{1,3}+$ $\gamma_{4,1}$	$\beta_4\Pi_{1,4}+$ $\gamma_{4,2}$								$\beta_4\Pi_{1,12}$	$\beta_4\Pi_{1,13}$	$\beta_4\Pi_{1,14}$	$\beta_4\Pi_{1,15}+$ c_4
3	$\beta_5\Pi_{1,1}+$ $\gamma_{5,1}$	$\beta_5\Pi_{1,2}+$ $\gamma_{5,2}$	$\beta_5\Pi_{1,3}+$ $\gamma_{5,3}$	$\beta_5\Pi_{1,4}+$ $\gamma_{5,4}$	$\gamma_{5,5}$		$\gamma_{5,6}$					$\beta_5\Pi_{1,12}$	$\beta_5\Pi_{1,13}$	$\beta_5\Pi_{1,14}$	$\beta_5\Pi_{1,15}+$ c_5
4	$-\alpha_1+$ $\beta_6\Pi_{1,1}$	$-\delta\gamma_{1,2}+$ $\beta_6\Pi_{1,2}$	$-\alpha_2+$ $\beta_6\Pi_{1,3}$	$-\alpha_3+$ $\beta_6\Pi_{1,4}$	$\gamma_{6,1}$	$\gamma_{6,2}$	$\gamma_{6,3}$	$\gamma_{6,4}$	$\gamma_{6,5}$			$-\beta_1\delta\gamma_{2,4}+$ $\beta_6\Pi_{1,12}$	$-\beta_1\delta\gamma_{2,5}+$ $\beta_6\Pi_{1,13}$	$-\beta_1\delta\gamma_{2,6}+$ $\beta_6\Pi_{1,14}$	$-\beta_1\delta c_2+$ $\beta_6\Pi_{1,15}+$ c_6
5	$\beta_{7,1}\alpha_1+$ $\beta_{7,2}\Pi_{1,1}+$ $\beta_{7,3}\Pi_{4,1}$	$\beta_{7,1}\delta\gamma_{1,2}+$ $\beta_{7,2}\Pi_{1,2}+$ $\beta_{7,3}\Pi_{4,2}$	$\beta_{7,1}\alpha_2+$ $\beta_{7,2}\Pi_{1,3}+$ $\beta_{7,3}\Pi_{4,3}$	$\beta_{7,1}\alpha_3+$ $\beta_{7,2}\Pi_{1,4}+$ $\beta_{7,3}\Pi_{4,4}$	$\beta_{7,3}\Pi_{4,5}+$ $\gamma_{7,1}$	$\beta_{7,3}\Pi_{4,6}+$ $\gamma_{7,2}$	$\beta_{7,3}\Pi_{4,7}+$ $\gamma_{7,3}$	$\beta_{7,3}\Pi_{4,8}$	$\beta_{7,3}\Pi_{4,9}$			$\beta_{7,1}\beta_1\delta\gamma_{2,4}+$ $\beta_{7,2}\Pi_{1,12}+$ $\beta_{7,3}\Pi_{4,12}$	$\beta_{7,1}\beta_1\delta\gamma_{2,5}+$ $\beta_{7,2}\Pi_{1,13}+$ $\beta_{7,3}\Pi_{4,13}$	$\beta_{7,1}\beta_1\delta\gamma_{2,6}+$ $\beta_{7,2}\Pi_{1,14}+$ $\beta_{7,3}\Pi_{4,14}$	$\beta_{7,1}\beta_1\delta c_2+$ $\beta_{7,2}\Pi_{1,15}+$ $\beta_{7,3}\Pi_{4,15}+$ c_7
6	$\beta_{8,1}\alpha_1+$ $\beta_{8,2}\Pi_{4,1}$	$\beta_{8,1}\delta\gamma_{1,2}+$ $\beta_{8,2}\Pi_{4,2}$	$\beta_{8,1}\alpha_2+$ $\beta_{8,2}\Pi_{4,3}$	$\beta_{8,1}\alpha_3+$ $\beta_{8,2}\Pi_{4,4}$	$\beta_{8,2}\Pi_{4,5}+$ $\gamma_{8,1}$	$\beta_{8,2}\Pi_{4,6}$	$\beta_{8,2}\Pi_{4,7}$	$\beta_{8,2}\Pi_{4,8}+$ $\gamma_{8,2}$	$\beta_{8,2}\Pi_{4,9}$	$\gamma_{8,3}$		$\beta_{8,1}\beta_1\delta\gamma_{2,4}+$ $\beta_{8,2}\Pi_{4,12}$	$\beta_{8,1}\beta_1\delta\gamma_{2,5}+$ $\beta_{8,2}\Pi_{4,13}$	$\beta_{8,1}\beta_1\delta\gamma_{2,6}+$ $\beta_{8,2}\Pi_{4,14}$	$\beta_{8,1}\beta_1\delta c_2+$ $\beta_{8,2}\Pi_{4,15}+$ c_8
7	$\beta_{9,1}\alpha_1+$ $\beta_{9,2}\Pi_{1,1}+$ $\beta_{9,3}\Pi_{6,1}$	$\beta_{9,1}\delta\gamma_{1,2}+$ $\beta_{9,2}\Pi_{1,2}+$ $\beta_{9,3}\Pi_{6,2}$	$\beta_{9,1}\alpha_2+$ $\beta_{9,2}\Pi_{1,3}+$ $\beta_{9,3}\Pi_{6,3}$	$\beta_{9,1}\alpha_3+$ $\beta_{9,2}\Pi_{1,4}+$ $\beta_{9,3}\Pi_{6,4}$	$\beta_{9,3}\Pi_{6,5}+$ $\gamma_{9,1}$	$\beta_{9,3}\Pi_{6,6}+$ $\gamma_{9,2}$	$\beta_{9,3}\Pi_{6,7}$	$\beta_{9,3}\Pi_{6,8}$	$\beta_{9,3}\Pi_{6,9}$	$\beta_{9,3}\Pi_{6,10}$		$\beta_{9,1}\beta_1\delta\gamma_{2,4}+$ $\beta_{9,2}\Pi_{1,12}+$ $\beta_{9,3}\Pi_{6,12}$	$\beta_{9,1}\beta_1\delta\gamma_{2,5}+$ $\beta_{9,2}\Pi_{1,13}+$ $\beta_{9,3}\Pi_{6,13}$	$\beta_{9,1}\beta_1\delta\gamma_{2,6}+$ $\beta_{9,2}\Pi_{1,14}+$ $\beta_{9,3}\Pi_{6,14}$	$\beta_{9,1}\beta_1\delta c_2+$ $\beta_{9,2}\Pi_{1,15}+$ $\beta_{9,3}\Pi_{6,15}+$ c_9
8	$\beta_{10,1}\alpha_1+$ $\beta_{10,2}\Pi_{6,1}$	$\beta_{10,1}\delta\gamma_{1,2}+$ $\beta_{10,2}\Pi_{6,2}$	$\beta_{10,1}\alpha_2+$ $\beta_{10,2}\Pi_{6,3}$	$\beta_{10,1}\alpha_3+$ $\beta_{10,2}\Pi_{6,4}$	$\beta_{10,2}\Pi_{6,5}+$ $\gamma_{10,1}$	$\beta_{10,2}\Pi_{6,6}$	$\beta_{10,2}\Pi_{6,7}$	$\beta_{10,2}\Pi_{6,8}+$ $\gamma_{10,2}$	$\beta_{10,2}\Pi_{6,9}$	$\beta_{10,2}\Pi_{6,10}$	$\gamma_{10,3}$	$\beta_{10,1}\beta_1\delta\gamma_{2,4}+$ $\beta_{10,2}\Pi_{6,12}$	$\beta_{10,1}\beta_1\delta\gamma_{2,5}+$ $\beta_{10,2}\Pi_{6,13}$	$\beta_{10,1}\beta_1\delta\gamma_{2,6}+$ $\beta_{10,2}\Pi_{6,14}$	$\beta_{10,1}\beta_1\delta c_2+$ $\beta_{10,2}\Pi_{6,15}+$ c_{10}

With $\beta_{8,2}$ known, we have

$$\beta_6 = \frac{c\,\pi_{4,1} - \pi_{4,2}}{c\,\pi_{1,1} - \pi_{1,2}} \quad \text{with} \quad c = \frac{\pi_{6,2} - \beta_{8,2}\pi_{4,2}}{\pi_{6,1} - \beta_{8,2}\pi_{4,1}}$$

With β_6 known, we have

$$\beta_1 = \frac{\pi_{4,12} - \beta_6\pi_{1,12}}{-\pi_{1,12}} \quad \text{and} \quad \beta_2 = \frac{-\pi_{1,2}}{\pi_{4,2} - \beta_6\pi_{1,2}}$$

$$\alpha_1 = \beta_6\pi_{1,1} - \pi_{4,1} \quad ; \quad \alpha_2 = \beta_6\pi_{1,3} - \pi_{4,3} \quad ; \quad \alpha_3 = \beta_6\pi_{1,4} - \pi_{4,4}$$

With β_1 and β_2 known, we have $\delta = \dfrac{1}{1 - \beta_1\beta_2}$

With β_2 and δ known, we have $\gamma_{1,2} = \dfrac{\pi_{1,2}}{\beta_2\delta}$

With α_1 , $\gamma_{1,2}$, δ and $\beta_{7,3}$ known, we have

$$\beta_{7,1} = \frac{\pi_{1,1}(\pi_{5,2} - \beta_{7,3}\pi_{4,2}) - \pi_{1,2}(\pi_{5,1} - \beta_{7,3}\pi_{4,1})}{\pi_{1,1}\delta\gamma_{1,2} - \pi_{1,2}\alpha_1}$$

With α_1 , $\beta_{7,1}$ and $\beta_{7,3}$ known, we have

$$\beta_{7,2} = \frac{\pi_{5,1} - \beta_{7,1}\alpha_1 - \beta_{7,3}\pi_{4,1}}{\pi_{1,1}}$$

With α_1 and $\beta_{8,2}$ known, we have $\beta_{8,1} = \dfrac{\pi_{6,1} - \beta_{8,2}\pi_{4,1}}{\alpha_1}$

With α_1 , δ , $\gamma_{1,2}$ and $\beta_{9,3}$ known, we have

$$\beta_{9,1} = \frac{\pi_{1,1}(\pi_{7,2} - \beta_{9,3}\pi_{6,2}) - \pi_{1,2}(\pi_{7,1} - \beta_{9,3}\pi_{6,1})}{\pi_{1,1}\delta\gamma_{1,2} - \pi_{1,2}\alpha_1}$$

With α_1 , $\beta_{9,1}$ and $\beta_{9,3}$ known, we have

$$\beta_{9,2} = \frac{\pi_{7,1} - \beta_{9,1}\alpha_1 - \beta_{9,3}\pi_{6,1}}{\pi_{1,1}}$$

With α_1 and $\beta_{10,2}$ known, we have $\beta_{10,1} = \frac{\pi_{8,1} - \beta_{10,2}\pi_{6,1}}{\alpha_1}$

With all α's and β's (and δ) known, all c's and γ's can be identified,

$$\text{e.g. } c_2 = \frac{\pi_{1,15}}{\delta} \quad , \quad \gamma_{2,4} = \frac{\pi_{1,12}}{\delta} \quad , \quad \text{etc.}$$

Now we are still left with the identification of

$$\psi_{i,i} \quad i = 1, \ldots.., 10 \ (\psi_{i,i} = E\varepsilon_i^{\,2}).$$

The first, fourth, and sixth elements of the reduced-form disturbance vector are:

$\bar{y}_1$ eq.: $\beta_2\delta\varepsilon_1 + \delta\varepsilon_2 + \varepsilon_3$

$\bar{y}_4$ eq.: $\delta(\beta_6\beta_2 - 1)\varepsilon_1 + \delta(\beta_6 - \beta_1)\varepsilon_2 + \beta_6\varepsilon_3 + \varepsilon_6$

$\bar{y}_6$ eq.: $\delta\left[\beta_{8,1} + \beta_{8,2}(\beta_6\beta_2 - 1)\right]\varepsilon_1 + \delta\left[\beta_{8,1}\beta_1 + \beta_{8,2}(\beta_6-\beta_1)\right]\varepsilon_2 +$
$+ \beta_6\beta_{8,2}\varepsilon_3 + \beta_{8,2}\varepsilon_6 + \varepsilon_8$

By writing the "covariance equations" $Ey_1^{\,2}$, Ey_1y_4 , $Ey_4^{\,2}$ and Ey_4y_6 we get four equations with four structural parameters ($\Psi_{1,1}$,$\Psi_{2,2}$,$\Psi_{3,3}$ and $\Psi_{6,6}$).
Solving these equations, using $E\varepsilon_i\varepsilon_j = 0$ for $i \neq j$, we find

$$\Psi_{2,2} = \frac{-1}{\beta_1\delta\beta_{8,1}}\left[\beta_2\beta_{8,2}Ey_4^2 + \beta_{8,1}(1-\beta_6\beta_2)Ey_1y_4 - \beta_2Ey_yy_6 + \right.$$
$$\left. - \beta_6\beta_{8,1}(1-\beta_6\beta_2)Ey_1^2\right] .$$

With β_1, β_2, δ, β_6 and $\Psi_{2,2}$ known, we have

$$\Psi_{1,1} = \frac{-1}{\beta_2\delta^2}\left[Ey_1y_4 - \beta_6 Ey_1^2 + \beta_1\delta^2\Psi_{2,2}\right]$$

With all β's, $\Psi_{1,1}$ and $\Psi_{2,2}$ known, the identification of Ψ_{ii} $i = 3,..,10$ is straightforward, because of the recursive structure of the last seven equations of the model. For instance:

$$\Psi_{3,3} = Ey_1^2 - \beta_2^2\delta^2\Psi_{1,1} - \delta^2\Psi_{2,2} .$$

Appendix 3.

The matrices of parameters B and Γ look as follows:

$$
B = \begin{bmatrix}
1 & -\beta_1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
-\beta_2 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & -1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & -\beta_4 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & -\beta_5 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\
1 & 0 & -\beta_6 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \\
-\beta_{71} & 0 & -\beta_{72} & 0 & 0 & -\beta_{73} & 1 & 0 & 0 & 0 \\
-\beta_{81} & 0 & 0 & 0 & 0 & -\beta_{82} & 0 & 1 & 0 & 0 \\
-\beta_{91} & 0 & -\beta_{92} & 0 & 0 & 0 & 0 & -\beta_{93} & 1 & 0 \\
-\beta_{10,1} & 0 & 0 & 0 & 0 & 0 & 0 & -\beta_{10,2} & 0 & 1
\end{bmatrix}
$$

$$
\Gamma = \begin{bmatrix}
\gamma_{11} & \gamma_{12} & \gamma_{13} & \gamma_{14} & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
\gamma_{21} & 0 & \gamma_{22} & \gamma_{23} & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \gamma_{24} & \gamma_{25} & \gamma_{26} & c_2 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & \gamma_{41} & \gamma_{42} & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & c_4 \\
\gamma_{51} & \gamma_{52} & \gamma_{53} & \gamma_{54} & \gamma_{55} & 0 & \gamma_{56} & 0 & 0 & 0 & 0 & 0 & 0 & 0 & c_5 \\
0 & 0 & 0 & 0 & \gamma_{61} & \gamma_{62} & \gamma_{63} & \gamma_{64} & \gamma_{65} & 0 & 0 & 0 & 0 & 0 & c_6 \\
0 & 0 & 0 & 0 & \gamma_{71} & \gamma_{72} & \gamma_{73} & 0 & 0 & 0 & 0 & 0 & 0 & 0 & c_7 \\
0 & 0 & 0 & 0 & \gamma_{81} & 0 & 0 & \gamma_{82} & 0 & \gamma_{83} & 0 & 0 & 0 & 0 & c_8 \\
0 & 0 & 0 & 0 & \gamma_{91} & \gamma_{92} & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & c_9 \\
0 & 0 & 0 & 0 & \gamma_{10,1} & 0 & 0 & \gamma_{10,2} & 0 & 0 & \gamma_{10,3} & 0 & 0 & 0 & c_{10}
\end{bmatrix}
$$

Notes

[1]See Appendix 1 for the mean and standard deviation of each variable.

[2]We estimated the model with a disturbance term added to equation (2). The estimated correlation between this error term and ε_3 in equation (3) appeared to be -0.999. We therefore estimated the model as specified in equation (2). Compare Zellner (1970), Goldberger (1972b) and Griliches (1974).

[3]We have no indicators for the "risk aversion" (Pratt, 1964) of a family or individual. We are expanding our data base so as to be able to make the demand for insurance covering general care endogenous.

[4]Since we have only a limited number of variables available for estimating permanent income, we prefer to use observed rather than permanent income in the demand equations.

[5]Observed rather than permanent income is used for the same reason as given in footnote 4. Andersen and Benham (1970) found that within the context of their model, with "other things being equal", consumption of physician services is not more closely associated with permanent than with observed income. They conclude that the use of measured rather than permanent income to obtain elasticity estimates for physician expenditures may not be as misleading as has often been suggested.

[6]Because we estimated this model using the data for male family heads, the variable SEX is irrelevant, and AGE and EDUC equal AGEH and EDUCH respectively.

[7]Note that most of the dependent variables are truncated from below by zero, and indeed many of them are zero (like HOSP). In order not to complicate the model any further we will neglect this.

[8] In The Netherlands every employee with an annual income below Dfl. 30.900 (1976) is compulsorily insured with the Sick Fund Organization, which offers complete insurance for the whole family. Self-employed and aged people with an annual income below Dfl. 30.900 can buy voluntary insurance with the Sick Fund Organization. In this way about 70% of the Dutch population is completely insured against (nearly) all medical expenses. The other 30% consists of higher income groups, and nearly all of them have private health insurance.

[9] Partially answered questionnaires were deleted from the analysis.

[10] Acton (1975) found a comparable elasticity of 0.14.

[11] We did not calculate the elasticities for HOSP, since HOSP refers to consumption in one year while the other variables in medical care refer to a six-month period.

[12] Our results indicate that a person who is insured for GPCON with a coinsurance rate of 0.20 is expected to have about 40% more GP-contacts than a noninsured person; these findings differ from those of Phelps (1975; p. 125, Table 7-10A), who estimated a 130% difference.

[13] See footnote 5.

[14] Compare, e.g., Phelps (1975) who found an income elasticity for expenses on doctor visits of 0.11; Benham and Benham (1975) estimated an income elasticity for mean number of physician visits of 0.27; Colle and Grossman (1975) found an income elasticity for doctors' visits for children of 0.38, but they stated that their findings contrasted with the lower and insignificant results typically reported in studies of the demand for medical care by adults.

[15] Andersen and Benham (1970) found income elasticities for physician expenditures, other things being equal, of 0.17 to 0.30.

[16] The estimations of Rutten (1978) and Van der Gaag (1978) are based on data for patients in The Netherlands insured by the Sick Fund, while our results refer to privately insured.

[17] For this indirect effect compare, e.g., Van der Gaag and Van de Ven (1978) who estimated that a variable defined as "problem behavior in the family" (i.e., at least one person with a behavior problem) had a significantly positive effect on the medical care consumed by family members who did not themselves evidence such behavior problems.

[18] The effect of a change in family size from 1 to 2 equals (ln2 - ln1) + 0.140 = 0.097.

[19] Minus twice the logarithm of the likelihood-ratio is, in large samples, distributed χ^2 with, in our case, 156-66=90 degrees of freedom. Of course, the χ^2-test may be used for comparison of models which differ with respect to one (or a few) of the parameters only.

[20] Data from the New Jersey Income Maintenance Experiment.

[21] For that purpose we need other indicators of health than health-care utilization, e.g., objective norms like urine and blood tests, blood pressure, or presence or absence of some symptoms, or subjective norms like the self-perceived general state of health.

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