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THE DEMAND FOR DEDUCTIBLES IN PRIVATE HEALTH INSURANCE

A Probit Model with Sample Selection*

Wynand P.M.M. VAN DE VEN and Bernard M.S. VAN PRAAG

Leiden University, 2311 XK Leiden, The Netherlands

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In this paper we analyse the decision to prefer a health insurance with a deductible to one with complete coverage. We focus on health, medical consumption, and on socio-economic characteristics like age, income, education and family size. The analysis is based on a sample of 8000 privately insured families; about 60 percent of them did not wish to have a health insurance policy with a deductible. A corrective method for sample selectivity, analogous to Heckman's (1979) method, has been applied in probit analysis; the estimation results are compared with the maximum-likelihood estimates. Health, medical consumption and income are found to have a significant influence on the decision with respect to the type of insurance. Our results give an indication of the degree of adverse selection that may take place if health insurance policies are offered with the option to take a deductible in exchange of a premium reduction.

1. Introduction

In The Netherlands about 30% of the population is covered against medical costs by private insurance companies. The other 70% is insured under a National Health Insurance scheme. All employees (and their families) whose annual income is below a certain amount[1] are compulsorily insured under the NHI scheme, so that the boundary between both parties of the population roughly corresponds to the 70% quantile of the income distribution. Contrary to American practice, the insurance under both systems presents a fairly complete

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[1]In 1976 this threshold amount was 30,900 guilders (two guilder equals approximately one U.S. dollar). Self-employed and aged people whose family income is below 30,900 builders are allowed to insure themselves on a voluntary base under the NHI scheme.

covering of the whole spectre of medical facilities without co-insurance or deductibles. In recent years, perhaps under American influence, *private* insurance companies are reviewing their strategy and they try to extend their market by offering policies with several kinds of deductibles.

In 1976 one of these companies, in an attempt to estimate potential demand shifts, carried out a postal survey under 20,000 of its policy holders to enquire whether they would prefer deductibles with a reduced premium if the company would offer this option, or whether they would stick to their old policy conditions without deductibles but also a non-reduced premium. Such survey information is one of the few ways to gain some insights about the shape of the price–demand relation for health insurance.

Many aspects of health insurance have already been studied during the last years. The effect of health insurance on demand for medical care has been studied by e.g., Rosett and Huang (1973), Feldstein (1973), Phelps (1975) and Newhouse and Marquis (1978). A large-scale experiment has been carried out in California in order to compare the effects of an insurance with a deductible (i.e., coverage of medical costs above the deductible amount) with those of complete coverage [Brians and Gibbens (1974), Roemer et al. (1975) and Helms et al. (1978)]. In another health insurance experiment 2,750 families were enrolled in one of several insurance plans that differed with respect to the co-insurance rate and the upper limit in out-of-pocket expenditures by the families; the design of this experiment is described in Newhouse (1974), and the first results of this experiment are given in Manning et al. (1981) and Newhouse et al. (1981). The effect of deductibles on the demand for medical services has also been studied by Newhouse et al. (1980). For a review of the literature on how out-of-pocket payments affect the demand for personal medical care services, see Newhouse (1978b) and Chassin (1978). The selection of optimal deductibles for an (health) insurance policy has theoretically been studied by Pashigian et al. (1966), Gould (1969), Arrow (1973, 1976) and Keeler et al. (1977a, 1977c). The demand for complete and supplementary health insurance has been estimated e.g. by Phelps (1973, 1976) and Keeler et al. (1977b), respectively.

In this paper we will be concerned with the propensity of the consumer to prefer a health insurance with deductibles, to one with complete coverage. We shall attempt to explain this preference on the basis of the survey mentioned. The explanatory variables are income, health status, medical consumption and other socio-economic characteristics of the family concerned. Apart from its apparent relevance from the point of economic science and its commercial relevance for the company, the estimation of this relationship has some interesting methodological aspects. In section 2 we consider the data employed, in section 3 the functional specification of our relation based on some theoretical arguments is presented, and in section 4 we describe the estimation technique where we apply Heckmann's (1979) ideas on correcting for systematic non-response bias on a probit-type equation. In section 5 the results are presented and discussed. Section 6 concludes.

2. Data

The insurance company 'Het Zilveren Kruis' is one of the large Dutch non-profit health insurance companies. Its legal status is that of a foundation. In 1976 it selected at random 20,000 policy-holders, who were then approached by a postal questionnaire. It had to be filled in by the policy-holder and returned to the Research Center. In the questionnaire the respondent was identified by a number. Corresponding to the same number the insurance company provided additional information from its files to the Research Center. Hence, both information parts were anonymous; the questionnaire identifiable to the company had been sent to the Research Center, while researchers did not know the names of the respondents. 8,000 questionnaire responses have been received.

One of the main questions[2] read as follows: 'Would you like to have a health insurance policy with deductibles if you would get an appropriate premium reduction?' About 40% of the respondents answered in the affirmative and the answer to this question is to be investigated on the basis of various variables corresponding to other questions posed.

All health insurance policies are family insurance plans (no group insurance). Contrary to U.S. practice, health insurance is not provided as a fringe benefit. The premium is completely paid by the employee. The employer, however, may give his employees a compensation for the health insurance premium, but this compensation is taxable.

The main variable determining one's attitude to deductibles can be identified as the expected medical consumption. As an indication of the latter we took various aspects of the family's medical consumption during the half year before the date of response.[3] The data are the number (GP) of consultations of the *general practitioner*, the number ($SPEC$) of *outpatient specialist* consultations, and the money value (MED) of the *medicine* prescriptions during a half year. All values are taken as reported by the respondent. To our question how many days the family members had been ill, we got a lot of partial response corresponding to some, but not all family members. So we defined the variable ILL as the maximum number of illness days, the maximum taken over all reported family members.

The second main determinant is the policy-holder's material well-being. This is represented by the annual after-tax family income (INC), again as reported by the respondents. The position of the family head in the labor market is described by

[2]Other questions in the questionnaire were related a.o. to family background information, to the medical consumption not covered by the insurance policy, to the policy-holder's satisfaction with the company's service, and to the maximum deductible amount one was prepared to take in exchange for a given premium reduction. The answers to this last question are analyzed in Van de Ven and Van Praag (1981).

[3]Because the insurance policy relates to the whole family, we used total family medical consumption (instead of medical consumption per insured).

two dummy variables: $EMPL$ equals 1 if the family head is employee, and $SELF$ equals 1 if the family head is self-employed. We observe that, if $SELF=EMPL=0$, the family's main income will be non-labour income. We notice that the explanatory value of those income variables will be less than in other studies pertaining to the USA [Phelps (1973) and Feldstein (1973)], since our sample is only drawn from the upper three deciles of the income distribution. Moreover, the interpretation of the income elasticity will be different, because in the Dutch tax structure, as distinct from the U.S. structure, only extraordinarily high medical costs are tax-deductible. Three other variables of interest are: $EDUC$ (defined as the number of years spent at school by the head of the family), AGE (defined as the age of the family head), and FS (defined as the family size).

3. Expected utility gain

Let us denote the annual costs of medical care per family by z, which can be considered as a random variable with distribution function $F(z)$. The insurance company fixes its premium π such that premium revenues equal at least expected costs, i.e.,

$$\pi=(1+l)\int_0^\infty z\,\mathrm{d}F(z), \tag{1}$$

where l is the loading charge, which includes administration costs, selling costs and the company's profit.

Consider a policy holder with a concave utility function of income, U. His utility loss caused by a known premium payment equals $U(y)-U(y-\pi)$, where y is income. However, if he is not insured his expected loss of utility caused by medical expenditures equals

$$U(y)-\int_0^\infty U(y-z)\,\mathrm{d}F(z).$$

So the choice between insurance and non-insurance depends on the sign of the difference,

$$d(y)=U(y-\pi)-\int_0^\infty U(y-z)\,\mathrm{d}F(z) \tag{2}$$

[cf. Friedman and Savage (1948), Newhouse (1978a, pp. 19–20), Feldstein (1979, pp. 107–115)]. If U is concave and $l=0$, then the expression $d(y)$ is positive according to Jensen's inequality for concave functions, hence people insure. From the equation $d(y)=0$ we may deduce the maximum loading charge l the consumer is prepared to pay in excess to the actuarially fair premium. For a given value of l, the magnitude of $d(y)$ depends on two factors. First, $U(y)$ becomes flatter with increasing y, implying that $d(y)$ decreases with increasing income. This accounts for the empirical observation, as found e.g. by Friedman (1974), that people with increasing income are less risk-averse and less inclined to insure. Second, $d(y)$ increases when the distribution of z becomes more dispersed about its mean value. In other words, uncertainty makes insurance more attractive [for a detailed analysis of the demand for insurance, see e.g. Pratt (1964)].

The acceptance of a deductible can be interpreted as a partial return from the state of complete insurance to the state of non-insurance.

We split an insurance with complete coverage up into two components: (1) an insurance for all small expenses ($\leq D$) with premium π_1, and (2) an insurance for all catastrophic expenses ($>D$) with premium π_2,

$$\pi = \pi_1 + \pi_2,$$

$$\pi_1 = (1+l_1)\left[\int_0^D z\,\mathrm{d}F(z) + \int_D^\infty D\,\mathrm{d}F(z)\right], \tag{3}$$

$$\pi_2 = (1+l_2)\int_D^\infty (z-D)\,\mathrm{d}F(z),$$

where l_1 and l_2 are loading charges.

The choice between complete or partial coverage depends on the Expected Utility Gain (EUG) in case of a deductible, say D, as compared with complete coverage,

$$EUG(D,y) = \int_0^D U(\tilde{y}-z)\,\mathrm{d}F(z) + \int_D^\infty U(\tilde{y}-D)\,\mathrm{d}F(z) - U(\tilde{y}-\pi_1), \tag{4}$$

$$\tilde{y} = y - \pi_2.$$

Finally we admit for personal circumstances a, such that family i, $i=1,2,\ldots,N$, can be classified to belong to a specific risk class $a_j = a_j(i)$, $j=1,2,\ldots,m$, with corresponding *conditional* distribution function $F(z|a_j)$ and utility function $U(y|a_j)$. The insurance company, however, does not know the personal circumstances a, so that the premiums π_1 and π_2 are determined independently of the risk class.[4]

When the distribution of risk classes is given by $P(a=a_j)=p_j, j=1,2,\ldots,m$, we have

$$F(z) = \sum_{j=1}^{m} p_j \cdot F(z\,|\,a_j). \tag{5}$$

[4]In practice, the insurance company may be able to roughly divide the policy-takers in some risk classes, e.g. based on age. In that case, the distribution function $F(z)$ relates to just one subgroup; within this subgroup, however, the insurance company does not know the relevant personal circumstances a.

Now family i's inclination to take a deductible D is reflected by their Expected Utility Gain

$$EUG_i(D, y_i, a_j) = \int_0^D U(\tilde{y}_i - z \mid a_j)\, \mathrm{d}F(z \mid a_j)$$

$$+ \int_D^\infty U(\tilde{y}_i - D) \mid a_j)\, \mathrm{d}F(z \mid a_j) - U(\tilde{y}_i - \pi_1 \mid a_j). \tag{6}$$

Our main concern in this paper will be to explain this Expected Utility Gain by the variables mentioned in the previous section. In analyzing only some general propensity to take a deductible, we drop the parameter D (the exact deductible amount) and we specify the Expected Utility Gain in case of a deductible as compared with complete insurance to be a function of the following previously defined variables:

$$EUG_i = G(ILL_i, GP_i, SPEC_i, MED_i, INC_i, EDUC_i,$$

$$AGE_i, FS_i, EMPL_i, SELF_i). \tag{7}$$

The functional specification of G will be given in the next section. We assume the effect of ILL, GP, $SPEC$ and MED to be negative; the effect of AGE may be ambiguous; the effect of the other variables are assumed to be positive.

The reasoning for these statements may be sketched as follows: The variables ILL, GP, $SPEC$ and MED may be considered as health indicators. When, for example, ILL increases we have

$$\frac{\partial F(z \mid a_j, ILL)}{\partial ILL} < 0,$$

which indicates that for any z, and a_j being fixed, the chance on future medical costs less than z decreases with an increase in the days of illness experienced. Assuming, for the time being, that

$$U(\tilde{y}_i - \pi_1 \mid a_j, ILL) = U(\tilde{y}_i - \pi_1 \mid a_j),$$

i.e., the utility function of income does not depend on health, an increase of ILL will reduce the first and second term in the right-hand member of (6), which yields a decrease of EUG_i, the expected utility gain of taking a deductible under *ceteris paribus* conditions. The same reasoning holds for the variables GP, $SPEC$ and MED. An increase of income implies that the concavity of

$$U(\tilde{y}_i - \pi_1 \mid a_j)$$

is reduced. The less marked the concavity of U, the larger EUG_i; in other words, EUG_i is an increasing function of INC. This accounts for the positive effect of INC. The effect of $EDUC$ is both direct and indirect. Because the function $F(z|a_j)$ is unknown to the insured individual, we assume that his decision is influenced by his subjective probability distribution. The uncertainty about his health status, i.e., the dispersion of the random variable z decreases if one is better informed. This is the *direct* effect of better education. On the other hand, there is also a positive correlation between $EDUC$ and expected increase in income; in addition, more educated people are assumed to have a more efficient production function of health [Grossman (1972)], so, in general, they expect, other things being equal, a relatively better health. These are the *indirect* effects of $EDUC$ suggesting a positive effect.

The effect of AGE is more complicated. Given the *actual* medical consumption and income, we interpret AGE both as *expected* family medical consumption (health status) and as stock of wealth. These factors have respectively a negative and a positive influence on the demand for deductibles, so the net effect of AGE is indeterminate. Young families are generally relatively less well-off and rather healthy, although they may expect high medical costs because of births and childhood diseases; at middle age the financial status improves, while at the end of life the health status is expected to worsen. We conjecture that the influence of AGE in the beginning should be positive, and later on negative.

Increasing family size causes the law of large numbers to work. Its impact is a variance reduction of expected medical costs per person. *Given* the total medical consumption of the family, an increase in family size also implies a decrease of medical consumption per insured, making a deductible attractive. We will return to the interpretation of the coefficient of family size when discussing the estimation results.

The variables $EMPL$ and $SELF$ are included in order to correct for differences in one's labor position, which is one of the criteria for being eligible for public insurance.

4. Probit with sample selection

Our main concern in this paper will be the estimation of eq. (7), which we shall specify as follows:

$$EUG_i = \alpha' X_i + \varepsilon_{1i}, \tag{8}$$

with α a $(K \times 1)$ vector of unknown parameters; X_i a $(K \times 1)$ vector of the exogenous values for observation i: ILL, GP, $SPEC$, MED, INC, $EDUC$, $\widetilde{AGE}$, FS, $EMPL$, $SELF$ and a constant term $(K=11)$; and $\varepsilon_{1i} \sim N(0, \sigma_1^2)$.

Since all medical expenses above the deductible are covered by the insurance company, we expect a decreasing marginal effect of the variables ILL, GP, $SPEC$

and *MED* on *EUG*, so they are redefined as the corresponding logarithms on the variables, as introduced in section 2, *plus* one in order to avoid the nuisance value zero. In the same way *INC*, *EDUC* and *FS* are redefined as the logarithms of the corresponding variables defined in section 2. *EMPL* and *SELF* are dummy variables. The variable $\tilde{AGE}$ involves a rather complex redefinition. According to our reasoning that *AGE* will not have a monotonic influence, we tried various polynomials of higher degree and some other transformations of *AGE*. Finally, we used the lognormal density function $\lambda(AGE;\mu,\sigma^2)$ as a rather flexible two-parameter function.[5] We shall discuss the result of this specification in the following section.

We cannot observe the expected utility gain *EUG*, but we know (the answer to the question) whether or not the family prefers a health insurance with deductible to complete coverage. Thus we have an indicator of whether or not $EUG \geqq 0$ is true.

We define for each family i a dummy variable γ_i as follows:

$$\begin{aligned} \gamma_i &= 0 \quad \text{iff} \quad EUG_i < 0 \quad \text{(does not take a deductible)}, \\ &= 1 \quad \text{iff} \quad EUG_i \geqq 0 \quad \text{(does take a deductible).} \end{aligned} \tag{9}$$

The conditional probability that for family i, given X_i, we observe $\gamma_i = 1$ (prefers deductible) is given by

$$P(\gamma_i = 1 \mid X_i) = P(\alpha' X_i + \varepsilon_{1i} \geqq 0 \mid X_i) = H\left(\frac{\alpha' X_i}{\sigma_1}\right), \tag{10}$$

where H is the cumulative standard normal distribution function. The conditional chance on $\gamma_i = 0$ is

$$P(\gamma_i = 0 \mid X_i) = 1 - H\left(\frac{\alpha' X_i}{\sigma_1}\right). \tag{11}$$

Hence the probability on our observed sample is

$$\prod_{i=1}^{N_1}\left[H\left(\frac{\alpha' X_i}{\sigma_1}\right)\right] \cdot \prod_{N_1+1}^{N}\left[1 - H\left(\frac{\alpha' X_i}{\sigma_1}\right)\right], \tag{12}$$

where we assume that the first N_1 families observed do prefer the deductible, while the latter $(N - N_1)$ do not. Using the well-known probit-normalization $\sigma_1 = 1$,[6] we get by maximizing the nonlinear likelihood function (12) an

[5] $\lambda(y;\mu,\sigma^2) = \frac{1}{\sqrt{2\pi}} \cdot \frac{1}{y} \cdot \exp -\frac{1}{2}\left(\frac{\ln y - \mu}{\sigma}\right)^2.$

[6] See e.g. Goldberger (1964, ch. 5).

asymptotically efficient estimate of α. The price we have to pay because we only 'observe' γ_i instead of EUG_i is that we can estimate α only up to a factor of proportionality.

The conditional expected value of γ_i, $E(\gamma_i|X_i)=H(\alpha' X_i)$, always falls within the [0, 1] interval and may be interpreted as the probability that the individual, given the values of the exogenous variables, prefers a health insurance *with* a deductible.

In this way we may interpret the coefficients α both as the change (after normalization) in the expected utility gain as a consequence of a change in an exogenous variable [see eq. (8)] as well as the change (after transformation with H) in the probability that someone prefers a policy with a deductible [see eq. (10)].

Before going on to the estimation results we have to get rid of an annoying feature of the data. When inspecting the answers on the questions we discovered that a considerable percentage of the respondents did not answer several questions; thus, these observations could not be used in estimating the coefficients α. When differentiating with respect to the variables *Family Size*, *AGE* and *SEX*, which were also known with respect to non-respondents from the information supplied by the insurance company, we got the following marginal table (table 1).

Table 1

Percentage complete observations in the total sample ($N=7928$).

FS	% complete observations	*AGE*	% complete observations	*SEX*	% complete observations
1	57.2	$\leqq 29$	79.1	Male	64.4
2	60.8	30–39	73.0	Female	54.6
3	67.7	40–49	65.2		
4	67.8	50–64	58.5		
5	64.4	$\geqq 65$	45.4		
6	60.2				
$\geqq 7$	52.0				
				Total	62.9

This table suggests:

(a) that family size seems to have an influence on the response rate,
(b) the older the respondent, the less he is inclined to answer all questions, and
(c) a male respondent is more responsive than a female.

This behaviour may also be analyzed by means of probit analysis. We define for each family the variable response behaviour δ_i being one if the questionnaire has been filled in completely, and zero otherwise,

$$\begin{aligned} \delta_i &= 0 \quad \text{if} \quad I_i^* < 0, \\ &= 1 \quad \text{if} \quad I_i^* \geqq 0, \end{aligned} \tag{13a}$$

$$I_i^* = \beta' Z_i + \varepsilon_{2i}, \tag{13b}$$

with I_i^* an unobserved index of response propensity, β a (4×1) vector of unknown parameters, Z a (4×1) vector of exogenous variables $[Z = (\tilde{FS}, AGE, SEX,$ constant term)], and $\varepsilon_{2i} \sim N(0,1)$. $\tilde{FS}$ and AGE are the non-transformed *Family Size* and AGE, and SEX equals zero for a female respondent and one for a male.

Table 2

Estimated probit and MLE coefficients of the yes or no complete observation equation (yes = 1, no = 0); t-values between parentheses; the squared correlation coefficient (in the independent probit equation, first row) between the dependent variable and its predicted value equals 0.055.

	$\tilde{FS}$ $\times 10^{-2}$	AGE $\times 10^{-2}$	SEX $\begin{pmatrix} =0 \text{ male} \\ =1 \text{ female} \end{pmatrix}$ $\times 10^{-1}$	Constant	Log likelihood
Probit All families; $N = 7928$	−6.02 (5.46)	−2.01 (19.7)	−1.70 (3.74)	1.54 (21.5)	−5006.51
MLE All families; $N = 7928$	−6.15 (5.61)	−2.03 (20.0)	−1.62 (3.61)	1.55 (21.8)	−5006.55
MLE Families with $AGE \leqq 34$; $N = 1787$	−8.72 (2.75)	−0.21 (0.18)	−2.27 (2.01)	1.09 (3.41)	−955.23
MLE Families with $45 \leqq AGE \leqq 44$; $N = 1703$	−7.00 (2.72)	−1.74 (1.54)	0.11 (0.08)	1.46 (3.28)	−1050.01
MLE Families with $45 \leqq AGE \leqq 59$; $N = 2317$	−5.95 (3.23)	−1.72 (2.63)	−1.52 (1.71)	1.38 (3.78)	−1546.01
MLE Families with $AGE \geqq 60$; $N = 2121$	−1.98 (0.62)	−1.89 (4.65)	−1.70 (2.51)	1.37 (4.45)	−1452.16

In table 2 (row 1) the estimates $\hat{\beta}$ on response behaviour are given. As expected, AGE appears to be a main variable in explaining response behaviour: the older the respondent, the less the probability of a completely filled in questionnaire. This phenomenon might partly be explained by the less capability of elder people to do so, but realizing that older people on the average have a high medical consumption, it may also be an indication that people with large expected medical expenses are less likely to fill out the questionnaire. Because expected medical expenses is a main variable in explaining one's preference for a deductible, the error terms in both probit equations might contain some common omitted variables, i.e., the correlation coefficient ρ between ε_1 and ε_2 might be unequal to zero. The influence of *Family Size* is as could be expected: the larger the family, the smaller the chance that all family members have answered all questions.

This result implies that there may be a case for a serious sample selection bias. As a consequence, estimation of the coefficients α on the basis of 'only complete observations' yields inconsistent estimates if ρ is unequal to zero. We correct for this potential bias by applying a device which Heckman (1979) introduced for an analogous problem when explaining a non-dichotomous variable. Here we will use the same device in probit analysis.

The population regression function for eq. (8) may be written as

$$E(EUG_i|X_i)=\alpha' X_i. \tag{14}$$

The regression function for the subsample of complete observations ($I_i^* \geqq 0$) is

$$E(EUG_i|X_i, I_i^* \geqq 0)=\alpha' X_i + E(\varepsilon_{1i}|X_i, I_i^* \geqq 0). \tag{15}$$

Assuming that ε_1 and ε_2 are bivariate standard normally distributed with correlation coefficient ρ, we have

$$E(\varepsilon_{1i}|X_i, I_i^* \geqq 0)=\rho\lambda_i,^{7} \tag{16}$$

with

$$\lambda_i = h(A_i)/H(-A_i) \quad \text{and} \quad A_i = -[\beta_1 F\tilde{S}_i + \beta_2 AGE_i + \beta_3 SEX_i + \beta_4],$$

where h and H are the standard normal pdf and cdf, respectively. The regression equation for the subsample of complete observations ($I_i^* \geqq 0$) reads as follows:

$$EUG_i = \alpha' X_i + \rho\lambda_i + \tilde{\varepsilon}_{1i}, \tag{17}$$

where

$$E(\tilde{\varepsilon}_{1i}|I_i^* \geqq 0)=0 \quad \text{and} \quad E(\tilde{\varepsilon}_{1i}^2|I_i^* \geqq 0)=\tau_i^2,$$

with

$$\tau_i^2 = 1+\rho^2\lambda_i(A_i-\lambda_i).$$

[For a derivation of τ_i^2, see e.g. Heckman (1979, pp. 156–157).]

[7]Without normalizing $\sigma_1 = 1$, this expression equals $\sigma_1\rho\lambda_i$.

In this way Heckman has shown that, in the case that EUG is observable, estimates of the coefficients α in eq. (8) from a non-random subsample are biased if $\rho \neq 0$; this bias may be interpreted as arising from an ordinary specification error with the conditional mean (16) deleted as a regressor. Including the unknown λ_i as an explanatory variable [eq. (17)] would lead then to unbiased coefficients. In practice we do not know λ_i. But in a censored sample it is possible to obtain a consistent estimate $\hat{\lambda}_i$ based on the estimated coefficients $\hat{\beta}$ of the probit equation explaining whether or not the observation belongs to the selected subsample. After replacing λ_i by $\hat{\lambda}_i$, consistent OLS estimates of α and ρ may be obtained using only the selected subsample ($I_i^* \geqq 0$).

In our case, however, we only know whether or not $EUG_i \geqq 0$ holds. By dividing eq. (17) by $\tau_i (\tau_i > 0)$, we get from (9) and (17) the following model for the subsample of complete observations ($I_i^* \geqq 0$):

$$\begin{aligned} y_i &= 0 \quad \text{if} \quad \alpha'(X_i/\tau_i) + \rho(\lambda_i/\tau_i) + \varepsilon_i < 0, \\ &= 1 \quad \text{if} \quad \alpha'(X_i/\tau_i) + \rho(\lambda_i/\tau_i) + \varepsilon_i \geqq 0, \end{aligned} \tag{18}$$

with $E(\varepsilon_i | I_i^* \geqq 0) = 0$ and $E(\varepsilon_i^2 | I_i^* \geqq 0) = 1$.

Using the same argument (i.e., the sample selection bias arises because the conditional mean of ε_{1i} is not included as a regressor) in the case of a limited dependent variable[8] and replacing the unknown λ_i and τ_i by consistent estimates $\hat{\lambda}_i$ and $\hat{\tau}_i$, we will estimate α and ρ in (18) using the subsample of 4987 completely filled in questionnaires. Consistent estimates $\hat{\lambda}_i$ and $\hat{\tau}_i^2$ are based on the probit estimates $\hat{\beta}$ (table 2, row 1) and the consistent OLS estimate $\hat{\rho}$ from the linear probability function. (The OLS estimates of the linear probability model are consistent,[9] even after inclusion of $\hat{\lambda}_i$ as a regressor.)

We apply the probit estimation technique to eq. (18) although by assumption the error term ε_i is not normally distributed. Therefore, when the correction term is included, the probit estimates should be considered as an approximation. In the next section we will compare these estimates with the maximum likelihood estimates,[10] the probit estimates without correction term and the estimates of the linear probability model (OLS).

Assuming that ε_1 and ε_2 are bivariate standard normally distributed with correlation coefficient ρ and cumulative distribution function H_2, the likelihood

[8]See Heckman (1976, fn. 5, p. 478).

[9]The main disadvantages of the linear probability model (OLS) are that the predicted change may fall out of the (0, 1) interval, and the inefficiency due to the heteroskedastic error term.

[10]Originally we developed the simple estimator for the probit model with sample selection in order to avoid the (high) expenses of evaluating the MLE computer program. After a presentation of an earlier draft of this article, Professor D.A. Wise (Harvard University) placed the relevant MLE computer program at our disposal. This computer program has been written by Rob Meyer and Steve Venti, and is based on the modified scoring algorithm of Berndt et al. (1974).

[based on eqs. (8), (9) and (13)] is

$$\prod_{i=1}^{N_1} H_2(\alpha' X_i, \beta' Z_i; \rho) \cdot \prod_{i=N_1+1}^{N} H_2(-\alpha' X_i, \beta' Z_i; \rho) \cdot \prod_{i=N+1}^{M} H(-\beta' Z_i), \tag{19}$$

where the first N_1 observations have $\gamma_i = \delta_i = 1$ (completely filled in questionnaire, preference for deductible), the following $N - N_1$ observations have $\gamma_i = 0$ and $\delta_i = 1$ (completely filled in questionnaire, no preference for a deductible), and the last $M - N_2$ observations have $\delta_i = 0$ (no completely filled in questionnaire).

5. Estimation results

In table 3 the estimates of the coefficients α in the linear probability model and the probit model (both with and without the sample selection correction term) and the ML estimates are presented.[11] The ML estimates of β (presented in table 2) correspond to the estimates of the independent probit equation explaining yes or no complete observation.

The estimated coefficient of the sample selection correction term in the yes or no deductible equation (table 3) is in both cases (OLS and probit) significantly (0.05) different from zero. After inclusion of this term, some four coefficients changed more than 10%.

Though the OLS and probit coefficients are not directly comparable (because of the transformation with H in the probit model), the level of significance of the estimated coefficients correspond. The consistent estimate $\hat{\rho} = 0.401$ (from the OLS equation) has been used to compute the correction term $\hat{\tau}_i$ for the probit model with sample selection correction.

The ML estimates, which are asymptotically efficient, and the estimates of the probit model with sample selection correction, which are approximates, show a striking resemblance (table 3). The difference between MLE and probit *with* correction is just a fraction (on the average about 14%) of the difference between MLE and probit *without* correction.[12] In interpreting and discussing the estimated coefficients we will further concentrate on the MLE.

The number of consultations with specialists (*SPEC*), the amount spent on medicine (*MED*) and the number of days ill (*ILL*) have a significantly (0.05) negative influence on Expected Utility Gain. The lower significance level of the number of GP consultations may be explained by the multi-collinearity between these variables.

[11] Although the coefficients of the probit model without sample selection correction are also estimated by means of the maximum likelihood method, we will reserve the term 'ML estimates' here for those estimates that maximize eq. (19).

[12] A comparable result was found by Griliches et al. (1978, p. 149), who compared OLS, OLS with Heckman's correction term (without adjusting for the heteroskedastic nature of the error term) and MLE.

Table 3

Estimated OLS, probit and MLE coefficient of the yes or no deductible equation; t-values between parentheses;[a] $N=4987$; R^2 in the probit equation is the squared correlation coefficient between the dependent variable and its predicted value.

	ILL $\times 10^{-2}$	GP $\times 10^{-2}$	$SPEC$ $\times 10^{-2}$	MED $\times 10^{-2}$	INC $\times 10^{-1}$	$EDUC$ $\times 10^{-1}$	$\lambda(AGE;\mu,\sigma^2)$ $\mu=\ln 36$; $\sigma=25$ $\times 10$	FS $\times 10^{-1}$	$EMPL$ $\times 10^{-1}$	$SELF$ $\times 10^{-1}$	Constant	Sample selection correction term OLS: $\hat{\lambda}_i$ Probit: $\hat{\lambda}_i/\hat{\tau}_i$	$\hat{\rho}$	Log likelihood	OLS: $\bar{R}^2$ Probit: R^2
OLS Linear probability model	−1.16	−1.78	−3.14	−1.64	1.16	0.97	0.367	1.13	0.28	1.16	−1.14	—	—	—	0.1001
	(2.01)	(1.79)	(3.80)	(4.42)	(5.75)	(4.18)	(7.23)	(7.64)	(1.20)	(4.53)					
OLS with sample selection correction term	−1.15	−1.71	−3.24	−1.68	1.16	1.03	0.488	1.01	0.59	1.45	−1.30	0.188	0.401[c]	—	0.1009
	(2.00)	(1.72)	(3.90)	(4.51)	(5.75)	(4.40)	(6.70)	(6.35)	(2.18)	(5.09)		(2.32)			
Probit	−3.31	−4.97	−8.71	−4.61	3.37	2.92	0.97	3.18	1.37	3.78	−4.79	—	—	−3122.52	0.1046
	(2.03)	(1.78)	(3.75)	(4.41)	(5.87)	(4.42)	(6.93)	(7.66)	(1.97)	(5.10)	(8.87)				
Probit[b] with sample selection correction term	−3.11	−4.52	−8.56	−4.50	3.20	2.89	1.21	2.71	1.97	4.24	−4.93	0.443	0.443	−3120.85	0.1052
	(1.99)	(1.70)	(3.84)	(4.50)	(5.85)	(4.56)	(6.14)	(6.34)	(2.61)	(5.40)	(9.00)	(1.99)			
Maximum likelihood	−3.11	−4.50	−8.53	−4.47	3.18	2.88	1.19	2.70	1.94	4.21	−4.89		0.422	−3120.77	
	(2.00)	(1.71)	(3.83)	(4.39)	(5.57)	(4.50)	(7.35)	(5.29)	(2.78)	(5.98)	(9.52)		(1.954)		

[a] In the second row, the t-values are only approximate because of the neglected heteroskedastic error term.
[b] When the correction term is included, the error term is by assumption no longer normal, so these probit estimates are to be considered as approximates.
[c] In the OLS equation $\hat{\rho}$ equals the coefficient of the sample selection correction term divided by $\hat{\sigma}_1$ ($\hat{\sigma}_1=0.469$).

The variables *INC* and *EDUC* have a strong positive influence. The positive coefficients of *EMPL* and *SELF* might imply that policy-holders not working in a paid job are more risk-averse than employees and self-employed people, the latter being least risk-averse.

To gain more insight into the influence of the explanatory variables we estimated the yes or no deductible equation separately for subsamples corresponding to four age brackets. The results are presented in table 4.

In the age group under 35 we see a large and significantly positive influence of *AGE*; in the other three groups the coefficient is non-significant but negative. Combination of these within-group differences with the between-group differences (which are given in the appendix) suggested the use of the lognormal density $\lambda(AGE; \ln 36, 0.25)$. The values of $\mu = \ln(36)$ and $\sigma = 0.25$ have been chosen as best fitting in the sense of nonlinear least squares. The use of this lognormal transformation yielded in the linear probability model a considerable increase in R^2 and the improvement in goodness-of-fit upon the linear specification is illustrated in fig. 1.

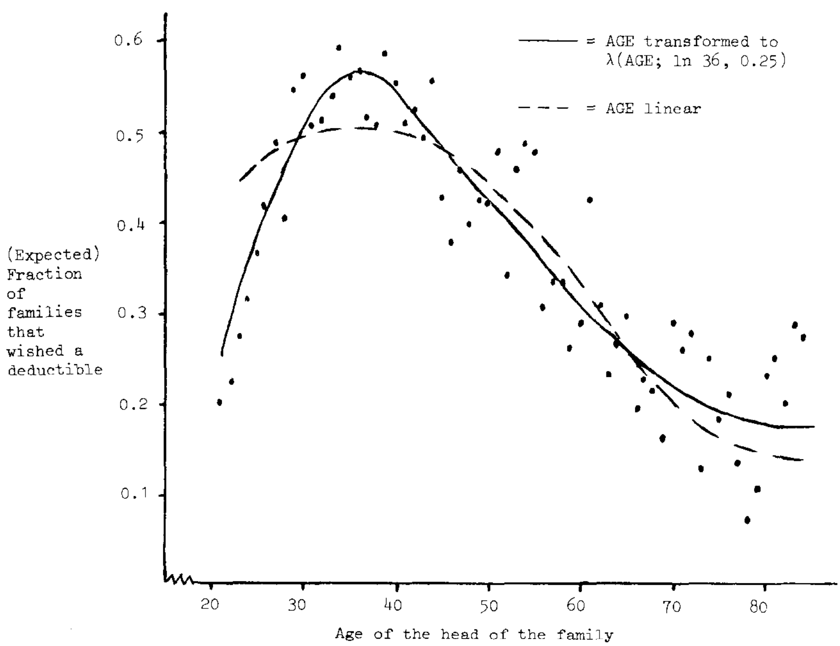

Fig. 1. Fraction of families that wished a deductible, per age of the head of the family. (For each age the calculated fraction of families that wished a deductible is given with a dot; in calculating the expected fractions, we took the average value of the explanatory variables for each age group. For *AGE* transformed to λ, see footnote 5.)

Table 4

Estimated MLE coefficients of the yes or no deductible equation per *AGE* group (age of the family head); t-values between parentheses.

	ILL $\times 10^{-2}$	*GP* $\times 10^{-2}$	*SPEC* $\times 10^{-2}$	*MED* $\times 10^{-2}$	*INC* $\times 10^{-1}$	*EDUC* $\times 10^{-1}$	*AGE* $\times 10^{-2}$	*FS* $\times 10^{-1}$	*EMPL* $\times 10^{-1}$	*SELF* $\times 10^{-1}$	Constant	$\hat{\rho}$	Log likelihood
Families with $AGE \leqq 34$; $N=1379$	−4.82 (1.67)	−7.69 (1.70)	−8.10 (2.14)	−3.88 (2.13)	1.74 (1.69)	3.46 (2.57)	4.76 (3.79)	2.68 (3.24)	−1.79 (0.51)	0.43 (0.12)	−3.65 (2.99)	−0.893 (3.10)	−908.32
Families with $35 \leqq AGE \leqq 44$; $N=1172$	−6.01 (1.50)	−4.96 (0.81)	−13.15 (1.88)	−5.61 (1.70)	4.47 (2.02)	1.66 (1.02)	−2.16 (1.52)	3.24 (1.10)	−1.96 (0.60)	−1.43 (0.44)	−4.20 (1.88)	0.528 (0.42)	−765.54
Families with $45 \leqq AGE \leqq 59$; $N=1406$	−1.07 (0.40)	−6.46 (1.29)	−8.90 (1.96)	−2.63 (1.38)	3.73 (2.70)	3.04 (2.14)	−0.76 (0.81)	2.13 (1.49)	4.02 (2.02)	6.76 (2.72)	−5.24 (3.12)	0.587 (0.80)	−892.73
Families with $AGE \geqq 60$; $N=1030$	0.108 (0.04)	4.83 (0.94)	−2.35 (0.51)	−4.35 (1.72)	2.13 (1.79)	2.99 (1.77)	−0.62 (0.70)	2.88 (2.27)	0.82 (0.73)	3.96 (2.17)	−3.58 (2.38)	0.788 (1.13)	−532.48

We conclude that age has a marked influence. In the first years of adulthood people are healthy, but poor, and have high expenditures, e.g. on housing; in addition, young families may expect high medical costs because of births and childhood diseases, and may be uncertain about the future health status of the family. As a result, the demand for deductibles in health insurance in the early twenties is rather low. In the thirties the financial status (family's wealth and savings) improves and deductibles become very attractive. Between, say, the age of 40 and 60 a sharp decline in the demand for deductibles arises because of the worsening health expectations, and at the lower end of the life cycle complete health insurance is desirable.

In order to get some idea about the relative influence on demand we calculated the elasticities of the probability $P(y=1 \mid X)$ with respect to some explanatory variables at the average value in the sample (see table 5).

In the age group of 60 years and over, the elasticities with respect to illness and medical consumption are negligibly small. Also the level of significance for the coefficients of these variables decreases with increasing age. Combining this with the result with respect to *AGE* we may conclude that for 'younger' families differences in decision behaviour whether or not to take a deductible are substantially influenced by differences in *current* health status and *current* medical consumption, while 'older' families have or expect to have a high level of medical consumption (= influence of *AGE*), so differences in their preference for a deductible are only slightly influenced by differences in current health status and current level of medical consumption.

The positive income elasticity (0.29) is as expected and can be explained by the decreasing risk aversion brought about by increasing income. A second explanation for the positive income elasticity may be as follows: the Dutch system of taxation permits medical expenses exceeding 12% of the income or exceeding 3,700 guilders[13] (1976) as tax deductions. So all 'regular' medical costs, including insurance premium, cannot reduce taxable income, but in case one really has to pay a high deductible amount of several thousand guilders, the tax profit will be more the higher one's income, because of the progressive tax rate.[14] This last argument may also explain why the income elasticities are highest for the two age groups with the highest average income (*AGE* between 35 to 59; see appendix).[15]

[13]4,650 guilders if the income is above 70,000 guilders.

[14]The marginal Dutch tax rate (1976) varies from 0 to 70 percent. Of course the actual marginal tax rate depends on all tax deductibles one has, but, on the average, the marginal tax rate for the population under this study will be 40–60%.

[15]The above sketched Dutch tax structure may be a reason for some policy-holders to pay the total premium for some years in advance within one fiscal year, in order to maximize their tax profit. For those policy-holders a deductible in their health insurance policy may be unfavourable because it reduces the premium and spreads the medical costs more evenly over different fiscal years. In order to test this hypothesis we included a dummy variable indicating whether or not the premium has been paid for more than one year together (this is true for less than 0.1 percent of the policy-holders). The coefficient for this dummy variable, and also for the interaction of this dummy variable with income, yielded no significant coefficients, while all other coefficients did not change. (We thank Joep Heesters for bringing this point to our attention.)

Table 5

Elasticities of the probability to take a deductible with respect to some explanatory variables, calculated at the *relevant* mean values;[a] elasticities between parentheses are not significantly different from zero at the 0.10^- level.

	Max. number of days ill	Total number of GP contacts	Total number of specialist contacts	Total amount spent on prescribed medicine	Income	Years of education (head of the family)	Family size
All families; $N=4987$	−0.0259	−0.0333	−0.0588	−0.0411	0.2948	0.2670	0.2503
Families with $AGE \leqq 34$; $N=1379$	−0.0341	−0.0502	−0.0450	−0.0314	0.1433	0.2850	0.2207
Families with $35 \leqq AGE \leqq 44$; $N=1172$	(−0.0394)	(−0.0297)	−0.0706	−0.0411	0.3313	(0.1230)	(0.2401)
Families with $45 \leqq AGE \leqq 59$; $N=1406$	(−0.0094)	(−0.0501)	−0.0672	(−0.0252)	0.3596	0.2931	(0.2054)
Families with $AGE \geqq 60$; $N=1030$	(0.0013)	(0.0493)	(−0.0235)	−0.0561	0.2763	0.2970	0.3736

[a]If $P(y^* \geqq 0 | X_1, X_2)$, the probability of taking a deductible, given X_1 and X_2, is equal to $F(I)$, with $I = \alpha_1 \log X_1 + \alpha_2 \log(X_2+1)$, then η_j, the elasticity of $P(y^* \geqq 0|X_1, X_2)$ with respect to X_j at the point $X=\bar{X}$ (i.e., $X_1=\bar{X}_1$ and $X_2=\bar{X}_2$) is given by

$$\eta_1 = \alpha_1[f(I)/F(I)]_{X=\bar{X}} \quad \text{and} \quad \eta_2 = \alpha_2[(X_2/(X_2+1))(f(I)/F(I))]_{X=\bar{X}}.$$

(In our case: X_1 may be *INC*, *EDUC* or *FS*; X_2 may be *ILL*, *GP*, *SPEC* or *MED*.)

For the whole population, the income elasticity (0.29) nearly equals the elasticity with respect to education (0.27). A striking result is the finding that in the age group under 35 the income elasticity is only half of the education elasticity.[16] This might be explained by the idea that young people see their education as a better proxy of future earnings than their current income.

The elasticity of the probability to take a deductible with respect to family size equals 0.25. Given the total medical consumption of the family, an increase in family size mostly implies a reduction of the ratio of benefits to premium,[17] which makes insurance unattractive.

Because the insurance policy relates to the whole family, the relevant variables in specifying eq. (7) are total family medical consumption. But even in the case when we replaced total family consumption by the medical consumption per insured, we found a significant (though less) positive coefficient,[18] allowing the following interpretation:

(1) a variance reduction due to the law of large numbers;
(2) large families as a rule consume less per head, which may be less than proportionally expressed in premium reduction;
(3) tax deduction for medical costs above a certain amount is, given a specific family income, easier reached in a large family than in a small family;
(4) at early ages, small families expect high medical costs because of births and childhood diseases.

Looking at the magnitude of the different elasticities, we see that, roughly speaking, the first four columns in table 5 contain small negative demand elasticities with respect to health and medical consumption, while the latter three columns contain large elasticities with respect to income, education and family size. *If* one becomes unhealthy, however, then the value of *ILL*, *GP*, *SPEC* and *MED* may increase simultaneously, so the total effect is a weighted sum of the small elasticities. Furthermore, in comparing the influence of different factors, we also have to keep in mind the variation of each factor in the population (in other words, besides looking at the effect *if* the factor changes, we also have to look at its degree of variation).

Therefore, we calculated the effect of a change in some exogenous variables from μ to $\mu+\sigma$ on the probability of taking a deductible, where μ and σ are the sample mean resp. the sample standard deviation of the relevant variable. These effects are given in table 6, for the whole population and for different age groups.

[16]In addition, the level of significance of the *EDUC* coefficient is highest in the age group under 35, while for the *INC* coefficient the reverse is true (table 4).

[17]Premium is paid per person. Children of 15 years and younger pay half the premium, and children of 16–27 years who are studying pay 75% of the premium of an adult. If a family has four or more children, not older than 15 years, they only have to pay for three of them.

[18]By replacing total family medical consumption by average medical consumption per individual, the elasticity of family size reduced from 0.25 to 0.17 (both significant at the 0.05 level).

Table 6

Effect (in percentages) of a σ change in an explanatory variable (from μ to $\mu+\sigma$) on the probability to take a deductible;[a] figures between parentheses are based on estimated coefficients that are not significantly different from zero at the 0.10^{-} level.

	Fraction of families that wish a deductible	Max. number of days ill	Total number of GP contacts	Total number of specialist contacts	Total amount spent on prescribed medicine	Income	Years of education (head of the family)	Family size
All families	0.422	−7.48%	−4.62%	−15.29%	−8.27%	11.83%	7.79%	12.31%
Families with $AGE \leqq 34$	0.484	−8.96%	−5.71%	−11.55%	−5.62%	4.44%	5.96%	9.13%
Families with $35 \leqq AGE \leqq 44$	0.536	(−10.47%)	(−3.93%)	−14.12%	−7.32%	11.21%	(3.01%)	(8.89%)
Families with $45 \leqq AGE \leqq 59$	0.401	(−2.64%)	(−8.16%)	−16.79%	(−4.97%)	14.24%	9.01%	(9.87%)
Families with $AGE \geqq 60$	0.239	(0.38%)	(6.67%)	(−6.78%)	−9.97%	15.17%	11.32%	18.69%

[a]The figures in this table are equal to $100 \times \sigma/\mu \times \eta$, where μ and σ are the sample mean and standard deviation of the relevant explanatory variable (given in the appendix) and η is the elasticity (given in table 5). Because the elasticities are relevant only for small changes in the explanatory variable, the figures in this table primarily serve for making a mutual comparison of the different effects. The effect of an $\alpha\sigma$ change (from μ to $\mu+\alpha\sigma$) is equal to α times the figure presented in this table.

From these figures it becomes clear, that in our sample the influence of health and medical consumption is more important than the influence of socio-economic factors (except for the age group above 60 years). A simultaneous change from μ to $\mu+\sigma$ in the variables *ILL*, *GP*, *SPEC* and *MED* causes — other things (e.g. age) being equal — a 36 percent decrease in the probability of taking a deductible, while for income and education these effects are $+12\%$, respectively $+8\%$. Because the fraction of families that wished a deductible equals 0.422, these percentage changes correspond to absolute probability changes which equal -0.151, $+0.050$ and $+0.033$. Comparing in this way the *absolute* effect of a simultaneous change from μ to $\mu+\sigma$ in *ILL*, *GP*, *SPEC* and *MED*, we see that for the age group of 60 years and over the probability change is very small as compared with the age group of 35 to 44 years (-0.023, respectively -0.192).[19]

6. Summary and conclusion

In this article we studied the propensity for accepting deductibles in private health insurance on the basis of stated preferences in an anonymous large-scale survey. As estimation method we used a probit model with sample selection. We applied a correction method analogous to Heckman's (1979) method. Our estimation results showed a clear resemblance to the ML estimates.

Our main conclusion is that, besides current health and medical consumption, income, education, family size and age have considerable influence. Although the elasticities of the probability to take a health insurance policy with a deductible, with respect to current health and medical consumption are low as compared to those with respect to socio-economic variables, the influence of health and medical consumption, after accounting for differences in the variation coefficients, appeared to be dominant. This might be an indication that a serious adverse selection might take place if people may choose between policies with different deductibles and appropriate premium reductions. Based on expectations about health and medical consumption, older families will generally prefer a complete insurance, while policy-holders between 30 and 45 will have the greatest demand for deductibles. Keeping age constant, actual health and medical consumption have an influence on the probability to take a deductible that far exceeds the influence of socio-economic factors. Only in the age group of 60 years and over, the influence of income, education or family size exceeds the influence of actual health and medical consumption.

In the years after 1976, the insurance company gradually introduced several kinds of policy with deductibles. We hope, when the relevant data are made available to us, to report on the new developments.

[19]The percentage changes in the age group of 60 years and over, and in the age group of 35 to 44 are respectively -9.70 $(=0.38+6.67-6.78-9.97)$ and -35.84 $(=-10.47-3.93-14.12-7.32)$. The corresponding absolute probability changes are respectively -0.023 $(=-9.70\times 0.00239)$ and $-0.192 (=-35.84\times 0.00536)$.

Appendix

Table A.1

Mean and standard deviation (before transformation).

	ILL	*GP*	*SPEC*	*MED*	*INC*	*EDUC*	*FS*	*AGE*	*SEX*	*EMPL*	*SELF*	Yes/no deductible 1 = yes 0 = no
All families; $N=4987$	8.709 (25.145)	3.978 (5.521)	2.899 (7.539)	110.98 (223.43)	30728.64 (12335.09)	12.772 (3.728)	3.079 (1.514)	46.151 (14.888)	0.136 (0.342)	0.648 (0.478)	0.194 (0.396)	0.422 (0.494)
Families with $AGE \leqq 34$; $N=1379$	6.083 (15.990)	3.831 (4.356)	2.067 (5.305)	62.14 (111.21)	29449.19 (9117.56)	14.183 (2.966)	2.868 (1.187)	29.492 (3.175)	0.099 (0.298)	0.838 (0.368)	0.155 (0.362)	0.484 (0.500)
Families with $35 \leqq AGE \leqq 44$; $N=1172$	7.660 (20.361)	4.207 (5.560)	2.630 (5.260)	87.765 (156.32)	33152.42 (11214.39)	13.372 (3.276)	3.926 (1.454)	39.358 (2.915)	0.078 (0.269)	0.791 (0.407)	0.198 (0.399)	0.536 (0.499)
Families with $45 \leqq AGE \leqq 59$; $N=1406$	10.643 (29.838)	4.126 (6.724)	3.619 (9.042)	128.30 (252.92)	33323.07 (13195.70)	12.154 (3.737)	3.385 (1.627)	51.593 (4.285)	0.120 (0.325)	0.692 (0.462)	0.257 (0.437)	0.401 (0.490)
Families with $AGE \geqq 60$; $N=1030$	10.781 (31.843)	3.709 (5.017)	3.337 (9.627)	179.16 (318.28)	26142.15 (14350.20)	11.045 (4.208)	1.979 (0.990)	68.754 (7.028)	0.271 (0.445)	0.169 (0.375)	0.157 (0.364)	0.239 (0.427)

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