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A Microeconometric Model of the Demand for Health Care and Health Insurance in Australia

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This paper develops a model for interdependent demand for health insurance and health care under uncertainty to throw light on the issue of insurance-induced distortions in the demand for health care services. The model is used to empirically analyse the determinants of the choice of health insurance type and seven types of health care services using micro-level data from the 1977-78 Australian Health Survey. Econometric implementation of the model involves, simultaneously, issues of discreteness of choice, selectivity and stochastic dependence between health insurance and utilization. Health status appears to be more important in determining health care service use than health insurance choice, while income appears to be more important in determining health insurance choice than in determining health care service use. For a broad range of health care services both moral hazard and self selection are found to be important determinants of utilization of health care services.

1. INTRODUCTION

The demand for health care and health insurance are intimately related, a point that has been recognized and researched since Arrow (1963) pointed to the existence of the moral hazard problem. By "distorting" the effective price of health care to the insured users, health insurance may lead to "overutilization" of health care services. The extent to which this may happen has been empirically investigated by Feldstein (1973) and Newhouse *et al.* (1982). This literature has emphasized that the demand for health care is conditioned by the health insurance status of the user. But what determines the health insurance status of the user? We have argued elsewhere, see Cameron *et al.* (1984), that the insurance decision itself will depend upon, *inter alia*, expected future consumption of health services.

This paper is an attempt to model this interdependent demand for health insurance and health care. We develop an economic model under uncertainty, exploiting some

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insights of Phelps (1976). Econometric implementation of this model is somewhat complex. Even without uncertainty it involves, simultaneously, issues of discreteness of choice, selectivity and stochastic dependence between health insurance and utilization. Discrete choice arises because government regulated insurance companies, which capture well over 90% of the Australian health insurance market, are permitted to offer only a very limited number and range of health insurance policies. The modelling problem has a certain resemblance to other choice models involving jointness of optimal discrete and continuous choices. Two recent examples are King (1980) who modelled the consumer's decision to rent or purchase a home and the expenditure on either, and Dubin and McFadden (1984) who modelled the jointness of electrical applicance holdings and electricity consumption. There are, to our knowledge, no similar studies in health economics, where the additional complication of uncertainty needs to be confronted.

The interdependence of the demand for health insurance and health care, given that future health states are uncertain, is illustrated in Section 2 for an expected utility maximizing consumer. For this purpose, a specific parametric form of a two-period utility function is postulated. Maximization is subject to two-period budget constraints and a given health production function. Optimization is by the method of dynamic programming, which involves deriving demand functions for health care services conditionally on the discrete choice of insurance type and subsequently optimizing over the set of discrete choices.

The empirical analysis is based on the Australian Health Survey (AHS) 1977-1978. The relevant aspects and limitations of the survey data, and the institutional details of the health insurance arrangements in Australia at that time, are described in Section 3. This factual-institutional material has important implications for estimation and interpretation of our econometric results.

Full structural identification and estimation of the joint demand model is difficult. Due to uncertainty, insurance choice is made not on the basis of indirect utility alone, but its expectation with respect to the consumer's *a priori* distribution of health states. A tractable structural model for insurance demand is therefore virtually impossible to obtain. Instead we use the economic model as the basis for a reduced form model of insurance choice, which is all that is needed for structural analysis of the demand for health services. A structural model for health services is obtained, though gaps in our data on the price of health services necessitate estimation of an approximation to this structural model.

We focus on the relative importance in the demand for health services of consumer's insurance level on the one hand and health status and socio-economic factors on the other. In Section 4 we present consistent estimates of the demand for health services, controlling for the selection bias that arises from endogeneity of insurance choice. These use as instruments predictions from the reduced form for insurance choice, whose estimates are presented. If selection bias is not a major problem, more efficient parameter estimates can potentially be obtained by estimating models for count data, since our data on health use are of this special form. Negative binomial model estimates of the demand for health services are accordingly also presented in Section 4. Section 5 concludes.

2. THE ECONOMIC MODEL

We wish to develop a structural model of the demand for health insurance and health care which will throw light on the question of whether insurance-induced distortion in the price of health services leads to significant "over-consumption" of such services. The

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theoretical challenge is to derive tractable, closed form and relatively unrestricted demand functions for health insurance and health care for a risk-averse consumer planning under uncertainty. At the econometric level, the critical task is to distinguish between the relative importance of the price of services, the so-called *moral hazard* problem, and self selection in determining the demand for health services. In this study we maintain the main focus on the demand for health care, examining the demand for health insurance only to the extent required for consistent estimation of the demand for health services.

Consider a consumer with a two-period utility function defined by $U[C_0, C_1(s), H(\boldsymbol{e}, s \mid \boldsymbol{A}, \boldsymbol{B})]$ where C denotes consumption and H denotes health measured as income equivalent. U and H are both increasing in their arguments. The subscripts 0 and 1 refer, respectively, to the current and future periods, s to the uncertain health state (or event) on which will depend the demand for health care services denoted by the K-dimensional vector $\boldsymbol{e}$. $\boldsymbol{A}$ refers to the vector of consumer's attributes or characteristics, and $\boldsymbol{B}$ to the vector of attributes of the insurance policy. $H(\boldsymbol{e}, s \mid \boldsymbol{A}, \boldsymbol{B})$ may be regarded as the health production function with inputs $\boldsymbol{e}$ in state s.[1]

Uncertainty arises because (and only because) at the time the insurance policy is chosen health status s is unknown. The consumer has a prior probability measure π of the health states, conditional on the attributes $\boldsymbol{A}$, denoted $\pi(s \mid \boldsymbol{A})$. The consumer can transfer purchasing power between periods using a risk-free asset, each unit of which has a price p_a, equal to $1/(1+r)$ at the constant market interest rate r. The consumer leaves no bequest and maximizes expected utility. The consumer may choose only between a discrete number J of mutually exclusive health insurance policies. This is a special feature of our model which is intended to reflect actual choices confronting Australians in the period covered by our data. Most studies, for other countries, characterize insurance policies by the coinsurance rate which is assumed to vary continuously from zero to unity.

Under the above assumptions the allocation problem is

$$\max_{\{j, C_0, C_1, a, e\}} EU_j = \int_s U(C_0, C_1, H(\boldsymbol{e}, s) \mid \boldsymbol{A}, \boldsymbol{B}))\, d\pi(s \mid \boldsymbol{A}) + w_j \tag{2.1}$$

subject to

$$Y_{0j} + P_j = Y_0, \qquad C_0(s) + a(s) = Y_{0j}, \qquad C_1(s) + \tilde{p}_j \boldsymbol{e}(s) = Y_1 + (1+r)a(s). \tag{2.2}$$

We attach s to C_0, a, e and C_1 in the budget constraints to emphasize that they must be satisfied for all s.

The first budget constraint in (2.2) specifies that just prior to the revelation of the state s, the consumer must allocate exogenous income Y_0 to the insurance premium for policy j, denoted P_j, and to saving Y_{0j}. In the next instant the true state s is revealed and, ignoring any (trivial) interest payments on the saving Y_{0j}, the second budget constraint says that the consumer chooses contingent consumption $C_0(s)$ and an asset $a(s)$ that pays $(1+r)$ per unit at date 1 (r is the interest rate between dates 0 and 1). The third budget constraint specifies that exogenously given second-period income Y_1, plus the realized value of assets, must finance second period consumption C_1 whose price p_0 has been normalized to unity, and net health expenditures $\tilde{p}_j \boldsymbol{e}$ where $\tilde{p}_j$ denotes the vector of price per unit of health care services $\boldsymbol{e}$ net of reimbursement under insurance policy j. We assume Y_1 does not depend upon s. It is straightforward to generalize the economic model to accommodate uncertainty in Y_1 due to health events (just replace Y_1 by $Y_1(s)$), but our data are not rich enough to be affected by such dependence.[2] w_j denotes an error term reflecting perhaps unobserved characteristics of the individual solving the choice problem.

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Optimization is by the dynamic programming approach. First, conditional on the choice of policy j, and each possible realization of the unknown health state s, solve for the optimizing values of C_1, C_0, a and e to obtain the demand equations. Next, substitute these optimum solutions and integrate over s to derive the indirect conditional expected utility associated with choice j, denoted EV_j. Then EV_j $(j=1,\ldots,J)$ form the basis of discrete choice of insurance policy, with j chosen to maximize EV_j, $j=1,\ldots,J$.

For econometric estimation, parametric forms for either the utility function or the demand function need to be specified. One approach (Dubin and McFadden (1984)) consists of specifying convenient mathematical forms for demand functions, obtaining the conditional indirect utility function by integration and then using the resulting equation to model the discrete choice decision. However, the discrete choice equations will not necessarily share the convenient mathematical features of the demand equations. An alternative approach is to use a tractable direct utility function to derive the demand equations. Even if the latter are econometrically tractable, the discrete choice equations may not be since the indirect utility function will not necessarily have a mathematically convenient form. Thus there are potential problems with either approach. We have followed the second approach.

The utility function is (neglecting constants)

$$U(\cdot)=C_0C_1^{\alpha+1}H(\boldsymbol{e}\,|\,s,\boldsymbol{A},\boldsymbol{B})^{\sigma+1}, \tag{2.3}$$

where the constant coefficient of relative risk aversion is $|\sigma|$, for the risk averse consumer where $-1<\sigma<0$, and the health production function is

$$H(\boldsymbol{e}\,|\,s,\boldsymbol{A},\boldsymbol{B})=\textstyle\prod_k e_k^{\alpha_k(s,\boldsymbol{A},\boldsymbol{B})} \tag{2.4}$$

where $\alpha_k(s,\boldsymbol{A},\boldsymbol{B})\geqq 0$ depends upon health state s, consumer's attributes $\boldsymbol{A}$ and the characteristics of choice j, denoted $\boldsymbol{B}$. Indeed this is the only route through which attributes enter our model. The dependence of α_k on $\boldsymbol{A}$ can be justified by the argument that the health care required in state s will often depend upon individual characteristics such as natural health endowment, location (rural or urban) and so forth. We have introduced the dependence on $\boldsymbol{B}$ because α_k may also depend upon the type of policy which could affect, for example, the quality of health care and hence the required subsistence quantity demanded.[3]

Application of the dynamic programming method yields the following demand equations for C_0, a, C_1 and e, conditional on insurance policy j and health state s:

$$C_0(s)=(1+r)^{-1}(1+\theta(s))^{-1}[Y_1+(1+r)Y_{0j}] \tag{2.5}$$

$$a(s)=Y_{0j}-(1+r)^{-1}(1+\theta(s))^{-1}[Y_1+(1+r)Y_{0j}] \tag{2.6}$$

$$e_k(s\,|\,j)=\frac{\alpha_k(s)(1+\sigma)(1+\theta(s))^{-1}}{\tilde{p}_{jk}}[Y_1+(1+r)Y_{0j}] \qquad k=1,\ldots,K \tag{2.7}$$

$$C_1(s)=(1+\sigma)(1+\theta(s))^{-1}[Y_1+(1+r)Y_{0j}] \tag{2.8}$$

where

$$\theta(s)=(1+\sigma)(1+\textstyle\sum_k \alpha_k(s)), \qquad \theta\neq -1. \tag{2.9}$$

The term in the square brackets in the demand equations (2.5), (2.7) and (2.8) measures total two-period income when policy j has been purchased and state s occurs. The dependence of α_k on the random state s induces the dependence of all planned expenditures on s.

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The simple mathematical form of the equations, analogous to the linear expenditure system, is a consequence of the assumption of homothetic preferences. (Hanoch (1977) has considered the consequences of relaxing the homotheticity assumption.) Equation (2.7) may be written in the familiar linear expenditure form by multiplying through by $\tilde{p}_{jk}$, the net price of service k under insurance policy j. If $\tilde{p}_{jk}$ and Y_1 depended upon s, it would be convenient to absorb $\tilde{p}_{jk}$ inside the square bracket in (2.7) and then regard the resulting compound variable as a function of $Y_1(s)$, Y_{0j} and $\tilde{p}_{jk}(s)$. Because of data limitations such state dependence is ignored.

θ defined in (2.9) is the α-adjusted coefficient of relative risk aversion (with respect to income). If the consumer is risk-averse $(0<1+\sigma<1)$ then $0<\theta<(1+\sum \alpha_k)$. The income and price elasticities for demands are unitary regardless of the level of risk aversion. However, the greater the degree of risk aversion, $|\sigma|$, the greater the proportion of income allocated to current consumption and the smaller the proportion allocated to health expenditures at the margin. That is, risk aversion affects the marginal budget shares.

The budget shares are also affected by the health production function parameters $\alpha_k(s)$. As $\alpha_k(s)$ increases, due to bad realization of health state s, consumption of the k-th medical service will increase and goods consumption in the two periods will decrease.

To obtain an estimable equation for the k-th medical service, rewrite (2.7) as

$$e_k(s \mid j)=\alpha_k(s)(1+\theta(s))^{-1} \exp [\log (1+\sigma)-\log \tilde{p}_{jk}+\log [Y_1+(1+r) Y_{0j}]] \quad (2.10)$$

We observe e_{kj} for a given realization of s, but do not know this realization. We model instead $E[e_k(s \mid j)]$, where the expectation is taken with respect to the distribution $\pi(s \mid \boldsymbol{A})$ of health states. First, assume $\int \alpha_k(s)(1+\theta(s))^{-1} d\pi(s \mid \boldsymbol{A})=\exp (\boldsymbol{Z}'\boldsymbol{\beta}_k+\varepsilon_k)$. Second, the net price of services charged to different patients in different locations are not recorded in our data set (see Section 3). We replace $-\log \tilde{p}_{jk}$ in (2.10) by $\eta_{jk} D_j$, where D_j is an insurance dummy variable which takes the value of unity if the j-th insurance policy is chosen and zero otherwise. *A priori* $\eta_{jk}<0$, and is more negative for insurance policies with higher net prices. If insurance policy l provides more cover than insurance policy j, so that $\tilde{p}_{lk}<\tilde{p}_{jk}$, then $\eta_{lk}-\eta_{jk}>0$. Third, since income may also enter the prior distribution $\pi(s \mid \boldsymbol{A})$, we simply include income in the same way as other regressors. Then (2.10) yields

$$E[e_k(s \mid j)]=\exp (\boldsymbol{Z}'\boldsymbol{\beta}_k+\eta_{jk} D_j+\varepsilon_k). \quad (2.11)$$

Finally, unconditional of insurance choice

$$E[e_k(s)]=\exp (\boldsymbol{Z}'\boldsymbol{\beta}_k+\textstyle\sum_{j=1}^{J} \eta_{jk} D_j+\varepsilon_k). \quad (2.12)$$

Now consider the expected utility associated with choice j. Substitution of (2.5), (2.7) and (2.8) into (2.1) yields

$$EV_j^*=\int_s U(C_0^*, C_1^*, H(\boldsymbol{e}^* \mid s, \boldsymbol{A})) d\pi(s \mid \boldsymbol{A})+w_j \quad (2.13)$$

$$=EV_j(\boldsymbol{A}, Y_1+(1+r) Y_{0j}), \tilde{p}_{j,})+w_j. \quad (2.14)$$

(2.14) gives the conditional indirect utility function associated with policy j, and provides the basis for a discrete choice model for insurance. The consumer chooses the policy for which EV_j^* is highest, with different stochastic assumptions about the w_j leading to different discrete choice models.

In practice the nonlinearity of $U(\cdot)$ makes it virtually impossible to obtain a tractable form for EV_j when we integrate with respect to the prior distribution of health states

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(particularly as going from (2.10) to (2.11) places restrictions on this distribution). The problem arises because of uncertainty. Choosing a linear form for $U(\cdot)$ would alleviate this problem; but only at the cost of assuming risk neutrality. For the purposes of estimating health care utilization equations, the insurance choice model is only of interest to enable us to control for endogeneity of the insurance dummy variables in (2.12). For these purposes a linearized version of EV_j in (2.14) is adequate, and this is what is used in Section 4. (This approach is similar to estimating a generalized tobit model for labour supply where the structural equation for hours of work is derived by utility maximization, but the participation decision is explained by a separate reduced form equation.)

The empirical analysis of this paper will be mainly concerned with utilization (demand) equations like (2.12), but in view of the endogeneity of the D_j variables it will be necessary to devote some space in Section 4 to the estimates of insurance choice equations based on (2.14). A more detailed econometric analysis of the insurance choice is in Trivedi *et al.* (1984). A necessary preliminary to the discussion of econometric analysis is a description of the survey data we have used and the institutional environment within which the decisions are analysed.

3. THE 1977-1978 ABS HEALTH SURVEY

Amongst all the problems faced by empirical investigators who wish to examine the interrelationships between the demand for health insurance and health care services, perhaps the most serious concerns the fragmentary nature of data typically available. To be able to make even approximately valid inferences we require not only good micro-level information on socio-economic characteristics of households but also rather detailed information on health status and utilization of health related services and facilities. See, for example, Manning *et al.* (1980). The 1977-1978 Australian Health Survey (AHS) was developed and conducted by the Australian Bureau of Statistics (ABS) to provide such data and was the first Australian interview survey to cover such a broad range of topics. It provides a reasonable starting point for an investigation such as ours. In what follows we attempt to describe those features of the survey and the data that are of special relevance to this investigation. For further details on the data see ABS (1982, 1984).

The survey was conducted between July 1977 and June 1978, with approximately 25% of the sample being interviewed in each quarter. This was a household survey based on a (weighted) random sample of all of Australia. The available data tape is based on questionnaire responses of 40,650 individuals, including entire families, but the critical omission of family identifiers compelled us to restrict our empirical analysis to the 6539 single people over 18 years of age.

The prevailing health insurance regime may be summarized as a levy-cum-opting-out system. For a complete description see the excellent survey by Scotton (1980). The original 1975 Medibank programme provided free universal basic health cover. Major changes were made in 1976, most notably the introduction of an income-based Medibank insurance levy, and lesser changes occurred in 1978 at the end of our sample period.

Under Medibank insurance, medical benefits covered 85% of the schedule fee for each service, with a maximum of \$5 payable by the individual for each service. Hospital benefits covered completely the cost of *public* (shared ward) accommodation in public hospitals with treatment provided by doctors employed by the hospital.

The Medibank insurance levy for single people in 1977-1978 commenced at an annual net taxable income of \$2604, with a rapid shading into the full rate of 2·5% at income of \$2805. The levy was at most \$150, so no additional levy was paid after \$6000.

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People who purchased from a government-regulated private health insurance fund an insurance policy that covered medical and hospital costs to at least an approved level were exempt from the Medibank levy. This was termed "opting out" of Medibank. The approved level provided the same medical cover as Medibank, but more generous hospital cover in that minimum fees charged to *private* patients in public hospitals were covered. As a private patient the consumer could be treated by the doctor of his or her choice and potentially received better quality service. In 1977-1978 the annual cost of such policies ranged from $153 (Tasmania, July 1977) to $247 (New South Wales, June 1978).

Disadvantaged people were also exempt from the levy. Those receiving pensions (old age, disability, widows or children of deceased veterans, etc.) from the government and those categorized as poor did not have to pay the levy (even if their income exceeded $2605). They received the same hospital cover and, if anything, better medical cover than Medibank levy payers. (Doctors were encouraged to directly bill the government for 85% of the schedule fee and not charge the patient at all. Over 60% of doctors bulk-billed at least some of their patients in March quarter 1978 (Scotton (1980), p. 208). Doctors were much more likely to do this for pensioners and the poor.)

The insurance types we study are given in Table I. (In addition the AHS decomposes FREEOTHER into pensioner and veteran, which we found to be very similar, and lists other or don't know and not stated or not applicable, which we discard.) As already mentioned the FREE categories receive a slightly better cover at a lower (free) premium. The LEVYPLUS category is defined to be anyone who had coverage as a private patient in a public hospital. This includes people who opted out of the Medibank levy. But it also includes people who paid the levy or received free basic cover and purchased supplementary private insurance solely to defray hospital charges to private patients in public hospitals. Such coverage cost between $68 and $96 per year in our sample period. The data do not permit us to distinguish between LEVYPLUS due to opting out of Medibank and LEVYPLUS due to levy payer (or free) purchasing supplementary hospital cover. The implications for modelling insurance choice are addressed in the estimation

TABLE I

Definitions of Health Insurance and Utilization Variables

Health Insurance Dummies	
LEVY	1 if covered by Medibank, 0 otherwise.
LEVYPLUS	1 if covered by private health insurance fund for private patient in public hospital (with doctor of choice), 0 otherwise.
FREEPOOR	1 if covered free by government because low income, recent immigrant, unemployed, 0 otherwise.
FREEOTHER	1 if covered free by government because of old age or disability pension, or because invalid veteran or family of deceased veteran, 0 otherwise.
Health Care Utilization Variables	
DOCTORCON	Number of consultations with a doctor or specialist in the past 2 weeks.
HOSPADMIS	Number of admissions to a hospital, psychiatric hospital, nursing or convalescent home in the past 12 months (up to 5 or more admissions).
HOSPDAYS	Number of nights in a hospital, etc. during most recent admission; taken, where appropriate, as the mid-point of the intervals 1, 2, 3, 4, 5, 6, 7, 8-14, 15-30, 31-60, 61-79, 80+ and 0 if no admission in past 12 months.
NONDOCCON	Number of consultations with non-doctor health professionals (chemist, optician, physiotherapist, social worker, district community nurse, chiropodist or chiropractor) in the past 4 weeks.
MEDICINES	Total number of prescribed and nonprescribed medications used in past 2 days.
PRESCRIBED	Total number of prescribed medications used in past 2 days.
NON-PRESCRIBED	Total number of nonprescribed medications used in past 2 days.

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section. (At 31 March 1978, 66·1% of Australians fell into the LEVYPLUS category, 56·6% having opted out and 9·5% receiving basic cover from the government and purchasing separate supplementary hospital cover. See Australian Department of Health (1978).)

Measures of health service utilization are also given in Table I. Even further disaggregated data are available. For example, separate data on the number of consultations with each of the eight types of non-doctor health professional (NONDOCCON) are available. For space reasons the only decomposition we consider is that of medicine usage into prescribed and non-prescribed medicines.

In Table II, socio-economic variables and health status measures are defined. GHQ measures the score on Goldberg's General Health Questionnaire consisting of twelve questions concerning general well being of the respondent. The questionnaire was originally developed to assist in the identification of respondents with non-psychotic psychiatric illness. An example of a question from the questionnaire is "have you recently been feeling unhappy and depressed?", to which an answer is chosen from four alternatives: "not at all", "no more than usual", "rather more than usual", "much more than usual". The first two responses score 0 and the next two score 1. The score for a respondent is the sum of the individual scores giving a score ranging from 0 to 12. A high score on

TABLE II

Definitions of Explanatory Variables

Socioeconomic	
SEX	0 for males, 1 for females.
AGE	Measured as the midpoint of 11 age groups from 15–19 years to 70+, the last having been replaced by 72, divided by 100.
MARITAL	0 if never married, 1 if married, permanently separated, widowed or divorced.
ORIGIN	Seven dummy variables correspond to U.K., Other English Speaking, Italy, Yugoslavia, Greece, Europe and Other. Standardized on Australia.
OCCUPATION	The dummy variables are D1 (professional, technical, administrative, executive, managerial), D2 (clerical, sales), D3 (farmers, fishermen), D4 (miners and related), D5 (transport and communication), D6 (tradesmen and process), D7 (service, sport, recreation and other). Standardized on "not employed" category.
REGION	Eleven dummy variables refer to N.S.W.-metropolitan (D1), N.S.W.-rest (D2), VIC.-metropolitan (D3), VIC-rest (D4), QLD-metropolitan (D5), QLD-rest (D6), SA-metropolitan (D7), SA-rest (D8), WA-metropolitan (D9), WA-rest (D10), Tasmania (D11), ACT/NT (D12). Standardized on D1.
EDUCATION	The dummy variables are D1 (left schooling at 15 no qualifications since), D2 (left school, qualifications since), D3 (over 15, no qualifications since), D4 (over 15, qualifications since). Standardized on D1.
INCOME CLASS	Taken, where appropriate, as the midpoint of the reported range of the coded categories Nil, <200, 200–1000, 1001–, 2001–, 3001–, 4001–, 5001–, 6001–, 7001–, 8001–10,000, 10,001–12,000, 12,001–14,000, 14,001–, divided by 100.
Health Status	
GHQ	General health questionnaire score using Goldberg's method. High score indicates bad health.
CHRONIC	Number of chronic conditions.
LIMCHRON	1 for those with chronic condition(s) but not limited in activity, 0 otherwise.
NONLIMCHRON	1 for those with chronic condition(s) and limited in activity. 0 otherwise.
ILLNESS	Number of illnesses in past two weeks, 0 to 5 or more.
LENGTHILL	Length of first illness.
CONCERNILL	Degree of concern caused by first illness.
ACTIVITY DAYS	Number of days of reduced activity in past two weeks due to illness of injury.
DOCTOR	Type of doctor usually consulted; three dummy variables corresponding to this are D1 for GP, D2 for specialist and D3 for hospital doctor. Standardized on no doctor consulted in past 3 months.

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the GHQ questionnaire could be indicative of poor non-psychotic psychiatric health status. Unfortunately, it could also be a reflection of the physical well-being of the respondent at or around the time of responding to the questionnaire. To the extent that the GHQ score is intended to be a measure of "normal" state of health, it is clearly undesirable for that measure to be contaminated by chance occurrence of episodes of illness uncorrelated with that "normal" state. Another health status variable, CHRONIC, chronic conditions of the respondent, was measured as follows. "Respondents were supplied with a list of chronic conditions which indicated the type of condition to be reported ... and were asked if they had any of those conditions and had had them for more than six months. Interviewers stressed that the listed chronic conditions were examples only and asked if the respondents had any others." Persons with a chronic condition also reported whether their activities were limited,[4] though not necessarily by one or more chronic conditions. The dummy variables LIMCHRON and NONLIMCHRON refer, respectively, to those with chronic conditions with activity limitations and those without. They are standardized on "no chronic conditions".

Excluding people who did not answer insurance and other key questions reduced the sample size to 5190. Two-way frequency tables on, respectively, insurance $\times$ sex, insurance $\times$ age, insurance $\times$ income and insurance $\times$ place of residence have been provided in Trivedi *et al.* (1984). From these the following characteristics of the sample emerge:

- Relative to males, few women chose the levy option, and in the free/other category there are significantly more women than men.
- Relative to the population, the 30–60 year age category is under-represented and the young and old are over-represented.
- The percentage choosing the levy option appears to decrease with age.
- The number of persons choosing the levy-plus option increases very markedly with income, and correspondingly the number choosing the levy option declines with income.
- Relative to the rest of Australia the levy option was more frequently chosen in Queensland which, unlike other states, had a system of free public hospitals.

Since the survey spanned a period of 12 months it is relevant to ask whether any changes to the Medibank system occurred in 1977–1978 which would have significant implications for our analysis. Medibank institutional arrangements were remarkably stable during this period. Pensioner health arrangements under the new Medibank came into effect on 25 November 1976, and the next change of any consequence did not occur until 1 July 1978 when the level of cover provided under the Medibank levy was reduced. The prices of health care and insurance did rise in the later part of our sample period. Schedule medical fees increased by 7·3% on 1 January 1978 and more importantly private insurance premiums which were stable during 1977 (at an artificially low level) increased by 20–30% between 1 February 1978 and 30 June 1978. A χ^2 test showed that there is no significant relation between quarters of interview and type of cover chosen. This is consistent with the view that the few changes to the Medibank system in 1977–1978 did not affect the distribution of individuals by insurance cover.

4. ECONOMETRIC ANALYSIS

The statistical model for health care utilization should take account of a special feature of the AHS data—medical and hospital use are recorded as counts (non-negative integer variables). We use the negative binomial model, a generalization of the Poisson, to model utilization conditional on insurance choice. This does not correct for the self-selection (or endogeneity) in choice of insurance. Traditional procedures for selectivity correction

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do not extend to models for discrete data such as the negative binomial. Our approach is to first present results based on count data models, and then present results based on selectivity models that ignore the discreteness.

The count data for health care utilization are summarized in Table III. With the possible exception of NONDOCCON the empirical distributions are unimodal. For the utilization variables other than medications used, the majority of observations are zero. For all variables the variance is greater than the mean, in some cases considerably so.

TABLE III

Summary of Health Care Utilization Data (Sample size = 5190)

	(1)	(2)[a]	(3)[b]	(4)	(5)	(6)	(7)
Pr $(y=0)$	0·798	0·865	0·865	0·909	0·429	0·594	0·735
Pr $(y=1)$	0·151	0·108	0·022	0·054	0·268	0·192	0·203
Pr $(y=2)$	0·034	0·018	0·017	0·016	0·139	0·098	0·044
Pr $(y=3)$	0·006	0·005	0·011	0·003	0·076	0·053	0·012
Pr $(y=4)$	0·005	0·001	0·011	0·005	0·042	0·030	0·003
Pr $(y=5)$	0·002	0·002	0·011	0·001	0·020	0·015	0·001
Pr $(y=6)$	0.002		0.006	0.002	0.012	0.008	0.000
Pr $(y=7)$	0.002		0.011	0.007	0.006	0.004	0.001
Pr $(y=8)$	0.001			0.001	0.008	0.005	0.000
Pr $(y=9)$	0.000			0.002			
Pr $(y=10)$				0.000			
Pr $(y=11)$				0.001			
$\bar{y}$ (mean)	0.302	0.174	1.334	0.215	1.218	0.863	0.356
s_y^2 (variance)	0.637	0.258	37·455	0·932	2·423	2·003	0·507
Variance/mean	2·109	1·483	28·077	4·335	1·989	2·321	1·424

The columns (1)–(7) refer to the utilization variables in the order listed in Table I: DOCTORCON, HOSPADMIS, HOSPDAYS, NONDOCCON, MEDICINES, PRESCRIBED, NONPRESCRIBED.

Notes

(a) For (2) the entry for Pr $(y=5)$ is actually Pr $(y=5$ or more).

(b) For (3) we have the further entries: Pr $(8 \leqq y \leqq 14) = 0{\cdot}024$, Pr $(15 \leqq y \leqq 30) = 0{\cdot}013$, Pr $(31 \leqq y \leqq 60) = 0{\cdot}006$, Pr $(61 \leqq y \leqq 79) = 0{\cdot}000$, Pr $(80 < y < 365) = 0{\cdot}002$. The mean and variance are computed using y in the middle of the ranges.

Count data models for utilization

Count data models are discussed in detail in Hausman, Hall and Griliches (1984) and Cameron and Trivedi (1986). The simplest and perhaps most common model is the Poisson regression model. For notational convenience we drop the subscripts j and k and let y denote the count data of interest, such as the number of doctor consultations. y takes one of the values 0, 1, 2,... For a sample of N individuals we observe y_i, $i=1,\ldots,N$. We suppose that y_i has the Poisson distribution with parameter $\xi_i > 0$. Then

$$\Pr(y_i = r) = \exp(-\xi_i)\frac{\xi_i^r}{r!} \qquad r = 0, 1, 2, \ldots \tag{4.1}$$

ξ_i can be expressed as a function of observable individual attributes, health characteristics and health insurance cover which are included in the p-dimensional vector $\boldsymbol{Z}_i$. To ensure that $\xi_i > 0$, a necessary condition for the Poisson model and its generalizations, it is customary to let $\xi_i = \exp(\boldsymbol{Z}_i'\boldsymbol{\beta})$. Substituting this into (4.1) yields the log-likelihood function for β which is globally concave and readily maximized.

However, for a number of reasons the Poisson model is unlikely to be adequate for our data. Given that most econometric models omit some relevant but unobservable

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characteristics from the set $\boldsymbol{Z}$, it is more appropriate to think of ξ_i as stochastic and to characterize the interperson heterogeneity in a mathematically convenient way. When such heterogeneity is a feature of the data we expect the count data to exhibit overdispersion, i.e. greater variance than is consistent with the Poisson model. Estimation under the Poisson assumption and neglect of overdispersion will lead to inefficient estimates (Cameron and Trivedi (1986)). As has been noted our *raw* data do show overdispersion. This does not by itself preclude a Poisson regression model since in the latter overdispersion implies var $[y_i | \boldsymbol{Z}_i] > E[y_i | \boldsymbol{Z}_i]$ rather than var $[y_i] > E[y_i]$. However, it can be shown that unless the fit of the model is extremely good the latter is likely to imply the former, so the observed overdispersion in our data suggests potential inadequacy of the basic Poisson model.

A simple extension of the Poisson model is the negative binomial which can be generated by assuming the Poisson parameter ξ_i to be gamma distributed. Let ξ_i be gamma distributed with parameters $\gamma_i > 0$ and $\delta > 0$, so

$$f(\xi_i = z) = \frac{1}{\Gamma(\gamma_i)} \delta^{\gamma_i} \exp(-\delta z) z^{\gamma_i - 1}, \tag{4.2}$$

with $E[\xi_i] = \gamma_i / \delta$ and var $(\xi_i) = \gamma_i / \delta^2$. Since y_i is Poisson (ξ_i), we have

$$\begin{aligned} \Pr(y_i = r) &= \int_0^\infty \Pr(y_i | \xi_i = z) f(\xi_i = z) dz \\ &= \frac{\Gamma(\gamma_i + r)}{\Gamma(r+1)\Gamma(\gamma_i)} \left(\frac{\delta}{1+\delta}\right)^{\gamma_i} \left(\frac{1}{1+\delta}\right)^r, \qquad r = 0, 1, 2, \ldots \end{aligned} \tag{4.3}$$

which is the negative binomial distribution with $E[y_i] = \gamma_i / \delta$ and var $(y_i) = \gamma_i(1+\delta)/\delta^2$. Since the variance is now greater than the mean, the model can account for overdispersion in the data. The special case of the Poisson model arises when $\delta \to \infty$. The parameter γ_i is specified to be

$$\gamma_i = \exp(\boldsymbol{Z}_i' \boldsymbol{\beta}). \tag{4.4}$$

Since the log-likelihood function is globally concave the model can be readily estimated by maximum likelihood.

A second inadequacy of the Poisson model arises from its underlying assumption of independence of events in time. It implies that the distribution of interval times between events is exponential (Amemiya (1985), p. 436).

The implication that each utilization of the health service is considered as an independent event is inconsistent with casual observation which suggests that such events will be bunched. For example, health state $1 \in S$ may result in 5 trips to the doctor, health state $2 \in S$ leads to 3 trips to the doctor, and so on. Doctor consultations, specialist consultations, days spent in hospital, to mention just some examples, may occur in spells. Also the health events themselves may occur in spells causing the utilization events to be similarly bunched. Thus the utilization events within a spell may be interdependent and those within different spells independent.

The possibility of utilization spells raises two interrelated issues. Firstly, how should one specify a model of spells of utilization? Secondly, will a compound Poisson model such as the negative binomial model used in this paper adequately fit the data generated by a spells model? Cresswell and Froggatt (1963) have specified a "spells" model for bus driver accidents which may be adaptable for econometric work but we have not pursued this alternative here. The answer to the second question is "yes" under certain

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circumstances; see, for example, Kemp (1967) who has shown in the context of accident theory that the negative binomial distribution can be given a "spells" interpretation. That is, negative binomial can provide a reasonable fit to data generated by spells and hence we have a second independent justification for using it. Of course, this also implies some ambiguity about the stochastic processes that generate a negative binomial distribution for the utilization data.

We apply the negative binomial model to the health care utilization variables listed in Table I. The parameter γ_i is δ times expected use of the k-th medical service, which is defined in (2.12). To proceed to an estimating equation we need to specify the elements of vector $\boldsymbol{Z}$. The vector comprises SEX, AGE, (AGE)^2, INCOME CLASS, ILLNESS, ACTIVITYDAYS, GHQ and CHRONIC conditions. (For more detailed description see Table II.) Further variables may be included, but add little to the general conclusions while adding considerably to computational time.

We distinguish between the four types of health insurance cover defined in Section 3. The insurance dummy variables are LEVY (Medibank levy), LEVYPLUS, FREEPOOR and FREEOTHER (free-veterans/pensioner combined). The omitted dummy variable is LEVY, i.e. we standardize on the individual who pays the Medibank levy and does not purchase any form of health insurance from a private health fund.

Although various Poisson (and OLS) models were also estimated for the utilization data, we shall concentrate our discussion on parameter estimates for the preferred negative binomial model, with all explanatory variables included. These estimates are given in Table IV.

One issue of specification, the superiority of the negative binomial over the Poisson model, can be dealt with at the outset. The estimates of δ are similar to the starting values suggested by the raw data, i.e., $E(y_i)/(\text{var}(y_i)-E(y_i))$. The estimates are actually higher, since including explanatory variables accounts for some of the "overdispersion" in the data so that δ will be larger than in the i.i.d. case. However, even with the 13 explanatory variables included, likelihood ratio tests strongly rejected the null hypothesis that the true model is the Poisson (against the negative binomial) for all of the utilization variables. (A major feature of the Poisson model estimates was that their t-ratios were much larger than those of the negative binomial model estimates, a consequence of evaluating standard errors under the null hypothesis that the true model is Poisson when in fact the Poisson model is not appropriate for our data.)

The explanatory power of the models differs across the utilization measures. The precision of parameter estimates is highest for health care services used relatively often, such as prescribed medicines and doctor consultations, and lowest for health care services used infrequently, such as hospitals and consultations with non-doctor health professions. These results are consistent with those of Newhouse *et al.* (1982) who found a statistically significant difference in medical expenditure across the insurance plans but found hospital expenditure much more unpredictable.

For the negative binomial model the interpretation of the coefficients of dummy variables (SEX, insurance levels, LIMCHRON and NONLIMCHRON) is relatively straightforward. Let $E[y_i]=1/\delta \exp(\bar{\boldsymbol{Z}}_i'\bar{\boldsymbol{\beta}}+d_{im}\beta_m)$, where d_{im} is the dummy variable of interest and $\bar{\boldsymbol{Z}}_i$ contains the remaining elements of $\boldsymbol{Z}_i$. Then $E[y_i\,|\,d_{im}=1]/E[y_i\,|\,d_{im}=0]=\exp(\beta_m)\simeq 1+\beta_m$, for β_m small. So the coefficient of a dummy variable is approximately the proportionate increase in $E[y_i]$ due to the dummy variable equalling unity rather than zero. The coefficients of explanatory variables other than dummies are similarly interpreted, since $E[y_i\,|\,Z_{im}=Z_{im}^0+\Delta]/E[y_i\,|\,Z_{im}=Z_{im}^0]=\exp(\beta_m\Delta)$. Where helpful such calculations are reported in the text.

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TABLE IV

Health Care Utilization Equations—Negative Binomial Estimates ($N = 5190$)[a]

	DOCTOR-CON	HOSP-ADMIS	HOSP-DAYS	NON-DOCCON	MEDI-CINES	PRE-SCRIBED	NON-PRE-SCRIBED
ONE	−1·4156	−0·2924	−2·7036	−3·5515	−0·1622	−1·6844	−1·0217
	(0·2253)	(·2873)	(0·2738)	(·3727)	(0·1516)	(0·1685)	(0·2073)
SEX	0·1641	−0·0311	−0·0598	0·3137	0·4154	0·5448	0·2391
	(0·0602)	(0·0793)	(0·0796)	(0·1054)	(0·0314)	(0·0404)	(0·0566)
AGE	0·2757	−4·0753	−5·2952	−2·6853	1·9538	2·0849	4·8167
	(1·1257)	(1·4827)	(1·5013)	(1·9506)	(0·5605)	(0·707)	(1·0549)
$(\text{AGE})^2$	0·0226	4·3533	5·7173	4·3721	0·9492	−0·3847	−6·1239
	(1·990)	(1·5973)	(1·6287)	(2·0450)	(0·5992)	(0·738)	(1·1806)
INCOME	−0·1345	−0·3172	−0·0323	0·1303	0·0451	−0·0013	0·0553
CLASS	(0·0957)	(0·1322)	(0·1363)	(0·1558)	(0·0471)	(0·0630)	(0·0798)
LEVYPLUS	0·2125	0·1580	0·1531	0·2041	0·1261	0·2723	−0·0452
	(0·0842)	(0·1006)	(0·1013)	(0·1431)	(0·0421)	(0·0588)	(0·0650)
FREEPOOR	−0·5375	0·1444	0·1891	−0·1207	−0·0698	−0·0986	−0·0762
	(0·2093)	(0·1982)	(0·1899)	(·3224)	(0·0970)	(0·1321)	(0·1417)
FREEOTHER	0·2085	0·0202	0·0590	0·0703	0·0984	0·2805	−0·2847
	(0·1038)	(0·1399)	(0·1334)	(0·1751)	(0·0511)	(0·0663)	(0·1014)
ILLNESS	0·1959	0·0809	0·0690	0·0743	0·2048	0·2005	0·2047
	(0·0206)	(0·0265)	(0·0275)	(0·0336)	(0·0101)	(0·0122)	(0·0198)
ACTIVITY	0·1123	0·0834	0·0883	0·0725	0·0242	0·0296	−0·0047
DAYS	(0·0055)	(0·0080)	(0·0079)	(0·0096)	(0·0035)	(0·0042)	(0·0083)
GHQ	0·0357	0·0560	0·0605	0·0379	0·0223	0·0182	0·0282
	(0·0105)	(0·0138)	(0·0142)	(0·0193)	(0·0059)	(0·0072)	(0·0117)
LIMCHRON	0·1327	0·3736	0·3959	0·4652	0·5050	0·7638	0·1355
	(0·0746)	(0.0978)	(0.0974)	(0.1275)	(0.0381)	(.0528)	(0.0610)
NONLIM-	0·1742	0·9033	0·9233	0·9062	0·6583	1·0028	0·0138
CHRON	(0·0890)	(0·1162)	(0·1167)	(0·1433)	(0·0472)	(0·0618)	(0·0907)
δ	2·1940	3·6661	0·0350	0·3413	4·2200	2·5542	3·4328
	(0·1955)	(0·5298)	(0·0032)	(1·0341)	(0·4514)	(0·2589)	(3314)
$-\log L$	3226·859	2350·809	4113·018	2169·189	6828·724	5425·564	3517·329
$\chi_3^{2\,(b)}$	17·464	3·842	3·128	3·466	11·458	26·650	8·534

Notes

(a) Standard error in parentheses.
(b) Test for joint significance of health insurance dummies.

Health care utilization is quite responsive to age and sex, and varies less with income. The number of doctor consultations is relatively unresponsive to changes in socio-economic characteristics, and to a lesser extent so too is hospital utilization. Consultations with non-doctor health professionals and use of prescribed medicines are very responsive to changes in socio-economic characteristics. The most interesting results are that the number of hospital admissions decrease with income (a \$5000 increase leads to a 17% decrease), that otherwise health care utilization (controlling for health insurance cover) is relatively income-intensive, and that the use of non-prescribed medicines actually decreases with age. The relative income insensitivity of health utilization should be contrasted to the income sensitivity of health insurance cover, a result which is reported and discussed briefly later.

The health status measures are generally significant, in some cases highly so and with large coefficients, and in all but one case (ACTIVITYDAYS in the NONPRESCRIBED medicines equation) have the expected positive coefficient. An increase in the number of illnesses in the past two weeks by one illness leads to roughly a 22% increase in doctor consultations and medicine usage (both prescribed and non-prescribed) and a much smaller increase in the use of hospital service and non-doctor health professional.

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An increase in the number of reduced activity days is associated with only slight increases in medicine use and larger increases in the use of the remaining services. An increase in the general health questionnaire score (GHQ) is associated the most with hospital utilization increases. Finally, the use of medical services is much, much higher for people with chronic conditions, especially those who are limited in their activity (LIMCHRON). Such people tend to use health services other than doctors and non-prescribed medicines by 50 to 100% more than people with chronic conditions.

The health status measures are statistically much more significant in explaining health utilization than socio-economic characteristics, with coefficients of similar order of magnitude (if anything higher) to those for the socio-economic characteristics. The parameter estimates are consistent with the view that short-term ailments are associated (relatively) more with doctor consultations and the use of prescribed and non-prescribed medicines, while more long-term ailments are associated (relatively) more with hospital stays, consultations with non-doctor health professionals and the use of prescribed medicines. The markedly greater use of health services by people with chronic conditions is especially noteworthy. The use is appreciably higher for those people with limiting rather than non-limiting chronic conditions.

From the $\chi^2(3)$ test statistic at the bottom of Table IV, the dummy variables for insurance cover are jointly significant (at significance level 5%) in the equations for doctor consultation and medicines use, and jointly insignificant (even at significance level 25%) in the equations for hospital use and consultations with non-doctor health professionals. The magnitude of the effect of different health insurance covers is appreciable, though not as large as that for sex, age and presence of chronic conditions. Health utilization is highest for people with levy plus insurance cover, followed by free-pensioner and veteran, Medibank levy (the omitted dummy variable) and free-poor (aside from hospital use).

It might be expected that *ceteris paribus* health utilization is higher for insurance policies for which the net price to the consumer of the health service is lower. The coefficients of the health insurance dummies are to be interpreted in the light of this, taking into account the way in which relative net prices under the various health insurance policies vary according to the medical service being considered.

An alternative interpretation of the results of Table IV may be based on whether one regards ILLNESS and ACTIVITYDAYS as health state or health status variables. If the former, then the demand equation is more like equation (2.10), and if the latter then it is more like equation (2.12) where averaging has taken place with respect to health states s. Although the health state and health status measures are potentially correlated with income, the first correlation will be mitigated within the AHS data set since the reported income is for the previous July–June financial year, rather than for a short period immediately preceding the interview.

For doctor consultations (DOCTORCON), the net price faced by the consumer not only varied with insurance cover, but even for a given insurance policy the net price varied according to the consumer's doctor. Due to higher rates of bulk-billing (see Section 3), the free categories certainly faced lower net prices than Medibank levy. People on levy-plus who purchased supplementary hospital insurance only, face the same net price for medical services as other Medibank levy or free people, except that private doctor consultations as a hospital in-patient are also covered. People on levy-plus through opting-out were likely to be charged more than the bulk-bill rate, but about half of them had additional insurance to cover the 15% medical gap, as well as services such as home visits not fully covered under basic cover. Thus the positive coefficients for LEVYPLUS

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and FREEOTHER are expected, but the negative coefficient for FREEPOOR is unexpected.

For hospital visits (HOSPADMIS and HOSPDAYS) different insurance policies differed more in quality of service covered than in the net price for a given service. All policies apart from levy-plus provided free shared-ward accommodation in public hospitals with free treatment by hospital-supplied doctors. Levy-plus additionally covered scheduled fees of the doctor of the patient's choice, and the option of even higher levels of coverage such as for private room. Our data do not measure such differences in the quality of service. Relative to individuals with levy coverage, hospital use is surprisingly only slightly higher for free-pensioner and veterans, and higher for those on levy-plus and free-poor, though the difference is statistically insignificant.

Consultation with health professionals other than doctors (NONDOCCON) are generally not covered by the insurance policies, with coverage most likely for those people on levy plus who also take out extra medical insurance. Thus the largest coefficient is for levy-plus individuals whose utilization is 22% higher than that for people with levy cover.

Most prescribed medicines were provided free to pensioners. For the remainder of the population these prescribed drugs were provided at a government subsidized price of \$2.00 per subscription, increasing to \$2.50 per subscription on 2 June 1978. Other prescribed medicines and all non-prescribed medicines were not subsidized. Some levy-plus individuals have additional insurance to cover prescribed medicines not subsidized by the government, but not enough to explain prescribed medicine use being 32% higher than for individuals with levy cover. Perhaps this is due to the higher utilization of other medical services such as doctor consultations. The medicine use of free-pensioner and veteran individuals gives strong support for the role of prices. Relative to those on levy cover the use of prescribed medicines (free to pensioners) is 33% higher, while the use of non-prescribed medicines is 33% lower!

The observed differences in utilization will be due to both self-selection of insurance cover and the response to the net prices of health care under the chosen insurance cover (moral hazard). Given the very low coinsurance rates for all the insurance policies considered here, particularly for hospital and medical services, it would be surprising if all the observed difference is due to moral hazard. Indeed the major impact of moral hazard is likely to lie in the difference between health care service utilization under the insurance policies studied here and what utilization would be if people were uninsured, with any "residual" moral hazard across insurance policies small enough to be difficult to detect. However, by using disaggregated data on health utilization and noting that coinsurance rates for a given insurance policy and relative coinsurance rates across policies vary across health care services some supportive evidence for a utilization response to lower net prices is found. For example, pensioners are the only group to receive free prescribed medicines, and we observe that pensioners' use of prescribed medicines is relatively very high while their use of non-prescribed medicines is relatively low.

Since estimation of the negative binomial model does not enable a precise weighting of the relative importance of self-selection and moral hazard we shall now turn to an investigation of the role of self-selection using an alternative estimation approach.

Instrumental variable estimates

The analysis of Section 2 indicates that insurance choice is based in part on expected future health care utilization. As a consequence of this self-selection, the health insurance

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dummies in the health care utilization equation are endogenous. We consider a linear version of the model for health care utilization

$$e_{ik} = \boldsymbol{Z}_i\boldsymbol{\beta}_k + \sum_{j=1}^{J} \eta_{jk} D_{ij} + \varepsilon_{ik} \tag{4.5}$$

and allow for D_{ij} being potentially correlated with ε_{ik}.

There are a number of ways to deal with dummy endogenous variables. Several are discussed in Heckman (1978) and Amemiya (1978) and implemented in Dubin and McFadden (1984). A selectivity correction can be made by adding the term $E[\varepsilon_{ik} | D_{ij}]$ to the right-hand side of (4.5) and estimating by OLS. D_{ij} in (4.5) may be replaced by reduced form predictions $\hat{D}_{ij}$, and the model estimated by OLS. Alternatively, (4.5) can be estimated by instrumental variables, using $\hat{D}_{ij}$ as instruments for D_{ij}. We choose the instrumental variables approach, which requires weaker stochastic assumptions and is not necessarily less efficient than the other approaches.

A discrete choice model for insurance needs to be estimated, to obtain instruments for D_{ij}. For the AHS data this poses a problem. There are four categories of insurance, but each individual really faces only a binary choice. If ineligible for FREEPOOR and FREEOTHER the choice is between LEVY and LEVYPLUS. If eligible for FREEOTHER (or FREEPOOR) the essential choice is between FREEOTHER (or FREEPOOR) and LEVYPLUS, since LEVY is clearly inferior to these. Our solution is to form a subsample where most people chose between LEVY and LEVYPLUS, and another subsample where FREEOTHER (or FREEPOOR) and LEVYPLUS are the choices.

People with incomes less than \$3000 are likely to be receiving a government pension of approximately \$2500 and hence are eligible for FREEOTHER, or eligible for FREEPOOR on grounds of low income. People with high incomes, say over \$6000, are unlikely to be eligible for either FREEOTHER or FREEPOOR. Between these incomes there is a grey area. For example, pensioners may have supplemental income so that income is over \$3000 but not high enough to disqualify them from FREEOTHER.

This demarcation is supported by Table V, which gives insurance category by income. For low income people (<\$3000), 81% of those not LEVYPLUS were in the FREE categories. For high income people (>\$6000), 93% of those not LEVYPLUS paid the LEVY. For incomes between there is more of a mix of insurance categories.

TABLE V

Insurance Category by Income

	Less than \$3000		\$3000–\$6000		More than \$6000	
	Number	%	Number	%	Number	%
LEVY	224	13·6	535	40·3	846	39·0
LEVYPLUS	450	27·5	509	38·2	1313	59·1
FREEPOOR	137	8·4	65	4·9	20	0·9
FREEOTHER	827	50·5	220	16·6	44	2·0
TOTAL	1638		1329		2223	

We therefore estimate separate binary choice equations for a poor sample (income below \$3000) whose choice is characterized as being between FREE and LEVYPLUS, and for a rich sample (income over \$6000) whose choice is between LEVY and LEVYPLUS.

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Letting insurance policy 2 be LEVYPLUS and policy 1 be the alternative policy (FREE for poor sample, LEVY for rich) we have from Section 2

$$\Pr(\text{LEVYPLUS}_i = 1) = \Pr(EV^*_{2i} + w_{2i} > EV^*_{1i} + w_{1i})$$
$$= \Pr(w_{1i} - w_{2i} < EV^*_{2i} - EV^*_{1i}).$$

The discrete choice model may be probit, logit or the linear probability model depending on the assumed distribution for $w_1 - w_2$. The analytic expression for EV^*_j is given in (2.14). This will be unlikely to yield a tractable form, especially as uncertainty necessitates integration over the prior distribution of health states. However, for instrumental variables estimation of (4.5), all we need are reduced form predictions of LEVYPLUS. For this purpose it is sufficient to let $EV^*_2 - EV^*_1 = \boldsymbol{X}'\boldsymbol{\beta}$, where $\boldsymbol{X}$ includes exogenous variables. These include the observable characteristics of the consumer, such as age, sex, occupation, location, educational background, health status and history; and economic variables such as income, cost of alternative types of insurance and the net prices of health services under different choices of insurance. The list of our explanatory variables does not include the last two. The cost of insurance variable is excluded because of lack of variation across individuals. LEVYPLUS cover premia varied only by region, which we include for other reasons anyway. (By law each private health insurance fund charged all individuals in a state the same premium, and competition led to little variation between funds.) In the poor sample, the alternative coverage FREEPOOR or FREEOTHER was free. In the rich sample the alternative coverage LEVY cost the ceiling price of \$150. (At incomes between \$2604 and \$6000 the cost of LEVY does vary with income, and some results using this variation are reported in Trivedi *et al.* (1984).) From Section 2, the difference in net prices of health services under different insurance policies is very complex, depending on the billing practices of the individual's doctors and type of service received. We lack such data, and instead include some variables with which price is expected to be correlated; e.g. the kind of doctor usually consulted (GP, specialist or hospital doctor) and location (state of residence and whether metropolitan or non-metropolitan).

Since the main objective in estimating the insurance model is to generate the instrument for the LEVYPLUS dummy, the logit estimates reported in Table VI will not be discussed in detail. For the most part the coefficients in the two sub-samples are similar. The results imply a relatively minor role for the health status variables (with the exception of chronic conditions variables), an important role for the socio-economic factors including the EDUCATION variables, and an important role for the INCOME variable. (Surprisingly negative in the poor sample.)

The instrumental variable estimates of the utilization equations for the poor sample are given in Table VII and those for the rich sample in Table VIII. These use the predictions of LEVYPLUS from Table VI as instruments for the LEVYPLUS dummy. A number of other estimators and variants of the specification were tried, including some which allowed for an interaction effect between the LEVYPLUS dummy and the INCOME variable. None produced results which were in any substantial sense different from those reported here. In particular, very similar IV estimates were obtained using linear probability model predictions for LEVYPLUS. NONDOCCON is omitted from the analysis as this type of service was not generally covered under insurance arrangements.

The results of Tables VII and VIII confirm the analysis based on the negative binomial model in one important sense, viz., that in explaining the utilization of health care services, health status variables (comprising ILLNESS, ACTIVITYDAYS, GHQ score and chronic conditions) are generally very important. At the same time these variables play a small

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TABLE VI

Logit Equations for Insurance Choice

Explanatory variables	Poor sample $n = 1638$		Rich sample $n = 2223$	
SEX (FEMALE)	0·61	(3·86)	0·79	(6·57)
AGE	1·00	(1·92)	2·05	(4·18)
MARITAL (MARRIED)	−0·30	(1·64)	0·13	(0·95)
ORIGIN:				
U.K.	−0·54	(2·48)	−0·56	(3·33)
OTHER ENGLISH	−0·56	(1·00)	−0·63	(2·28)
ITALY	−0·46	(0·67)	0·38	(0·92)
YUGOSLAVIA	0·07	(0·06)	−2·63	(2·47)
GREECE	−7·12	(0·34)	−0·027	(0·04)
EUROPE	0·28	(0·64)	−0·04	(0·18)
OTHER	−0·09	(0·20)	0·29	(0·85)
OCCUPATION:				
PROFESSIONAL	0·64	(1·63)	0·03	(0·16)
CLERICAL	0·58	(2·19)	0·61	(2·93)
FARMER	1·01	(2·83)	0·21	(0·71)
MINERS	0·95	(0·65)	0·70	(0·85)
TRANSPORT	0·33	(0·39)	0·10	(0·35)
TRADESMEN	0·20	(0·65)	−0·13	(0·63)
SERVICES	−0·58	(1·40)	−0·25	(0·95)
REGION:				
NSW (non-metro)	0·53	(2·25)	0·83	(3·37)
VICTORIA (metro)	0·77	(3·37)	−0·00	(0·01)
VICTORIA (non-metro)	−0·54	(1·89)	0·23	(1·03)
QLD (metro)	0·02	(0·06)	−0·46	(2·30)
QLD (non metro)	0·80	(3·49)	−0·44	(2·30)
SOUTH AUST (metro)	0·35	(1·44)	0·58	(2·72)
SOUTH AUST (non-metro)	0·94	(1·57)	0·76	(1·33)
WESTERN AUST (metro)	−0·34	(1·23)	0·18	(0·77)
WESTERN AUST (non-metro)	−1·39	(2·76)	−0·17	(0·49)
TASMANIA	−0·91	(2·79)	−0·24	(0·93)
ACT	−0·31	(0·97)	1·13	(6·64)
EDUCATION:				
QUALIFICATIONS (D2)	0·95	(2·52)	0·38	(1·30)
NO QUALIFICATIONS (D3)	0·54	(3·48)	0·56	(3·14)
QUALIFICATIONS (D4)	0·78	(3·61)	0·70	(3·70)
INCOME:	−3·60	(4·26)	1·53	(6·91)
HEALTH STATUS:				
ILLNESS	−0·01	(0·20)	0·02	(0·30)
CONCERNILL	−0·00	(0·84)	−0·00	(0·36)
LENGTHILL	−0·15	(0·94)	−0·00	(0.06)
GHQ	−0·00	(0·01)	−0·07	(2·39)
CHRONIC CONDITIONS:				
NO. OF CHRONIC COND.	0·03	(0·41)	0·06	(0·75)
NOT LIMITING	0·24	(1·27)	0·18	(1·14)
LIMITING	−0·17	(0·69)	0·37	(1·59)
TYPE OF USUAL DOCTOR:				
GP	0·09	(0·62)	0·34	(3·17)
SPECIALIST	0·78	(2·88)	0·46	(2·05)
HOSP. DOCTOR	−0·78	(2·76)	−0·33	(1·47)
PAST USAGE:				
NONSPECIALIST CONS	0·07	(1·36)	−0·03	(0·41)
HOSPADMIS	0·36	(3·42)	0·08	(0·74)
CONSTANT	−0·93	(1·40)	−4·93	(9·91)
LOG-LIKELIHOOD	−846·74		−12981·1	

(t-ratios given in parentheses)

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TABLE VII

Utilization Equations: Instrumental Variable Estimates (t-ratios)—Poor Sample ($n = 1638$)

	DOCTOR-CON	HOSP-ADMIS	MEDI-CINES	HOSP-DAYS	PRE-SCRIBED	NON-PRE-SCRIBED
ONE	0·0892	−0·2538	−0·939	0·63	−1·04	0·11
	(0·50)	(1·78)	(3·14)	(0·36)	(3·56)	(0·81)
SEX	−0·0111	−0·0976	0·432	−1·25	0·31	0·12
	(0·22)	(2·38)	(5·05)	(2·56)	(3·74)	(3·02)
AGE	−0·4784	−1·1942	1·4048	−23·51	−0·35	1·75
	(0·54)	(1·70)	(0·95)	(2·80)	(0·24)	(2·67)
$(\text{AGE})^2$	0·9232	1·433	0·0934	27·96	2·43	−2·34
	(0·97)	(1·89)	(0·06)	(3·09)	(1·55)	(3·29)
INCOME	−0·3097	0·9977	0·6806	9·31	1·09	−0·42
	(0·90)	(3·62)	(1·18)	(2·83)	(1·93)	(1·62)
LEVYPLUS	0·2261	1·0895	0·679	6·59	0·97	−0·29
	(1·47)	(8·86)	(2·64)	(4·50)	(3·83)	(2·54)
ILLNESS	0·0541	0·0244	0·402	0·14	0·33	0·07
	(3·19)	(1·81)	(14·18)	(0·87)	(11·86)	(5·54)
ACTIVITYDAYS	0·0987	0·0292	0·0588	0·34	0·06	−0·0004
	(13·93)	(5·15)	(14·96)	(5·09)	(5·06)	(0·0860)
GHQ	0·0183	0·0353	0·0537	0·32	0·047	0·0067
	(1·76)	(4·27)	(3·10)	(3·27)	(2·74)	(0·86)
LIMCHRON	0·0694	0·0480	0·0467	0·68	0·44	0·0231
	(1·26)	(1·09)	(5·09)	(1·29)	(4·90)	(0·562)
NONLIMCHRON	−0·0977	0·0586	0·9366	3·40	1·01	−0·077
	(1·33)	(5·73)	(7·62)	(4·86)	(8·35)	(1·39)
Mean of dep. variable	0·398	0·222	1·67	2·11	1·35	0·32
Standard deviation	0·398	0·591	1·82	8·21	1·75	0·65
Standard error of regression	0·871	0·696	1·46	8·29	1·43	0·65
R^2	0·17	0·14	0·38	0·08	0·36	0·046
H-statistic[a]	3·04	67·14	3·14	18·66	9·62	5·70

Note

(a) H-statistic is $\chi^2(1)$ test-statistic for endogeneity of LEVYPLUS.

role in the insurance decision. INCOME is found to be mainly significant in the poor sample, and then not uniformly important for all services, yet income is an important determinant of the choice of LEVYPLUS. Particularly for the poor sample there is strong evidence that even allowing for self-selection of insurance, lower coinsurance rates induce greater utilization.[5]

A natural test for self-selection of insurance policy is a Hausman specification test for endogeneity of the LEVYPLUS dummy. Under the null hypothesis that LEVYPLUS is exogenous, $H=(\hat{\eta}_{IV}-\hat{\eta}_{OLS})'(\hat{V}(\hat{\eta}_{IV})-\hat{V}(\hat{\eta}_{OLS}))^{-1}(\hat{\eta}_{IV}-\hat{\eta}_{OLS})$ is distributed as $\chi^2(1)$. This "H-statistic" is reported at the base of Tables VII and VIII. The null hypothesis is strongly rejected for hospital admissions and usage and prescribed medicines in the poor sample, and for doctor usage and non-prescribed medicines in the rich sample.

Since there are three estimators involved, viz., IV, OLS and NEGBIN, and since comparisons between the results of tables IV, VII and VIII require us to compare IV and NEGBIN rather than IV and OLS as is the case with the Hausman test, it is relevant to note that the analysis of Cameron and Trivedi (1986) suggests that the difference between IV and OLS would be similar to those between IV and NEGBIN. However, in comparing tables IV, VII and VIII, it has to be acknowledged that some of the differences are due to differences in the sample. Lack of sample variation is a likely cause of some variables becoming insignificant in the poor and rich samples.

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TABLE VIII

Utilization Equations: Instrumental Variable Estimates (t-ratios)—Rich Sample (n=2223)

	DOCTOR-CON	HOSP-ADMIS	MEDI-CINES	HOSP-DAYS	PRE-SCRIBED	NON-PRE-SCRIBED
ONE	−0·177	0·254	−0·28	2·44	−0·12	−0·15
	(1·69)	(3·46)	(1·46)	(4·05)	(0·83)	(1·18)
SEX	−0·011	−0·046	0·48	−0·088	0·30	0·18
	(0·34)	(1·99)	(8·07)	(0·47)	(6·38)	(4·40)
AGE	1·050	−0·56	0·42	−8·86	−1·07	1·49
	(1·82)	(1·37)	(0·40)	(2·67)	(1·30)	(2·10)
$(\text{AGE})^2$	−1·275	0·61	1·03	10·95	2·96	−1·92
	(1·89)	(1·27)	(0·84)	(2·81)	(3·04)	(2·30)
INCOME	−0·078	−0·11	0·064	−0·62	−0·09	0·15
	(1·37)	(2·81)	(0·62)	(1·90)	(1·09)	(2·19)
LEVYPLUS	0·253	0·070	0·20	0·081	0·35	−0·15
	(3·00)	(1·18)	(1·31)	(0·17)	(2·87)	(1·41)
ILLNESS	0·067	0·009	0·26	−0·10	0·15	0·10
	(5·79)	(1·10)	(12·18)	(1·51)	(9·28)	(7·06)
ACTIVITYDAYS	0·105	0·037	0·059	0·19	0·053	0·005
	(19·37)	(9·69)	(5·98)	(6·24)	(6·84)	(0·80)
GHQ	0·010	0·0098	0·037	0·10	0·017	0·020
	(1·42)	(1·91)	(2·86)	(2·40)	(1·63)	(2·30)
LIMCHRON	−0·033	0·023	0·40	0·48	0·34	0·06
	(1·13)	(1·14)	(7·53)	(2·86)	(8·01)	(1·72)
NONLIMCHRON	0·038	0·164	0·39	1·04	0·40	−0·48
	(0·80)	(4·84)	(4·50)	(3·75)	(5·73)	(0·08)
Mean of dep. variable	0·228	0·135	0·91	0·74	0·531	0·382
Standard deviation	−0·659	0·437	1·258	3·52	0·990	0·755
Standard error of equation	0·596	0·421	1·080	3·45	0·849	0·735
R^2	0·198	0·076	0·264	0·04	0·267	0·056
H-statistic[a]	10·20	N.A.	0·829	0·00	6·04	63·6

Note

(a) H-statistic is the $\chi^2(1)$ test-statistic for endogeneity of LEVYPLUS.

There is clearly a price effect and a selectivity effect in health-care utilization.

5. CONCLUSION

In this paper we have explored the relationship between the demand for health care and the demand for health insurance. This has a certain resemblance to other studies of joint discrete/continuous models. The added complication of uncertainty, and a lack of data on certain key variables, makes empirical implementation of such models difficult. Nonetheless the detailed nature of the Australian Health Survey (1977–1978) data affords some interesting and, for the most part also intuitively reasonable, results.

Health status appears to be more important in determining health care service use than health insurance choice, while income appears to be more important in determining health insurance choice than in determining health care service use. For a broad range of health services (doctor, hospital, medicines), we observe higher usage of service on average for those people with insurance policies with more generous coverage. Furthermore, this effect is greater for those services where net prices vary more with the type of insurance. This health insurance effect is found to be the result of both moral hazard and self-selection.

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NOTES

1. Two observations about the attribute variables $\boldsymbol{A}$ are pertinent. First, they can enter the model in other economically meaningful ways. For example, $\boldsymbol{A}$ might include demographic variables. Such variables could also enter the model through demographic scaling or demographic translation in the sense of Lewbel (1985). Second, there is an interesting issue concerning whether variables reflecting past health states can be included in $\boldsymbol{A}$. This would lend the model a dynamic feature which could have important statistical implications. This issue is discussed later in the paper.

2. For the AHS data, reported income is gross income in the preceding financial year.

3. In earlier versions of this paper we used the formulation of health production function

$$H(\boldsymbol{e} \mid s, \boldsymbol{A}, \boldsymbol{B}) = \Pi_k \, (e_k - E_k(s \mid \boldsymbol{A}, \boldsymbol{B}))^{\alpha_k}$$

where $E_k > 0$ are "subsistence" or committed levels of health utilization. This alternative specification allows the attributes $\boldsymbol{A}$ and $\boldsymbol{B}$ to enter into our model by a different route. Though appealing in some ways, the derivations and developments resulting from this specification are somewhat longer. As they do not provide any additional insights, the alternative proposed here has been adopted instead.

4. Respondents were shown a list of activity limitations and were aksed to indicate if they were limited in any of these ways: confined to bed, confined to home, need help in getting out of the house, not able to do any housework at all, able to do some housework but not all, able to do all housework but other activities, like shopping and sport, are restricted.

5. A qualification to this conclusion, albeit a small one, is that the logit equation for estimating the instrument for the insurance dummy did not include the exogenous variables $(\text{AGE})^2$ and ACTIVITYDAYS. As noted, however, results from alternative specification of the logit equation suggest that our final conclusions are quite robust.

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