DETERMINANTS OF ACCESS
TO PHYSICIAN SERVICES IN ITALY:
A LATENT CLASS PROBIT APPROACH

by

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Partha Deb [**] *and* ***Furio C. Rosati*** [*]

Abstract

We examine access to general practitioners, public and private specialists in Italy. We develop a novel model using finite mixtures of probit models that provides a rich and flexible functional form. The mixed distribution is flexible and can accommodate non-normality of response probabilities. The empirical analysis shows that patient behavior can be clustered in two latent classes, and that it changes according to the kind of physician service demanded and the latent class to which the individual belongs. We find that income strongly influences the mix of services. Richer individuals are less likely to seek care from GP's and more likely to seek care from specialists, and especially private specialists. Health status and societal vulnerability are the most important indicators of class membership.

Keywords: Health Care Demand, Latent Class Models, Probit, Italy.
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I. INTRODUCTION

Over the last two decades, there has been rising concern with the continuous increase in the cost of health care services. Italy has not been immune from these problems. During the 1980s, full implementation of the universalism principle (introduced in 1978) led to a sharp increase in health expenditures. To curb these increases in health care spending, several cost-containment measures were undertaken in the 1990's. Unfortunately, quite often these cost containment measures have been *ad hoc* interventions rather than policies aimed at rationalizing access and use of health care services. Today, one of the main sources of concern for policy makers in Italy is the design of a policy that, while abandoning the principle of providing health care services free to all, introduces a system of co-payments that is equitable for patients and financially affordable for the State (Commissione per la Povertà, 1998).

Potential inequality in health care access due to differences in income is an important concern in the health system reform. Gertham *et al.* (2000) argues that a significant income variable in the demand for health services implies income related health inequality if access positively affects health outcomes. For Italy, although there is no evidence on the determinants of the demand for health services, some evidence is available on health inequality issues (Atella, Brindisi and Rosati, 2000; Van Doorslaer *et al*., 1997). Consequently, reductions in the availability of free care may affect whether National Health

Services (NHS) equity goals are being met. Moreover, the demand for private sector services may affect the public sector if those who use private sector services become uncommitted to state financing of health care, thus leading to a lack of support for, and willingness to pay taxes for the NHS.

In this study, we examine access to general practitioner, NHS specialists and private specialist services in Italy. In the Italian NHS, physician services are provided by both General Practitioners (GPs) and by specialists through a referral system. GPs are paid on a capitation basis. Patients do not pay for visits to GPs, and there is no limit to the number of visits they can have. On the other hand, there are public (NHS) and private specialists. For each visit to a specialist in the public system, patients pay a small fee (about 35 Euros, quite low compared to the average fees in the private sector) but access is regulated by GPs. Visits to private specialists are unregulated.

While it is not the first time that the issue of access to health care services has been studied (see, among others, Hunt-McCool *et al*. 1994; Manning *et al*., 1987; Pohlemeier and Ulrich, 1995; Gerdtham, 1997), this study innovates in two dimensions. This is the first empirical study of the demand for physician services in Italy. Second, the existing literature on physician visits does not distinguish between types of physicians. Instead of analyzing access to a generic physician, we examine the joint decision to seek care from a general practitioner, an NHS specialist or private specialist. A recent paper (Propper, 2000) examines public and private health care choices in the U.K.. Although this work is related to our study, Propper neither distinguishes between general practitioners and specialists nor allows for the possibility of simultaneous use of private and public services.

We develop a novel model for estimating the determinants of demand for physician's visits. A logical candidate for the joint, or simultaneous, decision to seek care from one or more types of physicians is the multivariate probit model. This model assumes that responses are normally distributed and allows for correlated unobservables. This model has two undesirable features for our analysis. First, the multivariate probit model assumes that covariates have the same coefficient for all individual. Evidence in Deb and Trivedi (1997, 1999) suggests that the demand for health services differs across latent classes of individuals. Second, the multivariate probit assumes marginal and joint normality for the distribution of outcomes. We develop a latent class, or finite mixture, framework that allows for different coefficients across latent classes. Consequently, it is more flexible in a functional form sense. Moreover, although we assume normality of responses within latent classes, the mixed distribution is flexible and can accommodate non-normality of the marginal and joint distributions of response probabilities.

We place special emphasis on the role of income as a determinant of access. Income has a potentially important role to play in assessing the equity of the health care system. If access is significantly related to income, and access does positively influence health outcomes, then individuals in higher income brackets can be expected to be experiencing better health. This consideration obviously extends to the public – private choice. If the health care market is characterized by vertical product differentiation, i.e., specialists provide higher quality care than general practitioners, a positive effect of income on the public – private choice will imply that higher income individuals tend to access higher quality services. Note that in this case universalism does not eliminate health inequality as long as quality differences exist between public and private specialists. On the other hand, because the NHS is more intensive in the patient's time (queuing, unsuitable schedules, etc.), a positive effect of income on the demand for private versus public services may reflect a choice between services characterized by a different mix of a patient's time versus money. While it is difficult to distinguish among these two interpretations, we shall examine the pattern of substitution in demand among different kinds of physician visits to shed light on whether income driven inequalities are a potential issue.

The paper is organized as follows. Section 2 discusses the econometric methodology. Section 3 describes the data set. Section 4 presents the results of the empirical analysis. Finally some conclusion are drawn in Section 5.

2. ECONOMETRIC FRAMEWORK

We model the joint decision to seek care from a general practitioner (y_1), a public specialist (y_2) or a private specialist (y_3). Each of y_1, y_2, and y_3 is binary and we observe all eight combinations of values in the data. These two features of the data motivate a multivariate binary choice model. As discussed in the introduction, the multivariate probit is one logical candidate. But given its limitations vis-à-vis our data and hypotheses, we develop an alternative model using a latent class probit model.

Suppose that individuals belong to one of C latent classes. Denote the probability of belonging to a class c by π_c with $0< \pi_c <1$ and $\sum \pi_c = 1$. These latent classes may be motivated by differences in unobserved characteristics among individuals, perhaps on the basis of health status (as described in Deb and Trivedi, 1999) or risk aversion (as is likely to be the case in this study because we are simply modeling access to care, rather than intensity of care). Within a latent class we assume that the choice of each physician type can be modeled as an independent probit so the distribution of the joint outcome within a latent class for individual i is the product of probits, i.e.,

$$\Pr(y_{1i}, y_{2i}, y_{3i} | c, x_i) = \Phi[(2y_{1i} - 1)\, x_i \beta_c] \cdot \Phi[(2y_{2i} - 1)\, x_i \beta_c] \cdot \Phi[(2y_{3i} - 1)\, x_i \beta_c] \quad (1)$$

where x_i denotes the vector of covariates and β_c is the vector of parameters for an individual in class c. Note that although we have specified the covariates to be the same in the determination of each binary choice, in principle, each equation could be specified with a different set of covariates.

The probability of the observed joint response is then given by

$$\Pr(y_{1i}, y_{2i}, y_{3i} \mid c, x_i) = \sum_{c=1}^{C} \left\{ \Phi[(2y_{1i} - 1)\, x_i b_c] \cdot \Phi[(2y_{2i} - 1)\, x_i b_c] \cdot \Phi[(2y_{3i} - 1)\, x_i b_c] \right\} \tag{2}$$

and the log likelihood function for the data is given by

$$Log\,(L) = \sum_{i=1}^{N} \log \left\{ \sum_{c=1}^{C} \left\{ \Phi[(2y_{1i} - 1)\, x_i b_c] \cdot \Phi[(2y_{2i} - 1)\, x_i b_c] \cdot \Phi[(2y_{3i} - 1)\, x_i b_c] \right\} \right\} \tag{3}$$

The likelihood function is maximized using a constrained quasi-Newton optimisation algorithm in SAS/IML (SAS Institute, 1997). Upon convergence, inference is based on robust, sandwich standard errors.

In order to provide additional insight into the nature of the joint choices made by individuals, we calculate the marginal effects of covariates on the probabilities of choices of each type of physician as well as marginal effects of covariates on joint probabilities of each combination of physician choice. Although the prior probability of class membership is specified as a constant (π_c), the posterior probability of class membership conditional on observed covariates and outcome, which can be calculated post-estimation, varies across individuals. The posterior probability of membership in class c is given by

$$\Pr(h \in c \mid x_i, y_{ji}) = \frac{\left\{ \Phi[(2y_{1i} - 1)\, x_i b_h] \cdot \Phi[(2y_{2i} - 1)\, x_i b_h] \cdot \Phi[(2y_{3i} - 1)\, x_i b_h] \right\}}{\sum_{h=1}^{C} \left\{ \Phi[(2y_{1i} - 1)\, x_i b_h] \cdot \Phi[(2y_{2i} - 1)\, x_i b_h] \cdot \Phi[(2y_{3i} - 1)\, x_i b_h] \right\}} \tag{4}$$

where h =1,2,3 denotes the latent class type and j=1,2,3 refers to physician type. As described in detail later, we use the posterior probability to provide some insights into features of the heterogeneity that defines the latent classes.

This model has four main desirable features for our analysis. First, the it allows for different parameter values for individuals in different latent classes. Note that parameter differences based on observed characteristics can easily be accommodated in standard model with the use of interaction terms. However, in latent class analysis, individuals are assumed to differ in unobservable ways, which cannot be modeled by variable interactions. Second, although we assume normality of responses within latent classes, the mixed distribution is flexible and can accommodate non-normality of response probabilities. In fact, in general, the finite mixture model can serve as an approximation to any true, but unknown, probability density (Heckman and Singer, 1984, Lindsay, 1995). Third, the finite mixture model is computationally simpler than the multivariate probit model because it requires no numerical or stochastic integration to calculate the response probabilities; it requires only the evaluation of univariate normal probabilities. Fourth, although the response probabilities within each latent class are assumed to be independent, the overall response probabilities are not independently distributed. Therefore, like the multivariate probit model, our latent class probit model allows for correlated responses.

McLachlan and Basford (1988) and Titterington, Smith and Makow (1985) provide excellent surveys of the literature on finite mixture models and demonstrate the wide applicability of the model. Its growing popularity is reflected in an increase in the number of applications in labor economics (Heckman, Robb, and Walker, 1990; Gritz, 1993; Geweke and Keane, 1997), marketing (Wedel et al., 1993), development economics (Morduch and Stern, 1997), industrial organization (Wang, Cockburn, and Puterman, 1998), and health economics (Deb and Trivedi , 1997; Deb and Trivedi, 1999). Most of these studies find that only a small number of latent classes are needed to describe the data adequately.

3. DATA AND SUMMARY STATISTICS

The data used for the empirical analysis in this paper are from the fourth wave of the “Indagine Multiscopo sulle Famiglie” (IMF) conducted in 1991 by the Italian National Institute of Statistics (ISTAT. The original sample contains information on 65,264 individuals of all ages. After dropping individuals 12 years of age and younger and a few observations with missing values, the final sample used in this analysis has 53,821 observations. Young children were not considered because the rules governing their access to physicians in the NHS are quite different from those governing adult access.

The covariates used in our study are typical of those used in previous studies on the determinants of medical care. In particular, the explanatory variables include gender, age, and geographic location. Information on health status is provided by two dummy variables: one noting the presence of a chronic condition and another noting self-reported bad health.

Information on income is not directly available in the IMF database. However, excellent measures of income are available in the Household Survey conducted by the Bank of Italy. Therefore, we use data on household total disposable income, age and educational characteristics from this household survey to impute income for individuals in the IMF data (details are reported in Atella, Brindisi and Rosati, 2000). We recognize that the use of imputed income introduces measurement errors, however, the IMF is the only source of individual-level information on the demand for physician services in Italy.

In this study, we have not been able to use supply side variables, such as the number of physicians available for patients. This variable should be positively related with the number of visits, if one believe that a larger number of physicians leads to a better distribution of the supply on the territory and thus to lower transportation costs and shorter waiting lists. Unfortunately, IMF data allow recovering patient residency only at regional level. We believe that at this level of aggregation the relationship between the availability of physicians and the number of patients is lost. Thus, we do not use supply variables in the estimation, although we do control for regional geographic location.

In Table 1 we report some basic statistical information regarding the variables used in the empirical analysis. It shows that, in a given month, about 17 percent of individuals visit a general practitioner. In addition, approximately 5-6 percent of individuals seek care from public and private specialists. It is interesting to note that public and private specialist use is roughly the same, in spite of the fact that visits to private specialists are considerably more expensive. The sample is equally divided into males and females and with somewhat more people living in the North of Italy than in the South (the omitted region is the Center). A small fraction of individuals (7 percent) report being in poor bad health, although 51 percent report a chronic condition.

4. DISCUSSION OF THE EMPIRICAL RESULTS

In this section we report the results of our empirical analysis. We have estimated latent-class models with one (degenerate), two and three points of support and we begin by reporting results of model selection methods used to choose the number of points of support in the preferred model. The interaction between equations and covariates in the model is complex. Therefore, we first report parameter estimates and marginal effects of covariates on each individual outcome. Next, we characterize the marginal effects of covariates on joint outcomes. Finally, we describe characteristics of the latent classes.

4.1 Model performance

We have estimated models with one, two and three latent classes. The models have maximized log likelihood values of –43155.7, -42778.5 and –42679.1 and have 27, 55 and 83 parameters respectively. As shown in Deb and Trivedi (1997) and justified by Sakata and White

(1998), among others, the Bayesian Information Criterion is an appealing model selection criterion. Using the Bayesian Information Criterion, we find that the two class finite mixture model is superior to the one class degenerate model, but the three class model does not show enough improvement in the value of the maximized log likelihood to justify the additional parameters. Therefore, in subsequent analysis we report results from the model with two latent classes.

4.2 Estimates and marginal effects

Table 2 reports the estimates of the coefficients for the finite mixture model with two latent classes. Overall, the model is well determined and the parameter estimates are statistically significant. As expected, older individuals in each latent class are more likely to visit a GP. However, the likelihood of visiting a public specialist is not affected by age, and older individuals are significantly less likely to see a private specialist. Women are more likely to seek care from all types of providers. Individuals in bad health and those with chronic conditions are substantially more likely to seek care from each of the three types of providers. The effect of income is quite varied across types of providers and across latent classes. It is not significant in any of the latent classes in the equation for NHS specialists. It has a negative sign in the equations for GP, but the estimate is statistically significant only in the second latent class. However, income has a significantly positive effect on the probability of seeking care from a private specialist.

The theoretical structure of the demand for medical care underlying our econometric model assumes that individuals make joint decisions about whether to demand medical care and from which sources to receive such care. Therefore, although the analysis of the effects of covariates on individual outcomes reveals useful information, it is perhaps more insightful to examine the effects of covariates on the probabilities of the joint modes of care. Marginal effects on joint outcomes were calculated for each individual and averaged over the sample. Because the probabilities of the different joint outcomes have disparate magnitudes, it is difficult to interpret the marginal effects without some rescaling. In Panel A of Table 3, we report the marginal effects on a joint outcome relative to the sample average of the predicted probabilities of that outcome. Panels B and C report these relative marginal effects for each latent class.

There are some notable differences in the effects of covariates between the latent classes. Overall, older individuals are less likely to visit only a private specialist and more likely to seek publicly provided care – either from a GP or from a GP and a public specialist. The overall effect, however, masks different responses within each latent class. Individuals in latent class 1 drive the overall finding that older people are less likely to seek private care, but the increased likelihood of seeking public care is largely driven by the behavior of individuals in latent class 2. Women are generally substantially more likely to seek care from all combinations of providers. The exception is that women in latent class 1 are more likely to seek care from GP's along with public and private specialists than men. However, the likelihood of seeking care from all three types of providers is not significantly different for women as compared to men in latent class 2.

As reported earlier, health conditions are very important determinants of the decision to access health care services. The effects of both measures of health status are completely consistent with each other, so for brevity we discuss their effects as one. Sicker individuals are more likely to seek care from all combinations of providers. However, the effect of health status is differentiated across the two latent classes. Being ill increases the probability of care by a substantially greater amount for individuals in latent class 1 as compared to those in the other class. Sicker individuals in latent class 1 are more likely to seek forms of care that include a GP visit than healthier individuals, but they are less likely to seek care solely from specialists. On the other hand, sicker individuals in latent class 2 are more likely to seek all forms of care. Therefore, it appears that individuals in latent class 2 have a higher propensity to seek care from private specialists than their counterparts in latent class 1. In all other instances in which a public-private mix is observed, these events are not differentially influenced by health status.

Income affects mainly the choice between public and private providers, rather than the overall probability of having a visit. In fact, the latter is unchanged by income. Other studies have also observed this lack of income effect on the likelihood of seeking care. But because we have examined modes of care, we are able to provide valuable insights into the ways in which income does affect the demand for health services. Because of the importance of income in public policy debates regarding the restructuring of public health systems in Italy and elsewhere in Europe, we elaborate on the effect of income on the various modes of care.

4.3 - Income effects on the demand for physician services

If access to the health system depends positively on income, it has been argued (Gertham *et al.*, 2000) that this is an indication of the presence of inequality. Moreover, if private and public care are vertically differentiated products (with private care providing higher quality), then income is expected to guide selection between public and private care. Although we find that income does not determine access to some form of care, we do find substantial income effects on the choice between types of physicians. We illustrate these effects by simulating the probabilities predicted by the model at different income deciles. In addition to the overall effect, we simulate the effects for latent class separately. For ease of interpretation, the predicted probabilities have been transformed into relative risks taking the value for the lowest income decile as the reference. These are displayed for various combinations of physician types in Figure 1[1].

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[1] - The reader should be careful in noting that the scales on the y-axis change across the modes of care.

As shown in the panel labeled "no visit", the overall probability of not seeking care (and by implication of seeking some form of care) is not influenced by income, nor are significant differences recorded between latent classes. On the other hand, income influences strongly the mix of services accessed by the patients and especially the GP- specialist choice and the public – private specialist choice. The modes of care most responsive to income levels are, by far, those combinations in which private specialists are involved. In particular, individuals are less likely to seek care from GP's and more likely to seek care from specialists (both public and private) as income increases. As income increases, there is also an overall increase in the propensity to seek care from the private sector.

There are striking differences in the behavior of individuals regarding different combinations of physician services depending on the latent class to which they belong. In the case of "GP only" visits and "Specialists only" visits, although richer individuals in both latent classes are less likely to seek care from GP's and more likely to seek care from specialists, these effects are much more pronounced for individuals in latent class 2. Individuals in the highest income decile who belong to latent class 2 are 5 times less likely to have a GP visit and 3 times more likely to see both types of specialists as compared to individuals in the lowest income decile. In the case of "GP and private specialists" visits and "GP and specialists" visits, while richer individuals in latent class 2 are less likely to see a GP and either a private or both types of specialists, richer individuals in latent class 1 present the opposite behavior. Taken together, this evidence suggests that individuals in latent class 2 do not prefer entering the public sector as compared to individuals in latent class 1.

As discussed in the introduction, a positive effect of income in the choice between public and private providers could be the result of either vertical differentiation or the different input of patient's time required by the two kind of services. Our results seem to indicate that both hypotheses have support. The patient's time input is arguably similar between GP and NHS specialists, but the monetary cost of the latter is higher. Higher income persons are more likely to substitute NHS specialist care for GP visits. This indicates evidence in favor of a vertical differentiation hypothesis. However, there is also a slight preference for private specialists over public specialists by richer persons. This is evidence in favor of the time-cost hypothesis.

4.4 - Posterior probabilities

As we have demonstrated, individuals in the two latent classes behave quite differently. In order to shed some light on the types of individuals who might belong to one or the other class, we conduct a posterior analysis of the latent class membership. To do so, we first calculated the posterior probabilities of class membership for each individual using equation (4). Note that these posterior probabilities are conditioned on covariates *and* the outcome. It is the introduction of the additional information contained in the outcome that allows us to obtain information on the classes not available in "prior" analysis when the classes are assumed to be latent. Next, we assigned each individual to the class associated with the larger posterior probability. Finally, we estimated a probit regression of class membership on the observed covariates to examine whether class membership were related to any observable characteristics of the individuals. These regression results are presented in Table 4.

Health status is the most important indicator of class membership. In particular sicker individuals are more likely to be in class 1. Older individuals, women and those with low incomes are also more likely to be in class 1. Overall, it appears that individuals who might be classified as vulnerable in society in terms of their health and their ability to pay for health care are much more likely to be in class 1. Because individuals in class 1 respond differently to changes in income than individuals in class 2, any income-based policy aimed at helping vulnerable populations would have unintended consequences if aggregate marginal effects of income were used in the policy simulations. Instead, our model provides a basis for targeting policy more effectively, although a careful evaluation of policy issues is beyond the scope of this paper.

6. CONCLUSIONS

We have examined access to general practitioner, NHS specialists and private specialist services in Italy. Although there are several studies on access to health care services, the existing literature has generally not distinguished between types of physicians, nor between public and private sector choices. We develop a novel model for estimating the determinants of demand for physician's visits using finite mixtures of probit models. This model allows for different parameter values for individuals in different latent classes, thus providing a rich and flexible functional form. The mixed distribution is flexible and can accommodate non-normality of response probabilities. It also provides interesting class-specific implications.

The empirical analysis has shown that: *i)* patient behavior can be clustered in two latent classes, and *ii)* patient behavior changes according to the kind of physician service demanded and the latent class to which the individual belongs. We have placed special emphasis on the role of income as a determinant of access because of its prominence in debates regarding reform of national health care systems. The probability of seeking some form of care is not influenced by income, nor are significant differences recorded between latent classes. However, income strongly influences the mix of services. The modes of care most responsive to income levels are, by far, those combinations in which private specialists are involved. In particular, individuals are less likely to seek care from GP's and more likely to seek care from specialists as income increases. There is also an overall increase in the propensity to seek care from the private sector as income increases. There are differences in the behavior of individuals regarding different combinations of physician services depending on the latent class to which they belong. For example, although richer individuals in both latent classes are less likely to seek care from GP's and more likely to seek care from specialists, these effects are much more pronounced for individuals in latent class 2. Health status is the most important indicator of class membership, with sicker individuals more likely to be in class 1. Older individuals, women and those with low incomes are also more likely to be in class 1. Overall, it appears that vulnerable individuals, from a societal perspective, are much more likely to be in class 1.

Our findings have two important implications. First, income does not affect access to care in a general sense and this may indicate that the NHS, as a system of universal access, offers access to all people. However, as income increases individuals tend to use services provided by private specialists. Therefore, even in presence of the NHS, there exists a mechanism of self-selection that leads richer individuals to opt out of the NHS system. The reasons that determine such decision needs to be more deeply investigated, as they might be of importance for the new design of the NHS system. Second, because individuals in class 1 respond differently to changes in income than individuals in class 2, any income-based policy aimed at helping vulnerable populations would have unintended consequences if aggregate marginal effects of income were used in the policy simulations. Instead, our model provides a basis for targeting policy more effectively.

REFERENCES

Atella V., Brindisi F. and F.C. Rosati, Income variables matching between Bank of Italy "Survey on Household Income and Wealth" and ISTAT "Indagine Multiscopo sulle Famiglie", mimeo

Atella V., Brindisi F. and F.C. Rosati, Changing income-related health inequalities in Italy 1991-1994, mimeo.

Banca d'Italia (1993) "Indagine sui redditi delle famiglie", Roma

Commissione per la Compatibilità Macroeconomica delle Politiche Sociali (1998), "Rapporto Finale", Presidenza del Consiglio, Roma

Deb P. and P.K. Trivedi (1997), "Demand for Medical Care by the Elderly in the United States: A Finite Mixture Approach", *Journal of Applied Econometrics*, 12, 313-336.

Deb P. and P.K. Trivedi (1999), "The structure of demand for health care: Latent class versus Two-part Models", mimeo.

Gertham U.-G. (1997), "Equity in Health Care Utilization: Further Tests Based on Hurdle Models and Swedish Micro Data", *Health Economics*, 6, 303-319.

Gertham U.-G. and Johannesson Magnus (2000), "Income-Related Inequality in Life-Years and Quality-Adjusted Life-Years", *Journal of Health Economics*, 19, iss. 6, 1007-26.

Geweke, J. and M. Keane (1997), "Mixture of Normals Probit Models", Federal Reserve Bank of Minneapolis, Staff Report 237.

Gritz, M. (1993), "The Impact of Training on the Frequency and Duration of Employment", *Journal of Econometrics*, 57, 21-51.

Heckman, J.J., R. Robb, and M. Walker (1990), "Testing the Mixtures of Exponentials Hypothesis and Estimating the Mixing Distribution by the Method of Moments", *Journal of the American Statistical Association*, 85, 582-589.

Heckman, J. J. and B. Singer (1984), "A Method of Minimizing the Distributional Impact in Econometric Models for Duration Data", *Econometrica*, 52, 271-320.

Hunt-MeCool, J., B. F. Kiker, and Y. Ng (1994), "Estimates of the demand for medical care under different functional forms", *Journal of Applied Econometrics*, 9, 201 218.

ISTAT (1994), "Condizioni di salute e ricorso ai servizi sanitari" in Indagine Multiscopo sulle Famiglie - Anni 1987-91, n.10.

Laird, N. (1978), "Nonparametric Maximum Likelihood Estimation of a Mixing Distribution", *Journal of the American Statistical Association*, 73, 805-811.

Lindsay, B. J. (1995), *Mixture Models: Theory, Geometry, and Applications*, NSF-CBMS Regional Conference Series in Probability and Statistics, Vol. 5, IMS-ASA.

Manning, W. G., J.P. Newhouse, N. Duan, E.B. Keeler, A. Leibowitz and M. S. Marquis (1987), "Health Insurance and the Demand for Medical Care: Evidence from a Randomized Experiment", *American Economic Review*, 77, 251-277.

McLachlan, G.J., and K.E. Basford (1988), *Mixture Models: Inference and Application to Clustering*, New York: Marcel Dekker.

Morduch, J. and H.S. Stern (1997), "Using Mixture Models to Detect Sex Bias in Health Outcomes in Bangladesh", *Journal of Econometrics*, 77, 259-276.

Polhemeier, W. and V. Ulrich (1995), “An econometric mode] of the two-part decision-making process in the demand for medical care”, *Journal of Human Resources,* 30, 339-61.

Propper C. (2000), “The demand for private health care in UK”, *Journal of Health Economics*, 19, 855-876.

Sakata, S. and H. White (1998), “High Breakdown Point Conditional Dispersion Estimation with Application to S & P 500 Daily Returns Volatility”, Econometrica, 66, 529-567.

SAS Institute (1997), SAS/IML Software: Changes and Enhancements through Release 6.11, SAS Institute Inc.

Titterington, D.M., A.F.M. Smith and U.E. Makow (1985), *Statistical Analysis of Finite Mixture Distributions*. New York: John Wiley.

Van Doorslaer, E.; Wagstaff, A.; Bleichrodt, H.; Calonge, S.; Gerdtham, Ulf-G.; Gerfin, M.; Geurts, J.; Gross, L.; Hakkinen, U.; Leu, R. E.; O’Donnell, O.; Propper, C.; Puffer, F.; Rodrìguez, M.; Sundberg, G.; Winkelhake, O. (1997) “Income-related Inequalities in Health: Some International Comparisons”, *Journal of Health Economics*, Vol.16, pp.93-112.

Wang, P., I.M. Cockburn, and M. L. Puterman (1998), “Analysis of Patent Data - A Mixed Poisson Regression Model Approach”, *Journal of Business and Economic Statistics*, 16, 27-36.

Wedel, M., W.S. Desarbo, J.R. Bult, and V. Ramaswamy (1993), “A Latent Class Poisson Regression Model For Heterogeneous Count Data”, *Journal of Applied Econometrics*, 8, 397-411.

Table 1- Summary statistics

Variable	Mean	Std. dev.	Min	Max
Visit a general practitioner (GP)	0.168	0.374	0	1
Visit a NHS specialist	0.052	0.223	0	1
Visit a private specialist	0.059	0.235	0	1
Income (in million liras)	8.287	1.671	0	1
Family size	3.402	1.348	1	10
Female	0.516	0.499	0	1
Chronic condition	0.514	0.949	0	1
Age (/10)	4.340	1.928	1.3	9.9
North	0.434	0.496	0	1
South	0.369	0.482	0	1
Bad health status	0.071	0.257	0	1

N=53821.

Table 2 – Parameter values and marginal effects

Equations	Variables	Latent class 1			Latent class 2		
		Parameter	t-stat	Marginal	Parameter	t-stat	Marginal
General Practitioners	Constant	-0.989	-8.054		-3.058	-13.749	
	Age	0.072	5.783	0.019	0.279	12.994	0.021
	Female	0.243	8.420	0.065	0.088	1.447	0.007
	Family size	-0.028	-2.144	-0.008	-0.007	-0.227	0.000
	Income	-0.014	-1.380	-0.004	-0.060	-2.543	-0.005
	Chronic conditions	0.904	15.864	0.243	0.168	7.414	0.013
	Bad health status	1.189	8.209	0.320	0.324	4.182	0.025
	North	0.025	0.635	0.007	-0.044	-0.507	-0.003
	South	-0.137	-2.943	-0.037	0.317	3.900	0.024
NHS Specialists	Constant	-1.333	-10.152		-2.280	-15.392	
	Age	-0.004	-0.268	-0.001	0.026	1.716	0.002
	Female	0.112	2.971	0.016	0.132	3.180	0.010
	Family size	-0.029	-1.617	-0.004	-0.050	-2.457	-0.004
	Income	-0.017	-1.110	-0.002	0.021	1.246	0.002
	Chronic conditions	0.173	9.044	0.024	0.189	11.586	0.014
	Bad health status	0.191	2.899	0.027	0.620	10.983	0.046
	North	-0.005	-0.109	-0.001	0.192	3.623	0.014
	South	-0.081	-1.726	-0.011	-0.117	-1.955	-0.009
Private Specialists	Constant	-1.535	-10.801		-1.747	-14.544	
	Age	-0.050	-3.334	-0.007	-0.024	-2.050	-0.003
	Female	0.151	2.974	0.020	0.232	5.841	0.024
	Family size	-0.061	-2.801	-0.008	-0.065	-3.676	-0.007
	Income	0.048	2.854	0.006	0.025	1.851	0.003
	Chronic conditions	0.108	4.857	0.014	0.115	7.257	0.012
	Bad health status	0.153	2.150	0.020	0.358	7.087	0.037
	North	-0.145	-2.367	-0.019	0.066	1.326	0.007
	South	-0.045	-0.634	-0.006	-0.091	-1.531	-0.009
	p	0.366	15.427	---	---	---	---

Table 3 – Marginal effects of covariates on joint outcomes

Panel A - overall

Outcome								
GP visit	0	0	0	0	1	1	1	1
NHS specialist visit	0	0	1	1	0	0	1	1
Private specialist visit	0	1	0	1	0	1	0	1
Marginal effect								
Age	-0.021	-0.092	0.000	0.000	0.137	0.000	0.129	0.000
Female	-0.066	0.346	0.153	0.370	0.130	0.439	0.258	0.588
Family size	0.015	-0.115	-0.061	0.000	-0.007	-0.088	-0.065	0.000
Income	0.000	0.069	0.000	0.000	-0.029	0.088	-0.065	0.000
Chronic condition	-0.141	0.069	0.153	0.370	0.555	0.702	0.645	0.588
Bad health status	-0.225	0.346	0.583	1.111	0.750	0.965	0.968	1.176
North	-0.011	-0.023	0.215	0.370	0.014	-0.175	0.065	0.000
South	0.016	-0.139	-0.215	-0.370	0.036	-0.088	-0.129	0.000

Panel B – Latent class 1

Marginal effect								
Age	-0.024	-0.131	-0.028	0.000	0.061	-0.039	0.028	0.000
Female	-0.138	0.183	0.084	0.385	0.139	0.431	0.285	0.571
Family size	0.024	-0.104	-0.028	0.000	-0.006	-0.118	-0.057	-0.286
Income	0.002	0.104	-0.028	0.000	-0.013	0.078	-0.057	0.000
Chronic conditions	-0.421	-0.209	-0.112	0.000	0.631	0.745	0.712	0.857
Bad health status	-0.550	-0.235	-0.223	0.000	0.834	1.020	0.883	0.857
North	0.009	-0.287	0.000	-0.385	0.042	-0.235	0.028	-0.286
South	0.075	-0.026	-0.084	0.000	-0.081	-0.157	-0.199	-0.286

Panel C – Latent class 2

Marginal effect								
Age	-0.021	-0.087	0.000	0.000	0.456	0.303	0.488	0.000
Female	-0.040	0.433	0.227	0.741	0.101	0.606	0.244	0.000
Family size	0.011	-0.130	-0.097	-0.370	0.000	0.000	0.000	0.000
Income	0.000	0.065	0.032	0.000	-0.101	0.000	0.000	0.000
Chronic conditions	-0.038	0.195	0.325	0.370	0.228	0.303	0.488	0.000
Bad health status	-0.107	0.628	1.136	1.481	0.380	0.909	1.220	1.429
North	-0.017	0.108	0.390	0.370	-0.101	0.000	0.244	0.000
South	-0.006	-0.195	-0.292	-0.370	0.557	0.303	0.244	0.000

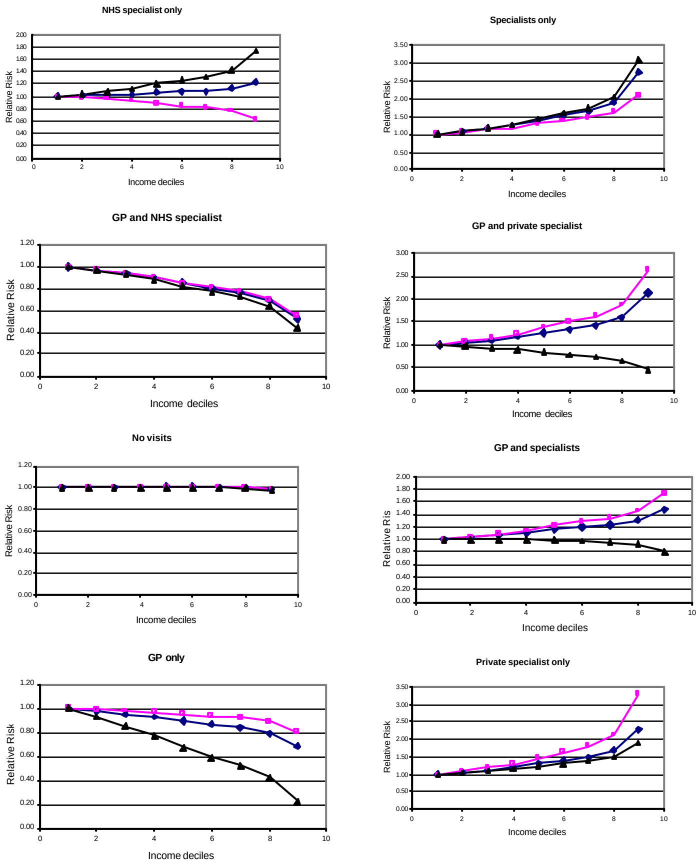
Reported marginal effects are scaled such that they are relative to the predicted probability of the joint outcome.

Table 4 - Posterior Probability determinants(*) - Probit estimates

Variable	Estimate	t value
Constant	-1.351	27.562
Age	0.091	21.293
Female	0.109	8.153
Family size	-0.009	1.445
Income	-0.024	4.805
Chronic conditions	0.254	34.091
Bad health status	0.337	13.943
North	-0.031	1.741
South	-0.008	0.422

(*) Dependent Variable: Dichotomized variable obtained from the posterior probability of being in Class 1 with cut-off point at 0.5.

Figure 1 – Relative event probabilities by income deciles



Notes: ♦ denotes the overall predicted probability,. Denotes the predicted probability for latent class 1 and denotes the predicted probability for latent class 2.