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Determinants Of Access To Physician Services In Italy: A Latent Class Seemingly Unrelated Probit Approach*

by

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Abstract

We examine access to general practitioners and specialists who work in the public and private sectors in Italy using a seemingly unrelated system of probits. We use a latent class formulation that provides a rich and flexible functional form and can accommodate non-normality of response probabilities. The empirical analysis shows that patient behavior can be clustered in two latent classes. 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, seemingly unrelated, Probit, Italy.
JEL code: I11, C35

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1. INTRODUCTION

Over the last two decades, there has been rising concern with the continuous increase in the cost of health care services. Today, one of the main sources of concern for policy makers in Europe 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. Potential inequality in health care access due to differences in income is an important concern in the health system reform (see [1]). In [2] it is argued that a significant income variable in the demand for health services implies income related health inequality if access positively affects health outcomes.

In this study, we examine access to general practitioners, specialists who work for the national health service system and specialists who work in the private sector in Italy. We develop a latent class, or finite mixture, seemingly unrelated probit model, which is flexible and accommodates correlations across choices. 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 experience better health. This consideration obviously extends to the public – private choice.

This study contributes to the literature on access to health care in two substantive 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 SSN specialist or a private specialist. Thus we are able to analyze choices between public and private sector alternatives in addition to choices between generalists and specialists. In mixed health care systems, 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 SSN. In this context, our work complements [3] who examines public and private health care choices in the U.K.. However, [3] neither distinguishes between general practitioners and specialists nor allows for the possibility of simultaneous use of private and public services.

Health services offered by the public and by the private sector can be thought of as vertically differentiated products for two reasons given that money prices for private sector services are considerably higher than any co-payments patients face in the public sector. First, it is possible that the quality of services is higher in the private sector, or at least that quality is perceived to be higher in the public sector. Second, even if quality is the same, it is possible that non-monetary costs of obtaining services in the public sector (comprised mainly of waiting times), are higher than those in the private sector. Our model does not allow us to distinguish between the two reasons for vertical differentiation, but it does suggest that if income is a significant determinant of demand for services, universal coverage in the public sector will not necessarily eliminate health inequality

The paper is organized as follows. Section 2 presents background on the Italian National health system. Section 3 discusses the econometric methodology. Section 4 describes the data set. Section 5 presents the results of the empirical analysis. Finally some conclusion are drawn in Section 6.

2. THE ITALIAN HEALTH CARE SYSTEM

Since 1978, the Italian health system has been regulated and administered through the a national health service (*Servizo Sanitario Nazionale*, referred to henceforth as SSN). The system is based on four main principles: universal coverage, full range of the health services provided, participation of citizens to the management of the SSN and organizational pluralism (State, Regions and Local Health Authorities). Until the late 1990s, the system was financed through compulsory worker contributions (around 50%), general taxation and borrowing (42%), patient co-payments (4%) and some other minor revenue sources. The public health care system coexisted with private provision of medical services. Here, about 90% of expenditures are financed by out-of-pocket payments by patients, with the remainder covered by private health insurance and company health plans.

In providing health care services the SSN uses a wide array of providers: hospitals with different forms of ownership (directly managed, public hospital trusts; public and private teaching hospitals; public and private research hospitals; non profit hospitals; for profit hospitals) GPs, public and private ambulatory care facilities (specialist and diagnostic), public and private rehabilitation facilities and private community nurses. Physician services are provided by both General Practitioners (GPs) and by specialists through a referral system. GPs are paid on a capitation basis. In general, they can serve at the most 1,500 patients and receive a salary that is based on the number of patients. 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 (SSN) and private specialists. For each visit to a specialist in the public system, patients pay a 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.

Patients enjoy greater freedom of choice of provider compared to any other European countries. Italian patients are only obliged to use providers in the province in which they reside and they must have a doctor's prescription for most forms of care. However, within a province, patients can change their GP as they wish, as long as the physician has a contract with the SSN and possesses the necessary capacity.

3. 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. We develop a latent class seemingly unrelated probit model for the joint choice of y_1, y_2 and y_3[1]. Suppose that individuals belong to one of C latent classes. Denote the

1 Our model is compared with the multivariate probit model, the leading alternative model in this context,

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 [4]) 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.,

$$\Pr(y_{1i}, y_{2i}, y_{3i} \mid c, x_i) = \Phi[(2y_{1i} - 1)\, x_i \beta_{GP,c}] \cdot \Phi[(2y_{2i} - 1)\, x_i \beta_{PUB.c}] \cdot \Phi[(2y_{3i} - 1)\, x_i \beta_{PRI,c}] \qquad (1)$$

where x_i denotes the vector of covariates and $\beta_{i,c}$ is the vector of parameters for an individual in class c and for a specific choice of care. 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

$$\Pr(y_{1i}, y_{2i}, y_{3i} \mid c, x_i) = \sum_{c=1}^{C} \pi_c \left\{ \Phi[(2y_{1i} - 1)\, x_i \beta_{GP,c}] \cdot \Phi[(2y_{2i} - 1)\, x_i \beta_{PUB,c}] \cdot \Phi[(2y_{3i} - 1)\, x_i \beta_{PRI,c}] \right\} \qquad (2)$$

and the log likelihood function for the data is given by

$$Log(L) = \sum_{i=1}^{N} \log \left\{ \sum_{c=1}^{C} \pi_c \left\{ \Phi[(2y_{1i} - 1)\, x_i \beta_{GP,c}] \cdot \Phi[(2y_{2i} - 1)\, x_i \beta_{PUB,c}] \cdot \Phi[(2y_{3i} - 1)\, x_i \beta_{PRI,c}] \right\} \right\} \qquad (3)$$

The likelihood function is maximized using a constrained quasi-Newton optimisation algorithm in SAS/IML ([6]). Although we are treating each individual as contributing independently to the likelihood function, it is possible that errors on observations for individuals within households are correlated.[2] Therefore, upon convergence, inference is based

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below.

[2] We thank an anonymous referee for pointing this out.

on cluster-robust standard errors, where clustering is assumed to be at the household level.

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

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

where c 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.

An alternative model, and one that is more standard in textbook treatments of seemingly unrelated binary choice models, is the multivariate probit model. This model assumes that responses are normally distributed and allows for correlated unobservables. Unfortunately, it has three undesirable features for our analysis. First, the multivariate probit model assumes that covariates have the same coefficients for all individuals. Evidence in [4] and [5] suggests that the demand for health services differs across latent classes of individuals. 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. On the other hand, the latent class model allows for different coefficients across latent classes. Consequently, it is more flexible in a functional form sense. In fact, in general, the latent class model can serve as an approximation to any true, but unknown, probability density (see [7] and [8]). Second, the multivariate probit assumes marginal and joint normality for the distribution of outcomes, which may be overly restrictive. The latent class model assumes normality of responses within latent classes but the mixed distribution is flexible and can accommodate non-normality of the marginal and joint distributions of response probabilities. Finally, the multivariate probit model requires the calculation of multivariate normal probabilities, which continues to be computationally intensive in spite of the advances in simulation-based methods. The latent class model, on the other hand, requires evaluations of only univariate normal probabilities, which is computationally much simpler.

Excellent surveys of the literature on finite mixture models that demonstrate the wide applicability of the model are provided in [9] and [10]. Its growing popularity is reflected in an increase in the number of applications in labor economics ([11], [12], [13]), marketing ([14]), development economics ([15]), industrial organization ([16]), and health economics ([4], [5]). Most of these studies find that only a small number of latent classes are needed to describe the data adequately. Note that, although there are a number of published applications of latent class models, there are relatively few applications in health economics. Those that exist consist of models for univariate outcomes. We are not aware of any other published work using a latent class framework for multivariate binary outcomes.

4. 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" (Multipurpose Household Survey - MHS) conducted in 1991 by the Italian National Institute of Statistics (ISTAT) [17]. The original sample contains information on 65,264 individuals of all ages. After dropping individuals less than 18 years of age and a few observations with missing values, the final sample used in this analysis has 53,821 observations. Children were not considered because the rules governing their access to physicians in the SSN 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, education, 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 MHS database. However, excellent measures of income are available in the Household Survey conducted by the Bank of Italy [18]. Therefore, we use data on household total disposable income, age and educational characteristics from this household survey to impute income for individuals in the MHS data (details are reported in [19]). We recognize that the use of imputed income introduces measurement errors and is likely to lead to attenuation bias. But the MHS is the only source of individual-level information on the demand for physician services in Italy. The income effect of the demand for health services is of central importance to health care policy in Italy (as well as in other countries) so we accept the possibility of attenuation bias and envision our findings as conservative estimates of income effects.

In this study, we have not been able to use supply side variables, such as the number of physicians available for patients. MHS data allow recovering patient residency only at regional level. Thus, instead of using available supply variables, we directly 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. The average age of the population (after dropping all children below 18 years) under investigation is 45 years.

We report the frequencies of each of the triplets of health care events in Table 2. In a given month, 74% of the sample does not seek any medical care. About 14% of individuals seek care only from GP's and 4% from only private specialists. Furthermore, about 3% of individuals apparently seek care only from public specialists. As a visit to a GP is a prerequisite to receive care from an SSN specialist, we believe most of these individuals would have their GP visit prior to the sampling month. These individuals should be behaviorally similar to the 2% of individuals who receive care from GP's and SSN specialists. Finally, very few individuals seek care from both types of specialists.

5. EMPIRICAL RESULTS

We begin by reporting results of model selection methods used to choose the number of points of support in the preferred model. Next, we report parameter estimates and marginal effects of covariates on each individual outcome. Then, we characterize the marginal effects of covariates on joint outcomes. Finally, we describe characteristics of the latent classes.

5.1 Model performance

We have estimated models with one, two and three latent classes. Table 3 reports maximized log likelihood values along with two model selection criteria, the Bayesian Information Criterion (BIC) and the Consistent Akaike Information Criterion (CAIC). Both have been used and justified in the context of latent class models ([4], [20]). Using either 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.

5.2 Estimates and marginal effects

Table 4 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.

Age has a statistically significant effect overall. When significant (private specialists in latent class 1 and GPs and public specialist in latent class 2), we find that the effect of age (on the probit index) is a quadratic function with an inverted-U shape. 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 SSN specialists. It has a negative sign in the equations for GP, but the estimate is statistically significant only in the second latent class. Finally, income has a significantly positive effect on the probability of seeking care from a private specialist in the first latent class. The effect of education is significant only in the equation for private specialists and for both latent classes: this means that for a given level of income, higher levels of education increase the probability to visit a private specialists[3].

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 5, 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.

[3] - We have also estimated a model without education in order to check if our results are affected by any relationship that could exist between our measure of income (that is obtained from a matching procedure) and education (used as explanatory variable in the matching procedure). The effect of income remains almost unchanged in terms of significance, sign and magnitude.

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.

Women are generally substantially more likely to seek care from all combinations of providers. In general, larger families are less likely to access physician services. Education plays only a minor role in influencing the probabilities of seeking different modes of care. This is particularly true for patients in the second latent class. Large differences exist in terms of effects of the region of residency. In general, compared to individuals who live in the center of Italy, those who live in the South are less likely to receive care from any mode that involves specialists.

Income affects mainly the choice between public and private providers, rather than the overall probability of having a visit. In fact, the latter is almost 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.

5.3 - Income effects on the demand for physician services

If access to the health system depends positively on income, it has been argued ([2]) that this is an indication of the presence of inequality. Moreover, if private and public care are vertically differentiated products (with private care providing either higher quality or having lower monetary costs), 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 2[4].

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, 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

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

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.[5]

5.4 - 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 latent class membership. 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 6.

Health status is the most important indicator of class membership. In particular sicker individuals are more likely to be in latent 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

[5] One should expect similar results for the triplets involving "GP and NHS specialist only" and "NHS specialist only". We find they are similar for patients belonging to the to latent class 1 (the relative risks are almost the same), but opposite behaviours are recorded for patients in latent class 2. We are unable to provide any explanation for this result, although it may simply be a statistically insignificant difference.

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, SSN 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 and can accommodate non-normality of response probabilities.

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. Individuals who might be considered vulnerable from a societal perspective, the sick, elderly, women and those with low incomes, are more likely to be clustered together in the same latent class.

Our findings have two important implications. First, income does not affect access to care in a general sense and this may indicate that the SSN, 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 SSN, there exists a mechanism of self-selection that leads richer individuals to opt out of the SSN system. The reasons for such decisions should be more investigated more thoroughly, as they are of importance for the re-design of the SSN system. Second, because individuals in different classes respond differently to changes in income, 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. Further investigation of class membership and its determinants may be insightful.

REFERENCES

1. 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.
2. Gertham U.-G. and Johannesson Magnus (2000), "Income-Related Inequality in Life-Years and Quality-Adjusted Life-Years", *Journal of Health Economics*, 19, 1007-26.
3. Propper C. (2000), "The demand for private health care in UK", *Journal of Health Economics*, 19, 855-876.
4. 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.
5. Deb P. and P.K. Trivedi (2002), "The structure of demand for health care: Latent class versus Two-part Models", *Journal of Health Economics*, forthcoming.
6. SAS Institute (1997), SAS/IML Software: Changes and Enhancements through Release 6.11, SAS Institute Inc.
7. Heckman, J. J. and B. Singer (1984), "A Method of Minimizing the Distributional Impact in Econometric Models for Duration Data", *Econometrica*, 52, 271-320.
8. Lindsay, B. J. (1995), *Mixture Models: Theory, Geometry, and Applications*, NSF-CBMS Regional Conference Series in Probability and Statistics, Vol. 5, IMS-ASA.
9. McLachlan, G.J., and K.E. Basford (1988), *Mixture Models: Inference and Application to Clustering*, New York: Marcel Dekker.
10. Titterington, D.M., A.F.M. Smith and U.E. Makow (1985), *Statistical Analysis of Finite Mixture Distributions*. New York: John Wiley.
11. 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.
12. Gritz, M. (1993), "The Impact of Training on the Frequency and Duration of Employment", *Journal of Econometrics*, 57, 21-51.
13. Geweke, J. and M. Keane (1997), "Mixture of Normals Probit Models", Federal Reserve Bank of Minneapolis, Staff Report 237.
14. 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.
15. 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.
16. 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.
17. Banca d'Italia (1993) "Indagine sui redditi delle famiglie", Roma
18. ISTAT (1994), "Condizioni di salute e ricorso ai servizi sanitari" in Indagine Multiscopo sulle Famiglie - Anni 1987-91, n.10.

19. 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
20. 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.

Table 1 - Summary statistics

Variable	Mean	Std. dev.	Min	Max
Visit a general practitioner (GP)	0,178	0,383	0,000	1,000
Visit a SSN specialist	0,055	0,228	0,000	1,000
Visit a private specialist	0,060	0,238	0,000	1,000
Age (/10)	4,592	1,807	1,800	9,900
Age squared	24,356	17,902	3,240	98,010
Sex Female	0,518	0,500	0,000	1,000
Family size	3,316	1,334	1,000	10,000
Income (in million liras)	8,264	1,684	5,600	18,243
Years of education of hh	8,422	3,912	0,000	17,000
Chronic condition	0,556	0,978	0,000	10,000
Bad health status	0,077	0,267	0,000	1,000
North	0,439	0,496	0,000	1,000
South	0,362	0,481	0,000	1,000

N= 49.414

Table 2 – Frequencies of Joint Outcomes

Visit a GP	Visit a SSN specialist	Visit a private specialist	Frequency (percent)
No	No	No	74.39
No	No	Yes	4.31
No	Yes	No	3.22
No	Yes	Yes	0.25
Yes	No	No	14.49
Yes	No	Yes	1.32
Yes	Yes	No	1.86
Yes	Yes	Yes	0.15

Table 3 – Model selection results

Model	Log. Lik	No. Param.	BIC	CAIC
1-component degenerate mixture	-40826,95	33	-41005,28	-41021,78
2-component finite mixture	-40454,01	67	-40816,07	-40849,57
3-component finite mixture	-40295,21	101	-40841,01	-40891,51

Table 4
Parameter values and marginal effects

Equations	Variables	Latent class 1			Latent class 2		
		Parameter	t-stat	Marginal	Parameter	t-stat	Marginal
General Practitioners	Constant	-0,7536	-4,5481		-3,7693	-7,9137	
	Age	-0,0418	-0,6830	-0,0114	0,5668	4,1015	0,0458
	Age squared	0,0117	1,5138	0,0032	-0,0248	-2,3966	-0,0020
	Female	0,2580	8,5181	0,0701	0,0722	1,2179	0,0058
	Family size	-0,0374	-2,5780	-0,0102	0,0060	0,1938	0,0005
	Income	-0,0053	-0,4639	-0,0014	-0,0683	-2,2710	-0,0055
	Education years	-0,0068	-1,3886	-0,0019	-0,0015	-0,1351	-0,0001
	Disease	0,8960	13,3725	0,2435	0,1652	6,9086	0,0134
	Bad health status	1,1370	6,5469	0,3090	0,3716	4,4341	0,0300
	North	0,0524	1,2010	0,0142	-0,0986	-1,0378	-0,0080
	South	-0,0944	-1,9437	-0,0256	0,2740	3,0564	0,0222
SSN Specialists	Constant	-1,3495	-6,1596		-2,8117	-6,6539	
	Age	0,0085	0,1141	0,0012	0,2538	1,8122	0,0193
	Age squared	-0,0034	-0,5161	-0,0005	-0,0199	-1,8149	-0,0015
	Female	0,1356	2,7602	0,0195	0,1173	2,1197	0,0089
	Family size	-0,0343	-1,7907	-0,0049	-0,0415	-1,9076	-0,0032
	Income	-0,0141	-0,7728	-0,0020	0,0121	0,6036	0,0009
	Education years	0,0046	0,7572	0,0007	-0,0003	-0,0516	0,0000
	Disease	0,1837	8,7528	0,0265	0,1784	9,8949	0,0136
	Bad health status	0,1950	2,6990	0,0281	0,6239	10,6431	0,0476
	North	-0,0113	-0,2135	-0,0016	0,1878	3,2111	0,0143
	South	-0,0999	-1,6856	-0,0144	-0,0771	-1,0437	-0,0059
Private Specialists	Constant	-2,0504	-9,0873		-1,9039	-10,8127	
	Age	0,1495	2,1216	0,0196	0,0176	0,3454	0,0019
	Age squared	-0,0204	-2,7983	-0,0027	-0,0027	-0,5646	-0,0003
	Female	0,1839	3,6299	0,0242	0,2201	5,6430	0,0236
	Family size	-0,0462	-2,0110	-0,0061	-0,0491	-2,6751	-0,0053
	Income	0,0317	1,7043	0,0042	0,0016	0,1058	0,0002
	Education years	0,0168	2,2463	0,0022	0,0220	3,8431	0,0024
	Disease	0,1223	5,2016	0,0161	0,1171	7,2275	0,0125
	Bad health status	0,1768	2,2242	0,0232	0,3843	7,1807	0,0412
	North	-0,1348	-2,1410	-0,0177	0,0710	1,5005	0,0076
	South	-0,0319	-0,4964	-0,0042	-0,0955	-1,7770	-0,0102
	Π	0,3684	12,3579				

Table 5
Marginal effects of covariates on joint outcomes [(*)]

Outcome								
GP visit	0	0	0	0	1	1	1	1
SSN specialist visit	0	0	1	1	0	0	1	1
Private specialist visit	0	1	0	1	0	1	0	1
Marginal effect	**Panel A - overall**							
Sample average of joint probability	0,743	0,044	0,034	0,003	0,147	0,012	0,017	0,002
Age	-0,048	0,068	0,235	0,333	0,116	0,333	0,176	0,500
Age squared	0,003	-0,023	-0,029	0,000	0,000	0,000	0,000	0,000
Female	-0,070	0,364	0,147	0,667	0,122	0,500	0,294	0,500
Family size	0,013	-0,091	-0,059	0,000	-0,007	-0,083	-0,059	0,000
Income	0,003	0,023	0,000	0,000	-0,027	0,000	-0,059	0,000
Education years	-0,001	0,045	0,000	0,000	-0,007	0,000	0,000	0,000
Disease	-0,144	0,068	0,147	0,333	0,524	0,667	0,647	0,500
Bad health status	-0,233	0,386	0,588	1,000	0,701	1,000	0,882	1,000
North	-0,011	0,000	0,206	0,333	0,014	-0,167	0,059	0,000
South	0,011	-0,136	-0,176	-0,333	0,048	0,000	-0,118	0,000

Panel B – Latent class 1

Marginal effect								
Sample average of joint probability	0,530	0,037	0,037	0,003	0,327	0,026	0,037	0,004
Age	-0,002	0,297	0,027	0,333	-0,055	0,269	-0,027	0,250
Age squared	-0,002	-0,054	0,000	0,000	0,012	-0,038	0,000	0,000
Female	-0,157	0,216	0,108	0,333	0,131	0,500	0,324	0,500
Family size	0,028	-0,054	-0,054	0,000	-0,012	-0,115	-0,081	-0,250
Income	0,000	0,054	-0,027	0,000	-0,006	0,077	-0,027	0,000
Education years	0,000	0,027	0,000	0,000	-0,009	0,038	0,000	0,000
Disease	-0,440	-0,189	-0,108	0,000	0,593	0,769	0,730	0,750
Bad health status	-0,555	-0,216	-0,216	0,000	0,755	1,038	0,865	1,000
North	-0,004	-0,270	-0,027	-0,333	0,061	-0,231	0,027	-0,250
South	0,060	0,000	-0,135	-0,333	-0,043	-0,115	-0,216	-0,250

Panel C – Latent class 2

Marginal effect								
Sample average of joint probability	0,867	0,048	0,032	0,003	0,042	0,004	0,004	0,001
Age	-0,066	-0,063	0,406	0,333	0,881	0,750	1,250	1,000
Age squared	0,003	0,000	-0,031	0,000	-0,048	0,000	0,000	0,000
Female	-0,038	0,417	0,188	0,667	0,071	0,500	0,250	0,000
Family size	0,008	-0,083	-0,063	0,000	0,024	0,000	0,000	0,000
Income	0,005	0,000	0,031	0,000	-0,119	0,000	0,000	0,000
Education years	-0,002	0,042	0,000	0,000	0,000	0,000	0,000	0,000
Disease	-0,039	0,188	0,313	0,333	0,214	0,250	0,500	0,000
Bad health status	-0,118	0,646	1,125	1,667	0,452	1,000	1,500	1,000
North	-0,014	0,125	0,375	0,333	-0,214	0,000	0,250	0,000
South	-0,006	-0,208	-0,188	-0,333	0,476	0,250	0,250	0,000

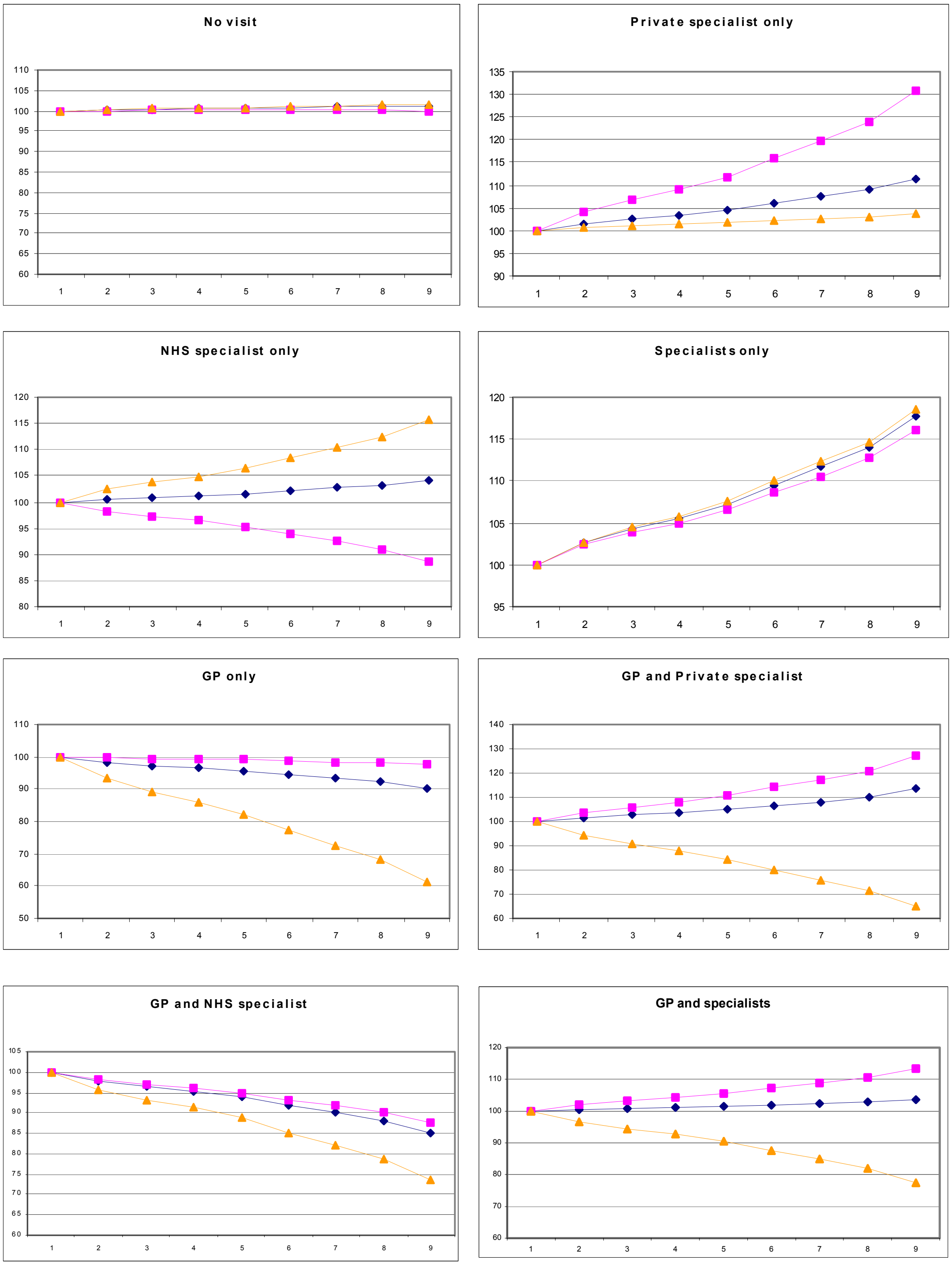
[(*)] Reported marginal effects are scaled such that they are relative to the predicted probability of the joint outcome.

Table 6
Posterior Probability determinants(*) - Probit estimates

Variable	Estimate	t - value
Constant	-1,216	-17,755
Age	0,006	0,290
Age squared	0,008	4,000
Female	0,144	10,464
Family size	-0,022	-3,400
Income	-0,008	-1,472
Education years	-0,006	-2,909
Disease	0,253	33,680
Bad health status	0,315	12,849
North	-0,009	-0,500
South	0,012	0,611

(*) 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.