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Health care utilisation in Europe: new evidence from the ECHP

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Abstract

The ECHP is used to analyse the utilisation of health care in Europe. We estimate a new latent class hurdle model for panel data and compare it with the latent class NegBin model and the standard hurdle model. Latent class specifications outperform the standard hurdle model but the latent class hurdle model reveals income effects on the probability of visiting a doctor that are masked in the NegBin model. For visits to specialist, low users are more income elastic than high users and the probability of using health care is more income elastic than the conditional number of visits.

Keywords: Inequality, inequity, health care utilisation, mixture models, latent class models, hurdle models, panel data, ECHP

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1. INTRODUCTION

This paper models health care utilisation in Europe, making use of a comparable panel data set. We exploit the full length of the European Community Household Panel User Database (ECHP-UDB), covering the period 1994 to 2001. Data from this survey have been used in previous analyses of health care utilisation. In particular, Jimenez-Martin et al (2002) use the first three waves to model specialist and GP visits in 12 European countries; van Doorslaer, Koolman and Puffer (2002) and van Doorslaer, Koolman and Jones (2004) provide cross-country comparisons of socioeconomic inequality and inequity in GP in the use of the same two types of doctor, using data from the third wave. In these studies, cross-section econometric methods are used to model the number of visits. The major contributions of the present study arise from the fact that we are now able to use the full ECHP dataset. Furthermore, we exploit the panel feature of the data and so the possibility to control for individual unobserved heterogeneity. An extension of the latent class panel data hurdle model (Bago d'Uva, 2006) that allows for correlated individual effects is estimated for the number of GP and specialist consultations, using all eight waves of the ECHP for 10 countries. This approach enables the analysis of the determinants of health care in different parts of the distribution of the number visits, as well as for different types of individuals. We show that the new model performs better than standard models and is able to provide different insights into the determinants of health care use.

Many studies of health care use have been motivated by the aim to test for and to measure the extent of horizontal inequity (for example: Gerdtham, 1997; Gerdtham and Trivedi, 2001; van Doorslaer, Koolman and Puffer, 2002; van Doorslaer, Koolman and Jones, 2004; van Ourti, 2004; Morris et al, 2005). The effect of income on health care utilisation, conditional on need factors, is key to the analysis of socioeconomic inequity, either via the computation of income-related inequity indices (van Doorslaer, Koolman and Puffer, 2002, van Doorslaer, Koolman and Jones, 2004, Van Ourti, 2004, Morris et al, 2005), or as a tool to test for inequity in the delivery of health care (this is the approach followed by Gerdtham, 1997, and Abasolo et al, 2001, who interpret the significance of socioeconomic variables, conditional on need, as departures from the null hypothesis of no horizontal inequity). While the direct measurement of inequity is not the purpose of this paper, it is nevertheless relevant to analyse in detail the effects of income, conditional on morbidity indicators and other socioeconomic factors, for different types of individuals and at different stages of the decision process. Using decomposition analysis, van Doorslaer, Koolman and Jones (2004) find that, besides income, education is the most important non-need factor contributing to pro-rich inequity in specialist visits, and that low levels of education provide an even greater contribution to pro-poor inequity in GP visits than income itself. We therefore complement the analysis of income effects by examining the results obtained for education.

Riphahn et al (2003) note the importance of accounting for individual unobserved heterogeneity, as unobserved individual specific characteristics influence health care demand. Amongst those, there can be factors such as attitudes towards health care, preferences, risk aversion, as well as genetic frailty and morbidity. Despite the importance of accounting for individual unobserved heterogeneity using panel data methods, this is seldom done in empirical modelling of health care utilisation. If we restrict our attention to the literature on health care inequity, we find only one exception to the general use of cross-sectional methods: Van Ourti (2004) developed a random effects hurdle model which he used to produce horizontal inequity indices for Belgium.

Cross section analyses often use a hurdle model, which assumes the participation decision and the positive count are generated by separate probability processes. For example, Mullahy (1986) introduced the hurdle specification for Poisson and exponential models, while Pohlmeier and Ulrich (1995) extended it by using a NegBin specification for both stages. The hurdle specification has become the norm in applied studies of health care (see Jones, 2000). Recently, the latent class model has appeared as a promising alternative (Deb and Trivedi, 1997, 2002; Deb and Holmes, 2000, and Gerdtham and Trivedi, 2001).

The latent class and hurdle specifications are brought together by Bago d'Uva (2006) who develops a latent class hurdle model that incorporates the panel feature of the data into the latent class specification. In this paper, we compare Bago d'Uva's latent class hurdle model with the latent class NegBin model (a panel data version of the model proposed by Deb and Trivedi, 1997) and the standard hurdle model. We find that the hurdle specification reveals differences in the effect of income on the probability of use and the conditional number of visits. On the other hand, the latent class framework reveals differences between types of users, especially for the use of specialists. On the whole, for specialist visits, low users are more income elastic than high users and the probability of using health care is more income elastic than the conditional number of visits. For low users the income elasticity of the conditional number of visits is often negative. For high users the elasticities are nearly all positive but smaller in magnitude.

2. THE ECHP-UDB DATASET

The data used in the analysis presented here are taken from the European Community Household Panel User Database (ECHP-UDB). The ECHP was designed and coordinated by the Eurostat, and it was carried out annually between 1994 and 2001 (8 waves). The survey contains socioeconomic, demographic, health and health care utilisation variables, for a panel of individuals aged 16 or older. The data result from a standardised questionnaire, which allows for cross-country comparisons as well as longitudinal analysis. We use data for 10 EU member states: Austria, Belgium, Denmark, Finland, Greece, Ireland, Italy, Netherlands, Portugal, and Spain. Austria joined the survey in 1995 (wave 2) and in Finland it started only in 1996 (wave 3). In the United Kingdom, Luxembourg and Germany, the ECHP was carried out from 1994 to 1997 (waves 1 to 3), after which it was replaced by national panel surveys; data for these three countries are not used in this study.

We analyse health care utilisation over the previous year, represented by the number of visits to a GP and the number of visits to a specialist. These data are available from wave 2 onwards (in wave 1, the information is not detailed by type of doctor). We focus especially on the effects of income on health care utilisation. The ECHP income variable is total net household income. We use this variable deflated by purchasing power parities (PPPs) and national consumer price indices (CPIs), in order to allow for comparability across countries and across waves. The income variable was scaled by the OECD modified equivalence scale in order to account for household size and composition. The variable used in the analysis is the logarithm of equivalised income.

Additionally, we condition on need factors and also on non-need variables other than income. We use two lagged health measures. One is derived from the responses to a question on self-assessed general health status as either very good, good, fair, poor or very poor. We collapse the two lowest categories as the country samples have less than 2% of observations with responses in the category very poor (in some countries even less than 1%), except for Portugal where that proportion is 4%. For Portugal, we further collapse the two best categories, due to a small proportion in the category very good, 4%. We then use dummy variables LSAH good (except for Portugal), LSAH fair and LSAH poor. The other health measure results from the questions "Do you have any chronic physical or mental health problem, illness or disability? (yes/no)" and, if so, "Are you hampered in your daily activities by this physical or mental health problem, illness or disability?". We use a dummy variable to indicate whether the individual is hampered by some health problem, LHampered. Gender and age are represented by the variables: Age, Age^2, a dummy variable for males

(Male), Age$\times$Male and Age$^2\times$Male. Apart from income, the following non-need variables are considered: (i) the highest level of general or higher education completed, i.e. recognised third level education (ISCED 5-7), second stage of secondary level of education (ISCED 3), or less than second stage of secondary education (ISCED 0-2, reference category); (ii) Marital status, distinguishing between married (reference category) and unmarried (including cohabiting); (iii) Activity status includes employed (reference category), self-employed and not working. Additionally, we include time dummies in the analysis. Observations with missing values on the variables used are dropped. The data form an unbalanced panel of individuals observed for up to 5 waves in the case of Finland, 6 waves for Austria and up to 7 waves for the remaining countries.[1]

Tables 1 and 2 contain sample averages, by country and wave, of GP visits and specialist visits. Table 1 shows that there is large variation in the average number of GP visits observed across countries, with the lowest values for Finland and Greece, while Belgium has the highest values (as well as Italy, towards the end of the period, and Austria, especially in the beginning and the end of the observed period). Table 2 shows that the levels of utilisation of specialist care also vary considerably across Europe. Ireland is the country with the lowest average utilisation throughout the observed years, followed by Finland and Denmark which have a similar pattern. Table 3 shows sample averages of equivalised and deflated household income. The countries with the lowest income levels are Portugal and Greece, followed by Spain and Italy. In general, there was an increase in equivalised real income throughout the panel,

[1]For the 8 countries that were part of the ECHP for all 8 waves, we use waves 2 to 8, as detailed utilisation information by type of doctor is not available in wave 1. For these countries, no additional wave is lost when the health variables are lagged, since these are available for every wave. However, the use of lagged health variables means that we need to drop the first available waves for Austria and Finland.

especially for Ireland (29%), Spain (22%) and Portugal (31%).

Insert Tables 1 to 3 here

3. ECONOMETRIC MODELS

This paper exploits the possibility to control for individual unobserved heterogeneity that is offered by the panel data dimension of the ECHP. We adopt a latent class (or finite mixture) approach for modelling individual effects. Individuals are assumed to be drawn from a finite number classes, which, in the context of panel data, means that the individual effects are approximated by a distribution with a finite number of mass points. In empirical analyses of health care utilisation, this framework has been more commonly applied to cross-sectional data. Deb and Trivedi (1997) propose a count data finite mixture model in which, conditional on the latent class the individual belongs to, the count measure of health care use is distributed according to a NegBin model. Deb and Trivedi (2002) argue that the latent classes can be regarded as types, or groups, of individuals, where the segmentation represents individual unobserved characteristics. Other applications of the cross-section finite mixture NegBin model to count measures of health care use include: Deb and Holmes (2000), Gerdtham and Trivedi (2001) and Jimenez-Martin et al (2002). In Atella et al (2004), the latent class approach is used in the development of a joint model for the decisions of consulting three types of physician. It is assumed that, within each latent class, the decisions regarding health care follows three independent probits. Therefore, conditional on the class the individual belongs to, the joint density of the three binary outcomes is a product of probit densities. Deb (2001) makes use of the latent class methodology to develop a discrete random effects probit. In this model, the distribution of the random intercept is approximated by a discrete density, relaxing the usual normality assumption. This model is then applied to a cross-section of individuals, where the random effect represents unobserved family effects. It is therefore assumed that every individual in each family belong to the same latent class. The goal of that paper is to approximate the distribution of the random (family) intercepts, and so the model allows only for the constant term to vary across latent classes (intercept heterogeneity), whereas slope heterogeneity is not considered.

The latent class approach for modelling unobserved heterogeneity has been applied extensively in other fields, especially using cross-sectional rather than panel data (e.g. Wang et al, 1998; Wedel et al, 1993; Nagin et al, 1993; Uebersax, 1999). Greene (2001) argues however the latent class model is "only weakly identified at very best by a cross-section". In recent years, some latent class panel data models have been proposed, such as: a dynamic random effects bivariate probit model model for smoking behaviour of couples, with a discrete approximation for the individual effects (Clark and Etilé, 2003); a latent class ordered probit model for reported well-being, with individual time invariant heterogeneity both in the intercept and in the income effect (Clark et al, 2005); a latent class hurdle model for count measures of health care use that allows for a two-part decision process within each the class, as well as intercept and slope heterogeneity in both parts (Bago d'Uva, 2006). In this paper, we use the latent class hurdle model, extending it further to allow the probabilities of class membership to depend on time invariant individual characteristics.

Consider individuals i observed T_i times, where T_i can take values up to 7 for eight of the ten countries considered here, while in the cases of Finland and Austria, the maximum number of observed periods is 5 and 6, respectively. Let y_{it} represent the number of visits in year t. Denote the observations of the dependent variable over the panel as $y_i = [y_{i1}, \ldots, y_{iT_i}]$. We assume that each individual i belongs to a latent class j, $j = 1, \ldots, C$, and that individuals are heterogeneous across classes. The probability of belonging to class j is π_{ij}, where $0 < \pi_{ij} < 1$ and $\sum_{j=1}^{C} \pi_{ij} = 1$. Conditional on the class that individual i belongs to, the number of visits in a given year t,

y_{it}, is distributed according to $f_j\left(y_{it}|x_{it},\theta_j\right)$ and the θ_j are vectors of parameters specific to each class. Assuming independence, conditional on the latent class j, the joint density of y_{it} over the observed periods is obtained from the product of T_i independent densities $f_j\left(y_{it}|x_{it},\theta_j\right)$. The unconditional (on the latent class) joint density of $y_i = [y_{i1},\ldots,y_{iT_i}]$ derives from averaging out the individual unobserved heterogeneity represented by the latent classes:

$$g\left(y_i|x_i;\pi_{i1},\ldots,\pi_C;\theta_1,\ldots,\theta_C\right)=\sum_{j=1}^{C}\pi_{ij}\prod_{t=1}^{T_i}f_j\left(y_{it}|x_{it},\theta_j\right). \tag{1}$$

where x_i is a vector of covariates, including a constant, and θ_j are vectors of parameters.

Following Bago d'Uva (2006), the class-specific density of the number of visits in a given year, $f_j\left(y_{it}|x_{it},\theta_j\right)$, is defined as in the standard hurdle model, using a Negative Binomial as the parent distribution in both stages. Formally, for each component j, $j=1,\ldots,C$, the probability of zero visits and the probability of observing y_{it} visits, given $y_{it}>0$, are given by:

$$\begin{aligned} f_j\left(0|x_{it};\theta_{j1}\right) &= P\left[y_{it}=0|x_{it},\theta_{j1}\right]=\left(\lambda_{j1,it}^{1-k}+1\right)^{-\lambda_{j1,it}^{k}} \\ f_j\left(y_{it}|y_{it}>0,x_{it};\theta_{j2}\right) &= \frac{\Gamma\left(y+\frac{\lambda_{j2,it}^{k}}{\alpha_j}\right)\left(\alpha_j\lambda_{j2,it}^{1-k}+1\right)^{-\frac{\lambda_{j2,it}^{k}}{\alpha_j}}\left(1+\frac{\lambda_{j2,it}^{k-1}}{\alpha_j}\right)^{-y_{i,t}}}{\Gamma\left(\frac{\lambda_{j2,it}^{k}}{\alpha_j}\right)\Gamma\left(y_{it}+1\right)\left[1-\left(\alpha_j\lambda_{j2,it}^{1-k}+1\right)^{-\frac{\lambda_{j2,it}^{k}}{\alpha_j}}\right]}, \end{aligned} \tag{2}$$

where $\lambda_{j1,it}=\exp\left(x_{it}'\beta_{j1}\right)$, $\lambda_{j2,it}=\exp\left(x_{it}'\beta_{j2}\right)$, α_j are overdispersion parameters and k is an an arbitrary constant (most commonly set equal to 1 or 0, corresponding to the NegBin1 and NegBin2 models, respectively; we use the NegBin2 model). So, in this case, $\theta_j=\left(\beta_{j1},\beta_{j2},\alpha_j\right)$. As in the standard hurdle model, having $\beta_{j1}\neq\beta_{j2}$ means that the zeros and the positives are determined by two different processes. In other words, the determinants of care are allowed to have different effects on the two stages of the decision process regarding the number of visits to the doctor: i) the probability of seeking care and ii) the number of visits, given that this is positive. On the other hand, having $\theta_j \neq \theta_l$ when $j \neq l$ reflects differences between the latent classes. The same set of regressors x_{it} is considered in both parts of the model and across classes. Regarding the variation between classes, it can be assumed that all the slopes are the same, considering only intercept heterogeneity (i.e., variation in β_{j10} and β_{j20}). This represents a case where there is unobserved individual heterogeneity but not in the responses to the covariates (as in the model used in Deb, 2001). In the most flexible version of the latent class model, all elements of θ_j are allowed to vary across classes. This is the specification that we use here. Setting $\beta_{j1} = \beta_{j2}$ for some classes, corresponds to a finite mixture of some sub-populations with health care use is determined a NegBin (no distinction between the two decision processes) and others for which utilisation is determined by a hurdle model. If $\beta_{j1} = \beta_{j2}$ for all classes, then we have a latent class NegBin for panel data. It should be noted that this specification differs from the one proposed by Deb and Trivedi (1997) and used in Deb and Trivedi (2002), Deb and Holmes (2000), Gerdtham and Trivedi (2001) and Jimenez-Martin et al (2002), in that it accounts for the panel structure of the data. In the remainder of this paper, the label LC NegBin corresponds to the latent class NegBin for panel data. The original cross-section version of the LC NegBin is not considered here since it was shown to perform substantially worse than the panel data version, according to information criteria, in Bago d'Uva (2006).

Most empirical applications of latent class models to health care utilisation take class membership probabilities as parameters $\pi_{ij} = \pi_j, j = 1, \ldots, C$ to be estimated along with $\theta_1, \ldots, \theta_C$ (Deb and Trivedi, 1997 and 2002; Deb and Holmes, 2000; Deb, 2001; Jimenez et al; 2002, Atella et al, 2004). This is analogous to the hypothesis that individual heterogeneity is uncorrelated with the regressors in a random effects or random parameters specification. A more general approach is to parameterise the heterogeneity as a function of time invariant individual characteristics z_i, as in Mundlak (1978), thus accounting for the possible correlation between observed regressors and unobserved effects. This has been done in recent studies that consider continuous distributions for the individual effects, mostly by setting $z_i = \bar{x}_i$. To implement this approach in the case of the latent class model, class membership can be modelled as a multinomial logit (as in, for example, Clark and Etilé, 2003; Clark et al, 2005; Bago d'Uva, 2005):

$$\pi_{ij} = \frac{\exp\left(z_i'\gamma_j\right)}{\sum_{g=1}^{C} \exp\left(z_i'\gamma_g\right)}, \quad j = 1, \ldots, C, \tag{3}$$

with $\gamma_C = 0$. This specification makes it possible to uncover the determinants of class membership (more commonly done by means of posterior analysis). The vectors of parameters $\theta_1, \ldots, \theta_C$, $\gamma_1, \ldots, \gamma_{C-1}$ are estimated jointly by maximum likelihood.

The latent class framework offers a flexible way to model unobserved individual effects, in that no distribution is assumed. It can also be seen as a discrete approximation of an underlying continuous mixing distribution (Heckman and Singer, 1984). The number of points of support needed for the finite mixture model is low, usually two or three. We further allow for correlation between individual heterogeneity and the covariates. The conventional fixed effects count data models (Poisson and NegBin) also offer a distribution-free approach to the individual heterogeneity that is robust to correlation between covariates and individual effects. However, these account only for intercept heterogeneity and not for slope heterogeneity.

All estimation is done by maximum likelihood in TSP 4.5 (Hall and Cummins, 1999), using the Newton method for the models with one component and the Broyden-Fletcher-Goldfarb-Shanno (BFGS) quasi-Newton algorithm for the latent class models.[2] In order to avoid false (local) maxima, we repeat the estimation of latent class models using a number of different sets of starting values. These starting values are obtained either from the estimates of the one component version of the model or from

[2] The TSP code and equivalent code for Stata v.9 are available from the authors.

restricted versions of the latent class model (for example, with constant slopes across classes, or with constant class membership across individuals).

4. RESULTS

We estimate standard (pooled) hurdle and panel data LC hurdle models for specialist and GP visits, separately for each country. The standard hurdle model corresponds to a (degenerate) LC model with only one component, in which the panel structure of the data is not accounted for. Most applications of the latent class framework to health care counts have shown that the two-component model is sufficiently flexible. Additionally, it would be difficult to identify all the parameters of the class-specific hurdle model for a larger number of components. The LC hurdle model is therefore defined with 2 latent classes, $C = 2$ in equation (1). Deb and Holmes (2000) who also restrict the analysis to two latent classes, argue that their results support the existence of at least two groups. The underlying distribution in both stages, for all models, is a NegBin2, i.e. with $k = 0$ in equation (2). We also estimate a LC Negbin, in which the conditional distribution within each latent class is a NegBin2, instead of a hurdle model. In the LC NegBin, conditional on the latent class, the zeros and the positives are assumed to be determined by the same process. In both LC models, the class membership probabilities are defined as functions of time invariant individual characteristics, z_i, as in equation (3). In particular, $z_i = \bar{x}_i$, i.e, the average of the covariates over the observed panel. In the models with two latent classes, we assume class membership to be determined according to a logit model. Furthermore, all the coefficients (including overdispersion parameters) are allowed to vary across classes.

For each country and type of doctor, we compare the pooled hurdle, the LC NegBin and the LC hurdle according to the maximised log-likelihood and Schwarz information criterion (BIC). The BIC favours the LC hurdle model over the pooled hurdle in all cases, and the LC hurdle over the LC NegBin in all cases but two. Log-likelihood ratio tests of equality of the parameters in the two stages, always favour the LC hurdle over the LC NegBin. We then present the estimated effects of income and education on health care utilisation, conditional on the latent class, for the preferred model. It should be borne in mind that, in spite of the focus on the results for income and education, we are also controlling for morbidity (as measured by the two health variables considered), age and gender, marital status, economic activity status. For two countries – Portugal and Spain – we further compare the elasticities of income as estimated by the pooled hurdle, the LC NegBin and the LC hurdle.

GP visits

Table 4 provides a comparison between the three specifications according to the maximised log-likelihood and the BIC. Let us first compare the pooled hurdle with the LC Hurdle.[3] The panel data LC hurdle provides a considerable improvement in fit, it outperforms the cross-section hurdle, even when the additional number of parameters and the sample size is penalised by the BIC. These results give support to the existence of unobserved time-invariant individual heterogeneity for all countries analysed here. As is often the case with the Deb and Trivedi (1997) cross-section LC NegBin, the panel data version used here outperforms the standard hurdle model, but the combination of the hurdle model with a latent class specification leads to a further improvement. The comparison between the LC NegBin and the LC hurdle shows the importance of considering that, conditional on each latent class, the number of GP visits is determined by two different processes. The BIC again favours the most

[3] In the estimation of the LC hurdle for Portugal and Greece, the overdispersion parameter α_j in the class of low users is set equal to zero, since, in the estimation of the most flexible version of the model, that parameter comes very close to zero. Therefore, for those two countries, the LC hurdle corresponds to a mixture of a hurdle model composed by a logit and a truncated Negbin, for high users, and a hurdle model composed by a logit and a truncated Poisson, for low users.

flexible specification. We have also performed log-likelihood ratio tests of equality of parameters across the two parts, for both latent classes, and this hypothesis was clearly rejected in all cases (for all countries, $p - value < 0.001$).

Insert Table 4 here

Before analysing in more detail the estimation results of the LC hurdle model, we present the predicted use of health care for the two latent classes identified by the LC hurdle model, decomposed into the probability of having at least one GP visit and the conditional positive number of visits (Table 5). It can be seen that, across countries, the latent classes differ considerably both in terms of average probability of visiting a GP and in the expected conditional number of visits. We refer to the latent classes as 'high' and 'low' users. This classification makes intuitive sense as, for each country, the predicted probability of use and the predicted conditional number of visits are both larger for one of the classes, thus referred to as the class of 'high' users. This is an ex-post interpretation, rather than a classification imposed a priori. The latent classes differ consistently more in the conditional number of visits (ranging from 109% in Greece to 175% in Austria), than in the average probability of visiting a GP (from 23% in Austria to 64% in Finland). This is unsurprising, since the average probability that a low user visits a GP is larger than 0.5 for all countries, except for Greece (0.464). The class of high users is always predicted to have an average total number of visits which is at least 3 times larger than the class of low users (from 1:3.06 in Greece to 1:3.9 in Ireland).

Insert Table 5 here

The LC hurdle model that we estimate here allows for all the regressors to have different coefficients across latent classes in the two parts of the hurdle. We analyse in detail the estimated income effects on the utilisation of health care and how income might play a different role for high and low users both in the initial decision to visit a doctor and in the number of visits. In Table 6 we present the estimated coefficients of Log(Income), conditional on the remaining regressors and on the latent class. The estimated coefficients for the probability of visiting a GP are positive for most cases (for 6 countries, they are positive in both classes, and for 3 countries they are positive in one class), indicating that richer individuals tend to be more likely to visit a GP. These positive effects are statistically significant for low users in Belgium, Denmark and Italy, for high users in Ireland and the Netherlands and for both classes in Portugal. None of the estimated negative effects on the probability of visiting a GP is found to be statistically significant. The second part of the model shows very different results, with mostly negative results, indicative of a higher expected number of GP visits, conditional on the initial contact, for poorer individuals. The coefficients are negative in most cases, being statistically significant for both classes in Belgium, Ireland, Italy and Spain and the high users in the Netherlands. The estimated income effect on the conditional number of visits is only significantly positive in the case of high users in Austria and low users in Portugal. Only Portugal exhibits income effects of the same sign across parts and classes, these are all positive and statistically significant, except for the second part for high users. For three countries, the estimated effects are significant in only one part of the model: positive in the first part for Denmark (significant for high users); positive in the second part for Austria (significant for high users); for Greece, positive in second part only for high users and, for Spain, negative and significant in second part for both classes. For four countries there is evidence of positive income effects on the probability of visiting a GP and negative effects on the conditional positive number of visits: for Belgium and Italy, the income effect on the probability is positive and significant for high users, being negative and significant in the second part for both classes; for Ireland and the Netherlands, the effect on the probability is positive and significant for low users, whereas it is negative in the second part for both classes (insignificant only for low users in the Netherlands).

Insert Table 6 here

As we pointed out above, the estimated income effects differ across latent classes, in both parts. In most cases, the estimated effects are of the same sign for both classes, although it can be seen that these vary in magnitude and statistical significance. In order to better assess the magnitude of the income effects, as well as the differences between classes, we turn to the estimated income elasticities, given in Table 7. In most cases, the income elasticity of the probability of visiting a GP is larger in the class of low users, although this does not always reflect the significance of the respective income coefficients. Looking at the figures that correspond to significant coefficients (in bold) for the probability of visiting a GP, we can see that, for Ireland, the Netherlands and Portugal, the elasticity is larger in the class of low users. For Belgium and Italy, the elasticities in the first part are larger for high users. Finally, for Denmark, this elasticity is slightly larger for high users, whilst the corresponding coefficient is more significant for low users. The relationship between the two classes with respect to the income elasticities of the conditional number of visits is even more heterogeneous across countries: the income elasticity is larger, in absolute value, for low users in Ireland, Italy, Spain (negative), and Portugal (positive); for high users in Austria, Greece (positive) the Netherlands and Belgium (negative). Comparing the magnitudes across countries, Portugal shows the highest positive income elasticities for both latent classes in the first part and for the low users, in the second part. Portugal also shows the highest positive income elasticities of the total number of visits (sum of the elasticities of the two parts), for both classes.

Insert Table 7 here

We extend the analysis of socioeconomic effects on health care use by looking at the results for the education variables. Table 8 contains the estimated coefficients and Table 9 shows the resulting average effects on the probability of visiting a GP and on the expected number of subsequent visits, for high and low users of primary care. The results are not always in accordance with the results for income, in the sense that we do not always see a positive (negative) education gradient where there is a positive (negative) income effect. Only for Ireland and the Netherlands, are the results broadly in line with the income results, with a positive gradient in the probability of seeking primary care and a negative gradient in the expected positive number of visits. In general, there appears to be more evidence of a negative socioeconomic gradient by education than there is for income. In particular for Portugal, where the results indicate that richer individuals are more likely to visit a GP and, amongst the low users, income also affects the conditional number of visits positively, the education gradient is mostly negative (the exception is a positive effect of ISCED 3 on the probability of visiting a GP for high users).

Insert Tables 8 and 9 here

We define class membership probabilities in the latent class models as functions of the averages of the covariates across the panel, as specified in equation (3). In particular, in a model with two latent classes, the probability that an individual belongs to the class of high users is determined by a logit model (estimated within the LC model). Since class membership is time invariant in this model and the covariates considered are averages across the panel, the estimated coefficients represent a long-term associations with the probability of being a high user. This differs from the meaning of the coefficients in the class-conditional distribution of the number of visits, that represent short-term effects. The estimation results for this part of the model are presented in Table 10. For all countries, the most important correlate of being a high user is poor health, measured by the two morbidity variables considered. Age and gender also play an important role for most countries. In the case of Belgium only, class membership is associated solely to the health indicators, age and gender, while no significant association is found with the socioeconomics variables considered here. For Austria and Denmark, a positive effect is found for income, and, for Greece, there is a negative effect of having completed the second stage of secondary level of education (ISCED 3). In all other cases, marital status and economic activity also play an important role. For Italy and Spain there is an evidence of a positive education gradient and, in Finland and Portugal, a positive effect is found only for the secondary stage of secondary level of education (ISCED 3) but not for the third level (ISCED 5-7). The estimated effects of being self-employed and out of the work force are mostly negative, as is the effect of not being married. As to income, which here represents a long-term association with the probability of being a high user, we find positive and significant coefficients for Austria, Denmark, Finland and Portugal and negative and significant coefficients for Italy and Spain.

Insert Table 10 here

To illustrate the impact of the different model specifications for the implications of the empirical results, Table 11 presents a comparison of the income elasticities obtained with the hurdle model, LC NegBin and LC hurdle for Portugal and Spain. For Portugal, the hurdle model estimates a positive and significant income effect in the first part of the model. The LC hurdle allows for the effects to be different across latent classes. This leads to a positive and significant income elasticity in the first stage, which is larger for the low users of primary care. The LC Hurdle further identifies a positive effect of income in the second stage, significant only for low users.

Consequently, the total elasticity is larger for low users. The LC NegBin estimates a positive income effect for low users and a negative effect for high users, none of which are significant. For Spain, the hurdle model results in significantly negative effects in both parts. In the LC hurdle, the estimated effects in the first part are not significant, whilst the ones in the second part are negative and significant, especially for low users. The resulting negative income elasticity of the total number of GP visits is larger (in absolute value) for low users. The LC NegBin estimates negative and significant income effects for both latent classes. Similarly to the LC hurdle, the LC NegBin estimates a larger (in absolute value) income elasticity for low users, but the difference is larger in the LC hurdle. This seems to be due to the fact that this model captures better the differences between the two classes in the second part, whilst class-specific effects in the LC NegBin are driven by income coefficients that are constrained to be the same in the probability of seeking medical care and in the decision regarding subsequent visits.

Insert Table 11 here

Specialist visits

The maximised log-likelihood and the BIC for the hurdle model, the LC NegBin and the LC hurdle are shown in Table 12.[4]. Within the hurdle specification, it can be seen

[4] The estimation of the LC hurdle with the full samples of Belgium, the Netherlands, Ireland and Denmark returned implausibly large estimates of one α. Abnormal $\alpha^{\text{'s}}$ have been seen in the literature, for example, in a hurdle models for hospital stays (Gerdtham, 1997, and Gerdtham and Trivedi, 2001), in a LC NegBin model for hospital outpatient visits (Deb and Trivedi, 1997) and Jimenez-Martin et al (2002) in hurdle models for specialist visits. The anomalous $\alpha^{\text{'s}}$ in the LC hurdle models for the Netherlands, Ireland and Denmark are avoided here by dropping individuals that do not visit a specialist during the observed panel except for one wave in which they report at least monthly visits, on average (66 Dutch individuals, 13 Irish and 26 Danish). For Belgium, we

that accounting for the panel structure of the data by means of the LC hurdle leads to a considerable improvement in fit, for nearly all countries. The Schwarz information criterion (BIC) favours the LC hurdle over the hurdle model, even penalising for the inclusion of additional parameters. The importance of allowing for a hurdle process in the latent class framework can be assessed by comparing the LC NegBin and the LC hurdle. The BIC favours the LC hurdle over the LC NegBin for all countries, except for Ireland and Denmark.[5] This is reinforced by the fact that in log-likelihood ratio tests of equality of parameters in both stages, for both classes, the null hypothesis was consistently rejected ($p - value < 0.001$ for all countries).

Insert Table 12 here

The averages of predicted utilisation, decomposed into the probability of visiting a specialist at least once and the conditional number of visits, are shown in Table 13, for both latent classes. The differences between latent classes are evident. The ratio of the average probability that a high user visits a specialist and that of a low user ranges between 1:1.95 (Greece) and 1:4.50 (Ireland). On the other hand, the average predicted number of specialist visits for the high users, given that it is positive, is between 1:1.69 (Finland) and 1:2.54 (Greece) larger than the average number predicted for the low users. The relative differences between high and low users are larger for the probability of visiting a specialist than for the conditional number of visits, except for Austria and Greece. The class of high users is always predicted to have an average total number of specialist visits which is at least 4 times larger than the one in the class of low users (ranging from 1:4.50 for Austria to 1:7.80 for Ireland).

had to resort to further dropping 17 individuals (39 in total) that reported more than 12 visits in one wave, one visit in another and no visits in the remaining periods.

[5] However, the Akaike information criterion (AIC), which penalises the number of parameters less heavily, clearly favours the LC Hurdle over the LC NegBin for all countries.

Insert Table 13 here

We now look in detail at the income effects, conditional on remaining covariates, as estimated by the LC hurdle model (Table 14). The hurdle feature of the model reveals differences in the role of income in the two stages of the decision process, especially for those in the class of low users of specialist care. The coefficients of income in the probability of seeking specialist care are all positive, except for the insignificantly negative coefficient for high users in the Netherlands. For the remaining countries, the income coefficient in the probability is significantly positive for both classes, except for Belgium and Denmark (insignificant for both class), and for Finland (significant only for low users). Regarding the decision of how many times to visit a specialist, given that there is at least one visit, for high users, the income effects are mostly positive, being significant only for Austria, Greece and Portugal. None of the negative coefficients in the conditional positive number of visits in the class of high users is significant. The estimated income coefficients in the second stage for low users are quite different. These are negative and significant for Finland, Italy, Netherlands, Portugal and Spain. They are only positive, albeit nonsignificant, for Austria, Greece and Ireland.

Insert Table 14 here

Let us now turn to the comparison of the estimated income elasticities across latent classes for both parts (Table 15). The estimated income effects on the probability of seeking specialist care are positive in almost all cases. These effects translate into positive elasticities that are larger for low users than for high users, across countries. Except Finland in the case of low users, the countries with the largest income elasticities of the probability of visiting a specialist are Ireland (amongst high users) and

Portugal (amongst low users). As to the income elasticities of the conditional positive number of visits, reflecting the sign of the estimated coefficients, these are mostly positive for high users and negative for low users. For low users, the larger elasticities (in absolute value) of the expected positive number of visits are found for the Netherlands and Finland. Austria and Greece show the highest positive elasticities amongst high users of specialist care. The income elasticities of the total number of specialist visits (sum of the elasticities in both parts) are positive in all cases, except for the Netherlands and Belgium, in both classes, and Denmark, in the high users class. For 6 of the 7 countries with positive income elasticities of the total number of visits, that value is larger in the class of low users, the exception being Spain, where it is slightly larger for high users. In the Netherlands, the (negative) elasticity is larger in absolute value for low users. Finally, for Belgium, the estimated negative elasticity is slightly larger in absolute value for high users, but these result from insignificant income coefficients. The largest income elasticities of the expected (total) number of specialist visits are obtained for Ireland (for low users, 0.179; for high users, 0.088), Portugal (low users, 0.152; high users, 0.127), Greece (low users; 0.138, high users, 0.115) and Austria (low users, 0.116; high users, 0.10).

Insert Table 15 here

We now examine the extent to which the level of education completed is associated with the decisions regarding the use of specialist care, namely, how the effects of higher education levels compare with those of higher income. Tables 16 and 17 report the education coefficients and average effects, respectively. The results obtained for Austria, Ireland, Italy and Spain are broadly in accordance with the ones obtained for income, with positive/negative education gradients coinciding with positive/negative income. This is also the case for Portugal, except in the second stage for low users, where the negative effect of income is in line with a negative effect of education at lower levels (ISCED 3) but not at the highest level. In the cases of Belgium and Denmark, where none of the individual income coefficients is significant, we find some significant education effects: for Belgium, a positive effect of having completed the third level of education (ISCED 5-7) appears in the probability of seeking a specialist; for Denmark a negative gradient appears in the positive number of visits for low users. For Finland, a stronger socioeconomic gradient is found in terms of education than in terms of income, with individuals who achieved higher educational levels having a higher probability of seeking a specialist and a higher expected number of subsequent visits, across classes. Consequently, Finland now comes close to Austria amongst the countries with highest education effects, while Portugal is still the country where more education increases the probability of visiting a specialist the most.

Insert Tables 16 and 17 here

Table 18 presents the results of the logit model for the probability of being a high user, within the LC hurdle for specialist visits. For most countries, class membership is especially associated with indicators of morbidity, and age and gender are also significant determinants. There is evidence of a positive education gradient in the probability of being a high user, for all countries, except Italy and Portugal, for which the association between more education and being a high user is evident only at the level ISCED 3. Similarly to the model for GPs, self-employed individuals, those out of the work force and not married are more likely to be low users. Long-term richer individuals are consistently more likely to be high users.

Insert Table 18 here

The extent to which the standard hurdle, the LCNegBin and the LC hurdle tell different stories, in particular, regarding the way in which specialist care use is responsive to income, is assessed in Table 19 for two examples, Portugal and Spain. In the case of Spain, the estimation of the standard hurdle model returns a positive and significant impact of income on both stages. The LC hurdle model further estimates that the income elasticity on the first stage is greater for low users of specialist care. For low users, the income elasticity in the second part is estimated to be negative, whereas it is not significant for high users. The estimated income elasticity of the total number of visits for low users is estimated to be slightly lower than the one for high users. The LC NegBin estimates a positive income elasticity for both classes of users, which is slightly larger for low users. Since the LC NegBin does not allow for a two part decision process, it does not reveal a negative effect of income on the second part, for low users, as the LC hurdle does. On the other hand, for high users, the LC Negbin estimates a greater income elasticity in the second part, unlike the LC hurdle. The above comparisons between the three models for Spain also apply for Portugal, except that the income elasticity of the total number of visits is estimated to be greater for low users than for high users in the LC hurdle and the opposite in the LC Negbin.

Insert Table 19 here

5. CONCLUSION

We use a comparable panel data set to model GP and specialist visits in Europe. The panel feature of the data is taken into account by means of a latent class framework. The newly developed latent class hurdle model outperforms the standard hurdle model and a panel version of the latent class NegBin model on statistical criteria for most countries and for both measures of utilisation. The latent classes can be interpreted in terms of low and high users and parameterising the probability of class membership shows that it is mostly associated with measures of health, although socioeconomic factors such as education and income play a role as well. For each latent class, we examine in detail the effects of income and education, controlling for need and other socioeconomic factors. Both of the latent class specifications outperform the standard hurdle model. Furthermore, the latent class hurdle reveals differences in the effect of income on the probability of use and the conditional number of visits that are masked in the latent class NegBin model. On the other hand, the latent class framework reveals differences between types of users, especially for the use of specialists. On the whole, for specialist visits, low users are more income elastic than high users and the probability of using health care is more income elastic than the conditional number of visits. For low users the income elasticity of the conditional number of visits is often negative. For high users the elasticities are nearly all positive but smaller in magnitude. Differences on the effects of health care determinants such as income, not only across classes of users, but also in the different parts of the decision process regarding utilisation of health care, cannot be revealed with the LC NegBin model.

In accordance with the analysis of income-related inequity in van Doorslaer, Koolman and Jones (2004), the effects of income on the use of primary care obtained here are mostly negative or insignificant. However, positive income elasticities of the total number of GP visits are found here for Portugal for both classes of users (especially in the probability of initial contact and for low users), and Austria and Greece for high users (with income determining positively the frequency of visits once the decision to visits a GP has been taken). To the extent that the highest level of education attained is positively correlated with income, the education results tell a different story for those three countries: with the exception of the initial contact stage in the case of high users, negative education gradients are found.

For almost all countries in the analysis, richer individuals are expected to use more specialist care, conditional on need and other non-need factors. Considering the individuals in the class of low users, income elasticity of the total number of visits is highest for Ireland, followed by Portugal, which were the countries with highest indices of horizontal inequity in specialist visits in van Doorslaer, Koolman and Jones (2004), with Ireland second to Portugal. In this paper, we find that Greece and Austria have higher income elasticities than Ireland for high users, with Portugal on top of the list. Analysis of the education effects confirms Austria and Portugal as countries with comparatively high evidence of socioeconomic inequity in specialist visits, along with Finland, where stronger socioeconomic gradients are found by education than by income.

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Table 1: Average number of GP visits in previous year

	95	96	97	98	99	00	01
Austria		5.17	4.55	4.76	4.58	4.76	4.83
Belgium	4.95	4.95	4.80	5.04	4.99	4.95	4.85
Denmark	2.83	2.89	2.86	3.10	2.77	2.71	2.99
Finland			2.12	2.08	2.11	2.12	2.05
Greece	2.22	2.25	2.35	2.11	2.02	2.18	1.94
Ireland	3.53	3.44	3.58	3.69	3.65	3.54	3.58
Italy	3.93	4.29	4.63	4.49	4.67	4.65	4.68
Netherlands	2.86	2.75	2.77	2.91	2.86	2.85	2.83
Portugal	3.09	3.21	3.15	3.23	3.18	3.11	2.99
Spain	3.94	3.63	4.45	3.89	3.73	3.60	4.13

Table 2: Average number of specialist visits in previous year

	95	96	97	98	99	00	01
Austria		2.60	2.09	2.07	2.09	2.15	2.11
Belgium	1.90	1.92	1.93	2.07	1.99	2.02	2.05
Denmark	0.86	0.98	0.98	1.06	1.03	1.02	1.07
Finland			1.02	1.03	1.04	1.08	1.05
Greece	1.66	1.66	1.91	1.66	1.73	1.80	1.75
Ireland	0.67	0.62	0.68	0.66	0.67	0.66	0.68
Italy	1.09	1.21	1.41	1.29	1.31	1.29	1.33
Netherlands	1.76	1.66	1.51	1.67	1.62	1.69	1.66
Portugal	1.03	1.21	1.22	1.26	1.29	1.34	1.26
Spain	1.70	1.50	1.69	1.62	1.57	1.60	1.70

Table 3: Average equivalised annual household income (real terms, common currency)

	95	96	97	98	99	00	01
Austria		13872	13348	13359	13861	13975	13671
Belgium	14683	14560	14526	14769	15649	15744	16012
Denmark	13655	11290	13712	14099	14243	14270	14454
Finland			11790	12024	12319	12384	12715
Greece	7028	7039	7252	7582	7651	7914	7987
Ireland	11259	11421	11967	12627	13337	13510	14526
Italy	9949	9941	9836	10291	10559	10667	10829
Netherlands	12736	12826	12968	13098	13393	13211	13388
Portugal	6345	6666	6934	7307	7670	7888	8342
Spain	8367	8551	8660	8953	9567	9909	10189

Table 4: Comparison of models for GP visits

	Hurdle		LC NegBin		LC Hurdle	
Country	LogL	BIC	LogL	BIC	LogL	BIC
Austria	-84610.0	169605.9	-81597.4	163733.3	-81280.9	163477.2
Belgium	-85071.9	170542.4	-81385.3	163319.8	-81051.9	163042.7
Denmark	-58803.6	117999.6	-56765.7	114072.0	-56529.9	113914.3
Finland	-52943.6	106256.9	-51287.1	103097.2	-51088.7	103061.1
Greece	-111658.0	223743.1	-110753.0	222094.4	-108677.0	218360.0
Ireland	-77216.5	154838.6	-74468.2	149495.3	-74200.9	149357.3
Italy	-245796.0	492037.6	-238287.0	477188.0	-237225.0	475499.7
Netherlands	-115387.0	231196.5	-111246.2	223074.5	-111000.0	222995.1
Portugal	-149261.0	298950.1	-144568.3	289726.4	-143235.1	287478.6
Spain	-200121.0	400684.5	-195404.5	391418.6	-194877.0	390796.3

Table 5: Average number of GP visits and decomposition by parts for each latent class

	Low users			High users		
Country	P(Y>0)	E(Y|Y>0)	E(Y)	P(Y>0)	E(Y|Y>0)	E(Y)
Austria	0.775	2.926	2.311	0.956	8.049	7.747
Belgium	0.768	2.841	2.248	0.965	7.681	7.432
Denmark	0.598	2.009	1.266	0.912	4.995	4.616
Finland	0.555	1.813	1.024	0.908	3.843	3.505
Greece	0.464	2.219	1.144	0.716	4.636	3.503
Ireland	0.607	2.328	1.489	0.891	6.403	5.808
Italy	0.683	3.112	2.315	0.908	7.714	7.184
Netherlands	0.568	2.066	1.217	0.906	4.881	4.482
Portugal	0.532	2.439	1.400	0.853	5.433	4.777
Spain	0.573	2.745	1.669	0.854	6.872	5.968

Table 6: Estimated income coefficients in latent class hurdle models for GP visits

Country		Low users		High users	
Austria	P(Y>0)	-0.051	(-1.467)	-0.109	(-0.872)
	E(Y|Y>0)	0.012	(0.693)	**0.039**	(2.167)
Belgium	P(Y>0)	0.035	(1.002)	**0.292**	(4.004)
	E(Y|Y>0)	**-0.052**	(-3.125)	**-0.055**	(-4.030)
Denmark	P(Y>0)	0.083	(1.746)	**0.261**	(2.302)
	E(Y|Y>0)	0.042	(0.992)	-0.030	(-1.009)
Finland	P(Y>0)	0.054	(1.358)	-0.030	(-0.263)
	E(Y|Y>0)	0.007	(0.237)	-0.048	(-1.706)
Greece	P(Y>0)	0.012	(0.565)	0.015	(0.447)
	E(Y|Y>0)	-0.024	(-1.864)	**0.026**	(1.967)
Ireland	P(Y>0)	**0.164**	(4.754)	0.026	(0.339)
	E(Y|Y>0)	**-0.095**	(-3.865)	**-0.049**	(-2.528)
Italy	P(Y>0)	-0.001	(-0.054)	**0.116**	(3.766)
	E(Y|Y>0)	**-0.044**	(-4.944)	**-0.024**	(-2.691)
Netherlands	P(Y>0)	**0.082**	(2.897)	0.094	(1.739)
	E(Y|Y>0)	-0.037	(-1.484)	**-0.085**	(-5.446)
Portugal	P(Y>0)	**0.223**	(10.888)	**0.243**	(8.070)
	E(Y|Y>0)	**0.027**	(2.302)	0.001	(0.078)
Spain	P(Y>0)	-0.015	(-0.997)	0.037	(1.261)
	E(Y|Y>0)	**-0.053**	(-4.401)	**-0.025**	(-2.324)

Notes: t-statistics in parentheses. Bold indicates significance at 5%.

Table 7: Estimated income elasticities in latent class hurdle models for GP visits

Country		Low users	High users
Austria	P(Y>0)	-0.012	-0.005
	E(Y|Y>0)	0.009	**0.035**
Belgium	P(Y>0)	0.008	**0.010**
	E(Y|Y>0)	**-0.037**	**-0.050**
Denmark	P(Y>0)	0.033	**0.023**
	E(Y|Y>0)	0.021	-0.024
Finland	P(Y>0)	0.024	-0.003
	E(Y|Y>0)	0.004	-0.037
Greece	P(Y>0)	0.006	0.004
	E(Y|Y>0)	-0.015	**0.020**
Ireland	P(Y>0)	**0.064**	0.003
	E(Y|Y>0)	**-0.057**	**-0.043**
Italy	P(Y>0)	0.000	**0.011**
	E(Y|Y>0)	-0.031	**-0.021**
Netherlands	P(Y>0)	**0.035**	0.009
	E(Y|Y>0)	-0.019	**-0.068**
Portugal	P(Y>0)	**0.104**	**0.036**
	E(Y|Y>0)	**0.018**	0.001
Spain	P(Y>0)	-0.006	0.005
	E(Y|Y>0)	**-0.034**	**-0.021**

Note: The figures in boldface correspond to significant (at 5%) coefficients in the LC hurdle.

Table 8: Estimated education coefficients in latent class hurdle models for GP visits

Country			Low users		High users	
Austria	P(Y>0)	ISCED 5-7	**-0.371**	(-4.526)	0.468	(1.591)
		ISCED 3	**-0.132**	(-2.956)	**0.384**	(2.968)
	E(Y|Y>0)	ISCED 5-7	**-0.179**	(-3.819)	**-0.128**	(-2.493)
		ISCED 3	**-0.062**	(-2.760)	0.002	(0.079)
Belgium	P(Y>0)	ISCED 5-7	**-0.255**	(-5.103)	0.232	(1.449)
		ISCED 3	0.069	(1.498)	-0.100	(-0.777)
	E(Y|Y>0)	ISCED 5-7	**-0.142**	(-5.193)	**-0.223**	(-10.167)
		ISCED 3	-0.017	(-0.721)	**-0.074**	(-4.261)
Denmark	P(Y>0)	ISCED 5-7	**0.151**	(2.366)	**0.476**	(3.791)
		ISCED 3	**0.163**	(2.916)	**0.241**	(2.316)
	E(Y|Y>0)	ISCED 5-7	-0.098	(-1.706)	**-0.129**	(-3.781)
		ISCED 3	-0.051	(-1.028)	-0.035	(-1.251)
Finland	P(Y>0)	ISCED 5-7	**-0.132**	(-2.165)	0.207	(1.541)
		ISCED 3	0.001	(0.022)	0.181	(1.659)
	E(Y|Y>0)	ISCED 5-7	0.029	(0.593)	**-0.232**	(-6.583)
		ISCED 3	-0.019	(-0.446)	**-0.141**	(-4.936)
Greece	P(Y>0)	ISCED 5-7	**-0.269**	(-5.513)	0.050	(0.586)
		ISCED 3	-0.059	(-1.783)	-0.007	(-0.112)
	E(Y|Y>0)	ISCED 5-7	**-0.066**	(-2.053)	**-0.311**	(-7.279)
		ISCED 3	-0.044	(-1.934)	-0.001	(-0.034)
Ireland	P(Y>0)	ISCED 5-7	0.103	(1.795)	**0.624**	(4.534)
		ISCED 3	**0.092**	(2.346)	0.133	(1.429)
	E(Y|Y>0)	ISCED 5-7	**-0.098**	(-2.138)	**-0.162**	(-4.183)
		ISCED 3	**-0.106**	(-3.319)	**-0.077**	(-3.147)
Italy	P(Y>0)	ISCED 5-7	**-0.642**	(-13.259)	0.033	(0.359)
		ISCED 3	-0.039	(-1.575)	0.048	(0.892)
	E(Y|Y>0)	ISCED 5-7	**-0.302**	(-9.22)	**-0.376**	(-14.896)
		ISCED 3	**-0.101**	(-6.501)	**-0.109**	(-7.090)
Netherlands	P(Y>0)	ISCED 5-7	0.070	(1.232)	**0.270**	(2.074)
		ISCED 3	**0.104**	(2.354)	**0.211**	(2.281)
	E(Y|Y>0)	ISCED 5-7	-0.055	(-1.006)	**-0.147**	(-4.448)
		ISCED 3	-0.071	(-1.740)	0.010	(0.443)
Portugal	P(Y>0)	ISCED 5-7	**-0.455**	(-6.726)	0.117	(1.048)
		ISCED 3	-0.044	(-0.966)	**0.234**	(3.244)
	E(Y|Y>0)	ISCED 5-7	**-0.241**	(-5.427)	**-0.216**	(-6.036)
		ISCED 3	**-0.180**	(-5.765)	**-0.069**	(-2.728)
Spain	P(Y>0)	ISCED 5-7	**-0.314**	(-8.809)	0.042	(0.626)
		ISCED 3	**-0.081**	(-2.754)	-0.005	(-0.077)
	E(Y|Y>0)	ISCED 5-7	**-0.243**	(-8.107)	**-0.283**	(-10.519)
		ISCED 3	**-0.157**	(-6.286)	**-0.089**	(-3.709)

Notes: t-statistics in parentheses. Bold indicates significance at 5%.

Table 9: Estimated average effects of education in latent class hurdle models for GP visits

Country			Low users	High users
Austria	P(Y>0)	ISCED 5-7	**-0.066**	0.020
		ISCED 3	**-0.022**	**0.017**
	E(Y|Y>0)	ISCED 5-7	**-0.378**	**-0.896**
		ISCED 3	**-0.139**	0.012
Belgium	P(Y>0)	ISCED 5-7	**-0.045**	0.007
		ISCED 3	0.011	-0.004
	E(Y|Y>0)	ISCED 5-7	**-0.290**	**-1.535**
		ISCED 3	-0.036	**-0.554**
Denmark	P(Y>0)	ISCED 5-7	**0.034**	**0.037**
		ISCED 3	**0.036**	**0.021**
	E(Y|Y>0)	ISCED 5-7	-0.105	**-0.514**
		ISCED 3	-0.056	-0.147
Finland	P(Y>0)	ISCED 5-7	**-0.032**	0.017
		ISCED 3	0.000	0.015
	E(Y|Y>0)	ISCED 5-7	0.027	**-0.703**
		ISCED 3	-0.017	**-0.448**
Greece	P(Y>0)	ISCED 5-7	**-0.053**	0.009
		ISCED 3	-0.012	-0.001
	E(Y|Y>0)	ISCED 5-7	**-0.094**	**-1.038**
		ISCED 3	-0.065	-0.004
Ireland	P(Y>0)	ISCED 5-7	0.023	**0.051**
		ISCED 3	**0.020**	0.013
	E(Y|Y>0)	ISCED 5-7	**-0.144**	**-0.873**
		ISCED 3	**-0.154**	**-0.436**
Italy	P(Y>0)	ISCED 5-7	**-0.132**	0.003
		ISCED 3	-0.007	0.004
	E(Y|Y>0)	ISCED 5-7	**-0.633**	**-2.282**
		ISCED 3	**-0.237**	**-0.756**
Netherlands	P(Y>0)	ISCED 5-7	0.016	**0.021**
		ISCED 3	**0.024**	**0.017**
	E(Y|Y>0)	ISCED 5-7	-0.061	**-0.553**
		ISCED 3	-0.079	0.043
Portugal	P(Y>0)	ISCED 5-7	**-0.102**	0.013
		ISCED 3	-0.010	**0.026**
	E(Y|Y>0)	ISCED 5-7	**-0.372**	**-0.945**
		ISCED 3	**-0.287**	**-0.324**
Spain	P(Y>0)	ISCED 5-7	**-0.074**	0.005
		ISCED 3	**-0.019**	-0.001
	E(Y|Y>0)	ISCED 5-7	**-0.427**	**-1.529**
		ISCED 3	**-0.288**	**-0.529**

Note: The figures in boldface correspond to significant (at 5%) coefficients in the LC hurdle.

Table 10: Estimation results of logit model for probability of being a high user in the model for GP visits

Variable	Austria		Belgium		Denmark		Finland		Greece		Ireland		Italy		Netherlands		Portugal		Spain	
Constant	**-4.014**	(-4.404)	-0.568	(-0.648)	**-4.682**	(-3.636)	**-3.496**	(-3.203)	-0.639	(-0.934)	1.763	(1.817)	**-0.621**	(-1.986)	**-1.681**	(-2.167)	0.739	(1.442)	0.444	(0.776)
Age	0.017	(0.867)	**-0.057**	(-2.994)	0.041	(1.877)	-0.019	(-0.836)	**-0.039**	(-2.15)	-0.038	(-1.880)	-0.012	(-1.009)	0.004	(0.230)	**-0.111**	(-8.256)	**-0.051**	(-3.084)
Age^2	0.000	(-0.696)	**0.001**	(3.445)	0.000	(-1.459)	0.000	(0.743)	**0.000**	(2.315)	0.000	(1.359)	0.000	(-1.872)	0.000	(-0.038)	**0.001**	(6.222)	**0.000**	(2.583)
Male	0.684	(1.156)	**-1.646**	(-2.683)	1.014	(1.545)	-0.199	(-0.277)	-0.259	(-0.427)	-1.087	(-1.928)	0.070	(0.197)	1.090	(1.904)	**-1.552**	(-3.571)	-0.310	(-0.600)
Male×Age	-0.039	(-1.542)	**0.066**	(2.532)	-0.052	(-1.835)	0.026	(0.867)	0.011	(0.477)	-0.001	(-0.037)	-0.008	(-0.487)	**-0.055**	(-2.162)	**0.046**	(2.478)	-0.012	(-0.533)
Male×Age^2	0.000	(1.592)	**-0.001**	(-2.763)	0.000	(1.767)	0.000	(-1.441)	0.000	(-0.550)	0.000	(0.726)	0.000	(1.208)	0.000	(1.739)	0.000	(-1.751)	0.000	(1.109)
LSAH good	**1.061**	(7.955)	**0.938**	(7.380)	**1.044**	(7.663)	**0.944**	(6.007)	**0.906**	(6.517)	**0.819**	(6.799)	**0.960**	(10.122)	**1.377**	(11.178)	-	-	**1.132**	(8.839)
LSAH fair	**2.397**	(13.790)	**2.171**	(13.672)	**1.525**	(7.927)	**1.840**	(9.517)	**2.279**	(12.917)	**2.917**	(14.097)	**2.020**	(19.332)	**3.124**	(19.194)	**1.819**	(17.306)	**3.256**	(21.121)
LSAH poor	**3.270**	(11.488)	**2.828**	(9.463)	**1.247**	(3.991)	**2.544**	(7.992)	**2.637**	(10.008)	**5.865**	(5.152)	**3.250**	(18.906)	**3.185**	(10.860)	**3.568**	(21.482)	**3.631**	(14.654)
LHampered	**0.847**	(5.195)	**0.840**	(5.484)	**0.823**	(4.521)	**1.151**	(8.328)	**1.121**	(5.773)	**1.647**	(7.744)	**1.190**	(8.755)	**0.425**	(3.213)	**0.663**	(5.127)	**1.340**	(7.245)
ISCED 5-7	0.031	(0.161)	0.001	(0.007)	-0.163	(-1.155)	0.107	(0.793)	0.199	(1.330)	0.238	(1.576)	**0.783**	(7.769)	-0.149	(-0.910)	0.102	(0.666)	**0.270**	(2.654)
ISCED 3	-0.020	(-0.212)	-0.133	(-1.300)	-0.065	(-0.527)	**0.287**	(2.407)	**-0.277**	(-2.438)	0.006	(0.056)	**0.274**	(4.352)	-0.126	(-1.203)	0.229	(2.087)	0.064	(0.656)
Self-employed	-0.243	(-1.402)	-0.005	(-0.030)	-0.197	(-0.941)	**-0.641**	(-3.806)	-0.240	(-1.727)	**-0.527**	(-3.106)	**-0.315**	(-3.549)	-0.155	(-0.713)	0.130	(1.239)	**-0.348**	(-2.809)
Not working	-0.039	(-0.338)	-0.067	(-0.609)	-0.051	(-0.363)	**-0.563**	(-4.362)	-0.064	(-0.491)	**-0.549**	(-4.571)	0.084	(1.251)	**-0.450**	(-4.885)	**-0.407**	(-4.683)	-0.125	(-1.404)
Not married	-0.064	(-0.648)	0.002	(0.020)	-0.147	(-1.348)	-0.185	(-1.672)	-0.195	(-1.858)	**-0.356**	(-3.171)	**-0.252**	(-3.707)	**-0.259**	(-2.924)	**-0.304**	(-4.042)	-0.071	(-0.863)
Log(Income)	**0.184**	(2.102)	0.039	(0.498)	**0.288**	(2.277)	**0.252**	(2.348)	-0.019	(-0.299)	-0.158	(-1.740)	**-0.176**	(-4.084)	0.009	(0.129)	**0.128**	(2.576)	**-0.126**	(-2.544)
$\overline{\pi}$	0.359		0.432		0.428		0.398		0.330		0.403		0.391		0.440		0.551		0.431	

Notes: t-statistics in parentheses. Bold indicates significance at 5%. Variables are individual averages over the observed panel.

Table 11: Comparison of estimated income elasticities for GP visits

		Hurdle	LC NegBin		LC Hurdle	
			Low	High	Low	High
Portugal	P(Y>0)	**0.069**	0.016	-0.002	**0.104**	**0.036**
	E(Y|Y>0)	-0.005	0.020	-0.008	**0.018**	0.001
	E(Y)	**0.063**	0.036	-0.010	**0.122**	**0.036**
Spain	P(Y>0)	**-0.010**	**-0.014**	**-0.004**	-0.006	0.005
	E(Y|Y>0)	**-0.044**	**-0.019**	**-0.020**	**-0.034**	**-0.021**
	E(Y)	**-0.053**	**-0.033**	**-0.024**	**-0.041**	**-0.016**

Note: The figures in boldface correspond to significant (at 5%) coefficients in the respective models.

Table 12: Comparison of models for specialist visits

	Hurdle		LC NegBin		LC Hurdle	
Country	LogL	BIC	LogL	BIC	LogL	BIC
Austria	-61254.1	122893.8	-59657.4	119852.8	-59006.9	118928.4
Belgium	-58583.0	117564.3	-56756.4	114061.6	-56215.5	113369.2
Denmark	-32293.7	64979.6	-31400.6	63341.5	-31247.5	63418.8
Finland	-35858.5	72086.7	-34951.2	70425.4	-34423.2	69730.1
Greece	-97487.9	195399.3	-95900	192383.5	-94567.4	190132.5
Ireland	-31141.1	62687.7	-30031.2	60621.1	-29876.0	60707.2
Italy	-139773.0	279991.6	-135648.0	271909.9	-134631.0	270311.7
Netherlands	-80407.1	161236.4	-77579.9	155741.5	-77117.9	155230.3
Portugal	-94797.3	190022.1	-91489.5	183568.0	-90620.8	182248.6
Spain	-134550.0	269542.5	-131339.8	263289.2	-130555.0	262152.3

Table 13: Average number of specialist visits and decomposition by parts for each latent class

	Low users			High users		
Country	P(Y>0)	E(Y|Y>0)	E(Y)	P(Y>0)	E(Y|Y>0)	E(Y)
Austria	0.423	1.774	0.753	0.860	3.911	3.393
Belgium	0.330	2.261	0.766	0.820	4.223	3.501
Denmark	0.163	1.922	0.327	0.576	3.837	2.264
Finland	0.234	1.730	0.410	0.758	2.917	2.209
Greece	0.304	2.065	0.678	0.593	5.240	3.186
Ireland	0.120	1.917	0.238	0.539	3.404	1.856
Italy	0.228	1.830	0.440	0.665	3.552	2.402
Netherlands	0.225	2.424	0.571	0.706	4.806	3.445
Portugal	0.216	2.006	0.449	0.666	3.604	2.472
Spain	0.280	2.191	0.630	0.699	4.414	3.116

Table 14: Estimated income coefficients in latent class hurdle models for specialist visits

Country		Low users		High users	
Austria	P(Y>0)	**0.191**	(3.743)	**0.211**	(3.556)
	E(Y|Y>0)	0.014	(0.210)	**0.105**	(3.858)
Belgium	P(Y>0)	0.054	(1.399)	0.079	(1.348)
	E(Y|Y>0)	-0.112	(-1.611)	-0.049	(-1.920)
Denmark	P(Y>0)	0.053	(0.738)	0.079	(1.123)
	E(Y|Y>0)	-0.053	(-0.434)	-0.082	(-1.120)
Finland	P(Y>0)	**0.203**	(3.525)	0.167	(1.909)
	E(Y|Y>0)	**-0.229**	(-2.985)	0.025	(0.487)
Greece	P(Y>0)	**0.184**	(7.641)	**0.148**	(5.413)
	E(Y|Y>0)	0.017	(0.878)	**0.067**	(4.192)
Ireland	P(Y>0)	**0.172**	(3.274)	**0.313**	(4.367)
	E(Y|Y>0)	0.063	(0.738)	-0.091	(-1.838)
Italy	P(Y>0)	**0.136**	(6.251)	**0.190**	(7.918)
	E(Y|Y>0)	**-0.084**	(-2.787)	0.000	(-0.026)
Netherlands	P(Y>0)	**0.071**	(2.085)	-0.055	(-1.084)
	E(Y|Y>0)	**-0.250**	(-4.377)	-0.008	(-0.299)
Portugal	P(Y>0)	**0.252**	(9.190)	**0.295**	(9.454)
	E(Y|Y>0)	**-0.087**	(-3.292)	**0.041**	(2.340)
Spain	P(Y>0)	**0.112**	(5.680)	**0.138**	(5.189)
	E(Y|Y>0)	**-0.070**	(-2.460)	0.017	(1.026)

Notes: t-statistics in parentheses. Bold indicates significance at 5%.

Table 15: Estimated income elasticities in latent class hurdle models for specialist visits

Country		Low users	High users
Austria	P(Y>0)	**0.110**	**0.030**
	E(Y|Y>0)	0.006	**0.070**
Belgium	P(Y>0)	0.036	0.014
	E(Y|Y>0)	-0.052	-0.035
Denmark	P(Y>0)	0.045	0.034
	E(Y|Y>0)	-0.022	-0.050
Finland	P(Y>0)	**0.155**	0.041
	E(Y|Y>0)	**-0.090**	0.014
Greece	P(Y>0)	**0.128**	**0.060**
	E(Y|Y>0)	0.010	**0.055**
Ireland	P(Y>0)	**0.152**	**0.144**
	E(Y|Y>0)	0.027	-0.057
Italy	P(Y>0)	**0.105**	**0.063**
	E(Y|Y>0)	**-0.035**	0.000
Netherlands	P(Y>0)	**0.055**	-0.016
	E(Y|Y>0)	**-0.129**	-0.006
Portugal	P(Y>0)	**0.198**	**0.099**
	E(Y|Y>0)	**-0.045**	**0.028**
Spain	P(Y>0)	**0.080**	**0.042**
	E(Y|Y>0)	**-0.033**	0.012

Note: The figures in boldface correspond to significant (at 5%) coefficients in the LC hurdle.

Table 16: Estimated education coefficients in latent class hurdle models for specialist visits

Country			Low users		High users	
Áustria	P(Y>0)	ISCED 5-7	**0.400**	(3.072)	**0.678**	(3.806)
		ISCED 3	0.036	(0.594)	**0.211**	(2.465)
	E(Y|Y>0)	ISCED 5-7	0.163	(0.979)	**0.243**	(3.916)
		ISCED 3	0.001	(0.007)	**0.091**	(2.576)
Belgium	P(Y>0)	ISCED 5-7	**0.148**	(2.585)	**0.254**	(2.675)
		ISCED 3	0.012	(0.247)	0.139	(1.678)
	E(Y|Y>0)	ISCED 5-7	0.002	(0.020)	-0.020	(-0.510)
		ISCED 3	-0.068	(-0.814)	0.011	(0.301)
Denmark	P(Y>0)	ISCED 5-7	0.121	(1.361)	-0.094	(-0.992)
		ISCED 3	0.100	(1.454)	-0.051	(-0.599)
	E(Y|Y>0)	ISCED 5-7	**-0.410**	(-2.667)	-0.130	(-1.603)
		ISCED 3	-0.033	(-0.287)	0.059	(0.780)
Finland	P(Y>0)	ISCED 5-7	**0.459**	(6.008)	**0.475**	(4.347)
		ISCED 3	**0.241**	(3.808)	**0.305**	(3.166)
	E(Y|Y>0)	ISCED 5-7	**0.227**	(2.081)	**0.175**	(3.013)
		ISCED 3	0.106	(1.113)	0.032	(0.589)
Greece	P(Y>0)	ISCED 5-7	0.095	(1.833)	0.094	(1.493)
		ISCED 3	**0.097**	(2.345)	**0.149**	(3.024)
	E(Y|Y>0)	ISCED 5-7	**-0.117**	(-2.409)	0.047	(1.184)
		ISCED 3	-0.067	(-1.900)	**-0.060**	(-2.078)
Ireland	P(Y>0)	ISCED 5-7	**0.374**	(3.738)	0.134	(1.227)
		ISCED 3	**0.160**	(4.194)	**0.297**	(3.316)
	E(Y|Y>0)	ISCED 5-7	-0.078	(-0.498)	0.067	(0.772)
		ISCED 3	0.092	(0.890)	0.012	(0.193)
Italy	P(Y>0)	ISCED 5-7	**0.357**	(4.913)	**0.237**	(3.779)
		ISCED 3	**0.161**	(4.040)	**0.235**	(6.787)
	E(Y|Y>0)	ISCED 5-7	-0.055	(-1.234)	-0.033	(-0.366)
		ISCED 3	-0.015	(-0.580)	-0.025	(-0.452)
Netherlands	P(Y>0)	ISCED 5-7	0.042	(0.623)	0.199	(1.941)
		ISCED 3	0.084	(1.644)	0.086	(1.056)
	E(Y|Y>0)	ISCED 5-7	-0.128	(-1.124)	0.076	(1.403)
		ISCED 3	-0.007	(-0.080)	**0.137**	(3.337)
Portugal	P(Y>0)	ISCED 5-7	**0.890**	(10.592)	**0.693**	(5.703)
		ISCED 3	**0.342**	(5.152)	**0.348**	(5.105)
	E(Y|Y>0)	ISCED 5-7	**0.175**	(2.136)	**0.245**	(4.645)
		ISCED 3	**-0.173**	(-2.157)	0.024	(0.626)
Spain	P(Y>0)	ISCED 5-7	**0.195**	(4.762)	**0.242**	(3.959)
		ISCED 3	**0.193**	(5.248)	**0.157**	(2.844)
	E(Y|Y>0)	ISCED 5-7	**-0.289**	(-4.246)	-0.031	(-0.864)
		ISCED 3	**-0.240**	(-3.805)	0.018	(0.530)

Notes: t-statistics in parentheses. Bold indicates significance at 5%.

Table 17: Estimated average effects of education in latent class hurdle models for specialist visits

Country			Low users	High users
Austria	P(Y>0)	ISCED 5-7	**0.091**	**0.068**
		ISCED 3	0.008	**0.025**
	E(Y|Y>0)	ISCED 5-7	0.125	**0.696**
		ISCED 3	0.000	**0.243**
Belgium	P(Y>0)	ISCED 5-7	**0.032**	**0.035**
		ISCED 3	0.002	0.020
	E(Y|Y>0)	ISCED 5-7	0.002	-0.061
		ISCED 3	-0.072	0.032
Denmark	P(Y>0)	ISCED 5-7	0.016	-0.022
		ISCED 3	0.013	-0.012
	E(Y|Y>0)	ISCED 5-7	**-0.314**	-0.299
		ISCED 3	-0.029	0.146
Finland	P(Y>0)	ISCED 5-7	**0.079**	**0.084**
		ISCED 3	**0.039**	**0.056**
	E(Y|Y>0)	ISCED 5-7	**0.160**	**0.313**
		ISCED 3	0.071	0.054
Greece	P(Y>0)	ISCED 5-7	0.017	0.021
		ISCED 3	**0.018**	**0.033**
	E(Y|Y>0)	ISCED 5-7	**-0.142**	0.207
		ISCED 3	-0.084	**-0.254**
Ireland	P(Y>0)	ISCED 5-7	**0.041**	0.031
		ISCED 3	**0.016**	**0.069**
	E(Y|Y>0)	ISCED 5-7	-0.062	0.147
		ISCED 3	0.080	0.026
Italy	P(Y>0)	ISCED 5-7	**0.040**	**0.071**
		ISCED 3	**0.040**	**0.033**
	E(Y|Y>0)	ISCED 5-7	-0.026	-0.126
		ISCED 3	-0.020	-0.035
Netherlands	P(Y>0)	ISCED 5-7	0.007	0.037
		ISCED 3	0.014	0.016
	E(Y|Y>0)	ISCED 5-7	-0.157	0.272
		ISCED 3	-0.009	**0.505**
Portugal	P(Y>0)	ISCED 5-7	**0.165**	**0.126**
		ISCED 3	**0.057**	**0.067**
	E(Y|Y>0)	ISCED 5-7	**0.206**	**0.693**
		ISCED 3	**-0.169**	0.060
Spain	P(Y>0)	ISCED 5-7	**0.038**	**0.047**
		ISCED 3	**0.038**	**0.031**
	E(Y|Y>0)	ISCED 5-7	**-0.292**	-0.097
		ISCED 3	**-0.247**	0.059

Note: The figures in boldface correspond to significant (at 5%) coefficients in the LC hurdle.

Table 18: Estimation results of logit model for probability of being a high user in the model for specialist visits

Variable	Austria		Belgium		Denmark		Finland		Greece		Ireland		Italy		Netherlands		Portugal		Spain	
Constant	**-3.732**	(-3.720)	**-6.209**	(-5.508)	**-12.217**	(-6.817)	**-12.395**	(-8.857)	**-2.028**	(-2.940)	**-7.854**	(-5.909)	**-3.528**	(-8.864)	**-5.787**	(-6.416)	**-7.254**	(-11.328)	**-6.902**	(-9.975)
Age	**-0.059**	(-2.661)	-0.005	(-0.216)	0.017	(0.557)	0.024	(0.825)	**-0.090**	(-4.968)	0.045	(1.602)	**0.033**	(2.173)	-0.024	(-1.353)	**-0.037**	(-2.287)	0.004	(0.208)
Age^2	0.000	(1.160)	0.000	(0.097)	0.000	(-0.770)	0.000	(-1.077)	**0.000**	(2.204)	-0.001	(-2.190)	**-0.001**	(-4.113)	0.000	(1.574)	0.000	(0.177)	0.000	(-2.110)
Male	**-2.272**	(-3.062)	-1.615	(-1.860)	**2.816**	(2.861)	-0.132	(-0.151)	**-3.288**	(-5.248)	-0.883	(-0.894)	-0.817	(-1.797)	0.533	(0.811)	**-1.556**	(-3.089)	**-1.586**	(-2.471)
Male×Age	0.032	(1.020)	0.026	(0.747)	**-0.128**	(-3.148)	-0.049	(-1.297)	**0.073**	(2.836)	**0.003**	(0.079)	-0.002	(-0.083)	-0.052	(-1.947)	0.021	(1.005)	0.028	(1.020)
$Male \times Age^2$	0.000	(-0.143)	0.000	(-0.144)	**0.001**	(2.992)	0.001	(1.483)	0.000	(-1.600)	**0.000**	(0.407)	**0.000**	(1.133)	**0.001**	(2.639)	0.000	(0.038)	0.000	(-0.277)
LSAH good	**0.728**	(5.618)	**0.545**	(3.902)	**1.070**	(6.264)	0.222	(1.459)	**1.167**	(7.866)	**0.986**	(5.905)	**0.847**	(7.228)	**0.903**	(6.113)	-	-	**0.707**	(4.784)
LSAH fair	**1.338**	(7.525)	**1.756**	(10.339)	**1.042**	(4.493)	**0.599**	(3.141)	**3.427**	(15.906)	**2.099**	(9.498)	**1.962**	(15.493)	**1.888**	(11.122)	**1.439**	(13.019)	**3.056**	(17.614)
LSAH poor	**1.890**	(7.116)	**2.750**	(8.664)	**1.443**	(4.422)	**0.745**	(2.577)	**4.051**	(11.867)	**1.955**	(5.637)	**3.340**	(16.799)	**2.547**	(9.214)	**1.787**	(10.444)	**3.721**	(16.300)
LHampered	**0.759**	(4.477)	**0.674**	(4.214)	**1.250**	(6.073)	**1.411**	(9.502)	**2.688**	(10.300)	**1.489**	(7.463)	**1.475**	(10.021)	**1.393**	(11.174)	**1.193**	(8.579)	**1.224**	(7.756)
ISCED 5-7	**0.919**	(4.456)	**0.693**	(5.615)	**1.049**	(5.642)	**0.308**	(2.240)	**0.432**	(3.214)	**0.351**	(1.672)	0.228	(1.919)	0.145	(0.860)	-0.196	(-1.031)	**0.471**	(4.288)
ISCED 3	**0.598**	(5.551)	**0.361**	(3.161)	**0.697**	(4.461)	0.054	(0.427)	0.214	(1.875)	0.125	(0.846)	**0.300**	(4.093)	0.121	(1.069)	**0.270**	(2.187)	**0.367**	(3.290)
Self-employed	**-0.530**	(-2.651)	-0.085	(-0.461)	-0.046	(-0.150)	-0.275	(-1.715)	0.057	(0.431)	**-0.582**	(-2.425)	-0.079	(-0.785)	-0.181	(-0.779)	0.098	(0.863)	-0.195	(-1.357)
Not working	0.115	(0.919)	0.078	(0.619)	0.214	(1.229)	-0.214	(-1.590)	-0.123	(-1.015)	**-0.705**	(-4.291)	0.115	(1.457)	**-0.340**	(-3.371)	**-0.279**	(-2.858)	-0.049	(-0.508)
Not married	**-0.485**	(-4.470)	**-0.208**	(-2.033)	0.042	(0.324)	-0.167	(-1.429)	**-0.966**	(-8.137)	-0.238	(-1.363)	-0.017	(-0.208)	0.004	(0.042)	**-0.348**	(-3.948)	**-0.357**	(-3.876)
Log(Income)	**0.543**	(5.596)	**0.533**	(5.380)	**1.035**	(6.071)	**1.193**	(9.197)	**0.412**	(5.882)	**0.588**	(4.881)	**0.707**	(13.346)	**0.460**	(5.398)	**0.870**	(14.152)	**0.620**	(9.675)
$\overline{\pi}$	0.482		0.397		0.315		0.320		0.353		0.234		0.377		0.322		0.338		0.346	

Note: t-statistics in parentheses. Bold indicates significance at 5%. Variables are individual averages over the observed panel.

Table 19: Comparison of estimated income elasticities for Specialist visits

		Hurdle	LC NegBin		LC Hurdle	
			Low	High	Low	High
Portugal	P(Y>0)	**0.299**	**0.041**	**0.035**	**0.198**	**0.099**
	E(Y|Y>0)	**0.055**	**0.036**	**0.075**	**-0.045**	**0.028**
	E(Y)	**0.354**	**0.077**	**0.110**	**0.152**	**0.127**
Spain	P(Y>0)	**0.125**	**0.018**	**0.008**	**0.080**	**0.042**
	E(Y|Y>0)	**0.029**	**0.017**	**0.025**	**-0.033**	0.012
	E(Y)	**0.155**	**0.035**	**0.033**	0.047	**0.054**

Note: The figures in boldface correspond to significant (at 5%) coefficients in the respective models.