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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 health care utilisation 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 and the latent class hurdle model reveals income effects that are masked in the NegBin model. For specialist visits, low users are more income elastic than high users and the probability of using care is more income elastic than the conditional number of visits. The effects of income on total use of GPs are mostly negative or insignificant but positive elasticities are found for Austria, Greece and, to a greater extent, Portugal. On the whole, richer individuals tend to use more specialist care, especially in Portugal, Ireland, Finland, Greece and Austria. Features of the health care systems of these countries may contribute to the observed inequities.

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

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1. INTRODUCTION

European countries have over recent decades pursued a goal of universal coverage for physician services. In principle, appropriate health care should be available to all in need of it, either publicly provided at low or zero cost, or through private insurance plans for the better-off that are capable of affording such coverage. The goal of ensuring that utilisation of health care should depend only upon the need for such care has long been pursued in Europe. However, barriers to access still persist that may contribute to different levels of utilisation for individuals with equal need, depending on socioeconomic factors such as income or education. Health care systems in European countries differ substantially regarding aspects that may influence the extent to which health care utilisation is associated with socioeconomic characteristics, given the need for such care, such as: user charges in the public sector; the importance of the private sector; payment systems for doctors, which in some cases may create incentives to provide more extensive treatment to the better-off. For example, the existence of a large private sector where doctors are mainly paid fee-for-service may lead to large differences in utilisation by income because richer individuals are better able to afford private care and are also more likely to be insured against the costs of such care, and so they are more likely to opt for private care in order to side-step waiting lists. On the other hand, better-off patients will be more attractive to doctors who will have greater incentives to induce demand in the private sector. These effects may be exacerbated when doctors are allowed to work both in the public and the private sector, encouraging them further to transfer patients from the public to the private sector, when they are salaried in the former. Additionally, disparities in provision of services across regions may favour the better-off as these may not only be more likely to reside in better endowed regions but are also better able to afford the costs associated with covering the distances necessary to reach health care providers.

This paper models health care use - GP and specialist consultations - in Europe, paying special attention to associations with socioeconomic factors. Table 1 presents relevant features of the health care systems that may influence associations between health care use and socioeconomic factors, for the 10 countries under analysis. The differences in the characteristics of health systems are noticeable. First, despite the near universal coverage of the population for physician services, we can see that in some countries the type and degree of coverage differ substantially across groups of individuals. Large proportions of the Dutch and Irish populations, those with sufficiently high incomes, are privately rather than publicly insured¹, while in most other countries public coverage is close to universal. In these cases, the degree of coverage can still vary if some individuals are also covered by private insurance plans purchased individually or provided by employers. High-income individuals are more likely to purchase private health insurance, while enjoying in some countries partial deductions of insurance premiums from taxable income (e.g., Portugal and Spain, Masseria et al., 2004, Oliveira and Gouveia Pinto, 2005). Additionally, occupation-based insurance schemes like those existing in Spain (special regime for civil servants) and in Portugal (private and public sub-systems) provide more extensive coverage to some groups, which in Portugal have higher levels of education, income and self-assessed health (Oliveira and Gouveia Pinto, 2005). Regional disparities in the provision of health care services may also arise in most countries analysed here, whose regions enjoy some degree of autonomy in the organisation and or financing of health care (Masseria et al., 2004). On the other hand, features such as free health care at the point of delivery or positive discrimination of deprived individuals in some countries are expected to promote more equitable use of health care services. Some public systems however charge co-payments for doctor consultations, like Austria, Belgium, Finland,

¹Since January 2006, there is a new health insurance system in The Netherlands which mandates that all residents, and not just the ones with sufficiently high incomes, are privately insured.

Italy (for specialists) and Portugal. The remuneration systems for doctors vary somewhat across these countries but, on the whole, they are mainly salaried in the public sector and paid fee-for-service in the private sector, except for Denmark, Italy and The Netherlands, where GPs are paid mainly by capitation, and Greece where it is common even for salaried doctors in the public sector to receive informal payments (Masseria et al., 2004). There are therefore incentives for doctors to work privately instead of or in addition to their public employment, which is allowed in all countries but Belgium, although restrictions exist in some countries. Portuguese NHS doctors earned in 1993 less than half of the EU average, while private services were charged on average about 30% higher than in the EU, which has also encouraged doctors working in both sectors to transfer patients from the public to the private sector (Oliveira and Gouveia Pinto, 2005). Given substantial differences in their health systems, it is likely that these European countries differ in the degree to which utilisation of health care is determined by socioeconomic factors, over and above the need for such care. It is also to be expected that different groups of individuals are affected differently by these factors, and that these play different roles on the decision to seek medical care (mostly taken by the individual) and on the decision regarding the subsequent number of visits (taken jointly by the patient and the doctor).

Insert Table 1 here

We use a comparable panel data set across countries, the European Community Household Panel User Database (ECHP-UDB), covering the period 1994 to 2001. Jiménez-Martín et al. (2002) use the first three waves of the ECHP 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 the use of the same two types of doctor, using the third wave. These studies use cross-section econometric methods 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 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. 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 (e.g., Van Doorslaer, Koolman and Jones, 2004, Van Ourti, 2004), 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). 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. In this study, we analyse the effects of income and education, conditional on morbidity indicators and other sociodemographic factors, on the decision to seek medical care and on the decision regarding the subsequent number of visits, for different types of individuals.

Riphahn et al. (2003) note the importance of accounting for individual unobserved heterogeneity, as unobserved individual specific characteristics, such as attitudes to-

wards health care, preferences, risk aversion, genetic frailty and morbidity, influence health care demand. Panel data methods have however seldom been used in empirical modelling of health care utilisation. In particular in the literature on health care inequity, a notable exception is Van Ourti (2004). Cross section analyses often use a hurdle model, which assumes the participation decision and the positive count are generated by separate probability processes (Mullahy, 1986; Pohlmeier and Ulrich, 1995). This specification has become the norm in applied studies of health care (see Jones, 2000), while recently the latent class model has appeared as a promising alternative (e.g. Deb and Trivedi, 1997, 2002).

The latent class and hurdle specifications are brought together by Bago d’Uva (2006) who developed a latent class hurdle model that incorporates the panel feature of the data. In this paper, we compare an extension of 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 different effects 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. 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. In the models for GP visits, estimated income effects are mostly positive on the probability of seeking GP care and negative on the number of subsequent visits. We also observe differences in the estimated income elasticities for different latent classes of users and different stages of the decision process. These are however more irregular across countries than in the case of specialist visits.

The most important effects of socioeconomic factors on the total number of specialists

visits were found for Portugal and Austria (both income and education), Finland (especially education), Ireland and Greece (mainly income). Regarding the use of primary care, the income elasticities of the total number of visits are mostly very small or negative. The exception is Portugal, where evidence is found of positive income elasticities, especially for high but also for low users. The estimated effects of education are more consistently negative across countries, including for Portugal.

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 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 and Finland joined the survey in 1995 (wave 2) and 1996 (wave 3), respectively.²

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), for comparability across countries and across waves. The income variable was scaled by the OECD

²In 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 here.

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%. The other health measure indicates whether the individual is hampered by some health problem and 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?”. Gender and age are accounted for by a gender dummy, a quadratic polynomial for age interacted with gender. 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); (ii) Marital status (married or unmarried, including cohabiting); (iii) Activity status (employed, self-employed or not working).

We also include time dummies in the analysis. The time dummies capture effects of system-wide reforms in the countries in the analysis as well as general trends in the utilisation of health care. Our analysis is constrained by the range of variables in the ECHP and so the effects of some variables may capture the effect of others. We were, for example, not able to include information regarding individual private insurance coverage because this is not available for waves 5 to 8 of the panel, and it is not available at all for Finland. As we note in Section 4, the estimated effects of

income on health care use may therefore be partially driven by the association with private insurance coverage (that is more common amongst the richer individuals). Our measurement of need factors was also constrained by the fact the ECHP, as is commonly the case with general household surveys that have been used for modelling health care utilisation, has limited and only self-reported information on individual health status. Our approach however controls for individual unobserved heterogeneity, allowing it to be related to need and non-need factors. 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.

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, assuming that, conditional on the latent class the individual belongs to, the dependent variable is distributed according to a NegBin model (Deb and Trivedi, 1997, 2002; Jiménez-Martín et al., 2002). The latent class approach has also been used to model jointly the decisions of using different types of health care (Atella et al., 2004) and to approximate the distribution of the random (family) intercepts in a cross-section of individuals (Deb, 2001), in this case allowing only for the constant term to vary across latent classes (intercept heterogeneity), and not considering slope heterogeneity. In recent years, some latent class panel data models have been proposed for binary data (Clark and Etilé, 2006),

ordered data (Clark et al., 2005) and count data (Bago d’Uva, 2006). In this paper, we use the latent class (LC) hurdle model proposed by Bago d’Uva (2006), which allows for a two-part decision process within each class, as well as intercept and slope heterogeneity in both parts, 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 5 and 6 for Finland and Austria, and values up to 7 for the remaining eight countries considered here. Denote the observations of the dependent variable over the panel as $y_i = [y_{i1}, \dots, y_{iT_i}]$, where y_{it} represents the number of visits in year t . We assumed that each individual i belongs to a latent class j , $j = 1, \dots, C$, 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 $f_j(y_{it}|x_{it}, \theta_j)$ 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 $f_j(y_{it}|x_{it}, \theta_j)$. The unconditional (on the latent class) joint density of $y_i = [y_{i1}, \dots, y_{iT_i}]$ derives from averaging out the individual unobserved heterogeneity represented by the latent classes:

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

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, $f_j(y_{it}|x_{it}, \theta_j)$, is defined as in the standard hurdle model, using a Negative Binomial as the parent distribution in both stages. Formally, for each component j , $j = 1, \dots, C$, the probability of zero visits and the probability of observing y_{it} visits,

given $y_{it} > 0$, are given by:

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

where $\lambda_{j1,it} = \exp(x'_{it}\beta_{j1})$, $\lambda_{j2,it} = \exp(x'_{it}\beta_{j2})$, α_j are overdispersion parameters and k is an arbitrary constant (most commonly set equal to 1 or 0, corresponding to the NegBin1 and NegBin2 models, respectively; we use the NegBin2 model). The vectors of parameters driving the probability of seeking care, β_{j1} , and the number of visits, given that this is positive, β_{j2} , are allowed to be different which means that the determinants of care may have different effects on the two stages of the decision process. This is also the case in the standard hurdle model, which corresponds to a (degenerate) LC model with only one latent class (that is, not accounting for the panel structure of the data). All elements of $\theta_j = (\beta_{j1}, \beta_{j2}, \alpha_j)$ are allowed to vary across classes. The LC hurdle nests: *i*) a model in which there is only intercept but not slope heterogeneity (if only the constant terms in β_{j1} and β_{j2} are allowed to vary across the classes j) as well as *ii*) models in which in some, or all, latent classes health care use is determined by a Negbin rather than by a hurdle model (if $\beta_{j1} = \beta_{j2}$ for the respective classes j). It should be noted that considering a NegBin model for all classes corresponds to a different model from the one used by Deb and Trivedi (1997, 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 $\pi_{ij} = \pi_j, j = 1, \dots, C$ to be estimated along with $\theta_1, \dots, \theta_C$ (e.g., Deb and Trivedi, 1997, 2002; Deb, 2001; Jiménez-Martín et al.; 2002, Atella et al., 2004; Bago d’Uva, 2006). 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, e.g., Clark and Etilé, 2006; Clark et al., 2005; Bago d’Uva, 2005):

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

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 $\theta_1, \dots, \theta_C, \gamma_1, \dots, \gamma_{C-1}$ 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 but these account only for intercept heterogeneity and not for slope heterogeneity.

We estimate separate models for GPs and specialists throughout, without consid-

ering that the level of usage of one of them may influence the other. We recognise that there may be substitutions and/or complementaries between the demand for GP and specialist care. We follow nevertheless what is more commonly done in the literature, which is to estimate reduced forms for the demand for the two types of care (e.g., Jiménez-Martín et al., 2002; Van Ourti, 2004; Van Doorslaer et al., 2004). The consideration of a structural model would raise issues of endogeneity that our dataset cannot accommodate and that would require the latent class hurdle model to be extended beyond the scope of this paper.

Estimation is done by maximum likelihood in TSP 4.5 (Hall and Cummins, 1999) and Stata v10.0MP, 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.³ 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 restricted versions of the latent class model (for example, with constant slopes across classes, or with constant class membership across individuals).

4. RESULTS

We first estimate standard hurdle and panel data LC hurdle and LC NegBin models for specialist and GP visits, jointly for all countries, and focus on the estimated income and education effects. We then analyse the heterogeneity of these effects across countries and the extent to which this heterogeneity can be explained by some health system features. 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 parameters of the class-specific hurdle model for a larger number of components. The LC models are therefore defined with 2 latent

³The TSP code and equivalent code for Stata v.10.0 are available from the authors.

classes, $C = 2$ in equation (1).⁴ 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. All coefficients (including overdispersion parameters) are allowed to vary across classes.

For all specifications and separately for GP and specialist visits, we compare the pooled hurdle, the LC NegBin and the LC hurdle according to the maximised log-likelihood and Schwarz information criterion (BIC). The panel data LC hurdle always outperforms the cross-section hurdle, which gives support to the existence of unobserved time-invariant individual heterogeneity in all cases 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 LC Hurdle 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 doctor visits is determined by two different processes. The BIC again favours the most flexible specification in all cases but two⁵. 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 ($p - value < 0.001$). For the first, homogeneous, specification (section 4.1), we further present results of selection between the LC hurdle and the LC NegBin from cross-validation, which again favour clearly the former. We present estimated effects of income and education on health care utilisation, conditional on the latent class, for the preferred models. 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),

⁴Deb and Holmes (2000) who also restrict the analysis to two latent classes, argue that their results support the existence of at least two groups.

⁵These are the cases for specialists visits for Denmark and Ireland, although the Akaike information criterion (AIC), which penalises the number of parameters less heavily, clearly favours the LC Hurdle over the LC NegBin in all cases.

age and gender, marital status and economic activity status.

4.1 Homogeneous/pooled models

In this section, we present results of estimation of pooled models across countries, allowing only for heterogeneity in the intercepts, i.e., including country dummies. Table 2 shows that the LC Hurdle is clearly preferred over the standard hurdle model and LC NegBin, for both for GPs and specialists, according to the log-likelihood and the BIC. Additionally, log-likelihood ratio tests of equality of parameters across the two parts for both latent classes, which corresponds to testing the null hypothesis of correct specification of the LC NegBin against the LC Hurdle, rejected that hypothesis for both cases ($p - value < 0.001$).

Insert Table 2 here

We have checked if the better in-sample performance of the LC hurdle over the LC NegBin is due to over-fitting, by performing out of sample evaluation of these two specifications. We considered a training sample of 80% randomly selected individuals, which we used for estimation. We then used the estimated parameters to compute the log-likelihood and the Akaike information criterion (AIC), for both training and hold-out samples (remaining 20%). We use the AIC rather than the BIC because this adds a penalty for sample size that is not appropriate for this type of exercise (Deb and Trivedi, 2002). The exercise was replicated 20 times. As can be seen in Table 3, the evaluation clearly favours the LC Hurdle over the LC Negbin for both GP and specialist visits.

Insert Table 3 here

Table 4 presents 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

doctor visit and the conditional positive number of visits . The latent classes differ considerably both in terms of average probability of visiting a doctor 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, in each case, 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 of GP users differ more in the conditional number of visits (146%) than in the average probability of visiting a GP (47%), which is partly due to the fact that even the average probability that a low user visits a GP is 0.598. The class of high users is predicted to have an average total number of visits which is 3.45 larger than the class of low users. In the case of specialist visits, the relative differences between high and low users are larger for the probability of having at least one visit (177%) than for the conditional number of visits (98%) and the class of high users is predicted to have an average total number of specialist visits 5.42 times larger than that of the class of low users.

Insert Table 4 here

The extent to which the LCNegBin and the LC hurdle tell different stories regarding the way in which specialist care and GP use are responsive to income, is assessed in Table 5. For GPs, the LC hurdle model estimates positive and significant income effects in the first part of the model and the opposite in the second part. The estimated income elasticity in the first stage is larger for the low users of primary care, while virtually the same result is obtained for high and low users in the second stage, which leads to a slightly more negative total elasticity for high users. The LC NegBin estimates negative effects for both classes, significant only for high users. So, this specification does not reveal the positive income elasticity of the probability of seeking

primary care as it does not allow for different effects on the two parts of the decision process for each latent class. Income effects are on the whole greater in the model for specialist visits. The LC hurdle model shows a positive and significant impact of income on the first stage for both classes, with a greater elasticity being found for low users. We find a different role of income in the two stages of the decision process, especially for those in the class of low users of specialist care. For low users, the income elasticity in the second part is estimated to be negative, whereas it is positive and significant for high users. The estimated income elasticity of the total number of visits for low users is greater than the one for high users. The LC NegBin estimates a positive income elasticity for both classes of users, which is also larger for low users. However, 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.

Insert Table 5 here

For GPs, there appears to be more evidence of a negative socioeconomic gradient by education (results available from the authors) than there is for income, with positive effects being found only in the first part, for high users. For specialists, the education results broadly in accordance with those of income.

4.2. Heterogeneity in income and education effects and the role of health care system characteristics

In this section, we use LC hurdle models to test for differences in income and education effects across countries and attempt to learn how these can be explained by health system characteristics. We do so by estimating models with: *i*) country dummies and interactions of these with income and education variables; *ii*) variables

representing features of health care systems and interactions of these with income and education variables. We compare the performance of specifications *i*) and *ii*) to gauge the extent to which the latter is capable of explaining the differences across countries.

The variables used to represent health system features are based on the information contained in Table 1, except for the level of public coverage and the level of private expenditures (as a proportion of total health expenditures), for which we have used detailed information for each year covered. For specialist visits, we consider indicators of whether: *i*) specialists are paid on a fee-for-service (FFS) basis (as opposed to salaries), in the statutory system; *ii*) there are copayments in the statutory system; *iii*) GPs are gatekeepers and *iv*) specialists working for public hospitals are also allowed to work in private practices (as opposed to being allowed, with restrictions, or not being allowed because there is no private provision, the case of Belgium). For GP visits we consider indicators of whether: *i*) GPs are paid on a FFS basis or mixture of FFS and capitation, or by capitation, or are salaried, in the statutory system; *ii*) there are copayments in the statutory system; *iii*) GPs are gatekeepers.⁶ In both cases, we consider also the weight of private expenditures on total health expenditures and a measure of coverage of population by public system (outpatient medical expenditure funded by government or social health insurance as proportion of total population). We recognise the limitations of these crude variables, which vary little across countries. Where we tried to use more detailed information (such as dual practice with and without restrictions, or more or less strict gatekeeping system), identification has proven difficult due to collinearity among some indicators. Only the variables for private expenditure and public coverage are time-variant but they

⁶For Belgium and Ireland, we have considered the features that apply to the respective Groups I (see Table 1), i.e., the ones entitled to comprehensive public coverage. Unfortunately, our data do not allow us to identify the groups that individuals belong to.

show little variation, especially the latter, which always equals 100% for five countries, and does not vary much across time in most other countries. It would have also been important to take into account variation in other factors such as waiting lists/times. However, unlike for surgery, there is very limited information on waiting lists for doctor visits.⁷

The maximised log-likelihoods of pooled LC Hurdle models with system features and interactions of these with income and education variables are shown in Table 6 below. For GPs and specialists, we have obtained significant coefficients for all those variables and interactions at least in one part of the model and/or for one latent class, which confirms that, as expected, the system features considered impact not only the level of primary care used but also the way in which it responds to income and education (results available upon request).

Role of system characteristics

Paying GPs on a FFS basis or a mixture of FFS and capitation, as opposed to salaries, tends to lead to a higher number of GP visits, while the same is observed for capitation but only on the probability of seeking GP care. As could be expected, the existence of a gatekeeping system is also associated with more GP visits. On the other hand, the existence of copayments and the weight of private expenditures on total health expenditures are associated with lower probabilities of using primary care and lower number of visits, conditional on at least one visit, for both classes. The interactions of the system characteristics with income, show that, where GPs are mostly paid FFS, the income effects tend to be lower, the same being observed in the

⁷For example, in Portugal, although it is known that there are frequently delays in obtaining a specialist consultation, data on waiting times for specialist care do not exist (Pita Barros and Almeida Simões, 2007). Hurst and Siciliani (2003), examine six other countries covered here but only report data on waiting times for specialist visits for Spain and Denmark.

case of payment by capitation, for the conditional number of visits. The existence of a gatekeeping system also appears especially associated with lower income effects, which, similar to the positive effects of that system on the number of visits, could reflect the restrictions on patient choice implied by the system. Finally, we found that payment by capitation and the level of public coverage impact the education gradient negatively. Where GPs act as gatekeepers, the better educated low users are more likely to visit a GP, while they tend to visit GPs more often, conditional on having done so at least once.

In the models for specialists, we found that high users are less likely to visit this type of doctor where these are paid FFS, where access requires a referral from a GP and where the extent of public coverage is larger. Perhaps unexpectedly, the weight of private expenditures on total expenditures is associated with less specialist visits (although this is only significant for the probability of having at least one visit, for high users). Less restrictions in dual practice of specialists in the public and private sector are also especially associated with less visits. We also found significant interactions between system characteristics and income. There is mostly a positive association with the existence of copayments but this is significant only for low users in the second part of the model. Dual practice is associated with higher income effects on the probability of visiting a specialist but negative on the conditional number of visits, for low users. The level of coverage by the public system is associated with larger income effects, for high users. The importance of private expenditures is also associated with greater income effects but only significantly so in the second part of the model, and for low users. Associations were also found of education effects with the system features considered. Payment by FFS, gatekeeping system and less restrictions to dual practice (and, less consistently and significantly so, the existence of copayments), were found to be mostly associated with larger education gradients. The level of public coverage and the weight of private expenditures are associated

with greater education effects on the probability of seeking specialised care.

Testing for heterogeneity across countries

We test for further heterogeneity of income and education effects across countries, by interacting of those variables with country dummies (model (2) in Table 6). The null hypothesis of equality of income and education effects across countries is clearly rejected (test (1-2)). We can also see that the pooled model with country specific income and education effects (2) outperforms the one where those vary with system characteristics (3). This means that other factors not considered here or not fully captured by our crude variables also play an important role in explaining the variability of income and education effects across countries. For example, we were only able to consider a dummy variable for the existence of copayment rates - while these vary substantially across countries and also within some countries across pension funds and regions, and due to exemptions - and the gatekeeping system may be implemented more strictly in some countries than others.

Insert Table 6 here

The equality of coefficients of the remaining parameters across countries is also rejected (test (3-4)). The LR test of the model without interactions against the fully heterogeneous model (test (1-4)) decreases only about 11% and 13%, respectively for GPs and Specialists, when interactions of income and education with country dummies are added (test (2-4)), with the remaining heterogeneity left unexplained. The full heterogeneous specification is therefore our preferred one, i.e., with country specific models allowing for different coefficients of all covariates across latent classes and parts of the model, and on class membership probabilities, as well as different overdispersion parameters.

Country-specific models for GP visits

Table 7 shows that the LC Hurdle is clearly preferred for all countries, according to the maximised log-likelihood and the BIC.⁸ Log-likelihood ratio tests of equality of parameters across the two parts (ie, of the LC NegBin, against the LC hurdle), for both latent classes rejected that hypothesis in all cases ($p - value < 0.001$).

Insert Table 7 here

As done above for the homogeneous LC Hurdle model, we refer to the latent classes obtained for each country as ‘high’ and ‘low’ users, where the former is the one with both larger predicted the predicted probability of use and predicted conditional number of visits. The differences in these predictions across latent classes follow the pattern observed in the homogeneous model (Table 4), with greater differences in the conditional number of visits - from 109%, Greece, to 175%, Austria - than in the average probability of visiting a GP - from 23%, Austria, to 64%, Finland.⁹ The predicted total number of users is at least 3 times larger than the class of low users (from 1:3.06, Greece, to 1:3.9, Ireland).

The pooled country analysis showed a very different role of income on the initial decision to visit a doctor and in the number of visits (Table 5) as well as evidence of heterogeneity (jointly in income and education effects) across countries (Table 6). We now analyse the extent to which the country specific income effects depart from the general pattern. Table 8 shows the estimated coefficients of $\text{Log}(\text{Income})$, conditional

⁸In 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.

⁹Full set of results available in Bago d’Uva and Jones, 2006, hereafter BUJ.

on the remaining regressors and on the latent class, and the corresponding elasticities. In most cases, the estimated effects are of the same sign for both classes but they vary in magnitude and statistical significance. The homogeneous model (Table 5) has shown that richer individuals tend to be more likely to visit a GP and that is indeed the most common pattern observed here with 6 countries having positive effects in both classes and 3 countries with positive effects one class. These positive effects are however only statistically significant for high users in Belgium, Denmark and Italy, for low users in Ireland and The Netherlands and for both classes in Portugal (where the income elasticity is larger for the class of low users). In contrast, the second part of the homogeneous model showed a higher expected number of GP visits, conditional on the initial contact, for poorer individuals. Here we find also mostly negative coefficients which are statistically significant for both classes in Ireland, Italy and Spain (with higher elasticity in absolute value for low users), Belgium (higher elasticity in absolute value for high users). For The Netherlands, only the negative estimate for high users is significant. Austria, Greece and Portugal differ from the average pattern, showing positive and significant income effects on the conditional number of visits (for high users in Austria and Greece, and for low users in Portugal).

Insert Table 8

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, similar to the homogeneous model.¹⁰ Only for Portugal do we obtain positive income effects across parts and classes (insignificant only for the second part for high users), which

¹⁰: Belgium and Italy (positive and significant effect on the probability for high users, negative and significant effect in the second part for both classes); Ireland and The Netherlands (positive and significant effect on the probability for low users, and negative in the second part for both classes, insignificant only for low users in The Netherlands).

correspond to the highest positive income elasticities (again, except for the second part for high users), leading to the highest elasticities of the total number of visits (sum of the elasticities of the two parts), for both classes. For all other countries, these elasticities are negligible or negative. These results suggest that in Portugal there are barriers to the consumption of primary care related to income, especially for the low users of primary care but also, to a lesser degree, for high users. This is likely to arise within, or because of deficiencies in, the NHS, as patients largely choose the public sector for GP care (Oliveira and Gouveia Pinto, 2005). A factor that may contribute to unequal use by income in Portugal, conditional on need, is the existence of copayments for GP visits (found to be associated with a larger income effect in the pooled model with heterogeneous income effects by system features), although, in other countries where that is also the case (Austria, Belgium and Finland) and where fees charged tend to be higher than in Portugal, we observe smaller income effects. Other factors that may play a role in the Portuguese case, and that we were not able to account for in the pooled model are the large geographical disparities in the distribution of doctors, as well as the coverage by health sub-systems that assure better access for certain groups of the population, that tend to be better-off and healthier (*ibid*). The homogeneous model showed more evidence of a negative socioeconomic gradient by education than for income, with positive education effects only in the first part for high users, and this is also the pattern most commonly observed in the country specific models (results available in BUJ, 2006), suggesting that, on the whole, better educated European individuals are less inclined to visit GPs, possibly due to taste differences.

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 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 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 results for this part of the model (available in BUJ, 2006) show that, for all countries, the most important correlate of being a high user is poor health, measured by the two morbidity variables considered, while age and gender also play an important role for some countries. Associations with other variables are also found in all countries, except for Belgium. There is some evidence that not being married and not working are associated with a higher probability of being a lower user, while, in some countries, better educated individuals tend to be high users. There is mixed evidence regarding the long-term association between income and the probability of being a higher user, which is positive for Austria, Denmark, Finland and Portugal and negative for Italy and Spain.

Country-specific models for specialist visits

The maximised log-likelihood and the BIC (Table 7¹¹) again favour the Lc Hurdle over the LC NegBin for all countries (except Ireland and Denmark, where the BIC

¹¹The estimation of the LC hurdle with the full samples of Belgium, The Netherlands, Ireland and Denmark returned implausibly large estimates of one α . Abnormal α 's have been seen in the literature, for example, in 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 Jiménez-Martín et al. (2002) in hurdle models for specialist visits. The anomalous α '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 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.

favours the LC NegBin¹²). 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 is consistently rejected ($p - value < 0.001$).

There are large differences in the averages of predicted utilisation of the two latent classes, decomposed into the probability of visiting a specialist at least once and the conditional number of visits (available in BUJ, 2006). The high/low users ratio of the average probability of visiting a specialist is between 1:1.95 (Greece) and 1:4.50 (Ireland), while that of the average predicted number of specialist visits, given that it is positive, is between 1:1.69 (Finland) and 1:2.54 (Greece). 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 at least 4 times larger than that of the class of low users (from 1:4.50, Austria, to 1:7.80, Ireland).

Table 8 shows estimated income effects, conditional on remaining covariates, as estimated by the LC hurdle model. The homogeneous LC hurdle model estimated a positive income effect in the first part and a negative one in the second part, for low users, whereas for high users positive effects were found in both parts (Table 5). Exceptions to the generally positive and significant income effect on the probability of seeking specialist care are Finland (positive effect insignificant for high users) and Belgium and Denmark (positive effects insignificant for both classes) and The Netherlands (insignificantly negative coefficient for high users). Overall, the elasticities are larger for low users than for high users and are largest for Portugal, Finland and Ireland (for low users), and for Ireland and Portugal (for high users). As to the decision of how many times to visit a specialist, for high users, the (mostly) positive

¹²However, 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.

income effects are significant only, in order of magnitude, for Austria, Greece and Portugal. For low users, those effects are mostly negative and are significant for The Netherlands, Finland, Portugal, Italy and Spain.

The income elasticities of the total number of specialist visits (sum of the elasticities in both parts) are always positive, except for The Netherlands and Belgium, in both classes, and Denmark, for high users. Waiting lists may be driving the positive income effects of specialist visits, because the richer are better able to bypass the waiting lists in the public sector by using the private sector. 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 (only slightly larger for high users, in Spain) and, in The Netherlands, the elasticity is more negative for low users. The largest income elasticities of the expected (total) number of specialist visits are obtained for Ireland, Portugal, Greece and Austria. One possible partial explanation for these results is the fact that in these four countries specialists employed in the public sector (receiving salaries) are also allowed to receive fees for private practice (albeit with restrictions in the case of Austria), possibly creating incentives to transfer patients from the public to the private sector, if the salaries in the former are low and the fees in the latter are relatively high. The pooled model with heterogeneity in income effects by system features did indicate a greater income effect on the probability of seeking specialised care for countries with unrestricted dual practice but these include also Denmark, for which we observe low and insignificant income effects. One could also think that the very high private share of total expenditures in Greece, and relatively high for Portugal, albeit lower than in The Netherlands, may play role in explaining the high income effects but this is not supported by the pooled model.

Other factors not accounted for in that pooled model that may be driving the results obtained for Greece are the wide urban-rural disparities on service provision, as well as across insurance funds, and the importance of informal direct payments (Masseria et

al., 2004). In Portugal, barriers to access related to income may also arise from uneven geographical distribution of specialists (Oliveira and Gouveia Pinto, 2005). Moreover, in this country, the private sector provides a large share of specialist care, with fees either paid in full by the patients or partly reimbursed by private insurance plans (purchased especially by high-income individuals), while generous rules for deductions of private health expenditures (including insurance premiums) from taxable income benefit especially the better-off (*ibid*). Richer individuals in Portugal may also have a preference for private specialised care - that they are better able to pay and for which they are more likely to be covered - as a substitute for public primary care, in order to ensure quicker care and of better quality.¹³ We are however not able to confirm this with our results as the separate model for GP visits also indicated positive effects for income. A further contribution to the unequal level of care by income may arise from the existence of occupation-based sub-systems that provide better access to about 20% of the Portuguese population that tend to be richer and better educated (*ibid*). In Austria, patients are required to pay co-payments in amounts that vary across social health insurance institutions and regions. The rules for exemption of co-payments are not gradually structured, so those are considered to be a hardship for vulnerable groups (Stepan and Sommersguter-Reichmann, 2005). The high income gradient in Ireland may also be driven by the fact that a large proportion of the population, with high incomes, opt to buy private insurance to cover the costs of specialist care (that otherwise they would have to pay in full).

The homogeneous model for specialist visits showed education effects broadly in accordance with income effects, that is, positive effects on the first part for both classes and on the second part for low users. We also found education effects broadly in line with income effects in most country-specific models (results in BUJ, 2006). However, for Belgium and for Finland, relatively stronger gradients are found for education than

¹³We thank an anonymous referee for point this out to us.

for income. Consequently, Finland approaches Austria as one of the countries with greatest education effects, while Portugal is still the country where more education increases the probability of visiting a specialist the most. The Portuguese health care system has four of the features that showed some association with a greater education gradient in the pooled model - existence of copayments for specialist visits, gatekeeping system, less restricted dual practice of specialists in the private and public sectors, and relatively high share of private expenditures - while the Austrian and Finnish system have two of them. The inequities in Portugal may be exacerbated by better coverage of around 20% of the population (that tend to have higher levels of education), through sub-systems. Overall, the positive effects of education may be capturing differences in tastes regarding health care, as better educated individuals may have a preference for more extensive use of specialised care, in some cases, instead of primary care.

The results of the logit model for the probability of being a high user, within the LC hurdle for specialist visits (available in BUJ, 2006) have shown that, for most countries, class membership is especially associated with indicators of morbidity and, to a lesser degree, age and gender. On the whole, it was also found that better educated and long-term richer individuals are more likely to be high users, while, 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.

5. CONCLUSION

We use a comparable panel data set to model GP and specialist visits in Europe and account for the panel feature of the data 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 in almost all cases. 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 also play a role. For each latent class, we examine the effects of income and education, controlling for need and other socioeconomic factors. The latent class framework reveals differences between types of users, especially for the use of specialists, while the latent class hurdle reveals further differences in the effect of income on the probability of use and 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. 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. As to GP visits, the relation between income elasticities for low and high users and across the two parts of the model is more irregular across countries than in the case of specialists. We note nevertheless that the income effects are mostly positive on the probability of seeking GP care and mostly negative on the conditional number of visits. Differences on the effects of health care determinants, 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), we obtain mostly negative or insignificant effects of income on the total number of GP visits. However, we find positive income elasticities of the total number of GP visits for Austria and Greece for high users (driven by the effect on the positive number of visits) and, to a larger extent and for both classes of users, for Portugal (especially in the probability of initial contact and for low users). 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: mostly negative education gradients were found, possibly due to differences in preferences regarding health care.

For almost all countries studied, richer individuals are expected to use more specialist care, conditional on need and other non-need factors. Waiting lists for this type of care may be driving this result, as the richer are better able to bypass the waiting lists in the public sector by using the private sector. Considering the individuals in the class of low users, income elasticity of the total number of visits is highest for Ireland and Portugal, the countries with highest indices of horizontal inequity in specialist visits in Van Doorslaer, Koolman and Jones (2004). 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. The positive income elasticities for Portugal, Ireland and Finland are observed especially in the probability of seeking specialist care, whereas those for high users in Greece and Austria appear also on the subsequent number of visits, perhaps due to greater influence of doctors on this type of users in these two countries. 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. Several features of the health systems in these countries may contribute to these findings, such as: possibility of doctors to work both in the public sector (receiving salaries) and in the private sector (receiving fee for service), permitting higher earnings in the private sector, especially for Portugal; unequal coverage across social insurance funds (in Greece and Austria), better and more extensive coverage for those entitled to occupation-based Portuguese health sub-systems (that tend to be richer and better educated); wide geographical disparities in the provision of specialised care (Portugal and Greece); co-payments required by the Austrian social health insurance institutions and the informal payments to Greek doctors that seem to represent a burden for the most vulnerable (Stepan and Sommersguter-Reichmann, 2005; Mossialos et al., 2005). The importance of the private sector in the provision of specialised care may also partially explain the socioeconomic inequities in utilisation

of specialists, especially in Ireland, where a large proportion of high-income individuals insure against the fees, and Portugal, where although a smaller proportion of the population is privately insured, a large share of specialist visits occur in the private sector. Generous tax benefits in Portugal create further incentives for the better off to use the private sector.

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Table 1: Summary of health system characteristics

| | Coverage | | Private expenditure ^a (% of total expenditure) | GP consultations | | | Specialist consultations | | |
|-------------|--|--------------------------------|--|--|---|-------------------------------------|---|----------------------------------|-----------------------------|
| | Main types | % Public coverage ^a | | Gatekeeper | Copayments ^b | Payments to doctors ^b | Copayments ^b | Payments to doctors ^b | Dual practice |
| Austria | Social Health Insurance (SHI) Supplementary private health insurance (PHI) covers 30% of population. | 99% | 25.6% | Yes, but often ignored due to emergency exemption. | Yes (variable and with exemptions) | Salaried. | Yes (variable and with exemptions). | Salaried. | Allowed, with restrictions. |
| Belgium | Universal public coverage, except for self-employed. PHI covers most self-employed. Complementary PHI offered by many employers. | 94% | 22.9% | No | Yes (30% rate, reduced for lower SES). | FFS | Yes (40% rate, reduced for lower SES). | FFS | No (just public provision). |
| Denmark | Choice between group I - 98% of pop., free care - and group II - co-payments. Complementary PHI covers 30% of population (limited coverage). | 100% | 17.6% | Yes, for group I. | No, for group I. | Mix of capitation and FFS. | No, for group I. | Salaried. | Allowed. |
| Finland | Universal public coverage through municipalities. Occupational care provided by some employers. | 100% | 24.3% | Yes, but not strictly enforced. | Flat rate (10€). | Salaried. | Flat rate (17€). | Salaried. | Allowed, with restrictions. |
| Greece | SHI. Supplementary PHI covers about 8% of pop. | 100% | 49.3% | No (in practice). | No. | Salaried. | Yes. | Salaried. | Allowed. |
| Ireland | Group I has full coverage – poorest 1/3 - and Group II has limited coverage. Complementary PHI covers 44% of pop. | 33.3% | 27.2% | Yes, for group I (can be bypassed by emergency units). | No, group I. Full payment, group II. | Capitation, group I. FFS, group II. | No, group I. Copayments for some services, group II. | Salaried. | Allowed. |
| Italy | Universal NHS coverage. Supplementary PHI covers 5-10% of pop. | 100% | 28.5% | Yes, with exceptions. | No. | Capitation. | Flat rate payment (about 35€). | Salaried. | Allowed, with restrictions. |
| Netherlands | SHI. Substitutive PHI for high incomes and self-employed. | 63.1% | 34.6% | Yes. | No (for public patients). | Capitation. | No. | Salaried. | Allowed, with restrictions. |
| Portugal | Universal NHS coverage. PHI coverage (mostly provided by employer) for 10% of pop. (double coverage). Occupation-based insurance (private and public sub-systems) for 20% of pop. (multiple coverage). | 100% | 32.5% | Yes, but often bypassed due to emergency exemption. | Flat rate (about € 1.5), with exemptions. | Salaried. | Flat rate (about 3€ for outpatient and 5€ for emergency visits), with exemptions. | Salaried. | Allowed. |
| Spain | Universal NHS coverage. PHI covers about 10% of pop. (double coverage). Special regime with choice of public or private health care provider for civil servants. | 98.6% | 28% | Yes, with exceptions. | No. | Salaried. | No. | Salaried. | Allowed, with restrictions. |

Sources: Hurst and Siciliani (2003), Van Doorslaer, Masseria et al. (2004), Stepan and Sommersguter-Reichmann (2005), Oliveira and Gouveia Pinto (2005), Mossialos et al. (2005), Atella et al. (2004), .^a Average for the period covered, from OECD data 2007. ^b Features of the statutory health care system.

Table 2: Comparison of pooled models for GP and Specialist visits

| Country | Hurdle | | LC NegBin | | LC Hurdle | |
|-------------|------------|-----------|------------|-----------|------------|-----------|
| | LogL | BIC | LogL | BIC | LogL | BIC |
| GPs | -1189299.0 | 2379331.8 | -1155544.2 | 2312125.4 | -1147484.7 | 2296728.7 |
| Specialists | -771788.0 | 1544309.9 | -750839.7 | 1502716.2 | -743979.6 | 1489718.2 |

Table 3: Model selection from cross-validation - pooled models for GP and Specialist visits

| | Sample | LC Hurdle preferred % | | logL(LC Hurdle) - logL(LC NegBin) | | |
|-------------|----------|-----------------------|-----|-----------------------------------|---------|---------|
| | | LogL | AIC | Mean | Minimum | Maximum |
| GPs | Training | 100 | 100 | 6455 | 6310 | 6550 |
| | Holdout | 100 | 100 | 1594 | 1502 | 1739 |
| Specialists | Training | 100 | 100 | 5480 | 5398 | 5579 |
| | Holdout | 100 | 100 | 1368 | 1270 | 1447 |

Notes: The training sample consists of 80% randomly chosen observations from the original sample. The hold-out sample consists of the remaining 20%. The exercise was replicated 20 times. LC Hurdle preferred % represents the percentage of replications in which LC Hurdle is preferred to LC NegBin according to the LogL or the AIC.

Table 4: Average number of specialist and GP visits and decomposition by parts for each latent class – pooled LC Hurdle

| | Low users | | | High users | | |
|-------------|-----------|----------|-------|------------|----------|-------|
| | P(Y>0) | E(Y Y>0) | E(Y) | P(Y>0) | E(Y Y>0) | E(Y) |
| GPs | 0.598 | 2.513 | 1.614 | 0.877 | 6.189 | 5.572 |
| Specialists | 0.247 | 2.020 | 0.515 | 0.682 | 4.007 | 2.790 |

Table 5: Comparison of estimated income elasticities for GP and specialist visits – pooled models

| | | LC NegBin | | LC Hurdle | |
|-------------|----------|--------------|---------------|---------------|---------------|
| | | Low | High | Low | High |
| GPs | P(Y>0) | -0.001 | -0.003 | 0.014 | 0.008 |
| | E(Y Y>0) | -0.001 | -0.014 | -0.022 | -0.022 |
| | E(Y) | -0.002 | -0.016 | -0.008 | -0.014 |
| Specialists | P(Y>0) | 0.041 | 0.014 | 0.128 | 0.054 |
| | E(Y Y>0) | 0.034 | 0.037 | -0.033 | 0.016 |
| | E(Y) | 0.076 | 0.051 | 0.094 | 0.070 |

Note: Elasticities are calculated for each individual and averaged over the sample. The figures in bold correspond to (5%) coefficients in the respective models.

Table 6: Comparison of LC Hurdle models for GP and Specialist visits

| Model | GPs | | | Specialists | | |
|--|------------|------|-----------|-------------|------|-----------|
| | logL | df | BIC | LogL | df | BIC |
| (1) pooled with country dummies | -1147484.7 | 151 | 2296729.0 | -743979.6 | 151 | 1489718.0 |
| (2) pooled with country dummies and interactions with income and education | -1146607.0 | 286 | 2296545.0 | -743219.4 | 286 | 1489771.0 |
| (3) pooled with system chars and interactions with income and education | -1150444.2 | 226 | 2303522.0 | -745503.1 | 226 | 1493639.0 |
| (4) sum heterogeneous model | -1139166.4 | 1048 | 2290543.2 | -738261.2 | 1048 | 1488720.1 |
| LR tests | | | | | | |
| (1-2) | 1755.4 | 135 | 0.000 | 1520.4 | 135 | 0.000 |
| (1-4) | 16636.6 | 897 | 0.000 | 11436.8 | 897 | 0.000 |
| (2-4) | 14881.2 | 762 | 0.000 | 9916.4 | 762 | 0.000 |

Table 7: Comparison of models for GP and specialist visits – country specific models

| Country | GPs | | | | Specialists | | | |
|-------------|-----------|----------|-----------|----------|-------------|----------|-----------|----------|
| | LC NegBin | | LC Hurdle | | LC NegBin | | LC Hurdle | |
| | LogL | BIC | LogL | BIC | LogL | BIC | LogL | BIC |
| Austria | -81597.4 | 163733.3 | -81280.9 | 163477.2 | -59657.4 | 119852.8 | -59006.9 | 118928.4 |
| Belgium | -81385.3 | 163319.8 | -81051.9 | 163042.7 | -56756.4 | 114061.6 | -56215.5 | 113369.2 |
| Denmark | -56765.7 | 114072.0 | -56529.9 | 113914.3 | -31400.6 | 63341.5 | -31247.5 | 63418.8 |
| Finland | -51287.1 | 103097.2 | -51088.7 | 103061.1 | -34951.2 | 70425.4 | -34423.2 | 69730.1 |
| Greece | -110753.0 | 222094.4 | -108677.0 | 218360.0 | -95900 | 192383.5 | -94567.4 | 190132.5 |
| Ireland | -74468.2 | 149495.3 | -74200.9 | 149357.3 | -30031.2 | 60621.1 | -29876.0 | 60707.2 |
| Italy | -238287.0 | 477188.0 | -237225.0 | 475499.7 | -135648.0 | 271909.9 | -134631.0 | 270311.7 |
| Netherlands | -111246.2 | 223074.5 | -111000.0 | 222995.1 | -77579.9 | 155741.5 | -77117.9 | 155230.3 |
| Portugal | -144568.3 | 289726.4 | -143235.1 | 287478.6 | -91489.5 | 183568.0 | -90620.8 | 182248.6 |
| Spain | -195404.5 | 391418.6 | -194877.0 | 390796.3 | -131339.8 | 263289.2 | -130555.0 | 262152.3 |

Table 8: Estimated income coefficients and elasticities for GP and specialist visits – country specific LC Hurdle models

| Country | | GPs | | | | | | Specialists | | | | | |
|-------------|----------|-----------------------|----------------------|-----------------------|----------------------|-----------------------|----------------------|-----------------------|----------------------|-----------------------|----------------------|----------|--------------|
| | | Low users | | | High users | | | Low users | | | High users | | |
| | | Estimated coefficient | Estimated elasticity | Estimated coefficient | Estimated elasticity | Estimated coefficient | Estimated elasticity | Estimated coefficient | Estimated elasticity | Estimated coefficient | Estimated elasticity | | |
| Austria | P(Y>0) | -0.051 | (-1.467) | -0.012 | -0.109 | (-0.872) | -0.005 | 0.191 | (3.743) | 0.110 | 0.211 | (3.556) | 0.030 |
| | E(Y Y>0) | 0.012 | (0.693) | 0.009 | 0.039 | (2.167) | 0.035 | 0.014 | (0.210) | 0.006 | 0.105 | (3.858) | 0.070 |
| Belgium | P(Y>0) | 0.035 | (1.002) | 0.008 | 0.292 | (4.004) | 0.010 | 0.054 | (1.399) | 0.036 | 0.079 | (1.348) | 0.014 |
| | E(Y Y>0) | -0.052 | (-3.125) | -0.037 | -0.055 | (-4.030) | -0.050 | -0.112 | (-1.611) | -0.052 | -0.049 | (-1.920) | -0.035 |
| Denmark | P(Y>0) | 0.083 | (1.746) | 0.033 | 0.261 | (2.302) | 0.023 | 0.053 | (0.738) | 0.045 | 0.079 | (1.123) | 0.034 |
| | E(Y Y>0) | 0.042 | (0.992) | 0.021 | -0.030 | (-1.009) | -0.024 | -0.053 | (-0.434) | -0.022 | -0.082 | (-1.120) | -0.050 |
| Finland | P(Y>0) | 0.054 | (1.358) | 0.024 | -0.030 | (-0.263) | -0.003 | 0.203 | (3.525) | 0.155 | 0.167 | (1.909) | 0.041 |
| | E(Y Y>0) | 0.007 | (0.237) | 0.004 | -0.048 | (-1.706) | -0.037 | -0.229 | (-2.985) | -0.090 | 0.025 | (0.487) | 0.014 |
| Greece | P(Y>0) | 0.012 | (0.565) | 0.006 | 0.015 | (0.447) | 0.004 | 0.184 | (7.641) | 0.128 | 0.148 | (5.413) | 0.060 |
| | E(Y Y>0) | -0.024 | (-1.864) | -0.015 | 0.026 | (1.967) | 0.020 | 0.017 | (0.878) | 0.010 | 0.067 | (4.192) | 0.055 |
| Ireland | P(Y>0) | 0.164 | (4.754) | 0.064 | 0.026 | (0.339) | 0.003 | 0.172 | (3.274) | 0.152 | 0.313 | (4.367) | 0.144 |
| | E(Y Y>0) | -0.095 | (-3.865) | -0.057 | -0.049 | (-2.528) | -0.043 | 0.063 | (0.738) | 0.027 | -0.091 | (-1.838) | -0.057 |
| Italy | P(Y>0) | -0.001 | (-0.054) | 0.000 | 0.116 | (3.766) | 0.011 | 0.136 | (6.251) | 0.105 | 0.190 | (7.918) | 0.063 |
| | E(Y Y>0) | -0.044 | (-4.944) | -0.031 | -0.024 | (-2.691) | -0.021 | -0.084 | (-2.787) | -0.035 | 0.000 | (-0.026) | 0.000 |
| Netherlands | P(Y>0) | 0.082 | (2.897) | 0.035 | 0.094 | (1.739) | 0.009 | 0.071 | (2.085) | 0.055 | -0.055 | (-1.084) | -0.016 |
| | E(Y Y>0) | -0.037 | (-1.484) | -0.019 | -0.085 | (-5.446) | -0.068 | -0.250 | (-4.377) | -0.129 | -0.008 | (-0.299) | -0.006 |
| Portugal | P(Y>0) | 0.223 | (10.888) | 0.104 | 0.243 | (8.070) | 0.036 | 0.252 | (9.190) | 0.198 | 0.295 | (9.454) | 0.099 |
| | E(Y Y>0) | 0.027 | (2.302) | 0.018 | 0.001 | (0.078) | 0.001 | -0.087 | (-3.292) | -0.045 | 0.041 | (2.340) | 0.028 |
| Spain | P(Y>0) | -0.015 | (-0.997) | -0.006 | 0.037 | (1.261) | 0.005 | 0.112 | (5.680) | 0.080 | 0.138 | (5.189) | 0.042 |
| | E(Y Y>0) | -0.053 | (-4.401) | -0.034 | -0.025 | (-2.324) | -0.021 | -0.070 | (-2.460) | -0.033 | 0.017 | (1.026) | 0.012 |

Notes: t-statistics of coefficients in parentheses. Coefficients in bold are those significant at 5%. Elasticities are calculated for each individual and averaged over the sample. Elasticities in bold correspond to significant coefficients.