Explaining income-related inequalities in doctor utilisation in Europe:
a decomposition approach

by

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Abstract

This paper presents new international comparative evidence on the factors driving inequalities in the use of GP and specialist services in 12 EU member states. The data are taken from the 1996 wave of the *European Community Household Panel* (ECHP). We examine two types of utilisation (the probability of a visit and the conditional number of positive visits) for two types of medical care: general practitioner and medical specialist visits using probit, truncated Negbin and generalized Negbin models. We find little or no evidence of income-related inequity in the probability of a GP visit in these countries. Conditional upon at least one visit, there is even evidence of a somewhat pro-poor distribution. By contrast, substantial pro-rich inequity emerges in virtually every country with respect to the probability of contacting a medical specialist. Despite their lower needs for such care, wealthier and higher educated individuals appear to be much more likely to see a specialist than the less well-off. This phenomenon is universal in Europe, but stronger in countries where either private insurance cover or private practice options are offered to purchase quicker and/or preferential access. Pro-rich inequity in subsequent visits adds to this access inequity but appears more related to regional disparities in utilisation than other factors.

Key words: equity, inequality, decomposition, doctor visits,

1. Introduction

It is well known that, despite many years of near universal coverage for physician services, income-related inequalities in the use of such services continue to persist in many European countries. There is abundant evidence that in many countries - European and non-European alike - both the probability of seeing a doctor and the number of contacts, given at least one contact, are not identically distributed across income groups after correcting for differences in the need for such care at different income levels. But there are also important differences between countries in the degree to which this occurs. Previous cross-country comparative work has concentrated on the measurement and testing of horizontal inequity in the use of physician services by assessing to what extent any observed differentials in use across income groups cannot be accounted for by need differences [1]. The premise of this research was that those in equal need ought to be treated equally, irrespective of income position and that violations of this principle constitute empirical evidence of horizontal inequity [2-4].

More recently, attention has shifted from the measurement to the explanation of the differences in the degree of horizontal inequity observed in different countries. Using ECHP data, Van Doorslaer *et al*. [5] not only generated comparable estimates of horizontal inequity, they also explored the role of differences in private health insurance status and region of residence in the generation of these findings. As in earlier work [4], they found relatively little evidence of income-related inequity in the GP visits but substantial evidence of inequity favouring the rich in visits to a medical specialist: after controlling for need differences, higher income individuals report significantly more specialist visits than lower income individuals. Moreover, they found that – while insurance and location of residence do contribute to these findings – these two determinants do not "explain away" the inequity results.

This paper goes beyond the earlier work in a number of ways. First, it explicitly incorporates the two-stage decision process in physician utilisation. It examines inequity in the probability of a visit and the conditional (positive) number of visits separately by adopting two-part models and comparing these to a one-part model. This allows for an analysis of total inequity, as well as first and second part inequity. Secondly, it adopts a new (indirect) need standardisation approach by using the *partial* contributions of the need indicators as estimated in the decomposition procedure. Third, it allows for a decomposition 'by factors' of inequality [6]. The paper starts with an outline of the measurement and decomposition methodology in section 2. Section 3 provides a description of the data and estimation methods and section 4 presents the main results. We conclude with a discussion of the implications of the findings in section 5.

2. Explaining inequity in health care utilisation

2.1 Measuring and decomposing inequality in use

The method we use in this paper to explain inequality in health care utilisation is conceptually identical to the method used in Van Doorslaer and Koolman [7] to explain health inequality. We use a concentration index as our measure of relative income-related inequality in use of health care.

For weighted data, CM can be computed conveniently using the (weighted) covariance between yi and the fractional rank (based on weights) [8] as:

(1) $$C_M = \frac{2}{N\bar{y}} \sum_{i=1}^{N} w_i \left(y_i - \bar{y} \right)\left(R_i - \tfrac{1}{2} \right) = \frac{2}{\bar{y}} \; cov_w(y_i , R_i)$$

where cov_w denotes the weighted covariance. N is the sample size, $\bar{y}$ is the (weighted) mean health care use, w_i is the sampling weight of each individual i (with the sum of w_i equal to N). R_i is the relative fractional rank (based on weights) of the *i*th individual which indicates the weighted cumulative proportion of the population up to the midpoint of each individual weight [10].

A straightforward way of decomposing the measured degree of inequality into the contributions of explanatory factors was proposed by [6] in the context of a linear additive explanatory model such as:

(2) $$y_i = \alpha + \sum_k \beta_k x_{ki} + \varepsilon_i$$

where *y* is our medical care measure, the *x* variables include the determinants of health care demand and ε is a disturbance term. One could think of this equation as a reduced form of a demand for health care equation where all the *x* variables are exogenous determinants. Given the relationship between y_i and x_{ki} in eqn (5), the concentration index can be written as [6]:

(3) $$C_M = \sum_k (\beta_k \bar{x}_k / \bar{y}) C_k + GC_\varepsilon / \bar{y},$$

where is the mean of *y*, $\bar{x}_k$ is the mean of x_k, C_k is the concentration index for x_k (defined analogously to C_M) and GC_ε is the generalized concentration index for ε_i. Eqn (3) shows that C_M can be thought of as being made up of two components. The first is the deterministic component, equal to a weighted sum of the concentration indices of the *k* regressors, where the weight or "share" for, say, x_k, is simply the elasticity of *y* with respect to x_k. The second is a residual component, captured by the last term. This reflects the inequality in health that cannot be explained by systematic variation across income groups in the x_k. Thus eqn (3) shows that, by coupling regression analysis with distributional data, we can partition the causes of inequality into inequalities in each of the x_k.

The decomposition also makes clear how each determinant *k*'s separate contribution to total income-related inequality in health care demand can be decomposed into two meaningful parts: (i) its impact on demand, as measured by the demand elasticity (η_k), and (ii) its degree of unequal distribution across income, as measured by the (income) concentration index (C_k). This decomposition method therefore not only allows us to separate the contributions of the various determinants, but also to identify the importance of each of these two components within each factor's total contribution. This property makes it a powerful tool for unpacking the mechanisms contributing to a country's degree of inequality in use of health care.

One problem in this context is that demand for health care may not be very well modelled using linear estimation techniques such as OLS. Typically, models are intrinsically non-linear, either because of the probability or count data nature of the utilisation variables or because of the two-part structure of the demand decision process [9]. In section 2.3 below we indicate how we have dealt with the non-linearity of the estimated models.

2.2 Measuring horizontal inequity in health care utilisation

Many OECD countries have explicitly included equity in the use of to health care as one of the main objectives in their health policy documents [1] [10]. In most European countries, an egalitarian viewpoint of social justice seems to have been an important source of inspiration for these positions with respect to health care access. Usually, the horizontal version of the egalitarian principle is interpreted to require that people in equal need of care are treated equally, irrespective of characteristics such as income, place of residence, race, etc. In line with most of the previous work in this area (cf [11], for a review), the present study uses this principle of *horizontal inequity* (*HI*) as the yardstick for the international comparisons. While the concentration index of medical care use (C_M) measures the degree of inequality in the use of medical care by income, it does not yet measure the degree of inequity. For any inequality to be interpretable as inequity, legitimate or need-determined inequality has to be taken into account.

There are two broad ways of standardising distributions for need differences: the direct and the indirect method. The direct method proceeds by computing a concentration index for the medical care use that would emerge if each individual (or income group) had the same need characteristics as the population as a whole. Wagstaff *et al.* [12] have used this procedure to compute what they call HI_{WVP} indices, which are essentially directly standardised concentration indices. More recently, Wagstaff and Van Doorslaer [3] have advocated the technique of indirect standardisation for the measurement of so-called HI_{WV} indices on the grounds that it is computationally easier and does not rely on grouped data. A measure of the need for medical care is obtained for each individual as the predicted use of a regression on need indicators. This means that in order to statistically equalize needs for the groups or individuals to be compared, one is effectively using the average relationship between need and treatment for the population as a whole as the vertical equity norm and horizontal inequity is measured by systematic deviations from this norm by income level.

Wagstaff and van Doorslaer [3] proposed to measure HI by the difference between the inequality in actual and needed use of medical care:

$$HI_{WV} = C_M - C_N \tag{6}$$

where C_M and C_N denote the concentration index corresponding to actual and needed use of medical care, respectively. C_N is computed using predicted values $\hat{y}_i$, which can be estimated for each individual i as the expected amount of medical care he or she would have received if he or she had been treated as others with the same need characteristics were, on average, treated by the system. Typically, these are obtained from regressing actual y_i on a set of need indicators like health status and morbidity measures and demographics. The average relationship between need indicators and utilization, as embodied in the regression coefficients, is the implied norm for assessing equity in this health care system. A positive (negative) value of HI_{WV} indicates horizontal inequity favoring the better-off (worse-off). A zero index value indicates no horizontal inequity, i.e. that medical care and need are proportionally distributed across the income distribution. It is worth emphasizing that coinciding concentration curves for need and actual use provide a sufficient but not a necessary condition for no inequity. These indices were used to measure, test and compare horizontal inequity across countries in van Doorslaer *et al.* [4].

One further step in the direction of explaining horizontal inequity was made in [5] by including other, non-need determinants in the (indirect) need standardisation process. In their search for an explanation of cross-country differences in the HI_{WV} indices, they found, for instance, that inclusion of factors like health insurance and regional fixed effects in the standardisation did reduce the degree of pro-rich inequity in specialist use, but seldom to an extent that made it insignificant. They interpreted this as evidence that health insurance and regional variation do play a role in explaining the occurrence and degree of horizontal inequity.

The issue of the role of explanatory models in the measurement of inequity deserves some further attention. Recently, some authors have drawn attention to the potential biases involved in these standardisation procedures. First, the problem of determining which systematic variations in medical care use by income are “needed” and therefore, in a sense, justifiable, and which are not, bears some resemblance to the problem of determining legitimate compensation in the risk adjustment literature. Schokkaert and Van de Voorde [13] have argued that while there is a difference between the positive exercise of *explaining* medical care expenditure (or use) and the normative issue of justifying medical expenditure (or use) differences, the results of the former exercise have relevance for the second. Drawing on the theory of fair compensation, they show that failure to include ‘responsibility variables’ (which *do not* need to be compensated for in the capitation formula) in the equation used for estimating the effect of ‘compensation variables’ (which *do* need to be compensated for) may give rise to omitted variable bias in the determination of the ‘appropriate’ capitations (or fair compensations). Their proposed remedy to this problem is to include the 'omitted variables' in the estimation equation but to 'neutralize' their impact by setting these variables equal to their means in the need-prediction equation. They claim that the argument that even this more fully specified model may suffer from omitted variable bias due to the unavailability of certain variables cannot be used as an excuse for not including what is available. Schokkaert and Van de Voorde point out that the procedure to neutralize the responsibility variables does not hold if the model is not linearly additive.

A similar argument to Schokkaert and Van de Voorde was made and taken further by Gravelle [14] in the context of the measurement of income-related inequality of health or health care. He uses an 'augmented partial concentration index' which is defined as the (directly) standardised concentration index, but controlling for income and other non-standardising variables in the process. In effect, he distinguishes between three types of x_k variables in eq. (2): income itself (x^r), need standardising variables (a vector x^n) and other, possibly policy-relevant variables (a vector x^p):

(5) $$y_i = \alpha + \beta_r x_i^r + \sum_n \beta_n x_i^n + \sum_p \beta_p x_i^p + \varepsilon_i$$

The equivalent of eq. (3) for this specification then becomes:

(6) $$\hat{C} = (\beta_r \bar{x}_r / \bar{y})\hat{C}_r + \sum_n (\beta_n \bar{x}_n / \bar{y})\hat{C}_n + \sum_p (\beta_p \bar{x}_p / \bar{y})\hat{C}_p + GC_\varepsilon / \bar{y}$$

where the first term denotes the (partial) contribution of income inequality ($\hat{C}_r$ equals the Gini coefficient of income inequality if income is entered linearly), the second the contribution of need variables, the third the contribution of other, potentially policy-relevant variables and the last term is, as before, the generalised concentration index of ε. Gravelle [14] labels the first term the partial concentration index and the sum of the first and third term the 'augmented partial concentration index'.

In the context of a linear model, equation (6) therefore provides a neat way to decompose the total measured inequality in medical care use into four sources: (a) the contribution of income, defined as the product of the income elasticity of medical care use and the concentration index of income; (b) the contribution of the need variables, (c) the contribution of other variables, potentially amenable to policy intervention, and (d) a residual term which basically captures the degree to which the residual is correlated with income rank. Assuming that eq. (5) leads to a better estimate of the (partial) need contribution, then a model without the x^r and x^p variables, eq. (6) provides an alternative estimate of horizontal inequity as the C_M minus the second term, or equivalently as the sum of (a), (c) and (d).

So long as model for y is linear, as in equation (7), then the Schokkaert and Van de Voorde [15] approach of estimating the linear regression and then neutralizing the non-need variables by setting them equal to their mean (or, in fact, any constant value) and the decomposition approach lead to the same measure of horizontal inequity (see Appendix).

The decomposition approach has the additional advantage of greater transparency in the presentation of results. Estimating the regression model for use of health care does not require *a priori* agreement on what constitute 'justifiable' and 'unjustifiable' causes of inequality in health care use by income. Some may, for instance, prefer to exclude variables like gender or age from the x^n vector and to include them in the x^p vector, on the grounds that, after having controlled for other health differences, age and gender in and of themselves do not constitute legitimate reasons for differential medical care consumption. Similarly, the question arises whether the residual contribution - term (d) in eq. (8) - needs to be attributed to justifiable or unjustifiable sources of inequality. In our approach, we have decided to classify all of it as unjustifiable variation. At the other extreme, it could be argued that the residuals mainly capture unmeasured need and hence that the residual contribution should be subtracted from *HI*. The decomposition method and, in particular the graphical analysis of the results, make the implications of these different assumptions transparent.

2.3 Nonlinear regression models

One important problem with measuring horizontal inequity and applying the decomposition analysis in the present context is that they will not be linear because the dependent variable in health care demand models is modeled as a nonlinear function of the *x* variables. Our empirical models of health care use are based on logistic and truncated and generalized negative binomial regression models, which are intrinsically nonlinear. The general functional form *G* of such a nonlinear model can be written as:

$$y_i = G(\sum_k \beta_k x_i^k) + \varepsilon_i \tag{7}$$

To compute horizontal inequity in the context of a nonlinear model, again we have used a two-step approach. In the first step we predict need-expected utilisation based on the actual values of the x_n variables, but these predictions are contingent on the level of the non-need variables (x^r and x^p) that is selected. By analogy with the linear case, we have chosen to set the non-need variables equal to their sample means. So,

$$\hat{y}_i \ = \mathrm{E(y|}\ \hat{y}_i = E(y \ \left| x_i^n, \overline{x}^r, \overline{x}^p \right.) = G(\sum_n \hat{\beta}_n x_i^n + \sum_r \hat{\beta}_r \overline{x}_i^r + \sum_p \hat{\beta}_p \overline{x}_i^p) \tag{8}$$

As before, in the second step the HI index is then obtained by subtracting the concentration index of $\hat{y}$ the concentration index of y minus. A complication compared to the linear case is that the HI index for the nonlinear model is contingent on the values used for the non-need variables and therefore their effect is not completely neutralised.

It was noted above that, in the context of linear models, the two-step approach to neutralizing the non-need variables and the decomposition approach give the same measure of horizontal inequity. This does not hold for a nonlinear model, as the linear decomposition does not directly apply to equation (7). However it is possible to approximate the decomposition analysis. To do this, we have opted to use the 'marginal effects' representation for the decomposition. This has the advantage of being a linear additive model of actual utilisation, but it is only an approximation. A linear approximation of this function is given by:

$$y_i = \sum_k \beta_k^m x_i^k + u_i \tag{9}$$

where the β_k^m are the partial effects of each *x* and u_i is the implied error term which includes approximation errors. For the dummy variables average local partial effects are computed using a procedure equal to computing treatment effects evaluated for the treated [15]. This means that β_k^m is measured by computing the average effect for each individual with characteristic *k* and then taking the sample mean over this sub-set of individuals. So, for instance, the average effect of unemployment is calculated as the mean of β_k^m for those who are unemployed. This captures the fact that the unemployed differ from the population as a whole in terms of other characteristics such as age, education, etc.

While eq. (9) is an approximation of the non-linear relationship estimated by the logit or the truncated or generalised Negbin models, it does allow us to restore the mechanics of the decomposition framework by writing the decomposition as:

$$C_M = \sum_k (\beta_k^m \overline{x}_k / \overline{y}) C_k + GC_u / \overline{y} \tag{10}$$

where GC_u now denotes the generalised concentration index of the error term of the linear approximation. Equation (10) forms the basis of our decompositions of the first and the second part of two-part models presented in section 5. These provide a sense of the contributions of individual factors to the overall level of inequality in use of health care, but because of the introduction of the linear approximation error, the HI estimate obtained through the decomposition equation (10) will, in general, not be identical to the HI estimate obtained through the two-step approach using eq. (6). One of the reasons for the discrepancy is that the need contribution, as estimated with the two-step procedure *does* allow for multiplicative interactions among the need regressors while the linearized model obviously does not.

2.4 Statistical inference

In addition to measuring inequality and inequity, we aim to test for cross-country differences. Standard errors for the *C* and *HI* indices were computed using the convenient regression procedure for weighted data. Given the complexity of the survey designs of the ECHP samples and the composition of the contribution terms, we have opted to use a "bootstrap" method [16, 17] to assess sampling variability and to obtain standard errors for the estimates of the contributions. A bootstrap procedure hinges on the assumption that the observed distribution is a random sample of the underlying population distribution, and that individuals within the sample are independent. This assumption does not hold for the complex multi-stage sampling designs used to gather the ECHP data. Therefore we have implemented the bootstrap using the following procedure. First, for the countries for which data were sampled in two stages (i.e. BE, UK, IE, IT, GR, ES, PT), we have drawn a random sub-sample (with replacement) of the primary sampling units (PSU) of a size equal to the original sample size. This step was not necessary for Germany, the Netherlands and Austria, where PSU information was not made available, or for Denmark and Luxembourg, where PSUs were not used. Second, we have drawn a random sub-sample (with replacement) of households within each of the sampled PSUs, and included all members of these households. Third, for each draw, we have normalised the sampling weights to a mean of one, and have run the entire (weighted) procedure to obtain the factor contributions, including the regressions, marginal effects, fractional rank construction and covariance computations. Fourth, repeating this whole process, we have generated 100 resample data sets each providing us with estimates of the contributions. Sixth, using these datasets we have computed the standard deviations as an estimate of the standard error of each factor's contribution and for the *HI* index.

3. Data and estimation methods

3.1 ECHP Data

The data are taken from the third wave (held in 1996) of the *European Community Household Panel* (ECHP) conducted by Eurostat, the European Statistical Office. The ECHP is a survey based on a standardised questionnaire that involves annual interviewing of a representative panel of households and individuals of 16 years and older in each EU member state [18]. It covers a wide range of topics including demographics, income, social transfers, health, housing, education, employment, etc. We use data for the following twelve member states of the EU: Austria, Belgium, Denmark, Germany, Greece, Ireland, Italy, Luxemburg, Netherlands, Portugal, Spain and the United Kingdom. The three missing member states are France (missing utilisation questions), Finland (missing income data) and Sweden (not taking part in ECHP). Analysis was restricted to individuals over the age of 16.

The ECHP income measure (our ranking variable) is disposable (i.e. after-tax) household income per equivalent adult, using the modified OECD equivalence scale (giving a weight of 1.0 to the first adult, 0.5 to the second and each subsequent person aged 14 and over, and 0.3 to each child aged under 4 in the household). Total household income includes all net monetary income received by the household members during the reference year (which is 1995 for the 1996 wave). It includes income from work (employment and self-employment), private non-labour income (from investments and property and private transfers to the household), pensions and other direct social transfers received. No account has been taken of indirect social transfers (e.g. reimbursement of medical expenses), receipts in kind and imputed rent from owner-occupied accommodation.

Measurement of utilisation of general practitioner (GP) and medical specialist services in the ECHP is based on the question "During the past 12 months, about how many times have you consulted a GP/medical specialist?" We use one-year lagged health measures from wave 2 (1995) based on two questions: (a) responses to a question on self-assessed general health status as either very good, good, fair, bad or very bad; and (b) responses to “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? (no; yes, to some extent; yes, severely)”. We use two dummies to indicate either some limitation or severe limitation.

Other regressors included in the analysis are the following. (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, distinguishing between married, separated/divorced, widowed and unmarried (including co-habiting); (iii) Activity status includes employed, self-employed, student, unemployed, retired, doing housework and ‘other economically inactive’. Region of residence uses the EU’s NUTS 1 level (Nomenclature of Statistical Territorial Units) except for countries where such information was withheld for privacy reasons (The Netherlands, Germany) or because the country is too small (Denmark, Luxembourg). Regional identifiers are presented in Table A5. Although most country’s sample sizes are between 7000 and 11,000 adults, some are larger (Spain, Italy) and some are smaller (Denmark and Luxembourg). Cross-sectional sample weights at the individual level were applied in all analyses.

All 12 countries included in this analysis had, by 1996, achieved close to universal coverage of their population for the majority of physician services, but some important between-country differences remain with respect to potentially equity-relevant features of their financing and delivery systems. Van Doorslaer *et al.* [5] have summarized some of the salient system characteristics which may have an impact on any differential utilisation of the general practitioners or medical specialists by income level. In some countries, there are different groups of insured with varying degrees of coverage or rules of reimbursement at different levels of income. This is the case for rather small numbers of high-income earners with private coverage in Denmark and Germany, but it concerns sizeable portions of the population in Ireland and the Netherlands. Some countries’ public insurance have substantial co-payments for GP and specialist consultations (e.g. up to 30-40% of fees in Belgium and Luxembourg; €20 for higher income patients in Ireland), some charge small co-payments (e.g. Portugal) while in many other countries (like Denmark, Germany, Greece, Spain and the UK) visits to public sector doctors are free at the point of delivery [cf tables in [19, 20] for details]. In some countries, notably Denmark, Ireland, Italy, The Netherlands, Portugal, Spain and the UK, the primary care physician acts as a “gatekeeper” referring to secondary care provided by medical specialists, whereas in other countries, there is direct access to all physicians. Some countries pay their general practitioners mainly by capitation (Denmark, Italy, Netherlands, UK) or salary (Greece, Portugal, Spain) whereas others rely mainly on fee-for-service payment. We will have to keep these system differences in mind when interpreting the cross-country comparative results.

3.2 Estimation methods

Health care utilisation data like physician visits are known to have a very skewed distribution to the left with typically the majority of survey respondents reporting zero or few visits and only a very small proportion reporting frequent use. In such cases, integer count data regression is appropriate and a variety of models have been proposed and used [21]. Many applied studies have found that the frequency of zeros in count data is greater than a Poisson model would predict. One source of excess zeros in count data is over-dispersion. The negative binomial, which allows for such overdispersion, has been applied extensively in studies of health care utilisation. Although over-dispersion can account for excess zeros, it may be that there is something special about zero observations *per se*, and an excess of zero counts may not be associated with increased dispersion throughout the distribution. This may reflect the role of the participation decision in the underlying economic model. Many studies of health care utilisation have emphasised the principal-agent relationship between doctor and patient and stressed the distinction between patient initiated decisions, such as the first contact with a GP, and decisions that are influenced by the doctor, such as repeat visits, prescriptions, and referrals [22]. The consequence, in statistical terms, is a two-part model which allows the participation decision (0,1) and the positive count, (1,2,3…), to be generated by separate probability processes. In the count data literature, unlike the limited dependent variable literature, hurdle and two-part (TPM) specifications are often treated as synonymous. The TPM model assumes separate probability processes generate the participation decision and the positive count. The two parts of the model can be estimated separately; with a binary process (LogL1) and the truncated at zero count model (LogL2). The two-part model has often been estimated using either a probit or a logit for the first stage and a negbin model for the second stage [23-26].

Pohlmeier and Ulrich [22] pointed out that a limitation of the hurdle model is that it implies that the measure of repeat visits to the doctor relates to a single spell of illness, an issue that may be especially problematic with annual data and especially for GP consultations. Deb and Trivedi [27] introduce a different approach to the zero count issue. Health care survey data are not usually specific to a period of illness but to a period of calendar time, during which the first recorded visit is not necessarily the initial one in a course of treatment. In this context, it is argued, a TPM specification cannot be justified by appeal to a principal-agent characterisation of the data generating process. Their alternative approach is based on the argument that observed counts are sampled from a mixture of populations that differ in respect of their underlying (latent) health, and so demands for health care. That is, there may be severely ill individuals, who are high frequency users, at one extreme and perfectly healthy individuals, who are non-users, at the other. This characterisation of the data can be captured by latent class models, for example, the finite mixture model (FMM).

Recently, Jimenez, *et al.* [28] have provided further evidence on the relative performance of the TPM and FMM specifications. They estimated (reduced form) demand for health care equations for 12 European countries using three waves of data from the *European Community Household Panel,* distinguishing between utilisation of general practitioners (GPs) and specialists. For GP visits, the results suggest the FMM is more consistent with the data than the TPM. This is true both when parameter homogeneity is imposed across countries and for the vast majority of comparisons on a country-by-country basis. For specialists, a different picture emerges; for the homogeneous parameter specification, the TPM is favoured and this is true for 6 of the 12 individual country comparisons. The authors explain the difference in the preferred specification for GP and for specialist visits by the fact that, over a period of 12 months, multiple spells of illness/ treatment are much more likely to be observed for GP visits, whereas for specialist visits are more likely to represent a single spell. As a result, the TPM, with its rationalisation through the principal-agent story, should be more suited to representing (annual) specialist visit data than GP visit data. Despite the favourable evidence with respect to GP visits, Jimenez *et al*. also express some reservation about the latent class approach because its specification is not derived from an economic theory of health care demand and the large number of parameters to be estimated can lead to problems of non-convergence of the likelihood and to over-parameterisation. Jimenez *et al*. have also examined heterogeneity in the demand for health care across European countries. They have tested both the extent to which the behavioural response of health care utilisation to certain factors, such as health and income, varies across countries and the impact of health system characteristics on utilisation. Despite the similarities in the effect of variables such as the health stock, income or family structure on utilisation, their tests reject the hypothesis of parameter homogeneity across countries.

In this paper we have chosen to adopt a TPM estimation model combining a logit and a truncated negbin for both the GP and specialist demand equations on the grounds that the distinction between a first and subsequent contacts makes sense theoretically when one is focusing on the effect of income. A disadvantage is that the inequity and inequality in the total number of visits cannot simply be derived from the results for these two parts. We have therefore, in addition, also estimated equations for the total number of visits using the generalised Negbin model (cf [9]). The generalisation consists of modelling the excess zeros as unobservable heterogeneity; allowing the heterogeneity parameter (alpha) to be a function of the *x*'s rather than being constant.

Like [28], we have exploited the availability of previous waves of the ECHP to use lagged values of the health variables in order to reduce the risk of endogeneity in the health status variables. Because of their rejection of cross-country homogeneity, we have chosen not to pool the data across countries. For all countries and surveys, cross-sectional sample weights were used in all computations in order to make the results more representative of the countries' populations. Robust standard errors were obtained by applying White-Huber-sandwich estimator that corrects for heteroskedasticity of unknown form. This estimator was adjusted to also correct cluster sampling. We clustered on households, as this is the smallest cluster unit and information on the primary sampling units was not available for all countries.

4. Results

While the focus of this paper is on the differences in relative inequality in utilisation by income level *within* European countries, it is clear that there is tremendous variation also in the average levels of physician utilisation *across* these countries. In [5], it is shown that the mean annual number of visits to a GP varies from a low of 2.19 in Greece to a high of 5.39 in Austria, and mean visits to a specialist from a low of 0.62 in Ireland to a high of 3.29 in Germany. Some countries, notably Germany and Austria, have above-European average rates of utilization for both GP and specialist visits. Countries with below-average utilisation rates for both types of visits include Ireland, Netherlands, Denmark, UK, Portugal, Spain and Greece. Belgium and Italy have above-average GP visit rates only and Luxemburg is the only country with above-average specialist visit rates only. These inter-country differences in mean utilisation levels are probably closely related to GP and specialist availability and remuneration across countries. They have to be interpreted carefully given the cross-country differences in the definition of GP visits (office, home, health centre) and specialist visits (private practice, in hospital, etc).

The C_M and *HI* results for the total number of GP and specialist visits summarized in Tables 2 and 3 for can directly be compared with those obtained in [5]. The difference is that here a (one-part) generalized negative binomial model was used, and that *partial* need effects were used to compute C_N. We also decompose the findings *by parts* (of the decision process) and *by sources* (or explanatory variables).

We illustrate and explain the mechanics of the decomposition using an example taken from table A3 for the specialist visit probability in Spain. The table shows how the means, concentration indices and marginal effects for each variable and how they translate into inequality contributions. The omitted categories are for young (16-29) males with very good health no health limitations, low education, employed, married and living in the North-west of Spain. All the need variables (age, gender, SAH and activity limitations because of a chronic condition) show negative inequality contributions. This is because generally those who are older, female and in less good health also tend to have lower incomes (negative CI) and are more likely to see a specialist. The main exception is females aged 30-44 who tend to have better (household) incomes than young men, resulting in a positive inequality contribution. Especially the main need proxies (i.e. the lagged health variables) produce significant negative inequality contributions. A better education, by contrast, is associated with higher incomes and, *ceteris paribus*, a greater specialist contact probability, resulting in a strong contribution. It is smaller than the contribution of income itself, of course. Those not in paid employment because of housework or otherwise inactive also contribute negatively while marital status does not influence inequality. Finally, regional effects contribute substantially to greater pro-rich inequality in Spain, mainly because the three richer regions (Madrid, the East and the North-east) also have higher specialist visit probabilities. If there were no income or consumption differentials, the income-related inequity in specialist visit probability would be 22% smaller. Nonetheless, even after controlling for all of these other variables, the partial contribution of income itself still accounts for the largest contribution (65% of HI) to pro-rich inequity. It is conceivable that some of this influence is channeled through the purchase of private health insurance and the use of private care [29].

Table 1: Decomposition example: specialist visit probability Spain

	Mean	CI	logit marg eff	Contrib	t-val	Sum
actual y	0.4070	0.0439		0.0439		
y predicted	0.4070	0.0432		0.0434		
HI				0.0658	8.93	
Log (inc)	8.9377	0.0394	0.0487	0.0422	6.96	0.0422
m30-44	0.1310	0.0798	-0.0099	-0.0003	-0.56	
m45-59	0.1003	0.0003	0.0439	0.0000	0.02	
m60-69	0.0636	-0.0061	0.0788	-0.0001	-0.33	
m70+	0.0457	-0.0522	0.1134	-0.0007	-2.39	-0.0010
f16-29	0.1345	-0.0458	0.1168	-0.0018	-3.16	
f30-44	0.1380	0.0546	0.1510	0.0028	3.58	
f45-59	0.1115	-0.0034	0.1661	-0.0002	-0.25	
f60-69	0.0688	-0.0254	0.1786	-0.0008	-1.52	
f70+	0.0718	-0.0994	0.0589	-0.0010	-2.24	-0.0009
SAH good	0.4579	0.0467	0.0352	0.0018	2.72	
SAH fair	0.2187	-0.0430	0.1667	-0.0039	-4.85	
SAH poor	0.1031	-0.1563	0.2381	-0.0094	-8.43	
SAH v poor	0.0222	-0.1325	0.2576	-0.0019	-4.16	-0.0133
Some limit	0.1026	-0.1281	0.1127	-0.0036	-5.07	
Severe limit	0.0614	-0.1584	0.1125	-0.0027	-3.75	-0.0063
Second educ	0.1786	0.1455	0.0394	0.0025	3.17	
Higher educ	0.1422	0.4329	0.0630	0.0095	4.71	0.0120
Self-employed	0.0924	-0.0704	-0.0179	0.0003	1.05	
Student	0.0840	-0.0210	-0.0044	0.0000	0.17	
Unemployed	0.1076	-0.2541	-0.0036	0.0002	0.24	
Retired	0.1248	-0.0027	0.0431	0.0000	-0.22	
Housework	0.2149	-0.1329	0.0387	-0.0027	-2.40	
Other inactive	0.0778	-0.1083	0.0805	-0.0017	-3.44	-0.0039
Sep/divorced	0.0138	-0.0945	-0.0303	0.0001	0.81	
Widowed	0.0776	-0.0514	-0.0452	0.0004	1.82	
Not married	0.2673	0.0212	-0.0443	-0.0006	-2.11	-0.0001
Noreste	0.1025	0.1375	0.0206	0.0007	1.04	
Madrid	0.1254	0.2987	0.1110	0.0102	6.04	
Centro	0.1304	-0.1529	-0.0014	0.0001	0.08	
Este	0.2770	0.0988	0.0755	0.0051	4.39	
Sur	0.2067	-0.2046	0.0184	-0.0019	-1.06	
Canarias	0.0411	-0.2375	-0.0210	0.0005	0.83	0.0147

We have included inequality contributions by type of utilisation and by country in four summary Tables A1-A4, but not the underlying tables. [*The full decomposition tables for 12 countries and 6 dependent variables with regression coefficients, means and concentration indices of all explanatory variables can be made available on the internet*]. Here we concentrate on the broad picture by looking at the inequality decomposition into the contribution of four sources: (i) income itself, (ii) need variables, including health status at the beginning of the reference period and age and gender dummies, (iii) other demand determinants like education, labour force or marital status and region, and (iv) the residual term. As explained in section 2.1, each of these determinants will contribute to the total income-related inequality in use to the extent that (a) it has a significant demand elasticity, and (b) it is unequally distributed by income.

4.1 Decomposing inequality and inequity in GP care utilisation

The results summarized in Table 2 can be compared with those we obtained in [5] for the total number of visits, but here the findings are decomposed *by parts* of the decision process. Statistically significant contributions are indicated in bold. Virtually all concentration indices for the probability of a visit, the conditional and the total number of visits are negative. This means that generally lower income groups are *both* more likely to seek care from a GP than higher income groups, *and* they do so more frequently. But the unequal distribution of GP care to a large extent appears to be in line with the similarly unequal distribution of the need for such care. After controlling for the unequal need distributions, the resulting horizontal inequity indices are insignificant in seven countries, pro-poor in Spain and Denmark, and significantly pro-rich in Belgium, UK and the Netherlands. However, in all countries, the horizontal inequity (*HI*) index for the visit probability is fairly small, i.e. within the range [-0.01; 0.02]. There appears to be only a very small degree of income-related horizontal inequity in the GP contact probability.

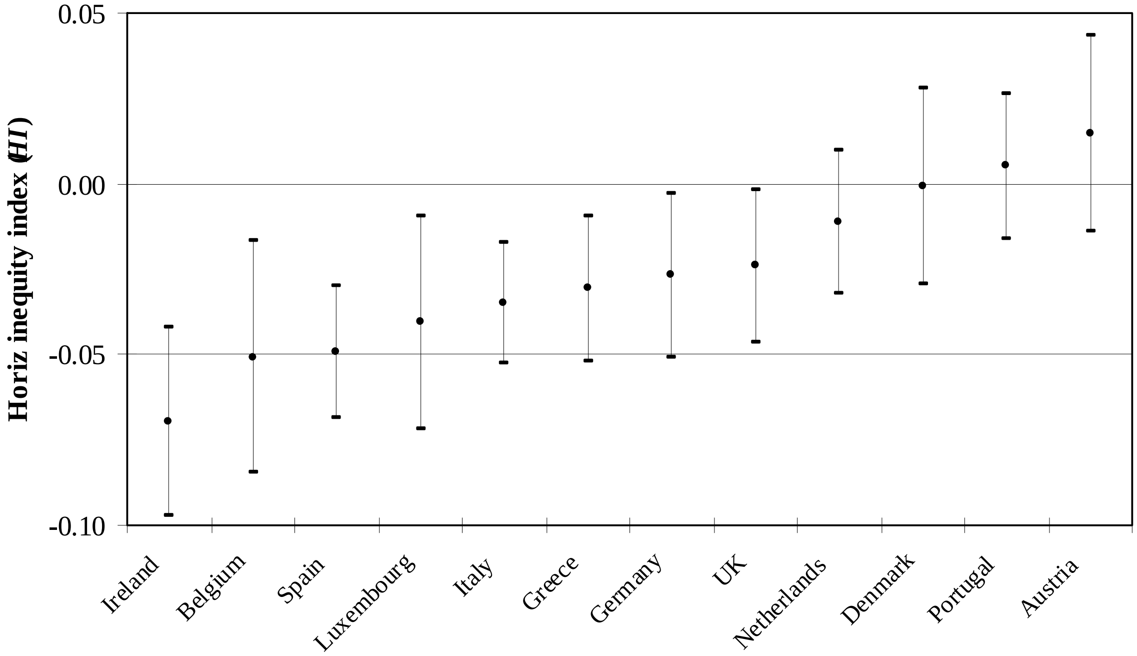
Table 2: Inequality and inequity in GP visits, ECHP, 1996

GP visits	Probability of a visit		Conditional # of visits		Total # of visits	
	Inequality (C_M)	Inequity (HI)	Inequality (C_M)	Inequity (HI)	Inequality (C_M)	Inequity (HI)
Ireland	**-0.0187**	0.0035	**-0.1136**	**-0.0657**	**-0.1323**	**-0.0696**
Belgium	0.0037	**0.0121**	**-0.1183**	**-0.0564**	**-0.1145**	**-0.0508**
Spain	**-0.0294**	**-0.0167**	**-0.0612**	**-0.0371**	**-0.0906**	**-0.0492**
Luxembourg	-0.0076	0.0002	**-0.0841**	**-0.0428**	**-0.0918**	**-0.0406**
Italy	-0.0055	-0.0002	**-0.0594**	**-0.0322**	**-0.0649**	**-0.0349**
Greece	**-0.0413**	-0.0041	**-0.0845**	**-0.0212**	**-0.1258**	**-0.0308**
Germany	**-0.0124**	**-0.0082**	**-0.0513**	-0.0173	**-0.0636**	**-0.0268**
UK	-0.0076	**0.0109**	**-0.0930**	**-0.0301**	**-0.1006**	**-0.0240**
Netherlands	-0.0019	**0.0103**	**-0.0517**	**-0.0201**	**-0.0535**	-0.0113
Denmark	**-0.0200**	0.0061	**-0.0631**	-0.0085	**-0.0831**	-0.0008
Portugal	**-0.0143**	0.0099	**-0.0549**	-0.0038	**-0.0692**	0.0051
Austria	**-0.0082**	-0.0018	**-0.0417**	0.0114	**-0.0499**	0.0146

Notes: Countries ranked by inequity index for total visits (last column). Inequity indices computed using a logit model for the probability, a truncated negbin model for the conditional number and a generalised negbin for the total number of visits. Significant *HI* indices in bold (P<0.05).

The picture is somewhat different for the second stage of the demand process, i.e. for the *conditional (positive) number* of visits. Table 2 shows that income-related inequity is more negative (i.e. favouring the lower income groups) and significant in eight of the twelve countries in the second part of the demand model. Both the C_M and the *HI* indices here are generally more negative than for the probability of a visit. As a result, we also find substantial inequity in *total* GP visits, which are concentrated among the poorer segments in most countries, with significant inequity favouring the lower income groups in eight of the countries. The index values with the corresponding 95% confidence intervals for total number of GP visits are shown graphically in Figure 1. All the significant values are in the range [-0.02; -0.05] except for Ireland, for which it equals -0.07. In only four countries — Austria, Denmark, Portugal and Netherlands — the hypothesis of no inequity cannot be rejected. There does not appear to be one system characteristic that explains this finding since these four countries all have very diverse characteristics. There appears to be a general tendency — irrespective of the system characteristics — for lower income groups to have more frequent GP visits in European countries. In the two countries with most negative index values, this tendency is exacerbated by pro-poor discrimination. In Ireland, only the 30% on the lowest incomes are medical cardholders and entitled to free GP services, while others must pay out-of-pocket. In Belgium, elderly and chronically ill on low incomes pay much reduced co-payments.

Fig. 1: Inequity indices for number of GP visits (with 95% confid intervals)

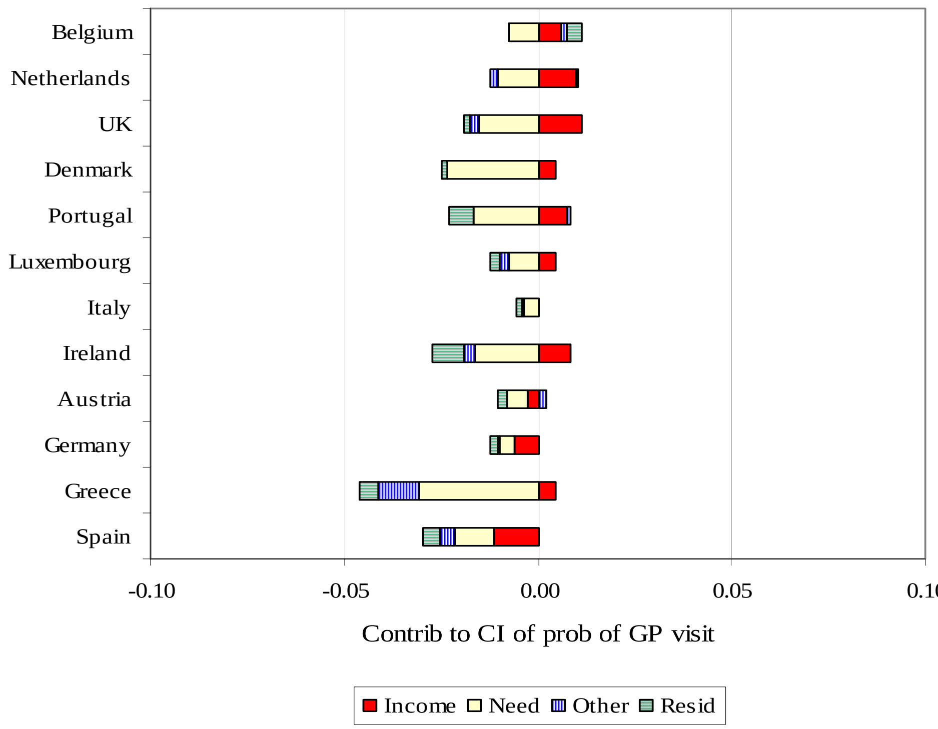


As explained in section 2.3, in the nonlinear model setting, the degree of horizontal inequity can only be decomposed approximately using an equation like eq. (10). The generalized concentration index of the error term then includes both an estimation error and an approximation error. This is an inevitable price to be paid to restore linearity. As a result, the HI indices estimated using the two-step approach explained in eq. (6) with the need predictions generated by eq. (8) will not, in general, be identical to estimates generated with the linear approximation of the decomposition. The approximate contribution estimates nonetheless provide some useful insight into the direction and magnitude of the various source contributions.

Figure 2 presents the contributions of the four sources of inequality as distinguished in eq. (6). Inequality in the *probability* of a GP visit in each of the 12 countries is (approximately) decomposed into the partial contributions of (a) (the log of) household income, (b) need indicators like self-reported morbidity, age and sex, (c) other non-need variables like education, marital and activity status and region and (d) a residual term. As explained in section 2.3, the latter term includes both a prediction error and an error generated by the linear approximation used to obtain the marginal effects. It is to be noted that aggregating the contributions of several (dummy) variables means that positive and negative contributions may cancel out in the aggregate so that a small contribution may 'hide' the summation of larger positive and negative contributions.

Fig. 2: Decomposition of inequality in GP visit probability

Note: Decomposition based on linear approximation using marginal effects from a logit regression. Countries ranked by degree of horizontal inequity



One way of reading the chart is as follows. In a country where the probability of a GP visit were equally distributed across income, the sum of the bars would be zero. In a country with a perfectly equitable distribution of GP visits across income, the sum of the bars would be equal to the need bar, which indicates the distribution of need by income. As soon as discrepancies emerge between the actual and the need-expected distribution, the other bars appear. They indicate what share of the discrepancy between need and use is due to either income itself, or to other variables included in the equation, or to variables not included.

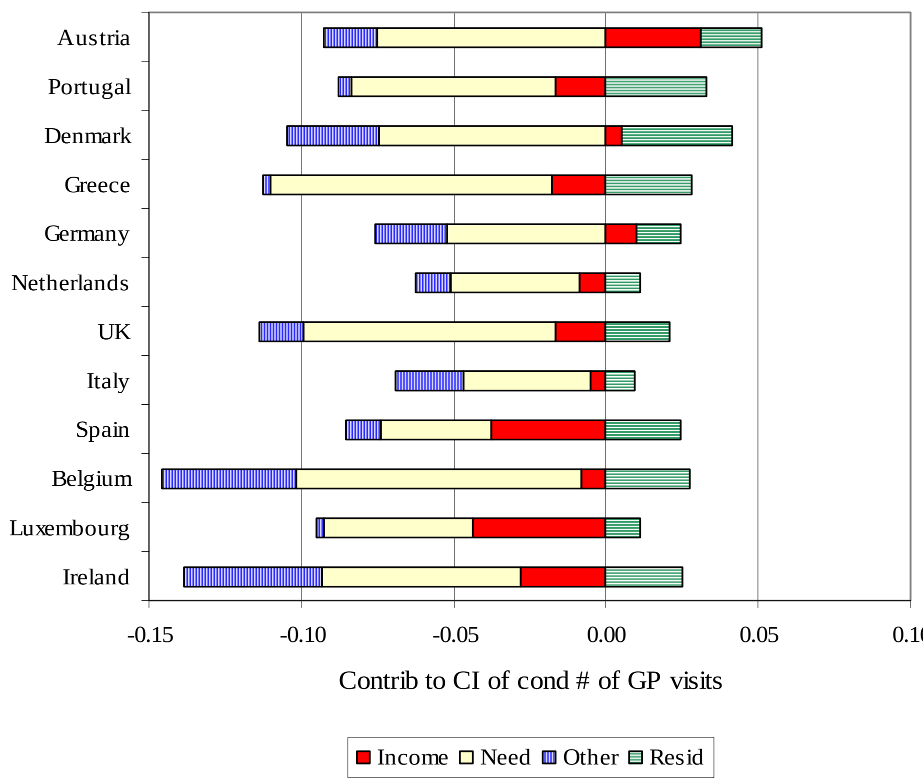
We can see that inequality in the GP use probability is fairly small and pro-poor, and mainly accounted for by the contribution of need factors in all countries. This means that the distribution is pro-poor because the need distribution is pro-poor. The partial contribution of income is generally positive but rather modest. All other variables show negative but small contributions. The (sub)decomposition into the contributions of each variable presented in Table A1 shows that this summary picture may conceal significant positive and negative contributions which cancel out in the aggregate. Where inequality is substantial, as in Greece, it is mainly a consequence of the unequal distribution of *education* by income: the higher educated tend to be richer but, *ceteris paribus*, less likely to use GP services. The influence of education may capture differences in communication skills or simply taste differences.

Figure 3 shows greater inequality in the distribution of the conditional (positive) number of GP visits. It is more pro-poor, but again this is mainly due to the greater needs of the poor. The often negative partial contribution of income indicates pro-poor treatment patterns (except in Austria, Germany and Denmark). Table A2 shows that important ‘other’ non-need variables contributing to the pro-poor distribution are education (in all countries except Denmark, Netherlands, Luxembourg and Austria), non-active status like retired, unemployed, housewives, inactive status in Belgium, Ireland, and Italy (in all countries except Netherlands, Luxembourg and Greece) and region (in the Mediterranean countries). To the extent that some of these categories may reflect a greater need for care (like e.g. inactive status may include recipients of disability pensions) and have a negative contribution, we may, in effect, be underestimating the need contribution and therefore overestimating the degree of pro-poor inequity.

In general, we tend to find that the contribution of the residual term is positive (pro-rich), unlike the contribution of the measured need variables that is negative (pro-poor).

Fig. 3: Decomposition of inequality in conditional number of GP visits

Note: Decomposition based on linear approximation using marginal effects from a truncated negbin regression. Countries ranked by degree of horizontal inequity



4.2 Decomposing inequality and inequity in specialist care utilisation

The distribution of specialist care utilisation by income, summarized in Table 3, looks dramatically different from the use of GP services. In all but three countries (the Netherlands, Denmark and Greece), higher income groups are *more* likely to report at least one visit to a specialist, while the need for such care is invariably higher among the lower income groups. It is therefore not a surprise that, after controlling for these need differences, we find substantial degrees of horizontal inequity favouring the rich for this probability, which are statistically significant in all countries except Denmark. In seven of the countries, this is compounded by similar pro-rich inequity in the conditional number of specialist visits. Overall, we see a high and significant degree of pro-rich inequity in total specialist visits in all countries except Luxembourg and Belgium. Luxembourg is a somewhat special case because of its small size (and sample), the lack of academic hospitals, the high degree of cross-border care delivery and the unclear distinction between a specialist and a general practitioner. Belgium's more equal distribution may be due to its positive discrimination in favour of certain lower income groups through lower rates of co-payment.

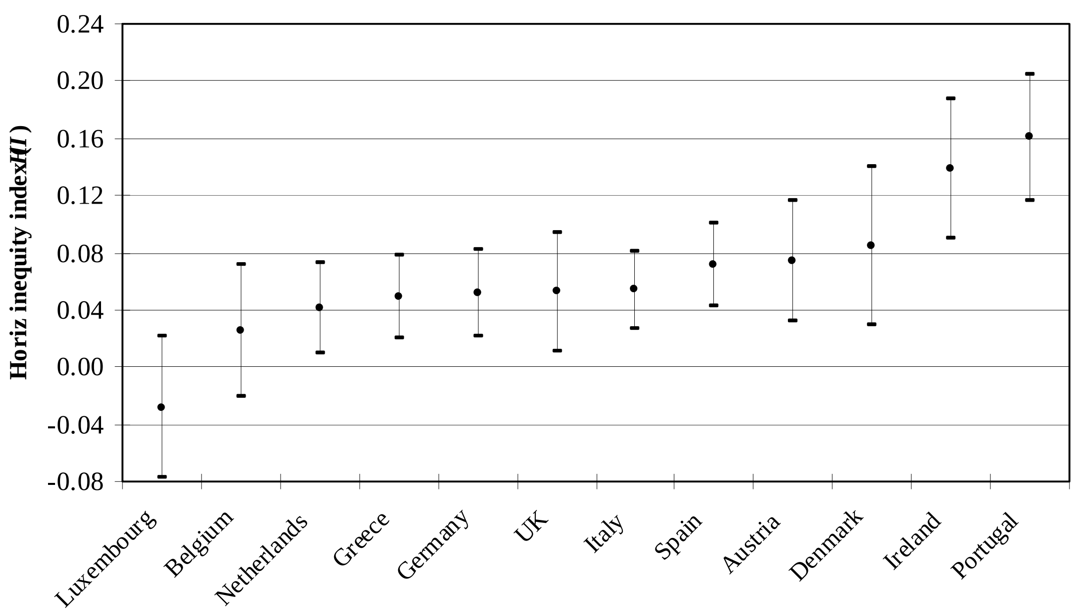
Table 3: Inequality and inequity in specialist visits, ECHP 1996

	Probability		Cond Number		Total	
	Inequality (C_M)	Inequity (*HI*)	Inequality (C_M)	Inequity (*HI*)	Inequality (C_M)	Inequity (*HI*)
Luxembourg	0.0195	**0.0346**	**-0.0899**	**-0.0594**	**-0.0704**	-0.0282
Belgium	0.0125	**0.0344**	-0.0394	-0.0008	-0.0269	0.0255
Netherlands	-0.0041	**0.0307**	-0.0137	0.0197	-0.0178	**0.0413**
Greece	-0.0175	**0.0355**	-0.0242	0.0216	**-0.0418**	**0.0492**
Germany	**0.0130**	**0.0243**	0.0029	**0.0269**	0.0158	**0.0517**
UK	0.0163	**0.0723**	**-0.0397**	-0.0062	-0.0234	**0.0524**
Italy	**0.0416**	**0.0617**	-0.0237	-0.0035	0.0179	**0.0537**
Spain	**0.0439**	**0.0658**	-0.0171	0.0121	0.0267	**0.0714**
Austria	0.0108	**0.0214**	0.0237	**0.0554**	0.0345	**0.0740**
Denmark	-0.0074	0.0223	0.0297	**0.0581**	0.0223	**0.0844**
Ireland	**0.0621**	**0.1168**	0.0149	0.0299	**0.0770**	**0.1388**
Portugal	**0.0774**	**0.1103**	0.0197	**0.0549**	**0.0971**	**0.1604**

Note: Countries ranked by total inequity index (last column). Contributions computed using a logit model for the probability, a truncated negbin model for the conditional number and a generalised negbin for the total number of visits. Significant *HI* indices in bold (P<0.05).

Figure 4 graphically illustrates the between-country differences and confidence intervals. Most countries show inequity indices between 0.04 and 0.08 which are not significantly different from one another. Portugal and Ireland, in particular, show significantly horizontal inequity index values than many of the other countries, and only the indices for Luxembourg and Belgium are not significantly different from zero. The reason for the strong pro-rich pattern in Ireland seems fairly obviously related to the dual insurance system by income level in this coutnry, where low income groups with a medical card (30%) are entitled to free GP services but higher income groups have to pay out-of-pocket and increasingly buy private insurance to cover outpatient (specialist service) charges. The situation is different in Portugal where much of the pro-rich distribution appears related to the high share paid for out-of-pocket (or through private insurance) for private consultations and the low access to specialist services in poorly endowed regions.

Fig 4: Inequity indices for total number of specialist visits (with 95% confid intervals)



From the (aggregate) decomposition in figure 5 we can see that pro-rich inequity is mainly the result of a strong partial contribution of income in most countries (lowest in Austria and the Netherlands), which is exacerbated by the contribution of other variables in some countries, notably in Ireland, Spain, Italy and Portugal. Appendix table A2 shows that the effect of these ‘other variables’ is primarily due to the very pro-rich contribution of higher education. While we did not include a variable indicating coverage by private health insurance in these reduced form equations, it is likely that such private cover will contribute significantly to the pro-rich distribution of specialist visit probabilities. It may not be a coincidence that the highest pro-rich inequity indices are found for precisely the five countries for which such ‘duplicate private coverage’ is most prevalent (i.e. Ireland, Portugal, UK, Spain and Italy). In other words, much of the income and ‘other’ variable contributions may, in fact, reflect the role of the unequal distribution of private insurance coverage (cf. [5]).

Fig 5: Decomposition of inequality in specialist visit probability

Note: Decomposition based on marginal effects from logit regression; countries ranked by degree of horizontal inequity

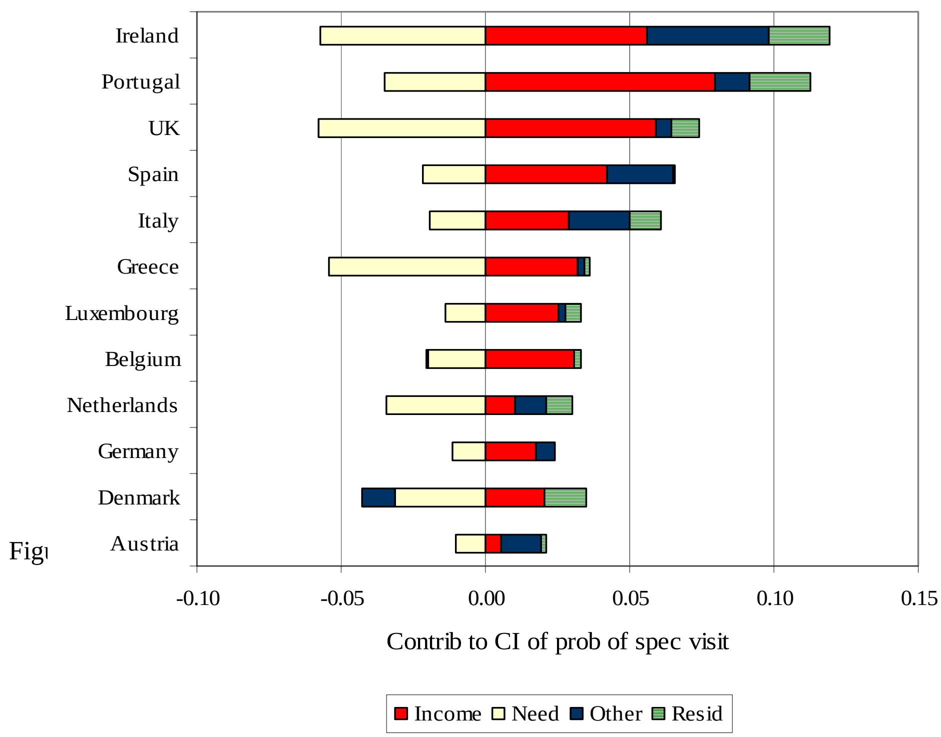
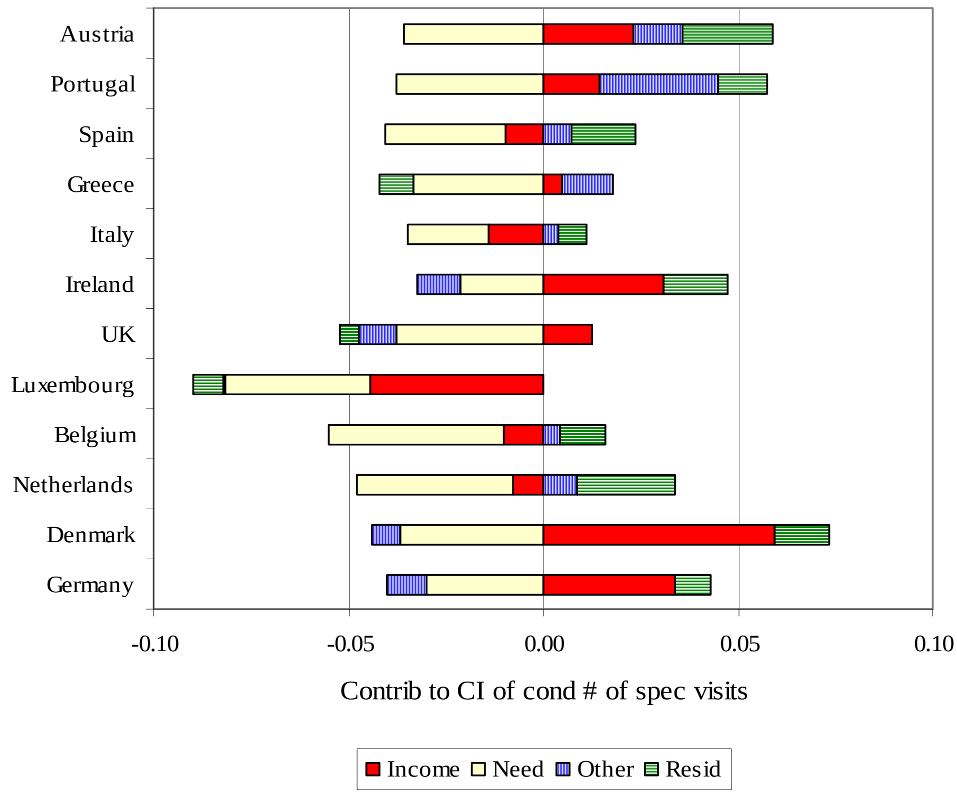


Figure 6, on the other hand, shows that the contribution of income is less important for inequity in subsequent specialist visits. It is only significantly positive in Denmark and Germany, and significantly negative in Luxembourg. In a few countries, e.g. Portugal, Spain and Greece, other variables contribute more to the pro-rich distribution of these visits. Table A4 reveals that in this case it is the regional disparities which play an important role. In the three southern countries, a sizeable share of the pro-rich inequity is due to the much higher use of specialist visits in the richer capital regions of Madrid, Lisbon and Athens. This finding highlights the usefulness of the decomposition approach to trace the sources of inequality patterns in medical care use.

Fig. 6: Decomposition of inequality in conditional number of specialist visits

Note: Decomposition based on linear approximation using marginal effects from a truncated negbin regression. Countries ranked by degree of horizontal inequity



5. Conclusion and discussion

This paper provides new evidence on the sources of differences between European countries in the degree to which health care use is unequally distributed by income. While it builds on previous international comparative work, it also offers a number of advances, both in terms of new data analysed and in terms of new methods used. First, it exploits new and highly comparable data on the use of general practitioner and specialist services in 12 EU member states collected in the *European Community Household Panel* survey of 1996. Secondly, it employs new methods for decomposing the total observed inequality in utilisation by 'sources'. While such methods have been deployed previously and successfully for the decomposition of inequalities in health, they have hitherto not been used to examine the sources of inequality in utilisation. The main reason for this is that the decomposition method was developed for linear models, while it is well known that medical care use is typically and most appropriately modelled using inherently non-linear models. We show that a linear approximation of these models using a 'marginal effects' representation of the decomposition is one way of dealing with this non-linearity problem. As a result, we can decompose (an approximation of) the inequality in *actual* use, not in the latent index representing the propensity to use medical care. Thirdly, we also perform a decomposition 'by parts' of the decision process by doing this separately for the probability of a visit and for the conditional positive number of visits. As such, we are better able to distinguish between factors driving inequality in initial visits and in subsequent visits. Finally, we illustrate how statistical inference can be based on standard error estimates of the inequality contributions generated with bootstrapping methods.

The results provide a number of new insights. First, we find that in *all* European countries, both the need for GP services and the use of such care are more concentrated among the poorer population segments. But in many cases the actual distribution is even more pro-poor than the need distribution. Violations of the principle of "equal treatment for equal need" by income are very modest: rich and poor face very similar probabilities of seeing a GP when need differences have been adjusted for. Some pro-poor inequity emerges for the conditional number of visits, but it is relatively small. To the extent that the decision for subsequent or repeated visits is more likely to be influenced by the doctor than by the patient, this pro-poor discrimination may be doctor-driven.

Secondly, the findings are dramatically different in the case of specialist visits. While needs are often greater among the poor, specialist use is often higher among the rich or, at best, distributed fairly equally. Consequently, after controlling for the greater needs of the poor, substantial degrees of horizontal inequity favouring the rich emerge in *all* countries. Everywhere in Europe, the use of specialist visits is higher (than expected on the basis of need) for the rich and lower for the poor, but the degree to which occurs differs substantially between countries: the pro-rich pattern is strongest in Ireland and Portugal, and weakest in the Benelux countries. But also the 'decomposition by parts' provides a different picture for specialist visits: the probability of an (initial) visit is much more important than the (conditional) number of (subsequent) visits in generating the observed patterns of income-related horizontal inequities. In most countries, by far the greater share of overall inequity in specialist use stems from the unequal distribution of an initial contact. This would suggest that inequity here is rather more patient-initiated than doctor-driven, although in countries with gatekeeping roles for GPs it may be GP-initiated. Notable exceptions to this rule are Austria and Denmark, where most of the inequity stems from the conditional number of positive visits and may therefore be related to specialist self-referral patterns.

Third, the paper also sheds light on the relative contributions of the factors driving the cross-country differences in inequalities. For GP care utilisation, the most important variables contributing to a more pro-poor distribution are not income itself but rather other indicators of social disadvantage, such as low education, retirement, and non-participation in the labour force. In so far as regional disparities can be captured with our data, they appear relatively unimportant here. This may either be interpreted as some sort of positive discrimination by GPs of lower socio-economic categories but an alternative and equally plausible explanation is measurement error in the need variables. It is not impossible that self-reporting of morbidity is systematically different among these categories. If these groups were to under-report morbidity compared to some objective measure of health then, for a given level of self-reported morbidity, their needs may actually be greater than those of other, more advantaged groups. Unfortunately, this hypothesis cannot be tested in the absence of a more objective measure of need. The non-linear models implicitly capture multiplicative interaction between need and non-need variables, but in the normative model used to measure inequity such interactions necessarily have to be suppressed as they would rule out the possibility to distinguish differential reporting tendencies from differential treatment patterns.

In the case of specialist visits, the contribution of income to the pro-rich distribution is much clearer, especially for the probability of seeing a specialist. Particularly in those countries where higher income can buy quicker or preferential access to a medical specialist, this contribution seems to be larger. It can be because those with higher incomes buy supplemental private insurance, as in Ireland, Spain and the UK, or because they are more likely to use the private sector, as in Portugal and Italy. It is less obvious why income also contributes substantially to a pro-rich distribution of specialist visits in a country like Denmark, where both private insurance and private practice (for specialist services) are nearly non-existent. In that country, the horizontal inequity definitely arises within the public system. Among the other non-need variables included in the analysis, education and region stand out as other important contributing factors. In almost all countries, the higher educated (which tend to be richer) also tend to be (much) more inclined to contact a specialist than the lower educated. Whether such medical consumption behaviour is 'more appropriate' is impossible to answer from this analysis, but it does mean that rich and poor do not get the same kind of treatment, given need. If it is the case that, given the same need, specialist visits represent higher quality treatment than GP visits, then the better-off are getting more out of their health care systems than the less well-off.

We conclude by reminding the reader of the limitations of our analysis. First of all, it only refers to diffences in quantities of use, not qualities. We cannot but assume that “a visit is a visit” since we have no means of controlling for differences in the quality of doctor visits within or between countries. Adjusting for quality differences (e.g. by distinguishing public from private visits) might make the differentials larger or smaller. A similar remark applies to the appropriateness of care use. We had to assume that the average relationship observed in a country between reported morbidity and use is the norm for “appropriateness of care” and register systematic relative deviations from this norm. In practice, it is almost certain that there are differences between countries in the extent to which such as a norm is indeed “appropriate”. Finally, while the ECHP data offer some fascinating new options for cross-European comparisons by coupling richd “appropriate”. Finally, while the ECHP data offer some fascinating new options for cross-European comparisons by coupling richverage. In particular, the limited information on the type and degree of insurance coverage and the type of health care use precludes a more detailed analysis of the public-private sector interactions in medical care utilisation.

But keeping these limitations in mind, we find that in European countries, despite decades of universal and fairly comprehensive coverage, utilisation patterns suggest that rich and poor are not treated equally. At equal levels of need, the access to and use of specialist services is greater for higher income groups. Only in some countries, like Ireland, Spain or Belgium, this seems to be somewhat compensated by pro-poor patterns in the use of GP care. Unless this finding is a consequence of a deliberate policy to offer such groups private access options over and above their public entitlements, we cannot but conclude that -- despite a long tradition of public intervention in health care -- there is still some way to go before equals are treated equally in Europe.

Appendix 1: Proof of equivalence of one-step and two-step estimator of horizontal inequity index in linear models

Using a method of indirect standardisation, Wagstaff and van Doorslaer [3] define an index of horizontal inequity for utilisation (y) as in eq. (6) as

$$(1.1) \quad HI_{WV} = C_M - C_N = C(y) - C(\hat{y}) = C(y - \hat{y})$$

where $\hat{y}$ is need-predicted utilisation from regressing y on a vector of need variables (x^n).

Following Schokkaert and van de Voorde [15], one could propose that, in order to use the partial effects of the need variables in the standardisation process, the estimated regression should also include a vector of non-need variables (x^p), but their effect should be 'neutralized' when generating the need predictions, e.g. by setting these equal to their mean values $(\bar{x}^p)$. For example, if

$$(1.2) \quad y = \beta' x^n + \alpha' x^p + \varepsilon$$

and

$$(1.3) \quad \hat{y}_{PN} = \beta' x^n + \alpha' \bar{x}^p$$

then a horizontal index defined on the basis of these partial need effects is

$$(1.4) \quad HI_{PN} = C(y) - C(\hat{y}_{PN})$$

Substituting (1.2) and (1.3.) in (1.4) gives

$$(1.5) \quad HI_{PN} = C(\beta' x^n + \alpha' x^p + \varepsilon) - C(\beta' x^n + \alpha' \bar{x}^p)$$

Using the covariance definition of a CI (eq. (1)) and additive separability of covariances

$$(1.6) \quad HI_{PN} = C(\beta' x^n) + C(\alpha' x^p) + C(\varepsilon) - C(\beta' x^n) - C(\alpha' \bar{x}^p)$$

Note that $C(\alpha' \bar{x}^p)$ = 0 because the covariance of a constant is zero, and this is true whatever fixed values for x^p are used. So,

$$(1.7) \quad HI_{PN} = C(\alpha' x^p) + C(\varepsilon)$$

This expression is equivalent to the HI definition based on the decomposition methods in eq. (8) (if income x^r is included in the non-need vector x^p). Note that the equivalence of both approaches relies on the linearity of eq. (1.2) but not on the choice of the fixed values for x^p.

References

1. Van Doorslaer, E., A. Wagstaff, and F. Rutten, eds. *Equity in the finance and delivery of health care: An international perspective*. 1993, Oxford University Press: Oxford.

2. Van Doorslaer, E., A. Wagstaff, and e. al. (1992). Equity in the Delivery of Health Care: Some International Comparisons. *Journal of Health Economics*, **11**(4): 389-411.

3. Wagstaff, A. and E. van Doorslaer (2000). Measuring and testing for inequity in the delivery of health care. *Journal of Human Resources*, **35**(4): 716-733.

4. Van Doorslaer, E., et al. (2000). Equity in the delivery of health care in Europe and the US. *Journal of Health Economics*, **19**(5): 553-583.

5. Van Doorslaer, E., X. Koolman, and F. Puffer, *Equity in the use of physician visits in OECD countries: has equal treatment for equal need been achieved?*, in *Measuring Up: Improving Health Systems Performance in OECD Countries*, OECD, Editor. 2002, OECD: Paris. p. 225-248.

6. Wagstaff, A., E. Van Doorslaer, and N. Watanabe (2003). On decomposing the causes of health sector inequalities, with an application to malnutrition inequalities in Vietnam. *Journal of Econometrics*, **112**(1): 219-27.

7. Van Doorslaer, E., and X. Koolman (2002). *Explaining the differences in income-related health inequalities across European countries*. ECuity II Project Working Paper, #6, Erasmus University, Rotterdam,

8. Lerman, R.I. and S. Yitzhaki (1989). Improving the Accuracy of Estimates of Gini Coefficients. *Journal of Econometrics*, **42**(1): 43-47.

9. Jones, A.M., *Health Econometrics*, in *Handbook of Health Economics*, A.J. Culyer and J.P. Newhouse, Editors. 2000, Elsevier North-Holland: Amsterdam. p. 265-346.

10. Hurst, J.W., *Performance measurement and improvement in OECD health systems: overview of issues and challenges*, in *Measuring Up: Improving Health Systems Performance in OECD Countries*, OECD, Editor. 2002, OECD: Paris. p. 35-54.

11. Wagstaff, A. and E. Van Doorslaer, *Equity in health care finance and delivery*, in *Handbook of Health Economics*, A.J. Culyer and J.P. Newhouse, Editors. 2000, Elsevier North-Holland: Amsterdam. p. 1803-1862.

12. Wagstaff, A., E. Van Doorslaer, and P. Paci (1991). On the measurement of horizontal inequity in the delivery of health care. *Journal of Health Economics*, **10**(2): 169-205.

13. Schokkaert, E. and C. van de Voorde (2003). Risk selection and the specification of the risk adjustment formula. *Journal of Health Economics*, in press.

14. Gravelle, H. (2001). Measuring income related inequality in health: standardisation and the partial concentration index. *Health Economics*, **12**(10): 803-19.

15. Wooldridge, J.M. (2002).*Econometric analysis of cross-section and panel data*. Cambridge, Massachusetts: MIT Press.

16. Efron, B. and R.J. Tibshirani (1993).*An introduction to the bootstrap*. London: Chapman & Hall.

17. Deaton, A. (1997).*The analysis of household surveys: a microeconometric approach to development policy*. Baltimore: Johns Hopkins University Press.

18. Eurostat (1999). *European Community Household Panel (ECHP): selected indicators from the 1995 wave*. European Commission, Eurostat, Luxembourg,

19. Mossialos, E.a.S.T., *Voluntary health insurance in the European Union*, in *Funding health care: options for Europe*, E. Mossialos, A Dixon, J Figueras and J Kutzin, Editor. 2002, Open University Press: Buckingham. p. 128-60.

20. Robinson, R., *User charges for health care*, in *Funding health care: options for Europe*, E. Mossialos, A Dixon, J Figueras and J Kutzin, Editor. 2002, Open University Press: Buckingham. p. 161-183.

21. Cameron, A.C. and P.K. Trivedi (1998).*Regression analysis of count data*. Econometric Society monographs ; no. 30. Cambridge, UK ; New York, NY, USA: Cambridge University Press. xvii, 411.

22. Pohlmeier, W. and V. Ulrich (1995). An econometric model of the two-part decision-making process in the demand for health care. *Journal of Human Resources*, **30**(2): 339-361.

23. Grootendorst, P.V. (1995). A comparison of alternative models of prescription drug utilization. *Health Economics*, **4**(3): 183-198.

24. Gerdtham, U.-G. (1997). Equity in health care utilization: further tests based on hurdle models and Swedish micro data. *Health Economics*, **6**(3): 303-19.

25. Hakkinen, U., G. Rosenqvist, and S. Aro (1996). Economic depression and the use of physician services in Finland. *Health Economics*, **5**(5): 421-434.

26. Jones, A.M. and O. O'Donnell (2002).*Econometric analysis of health data*. Chichester, UK: John Wiley & Sons. x, 233.

27. Deb, P. and P.K. Trivedi (1997). Demand for medical care by the elderly: A finite mixture approach. *Journal of Applied Econometrics*, **12**(3): 313-336.

28. Jimenez-Martin, S., J.M. Labeaga, and M. Martinez-Granado (2002). Latent class versus two-part models in the demand for physician services across the European Union. *Health Economics*, **11**(4): 301-321.

29. Rodriguez, M., Stoyanova, A. (2003). The effect of private insurance access on the choice of GP/specialist and public/private provider in Spain. *Health Economics*, **(forthcoming)**.

APPENDIX

Table A1: Contributions to conc index of GP visit probability

	Germany	Denmark	Netherl	Belgium	Luxemb	UK	Ireland	Italy	Greece	Spain	Portugal	Austria
C (actual)	-0.0124	-0.0200	-0.0019	0.0037	-0.0076	-0.0076	-0.0187	-0.0055	-0.0413	-0.0294	-0.0143	-0.0082
C (pred)	-0.0105	-0.0186	-0.0022	0.0003	-0.0051	-0.0061	-0.0104	-0.0040	-0.0362	-0.0252	-0.0078	-0.0057
GC (resid)	-0.0019	-0.0015	0.0003	0.0035	-0.0025	-0.0015	-0.0083	-0.0015	-0.0051	-0.0042	-0.0064	-0.0025
HI	-0.0082	0.0061	0.0103	0.0121	0.0002	0.0109	0.0035	-0.0002	-0.0041	-0.0167	0.0099	-0.0018
CI contrib of:												
ln(inc)	-0.0062	0.0044	**0.0099**	**0.0059**	0.0046	**0.0113**	**0.0085**	0.0000	0.0048	**-0.0112**	**0.0076**	-0.0025
m30-44	-0.0005	-0.0017	0.0001	**-0.0016**	-0.0005	-0.0011	0.0001	-0.0002	**0.0021**	-0.0004	**0.0004**	-0.0002
m45-59	-0.0004	**-0.0040**	0.0005	-0.0006	-0.0001	-0.0015	-0.0003	0.0001	**0.0022**	0.0000	**0.0021**	-0.0003
m60-69	0.0000	-0.0006	0.0003	0.0001	0.0000	-0.0001	0.0000	**0.0003**	**-0.0018**	-0.0001	**-0.0012**	0.0000
m70+	0.0000	-0.0013	-0.0006	0.0002	-0.0001	0.0001	**-0.0011**	-0.0001	**-0.0086**	**-0.0004**	**-0.0028**	-0.0001
f16-29	**-0.0008**	**-0.0029**	**-0.0021**	0.0000	-0.0001	**-0.0013**	0.0008	**-0.0014**	-0.0001	**-0.0010**	**0.0016**	0.0000
f30-44	0.0000	**0.0017**	**-0.0013**	0.0000	0.0000	0.0003	-0.0001	0.0004	**0.0034**	**0.0006**	**0.0017**	0.0000
f45-59	0.0004	0.0012	**0.0022**	0.0000	-0.0001	**0.0022**	**0.0007**	**0.0007**	**0.0023**	-0.0001	0.0009	**0.0007**
f60-69	0.0000	-0.0008	-0.0005	-0.0002	-0.0001	-0.0003	**-0.0007**	**-0.0007**	**-0.0051**	-0.0003	**-0.0030**	-0.0005
f70+	0.0000	**-0.0040**	**-0.0027**	-0.0005	-0.0002	**-0.0030**	**-0.0042**	**-0.0011**	**-0.0110**	**-0.0010**	**-0.0043**	**-0.0020**
H good	**0.0020**	0.0003	**0.0022**	**0.0025**	0.0002	**0.0036**	**-0.0015**	**0.0025**	**0.0014**	**0.0021**	**0.0047**	0.0003
H fair	**-0.0025**	**-0.0048**	**-0.0042**	**-0.0046**	**-0.0025**	**-0.0077**	**-0.0059**	**-0.0012**	**-0.0072**	**-0.0023**	**-0.0027**	**-0.0017**
H poor	**-0.0012**	**-0.0033**	**-0.0015**	**-0.0018**	**-0.0028**	**-0.0035**	**-0.0008**	**-0.0023**	**-0.0063**	**-0.0048**	**-0.0094**	**-0.0006**
H v poor	-0.0003	-0.0013	-0.0002	**-0.0006**	0.0000	**-0.0005**	-0.0002	**-0.0005**	**-0.0024**	**-0.0006**	**-0.0025**	-0.0002
Some lim	-0.0001	**-0.0012**	**-0.0008**	**-0.0003**	-0.0010	**-0.0015**	**-0.0022**	**-0.0002**	0.0002	**-0.0013**	**-0.0010**	**-0.0004**
Severe lim	-0.0002	-0.0006	**-0.0018**	0.0002	-0.0001	**-0.0010**	**-0.0008**	-0.0001	0.0004	**-0.0008**	-0.0008	-0.0003
Second educ	0.0000	0.0000	-0.0001	0.0000	0.0013	0.0004	0.0009	-0.0006	**-0.0020**	-0.0007	**0.0027**	0.0010
Higher educ	**-0.0015**	0.0025	-0.0007	-0.0001	-0.0013	0.0013	**0.0045**	**-0.0022**	**-0.0051**	**-0.0049**	**-0.0040**	-0.0004
Self-employed	**-0.0012**	-0.0008	**-0.0008**	0.0005	-0.0009	**-0.0028**	**-0.0014**	**0.0003**	-0.0002	**0.0006**	-0.0004	**0.0007**
Student	0.0005	-0.0007	-0.0017	0.0003	-0.0012	-0.0002	0.0001	**0.0007**	0.0001	0.0000	**0.0007**	0.0001
Unemployed	0.0006	0.0001	0.0000	0.0003	0.0003	0.0000	0.0010	**0.0019**	-0.0001	0.0007	**0.0006**	0.0000
Retired	-0.0008	0.0015	-0.0003	0.0006	-0.0007	**-0.0034**	**-0.0018**	0.0000	**-0.0017**	0.0000	-0.0009	0.0002
Housewife	**0.0006**	0.0002	0.0010	0.0010	0.0001	-0.0005	**-0.0048**	0.0008	0.0004	-0.0010	0.0003	0.0010
Oth inactive	0.0001	0.0000	0.0005	-0.0002	0.0000	0.0000	**-0.0015**	-0.0001	-0.0001	0.0003	-0.0001	0.0001
Sep/divorced	0.0005	**-0.0013**	**-0.0007**	0.0000	0.0000	0.0001	0.0003	0.0000	0.0000	0.0001	0.0001	-0.0001
Widowed	0.0001	-0.0009	-0.0001	-0.0001	-0.0001	**0.0016**	0.0000	0.0000	-0.0003	-0.0002	-0.0004	0.0004
Not married	0.0004	-0.0002	**0.0013**	-0.0003	0.0001	-0.0001	0.0003	0.0002	**-0.0015**	-0.0002	**-0.0006**	-0.0003
region 2				0.0003		-0.0002	-0.0002	**-0.0016**	**-0.0009**	0.0001	0.0004	-0.0002
region 3				-0.0005		0.0000		**-0.0011**	0.0011	**0.0033**	**-0.0020**	-0.0002
region 4						0.0003		0.0001	0.0001	**-0.0016**	**0.0008**	
region 5						0.0011		**0.0005**		0.0001	**0.0007**	
region 6						0.0000		**0.0004**		-0.0007	0.0002	
region 7						0.0003		-0.0001		0.0002	**0.0027**	
region 8						-0.0001		-0.0006				
region 9						-0.0003		0.0001				
region 10						0.0005		0.0005				
region 11						0.0000		0.0002				

Note: Decomposition based on linear approximation using the average marginal effects from a logit regression. Significant HI indices and contributions in **bold** ($P<0.05$).

Table A2: Contributions to conc index of cond # of GP visits

	Germany	Denmark	Netherl	Belgium	Luxemb	UK	Ireland	Italy	Greece	Spain	Portugal	Austria
C (actual)	-0.0513	-0.0631	-0.0517	-0.1183	-0.0841	-0.0930	-0.1136	-0.0594	-0.0845	-0.0612	-0.0549	-0.0417
C (pred)	-0.0655	-0.0997	-0.0627	-0.1456	-0.0953	-0.1140	-0.1388	-0.0690	-0.1129	-0.0856	-0.0878	-0.0613
GC (resid)	0.0142	0.0366	0.0110	0.0273	0.0112	0.0210	0.0252	0.0097	0.0284	0.0245	0.0329	0.0196
HI	-0.0173	-0.0085	-0.0201	-0.0564	-0.0428	-0.0301	-0.0657	-0.0322	-0.0212	-0.0371	-0.0038	0.0114
CI contrib of:												
ln(inc)	0.0102	0.0051	-0.0085	-0.0083	**-0.0436**	-0.0164	**-0.0281**	-0.0054	**-0.0179**	**-0.0378**	**-0.0163**	**0.0312**
m30-44	-0.0010	-0.0011	0.0000	0.0010	0.0007	0.0005	-0.0011	-0.0003	**0.0013**	-0.0002	0.0004	-0.0001
m45-59	0.0017	0.0001	0.0005	**0.0015**	0.0014	**0.0048**	-0.0001	0.0002	**0.0028**	0.0004	**0.0016**	**0.0035**
m60-69	-0.0002	-0.0011	0.0012	**-0.0024**	-0.0009	-0.0009	-0.0001	0.0005	-0.0023	0.0009	**-0.0023**	-0.0002
m70+	0.0000	-0.0055	-0.0007	**-0.0058**	-0.0021	**-0.0055**	-0.0027	-0.0002	**-0.0178**	-0.0012	**-0.0048**	**-0.0049**
f16-29	-0.0003	**-0.0038**	**-0.0025**	0.0002	0.0005	-0.0036	**0.0025**	**-0.0004**	0.0002	**-0.0006**	**0.0010**	-0.0001
f30-44	0.0000	**0.0056**	-0.0017	0.0000	-0.0003	0.0013	0.0005	0.0003	**0.0022**	0.0006	**0.0012**	-0.0001
f45-59	0.0013	0.0028	**0.0053**	**0.0015**	-0.0002	**0.0080**	0.0000	**0.0013**	**0.0046**	0.0003	**0.0019**	**0.0037**
f60-69	-0.0023	-0.0027	-0.0008	**-0.0043**	-0.0030	**-0.0047**	**-0.0020**	**-0.0027**	**-0.0073**	-0.0010	**-0.0074**	**-0.0053**
f70+	**-0.0094**	-0.0062	**-0.0085**	**-0.0157**	**-0.0069**	**-0.0204**	**-0.0077**	**-0.0046**	**-0.0231**	**-0.0047**	**-0.0111**	**-0.0226**
H good	**0.0034**	0.0017	**0.0026**	**0.0056**	0.0015	**0.0060**	-0.0014	0.0011	**0.0019**	**0.0009**	0.0000	**0.0010**
H fair	**-0.0112**	**-0.0110**	**-0.0086**	**-0.0283**	**-0.0115**	**-0.0223**	**-0.0196**	**-0.0016**	**-0.0126**	**-0.0033**	-0.0014	**-0.0164**
H poor	**-0.0138**	**-0.0274**	**-0.0119**	**-0.0241**	**-0.0201**	**-0.0237**	**-0.0073**	**-0.0162**	**-0.0173**	**-0.0159**	**-0.0278**	**-0.0155**
H v poor	**-0.0106**	**-0.0089**	-0.0023	**-0.0072**	-0.0027	**-0.0062**	**-0.0045**	**-0.0072**	**-0.0112**	**-0.0034**	**-0.0098**	**-0.0078**
Some lim	-0.0006	**-0.0064**	**-0.0030**	**-0.0025**	-0.0035	**-0.0065**	**-0.0149**	**-0.0022**	**-0.0042**	**-0.0054**	**-0.0018**	**-0.0030**
Severe lim	**-0.0091**	**-0.0106**	**-0.0123**	**-0.0126**	-0.0022	**-0.0096**	**-0.0067**	**-0.0090**	**-0.0094**	**-0.0037**	**-0.0071**	**-0.0074**
Second educ	-0.0001	0.0000	-0.0002	**-0.0012**	-0.0016	0.0002	-0.0048	**-0.0020**	-0.0013	0.0000	0.0009	-0.0023
Higher educ	**-0.0042**	-0.0048	-0.0027	**-0.0076**	-0.0032	**-0.0055**	**-0.0098**	**-0.0021**	**-0.0067**	**-0.0032**	**-0.0051**	-0.0011
Self-employed	-0.0004	-0.0003	-0.0001	0.0001	0.0001	0.0002	-0.0019	**0.0003**	-0.0004	0.0005	**0.0017**	0.0005
Student	0.0002	0.0021	-0.0009	0.0002	-0.0009	0.0005	-0.0002	0.0001	0.0000	0.0001	**-0.0021**	0.0001
Unemployed	**-0.0040**	-0.0004	-0.0018	**-0.0059**	-0.0026	-0.0019	**-0.0055**	-0.0006	0.0001	-0.0004	-0.0002	-0.0002
Retired	**-0.0145**	**-0.0198**	0.0014	**-0.0126**	0.0010	-0.0017	**-0.0035**	**0.0013**	-0.0040	0.0005	-0.0030	**-0.0047**
Houswife	-0.0013	-0.0019	-0.0039	**-0.0100**	0.0033	0.0000	-0.0077	-0.0005	-0.0002	**-0.0049**	-0.0008	**-0.0061**
Oth inactive	-0.0012	0.0000	-0.0020	**-0.0035**	0.0015	0.0000	**-0.0058**	**-0.0012**	0.0000	**-0.0020**	0.0000	-0.0002
Sep/divorced	0.0002	-0.0019	0.0000	**-0.0033**	0.0003	-0.0002	-0.0021	-0.0001	-0.0004	-0.0001	0.0002	-0.0009
Widowed	0.0015	0.0010	-0.0019	-0.0008	-0.0001	-0.0045	-0.0027	**-0.0020**	-0.0008	-0.0008	0.0014	-0.0023
Not married	0.0003	**-0.0042**	0.0006	0.0003	-0.0004	0.0000	0.0000	-0.0001	0.0001	-0.0001	-0.0004	0.0000
region 2				0.0012		-0.0019	-0.0016	**0.0032**	0.0001	-0.0010	**0.0042**	0.0002
region 3				-0.0010		-0.0003		0.0006	**0.0112**	**0.0032**	**-0.0057**	-0.0003
region 4						-0.0002		**0.0017**	-0.0003	-0.0012	**0.0016**	
region 5						0.0051		**0.0009**		0.0018	0.0008	
region 6						0.0002		**0.0013**		**-0.0039**	**0.0007**	
region 7						-0.0003		**-0.0008**		-0.0001	**0.0015**	
region 8						0.0000		**-0.0057**				
region 9						-0.0018		**-0.0091**				
region 10						**-0.0028**		**-0.0062**				
region 11						0.0001		**-0.0016**				

Note: Decomposition based on linear approximation using the average marginal effects from a truncated negbin regression. Significant HI indices and contributions in **bold** (P<0.05).

Table A3: Contributions to conc index of specialist visit probability

	Germany	Denmark	Netherl	Belgium	Luxemb	UK	Ireland	Italy	Greece	Spain	Portugal	Austria
C (actual)	0.0130	-0.0074	-0.0041	0.0125	0.0195	0.0163	0.0621	0.0416	-0.0175	0.0439	0.0774	0.0108
C (pred)	0.0131	-0.0220	-0.0130	0.0099	0.0137	0.0066	0.0408	0.0306	-0.0198	0.0434	0.0567	0.0089
GC (resid)	-0.0001	0.0145	0.0089	0.0026	0.0058	0.0097	0.0212	0.0110	0.0023	0.0005	0.0207	0.0019
HI	0.0243	0.0223	0.0307	0.0344	0.0346	0.0723	0.1168	0.0617	0.0355	0.0658	0.1103	0.0214
CI contrib of:												
ln(inc)	**0.0173**	0.0206	0.0102	**0.0305**	**0.0250**	**0.0591**	**0.0561**	**0.0288**	**0.0321**	**0.0422**	**0.0793**	0.0054
m30-44	-0.0008	-0.0004	-0.0003	**-0.0039**	-0.0001	0.0015	-0.0017	-0.0006	0.0007	-0.0003	-0.0002	0.0004
m45-59	0.0005	0.0017	-0.0007	-0.0008	0.0003	**0.0054**	-0.0007	0.0002	**0.0019**	0.0000	0.0005	**0.0034**
m60-69	0.0000	-0.0006	0.0005	0.0002	-0.0001	-0.0011	0.0002	**0.0005**	**-0.0017**	-0.0001	-0.0007	0.0000
m70+	0.0000	-0.0029	**-0.0017**	0.0003	0.0002	**-0.0072**	-0.0008	-0.0001	**-0.0084**	**-0.0007**	-0.0017	**-0.0019**
f16-29	**-0.0057**	-0.0022	**-0.0019**	-0.0003	-0.0010	**-0.0024**	0.0010	**-0.0043**	-0.0004	**-0.0018**	**0.0023**	-0.0004
f30-44	-0.0002	0.0034	-0.0006	0.0000	-0.0004	0.0009	0.0000	0.0011	**0.0076**	**0.0028**	**0.0028**	-0.0024
f45-59	**0.0042**	0.0021	0.0018	0.0008	-0.0005	**0.0071**	0.0000	**0.0019**	**0.0022**	-0.0002	0.0012	**0.0056**
f60-69	**-0.0022**	-0.0026	-0.0008	0.0002	-0.0013	-0.0027	-0.0010	**-0.0012**	**-0.0050**	-0.0008	**-0.0025**	**-0.0031**
f70+	-0.0014	0.0024	**-0.0046**	-0.0010	-0.0005	**-0.0088**	-0.0068	**-0.0021**	**-0.0084**	**-0.0010**	0.0010	**-0.0053**
H good	**0.0014**	0.0007	**0.0022**	**0.0045**	0.0001	**0.0048**	**-0.0026**	**0.0027**	**0.0033**	**0.0018**	**0.0093**	0.0003
H fair	**-0.0030**	**-0.0119**	**-0.0101**	**-0.0079**	**-0.0032**	**-0.0194**	**-0.0200**	**-0.0025**	**-0.0170**	**-0.0039**	**-0.0053**	**-0.0029**
H poor	**-0.0016**	**-0.0078**	**-0.0060**	**-0.0047**	-0.0033	**-0.0139**	**-0.0055**	**-0.0085**	**-0.0151**	**-0.0094**	**-0.0271**	**-0.0025**
H v poor	**-0.0011**	**-0.0027**	-0.0012	**-0.0015**	-0.0003	**-0.0028**	**-0.0024**	**-0.0022**	**-0.0058**	**-0.0019**	**-0.0063**	-0.0005
Some lim	-0.0005	**-0.0036**	**-0.0039**	**-0.0025**	**-0.0027**	**-0.0106**	**-0.0139**	**-0.0016**	**-0.0029**	**-0.0036**	**-0.0025**	-0.0002
Severe lim	**-0.0009**	**-0.0066**	**-0.0069**	**-0.0035**	-0.0009	**-0.0086**	-0.0032	**-0.0029**	**-0.0049**	**-0.0027**	**-0.0058**	-0.0008
Second educ	-0.0001	-0.0003	**-0.0009**	0.0001	**0.0042**	**0.0015**	**0.0102**	**0.0088**	0.0015	**0.0025**	**0.0087**	**0.0060**
Higher educ	**0.0070**	**0.0120**	**0.0093**	**0.0092**	0.0069	**0.0127**	**0.0201**	**0.0043**	0.0010	**0.0095**	**0.0175**	**0.0051**
Self-employed	**-0.0011**	-0.0007	**-0.0011**	0.0000	0.0003	**-0.0042**	-0.0007	0.0002	-0.0005	0.0003	**-0.0031**	**0.0008**
Student	-0.0004	**-0.0059**	0.0006	0.0001	-0.0007	-0.0010	0.0000	0.0000	0.0002	0.0000	**0.0012**	-0.0001
Unemployed	-0.0002	-0.0010	-0.0006	-0.0010	-0.0019	-0.0018	0.0046	0.0014	**0.0014**	0.0002	-0.0001	-0.0001
Retired	-0.0014	-0.0063	0.0006	**-0.0047**	**-0.0050**	**-0.0110**	-0.0019	0.0002	**-0.0037**	0.0000	**-0.0080**	0.0002
Houswife	**0.0013**	-0.0007	-0.0002	-0.0013	0.0003	0.0013	0.0025	-0.0005	0.0003	**-0.0027**	-0.0015	0.0006
Oth inactive	-0.0001	-0.0001	0.0015	-0.0007	-0.0005	0.0000	**-0.0065**	**-0.0006**	**-0.0007**	**-0.0017**	**-0.0027**	0.0004
Sep/divorced	0.0004	-0.0012	0.0000	**-0.0017**	0.0001	0.0007	**0.0031**	0.0003	0.0003	0.0001	0.0002	0.0003
Widowed	0.0008	**-0.0063**	-0.0008	**0.0034**	0.0001	0.0036	0.0039	**0.0007**	0.0003	0.0004	0.0005	**0.0015**
Not married	**0.0007**	-0.0011	**0.0027**	-0.0006	-0.0014	-0.0003	0.0012	0.0006	**-0.0019**	**-0.0006**	**-0.0019**	-0.0002
region 2				**-0.0034**		-0.0009	**0.0057**	-0.0004	**-0.0017**	0.0007	0.0008	-0.0006
region 3				0.0001		0.0000		0.0004	**0.0053**	**0.0102**	-0.0015	0.0000
region 4						0.0005		0.0005	0.0004	0.0001	**0.0023**	
region 5						0.0021		-0.0001		**0.0051**	**0.0010**	
region 6						0.0001		**0.0009**		-0.0019	0.0002	
region 7						0.0004		0.0003		0.0005	**-0.0012**	
region 8						0.0002		-0.0009				
region 9						0.0007		0.0013				
region 10						0.0005		**0.0031**				
region 11						0.0002		0.0007				

Note: Decomposition based on linear approximation using the average marginal effects from a logit regression. Significant HI indices and contributions in **bold** (P<0.05).

Table A4: Contributions to conc index of cond # of specialist visits

	Germany	Denmark	Netherl	Belgium	Luxemb	UK	Ireland	Italy	Greece	Spain	Portugal	Austria
C (actual)	0.0029	0.0297	-0.0137	-0.0394	-0.0899	-0.0397	0.0149	-0.0237	-0.0242	-0.0171	0.0197	0.0237
C (pred)	-0.0064	0.0154	-0.0388	-0.0507	-0.0822	-0.0351	-0.0018	-0.0309	-0.0155	-0.0334	0.0075	0.0002
GC (resid)	0.0093	0.0144	0.0252	0.0113	-0.0078	-0.0047	0.0167	0.0072	-0.0087	0.0162	0.0121	0.0235
HI	0.0269	0.0581	0.0197	-0.0008	-0.0594	-0.0062	0.0299	-0.0035	0.0216	0.0121	0.0549	0.0554
CI contrib of:												
ln(inc)	**0.0338**	**0.0592**	-0.0078	-0.0099	**-0.0445**	0.0125	0.0307	-0.0142	0.0051	-0.0095	0.0143	0.0230
m30-44	0.0002	0.0040	-0.0001	-0.0005	0.0002	0.0012	-0.0026	**-0.0034**	-0.0046	-0.0003	-0.0001	-0.0005
m45-59	**0.0030**	0.0032	-0.0032	0.0000	0.0011	0.0004	-0.0009	0.0011	**-0.0073**	0.0002	0.0001	-0.0046
m60-69	0.0004	-0.0009	-0.0002	0.0011	-0.0005	0.0006	-0.0009	-0.0008	0.0036	0.0004	-0.0010	-0.0004
m70+	0.0001	-0.0055	-0.0001	0.0022	0.0012	-0.0009	-0.0006	0.0011	**0.0263**	0.0016	**0.0030**	0.0027
f16-29	**-0.0036**	-0.0012	**-0.0026**	-0.0001	-0.0019	-0.0004	0.0003	0.0006	-0.0019	-0.0003	0.0000	0.0000
f30-44	0.0002	**0.0112**	-0.0003	0.0002	-0.0005	0.0005	0.0020	-0.0020	**-0.0168**	0.0000	0.0004	0.0003
f45-59	0.0013	0.0045	0.0003	-0.0022	0.0001	-0.0028	-0.0001	-0.0023	**-0.0097**	0.0002	0.0008	-0.0029
f60-69	-0.0022	-0.0072	0.0002	0.0003	-0.0023	0.0006	0.0000	**0.0058**	**0.0087**	0.0000	-0.0005	0.0037
f70+	-0.0011	-0.0100	0.0022	0.0028	-0.0032	0.0098	0.0083	**0.0063**	**0.0235**	0.0029	0.0007	0.0095
H good	**0.0020**	0.0026	**0.0041**	0.0021	0.0006	**0.0061**	-0.0006	0.0020	**0.0029**	**0.0034**	0.0004	0.0005
H fair	**-0.0060**	**-0.0077**	**-0.0063**	**-0.0099**	-0.0053	**-0.0132**	**-0.0097**	-0.0010	**-0.0113**	**-0.0044**	0.0006	**-0.0129**
H poor	**-0.0089**	**-0.0112**	**-0.0131**	**-0.0203**	**-0.0208**	**-0.0137**	-0.0040	**-0.0132**	**-0.0180**	**-0.0189**	**-0.0268**	**-0.0149**
H v poor	**-0.0084**	-0.0072	-0.0027	**-0.0076**	-0.0019	**-0.0069**	-0.0043	**-0.0069**	**-0.0145**	**-0.0057**	**-0.0123**	**-0.0048**
Some lim	0.0006	-0.0021	**-0.0032**	-0.0014	-0.0014	**-0.0062**	-0.0041	**-0.0019**	**-0.0058**	**-0.0042**	0.0001	**-0.0043**
Severe lim	**-0.0076**	-0.0093	**-0.0149**	**-0.0120**	-0.0028	**-0.0127**	-0.0041	**-0.0062**	**-0.0083**	**-0.0060**	-0.0030	**-0.0070**
Second educ	-0.0001	0.0000	0.0000	0.0000	-0.0011	0.0014	**0.0092**	0.0014	0.0004	0.0006	0.0010	**0.0058**
Higher educ	-0.0019	**-0.0102**	-0.0002	**0.0112**	0.0058	-0.0035	0.0010	0.0014	**0.0115**	-0.0022	0.0057	**0.0059**
Self-employed	0.0001	-0.0009	-0.0004	-0.0001	-0.0016	-0.0001	-0.0014	0.0000	0.0000	0.0003	0.0010	0.0013
Student	**0.0009**	0.0047	**0.0041**	-0.0001	0.0004	0.0017	0.0010	0.0002	0.0001	0.0000	-0.0004	0.0000
Unemployed	-0.0001	0.0000	**0.0065**	0.0013	-0.0026	-0.0039	-0.0031	-0.0003	-0.0001	0.0004	-0.0008	-0.0002
Retired	**-0.0068**	-0.0063	0.0018	-0.0044	-0.0003	-0.0019	0.0003	0.0001	**-0.0067**	-0.0001	0.0005	-0.0004
Houswife	-0.0007	0.0006	-0.0011	-0.0018	-0.0009	0.0019	0.0026	0.0023	**-0.0022**	-0.0002	0.0019	-0.0015
Oth inactive	-0.0007	-0.0003	-0.0011	-0.0019	0.0003	0.0000	**-0.0151**	-0.0014	**-0.0037**	-0.0017	0.0010	0.0002
Sep/divorced	-0.0009	-0.0016	-0.0001	-0.0032	0.0001	-0.0034	-0.0009	0.0006	0.0006	-0.0007	0.0000	-0.0021
Widowed	-0.0009	**0.0118**	-0.0002	**0.0048**	-0.0005	-0.0024	-0.0013	-0.0001	0.0005	0.0003	0.0016	-0.0007
Not married	0.0007	**-0.0051**	-0.0004	-0.0021	0.0001	-0.0003	0.0009	-0.0007	-0.0009	-0.0008	-0.0002	0.0000
region 2				-0.0025		0.0011	-0.0044	0.0014	0.0009	0.0003	**0.0033**	**0.0039**
region 3				0.0031		0.0005		0.0017	**0.0121**	**0.0126**	**0.0181**	0.0003
region 4						-0.0005		0.0012	0.0003	-0.0016	0.0000	
region 5						0.0003		0.0009		**0.0038**	-0.0007	
region 6						-0.0002		0.0010		-0.0025	-0.0003	
region 7						0.0002		-0.0006		-0.0012	-0.0007	
region 8						0.0002		-0.0006				
region 9						0.0001		0.0021				
region 10						-0.0016		**-0.0049**				
region 11						0.0006		-0.0016				

Note: Decomposition based on linear approximation using the average marginal effects from a truncated negbin regression. Significant HI indices and contributions in **bold** (P<0.05).

Table A5: Region dummies by country

	BE	FR	UK	IE	IT	GR	ES	PT	AT
Region 1	Brussels	Île de France	North	Non-Dublin	Nord Ovest	Voreia Ellada	Noroeste	Norte	Ostösterreich
Region 2	Flanders	Bassin Parisien	Yorkshire and Humberside	Dublin	Lombardia	Kentriki Ellada	Noreste	Centro (P)	Südösterreich
Region 3	Wallonia	Nord - Pas-de-Calais	East Midlands		Nord Est	Attiki	Comunidad de Madrid	Lisboa e Vale do Tejo	Westösterreich
Region 4		Est	East Anglia		Emilia-Romagna	Nisia Aigaiou, Kriti	Centro (E)	Alentejo	
Region 5		Ouest	South East		Centro (I)		Este	Algarve	
Region 6		Sud-Ouest	South West (UK)		Lazio		Sur	Açores (PT)	
Region 7		Centre-Est	West Midlands		Abruzzo-Molise		Canarias (ES)	Madeira (PT)	
Region 8		Méditerranée	North West (UK)		Campania				
Region 9			Wales		Sud				
Region 10			Scotland		Sicilia				
Region 11			Northern Ireland (UK)		Sardegna				

Source: EUROSTAT, User's Database Documentation