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). A new method to decompose observed inequality is used to identify the sources of inequality and to obtain estimates of an index of horizontal inequity. 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. Bootstrapping is used for statistical inference on the contributions to inequality. 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. All in all, the evidence suggests that European countries appear to have achieved their equity goals of removing income barriers and equalizing access to GP care, either through positive discrimination or through regional distribution. But the same cannot be said about specialist care: the wealthier continue to enjoy greater access to medical specialist care in almost all countries, and this phenomenon is fuelled by regional disparities in availability of such care in some of the countries.

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, by coupling the measurement framework with an explanatory framework it allows for a decomposition 'by factors' of inequality and inequity [6]. Finally, it not only estimates but also tests for the statistical significance of the contributions using a bootstrap procedure. 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. The concentration curve *L(s)* plots the cumulative proportion of the medical care use y_i against the cumulative proportion (*s*) of the population (ranked by income, beginning with the lowest incomes). If *L(s)* coincides with the diagonal, everyone reports identical medical care use. If, by contrast, *L(s)* lies below the diagonal, inequalities in use exist and favour the richer members of society. The further *L(s)* lies from the diagonal, the greater the degree of inequality. The health care concentration index, C_M, is defined as twice the area between *L(s)* and the diagonal. C_M takes a value of zero when *L(s)* coincides with the diagonal and is negative (positive) when *L(s)* lies above (below) the diagonal. The minimum and maximum values of C_M using individual-level data are -1 and +1 respectively: these occur when all the population's use of health care is concentrated in the hands of the most and least disadvantaged persons respectively. Because of its relationship with a Robin Hood index , a concentration index value of, say, 0.2 is equivalent to saying that about 15% of all health care needs to be redistributed from the richest to the poorest half of the population in order to obtain equality [8]

For weighted data, the computation formula for C_M given by [9] can be modified as follows:

(1) $$C_M = \frac{2}{m}\sum_{i=1}^{N} w_i y_i R_i - 1$$

where,

(2) $$m = \sum_{i=1}^{N} w_i y_i$$

is the (weighted) mean health care use of the sample, N is the sample size, w_i is the sampling weight of individual *i* (with the sum of w_i equal to *N*), and R_i is the (weighted) relative fractional rank of the *i*th individual. The latter is defined as [10]):

(3) $$R_i = \tfrac{1}{N}\sum_{j=1}^{i-1} w_j + \tfrac{1}{2} w_i \qquad \text{where } w_0 = 0$$

and thus indicates the weighted cumulative proportion of the population up to the midpoint of each individual weight.

This means that C_M can be computed conveniently using the (weighted) covariance between y_i and the (weighted) fractional rank [10] as:

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

where cov_w denotes the weighted covariance.

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:

(5) $$y_i = a + \sum_k b_k x_{ki} + e_i$$

where y is our medical care measure, the x variables include the determinants of health care demand and e 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) $$C_M = \sum_k (\, b_k \bar{x}_k \,/\, m \,) C_k + GC_e \,/\, m\ ,$$

where m 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_e is the generalized concentration index for e_i. Eqn (6) 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 (6) shows, that by coupling regression analysis with distributional data, we can partition the causes of inequality into inequalities in each of the x_k. Of course, the population means, coefficients and residuals are unknown, but can be replaced by their sample estimates. If we define the estimated demand elasticity of determinant k as:

(7) $$\hat{\eta}_k \equiv \hat{b}_k \bar{x}_k \,/\, \bar{y}$$

and using estimated concentration indices, we can rewrite the decomposition as:

(8) $$\hat{C}_M = \sum_k \hat{\eta}_k \hat{C}_k$$

In other words, estimated inequality in predicted medical care use is just a weighted sum of the inequality in each of its determinants, with the weights equal to the elasticities of the determinants. 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 ($ç_k$), 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 [11]. In section 3.2 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] [12]. 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 [13], 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* [14] 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:

$$(9) \qquad HI_{WV} = C_M - C_N$$

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 coeficients, 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.

This brings us to the issue of the role of explanatory models in the mere measurement of inequity. 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 [15] 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 shown 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. They also point to the limitation that this procedure breaks down if the model is not linearly additive.

A similar argument was made and taken further by Gravelle [16] 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. (5): income itself (x^r), need standardising variables (a vector x^n) and other, possibly policy-relevant variables (a vector x^p):

$$y_i = \alpha + \beta_r x_i^r + \sum_n \beta_n x_i^n + \sum_p \beta_p x_i^p + \varepsilon_i \qquad (10)$$

The equivalent of eq. (8) for this specification then becomes:

$$\hat{C} = \hat{\eta}_r \hat{C}_r + \sum_n \hat{\eta}_n \hat{C}_n + \sum_p \hat{\eta}_p \hat{C}_p + GC_\varepsilon \qquad (11)$$

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 $\hat{\varepsilon}$. Gravelle [16] calls the first term the partial concentration index and the sum of the second and third term the 'augmented partial concentration index'.

Equation (11) 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. (10) leads to a better estimate of the (partial) need contribution, then a model without the x^r and x^p variables, eq. (11) 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). We will use this sum as our index of horizontal inequity in what follows.

The decomposition has the additional advantage of not requiring *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. (11) - 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 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.

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 [17]. 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 complete, 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.

4.2 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 [18]. 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 overdispersion. The negative binomial, which allows for such overdispersion, has been applied extensively in studies of health care utilisation. Although overdispersion 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 [19]. The consequence, in statistical terms, is a hurdle 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 the participation decision and the positive count are generated by separate probability processes $P_1(.)$ and $P_2(.)$.The log-likelihood for the hurdle model is:

$$(12) \qquad \begin{aligned} \text{LogL} &= \textstyle\sum_{y=0} \log[1-P_1(y>0|x)] + \sum_{y>0} \{ \log[P_1(y>0|x)] + \log[P_2(y|x,y>0)]\} \\ &= \{\textstyle\sum_{y=0} \log[1-P_1(y>0|x)] + \sum_{y>0} \log[P_1(y>0|x)]\} + \{\sum_{y>0} \log[P_2(y|x,y>0)]\} \\ &= \text{LogL}_1 + \text{LogL}_2 \end{aligned}$$

This shows that 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 [20-23].

Pohlmeier and Ulrich [19] 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. Deb and Trivedi [24] 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 which 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* [25] 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. Model selection is based on Akaike and Bayesian information criteria. 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. Aggregating the information criteria across countries also favours the TPM. 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 [11]). 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 [25], 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's correction for heteroskedasticity of unknown form. Huber's correction for cluster sampling was applied for countries where cluster sampling had been used and primary sampling unit information was made available. Two countries (Luxemburg, Denmark) did not apply cluster sampling three others (Germany, The Netherlands, Austria) did not provide the primary sampling unit information for privacy reasons

One important problem with applying the decomposition analysis to equations like eq. (10) in the present context is that they will not be linear because the dependent variable in health care demand models is modeled as a non-linear function of the *x* variables. We decompose both parts of the TPM separately using eq. (11) to highlight the differences in income-related inequality in initial and subsequent contacts. Since both parts are in themselves intrinsically nonlinear, one can only apply eq. (11) to the latent index underlying the logit and the truncated negbin, which is a transformation of the visit probability or the conditional number of visits. This has the drawback of being a decomposition of transformed use, not use itself. Instead, 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. If the general functional form *G* of such a non-linear model can be written as:

(14) $$y_i = G(\sum_k b_k x_{ki}) + e_i$$

then a linear approximation of this function is given by:

(15) $$y_i = \sum_k b_k^m x_{ki} + u_i$$

where the b_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 treatment effects evaluated for the treated are used [26]. This means that b_k^m is measured by computing the average effect for each observation and then taking the sample mean over the sub-set of individuals with the relevant characteristic. So, for instance, the average effect of unemployment is calculated as the mean of b_k^m for those who are unemployed. This captures the fact that the unemployed differ from the population as whole in terms of other characteristics such as age, education, etc.

While eq. (15) 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:

(16) $$C_M = \sum_k (b_k^m \bar{x}_k / m) C_k + GC_u / m$$

where GC_u now denotes the generalised concentration index of the error term of the linear approximation. Equation (16) forms the basis of our decompositions of the first and the second part of two-part models presented in section 5.

4.3 Statistical inference

In addition to measuring inequality and inequity, we aim to test for cross-country differences. Given the complexity of the survey designs of the ECHP samples and the composition of the contribution terms in eqn. (11), we have opted to use a "bootstrap" method [27, 28] to assess sampling variability and to obtain standard errors for the estimates of both C, *HI* and $h_k C_k$, for each *k*. 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 subsample (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 were not made available, or for Denmark and Luxembourg, where PSUs were not used. Second, we have drawn a random subsample (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.

4. Results

All of the 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 rules, like Portugal, France and Belgium, still require their citizens to pay substantial copayments while in many other countries (like Denmark, Germany, Spain, Portugal and the UK) visits to public sector doctors are free at the point of delivery. 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 (DK, I, NL, UK) or salary (Greece, Portugal, Spain) whereas others rely mainly on fee-for-service payment.

Jimenez *et al* [25] reported significant effects of certain of these health system characteristics on utilisation. They find, for example, that a GP gatekeeper arrangement increases frequency of visits to GPs and reduces those to specialists. Fee-for-service payment has the opposite effect on the relative demand for GPs and specialists, a finding which is consistent with induced demand theory. Total health care expenditure, and the fraction accounted for by the public sector, have no impact on GP use but do raise demand for specialist visits.

In this paper we focus on the differences in relative inequality in utilisation by income level *within* European countries, but 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 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.

We have included full decomposition results by type of utilisation and by country in four summary Tables A1-A4, but not the underlying tables. [The full 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 like health status at the beginning of the reference period and demographics, (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 1 generally confirm some of the patterns which emerged in [5] for the total number of visits, but it decomposes the findings by parts (of the decision process) and by sources (or explanatory variables). Statistically significant contributions are indicated in bold. Virtually all of the concentration indices for the probability of a visit, the conditional and the total number of visits are negative. This means that lower income groups are *both* more likely to seek care from a GP than higher income groups, *and* they do so more frequently. But this 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 distribution (by subtracting the partial need contributions), the resulting horizontal inequity indices generally tend to be quite small. Despite being still statistically significant in some countries, in all countries, the horizontal inequity (*HI*) index for the visit probability is fairly small, i.e. within the range [-0.2;0.1].

There appears to be a only a small degree of income-related horizontal inequity in the access to a general practitioner.

Table 1: Inequality and inequity in GP visits, ECHP, 1996

GP visits	Probability of visit		Cond # of visits		Total # of visits	
	Inequality (C_M)	Inequity (*HI*)	Inequality (C_M)	Inequity (*HI*)	Inequality (C_M)	Inequity (*HI*)
Ireland	-0.0187	-0.0025	-0.1136	**-0.0483**	-0.1323	**-0.0432**
Luxembourg	-0.0076	-0.0003	-0.0841	**-0.0349**	-0.0918	**-0.0334**
Spain	-0.0294	**-0.0192**	-0.0612	**-0.0250**	-0.0906	**-0.0322**
Belgium	0.0037	**0.0111**	-0.1183	-0.0251	-0.1145	-0.0241
Italy	-0.0055	-0.0019	-0.0594	**-0.0182**	-0.0649	-0.0199
Germany	-0.0124	**-0.0087**	-0.0513	0.0008	-0.0636	-0.0094
UK	-0.0076	0.0077	-0.0930	-0.0102	-0.1006	-0.0006
Netherlands	-0.0019	**0.0087**	-0.0517	-0.0090	-0.0535	0.0019
Greece	-0.0413	-0.0107	-0.0845	0.0077	-0.1258	0.0155
Denmark	-0.0200	0.0032	-0.0631	0.0115	-0.0831	0.0240
Portugal	-0.0143	0.0022	-0.0549	0.0125	-0.0692	**0.0347**
Austria	-0.0082	-0.0029	-0.0417	**0.0335**	-0.0499	**0.0371**

Notes: Countries ranked by inequity index for total visits (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.

The picture is somewhat different for the second stage of the demand process, i.e. for the *conditional (positive) number* of visits. Table 1 shows that income-related inequality and inequity is somewhat larger and mostly in favour of the lower income groups 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. But they are still quite small and rarely significantly different from zero. As a result, we find substantial inequality in *total* GP visits, which are concentrated among the poorer segments in all countries, but a much smaller degree of need-adjusted inequality (or inequity) in the *total* number of visits.

In general, the one-part model inequity indices obtained with the decomposition method are somewhat more pro-rich (or less pro-poor) than the HI_{WV} indices presented in [5]. There is some variation across countries, with Ireland, Luxembourg, Spain and Belgium showing pro-poor distributions. These are all countries which positively discriminate in favour of lower income groups by either offering these groups an exemption or a reduction of GP user fees (IRL, B) or lower charges for prescription medicines (E). Only in Austria and Portugal we find a (small but statistically significant) degree of pro-rich inequity. This is shown graphically in Figure 1 which shows the index values with the corresponding 95% confidence intervals. The general picture appears to be that in all countries the distribution of GP visits appears to be closely related to the distribution of need. After controlling for need differences across income groups, the probability of seeing a GP is fairly equal at all income ranks and the somewhat greater use of GP visits among the poor in three countries is mainly due to the higher conditional number of GP visits.

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

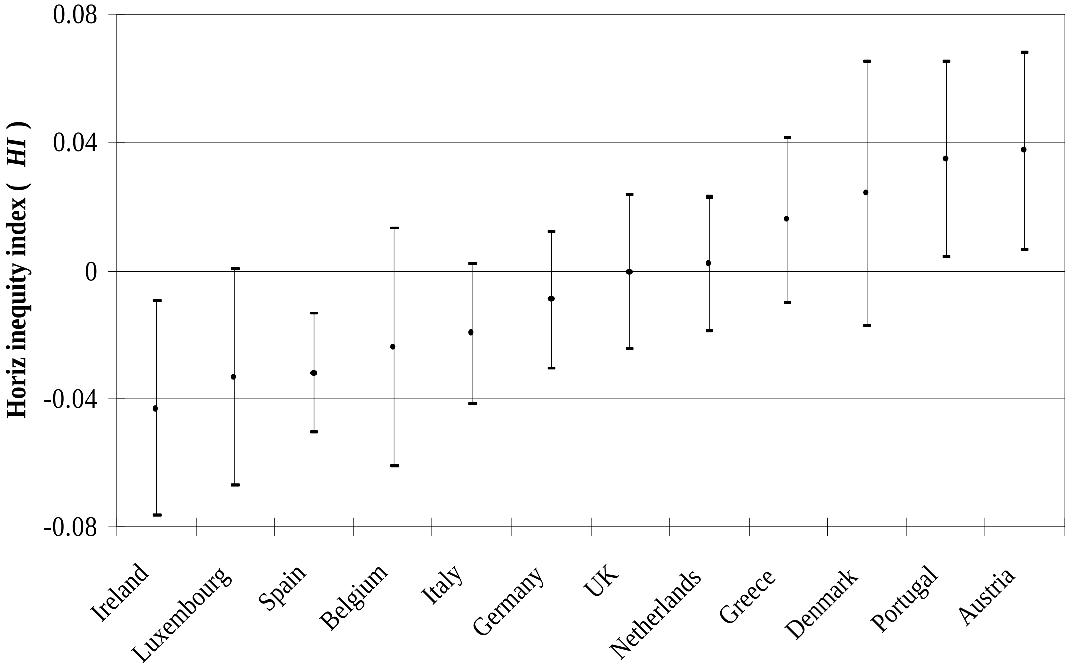
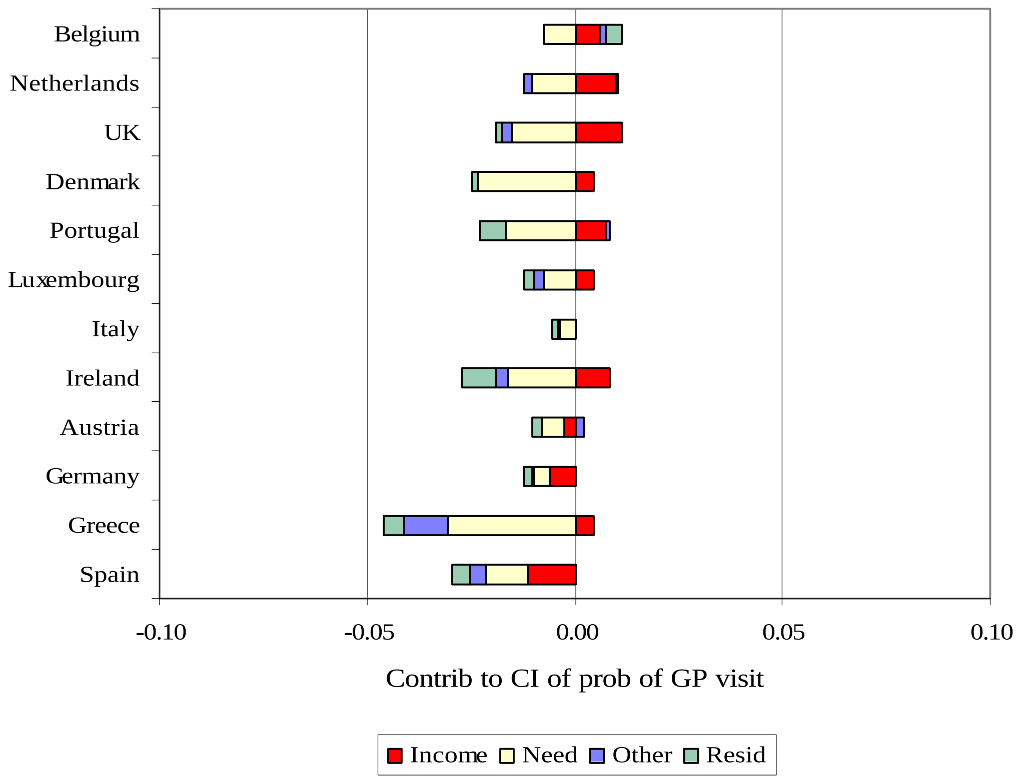


Figure 2 further unravels the picture by presenting the contributions of the four sources of inequality distinguished in eq. (11). Inequality in the *probability* of a GP visit in each of the 12 countries is decomposed into the partial contributions of (a) need indicators like self-reported morbidity, (b) (the log of) household income, (c) other non-need variables like education, marital and activity status and region and (d) a residual term. As explained in section 4.2, 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.

One way of reading the chart is as follows. In a country where the probability of a GP visit is equally distributed across income, the bars are zero. In a country with a perfectly equitable distribution of GP visits across income, there is only the need bar, which indicates the distribution of need by income. As soon as discrepancies emerge between the actual and the need-expected distribution, 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.

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



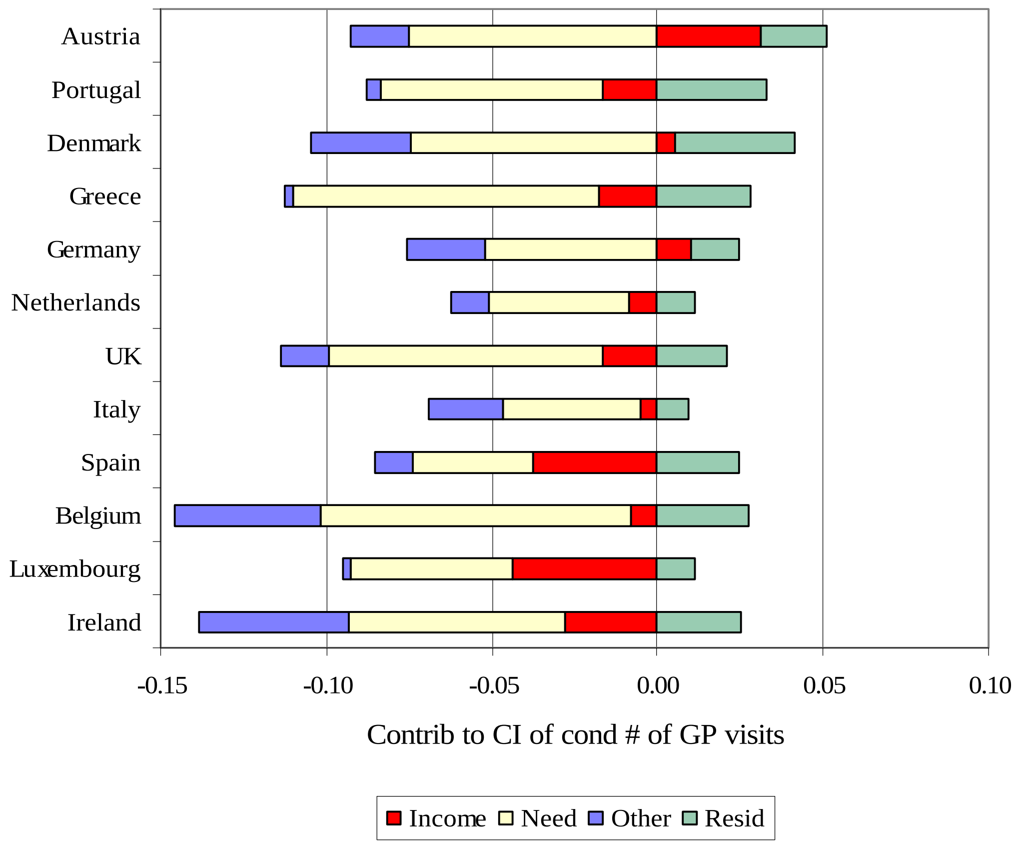
We can see that inequality in GP use probability is fairly small and pro-poor, and mainly accounted for by the contribution of need factors in all countries. This means that the distribution is pro-poor because the need distribution is pro-poor. The partial contribution of income is generally positive but rather modest. All other variables show negative but small contributions. The (sub)decomposition presented in Table A1 shows that this summary picture may conceal significant positive and negative contributions which cancel out in the aggregate. Where it 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.

Figure 3 shows that the distribution of the conditional (positive) number of GP visits is much more unequal. It is more pro-poor, but again this is mainly due to the greater needs of the poor for such care. The often negative partial contribution of income indicates some pro-poor discrimination (except in Austria, Germany and Denmark). Important 'other' non-need variables contributing to the pro-poor distribution are education (in all countries except DK, NL, L and A), non-active status like retired, unemployed, housewives, disabled educational status in Belgium, Ireland, and Italy (in all countries except NL. L and G) and region (in the Mediterranean countries). To the extent that some of these categories do reflect a greater need for care (like e.g. disability status) and have a negative contribution, we may, in effect, be underestimating 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 which is negative (pro-poor). This provides some support to our decision to treat the residual contributions as non-need factors in the estimation of inequity.

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 2, looks dramatically different from the use of GPs. 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 no surprise, therefore, 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 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 copayment.

Table 2: 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	**0.0333**	-0.0899	**-0.0526**	-0.0704	-0.0195
Belgium	0.0125	**0.0326**	-0.0394	0.0058	-0.0269	0.0412
Germany	0.0130	**0.0242**	0.0029	**0.0328**	0.0158	**0.0592**
Netherlands	-0.0041	**0.0301**	-0.0137	**0.0262**	-0.0178	**0.0622**
Italy	0.0416	**0.0611**	-0.0237	-0.0030	0.0179	**0.0633**
Spain	0.0439	**0.0654**	-0.0171	**0.0140**	0.0267	**0.0808**
Greece	-0.0175	**0.0364**	-0.0242	0.0091	-0.0418	**0.0810**
Austria	0.0108	**0.0212**	0.0237	**0.0592**	0.0345	**0.0820**
UK	0.0163	**0.0742**	-0.0397	-0.0020	-0.0234	**0.0851**
Denmark	-0.0074	0.0236	0.0297	**0.0663**	0.0223	**0.1014**
Ireland	0.0621	**0.1196**	0.0149	**0.0362**	0.0770	**0.1549**
Portugal	0.0774	**0.1124**	0.0197	**0.0573**	0.0971	**0.1737**

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.

Figure 4 illustrates that, in all but two countries, there is significant pro-rich inequity in overall specialist use: the 95% confidence interval includes the zero value only in Luxembourg and Belgium,. Portugal and Ireland, in particular, show a significantly higher degree of inequity than the other countries.

Pro-rich inequity is mainly the result of a strong partial contribution of income in most countries, which is exacerbated by the contribution of other variables, particularly in Ireland, Spain, Italy and Portugal. In Appendix table A2 we can see 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. IRL, P, UK, E and I). In other words, much of the income and 'other' variable contributions may, in fact, reflect the role of private insurance coverage.

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

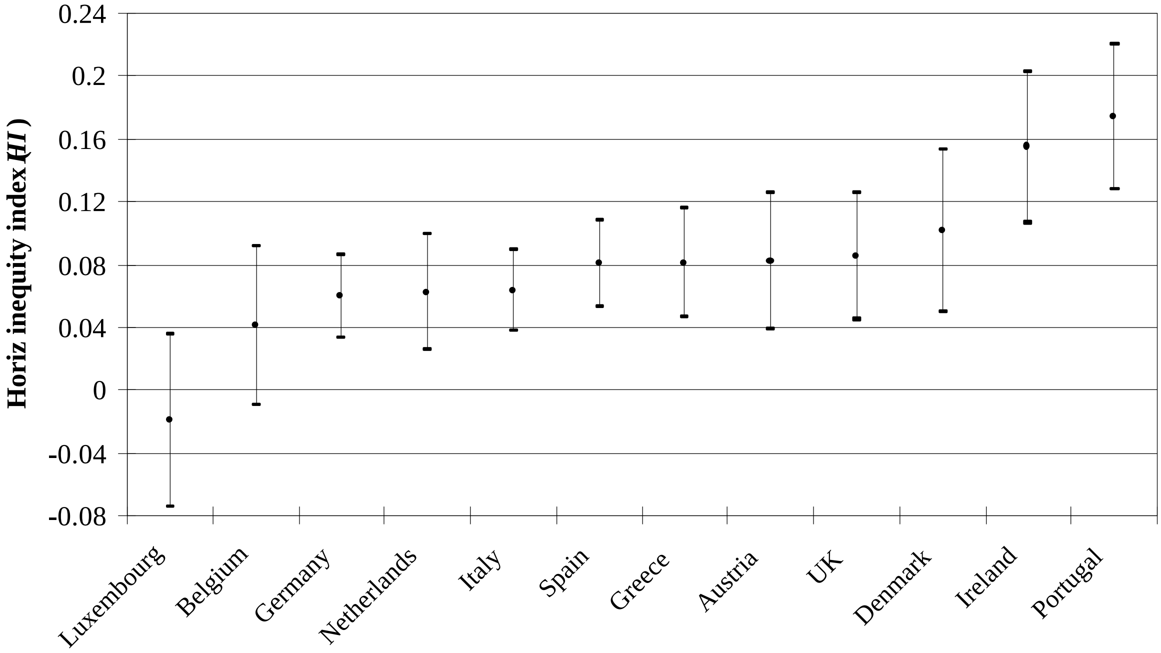


Fig 5: Decomposition of inequality in specialist visit probability

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

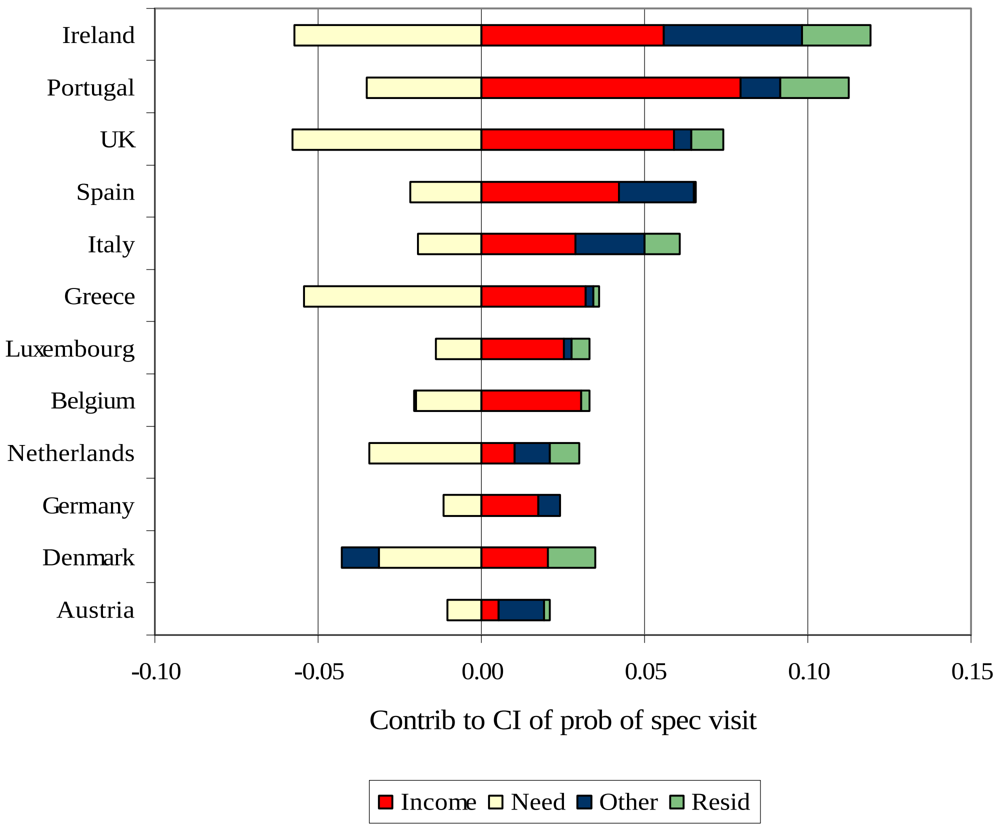
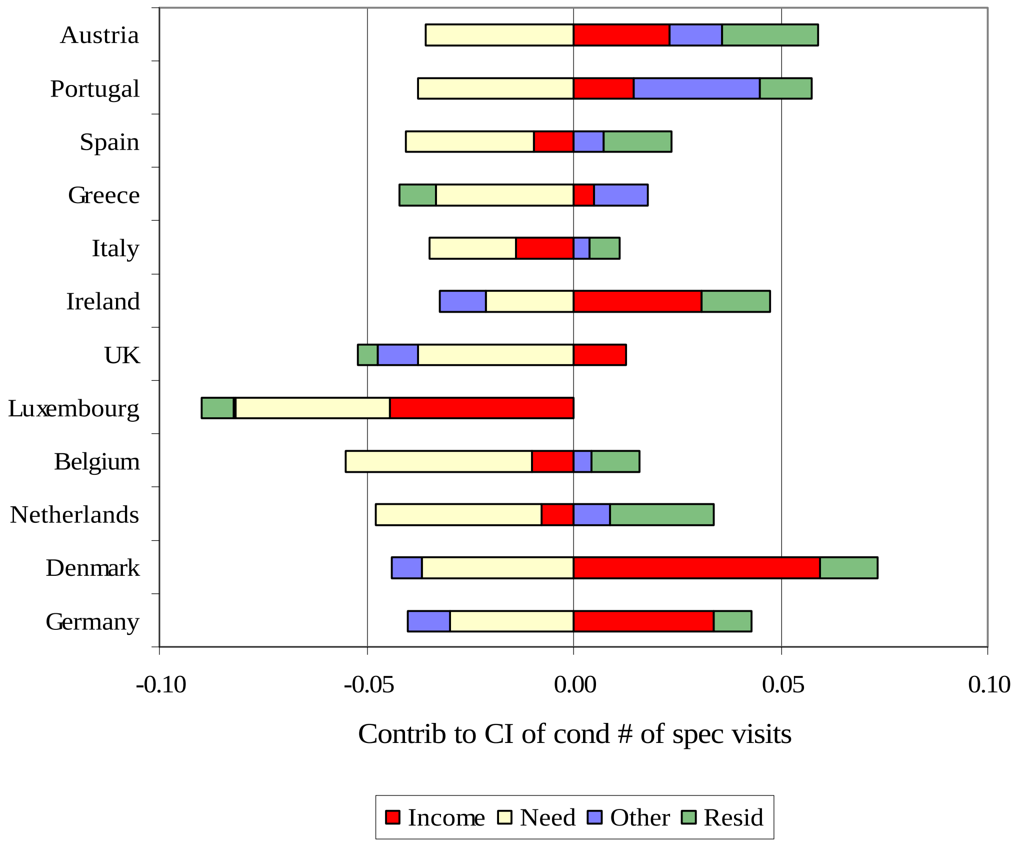


Figure 6, on the other hand, shows that the contribution of income is less important for inequity in subsequent specialist visits. It is only significantly positive in Denmark and Germany, and significantly negative in Luxembourg. In a few countries, e.g. Portugal, Spain and Greece, other variables contribute 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 causes 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 propose a new method of measuring horizontal inequity in use by standardizing for need using the decomposition approach and 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. The actual distribution is sufficiently pro-poor to correspond with this greater need for care. There is no serious violation of the principle of "equal treatment for equal need" by income: rich and poor have the same probability of seeing a GP when account has been taken of need differences. Some pro-poor inequity emerges for the conditional number of positive visits, but it is relatively small. To the extent that the decision for repeated visits is likely to be more influenced by the doctor than by the patient, this pro-poor discrimination appears to be doctor-driven.

Secondly, the findings are dramatically different in the case of specialist visits. While needs are greater among the poor, specialist use is often higher among the rich or, at best, distributed fairly equal. 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, rich and poor are treated differently in terms of specialist visits. 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 patient-initiated than doctor-driven. Notable exceptions to this rule are Austria and Denmark, where most of the inequity stems from the conditional number of positive visits.

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. Regional disparities appear relatively unimportant here. This may either be interpreted as some sort of positive discrimination by GPs of these 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 such a more objective measure of need. We could include interaction terms of need and non-need variables to test for differential need effects between socioeconomic groups, but we would then be unable to interpret any significant interactions as either differential reporting or differential treatment. Therefore, we cannot rule out the possibility that the (small) degree of pro-poor inequity we are observing is, in reality, due to reporting biases.

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 and the UK, or because they are more likely to use the private sector, as in Spain, 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 such services) are nearly non-existent. 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 need, specialist visits represent 'better' treatment than GP visits, the rich are getting more out of their health care systems.

We conclude by reminding the reader of the of 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 might make the differentials larger or smaller. A similar remark applies to the appropriateness of care use. We have 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 rich information on socio-economic characteristics with information on health and health care use, it is still constrained in its coverage. 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.

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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	**-0.0087**	0.0032	**0.0087**	**0.0111**	-0.0003	0.0077	-0.0025	-0.0019	-0.0107	**-0.0192**	0.0022	-0.0029
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	0.0008	0.0115	-0.0090	-0.0251	**-0.0349**	-0.0102	**-0.0483**	**-0.0182**	0.0077	**-0.0250**	0.0125	**0.0335**
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	**0.0242**	**0.0236**	**0.0301**	**0.0326**	**0.0333**	**0.0742**	**0.1196**	**0.0611**	**0.0364**	**0.0654**	**0.1124**	**0.0212**
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	**0.0328**	**0.0663**	**0.0262**	0.0058	**-0.0526**	-0.0020	**0.0362**	-0.0030	0.0091	**0.0140**	**0.0573**	**0.0592**
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

	Belgium	France	UK	Ireland	Italy	Greece	Spain	Portugal	Austria
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