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Measurement of Horizontal Inequity in Health Care Utilisation Using Europe

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Measurement of horizontal inequity in health care utilisation using European panel data

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Abstract

Measurement of inequity in health care delivery has focused on the extent to which health care utilization is or is not distributed according to need, irrespective of income. Studies using cross-sectional data have proposed various ways of measuring and standardizing for need, but inevitably much of the inter-individual variation in needs remains unobserved in cross-sections. This paper exploits panel data methods to improve the measurement by including the time-invariant part of unobserved heterogeneity into the need-standardization procedure. Using latent class hurdle models for GP and specialist visits estimated on 8 annual waves of the *European Community Household Panel* we compute indices of horizontal equity that partition total income-related variation in use into a need- and a non-need related part, not only for the observed but also for the unobserved but time-invariant component. We also propose and compare a more conservative index of horizontal inequity to the conventional statistic. We find that many of the cross-country comparative results appear fairly robust to the panel data test, although the panel based methods lead to higher estimates of horizontal inequity for most countries. This confirms that better estimation and control for need often reveals more pro-rich distributions of utilization.

Keywords: Inequality, inequity, health care utilisation, panel data, ECHP

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1. Introduction

An equitable system of health care delivery appears to remain a core objective in most of the OECD member states with comprehensive and universal coverage and proposed health system reforms usually quote equity preservation or improvement as an important goal (OECD, 2004). Because in many countries horizontal equity is being interpreted as the principle of equal treatment for equal need, health economists have typically approached the measurement of inequity using inequality measures (Wagstaff and Van Doorslaer, 2000a). In most empirical work, horizontal inequity is measured as the degree to which utilization is still related to income after differences in needs across the income distribution have been appropriately standardized for (Wagstaff and Van Doorslaer, 2000b). Several cross-country comparisons have adopted variants of these methods to compare across countries in the European Union (Van Doorslaer , Koolman and Jones, 2004), in the OECD (Van Doorslaer, Masseria et al, 2004) and in Asia (Lu et al, 2007).

Invariably, these comparative studies have relied on cross-sectional surveys and have adjusted for needs by comparing *actual* utilization distributions (by income) with *need-predicted* utilization using some regression-based standardization procedure. This means that adjustment can only be made for need differences that are observed in general, self-reported, health questions which are common across a large number of surveys. Typically, only a small fraction of the inter-individual variation in utilization measures like doctor visits can be explained by these models. And while an individual's demographic and self-reported health characteristics are known to be very strong – often by far the most powerful - predictors of health care utilization, it does nonetheless mean that most inter-individual variation remains unexplained.

This paper aims to go beyond the earlier approaches in at least three ways. First, the availability of the full eight waves of the *European Community Household Panel* (ECHP-UDB), corresponding to the period 1994 to 2001, and the development of appropriate models for analyzing panel utilization data (Bago d'Uva (2006); Bago d'Uva and Jones

(2006)) provides an opportunity to further examine the unexplained variation in use. The latent class model we use makes it possible to explicitly model the time-invariant components of individual unobserved heterogeneity and was the preferred specification to model our data on GP and specialist visits in Bago d'Uva and Jones (2006). Furthermore, by explaining the latent class membership probabilities dependent on the same set of covariates as the dependent variable, it becomes possible to partition their contribution to explained variation by need and non-need factors. In that way, some of the explicitly modelled individual heterogeneity can be included in the computation of the inequity index in the much same way as the observed heterogeneity.

Secondly, by using a multi-year period to assess the degree to which there are any deviations between actual and needed utilization distributions, we move from a short to a long-run perspective. Jones and Lopéz-Nicolás (2004) have used short-run and long-run measures of income-related health inequality, to examine the important dynamic phenomenon of health–related income mobility. Adapting this method to our analyses of inequity in health care use, we are able to assess the discrepancies in the short-run and the long-run perspectives resulting from this phenomenon. In other words: it allows us to test whether those who were upwardly mobile in the income distribution are more or less likely to use health care.

Finally, we propose a new measure of horizontal inequity in health care use that differs from the standard measure in the way that the variation left unexplained by the regression models is regarded. The conventional index of horizontal inequity is defined as a residual and labels as inequity all income-related inequality in use that is not demonstrably related to needs. That means that all the residual income-related variation, that is not explained by either the need or the non-need variables, is assumed to be inequitable. One problem with this approach is that some of this residual variation may in fact be due to need differences which are unobservable. An alternative estimate is to treat only the income-related inequality that is demonstrably related to non-need variables as our index of inequity. The difference between the two indices depends on the degree to which the income-related variation that is not due to included need and non-need variables is pro-rich or pro-poor. By comparing both approaches we examine whether, in practice, they lead to different results, and whether one leads to systematically higher or lower inequity estimates than the other

In what follows, we first explain how we will proceed with measuring inequity using panel data, then we describe the data we have used and the results obtained for the European countries we could include. In the final section we discuss what we can and cannot conclude from this study.

2. Methods for measurement of inequality

2.1 Cross-sectional and longitudinal measures of inequality

We measure income-related inequality in the utilisation of health care (GP and specialist visits) using the concentration index (Wagstaff et al, 1991; Kakwani et al, 1997). We compute the concentration index of the number of visits in wave *t*, CI_t, using the convenient covariance formula (for example, Kakwani, 1980):

$$CI_t = \frac{2}{\bar{y}_t} \mathrm{cov}\left(y_{it}, R_i^t\right) \tag{1}$$

where y_{it} is the number of visits to a doctor for individual *i* in period *t*, $\bar{y}_t$ is the average of y_{it} across individuals in period *t*, and R_i^t is the relative rank of individual *i* in the distribution of equivalised household income in period *t*. The concentration index takes on a positive/negative/zero value when there is pro-rich/pro-poor/no inequality.

The analysis of income-related inequality in health care utilisation is extended to the analysis of long-run inequality with panel data, following the methodology proposed by for the analysis of income-related inequality in health. Jones and Lopéz-Nicolás (2004) show that the long-run perspective uncovers important features of health inequality not identifiable in a cross-section or in repeated cross-sections. By analogy, we define the long-run concentration index of health care utilisation, CI^T, as the concentration index for the average number of visits across periods, using as ranking variable the average income across periods. Jones and Lopéz-Nicolás (2004) show that, only when the income ranking remains constant over time, the long-run concentration index equals the (weighted) average of the short-run concentration indices, defined as:

$$\sum_t w_t CI_t, \quad \text{where } w_t = \frac{\bar{y}_t}{T\bar{\bar{y}}_T}, \tag{2}$$

and $\bar{\bar{y}}_T$ equal to the average of $\bar{y}_t$ across *t*. This measure, that can be obtained using repeated cross-sections, differs from CI_T to the extent that income ranks change over time and those changes are associated with systematic differences in health care utilisation. In particular, if individuals that are upwardly income mobile tend to use more health care, the level of long-run inequality given by CI_T will be larger than the weighted average of the short-run indices.

2.2 Measurement of horizontal inequity: beyond the conventional approach

Income-related inequality in health care does not imply inequity in health care. In particular, variation in the use of health care attributable to differences in morbidity may be seen as unavoidable and hence legitimate sources of inequality (see e.g., Van Doorslaer, Koolman and Jones, 2004). The horizontal version of the egalitarian principle requires that people in equal need of care are treated equally, regardless of socioeconomic factors such as income, level of education, place of residence, race, etc.[1] The concentration index of medical care use (*CI*) measures the degree of inequality in the use of medical care by

[1] In this study, we focus solely on the issue of horizontal inequity, similar to most of the previous analyses of inequity in health care use. An exception is Sutton (2002) who studied both issues of vertical and horizontal inequity.

income, but does not control for need. Any measure of inequity in health care use has to account for the unequal distribution of need for such care.

In the recent literature on inequity in health care use, it has become the norm to measure horizontal inequity (HI) as the difference between the concentration index of actual use and that of predicted need-expected utilisation, obtained from an econometric model for health care use (e.g. Wagstaff and Van Doorslaer, 2000; Van Doorslaer et al, 2000; Van Doorslaer, Koolman and Jones, 2004, hereafter DKJ). In this paper, we refer to this as the "conventional" HI index. This index measures the extent to which the difference between actual utilisation of health care and the use that would be expected on the basis of need is systematically related to the income rank of individuals. In the first applications of this methodology, need for medical care for each individual was measured as the predicted use from a regression on need indicators (e.g., Wagstaff and Van Doorslaer, 2000; Van Doorslaer et al, 2000). Schokkaert and Van de Voorde (2000) and Gravelle (2003) have however argued against the exclusion of non-need factors from the regression as this may lead to omitted variable bias in the estimation of the contributions of the need factors.[2] More fully specified models can then be used for predicting need-expected health care utilisation, neutralising the impact of non-need variables by setting those equal to their means (e.g., DKJ, 2004).

One important problem with the measurement of HI is that the dependent variable in health care demand models is typically specified as a nonlinear function of the regressors. For example, in DKJ (2004) the empirical models of health care use are based on logistic and truncated and generalized negative binomial regression models, which are intrinsically nonlinear. As long as the model is linear, predicting need-expected use by setting the non-need variables equal to their mean (or, in fact, any constant value), achieves complete

[2] The concern in Schokkaert and van de Voorde (2000) is not with need-standardisation in inequity measurement but rather with the issue of legitimate compensation in risk-adjustment. The two problems are however analogous in that the need/non-need dichotomy in the former is similar to the one between "compensation" and "responsibility" variables in the latter.

neutralisation of these variables. This does not hold for a nonlinear model and so the estimated HI is contingent on the values chosen for the non-need variables.

The "conventional" HI index

The first step in the computation of the "conventional" HI index is the prediction of need-expected utilisation based on the actual values of the x^N variables. These predictions are contingent on the level of the non-need variables (x^{NN}) that is selected. By analogy with the linear case, we use sample means of the non-need variables. For a nonlinear functional form G(.), the need-expected level of care is predicted as:

$$\hat{y}_{it}^N = E\left[y \mid x_{it}^N, \bar{x}_t^{NN}\right] = G\left(\sum_N \hat{\beta}_N x_{it}^N + \sum_{NN} \hat{\beta}_{NN} \bar{x}_t^{NN}\right) \quad (3)$$

The "conventional" HI index is then obtained by subtracting the concentration index of $\hat{y}_{it}^N$, from the concentration index of y_{it}:

$$HI_t^{conv} = CI_t - CI(\hat{y}_{it}^N)\ , \quad (4)$$

We calculate short-run HI indices for each wave t, HI_t^{conv}, and long-run measures using the average predicted number of visits across periods $(\hat{y}_i^N)$, $HI_T^{conv} = CI_T - CI(\hat{y}_i^N)$. Additionally, we compute "average" short-run HI indices, as the difference between the weighted average of the short-run indices, as in equation (2), and what is obtained when that formula is applied to the concentration indices of predicted utilisation. Note that the estimated vector of coefficients $\hat{\beta}$, which embodies the implicit vertical equity norm of the country's system, and so determines what an individual needs, is country-specific but not wave-specific. We therefore assume that the norm of what constitutes needed and non-needed care use is constant across the period considered.

The predictions of need-expected number of doctor visits, $\hat{y}_{it}^N$, result from a regression model, and so are intrinsically contaminated by prediction error. DKJ (2004) argue that the contribution of the residuals has to be attributed to either justifiable or unjustifiable sources of inequity. In the "conventional" approach to HI measurement, followed in that paper, all that variation is classified as unjustifiable. In other words, any residual variation in health care use that is left unexplained, and that is systematically related to income rank, is assumed to be determined by non-need factors. This approach entails therefore a somewhat narrow definition of need, since it considers as legitimate health care use only what is shown (by the regression) to be systematically associated with need factors. However, DKJ (2004) note that their assumption is not indisputable, as some or all of the unexplained variation may capture unmeasured need.[3] If one is willing to assume that all that variation reflects (unmeasured) need, then a natural alternative to the "conventional" HI index is one that equals the concentration index of non-need-expected health care use. This is a more "conservative" approach in that only the inequality that results from the observed systematic association between income rank and non-need factors is considered inequitable, whilst the residual variation is considered justifiable. So, the definition of need in this alternative method is broader than in the "conventional" method. The treatment of unexplained variation is highly relevant since count data like reported doctor visits are notably difficult to predict, especially in the tails of the distribution.

The "conservative" HI index

The computation of the "conservative" HI index requires the prediction of non-need-expected utilisation, based on the actual values of the x^{NN} variables, and on the sample means of the need variables x^{N}:

$$\hat{y}_{it}^{NN} = E\left[y \mid \bar{x}_t^{N}, x_{it}^{NN}\right] = G\left(\sum_N \hat{\beta}_N \bar{x}_t^{N} + \sum_{NN} \hat{\beta}_{NN} x_{it}^{NN}\right) \tag{5}$$

[3] DKJ (2004) also decompose the "conventional" HI index in the contributions of different types of factors, including the residual contribution. The decomposition analysis makes the consequences of the assumptions transparent, as it makes it possible to assess whether the residuals make a pro-rich or a pro-poor contribution to HI. It should however be noted that in a nonlinear setting the decomposition requires a linear approximation which means that the residual contribution arises both from a prediction error and from a linear approximation error.

The "conservative" HI index equals the concentration index of $\hat{y}_{it}^{NN}$:

$$HI_t^{cons} = CI(\hat{y}_{it}^{NN}) \tag{6}$$

Again, we can define short-run HI indices for each wave, HI_t^{cons}, and long-run HI indices, $HI_T^{cons} = CI(\hat{y}_T^{NN})$, where $\hat{y}_T^{NN}$ is the average of $\hat{y}_{it}^{NN}$ across periods. We also compute "average" short-run HI indices, using equation (2) for $\hat{y}_{it}^{NN}$ instead of actual utilisation. Similar to the "conventional" HI index, this index is contingent on the values used for the need variables in the computation of $\hat{y}_{it}^{NN}$, which means that their effect is not completely neutralised.

2.3 Need adjustment with the latent class hurdle model

We now turn to the methods for predicting $\hat{y}_{it}^{N}$ and $\hat{y}_{it}^{NN}$, necessary in the computation of the HI indices described above. The availability of panel data makes it possible to control for unobserved individual heterogeneity when modelling the number of doctor visits. We use latent class hurdle models, as developed by Bago d'Uva (2006) and estimated with the ECHP data in Bago d'Uva and Jones (2006). A latent class (or finite mixture) framework is adopted in which individual effects are approximated using a discrete distribution. This framework offers an alternative representation of heterogeneity, where individuals are drawn from a finite number of latent classes. The latent class framework has been used previously in models for health care utilisation with cross-sectional individual data (e.g., Deb and Trivedi, 2002).

Let y_{it} represent the number of visits in year t. Denote the observations of the dependent variable over the panel as $y_i = [y_{i1}, \ldots, y_{iT_i}]$. Consider that individual i belongs to a latent class j, j=1,…,C, and that individuals are heterogeneous across classes. Conditional on the covariates considered, there is homogeneity within a given class j. Given the class that individual i belongs to, the dependent variable in a given year t, y_{it}, has density $f_j(y_{it} | x_{it}, \boldsymbol{\theta}_j)$. The joint density of the dependent variable over the observed periods is a product of T_i

independent densities $f_j(y_{it} \mid x_{it}, \theta_j)$, given class j. The probability of belonging to class j is π_{ij}, where $0<\pi_{ij}<1$ and $\Sigma^{C}_{j=1}\pi_{ij}=1$. Unconditional on the latent class the individual belongs to, the joint density of $y_i=[y_{i1},\ldots,y_{iTi}]$ is given by:

$$g(y_i \mid x_i; \pi_{i1},\ldots,\pi_{iC}; \theta_1,\ldots,\theta_C) = \sum_{j=1}^{C} \pi_{ij} \prod_{t=1}^{T_i} f_j(y_{it} \mid x_{it}; \theta_j) \tag{6}$$

where x_i is a vector of covariates, including a constant and θ_j are vectors of parameters. Conditional on the class that the individual belongs to, the number of visits in period t, y_{it}, is assumed to be determined by a hurdle model. The underlying distribution for the two stages of the hurdle model is the NegBin2. The latent class panel data model accounts for the panel feature of the data in a flexible way that imposes no distribution on the unobserved individual effects.

The discrete distribution of the heterogeneity has C mass points. In previous empirical applications of latent class model to health care utilisation, class membership probabilities were taken as parameters $\pi_{ij}=\pi_j$, j=1,… ,C, to be estimated along with θ_1, …, θ_C (see e.g., Deb and Trivedi, 1997 and 2002; Deb and Holmes, 2000; Deb, 2001; Jimenez et al; 2002, Atella et al, 2004). These can also be parameterised as functions of time invariant individual characteristics z_i. In this case, class membership is modelled as a multinomial logit (Clark et al, 2005; Clark and Etilé, 2006; Bago d'Uva and Jones, 2006):

$$\pi_{ij} = \frac{\exp(z'_i \gamma_j)}{\sum_{g=1}^{C} \exp(z'_i \gamma_g)}, \quad j=1,\ldots,C, \tag{7}$$

with $\gamma_C=0$. This uncovers the determinants of class membership.[4] In a panel data context, this parameterisation provides a way to account for the possibility that the observed regressors may be correlated with the individual effect. In particular, we define z_i. as the average over the observed panel of the observations on the covariates, $z_i = \bar{x}_i$.

[4] In previous latent class models for health care utilisation, this has been done through posterior analysis.

If one is interested in predicting the latent class that an individual belongs to, after the estimation of the model, it is possible to calculate the posterior probabilities of belonging to each given class. The posterior probability of membership in class *j* is given by:

$$P[i \in j] = \frac{\pi_{ij} \prod_{t=1}^{T_i} f_j\left(y_{it} \mid x_{it}; \theta_j\right)}{\sum_{j=1}^{C} \pi_{ij} \prod_{t=1}^{T_i} f_j\left(y_{it} \mid x_{it}; \theta_j\right)} \tag{8}$$

The individuals can then be assigned to the class with the highest posterior probability.

In order to calculate the "conventional" and "conservative" HI indices, we require predictions of need-expected and non-need expected number of visits. The computation of predictions from the highly non-linear latent class hurdle models is not straightforward. While, in the estimation stage, these models control for unobserved heterogeneity, which is desired, in the prediction stage, it becomes necessary to define whether the individual unobserved heterogeneity represents need, non-need or a combination of both. As noted by Van Ourti (2004), the unobserved individual heterogeneity may reflect need factors (such as unobserved health) as well as non-need factors (such as health care preferences).

The horizontal equity norm is that there is equal treatment for equal need. Therefore, the key condition that the predictions for need-based utilisation have to meet is that they vary only with need. Conversely, for the "conservative" HI index, it is required that predictions of non-need health care utilisation vary only with non-need factors. In the case of panel data models, these conditions may mean that different assumptions regarding the nature of the individual unobserved heterogeneity require different procedures to predict utilisation.

Suppose, for example, that we had estimates for a latent class model with constant class membership probabilities (that is, π_{ij} in equation (6) are constant parameters, π_j, j = 1,…,C). With such an estimated model, the need-expected number of visits can then be predicted as $\hat{y}_{it}^N = \sum_j^C \pi_j E_j\left[y_{it} \mid x_{it}^N, \bar{x}_t^{NN}\right]$, where x_{it}^N and $\bar{x}_t^{NN}$ are as defined above. In this case, as long as two individuals 'match' in terms of the need characteristics, x_{it}^{N}, their predicted utilisation is the same, even if they belong to different latent classes. Thus, the individual heterogeneity is treated as *non-need.* This treatment of the unobserved time-invariant heterogeneity resembles the treatment of the random effects in the panel data hurdle model used by Van Ourti (2004). Alternatively, if we assign each individual to the class of highest posterior probability, j^* (using the posterior class membership probabilities given by equation (8)), we can obtain the predicted number of visits in year t as the expected value of y_{it}, conditional on class j^*, x_{it}^{N} and $\bar{x}_{t}^{NN}$: $\hat{y}_{it}^{N} = E_{j^*}\left[y_{it} \mid x_{it}^{N}, \bar{x}_{t}^{NN}\right]$. In this case, given j^*, the predictions vary only with need. Even amongst individuals that have the same values for the need variables, there is still variation in the predicted use to the extent that individuals are predicted to belong to different latent classes. Therefore, the individual heterogeneity (represented by membership to different latent classes) is treated as *need.*

Consider now that the class membership probabilities are specified as functions of the covariates as in equation (7). Similarly to the x's, the time-invariant determinants of class membership, z, can include both *need* and *non-need* factors. In this specification, individual unobserved heterogeneity is not restricted to be solely need or non-need as in the example above and can therefore be standardised for need and non-need. This feature makes the more flexible specification with variable $\pi_{ij}(.)$ preferable for predicting (non-)need expected utilisation. Furthermore, the models estimated by Bago d'Uva and Jones (2006) do indeed show significant associations with both types of factors (especially with need) in almost all cases. The unobserved individual heterogeneity that we are able to partition into need and non-need, using this econometric specification, should not be confused with the variation that is unexplained by the regression, even if panel data are available. Inevitably, this variation cannot be partitioned and so has to be assumed to capture just non-need, as in the "conventional" approach, or just need, as in the "conservative" approach. Next, we explain how we predict need and non-need-expected utilisation from the latent class hurdle models.

__Need-expected utilisation (for "conventional" HI)__

The need based predictions of health care use can be computed as:

$$\hat{y}_{it}^{N} = \sum_{j}^{C} \hat{\pi}_{ij} \left(z_i^N, \bar{z}^{NN}\right) E_j \left[y_{it} \mid x_{it}^N, \bar{x}_t^{NN}\right], \tag{9}$$

where x_{it}^N and $\bar{x}_t^{NN}$ are as defined above, and $\bar{z}^{NN}$ are the sample averages of non-need variables characteristics that enter the class membership probabilities, $\pi_{ij}(.)$, and z_i^N are the actual values of the need variables in $\pi_{ij}(.)$. Since the class membership probabilities are computed for fixed values of the non-need variables, we are assuming that, across individuals, only the variation in $\pi_{ij}(.)$ that is related to need is legitimate. All the individuals with the same need are attributed the same class membership probabilities, regardless of the value of the non-need variables. Similarly, conditional on the latent class, the predictions vary only according to need. Therefore, the resulting predictions, unconditional on the latent class, $\hat{y}_{it}^N$, vary only with the observed need factors, in line with the horizontal equity norm.

__Non-need-expected utilisation (for "conservative" HI)__

The non-need based predictions of health care use can be computed as:

$$\hat{y}_{it}^{NN} = \sum_{j}^{C} \hat{\pi}_{j} \left(\bar{z}^N, z_i^{NN}\right) E_j \left[y_{it} \mid \bar{x}_t^N, x_{it}^{NN}\right], \tag{10}$$

where $\bar{x}_t^N$ and $\bar{z}^N$ are the sample averages of the need variables and x_{it}^{NN} and z_i^{NN} are the actual values of the non-need variables. The class membership probabilities are computed for fixed values of the need variables and therefore, all the variation in $\pi_{ij}(.)$ that is determined by non-need variables is considered illegitimate. Regardless of the need variables, all the individuals that are equal in terms of the non-need variables are predicted to have the same class membership probabilities and the same predicted use, conditional on the latent class. Consequently, the resulting unconditional predictions, $\hat{y}_{it}^{NN}$, vary only with observed non-need factors.

3. Data

The data are taken from the *European Community Household Panel User Database* (ECHP-UDB). The ECHP was designed and coordinated by Eurostat, and it was carried out annually between 1994 and 2001 (8 waves). This survey contains socioeconomic, demographic, health and health care utilisation variables, for a panel of individuals aged 16 or older. The data result from a standardised questionnaire, which allows for cross-country comparisons as well as longitudinal analysis. We use all the information that is available for 10 EU member states: Austria, Belgium, Denmark, Finland, Greece, Ireland, Italy, Netherlands, Portugal and Spain. Austria joined the survey in 1995 (wave 2) and in Finland it started only in 1996 (wave 3). In the United Kingdom, Luxembourg and Germany, the ECHP was carried out from 1994 to 1997 (waves 1 to 3), after which it was replaced by national panel surveys. For this reason we drop these three countries. Additionally, we do not consider France because the French data do not contain detailed information on the number of specialist visits.

We analyse health care utilisation over the previous year, represented by the number of visits to a GP and the number of visits to a specialist. These data are available from wave 2 onwards (in wave 1, the information is not detailed by type of doctor). The ECHP income variable is total net household income. We use this variable in PPPs and deflated by national CPIs, in order to allow for comparability across countries and waves. The income variable was further divided by the OECD modified equivalence scale in order to account for household size and composition. The sample used is an unbalanced panel of individuals observed for up to 6 waves in the case of Finland and up to 7 waves for the remaining countries. The analysis of inequality and inequity presented here uses cross-sectional individual weights.

Tables 1 to 3 contain the averages by country and wave of the three variables used in the measurement of socioeconomic inequality in health care: equivalised household income, specialist visits and GP visits. The countries with the lowest income levels are Portugal and Greece, followed by Spain and Italy. In general, there was an increase in the income levels throughout the panel, especially for Ireland (29%), Spain (22%) and Portugal (31%). There is substantial variation in the average number of reported GP visits (see Table 2) across countries, with the lowest values for Finland and Greece, while Belgium has the highest values (as well as Italy, towards the end of the period, and Austria, especially in the beginning and the end of the period). Table 3 shows that the levels of utilisation of specialist care also vary considerably across Europe. Ireland is the country with the lowest average utilisation throughout the observed years, followed by Finland and Denmark which show a similar pattern.

In the analysis of inequity in health care, we use an identical set of covariates across countries to represent need and non-need factors. As need indicators, we use demographics and one-year lagged health measures 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[5]; 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? We use one dummy variable to indicate whether the individual has some limitation. Gender and age are represented by the variables: Age, Age^2, a dummy variable for males (Male), $Age \times Male$ and $Age^2 \times Male$.

Apart from income, the following non-need variables are included: (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 and

[5] Across countries, the proportion of individuals that responds 'very bad' is very small, so we collapsed the categories 'bad and very bad'. For Portugal, the category 'very good' also contains a small proportion of individuals, so we collapsed the categories 'good' and 'very good' for this country.

unmarried (including cohabiting); (iii) Activity status includes employed, self-employed and not working. In additional, we include time dummies in the analysis to allow for time trends in mean utilization.

4. Results

This section presents an analysis of income-related inequality and horizontal inequity in the utilisation of primary (GP) and secondary (specialist) care for 10 EU member states. Latent class (panel data) hurdle models were estimated separately for each country and for GP and specialist visits in Bago d'Uva and Jones (2006). This econometric specification outperformed alternative specifications considered in that paper. In particular, it was shown to fit the data substantially better than the standard hurdle model, which does not account for the panel feature of the data, for all countries analysed here and for both GP and specialist visits. The results are used in this paper to obtain need-expected and non-need-expected health care use. In the estimation of LC models, the class membership probabilities π_{ij} were allowed to depend on covariates, and found to be associated especially with need but also with non-need factors, in almost all cases. We are able to account for this partition between need and non-need in the prediction of (non-)need-expected health care utilisation, as explained in Section 2.3. We then follow what was described in Section 2.2 to compute short-run indices (by wave), and their weighted average, and long-run HI indices, for each country, according to the "conventional" and the "conservative" versions of HI.[6] We mainly focus on the horizontal inequity indices based on all waves available (i.e., long-run and weighted averages of short-run indices), for each country, because these provide a more robust and reliable picture of inequity in

[6] We provide only point estimates of the inequality and horizontal inequity measures because the computation time involved in computing bootstrap confidence intervals is prohibitive in our case. This is due to the cost of obtaining maximum likelihood estimates of the panel data finite mixture hurdle model we use here to predict health care utilisation, which requires repeated estimations with a number of different sets of starting values, often facing convergence difficulties. These obstacles would then have to be overcome for each of the bootstrap replications.

health care utilisation across the entire period. For illustrative purposes, we only report year-specific results for the "conservative" approach.

GP visits

Table 4 presents results of long-run and short-run inequality and inequity in the number of GP visits for the 10 countries considered in the analysis, ranked by the values of the LR "conservative" HI index. Columns 2 and 3 of Table 4 show pro-poor inequality in GP visits for all countries. It is clear that pro-poor long-run income-related inequality in GP visits is larger for Ireland (-0.167), Greece (-0.158) and Belgium (-.161) than for the remaining countries. Finland is the country with the lowest long-run pro-poor inequality of GP visits (-.028). The rankings of countries by LR and average SR inequality coincide, except for the relative positions between Spain and Denmark that have almost equal indices. LR pro-poor inequality is underestimated by the average of the SR indices for all but one country (The Netherlands). This means that income ranking is not constant across time and that changes in income ranking are associated with systematic differences in health care utilisation. In particular, the results suggest that individuals that move downwards in the income ranking tend to have more GP visits than the ones that move upwards. This may be partly explained by the tendency for the downwardly income mobile to have relatively lower levels of health, as shown by Hernández et al (2006) for two health indicators in the ECHP.

Table 4

After controlling for unequal need distributions, and following the "conventional" HI approach (columns 4 and 5, Table 4), we can distinguish two groups of countries: for Finland, Portugal and Austria, the indices are positive (except for a slightly negative LR index for Austria); for the remaining countries, there is pro-poor inequity in the use of GPs. For Finland, all the short-run indices (on average, 0.028) as well as the long-run index (0.028) are larger than for the remaining countries, showing the largest pro-rich inequity. Averaged across waves, short-run pro-poor inequity is larger for Belgium (-

0.053), followed by Ireland (-0.045) and Spain (-0.039). In the long-run, pro-poor inequity is larger for Ireland and Belgium (-0.055, -0.054) and Spain (-0.038). Across countries, there are discrepancies between the short-run and the long-run measures of inequity. These long-run indices are larger than the weighted average of the short-run ones for 5 of the 10 countries but the differences are generally small.

Across countries, the results obtained here for 1996 wave of the ECHP (not shown) are of the same sign as the ones obtained in DKJ (2004) for the same wave. For 6 of the 9 countries in common in both studies, the 1996 inequity indices obtained here are larger (more pro-rich or less pro-poor) than the ones in the previous paper.

Let us now turn to the analysis of HI according to the new "conservative" approach. Table 4 and Figure 1 show results wave by wave, and their weighted average, as well as LR HI indices. Finland has the highest levels of pro-rich inequity in GP visits (average short-run, 0.033; long-run, 0.035), followed by Portugal and Austria. The remaining countries exhibit pro-poor inequity, and this is greater for Spain, Ireland, Belgium and Italy and less pronounced for Greece, Denmark and The Netherlands. Except for Greece and Italy, measured inequity increases when the long-run perspective is adopted, but the discrepancies are very small.

Figure 1

The "conservative" and "conventional" HI indices have the same index signs and therefore provide the same answers to the question of whether there is pro-rich or pro-poor inequity in GPs visits in the countries studied here. Similarly, the ranking of countries according to HI is generally robust to the approach chosen. An exception is Italy that belongs to the group of countries with smaller pro-poor "conventional" inequity, while it is among the ones with largest pro-poor "conservative" inequity. However, the "conservative" approach generally results in *larger* HI indices than the "conventional" approach. For Greece, this is only true for the LR indices; for Spain, the LR and average SR HI indices are equal, regardless of the approach; and for Italy the "conventional" approach gives higher SR and LR indices. This suggests that the differences between the "conventional" HI indices, that assume that the variation unexplained by the regression models used for the predictions of GP visits is all non-need, and the "conservative" HI indices, that only consider as non-need the variation that is demonstrably associated with non-need factors, are mostly due to pro-poor contributions. Our results show that the assumptions regarding the need/non-need nature of the residuals may influence the estimated level of horizontal inequity. In particular, if the residuals were pro-poor and due to need rather than non-need factors, horizontal inequity in GP visits would be underestimated by the "conventional" HI method for most of the countries studied in this paper.

Specialist visits

Income-related inequality in the number of specialist visits is summarised in the concentration indices in Table 5 (where the countries are ranked by long-run "conservative" inequity indices,). Portugal has the highest level of pro-rich inequality (LR and average SR indices equal 0.102 and 0.112), followed closely by Finland (HI_T = 0.085, average HI_t = 0.080). Belgium, Greece and the Netherlands have pro-poor inequality. Greece is the country that presents the largest pro-poor inequality (HI_T = -.068, average HI_t = -0.051). The rankings of countries according to LR and average SR indices are the same, except that LR pro-poor inequality is larger in Belgium than in The Netherlands, while the SR measure indicates the opposite. The LR measures are larger than the average of the SR indices for half of the countries studied. The Netherlands and Denmark are the countries for which the SR measure understates the LR measure most, indicating more clearly in these two countries that upwardly mobile individuals tend to use relatively more specialist care, even if there is pro-poor inequality (in the SR for both countries and only in The Netherlands, in the LR).

Table 5

Table 5 also shows estimates of horizontal inequity indices for specialist visits according to the "conventional" and "conventional" methods. We first analyse the results given by the "conventional" approach and compare them with the ones obtained by DKJ (2004). The LR and average SR HI indices are positive, indicating pro-rich inequity in specialist visits, for all countries. The largest levels of pro-rich inequity are observed for Portugal (long-run, 0.204; short-run, on average, 0.199) and Finland (long-run, 0.134; short-run, on average, 0.143). Pro-rich inequity is smaller in Belgium (long-run, 0.034; average short-run, 0.040) and the Netherlands (long-run, 0.026; average short-run, 0.050). Comparing the long-run and the weighted average of short-run indices in Table 5, we can see that, for 7 of the 10 countries considered, long-run pro-rich inequity is understated by the average of the short-run measures. For the exceptions — Austria, Greece and Italy — the long-run pro-rich inequity is slightly smaller than the short-run pro-rich inequity.

Like DKJ (2004), we find pro-rich inequity for all countries. Also, apart from Finland, not included in the previous study, and Luxembourg, not included here, the countries with the highest pro-rich inequity in both studies are Portugal and Ireland, while that inequity is lowest for Belgium and the Netherlands. However, for 7 of the 9 overlapping countries, the results obtained here for 1996 using the "conventional" method (not shown) are larger than the ones obtained in the previous paper. This suggests that the panel data model used in this paper to predict need-expected use may be more capable to account for need (observed and unobserved) than cross-section models. Except for Ireland, the long-run "conventional" HI indices presented here are also larger than the ones obtained for 1996 in DKJ (2004). On the whole, the longer-run picture provided in this paper indicates greater levels of horizontal inequity than the existing evidence.

We now turn to the results using the new "conservative" HI index, presented in Table 5 and Figure 2. Across waves and in the long-run, there is pro-rich inequity in specialist visits. Throughout the observed period, the largest inequity indices are obtained for Portugal (average short-run, 0.180; long-run, 0.195), followed by Ireland (average short-run, 0.142; long-run, 0.157) and Finland (average short-run, 0.142; long-run, 0.152). The lowest short-run indices are registered for The Netherlands (on average, 0.037), Belgium (on average, 0.052) and Denmark (on average, 0.057). These three countries are also the ones with the lowest levels of long-run HI (indices equal to 0.046, 0.066 and 0.078, respectively). For all countries, the long-run measure of inequity is larger than the weighted average of short-run indices. This suggests that, not only richer individuals tend to use more specialist care in the short-run (controlling for need) but, also, individuals that move up in the income distribution over time tend to have more specialist visits than the ones that move in the opposite direction. This feature of inequity in the use of specialists cannot be identified when inequity is measured in cross-sections, or when the panel feature of the data is not accounted for. The short-run perspective results in underestimations of long-run inequity ranging from 6% (Finland and Greece) to 27% (Denmark).

Figure 2

Both the "conventional" and the "conservative" approaches tell us that there is pro-rich inequity in all the countries under analysis. However, the more "conservative" method does not deliver lower but larger LR HI indices for 6 of the 10 countries and larger averaged SR indices, in all but two cases. The two methods result in rather similar rankings of countries according to LR horizontal inequity. Exceptions are Belgium, Ireland and Greece that move up the ranking the most, when going from the LR "conventional" HI to the LR "conservative" HI method, as a result of being the countries that show the largest discrepancies between the two methods. Recall that the two methods differ in their treatment of the variation unexplained by the need and non-need factors included in the regressions of the number of specialist visits. In the "conventional" method, this variation is considered to be non-need, while in the new "conservative" method, it is assumed to reflect need. The fact that the "conservative" HI indices are, on the whole, larger than the "conventional" ones indicates that the differences between the two represent pro-poor contributions to inequity. If it is the case that the residuals are pro-poor and that they capture mainly justifiable variation in the use of specialists, then the “conventional” approach underestimates inequity in specialist use in most countries, as that fraction of health care use that is attributed to non-need makes a pro-poor contribution to horizontal inequity.[7]

5. Conclusion

Achieving equitable access to health care for all citizens, irrespective of their incomes, remains an important public health policy goal in Europe’s largely publicly funded health care systems. Key to the monitoring of the extent to which various systems are successful in attaining this goal is the appropriate and reliable measurement of the degree of income-related inequity. Over the last two decades, Europe has invested heavily in the collection of comparable data to enable proper analysis and comparison of EU member countries’ relative performance. The completion of the *European Community Household Panel* surveys for the first time provides an opportunity to adopt a longitudinal perspective in this comparison.

This paper has exploited the full length of the European panel in an attempt to obtain more reliable estimates of inequity than what a single cross-section of data can provide. In doing so, we believe it makes three contributions. First, it exploits an important advantage of panel data in this context, which is the possibility to account for time-invariant individual unobserved heterogeneity in estimating models used for the prediction of health care use. Using latent class models, the required partitioning of the explained variation in use of care into need and not need related can be expanded to the time-invariant individual heterogeneity captured by the class membership probabilities. As a result, a greater share of variation can be explained and therefore used for the measurement of income-related inequity in health care use. We find that in almost all

[7] The results of decomposition analysis in DKJ (2004) provide some support to the argument that a pro-poor residual contribution may be mainly due to unobserved need. In that paper, the observed need variables make always a pro-poor contribution to inequity in specialist visits, while the contribution of income and other non-need variables is mostly pro-rich.

cases, this extension leads to higher (i.e. less pro-poor or more pro-rich) index values. This suggests that much of the variation associated with income that remains unexplained in cross-sectional models not accounting for heterogeneity derives from unobserved need heterogeneity.

Secondly, we document the differences between short (one year) and long (multi-year) run measures of horizontal inequity using indices which account for income mobility of users over time. We find that, for almost all countries, the long-run indices are higher than the average short-run indices, especially in the case of specialist visits. This suggests that upward income mobility contributes to more pro-rich (or less pro-poor) inequity while downward mobility does the opposite. In other words, given the same needs, doctors are not only consulted more often by those with higher incomes, but also by those with faster growing incomes. This is of interest, as it suggests a hitherto unappreciated role of income mobility in the generation of patterns of income-related inequity in use.

Thirdly, we have proposed a new, more "conservative" approach to the measurement of inequity that is not inherently related to the availability of panel data. It differs from the "conventional" method in the way that the unexplained variation in health care use is treated. In the new approach, only the income-related variation in health care use that is demonstrably related to non-need factors is considered as inequitable. While we have labeled this a more conservative approach than the conventional one, which defines all income-related variation that is not demonstrably need-related as inequitable, it nonetheless tends to give higher index estimates. This is a consequence of the fact that the difference between the two approaches can be either pro-poor or pro-rich distributed, and we find it generally to be more pro-poor.

Finally, we have investigated the effect of each of these methodological extensions using panel data from 10 EU countries. Like DKJ (2004), we confirm the finding of pro-poor inequality in GP visits in most countries and pro-rich inequality in specialist visits in all countries, across waves. The analysis of long-run inequity confirms some of the results on short-run inequity presented in DKJ (2004). For example, Portugal shows the highest long-run pro-rich inequity in specialist visits. Finland (not included in DKJ) presents the second (third) highest level of pro-rich long-run inequity in specialist visits according to the "conventional" ("conservative") approach. The rankings of countries by level of long-run inequity in the use of primary and specialised care are generally in accordance with those obtained for 1996 in DKJ (2004). The general result of pro-poor inequity in GP visits in most (7 out of 10) EU countries and pro-rich inequity in specialists in all countries studied does not change with the longitudinal perspective employed here or with the new "conservative" measurement of horizontal inequity. Similarly, the rankings of countries are fairly robust to variations in the approach.

All in all, our re-assessment based on panel data largely corroborates and strengthens the earlier cross-sectional findings. It appears then, that the earlier conclusion of people in equal need not all being treated equally also holds after analyzing the full panel data set of the ECHP. Our results however suggest that better control for need, adoption of a longer-run perspective and even using an arguably more conservative index all lead to more pro-rich estimates for specialist care and less pro-poor inequity in GP care.

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Table 1: Average equivalised annual household income (real terms, common currency)

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

Table 2: Average number of GP visits in previous year

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

Table 3: Average number of specialist visits in previous year

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

Table 4: Short-run (SR) and long-run (LR) inequality and inequity for number of GP visits

	Inequality (CI)		"Conventional" HI		"Conservative" HI								
	avg SR	LR	avg SR	LR	95	96	97	98	99	00	01	avg SR	LR
Spain	-0.099	-0.102	-0.039	-0.038	-0.038	-0.037	-0.038	-0.037	-0.039	-0.042	-0.043	-0.039	-0.038
Ireland	-0.150	-0.167	-0.045	-0.054	-0.038	-0.036	-0.035	-0.036	-0.036	-0.034	-0.034	-0.036	-0.035
Belgium	-0.146	-0.161	-0.053	-0.055	-0.028	-0.031	-0.032	-0.032	-0.032	-0.031	-0.031	-0.031	-0.033
Italy	-0.069	-0.071	-0.027	-0.024	-0.031	-0.031	-0.031	-0.037	-0.037	-0.039	-0.039	-0.035	-0.033
Greece	-0.134	-0.158	-0.016	-0.025	-0.020	-0.017	-0.020	-0.019	-0.018	-0.019	-0.018	-0.019	-0.021
Denmark	-0.098	-0.104	-0.020	-0.016	-0.016	-0.013	-0.015	-0.017	-0.016	-0.016	-0.020	-0.016	-0.014
Netherlands	-0.078	-0.072	-0.028	-0.022	-0.020	-0.020	-0.017	-0.012	-0.014	-0.011	-0.012	-0.015	-0.013
Austria	-0.080	-0.092	0.009	-0.001		0.009	0.010	0.012	0.012	0.009	0.007	0.010	0.011
Portugal	-0.081	-0.096	0.018	0.019	0.032	0.025	0.025	0.023	0.018	0.016	0.016	0.022	0.024
Finland	-0.024	-0.028	0.028	0.028			0.030	0.035	0.034	0.034	0.033	0.033	0.035

Table 5: Short-run (SR) and long-run (LR) inequality and inequity for number of specialist visits

	Inequality (CI)		"Conventional" HI		"Conservative" HI								
	avg SR	LR	avg SR	LR	95	96	97	98	99	00	01	avg SR	LR
Netherlands	-0.045	-0.021	0.026	0.050	0.036	0.040	0.041	0.045	0.043	0.035	0.020	0.037	0.047
Belgium	-0.036	-0.038	0.034	0.040	0.054	0.056	0.056	0.056	0.053	0.049	0.040	0.052	0.066
Denmark	-0.023	0.000	0.052	0.088	0.059	0.059	0.068	0.064	0.064	0.048	0.040	0.057	0.078
Austria	0.029	0.026	0.090	0.089		0.072	0.091	0.089	0.088	0.078	0.073	0.082	0.088
Spain	0.017	0.018	0.083	0.089	0.097	0.103	0.103	0.100	0.093	0.078	0.074	0.092	0.105
Greece	-0.051	-0.068	0.073	0.070	0.112	0.104	0.103	0.102	0.101	0.095	0.084	0.100	0.106
Italy	0.046	0.042	0.096	0.094	0.107	0.111	0.105	0.106	0.105	0.100	0.088	0.103	0.114
Finland	0.080	0.085	0.134	0.143			0.128	0.151	0.151	0.149	0.133	0.142	0.152
Ireland	0.015	0.015	0.123	0.128	0.145	0.142	0.150	0.147	0.142	0.138	0.129	0.142	0.157
Portugal	0.112	0.103	0.199	0.204	0.199	0.180	0.179	0.192	0.176	0.171	0.167	0.180	0.195

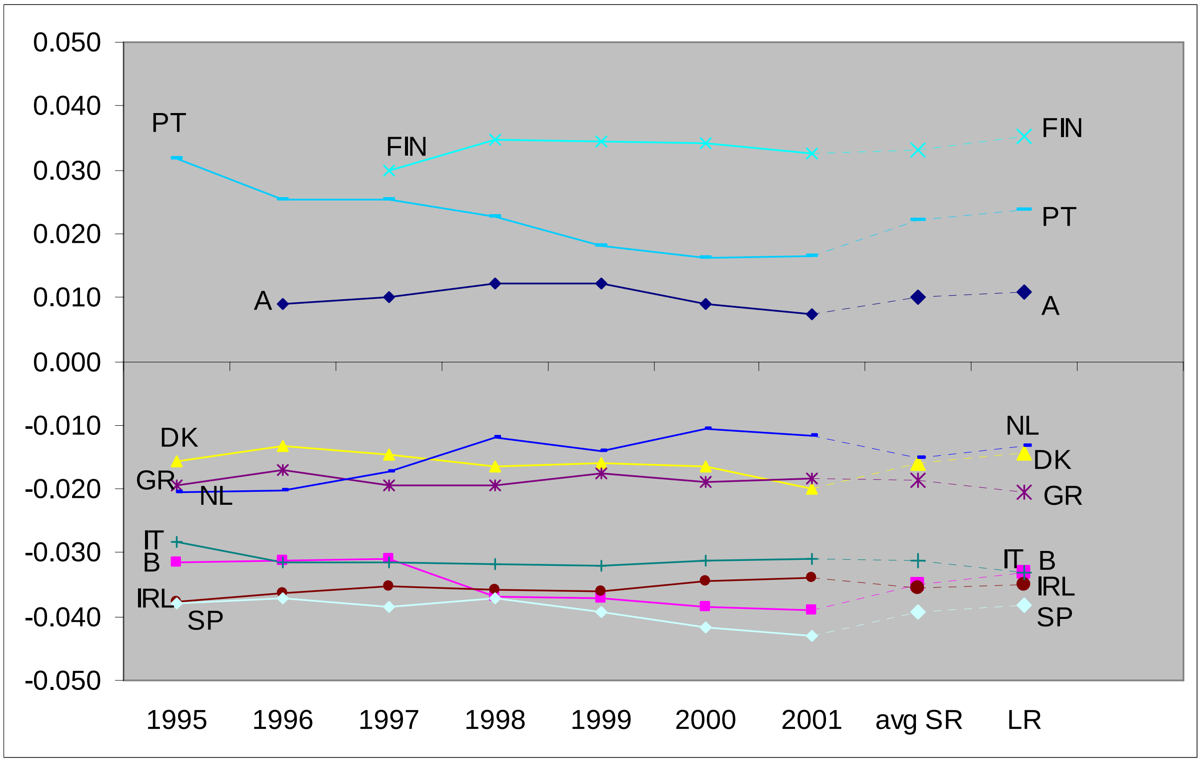

Figure 1: Short-run (SR) and long-run (LR) "conservative" inequity for number of GP visits, by country

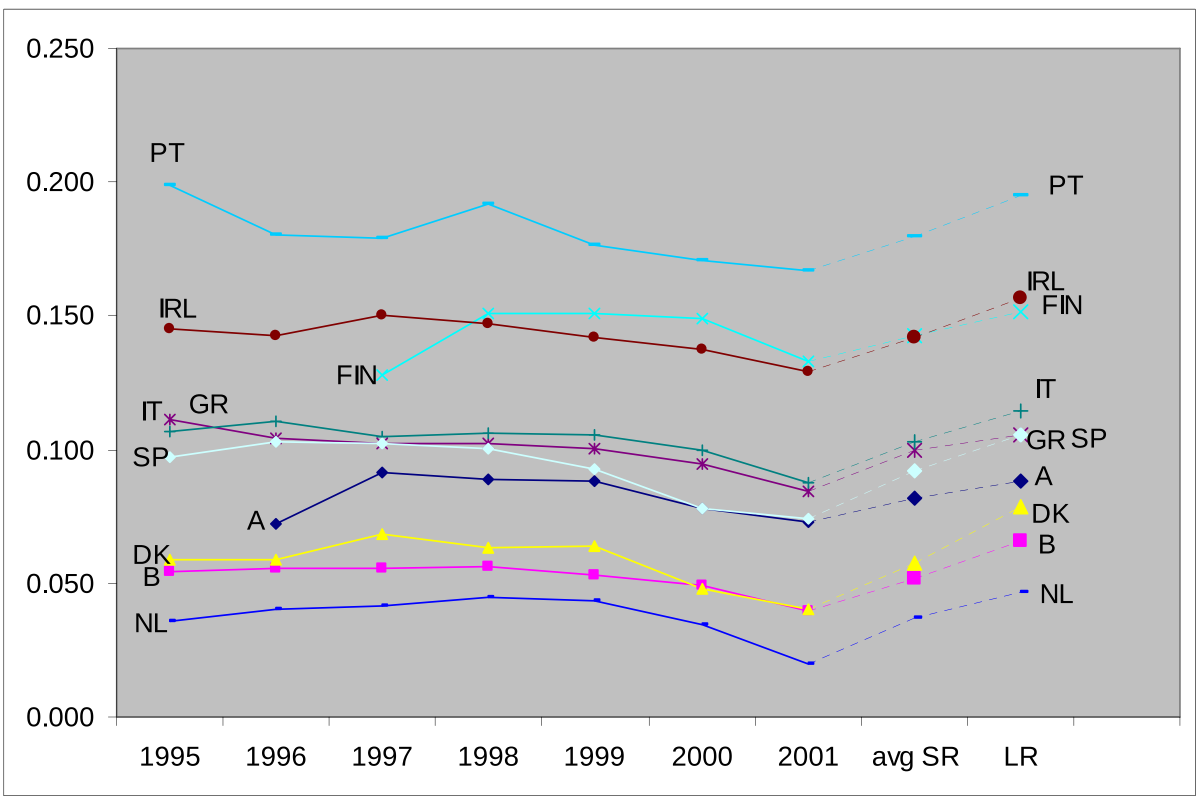

Figure 2: Short-run (SR) and long-run (LR) "conservative" inequity for number of specialist visits, by country