MEASURING HORIZONTAL INEQUITY IN HEALTH CARE USING BELGIAN PANEL DATA

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SUMMARY

We estimate the determinants of utilisation of physician and hospital services in Belgium using four different regression techniques. We apply a one- and two-part panel count data model, and a one- and two part cross-section count data model. We conclude that the two-part panel count data model is most appropriate as it controls for unobserved heterogeneity and allows for a two-part decision making process. The estimates of the determinants of utilisation of health care are then used to calculate indices of horizontal inequity. We find that there is little difference between the indices based on cross-section and the indices based on panel estimators. We further present longitudinal evidence on equity in Belgian health care and find that all indices are stable across years. We also find that general practitioner and hospital care are pro-poor distributed, while horizontal equity applies to specialist care. We further show that the inequity might be different for (i) the probability to contact the health care sector, (ii) the conditional number of visits, and (iii) the unconditional number of visits.

Key words: equity in health care, count data, two-part model, panel data

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INTRODUCTION

The index of Horizontal Inequity (HI) is commonly used to measure horizontal inequity in health care [1,2]. It compares actual usage of health care with estimates of the need for health care. If a difference is observed between use and need for health care and if this difference is systematically related to the income of the individuals, it is said that health care is inequitable distributed across income groups. It follows that the measurement of horizontal inequity crucially depends upon - among other things - the definition of need for health care. In the empirical literature, the concept of need has been defined as mean health care use, conditional on some covariates and is typically estimated using regression analysis. In the empirical literature on the demand for health care, it has been shown that unobserved heterogeneity is important if one is explaining the conditional mean of health care use. Panel data, rather than cross-section data, are advocated to control for this unobserved heterogeneity as it allows to control for individual specific effects [3]. The existing studies on equity in health care have exclusively used cross-section data, mainly because of problems with data availability. This paper complements the existing evidence on equity in health care by providing estimates of HI where the need for medical care has been estimated on Belgian panel data.

On the one hand, regression analysis of panel data is known to be more efficient than regression analysis of cross-section data. Especially its ability to control for unobserved individual heterogeneity makes it a powerful tool for analysing longitudinal data. Panel data techniques are also likely to be more efficient in terms of precision. Several examples of panel data analyses of health expenditures are available, including Manning *et al.* [4], and Wolfe and Goddeeris [5]. On the other hand, regression analysis of count data is particularly popular in the estimation of demand functions for medical care (e.g. Cameron *et al.* [6]). Count data methods are used since consumption of medical care is often recorded as the number of visits during a given time period. However, count data methods are rarely combined with panel techniques. A notable exception is

Schellhorn *et al.* [3] who use a one equation random effects model. In this paper random effects count data models are used to estimate the determinants of health care utilisation.

There have been serious advances in the methodology to measure horizontal inequity in health care. To my knowledge, Le Grand [7] was the first to study the distribution of health care. He examined the British case and concluded that the poor tend to make less use of the National Health Service for a given illness. O'Donnell and Propper [8] refined Le Grand's methodology and, given these refinements, found that the National Health Service is slightly favouring the lower income groups, in the sense that they consume more than they need vis-à-vis the richer income groups. Next, Wagstaff *et al.* [9] and Wagstaff and van Doorslaer [10] compared various methodologies and proposed HI that is based on concentration curves. This index has a firm grounding in the income inequality literature [11] and allows for a straightforward implementation of need for medical care. Need for medical care is defined as mean health care use, conditional on some covariates reflecting need (e.g. health status). Van Ourti [12] and Gravelle [13] discuss the procedure to estimate need for health care. They argue that additional covariates - not necessarily reflecting need - should be used to predict need for medical care. Finally, Koolman and van Doorslaer [14,15] propose a new interpretation and framework for measuring equity in health care. They argue that the concentration index - and thus HI - can be given a straightforward and simple interpretation. Moreover, they show that additional information is revealed if HI is calculated for the probability to contact the health care sector *and* for the number of visits (conditional on a positive contact probability), rather than calculating HI for the unconditional number of visits.

van Doorslaer *et al.* [1,2] report evidence on horizontal equity in health care in eleven European countries (including Belgium) and the United States. They find that the poor use medical care more intensively. However, the poor are also in higher need for medical care and overall there seems to be no serious problem with respect to horizontal equity. Results for single medical care services are

also obtained: visits to the general practitioner and inpatient care days are more or less in line with horizontal equity, while specialists are more often visited by the richer income groups than one would expect on the basis of estimates of need.

Belgium appears to be an outlier with respect to some of these findings. Horizontal equity does not apply for general practitioner visits and inpatient care days since lower income groups make more use of these services than one would expect on the basis of their needs. van Doorslaer *et al.* [2] argue that differences in out-of-pocket price might explain this deviation from other European countries. In Belgium, all medical services are subject to co-payments, but the population at large faces higher out-of-pocket prices than a specific group of low-income families because they have lower co-insurance rates. Therefore, these lower out-of-pocket prices might trigger additional consumption of medical care.

The main objective of this paper is threefold. First, estimates of the determinants of utilisation of physician and hospital services are derived using a two-part panel count data model (2PM-P). These estimates are compared with estimates based on (i) a one-part panel count data model (1PM-P), (ii) a two-part cross-section count data model (2PM-C), and (iii) a one-part cross-section count data model (1PM-C). These comparisons shed light on the (ir)relevance of the two-part structure and the (ir)relevance of controlling for unobserved heterogeneity. Second, the estimates of the determinants of utilisation of physician and hospital services allow for calculation of HI's. HI's based on panel and cross-section estimates are presented and possible differences are explained reverting to the regression technique. Third, the panel nature of the data allows us to present longitudinal evidence on equity in Belgian health care. The results supplement the evidence in van Doorslaer *et al.* [2] that is based on cross-section data and cross-country variation. However, longitudinal variation might make clear whether Belgium is truly an outlier as it comes to equity in health care. For these three purposes, we explore the unique panel characteristics of the Panel Study of Belgian Households (PSBH) [16].

The rest of the paper contains three sections. In the second section, we discuss the econometric techniques to estimate the determinants of health care utilisation and techniques to calculate HI. The third section describes the data. Results and comparisons of the various techniques are presented in section four. In section five, some conclusions are formulated.

METHODS

Consequently, we discuss the techniques and model selection criteria for estimating the determinants of health care when utilisation of health care is measured as a count variable. Next, the calculation of need for health care, based on these estimates is discussed. Finally, we discuss the technique to estimate HI.

ECONOMETRIC TECHNIQUES AND MODEL SELECTION CRITERIA

Four techniques are dealt with, namely cross-section negative binomial regression (1PM-C), a two-part cross-section count data model (2PM-C), random effects negative binomial regression (1PM-P), and a two-part panel count data model (2PM-P). Both 2PM-C and 2PM-P consist of a logit and log-linear model. In order to ease matters, we start with the least complex model. The discussion is based on Cameron and Trivedi [17], Pohlmeier and Ulrich [18], Jones [19], Hausman, Hall and Griliches [20], and Greene [21].

Consider the number of visits to a health service of individual i, m_i. Suppose m_i is Poisson distributed with intensity rate λ_i. Next, if one lets the intensity rate (exponentially) depend on a vector of observable explanatory variables, x_i, one gets the Poisson regression model with density:

$$f(m_i|x_i) = \frac{e^{-\lambda_i} \cdot \lambda_i^{m_i}}{m_i!} \qquad (1)$$

where $\lambda_i = \exp(x_i^{'}\beta^C)$ and C denotes 'cross-section'. This model imposes that the conditional mean should equal to the conditional variance, i.e. $E(m_i|x_i) = V(m_i|x_i) = \lambda_i$. The negative binomial regression relaxes this condition by including individual heterogeneity, v_i, in the intensity rate ($\lambda_i = \mu_i v_i$ & $\mu_i = \exp(x_i^{'}\beta^C)$) and assuming that v_i is gamma distributed with parameters $(1/\alpha, 1/\alpha)$. This assumption allows one to integrate out v_i from the density function. The resulting negative binomial density is given by:

$$g(m_i|x_i) = \frac{\Gamma(\alpha^{-1} + m_i)}{\Gamma(\alpha^{-1}{}_i)\Gamma(1 + m_i)}\left(\frac{\alpha^{-1}}{\alpha^{-1} + \mu_i}\right)^{\alpha^{-1}}\left(\frac{\mu_i}{\alpha^{-1} + \mu_i}\right)^{m_i} \qquad (2)$$

where $\Gamma(\ )$ denotes the gamma function. This model, abbreviated 1PM-C, can be estimated by maximum likelihood and reduces to the Poisson model if $\alpha = 0$. We use a simple t-test on α to discriminate between the negative binomial and Poisson regression model. This test always rejected the Poisson model.

Grootendorst [22], and Pohlmeier and Ulrich [18], among others, have demonstrated that two-part models (2PM-C) might be a better alternative than one-part models (1PM-C) if the dependent variable contains a large proportion of zeroes and if the dependent variable results from two separate decision-making processes. It is assumed that the (individual's) decision to contact the medical sector is generated separately from the (physician's) decision on successive utilisation of health services. The independence assumption between the two decision-processes enables one to estimate each decision process in turn, rather than estimating the two processes jointly. We model the contact decision by a logit model, namely $P(m_i > 0|x_i^I) = exp(x_i^{I'}\beta^{I,C})/1 + exp(x_i^{I'}\beta^{I,C})$ where I denotes 'Part I'. The decision on the number of visits, conditional on at least one visit $E(m_i|m_i > 0, x_i^{II})$ where II denotes 'Part II' and x_i^{II} may be different from x_i^I, is modelled by the estimation strategy proposed by Manning and Mullahy [23]. This procedure is used, rather than a truncated at zero count model, since panel truncated at zero count models are rather complicated and since we intend to use identical cross-section and panel estimators. During the discussion of 2PM-P, we come back to this point and discuss why a truncated at zero panel count data model was not considered.

Manning and Mullahy [23] consider ordinary least squares models with a log transformation of the dependent variable and generalised linear models, assuming that the dependent variable (which might be a count or continuous variable) is strictly positive. They examine the bias and precision of

these estimators under various data problems that are likely to be present in utilisation data, namely skweness, heavy tails, montonically declining and bell-shaped density functions, heteroskedasticity, etc. They show that none of the estimators is best under all data problems that were examined, but provide an algorithm for choosing the most appropriate estimator. This algoritm is applied in this research since "even if the estimators considered are consistent, there can be major losses in precision from selecting a less appropriate estimator" [23, p.461].

The considered least squares estimators are OLS on a log transformed dependent variable with (i) a homoscedastic and (ii) a heteroskedastic retransformation (see also Manning [24] and Mullahy [25] for additional discussion). For both models the regression model is $ln(m_i) = x_i^{II'} \beta^{II,C} + \varepsilon_i$ where $m_i > 0$ and ε_i is an error term. The first estimator uses the non-parametric homoscedastic smearing factor $E(\exp(\varepsilon_i))$, to retransform from 'log-scale', while the second estimator uses a heteroskedastic smearing factor, which is a non-parametric estimate of the variance function $E(\exp(\varepsilon_i)|x_i^{II})$. The heteroskedastic smearing factor is empirically implemented estimating $E(\varepsilon_i)^2 = \chi_0^C + f(x_i^{II'} \chi^{II,C})$, where $f(\ )$ can be any function.

The authors also consider three GLM estimators which all impose an exponentional conditional mean ($E(m_i|x_i^{II}) = exp(x_i^{II'} \beta^{II,C})$), but differ in the variance structure. The homoscedastic nonlinear regression imposes that the conditional variance is not related to the explanatory variables. The "Poisson-like" GLM imposes that the conditional variance is proportional to the conditional mean, while the "Gamma-like" GLM assumes a proportional relation between the conditional standard deviation and the conditional mean.

The authors propose an algorithm for choosing the most appropriate estimator based on evidence resulting from simulations and analyses on real data. The authors recommend to begin with an analysis of the log-scale residuals resulting from one of the consistent GLM-models (we always preferred the "Gamma-like" over the other two GLM's based on Park tests [23, p.471-472]). If the log-scale residuals have a coefficient of kurtosis smaller than three, one should stick to GLM.

However, a coefficient of kurtosis higher than three, points to the appropriateness of the OLS-models. Finally, a heteroskedasticity test on the log-scale residuals will allow one to discriminate between a homoskedastic or a heteroskedastic retransformation. We use a Breusch-Pagan test for heteroskedasticity. The test statistic is here computed as the number of observations multiplied by the R^2 of an auxiliary regression of ε_i^2 upon a constant and (a function of) x^{II}. The statistic is asymptotically χ^2 distributed with degrees of freedom equal to the number of variables in x^{II}. This auxiliary regression is also used as starting point for the heteroskedastic smearing estimator (see above).

Next, we discuss the panel analogs of the above models. Both the 1PM-P and 2PM-P result from the inclusion of individual effects which allow to control for unobserved individual heterogeneity. Either the effects are assumed deterministic resulting in a fixed effect model, or they are assumed stochastic, resulting in random effects. In general, random effects are preferred because such models are more efficient and identify time-invariant regressors. The major drawback, however, consists of the uncorrelatedness assumption between the regressors and the random effects. We tested for this assumption using Hausman tests in both the 1PM-P and 2PM-P. The resulting test statistics were always negative and the coefficients on the time-varying variables took implausible values in the fixed effects models. Since Schellhorn *et al.* [3] report similar findings and since the time-varying variables took implausible values, we stick to random effects and do not discuss fixed effect estimation.

To end up with the random effects negative binomial regression model (1PM-P), we start from equation (1) and add a time subscript t. Assuming that λ_{it} is gamma distributed with parameters (μ_{it}, δ), enables one to show that:

$$h(m_{it}|x_{it}) = \int_0^\infty \frac{e^{-\lambda_{it}} \cdot \lambda_{it}^{m_{it}}}{m_{it}!} f(\lambda_{it}) d\lambda_{it} = \frac{\Gamma(\mu_{it}+m_{it})}{\Gamma(\mu_{it})\Gamma(m_{it}+1)}\left(\frac{\delta}{1+\delta}\right)^{\mu_{it}}(1+\delta)^{-m_{it}} \qquad (3)$$

This density implies heterogeneity because of the gamma distributed λ_{it}, but random effects are not implemented yet. We replace δ by δ_i to include individual effects. It is now sufficient to choose a distribution for δ_i to end up with a random effects specification. In order to find an analytically tractable solution, we follow Hausman *et al.* [20] and impose that $(\delta_i/1+\delta_i)$ is beta distributed with parameters (r,s). We now have sufficient information to define the joint density function of the 1PM-P which can be used for maximum likelihood estimation:

$$
\begin{aligned}
& h\!\left(m_{i1},...,m_{iT_i}\big|x_{i1},...,x_{iT_i}\right) \\
& = \int_0^1 \prod_{t=1}^{T_i}\left[\frac{\Gamma(\mu_{it}+m_{it})}{\Gamma(\mu_{it})\Gamma(m_{it}+1)}\left(\frac{\delta_i}{1+\delta_i}\right)^{\mu_{it}}(1+\delta_i)^{-m_{it}}\right]f\!\left(\frac{\delta_i}{1+\delta_i}\right)d\!\left(\frac{\delta_i}{1+\delta_i}\right) \quad (4) \\
& = \frac{\Gamma(r+s)\Gamma\!\left(r+\sum_{t=1}^{T_i}\mu_{it}\right)\Gamma\!\left(s+\sum_{t=1}^{T_i}m_{it}\right)}{\Gamma(r)\Gamma(s)\Gamma\!\left(r+s+\sum_{t=1}^{T_i}\mu_{it}+\sum_{t=1}^{T_i}m_{it}\right)}\prod_{t=1}^{T_i}\left[\frac{\Gamma(\mu_{it}+m_{it})}{\Gamma(\mu_{it})\Gamma(m_{it}+1)}\right]
\end{aligned}
$$

Unlike in the case of the cross-sectional variant, the Poisson random effects model is not nested in the negative binomial random effects model. Therefore, we use the Akaike and Bayesian Information Criteria (AIC & BIC) which unanimously favoured the negative binomial specification.

Finally, we discuss the 2PM-P which consists of a random effect binary choice model (Part I) and a random effect generalisation of the estimation strategy proposed by Manning and Mullahy [23] (Part II). Part I is estimated using a random effect logit model. We assume that the random effects, α_i, are normally distributed with parameters $\left(0,\sigma_\alpha^2\right)$ such that the joint density equals:

$$
P\!\left(m_{i1},...,m_{iT_i}\big|x_{i1}^I,...x_{iT_i}^I\right)=\int_{-\infty}^{+\infty}\frac{e^{-\frac{\alpha_i^2}{\sigma_\alpha^2}}}{\sqrt{2\pi}\sigma_\alpha}\left(\prod_{t=1}^{T_i}\frac{exp\!\left(x_{it}^I\beta^{I,P}+\alpha_i\right)}{1+exp\!\left(x_{it}^I\beta^{I,P}+\alpha_i\right)}\right)d\alpha_i \quad (5)
$$

where P refers to panel data. Equation (5) is the basis for maximum likelihood estimation. The integral is approximated using a 12-point Gauss-Hermite quadrature using available routines in

STATA 7.0. Following StataCorp [26], we evaluate the quality of the quadrature by checking the coefficient stability for an 8 and 16-point quadrature.

In the context of a cross-section, Part II is usually estimated using a truncated at zero negative binomial model. As noted before, this model is not easily generalised to a panel context. Therefore, we first discuss the intractability of estimating a truncated at zero random effects negative binomial model. Next, we deal with the estimation strategy of Manning and Mullahy [23].

To derive the joint density for the truncated at zero random effect negative binomial model, we start from equation (3) to find the corresponding truncated at zero density:

$$h\left(m_{it}\middle|x_{it}^{II},m_{it}\geq 1\right)=\left[1-\left(\frac{\delta}{1+\delta}\right)^{\mu_{it}}\right]^{-1}\frac{\Gamma(\mu_{it}+m_{it})}{\Gamma(\mu_{it})\Gamma(m_{it}+1)}\left(\frac{\delta}{1+\delta}\right)^{\mu_{it}}(1+\delta)^{-m_{it}} \qquad (6)$$

If one replaces the expression in square brackets in equation (4) by equation (6), one can derive (after some algebra) the joint denisty for the truncated at zero random effect negative binomial:

$$h\left(m_{i1},\ldots,m_{iT_i}\middle|x_{i1}^{II},\ldots,x_{iT_i}^{II};\exists\,m_{it}>0\right)$$

$$=\int_0^1\prod_{t=1}^{T_i}\left[\left[1-(y_i)^{\mu_{it}}\right]^{-1}\frac{\Gamma(\mu_{it}+m_{it})}{\Gamma(\mu_{it})\Gamma(m_{it}+1)}y_i^{\mu_{it}}(1-y_i)^{m_{it}}\right]f(y_i)dy_i \qquad (7)$$

$$=\frac{\Gamma(r+s)}{\Gamma(r)\Gamma(s)}\cdot\left[\prod_{t=1}^{T_i}\frac{\Gamma(\mu_{it}+m_{it})}{\Gamma(\mu_{it})\Gamma(m_{it}+1)}\right]\cdot\int_0^1\left(\prod_{t=1}^{T_i}\left[1-(y_i)^{\mu_{it}}\right]^{-1}\right)(y_i)^{r-1+\sum_{t=1}^{T_i}\mu_{it}}(1-y_i)^{s-1+\sum_{t=1}^{T_i}m_{it}}dy_i$$

where $y_i=\delta_i/1+\delta_i$. From equation (7), it is clear that the log likelihood function will involve an integral, which cannot be approximated by readily available techniques such as Gauss-Hermite or Gauss-Laguerre quadrature. The less flexible random effect Poisson model neither offers an escape, as it can be shown that its log likelihood will also involve an integral which does not fit in the mentioned approximation techniques. It results that we prefer the estimation strategy proposed by Manning and Mullahy [23], rather than to revert into inegral approximation techniques.

This strategy can be applied to panel data without major adjustments. We use the same algorithm for choosing the most appropriate estimator, but replace the cross-section estimators by their panel counterparts. More exactly, we start with an analysis of the log-scale residuals resulting from a "Gamma-like" population averaged panel data model. We use $log(m_{it}-\hat{m}_{it})$ as an estimate of the

log-scale errors. If these log-scale errors have a coefficient of kurtosis smaller than three, we stick to the population averaged panel data model, while a coefficient higher than three points to the appropriateness of OLS-models. Instead of the cross-section OLS model, we use a linear random effects model on a log transformed dependent variable. Finally, the same Breusch-Pagan test on ξ_{it}^2 - where ξ_{it} results from $\ln(m_{it}) = x_{it}^{II'} \beta^{II,P} + \alpha_i + \xi_{it}$ - is a valid tool to discriminatie between the homoskedastic and heteroskedastic smearing factor (see e.g. Verbeek [27, p. 325]).

In the results section, we discuss estimates resulting from the four regression techniques. In order to select the most approporiate technique, we use the following strategy. First, we start with the 2PM-P including all available regressors. Likelihood Ratio and Wald tests are preformed to exclude redundant variables, while Likelihood Ratio and Lagrange Multiplier tests are used to test for the significance of unobserved individual heterogeneity. Second, we estimate the 2PM-C where only the non-redundant variables from the panel model are included. We discriminate between 2PM-P and 2PM-C using the log likelihood (evaluated at the estimates), AIC and BIC of the 'full model'. 'Full model' refers to the sum of 'Part1' and 'Part2' in case of the 2PM-P and 2PM-C, but for the latter we also sum across time periods [28]. Third, we estimate the 1PM-P and 1PM-C and use the same strategy to discriminate between both. Finally, we compare the 'best' 1PM-model with the 'best' 2PM-model using the log likelihood, AIC and BIC.

The comparisons between the panel and cross-section estimators might appear inappropriate as these comparisons focus on both the relevance of unobservedl heterogeneity *and* the relevance of time-varying coeffcients. It results that our model selection strategy in itself favours the cross-section estimators. However, if our strategy points to the appropriateness of panel estimators (as it does) we have a more powerful argument to prefer the panel estimators.

<div align="center">CALCULATION OF NEED FOR HEALTH CARE</div>

The estimates of the determinants of utilisation of physician and hospital services can be used to calculate the need for health care. In turn, need for health care is a prerequisite for calculating the

index of horizontal inequity (HI). In this section, we discuss the calculation of need for each of the four regression techniques.

Until recently, estimates of the determinants of utilisation were not considered to calculate need for health care. Rather, need for health care was defined as the predicted value of a regression of health care utilisation upon a set of variables reflecting need (i.e. sex, age and health status). Determinants of utilisation that are not considered to reflect need (e.g. education, income, etc.) were explicitly excluded from the regression analysis [10].

Following Schokkaert *et al.* [29], Van Ourti [12] and Gravelle [13] argue that the omission of these latter determinants might result in omitted variables bias. Therefore, they argue to include these determinants in the regression analysis. Need for health care is then defined as the predicted value of this regression, but the variables that do not reflect need are kept fixed across individuals. Gravelle [13] argues that the mean is the most obvious choice for the fixed value, but shows that in general the chosen value does matter for the calculation of HI if the underlying regression model imposes interaction (effects) between the variables reflecting and those not reflecting need.

We now deal with the calculation of need for health care in terms of the four regression techniques. We stress that need is always calculated for each time period t, but skip the subscript for the cross-section techniques. Suppose that the explanatory variables x_i are decomposed in x_i^{RN} and x_i^{NN}, where RN and NN correspond to variables reflecting need and variables not reflecting need. Calculation of need based on the 1PM-C proceeds then as follows:

$$N_i^{1PM-C} = E\left(m_i \middle| x_i^{NN} = \bar{x}^{NN}, x_i^{RN}\right) = \exp\left(\bar{x}^{NN'}\beta^{NN,C} + x_i^{RN'}\beta^{RN,C}\right) \tag{8}$$

where an upper bar refers to an average across individuals, and N_i^{1PM-C} stands for need based on 1PM-C. Starting from 1PM-P results in a slightly modified formula:

$$N_{it}^{1PM-P} = E\left(m_{it} \middle| x_{it}^{NN} = \bar{x}_t^{NN}, x_{it}^{RN}\right) = \delta_i^{-1} \cdot \exp\left(\bar{x}_t^{NN'}\beta^{NN,P} + x_{it}^{RN'}\beta^{RN,P}\right) \tag{9}$$

where we take an average across individuals for one time period since HI is calculated for each time period separately. Since δ_i is a random variable, we replace it by its expected value, namely $E(\delta_i) = r/s$. It results that unobserved individual heterogeneity is not reflected in the need for health care.

Calculation of need is less straightforward using a two-part model. Following Koolman and van Doorslaer [15], we calculate need for health care for 'Part 1' and for 'Part 2', but not for the 'full model'. It results that we calculate HI for 'Part 1' (the contact decision) and an index for 'Part 2' (the decision on the number of visits, conditional on a contact), but not an index for the 'full model' (the unconditional number of visits). Starting from 2PM-C gives the following formulas for need for health care:

$$N_i^{Part1-C} = P\left(m_i > 0 \middle| x_i^{I,NN} = \bar{x}^{I,NN}, x_i^{I,RN}\right) = \frac{\exp\left(\bar{x}^{I,NN'}\beta^{I,NN,C} + x_i^{I,RN'}\beta^{I,RN,C}\right)}{1 + \exp\left(\bar{x}^{I,NN'}\beta^{I,NN,C} + x_i^{I,RN'}\beta^{I,RN,C}\right)} \quad (10a)$$

$$N_i^{Part2-C} = E\left(m_i \middle| m_i > 0; x_i^{II,NN} = \bar{x}^{II,NN}, x_i^{II,RN}\right)$$
$$= \exp\left(\bar{x}^{II,NN'}\beta^{II,NN,C} + x_i^{II,RN'}\beta^{II,RN,C}\right) + E\left(\exp(\varepsilon_i)\middle| \bar{x}^{II,NN}, x_i^{II,RN}\right) \quad (10b)$$

where the last term in eqution (10b) is the heteroskedastic smearing factor, conditional on the mean value of the NN-variables. The formulas for the 2PM-P are:

$$N_{it}^{Part1-P} = P\left(m_{it} > 0 \middle| x_{it}^{I,NN} = \bar{x}_t^{I,NN}, x_{it}^{I,RN}\right) = \frac{\exp\left(\bar{x}_t^{I,NN'}\beta^{I,NN,P} + x_{it}^{I,RN'}\beta^{I,RN,P}\right)}{1 + \exp\left(\bar{x}_t^{I,NN'}\beta^{I,NN,P} + x_{it}^{I,RN'}\beta^{I,RN,P}\right)} \quad (11a)$$

$$N_{it}^{Part2-P} = E\left(m_{it} \middle| m_{it} > 0; x_{it}^{II,NN} = \bar{x}_t^{II,NN}, x_{it}^{II,RN}\right)$$
$$= \exp\left(\bar{x}_t^{II,NN'}\beta^{II,NN,P} + x_{it}^{II,RN'}\beta^{II,RN,P}\right) + E\left(\exp(\xi_{it})\middle| \bar{x}_t^{II,NN}, x_{it}^{II,RN}\right) \quad (11b)$$

where α_i is replaced by $E(\alpha_i) = 0$, because of its stochastic nature.

THE INDEX OF HORIZONTAL INEQUITY

We calculate HI for each period t according to the methods proposed by Wagstaff and van Doorslaer [10]. To simplify things, we neglect the t subscript, and assume a unique estimate of need N_i throughout the discussion.

HI is based on a concentration curve for health care utilisation and one for need. The concentration curve for utilisation/need is obtained by plotting the cumulative proportion of utilisation/need against the cumulative proportion of the individuals, ranked by socio-economic status y_i (beginning with the least advantaged). HI is then defined as twice the surface between the need and utilisation of health care concentration curve:

$$HI = 2\int_0^1 [L_N(p) - L_M(p)]dp = C_M - C_N \tag{12}$$

where $L(\ )$ stands for the concentration curve, p for the cumulative proportion of the individuals, C_M for the concentration index of health care use, and C_N for the concentration index of need. HI takes values between -2 and +2. A positive (negative) valued indicates pro-rich (pro-poor) inequity, i.e. the rich (poor) use more health care than one would expect on the basis of their needs. An index of zero indicates horizontal equity. Kakwani *et al*. [30] and Wagstaff and van Doorslaer [10] show that HI can be calculated using OLS-regression:

$$2\sigma_{R_y}^2\left(\frac{m_i}{\overline{m}} - \frac{N_i}{\overline{N}}\right) = \kappa_0 + \kappa_1 R_{i,y} + \eta_i \tag{13}$$

where $R_{i,y}$ is the fractional rank of y_i, $\sigma_{R_y}^2$ is the variance of $R_{i,y}$, and an upper bar indicates an average. It can be shown that κ_1 equals HI. The OLS-approach has several advantages relative to other calculation methods (e.g. integral approximation, discrete formulas). First, equation (13) is easily generalised for weighted data. Second, the standard error of κ_1 can be interpreted as a standard error for HI. Finally, the standard error can be corrected for autocorrelation [31] and for clustering at the household level [26].

DATA

We base our analysis on data from the Panel Study of Belgian Households (PSBH) [16]. The PSBH includes information on utilisation of health care and self-reported health of all members (over 15 years) of the participating households, but is essentially a household survey collecting socio-economic information. We do prefer the PSBH to the recently released first Belgian Health Interview Survey [32], since the Health Interview Survey lacks the panel dimension which is essential for the purposes of this paper. The PSBH started in 1991, has a yearly time dimension, and is a representative sample of the Belgian, non-institutionalised population. This is ensured by the sampling framework, and by using yearly weighting factors which correct for non-random attrition. We analyse data covering 1994-1997, and use information of 1993 for constructing some variables (see below). Data for 1991-1993 was not considered for analysis as it lacks information on utilisation of health care. After deleting missing observations, we end up with an unbalanced panel data set with 21290 observations. The variable definitions and descriptives statistics are summarised in tables 1 and 2.

[table 1]

We consider utilisation of three health care services (measured in counts). The PSBH informs on the number of visits during a year to a general practitioner (gp), the number of visits during a year to a specialist ($spec$), and the number of nights spent at a hosptial during the past twelve months ($hosp$). The suffixes ' $P1$ ' and ' $P2$ ' refer to 'Part 1' and 'Part 2' of a two-part regression model.

Four sets of socio-economic variables are used. First, individuals were asked to give their highest education degree ever obtained. It is represented by a set of four dummies, namely university degree ($univ$), higher education ($highedu$), higher secondary school ($highsec$), lower secondary school ($lowsec$), and primary school or no degree (the excluded category).

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Second, we constructed a set of dummies for monthly disposable net household income ($hinc1-7$). The dummy for household income above 200.000 BEF (+/- 4958 euro) is excluded. Although the estimation of the determinants of health care is carried out at the individual level, we believe that the specific Belgian situation provides justification for a measure at the household level as each household faces a co-payment ceiling determined by yearly household income. The economies of scale argument behind equivalence scales is met by including variables reflecting household structure (see below). We also did not explicitly correct for inflation. Instead we include time dummies and note that the dummies correspond to income ranges of at least 20.000 BEF.

Third, we constructed a continous measure of monthly disposable net household income ($hincrank$). This measure is not used in the estimation of the determinants of utilisation of health care since the set of dummies allows for more flexibility. Rather, we use the continuous measure for calculting HI. First, we use the set of income dummies ($hinc1-8$) to predict a continous measure for *all* households using interval regression. Since some, but not all households did report a continous income measure, we replace the predicted value of these households by the actual value. Appendix A gives additional information.

Fourth, all individuals are classified into three mutually exclusive occupational groups, namely the self-employed or professionals (*self*), the employees (*emp*), and individuals working less than 15 hours a week or not working at all (the excluded category). We choose this partitioning for two reasons. On the one hand, Belgian self-employed are likely to have a higher value of time, ceteris paribus, since they receive, relative to employees, less favourable replacement incomes during episodes of illness. In turn, employees typically have a higher value of time than those working less than 15 hours or not working. On the other hand, self-employed, relative to employees and those not working, have a limited public insurance package, which might result in a negative effect on demand. The effect is likely to be modest for those buying additional private insurance, but evidence shows that only 60% of the self-employed has additional insurance [33]. Besides *self* and *emp*, we also include two dummies at the household level (*selfhh* & *emphh*). These are included

to reflect the fact that not working members of the household (or working less than 15 hours a week) receive the same public insurance package and the same replacement incomes as the working members. Households without working individuals are the excluded category.

[Table 2]

Four demographic variables are considered. Sex is represented by a dummy variable (*male*) and age is measured continuously (*age*). The number of household members under 16 year is denoted by *child*, while *adult* measures the number of household members older than 15 year. These latter two variables are included to correct household income for household composition (see e.g. Gerdtham [34]).

We include four sets of dummies reflecting health status. First, *chron* measures chronic illness or handicap. Second, self-assessed health (*sahg − sahvb*) is measured on a five-point categorical scale ranging from very good to very bad (very good is excluded). The two lasting measures are also measured on a five-point categorical scale, but refer to the last three months before the interview. The first refers to depressive feelings (*deprese − deprefr*), while the second refers to physical symptoms (*phsymse − phsymfr*). In both cases, we excluded the category 'never'.

Health status is likely to be an endogenous covariate. Several strategies are available for dealing with this possible endogeneity. First, one could estimate a structural simultaneous equation model (e.g. Van de Ven and Van der Gaag [35]). Second, one could use the GMM-framework on the condition that suitable instruments are available (e.g. Mullahy [36] and Windmeijer and Santos Silva [37]). We follow a simpler strategy. Since information on health status is available in 1993, all four sets of dummies refer to the situation in the preceding year. As such, we avoid that utilisation of health care in year t is correlated with health status in year t. We do however not avoid that health status in year $t-1$ is correlated with health care in year $t-2$, $t-3$, etc.

Two dummies reflect the federal structure of Belgium, namely the Walloons (*wall*), Brussels (*bruss*), and Flanders (the excluded category).

Finally, we turn to variables not (explicitly) included in the estimation of the determinants of health care. First, we only have limited information on insurance status (see *emp* & *self*), which in Belgium typically determines the out-of-pocket price. Moreover, insurance (price) effects might also be reflected in the low income dummies (*hinc*1 − 2), since low-income households face lower co-payment levels in general. Second, information on the supply of medical care is not included. In principle we should be able to link supply information (which is available on municipality level [38]) with the residence of the individuals, but - because of privacy regulation - the PSBH provides no residence information (except for the federal dummies).

RESULTS

We start this section by discussing estimation results and model selection. Next, we deal with the indices of horizontal inequity.

ESTIMATION RESULTS AND MODEL SELECTION

We use STATA 7.0. to obtain estimates of the determinants of health care, resulting from the four techniques. All models are estimated by maximum likelihood, except for 'Part 2' of 2PM-P (C) that is estimated by GLS (OLS).

We estimate separate models for *gp*, *spec* and *hosp*. We start from specifications including all variables (except for *hincrank*) discussed in the data section. Rather than including *age*, we include a fourth order polynomial of age to pick up non-linearities. We also add interaction effects between this polynomial and *male*. The panel models are also supplemented with time dummies. We discriminate between the four regression techniques using AIC and BIC. The summary statistics in table 3 are based on the more parsimonious models (i.e. after excluding redundant variables). In all cases the panel estimators are preferred to the cross-section estimators *and* 2PM is always preferred to 1PM. With respect to general practitioner care, the latter is different from the findings of Schellhorn *et al.* [3], who argue that two-part models are not needed if the proportion of zeroes is modest.

[Table 3]

Since 2PM-P emerges as the most appropriate model, we mainly discuss the estimates resulting from this model. Remember, however, that the estimates are not exclusively intended to present evidence on the determinants of utilisation of physican and hopsital services in Belgium. The estimates are also used to assess the relevance of the four regression techniques in calculating HI. Therefore, we present the estimates resulting from the other regression techniques in appendix B. Table 4 shows the estimation results of 2PM-P. As shown by the Lagrange Multiplier test, it is

necessary to control for unobserved individual heterogeneity. Table 4 and 5 show that the heteroskedastic retransformation is appropriate.

[Table 4 & 5]

Males are less likely to visit any of the three types of health services. The age profile is always nonlinear, except for the conditional number of overnight visits at the hospital. Interaction effects between the *age* polynomial and *male* are primarily relevant for the number of visits to the specialist because of pregnancy consultations.

The health dummies always take the expected sign. A less favourable health status results in a higher contact probability and a higher conditional number of visits. Not all sets of health dummies are, however, equally important in 'Part 1' and 'Part 2' and across type of health service. Most striking are the differences in significance of the health dummies reflecting depressive feelings and physical symptoms, and the differences across type of health care in the proportional increase of the contact probability (and conditional number of visits) resulting from a worsening health status.

The educational dummies reveal that the higher educated (relative to the lower educated) tend to visit the general practitioner and hospital less and the specialist more often. The dummies reflecting the federal structure of Belgium reveal a higher number of visits for the Walloons relative to Flanders. Brussels has a lower number of visits to the general practitioner, but a higher number of specialist visits. The composition of the households only affects the contact probability for the general practitioner, while the occupational dummies mainly affect the conditional number of visits to the general practitioner. Finally, the set of income dummies is always jointly significant, but few dummies are significant. We find a positive effect of low income for hospital care and specialist care, while the middle income groups are more likely to visit the general practitioner.

RESULTS FOR INDICES OF HORIZONTAL INEQUITY

The previous section dealt with the first objective of this paper, namely estimation of the determinants of health care utilisation. We checked for the importance of the panel characteristics and two-part structure. This section handles the second and third objective. The second objective is a continuation of the first and amounts to a sensitivity analysis of the calculation of HI. The third objective is to present longitudinal evidence on horizontal equity in Belgian health care.

The need for health care is calculated using equations (8)-(11). *Male*, the polynomial of *age*, the four sets of health dummies, the interaction effects between the polynomial of *age* and *male*, and the time dummies are included in the set of variables reflecting need (x_i^{RN}). The individuals are ranked by continuous household income (*hincrank*), corrected for household composition. We apply the same equivalence scale as van Doorslaer *et al.* [2], namely $\sqrt{adult + 0.5child}$. The resulting indices based on the panel estimators are shown in table 6, while those based on the cross-section estimators are shown in table 7 (in appendix C, we show the concentration indices of health care utilisation). We present three indices per year per type of health service [15]. The first ($P(M = 1)$) is based on the first part of 2PM. The second ($E(M|> 0)$) is based on the second part of the 2PM. The last is based on the 1PM ($E(M)$).

[Table 6 & 7]

In order to concretize the second goal of this paper, we use the new interpretation of the concentration index proposed by Koolman and van Doorslaer [14]. The authors show that three quarters of the value of the concentration index equals the proportion of the total number of visits that needs redistributing from the richest to the poorest half of the population to reach horizontal equity. Since we aim to compare two HI's which are based on concentration curves, one can say that the difference between two HI's is equal to 75 percent of the proportion of health care that

should be redistributed. This gives us a nice benchmark to assess the difference between the HI's based on panel and cross-section data.

In general, one observes that the differences between the indices based on panel and cross-section estimators are fairly small. For instance the difference between the HI of general practitioner ($E(M|>0)$) for 1994 amounts to -0.001, which means that in order to reach horizontal equity according to the panel estimator requires an additional redistribution of 0.075% of all *gp* visits (compared with the index based on the cross-section estimator). There are however a few differences that are larger. First, the indices for general practitioner care based on $E(M)$ differ between 0.02 and 0.03, implying a difference of 1.5% to 2.25% in total health care that needs redistributed. Second, the difference between indices for hospital care in 1996 and 1997 also amounts to about 0.03.

We conclude that in general the choice for the cross-section versus panel estimator does not matter a great deal. We guess this reflects - among other things - the negelect of the random effects in predicting need for health care (see equations (8)-(11)). In some cases, however, there are differences that cannot be neglected. A quick look at table 4 and the tables in appendix B shows that time-variation in the parameters is driving these differences. Based on the information criteria in table 3, we prefer the HI's based on the panel estimators.

With respect to the third goal of the paper, we can say the following. First, the split up between inequity in the contact probability and inequity in the conditional number of visits is very clarifying. For instance, it shows that the inequity in the total number of visits to the general practitioner is mainly driven by inequity in the conditional number of visits. Second, the indices are fairly stable across time. Third, the results are in line with the results presented in van Doorslaer *et al.* [2]. Given the stability of the indices, this indicates that - as noted in the introduction - there is additional evidence that Belgium is an outlier in comparison with other European countries.

DISCUSSION

In this paper, we adressed three issues. First, we compared four regression techniques for estimating the determinants of utilisation of Belgian health care. We considered a panel and cross-section count data two-part model, and a panel and cross-section one equation count data model. These estimators differ in terms of their capability of controlling for unobserved individual heterogeneity, in terms of the assumed (two-part or one-part) underlying decision process, and in terms of precision and parameter stability across time periods. We estimated all four models on Belgian panel data and conclude that the panel count data two-part model is most appropriate for estimating the determinants of Belgian health care.

Second, we used the estimates resulting from the four models to calculate indices of horizontal inequity in Belgian health care. We found that the choice between the various estimators does not matter a great deal.

Third, we find that inequity in the number of visits to the general practitioner is favouring the less advantaged, meaning that they have more visits than expected on the basis of their needs. It is shown that inequity in the conditional number of visits, rather than inequity in the probability to contact the general practitioner, is the main driving factor. With respect to specialist care, we found the opposite. The rich have a higher probability to contact the medical sector than one would expect on the basis of their needs, but this does not lead to inequity in the conditional number of visits, nor in the unconditional number of visits. Compared to visits to the general practitioner and specialist, the number of nights spent at the hospital is characterised by the highest inequity. However, only two out of four indices are statiscally significant for the conditional and unconditional number of nights spent.

Across years, all indices are fairly stable. It follows that extrapolation of the results from previous to later years might be feasible. Furthermore, the stability of the indices could be a very useful finding for countries that do lack (good) panel data since such countries can still resort to cross-section data to get robust estimates of equity in health care utilisation.

Finally, we explore some routes for future research. First, it would be interesting to consider additional variables to explain health car utilisation in Belgium that were not available in our data. We think that information on the supply of medical care, better information on the insurance status of the individuals and more detailed information on health status is likely to improve the policy relevance of this analysis. Probably, policy makers are more interested in the effect of insurance status than in the effect of education. Moreover, the set of dependent variables did not cover all categories of medical care. Drug consumption, dentist care, eye doctors, physiotherapists and alternative medical care were not considered. A better data set is, however, the sole solution. Second, we should look for factors explaining violations of horizontal equity: 'measuring inequity is one exercise, finding possible explanations another'. One way to proceed would be to apply the decomposition methods developed by Wagstaff *et al.* [39]. This method has been shown to be a very powerful tool for explaining inequities within a year, across years and across countries.

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APPENDIX A: A CONTINOUS INCOME MEASURE

The results of the interval regression are presented in table A.1. Besides data for 1994-1997, we use data for 1993 since information on monthly disposable net household income is collected from 1993 onwards. We do not use panel techniques since the composition of households is time-varying. Instead, cross-section methods are applied on the pooled data. Contrary to the estimation of the determinants of utilisation of health care, the household is the unit of analysis.

[table A.1]

APPENDIX B: ESTIMATION RESULTS FOR 2PM-C, 1PM-P AND 1PM-C

[table B.1-B.4]

APPENDIX C: CONCENTRATION INDICES OF HEALTH CARE UTILISATION

[table C.1]

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