Socioeconomic Inequity in Health Care Use Among Elderly Europeans

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Abstract

We examine the extent of horizontal inequity present in the accessibility of healthcare in 14 European countries using the 2013 Survey of Health Aging and Retirement in Europe (SHARE), a cross-national panel database including data on health, socioeconomic status, and social and family networks of individuals. In particular, we estimate the impact of a variety of socioeconomic, demographic and health factors on an individual's annual contacts with a doctor and whether an individual visited a hospital in the past year. To account for unobserved heterogeneity in health we focus on a Latent Component Model (LCM) to ultimately derive a measure for need for healthcare that is based on an individual's health status. We use this measure to construct a horizontal inequity index for each country and plot concentration curves. We find that income, higher education, and gender are all highly significant predictors of an individual's access to healthcare. Comparing across countries, we find that the horizontal inequity index varies from -0.022 (Italy) to 0.058 (Austria). These results could be used to evaluate how successful progressive policies and healthcare systems are at attaining equitable outcomes.

[1]"This paper uses data from SHARE Waves 1, 2, 3 (SHARELIFE), 4 and 5 (DOIs: 10.6103/SHARE.w1.260, 10.6103/SHARE.w2.260, 10.6103/SHARE.w3.100, 10.6103/SHARE.w4.111, 10.6103/SHARE.w5.100), see Börsch-Supan et al. (2013) for methodological details.

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Contents

1 Introduction

Most European health care systems aim at ensuring an equitable distribution of health care, where (horizontal) equity is defined as equal use for equal need (Van Doorslaer et al., 2004). In other words, under socioeconomic (horizontal) equity, health care use should be equal for individuals of similar health needs - regardless of differences in socioeconomic status (SES). This study uses the 2013 Survey of Health Aging and Retirement in Europe (SHARE), a cross-national panel database including data on health, socioeconomic status, and social and family networks of individuals in 14 European countries, to create measures of health care need and usage across individuals of different socioeconomic status. Following the literature, this paper compares measures of health inequity using a simple OLS regression, negative binomial or probit regression, a two-step hurdle method, and a latent class model. To compare across countries and account for similarities in health within households, country fixed effects are included and data is clustered at the household level. To account for seasonal effects, time fixed effects are used for the month of interview.

Given the strengths of LCM in terms of accounting for unobserved heterogeneity in individuals' health needs, the LCM for doctor contacts ($hc002\_$) is our preferred specification. We use it to compute a unified measure of an individual's healthcare demand. By standardizing income, and recomputing this measure, we obtain a measure for demand of individuals absent the impact of income, i.e. "need" for healthcare. This need measure for each individual is used to compute measures of horizontal inequity for each of the 14 countries in the sample and concentration curves.

We find that across all specifications higher income and education levels are highly significant predictors of healthcare usage, and being female is in many. In our preferred specification, classifying individuals by health status, we can interpret this as showing that conditional on need, income and other socioeconomic factors still have predictive power. The horizontal inequity index ranges -0.022 (Italy) to 0.058 (Austria). Thus, Italy is actually pro-poor while Austria, and the majority of the the 12 other countries are pro-rich.

These analyses can be used to make policy recommendations to European health care systems that will improve socioeconomic equity in health care access.

2 Modeling Healthcare Demand

The main challenge to modeling healthcare demand and thus being able to measure "need" for services is the fact that true health status and thus main determinants of true healthcare need are almost certainly unobserved, despite the wealth of data in the SHARE sample. This unobserved heterogeneity threatens to bias the estimates and prevents identification in an OLS or standard non-linear settings. Further, such methods cannot distinguish between the extensive and intensive margins of healthcare demand. Many low levels of healthcare demand manifest as "zeroes" in the dataset, and we would like to be able to distinguish these outcomes from strictly positive counts of medical treatment. For outcomes that take on a count form, such as the number of doctor contacts ($hc002\_$), we can turn to an established literature to help solve this problem. Deb & Trivedi (1997) show that given the assumption that negative health events, following which individuals decide whether to seek treatment, are rare events, we are justified in viewing counts of utilization as a poisson random variable, which is a subset of the negative binomial distribution, with $\alpha = 0$, the dispersion parameter. However, healthcare utilization data is frequently thought to display overdispersion (some people never seek treatment - some people seek too much treatment), which suggests a negative binomial with positive dispersion, $\alpha > 0$.

2.1 Hurdle Method

The standard OLS model oversimplifies access to health care in two ways: firstly, it is not flexible enough to account for accessing health care on both the intensive and extensive margins; secondly, it assumes that the decision-making process to see a doctor - and to continue seeing a doctor - are made by the same individual. However, as pointed out by (Pohlmeier, 1995), "the decision to contact a physician and the decision about how often to contact a physician are determined by different decision-makers," and thus "need to be treated as two distinct processes." In many European countries, the decision to pursue health care proceeds as follows: first, the patient makes the decision on whether or not to see a doctor - and in most cases, which doctor to see. However, once the patient has decided to visit a doctor, the doctor takes over treatment levels and thus chooses the intensity of treatment.

To account for the two separate processes of the decision-making process, current literature such as (Pohlmeier, 1995} and (Jimenez-Martin 2002) implement a two-part hurdle model (TPM). Deb and Trivedi (1997, 2002) also estimate this class of model, in comparison with Latent Class Models (LCM), which we discuss below. Many have presented this as a familiar "principal - agent" problem, but that analogy is not necessary for the model to be valid (Deb & Trivedi, 2002). The first part treats the decision to seek care as a binary choice outcome. Conditional on choosing to seek care, i.e. passing the first hurdle, the second part treats the number of visits to physicians as a truncated count model, such as Poisson or Negative Binomial. In this paper, we follow the methodology of (Deb & Trivedi, 1997). First, define

$$\lambda_i = \exp\left(x_i'\beta\right)$$

$$\psi_i = \left(1/\alpha\right)\lambda_i^k$$

The first part of the hurdle process is specified as

$$Pr_h(y_i = 0|x_i) = \left(\frac{\psi_{h,i}}{\lambda_{h,i} + \psi_{h,i}}\right)^{\psi_{h,i}} \tag{1}$$

$$Pr_h(y_i > 0|x_i) = 1 - \left(\frac{\psi_{h,i}}{\lambda_{h,i} + \psi_{h,i}}\right)^{\psi_{h,i}}$$

where the subscript h denotes parameters associated with the "hurdle distribution." Following Deb & Trivedi, we make the assumption that $\alpha = 0$, which enables identification of β.

Conditional on passing the first hurdle, the data are assumed to have a negative binomial distribution. This is given by

$$f(y_i|x_i, y_i > 0) = \frac{\Gamma(y_i + \psi_i)}{\Gamma(\psi)\Gamma(y_i + 1)}\left[\left(\frac{\lambda_i + \psi_i}{\psi_i}\right)^{\psi_i} - 1\right]^{-1}\left(\frac{\psi_i}{\lambda_i + \psi_i}\right)^{y_i}$$

The first stage can be simplified for computational ease. Deb & Trivedi (1997) show that the negative binomial model with $k = 1$ generally outperforms that with $k = 0$ for similar set of healthcare data so we proceed with $k = 1$. Equation 1 thus simplifies to

$$\left(\frac{1}{2}\right)^{\lambda_{h,i}}$$

Note that the first and second stage depend on disjoint parameter sets, so we can compute independent maximum likelihood estimates. The first step was estimated using quasi-Newton methods; the second is accommodated via Stata's standard negative binomial regression.

2.2 Latent Class Method

The latent class method provides a compelling method for accounting for unobserved heterogeneity. It assumes that the population consists of individuals belonging to a finite set of different distributions. For example, perhaps the ill and the healthy belong to different distributions. Formally, borrowing from Deb & Trivedi (1997), the superpopulation is an additive mixture of C distinct populations in proportions $\pi_1, \ldots \pi_C$, where $\sum_{j=1}^{C} \pi_j = 1$, $\pi_j > 0$,

$$f(y_i|\Theta) = \sum_{j=1}^{C-1} \pi_j f_j(y_i|\theta_j) + \pi_C f_C(y_i|\theta_C)$$

The component distributions in the mixture follow the negative binomial distribution, specified as

$$f_j(y_i) = \frac{\Gamma(y_i + \psi_{j,i})}{\Gamma(\psi_{j,i})\Gamma(y_i + 1)} \left(\frac{\psi_{j,i}}{\lambda_{j,i} + \psi_{j,i}}\right)^{\psi_{j,i}} \left(\frac{\lambda_{j,i}}{\lambda_{j,i} + \psi_{j,i}}\right)^{y_i}$$

where $j = 1, 2, \ldots, C$ are the latent classes. We allow the parameters, β_j to differ across classes - healthy and ill individuals may respond different to the same factor.

Compared to TPM, LCM is intuitively more appealing. In TPM, only the users of care determine the number of visits. The sharp dichotomy between two types of people - "users" and "non-users" seems overly-rigid for healthcare. While different people respond different to a common cold, virtually everyone will seek treatment for a stroke. This is true particularly among the elderly, where even a healthy individual likely makes use of healthcare for reasons of precaution and health maintenance. The LCM provides a more appealing alternative between heavy users (ill) and light users (healthy), distinguishing between groups with high average demand and low average demand. It provides a posterior probability that each individual is a member of each class. Further, it does not rely on a principal-agent interpretation. More importantly, Deb & Trivedi (2002) argue that it is more robust to misspecifation than TPM. It is flexible in that it permits coefficients to be different for individuals in each class. For our purposes, it also provides a compelling way to estimate healthcare demand of each individual (and eventually a measure of need): we can calculate an individual's predicted demand given that he or she is healthy or unhealthy, and then examine how this would change based on income or other socioeconomic variables. This is precisely what we need to evaluate horizontal equity.

3 Data

Data for this paper come from the fifth wave of Survey of Health Aging and Retirement in Europe (SHARE), conducted in 2013. The data represent a cross-national panel database of 62,949 individuals from 14 European countries. Because we are studying the effects of socioeconomic inequities in healthcare among elderly Europeans, we initially keep only data observations that represent individuals who are at least 50 years old. After dropping 1,140 observations for individuals younger than 50 years old, we cleaned dataset comprises 61,809 individual observations.

3.1 Adjustments to SHARE Data

This section outlines adjustments made to SHARE data, particularly to categorical data. Our approach to choosing controls was to include as many measures of health, access to health care, and socioeconomic status as possible. Variables were only excluded if there were multiple variables that were likely to be highly collinear. In these cases, we would choose a single variable that best encompassed the information with the fewest missing observations.[1]

Factors affecting health needs are age, gender, self-reported physical health, depression, chronic disease, BMI, whether the individual smokes, alcohol consumption, activity level, recall ability, and mobility. Access to health care are measured by number of doctor visits in the last year and whether respondents have been in a hospital overnight during the last twelve months. Socioeconomic status and networks are given by income percentile, education, marital status, household size, and current job situation.

Additionally, several of the SHARE categorical variables were extremely refined. To avoid an excess of classes with few individuals each, we would also combine similar categories:

- Self-reported physical health: “sphus” is reclassified into three categories: “great” (for excellent or very good health), “average” (for good health), or “poor” (for fair or poor health).

- Depression: Similarly, “eurod” is reclassified into four categories: “not depressed” (for eurod equals 0), “low” (for eurod equals 1-4), “mid” (for eurod equals 5-8), and “high” (for eurod equals 9-12).

- Chronic Disease: Rather than split into individual chronic diseases, we recode “chronic_mod” to a binary variable that equals 1 if the individual has any chronic disease and 0 if not.

- BMI: based off the four BMI classifications, “bmi_mod” is recoded into underweight (BMI less than 18.5), normal (BMI between 18.5 and 25), overweight (BMI between 25 and 30), and obese (BMI over 30).

- Alcohol consumption: “br010” is recoded into low (during the last six months, the individual has drank once or twice a month or less) and high (during the last six months, the individual has drank more than once or twice a week or more).

- Strenuous activity: “br015” is recoded into “low” (hardly ever or never), “mid” (once a week to once a month), and “high” (more than once a week).

- Education: As given by the International Standard Classification of Education (ISCED) variable, “isced_r” was reclassified into “none”, “elementary school,” “middle school,” “high school,” and “college” to reflect each individual’s highest level of educational attainment.

- Marital Status: Under the assumption that couples who live together have similar health outcomes and access to health - whereas the correlation between couples who do not live together is less clear - “mar_stat” is reclassified into whether the individual lives with his or her significant other.

Additionally, many of the variables provided in the SHARE dataset are coded as “-15. no information” or “-12. Don’t know/refusal”. Some variables may also code an “other” category. As these essentially provide no information for that observation, we typically recode all of these as being missing (“NA”).

3.2 Summary Statistics

The 2013 SHARE data contains individuals from 14 European countries. Table 1 gives the number of individuals from each country in the data used for analysis. Table 2 gives overall summary statistics for all variables used in this data set.

[1] For example, recall ability is measured by recall_1 in our model, while recall_2 is ignored.

Table 2: Summary Statistics

A. Factors Affecting Health Needs				
	Mean	**Std. Dev.**	**Min**	**Max**
Age	67.06032	10.01937	50	103.5
Mobility Index	0.5326184	0.9699695	0	4
	NA	**Percent**		
Female	0%	55.36%		
Ever Smoked	1.36%	45.69%		
Has Chronic Disease	0.38%	63.61%		
	NA	**Great**	**Fair**	**Poor**
Self-Reported Physical Health	0.25%	25.28%	36.72%	37.74%
	NA	**None**	**Elementary**	**Middle**
Education	1.82%	4.59%	16.17%	18.45%
	NA	**Not Depressed**	**Low**	**Mid**
Depression	2.96%	21.43%	59.32%	14.59%
	NA	**Underweight**	**Normal**	**Overweight**
BMI	34.9%	0.83%	24.62%	26.54%
	NA	**Below**	**Above**	
Recall	2.87%	53.55%	46.45%	
	NA	**Consume little**	**Consume lot**	
Alcohol Consumption	0.28%	52.34%	47.38%	
	NA	**Low**	**Middle**	**High**
Strenous Activities	0.26%	43.13%	22.18%	34.43%
B. Access to Health Care				
	Mean	**Std. Dev.**	**Min**	**Max**
Doctor Visits	6.889173	9.845159	0	98
Stayed in Hospital in Last 12 Months	4.373289	1.453999	1	5
C. Socioeconomic Status Indicators				
	Mean	**Std. Dev.**	**Min**	**Max**
Income Percentile	5.477244	2.869363	1	10
Household Size	2.102542	0.9315675	1	12
	NA	**Percent**		
Live with Significant Other	1.13%	69.26%		
	NA	**Retired**	**Employed**	**Unemployed**
Current Job Situation	2.46%	58.26%	27.44%	2.90%

Table 1: Number of Individuals By Country

Country	Freq.	Percent
Austria	4,164	6.74
Germany	5,521	8.93
Sweden	4,487	7.26
Netherlands	4,077	6.6
Spain	6,320	10.23
Italy	4,614	7.46
France	4,364	7.06
Denmark	4,045	6.54
Switzerland	2,947	4.77
Belgium	5,508	8.91
Czech Republic	5,598	9.06
Luxembourg	1,590	2.57
Slovenia	2,903	4.7
Estonia	5,671	9.18
Total	61,809	100

4 Methods

4.1 Doctor Contacts

We begin analysis of ($hc002\_$) with an OLS regression including the variables discussed above. We use country fixed effects to account for unobserved heterogeneity across countries. This can help adjust for factors like the structure of national healthcare institutions or cultural attitudes towards healthcare and treatment. We also use month of interview to compute time fixed effects - this accounts for seasonal variation in health, which, given that recall of medical experiences is likely to be imperfect and some health measures are sensitive to the date of interview, could otherwise bias results. Errors are clustered by household to account for correlation in the outcomes of family members living together (and sharing the same income). Both sets of fixed effects and clustered standard errors are retained across all subsequent specifications.

Following OLS, we also can account for the fact that doctor contacts is not a continuous dependent variable, but a count. We fit a negative binomial model, in keeping with a large body of literature (Deb & Trivedi 1997, 2002, 2012; Pohlmeier 1995,;Van Doorslaer 2004; Van Doorslaer 2006).

We then proceed to run a TPM and LCM to account first for the "excess zeroes" problem, and also unobserved heterogeneity in the data. For now, LCM is computed with just two components, in keeping with the findings of Deb & Trivedi (1997). We can evaluate the model fit to determine which best fits the data. As in Deb & Trivedi (1997, 2002) we do so via the Log Likelihood, Akaike IC, and Bayesian IC. Note that, consistent with the literature and predictions of the theory made above, LCM outperforms TPM on all three metrics and is thus our preferred specification.

Finally, it is important to note that we have reason to believe that fixed effects are consistently estimated in this application. While Deb & Trivedi (2012) discuss the problems surrounding the estimation of fixed effects in non-linear models, we have far more data than their rough rule of thumb of $T \geq 8$; even Luxembourg has well over 1000 observations.

4.2 Hospital Visits

The variable measuring whether an individual has visited a hospital in the past year is binary, hence the count procedures previously discussed do not apply. Clearly there could be no second stage for TPM, and

LCM relies on having intensive margin data. The excess zeroes problem does not apply to this extensive-only data. Unfortunately, this means that the best method available, given no plausible IV or natural experiment/discontinuity is to proceed with well-selected (and consistently estimated) fixed effects. These provided a plausible measure of control for unobserved heterogeneity; at worst, they will provide a helpful comparison with our results from the count data. For completeness, we begin with an OLS specification, here a linear probability model (LPM), including fixed effects and clustered errors as for doctor contacts. However, given the well-known concerns associated with the LPM (predicted probabilities not between 0 and 1, etc.) we then proceed with a probit model as our preferred specification.

4.3 Equity Measures

Using our preferred specification, the LCM, we can compute an individual's demand for healthcare conditional on being a member of each class, $E\left[Y_i|x_i, i \in c\right]$. We can combine this pair of estimated values - one under good health, and one under bad health - to compute a unified healthcare demand for each individual, conditional on their covariates. We choose to average the two measures using weighting by the overall estimated posterior probability of being in each class. This affords each individual the same probability of being sick or healthy, so we are moving towards a valid measure of horizontal equity. If we were to use each individual's posterior of being in each class, this would suffer from the endogeneity under which the poor are unhealthy more often. For conciseness, we continue our analysis focusing on income as a determinant of horizontal inequity. These measures of demand depend on income, unless income is not found to be significant in the LCM. Thus, it is necessary to fix income to predict healthcare *need* for each individual independent of income. Instead of computing the predicted values using all characteristics x_i, we predict it conditional on x_i absent income, denoted as $\tilde{x}_i$, and the mean value of the income variable, $\bar{W}$. Thus our measure is

$$Need_i\left(x_i\right) = \pi\left(healthy\right) E\left[Y_i|\tilde{x}_i, \bar{W} i \in healthy\right] + \pi\left(sick\right) E\left[Y_i|\tilde{x}_i, \bar{W} \in ill\right]$$

Using this measure of need and the actual utilization as a measure of usage, we proceed to compute standard inequity measures found in the literature. Note that while each individual to be compared is not "the same" per se, their health status is, and we consider the analysis that follows a lower bound on the inequity present in our data. Adjusting for all characteristics would only inflate the inequity measures as argued by Van Doorslaer (2004).

We begin by computing the relative income-related concentration index for actual doctor contact use following Van Doorslaer (2004). First, we collapsed the data to find actual doctor contact use for each income decile N within each country, with which we calculate the relative fractional rank of each income group using Van Doorslaer (2004)'s aggregation: $R_i = \frac{1}{N}\sum_{j=1}^{i-1} w_j + 0.5 w_i, w_0 = 0$, where $N = 10$ refers to the 10 income deciles described in our data, and w_i refers to the weight, calculated as the fraction of individuals within a certain income group for a certain country c. After we find the relative fractional rank, we can calculate the actual concentration index as $C_m = \frac{2}{N\bar{y}}\sum w_i(y_i - \bar{y})(R_i - 0.5)$, where y_i describes the actual average doctor contact and $\bar{y}$ is the average actual doctors' visits across all individuals in that particular country. We then use our model to generate a analogous "fair" concentration index $C_n = \frac{2}{N\hat{\bar{y}}}\sum w_i(\hat{y}_i - \hat{\bar{y}})(R_i - 0.5)$, using our model's fitted values $\hat{y}_i$ for predicted actual doctor contact if we hold all else constant except for need.

Finally, we calculate a horizontal inequity index $HI = C_m - C_n$. When HI is positive (negative) then the current distribution of healthcare use is pro-rich (pro-poor). Table 4 shows an HI index for each country based on the Wave 5 SHARE results along with confidence intervals for each country. We use

Table 3: Sensitivity of Usage to Socioeconomic Factors

	Doctor Contacts					Hospital Visits	
	OLS	NB	TPM	LCM (healthy)	LCM (ill)	OLS	Probit
Income	0.094***	0.014***	0.009***	0.011***	0.018***	-0.007**	0.025***
	(0.016)	(0.002)	(0.002)	(0.002)	(0.004)	(0.002)	(0.003)
Female	-0.024	0.026**	-0.011	0.070***	0.013	0.126***	0.180***
	(0.080)	(0.011)	(0.011)	(0.010)	(0.021)	(0.013)	0.016
Primary Schooling	-0.022	-0.026	-0.022	0.020	-0.072*	-0.012	-0.029
	(0.206)	(0.025)	(0.024)	(0.021)	(0.044)	(0.030)	(0.041)
Lower Secondary	-0.004	-0.018	-0.006	-0.008	-0.040	-0.005	-0.068*
	(0.208)	(0.027)	(0.026)	(0.022)	(0.046)	(0.030)	(0.040)
Higher Secondary	0.479**	0.039	0.034	0.038*	0.039	-0.048	0.034
	(0.207)	(0.026)	(0.025)	(0.021)	(0.039)	(0.030)	(0.040)
Post-Secondary	1.028***	0.124***	0.104***	0.098***	0.136**	-0.088**	0.113**
	(0.211)	(0.027)	(0.026)	(0.022)	(0.046)	(0.030)	(0.041)
(0.041)	0.163	0.052				0.094	0.140
K	67	67	133	135		67	67
LLH	–	–	-293531	-170560		–	–
AIC	–	–	293797	17083		–	–
BIC	–	–	587196	341255		–	–
N							

Specifications are discussed in detail above. ** represents significance at the 95% level and *** at the 99% level. All SE's are clustered by household and all models include country and month fixed effects.

a parametric bootstrap method with 1,000 repetitions to estimate confidence intervals around our LCM estimates. The bootstrap assumes that the parameters estimated in the LCM regression are distributed according to a multivariate normal distribution with means and covariances given by the estimation process. Each bootstrap iteration is conducted in two steps. First, we randomly draw a new vector of coefficients from the estimated distribution. Second, we use these new coefficients to generate new predicted values of healthcare usage, again at the mean value of the income variable. This results in 1,000 predicted values of $Need_i$, which we use to calculate the 2.5 and 97.5 percentile values of the horizontal inequity index.

5 Results & Discussion

5.1 Regressions

Table 3 presents results from our various specifications for the subset of variables that we have determined are most related to socioeconomic status. These variables include household income, gender, and level of education. Our first specification uses OLS to estimate the correlation between health care usage and various need and non-need measures. This specification has several flaws, as noted above, but is useful for motivating the analysis and for its ease of interpretation. OLS also has historically been used in several papers examining similar topics, for example in Ruhm (2000, 2005, 2015) to estimate the impact of economic downturns on mortality rates. Also following Ruhm, we include location (country) and month fixed effects to control for omitted variables that are constant within countries over time or across countries in a given month. This allows us to instead isolate within-country variation in our outcome variables. Based on these results, we see that the number of doctor contacts is statistically significantly pro-rich (that is, the number of doctor contacts increases with income, holding need constant) while hospital visits is pro-poor. The number of doctor contacts is not strongly related to gender, while the probability of visiting a hospital is higher for women. Both outcomes also seem to be skewed towards more highly educated individuals.

Given the distribution of the dependent variables (doctor contacts is an integer greater than or equal to zero, and hospital visit is either zero or one), we also estimate an alternative functional form to better fit the data. For doctor visits, we use a negative binomial regression, and for hospital visits we use probit). The results are very similar to the OLS specifications, with higher income individuals obtaining significantly more healthcare, as do the better-educated and women.

We now move to the two candidates for our preferred specification for count data, which can deal with the issue of "excess zeros" and some of the identification problems. As noted in the text above, all model selection criteria favor the choice of LCM as our preferred specification for count data. However, both models find that the wealthy and educated are significantly more likely to seek medical care, and the LCM predicts that women are also.

These results offer a first pass at the role of socioeconomic status in determining access to healthcare. We find that demand for healthcare, conditional on two classes of need - which are represented by the two components of the LCM - is significantly impacted by income, higher education, and gender. These results are corroborated by the less-robust but still informative results for hospital visits. An interesting note on these results is how they contrast with Deb & Trivedi (1997) and Cartwright, Hu, & Huang (1992), who find that men are more likely to put off healthcare visits (as suggested by our preferred specification for count data), and thus are more likely to be in need of serious care when they do finally seek treatment. Thus, we would expect men more likely to spend time in hospital, or a negative coefficient on $female$ in these specifications. However, this discrepancy may owe to the aforementioned identification issues in the binary models. Our results could be understood as representing the fact that men on average suffer from more health problems, or that when faced by a binding budget constraint, men choose to allow their wives to seek medical care instead of going themselves.

5.2 Equity Measures

Table 4 displays the horizontal inequity index and concentration indices for each of the 14 countries. All are positive, or "pro-rich", except for Italy and Spain. They range from -0.022 (Italy) to 0.058 (Austria). The estimated values for Sweden, Italy, and France are significant at the 1% level (with Sweden and France being positive) and Denmark's is significant at the 1% level. While it is difficult to interpret the differences across countries, this is at worst suggestive evidence of a pro-rich bias in the majority of European countries studied.

Figure 1 and Figure 2 present the concentration curves for the country with maximum inequity, Austria (0.058), and minimum inequity, Italy (-0.022) . The blue dots represent cumulative actual healthcare use by decile, the red dots represent the cumulative estimated need by decile, and the 45-degree line represent the relationship that would hold under "equality". Similar figures were computed for all countries but were omitted for brevity.

6 Conclusion

We find that controlling for accurate measures of need, socioeconomic factors still have a highly significant impact on healthcare usage, meaning that horizontal inequity is present in Europe. This is particularly true for higher income and higher education, and somewhat true for being female. We focus on an LCM

Table 4: Horizontal Inequity Index by Country

Country	"Actual Use" (C_M)	"Fairness" (C_N)	HI ($C_M - C_N$)	0.025 Percentile	0.0975 Percentile
Austria	-0.004	-0.062	0.058	-0.021	0.055
Germany	-0.055	-0.077	0.021	-0.050	0.005
Sweden	-0.063	-0.091	0.028***	0.028	0.120
Netherlands	-0.062	-0.081	0.018	-0.028	0.044
Spain	-0.066	-0.058	-0.008	-0.015	0.041
Italy	-0.073	-0.050	-0.022***	-0.104	-0.046
France	-0.037	-0.074	0.037***	0.069	0.136
Denmark	-0.105	-0.109	0.004*	-0.001	0.070
Switzerland	-0.049	-0.069	0.020	-0.024	0.060
Belgium	-0.046	-0.062	0.016	-0.024	0.031
Czech Republic	-0.056	-0.056	0.000	-0.034	0.021
Luxembourg	-0.032	-0.061	0.029	-0.024	0.080
Slovenia	-0.024	-0.029	0.005	-0.044	0.039
Estonia	-0.032	-0.056	0.023	-0.028	0.036

** represents significance at the 95% level and *** at the 99% level. All SE's are clustered by household and all models include country and month fixed effects.

Figure 1: Concentration Curve for Austria

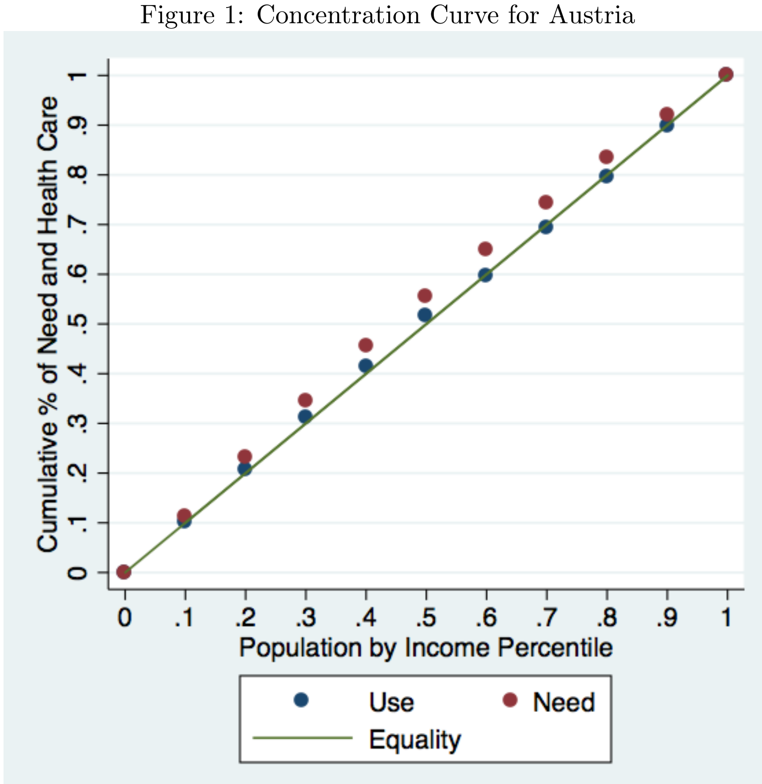
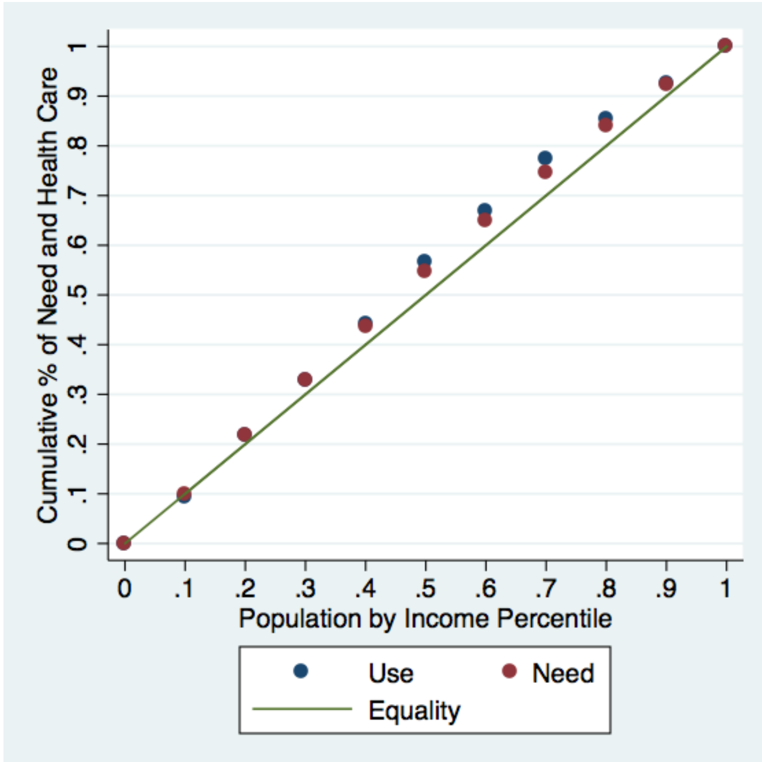


Figure 2: Concentration Curve for Italy



for count data on doctor contacts and a probit model for whether an individual visited a hospital. We use the LCM results to construct and an estimated measure of need to construct a horizontal inequality index and plot concentration curves for each country. We find that the majority of countries studied have positive or pro-rich horizontal inequity indices. For a subset of the countries, these are statistically significant from zero. Overall, these results are indicative of the presence of horizontal inequity in the 14 European countries analyzed. There is significant cross-country variation, with Austria displaying the highest degree of inequity and Italy the least. Combined with knowledge of policies and institutions in each country, these results could be used to evaluate how successful progressive policies and healthcare systems are at attaining equitable outcomes.

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