Econometric Game 2016, Case A

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April 7th, 2016

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.

The SHARE data collection has been primarily funded by the European Commission through the FP5 (QLK6-CT-2001-00360), FP6 (SHARE-I3: RII-CT-2006-062193, COMPARE: CIT5-CT-2005-028857, SHARELIFE: CIT4-CT-2006-028812) and FP7 (SHARE-PREP: N° 211909, SHARE-LEAP: N° 227822, SHARE M4: N° 261982). Additional funding from the German Ministry of Education and Research, the U.S. National Institute on Aging (U01_AG09740-13S2, P01_AG005842, P01_AG08291, P30_AG12815, R21_AG025169, Y1-AG-4553-01, IAG_BSR06-11, OGHA_04-064) and from various national funding sources is gratefully acknowledged (see www.share-project.org).

1 Introduction

Nowadays large emphasis is put on the issue of fairness in distribution of goods among people. This applies in particular to services provided by the government, such as health care. Many authors provided evidence on the fact that the health care is provided in an unequal manner to people with equal needs. This phenomenon, called in the literature horizontal inequity, seems to be present not only in developing economies where the democratic standards have not been fully introduced yet, but in European welfare states as well.

It is not sufficient to perceive the issues of inequity in the distribution of health services only by pointing out differences in access to health services with respect to different patient-level variables. Instead of employing such a simplified inequality approach one should ask why these inequalities arise and how it is connected with the subjective perception of fairness. That is why the inequity analysis involves also a part of normative economics. A researcher should specify the characteristics of an individual that do not affect the assessment of the health services. Obviously this procedure is arbitral and should be put in a socioeconomic context. In this paper we take the European welfare state model as a point of reference while evaluating failure in fair distribution of health services.

Horizontal inequities in access to health protection system are widely present in Europe. 3.6% of the population (around 18 million) in the EU-28 experienced unmet need for health care due to cost, travel distance of waiting time. The data also suggests, that the unmet need disproportionately affects older people, however the precise composition of the worst-affected groups varies across countries . Hence, it is legitimate to assess what are the socioeconomic inequities in health care use among elderly Europeans.

According to the literature, both binary health care usage and number of medical doctor consultations in a year are the most popular money-metric proxies of accessibility to the health care services.

Two groups of variables should be included to control for distinct aspects of individuals' characteristics. Needs variables will include health characteristics of a person such as self-assessment of a physical and mental health, measured on a standard Likert scale or a count variable describing a number of chronic health problems. The other covariates should be categorized in non-needs group and it may be gender, age, marital status, education or labour market situation.

Two main approaches to medical care utilization based on economic theory had been developed Deb and Trivedi (1997). The first one bases on consumer theory and assumes that demand on health care is determined mainly by a patient Grossman (1972), Muurinen (1982). The second one is based on principal – agent theory. In such a two-step approach, a doctor decides about medical care utilization on behalf of a patient, once an initial decision about participation in health care had been made W.G. Manning (1987). Two-step hurdles model has worked satisfactorily in several empirical studies (Pohlmeier and Urlich, 1995), (Gurmu, 1997) and usulay outperform standard one-step procedures.

The paper is structured as follows. Section 2 describes the data. Section 3 presents models used to asses inequity in health care across European countries. Results are presented in Section 4 and the last Section contains some concluding remarks.

2 Data

We use Survey of Health, Ageing and Retirement in Europe (SHARE) which is a cross-national and multidisciplinary panel database of micro data covering the interplay between health, economic and social factors. It examines the different ways in which people aged 50+ live in 20 European countries. The first wave of the SHARE survey was conducted in 2004 and the most recent fifth wave in 2013.

2.1 Socioeconomic variables

The following variables are included in the modelling: We control for month dummies as a proxy for seasonal variation in the demand for health services. For instance, one might expect increased number of visiting a physician during the period of a flu outbreak. One

Table 1: **Effective retirement age in selected European countries.**

Country	Sample frequency	Effective retirement age	
		Men	Women
Austria	3.7%	62.2	60.2
Germany	5.5%	62.7	62.7
Sweden	4.7%	65.2	64.2
Netherlands	4.6%	62.9	61.9
Spain	7.7%	62.2	63,1
Italy	6.0%	61.4	61.1
France	6.0%	59.4	59.8
Denmark	5.9%	63	60.6
Switzerland (German)	4.8%	66.1	64.5
Belgium (French)	10.3%	60	59.3
Czech Republic	12.7%	63.3	60.5
Luxemburg (French)	4.0%	61.9	60.8
Slovenia	8.0%	62.3	59.5
Estonia	16.0%	63.7	62.9

Source: Survey of Health Ageing and Retirement in Europe.

might consider including quarter or season dummies in order to increase the number of degrees of freedom in modelling. However, as our sample contains countries of various latitude, it would be inappropriate to assume that a given season would reflect the same time effects among countries. For the literature reference and further discussion see Ruhm (2005).

Unsurprisingly, there are less men in the sample. The average life duration is longer for women and simultaneously the elderly individuals are over-represented in the data.

We employ the age of the respondent at the moment of interview as a continuous variable. The sample is then divided into two parts including the elderly individuals, by which we mean they have crossed the threshold of effective retirement age reported by OECD (OECD, 2015). It is a better measure of elderliness than a legal age of the retirement as it accounts for economic agents‘ behavior rather than a legal threshold. Moreover, the age at which an individual quits a job provides a good proxy for the elderliness, because it is connected with a structural change of their life-cycle activities, which separates them from younger cohorts. Additionally, we cannot use the labor market status of individuals to distinguish the elderly as for some types of jobs the retirement age is incomparably lower than the average.

As the main research question in the paper concerns the inequity effects for the elderly, they should be subtracted from the whole sample and analyzed individually. Furthermore, the presence of younger individuals gives us an unique chance to compare the amount of inequity among the elderly with the effects on the younger generations. According to the fairness standards we assume in this paper, the equity in access to the medical services includes no difference with respect to age among the individuals.

Instead of years of education we use a categorical variable describing the highest level of education completed. The second one should be perceived as a proxy for achievement, affecting individual quality of life, whereas the first one might connect rather with the measure of effort. People are not equal with respect to educational abilities. Thus it implies the positive probability that two individuals with the same number of years of education differ a lot by means of degree they have obtained.

As we focus on the elderly subsample of population, additionally to the classical coding of marital status dummies we distinguish the widows. They certainly differ from single (including divorces) individuals at least in terms of the fact that they marriage has never been broken (which would have a negative impact on their health condition, for the reference see Cummings and Jackson (2008)). Nevertheless, their partner in no longer supporting them which might affect their demand for health services.

We control also for the household size, distinguishing between single, two-person, three-person and more than three-person households. The first three categories should not be controversial, as they include qualitatively different types of households. We join the rest of household in one category as the marginal impact on many socioeconomic features should be decreasing with the size of household. It also allows us to save some degrees of freedom.

We also control for employment status of the individual, as the retirement status would be mainly reflected by divided samples and inability to work caused by the health condition is implied by other health situation measures we apply as covariates. The income is reported on the household level which limits a bit the variation in data. Moreover, it is measured as a percentile of population distribution. Fortunately it makes no harm for our analysis as we need only the relative position of individual‘s income in further analysis.

The exact variable coding with descriptive statistics are provided in table A in Appendix.

2.2 Health variables

The given dataset contains 22 variables describing individual's physical and mental health and limitations and the health care use. First, we include both variables related to the latter category: number of contacts (seen or talked) with the medical doctor over last 12 months and a dummy indicating whether a person have been in a hospital overnight during last year. Next, we consider indicators that represent a need for a health care. Hence, in the first instance we control for the number of limitations with basic activities of daily living (the sum of dressing, bathing or showering and eating, cutting up food) and the number of limitations with instrumental activities of daily living (the sum of telephone calls, taking medications and managing money). We omit other available variables indicating particular functional limitations (mobility, large muscle, motor skills indexes), as we claim that they greatly coincide with the two previous ones. Also, we want to keep our analysis simple and our choice is already represented in the literature García-Gómez, Hernández-Quevedo, Jiménez-Rubio, and Oliva-Morenoda (2015). For the same reasons we do not include the maximum of grip strength measure. What is more, for the sake of clarity we convert the ADL and IADL indexes into dummies. The value 0 represents the absence of limitations, value 1 indicates presence of any number of difficulties (1, 2 or 3).

Furthermore, we include the number of chronic diseases, the presence of significant symptoms of depression and the presence of cognitive limitations with the recall of words, as we believe that these factors are potentially relevant. We created a dummy variable basing on the EURO-D symptom scale measures for the depression – the result 6 or more indicates serious depression. Also, we converted the number of words recalled in the delayed word recall task into a binary variable. Value 1 indicates, that the person scored 6 or more in the word recall task. We excluded the recall of words in the first trial, as this indicator is very similar to the delayed trial.

In addition, we choose to keep smoking, alcohol consumption and doing vigorous activities, as these factors are a well-known proxy of a general health condition. We believe, that the current smoking behavior usually reflects smoking in the past, hence we keep only the present measure. We factorize the drinking behavior measure into three levels. Value 0 stands for no or low alcohol consumption over the last 3 months, 1 stands for mediocre (1-4 days per week), and 2 indicates high alcohol consumption. Moreover we convert the indicator of the frequency of doing vigorous activities into dummy, as we are more interested in an extensive margin. Positive value of this variable informs, that a person exercises or does heavy physical work relatively often (once a week or more). We decided to exclude BMI, because of the high percentage of missing observations.

Finally, we select the self-perceived health and include it as a three-level factor, with category "very good" if the person reports excellent or very good health status and category "good" if she reports good or fair health condition. We decided to convert the variable into a three-level factor instead of a dummy, because we took into account the probability mass function of the original variable.

3 Models

3.1 Preliminary Horizontal Inequity Index

We start with the *preliminary horizontal inequity index* (PHI). The methodology is based on Wagstaff A. (2003) and has been subsequently used by E.v. Doorslaera and Jones (2004). The main idea is to standardize distributions of need differences among individuals. This method seems seemingly easy as it does not depend directly on grouped data. Following the mentioned literature we measure PHI by calculating the difference between the inequality in actual and needed use of health services. Let C_M denote the actual concentration index of the medical care and C_N the analogous index measuring the needed use of medical care i.e. that results from the poor health condition. Then:

$$PHI = C_M - C_N \tag{1}$$

In the preliminary approach we measure the relative income-related inequality in health, C_M, as the standardized covariance between the dependent variable y_i and relative ranking according to the socioeconomic status R_i. Furthermore, following E.v. Doorslaera and Jones (2004) in our specification we use the concentration index of $\hat{y}_i$ and R_i for C_N , where the former is the expected level of health care among individuals with the same characteristics. This expectation should reflect the level of health care that results from the need among the individuals with the same observable characteristics.

$$\begin{cases} C_M = \frac{2}{\bar{y}}\text{Cov}[y_i, R_i] \\ \\ C_N = \frac{2}{\bar{\hat{y}}}\text{Cov}[\hat{y}_i, R_i] \end{cases} \tag{2}$$

The line over the variable denote the average. We calculate the expected need-based health case use as fitted values from models estimating the conditional mean:

$$\hat{y}_i \equiv \mathbb{E}[y_i | x_{i,NEED}, x_{i,NO_NEED}] \equiv g(x_{i,NEED}, x_{i,NO\_NEED})$$

To achieve the inequity interpretation of the results, we set the values of x_{i,NO_NEED} to their sample average values, similarly to E.v. Doorslaera and Jones (2004).

We test three functional forms of $g(\cdot)$. We start with the simple OLS estimates taking advantage of the easy interpretation of the results. However, conditional expectation calculated by OLS might be negative, which would lead to biased results. Moreover, one should expect poor quality of estimates especially because of the zero-inflated character of data. Nevertheless they serve as a useful baseline specification. In the next step we will account for the count nature of data and calculate the expected number of visiting a doctor using a simple poisson regression. The expected values in this specification behave well with respect to being nonnegative, however we do not expect it to predict well the excessive number of zeros. Another problem that comes with ordinary poisson regression is that it does not account for the underlying economic behavior of agents postulated by theoretic literature (W.G. Manning, 1987). They model the number of physician visit in a principal-agent framework. A two step procedure is assumed. Firstly an individual decides whether to go to a physician, and conditionally on the first visit their total number is decided by both a doctor and an individual. To account for this scheme we apply the negative binomial hurdle model(Pohlmeier and Urlich, 1995; Deb and Trivedi, 1997). It outstrips the zero-inflated model, which is similar by construction, but does not allow for two-step decision process. Moreover, negative binomial specification account for the observed over-dispersion in data.

The standard errors come from bootstrap. At this moment some light should be shed also on validity of standard errors. The structure of data practically precludes the *iid* data generataing process. Data covers individuals living in various countries, at which the health services accessibility and quality differ. Moreover, one should expect that the outcomes for individuals living in the same household are correlated. That is why we consider each country separately as controlling for time dummies would not reflect the heterogeneous differences in health or socioeconomic outcomes[1]. Within a bootstrap procedure we account for a cluster structure on household level. Additionally, we present the results separately for the subsample of the elderly and younger generations in order to be able to extract the possible inequity effects of age with respect to the income.

[1]which is computationally more appealing than including a full interaction set of country dummies and the rest of variables

3.2 Modified Horizontal Inequity Index

In the second step we calculate an *modified horizontal inequity index* (MHI) using the methodology expolited by E.v. Doorslaera and Jones (2004) and later by E.Vd Poel and O'Donnell (2012) and García-Gómez, Hernández-Quevedo, Jiménez-Rubio, and Oliva-Morenoda (2015). The main difference between HMI and PHI lies in the way of achieving the inequity interpretation insetad of considering just inequalities. Assuming linear separability of the underlying numer of visitinig a doctor data generating process:

$$y_i = \alpha + \sum_{j \in \Omega_{NEED}} \beta_j x_{ij} + \sum_{j \in \Omega_{NO\_NEED}} \gamma_j x_{ij} + \varepsilon_i \tag{3}$$

Where Ω_{NEED} and Ω_{NO_NEED} denote the set of need and no-need covariates respecitvely. Then we can produce the MHI index by substracting the part that measures the part of variability in outcome variable connected with health condition necessity:

$$MHI = C_N - \frac{1}{\overline{y}} \sum_{j \in \Omega_{NEED}} \beta_j \overline{x}_j C_{x_j} \tag{4}$$

where C_{x_j} denotes the concentration index of $x_j \in \Omega_{NEED}$ with respect to the income. This approach allows us to evaluate the impact of particular covariates on the inequity index.

4 Results

There are two variables describing usage of health care in the database. There is an important question whether the models for this variables should be estimated separately or jointly. According to the literature, it is correct and justified to estimate equations in a two-step procedure sequentially without considering a correlation structure of them. Moreover, the correlation between variables is relatively slight what is another argument in favour of separate estimation. First of all we analyse health care use inequality relative to income described by C_M indicators. The next step is an analysis of this indicator in subsamples of retired and non-retired individuals to examine whether there are significant regime differences among elderly people.

HI indicators as measures of health care use inequity are counted in the next step. The resuls are calculated on a basis of OLS, Poisson and Hurdle models. The last step presents HI results calculated for a model for dummy hospital visit variable.

Table 2. shows relative inequalities in health care use described by a dummy for a physician consultation and a count for hospital visits in selected European countries. The results are presented for the whole population, without subdivision in respect to age. As can be seen in the table, every country in the dataset can be characterized as pro-poor what means that poorer people have better access to health care relatively to their needs.

To examine whether inequalities in health care use relative to an income vary across age

Table 2: Relative inequalities in health care use measured by a count for doctor consultations and a dummy for for hospital visit.

Country	C_M doctor consultations	C_M hospital visit
All	-0.05	-0.05
Austria	-0.005	-0.035
Germany	-0.054	-0.096
Sweden	-0.047	-0.104
Netherlands	-0.05	-0.121
Spain	-0.064	-0.077
Italy	-0.078	-0.044
France	-0.037	-0.11
Denmark	-0.102	-0.212
Switzerland (German)	-0.048	-0.094
Belgium (French)	-0.046	-0.087
Czech Republic	-0.058	-0.024
Luxemburg (French)	-0.026	-0.049
Slovenia	-0.03	-0.044
Estonia	-0.038	-0.061

groups (retired and non-retired) our analysis had been performed separately in subsamples. The results are presented in Table 3. Again, almost every country in the sample is characterized by pro-poor income equality, regardless of age group considered. However, in Austria there is pro-rich inequality in a group of retired people for health care use described by doctor consultation dummy. The indicator for non-retired individuals remains negative what means pro-poor inequality. Apparently there is a significant difference in health use inequality relative to income between retired and non-retired individuals in this country.

Table 4. shows the estimation results of the level of horizontal inequity index in access to health care services for two groups of people: elderly (those who are older than retirement effective age) and non-elderly. The values were obtained using three methods: standard OLS, Poisson count-regression, two-step hurdle. The estimates from the third variant are statistically significant at 0,01 alpha level, with one exception of the parameter value for the non-elderly Swedes, which is significant at 0,05 alpha level. Parameters obtained from Poisson count-regression remain statistically significant at any typical confidence level. Only one estimate for the group of retired Slovenians attains statistical significance at 0,1 alpha level. Finally, the results of the OLS regression are statistically insignificant only for 3 cases, the rest of them passes the t-test at the best confidence level.

We observe that on average there is a disproportionate concentration of the health care services on individuals with the highest level of income (regardless the age group). Three methods of estimation consequently reported the highest pro-rich inequality in access to health care services in Austria, and the strongest pro-poor inequality in Italy. Interestingly, the results for Spain and Denmark suggest not only different magnitude, but also different direction of inequality between retired and non-retired groups. The access to the health protection among retired individuals is slightly inequal in favor of richer part of population, whereas these services in the non-retired group are disproportionately

Table 3: Inequalities in health care use relative to an income in retired and non-retired subsamples.

Country	Retired		Non-retired	
	C_M doctor consultation	C_M hospital visits	C_M doctor consultation	C_M hospital visits
Austria	0.003**	-0.031***	-0.004	-0.013***
Germany	-0.053***	-0.083***	-0.04***	-0.067***
Sweden	-0.025***	-0.08***	-0.053***	-0.059***
Netherlands	-0.023***	-0.079***	-0.059***	-0.13***
Spain	-0.038***	-0.039***	-0.073***	-0.098***
Italy	-0.061***	-0.038***	-0.061***	0.024***
France	-0.025***	-0.091***	-0.046***	-0.121***
Denmark	-0.064***	-0.17***	-0.092***	-0.165***
Switzerland (German)	-0.031***	-0.046***	-0.026***	-0.059***
Belgium (French)	-0.042***	-0.064***	-0.029***	-0.1***
Czech Republic	-0.039***	-0.023***	-0.067***	0.027***
Luxemburg (French)	-0.01**	-0.017***	-0.035***	-0.082***
Slovenia	-0.03***	-0.041***	-0.009***	-0.018***
Estonia	-0.01***	-0.022***	-0.063***	-0.103***

concentrated among the relatively poor. The simple t-test for equality of means for two samples of country parameters estimates (for retired and non-retired groups) does not indicate the statistically significant difference. It means that there does not exist a general, cross-national different scale of inequity in access to health care services between retired and non-retired groups. Finally, the different methods of estimation returned coherent estimates regarding the direction of the inequality, however they differ in terms of magnitude.

Our results are in line with the current literature. García-Gómez, Hernández-Quevedo, Jiménez-Rubio, and Oliva-Morenoda (2015) reported positive and statistically significant values of horizontal inequity for community care services and for home care (long-term care services). E.v. Doorslaera and Jones (2004) found pro-rich inequity in the use of specialists visits, however he obtained pro-poor inequity in general medical care.

As can be seen in Table 5. HI inequity index is negative and significant for retired people in every country in the sample. It means that health care usage inequity can be described as pro-poor. However, in Austria, Germany, Italy, Czech Republic and Slovenia, health care inequity is definitely pro-rich for non-retired people. It confirms our conclusion, that two heterogeneous age groups may be extracted.

To explore which of socio-economic factors have the greatest influence on inequity index we used the methodology presented by E.Vd Poel and O'Donnell (2012) . We calculated contribution of each of socioeconomic variable to HI index. Age and marital status have highest pro-poor influence while employment status and household size have strong pro-rich contribution. Education has negligible contribution to HI index.

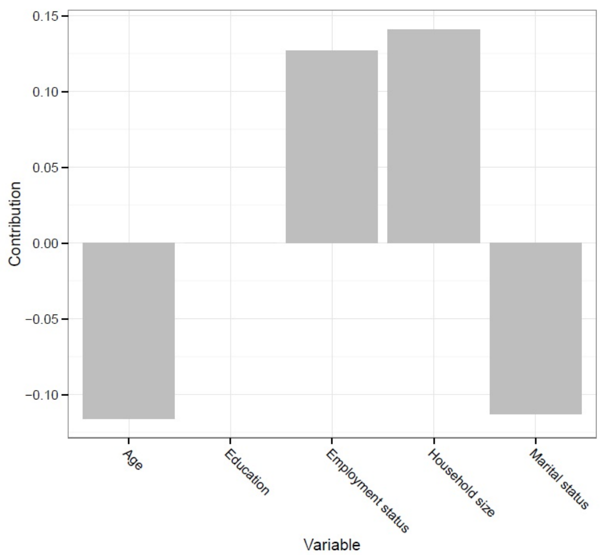
Table 4: HI indicator describing inequity relative to income counted on a basis of Hurdle, Poisson and OLS models.

Country	Hurdle		Poisson		OLS	
	retired	non-retired	retired	non-retired	retired	non-retired
Austria	0.045***	0.076***	0.044***	0.066***	0.045***	0.074***
Germany	0.011***	0.045***	0.006***	0.038***	0.005***	0.043***
Sweden	0.025***	-0.007**	0.015***	-0.009***	0.016***	0.001
Netherlands	0.035***	0.022***	0.034***	0.024***	0.037***	0.045***
Spain	0.017***	-0.024***	0.01***	-0.027***	0.012***	-0.015***
Italy	-0.013***	-0.041***	-0.019***	-0.038***	-0.019***	-0.036***
France	0.042***	0.021***	0.04***	0.024***	0.038***	0.042***
Denmark	0.006***	-0.028***	0.005***	-0.009***	0.011***	-0.012***
Switzerland (German)	0.01***	0.025***	0.009***	0.023***	0.01***	0.02***
Belgium (French)	0.013***	0.028***	0.008***	0.024***	0.007***	0.03***
Czech Republic	-0.012***	-0.013***	-0.016***	-0.017***	-0.016***	-0.011***
Luxemburg (French)	0.014***	0.043***	0.011***	0.044***	0.014***	0.028***
Slovenia	0.006***	0.029***	0.003*	0.025***	0.001	0.027***
Estonia	0.021***	-0.004**	0.02***	-0.009***	0.019***	-0.001

Table 5: HI indicator describing inequity relative to income counted on a basis of binomial regression with hospital visit as an endogenous variable.

	HI hospital visit	
Country	Retired	Non-retired
Austria	-0.031***	0.073***
Germany	-0.083***	0.047***
Sweden	-0.08***	-0.012***
Netherlands	-0.079***	0.006
Spain	-0.039***	-0.032***
Italy	-0.038***	0.049***
France	-0.091***	-0.004
Denmark	-0.17***	-0.096***
Switzerland (German)	-0.046***	-0.008
Belgium (French)	-0.064***	-0.008*
Czech Republic	-0.023***	0.098***
Luxemburg (French)	-0.017***	-0.005
Slovenia	-0.041***	0.071***
Estonia	-0.022***	-0.031***

Figure 1: Contribution of variables in ineqiuty index



4.1 Effects on quantiles of distribution

In this section we propose different approach to evaluate inequity among the elderly. Table 6. presents the quantile regression estimates where the distribution of the number of visiting doctor has been explained by the set of non-need covariates, controlling for need regressors as well as time and country dummies. Only the former are reported, as they are of main interest in our paper. However, the signs of coefficients for the latter variables were generally consistent with economic intuition.

The model was estimated on the pooled sample of elderly individuals. We rule out the younger generations, as the difference in inequity between them and the elders was analyzed in previous section. Similarly, the variation between countries was also examined. Therefore the interpretation of the parameters concern the overall situation in the mentioned countries. Nevertheless, the selection of countries may proxy the situation in Western Europe in a satisfactory way.

The inequity interpretation is obtained through evaluating the effects of non-need variables holding constant the rest of covariates. However, one should remember that these are effects for a distribution of the number of visiting doctor, not on the individual‘s outcome.

First of all, if we restrict our attention only to the elderly, the age does not differentiate them by means of the number of visiting doctor. Yet the effect on no quantile is statistically significant. Therefore we draw a conclusion that the number of visits for those, who visit the doctor less frequently than 90% of other individuals of the age t_1 is not significantly different in comparison with the subpopulation of the one year older.

If the education is concerned the results are qualitatively different. Among the individuals that have obtained lower than tertiary degree of education all the quantiles of the distribution on the dependent variable are systematically lower than for the highest educated elderly. For example let us consider an individual, who visits the doctor no more often than 75% of the rest individuals. If she has finished tertiary level of education then the expected number of visits for her is higher than for an individual with lower degree and

Table 6: Quantile regression estimates, dependent variable: the number of visiting doctor

quantile			education				marital status		household size			employed
		age	none	primary	lower sec.	upper sec.	non-couple	widowed	2	3	4+	
0.05	param	0.000	-0.101	-0.184	-0.175	-0.081	-0.068	-0.034	-0.031	-0.161	-0.160	-0.119
	p.val.	0.721	0.115	0.000	0.000	0.000	0.008	0.097	0.193	0.000	0.023	0.000
0.1	param	0.000	-0.145	-0.075	-0.094	-0.050	-0.025	0.000	-0.006	-0.176	-0.239	-0.113
	p.val.	1.000	0.000	0.001	0.000	0.004	0.197	1.000	0.759	0.014	0.000	0.000
0.25	param	0.002	-0.376	-0.340	-0.331	-0.237	-0.124	-0.043	-0.057	-0.306	-0.356	-0.299
	p.val.	0.362	0.000	0.000	0.000	0.000	0.035	0.484	0.334	0.000	0.000	0.000
0.5	param	0.007	-0.638	-0.444	-0.549	-0.395	-0.022	-0.058	-0.070	-0.375	-0.395	-0.392
	p.val.	0.085	0.000	0.000	0.000	0.000	0.832	0.573	0.467	0.001	0.027	0.000
0.75	param	0.007	-1.115	-0.684	-0.667	-0.448	0.296	0.089	-0.078	-0.392	-0.515	-0.534
	p.val.	0.312	0.000	0.000	0.000	0.000	0.069	0.587	0.609	0.026	0.012	0.000
0.9	param	-0.017	-1.669	-1.399	-1.063	-0.694	0.586	-0.010	0.013	-0.331	-0.512	-1.053
	p.val.	0.245	0.001	0.000	0.000	0.004	0.120	0.978	0.968	0.432	0.460	0.000
0.95	param	-0.014	-3.334	-2.617	-2.105	-1.151	0.605	0.113	0.218	-0.082	-1.053	-1.141
	p.val.	0.538	0.001	0.000	0.000	0.014	0.346	0.865	0.712	0.931	0.267	0.015

Note: This table present only the effects of non-need variables, estimated on the subsample of the elderly.

the same rest of the characteristics. Another interesting result is that the effects become stronger and stronger with the increasing values of quantiles. Therefore the highest educational status of an individual is an important factor inducing the inequity among the distributions of individuals. One might also analyze the effects between other subgroups, which would require a different reference category. We leave it for the further research as here the main goal is to identify the main sources of inequity.

The marital status of an individual (with reference to the married elderlies) has smaller differentiating impact on the distribution of the outcome of interest, being in general moderately negative for the lower quantiles and insignificant for the higher, similarly to the effects of household size (with comparison to the single households). The parameters for the employed elderlies are significant and increasing with respect to the quantile. Among the individuals who visit the doctor with the highest frequency (say, more often then 95% of the population), those who work have approximately one visit in a doctor‘s office less.

The effects on distribution are moderately small, as the average number of visits amounts to 6.74. The conclusion might be that the problem of inequity in the access to medical health is related more to individuals than to the distribution of the dependent variable for certain groups of individuals. However, the results of quantile only imperfect linear approximation to the true distribution of interest, as we applied the ordinary quantile regression to the count variable with significant number of zeros. Nevertheless, the results seem reasonable. They suggest that a policymaker should focus on the fighting against the inequities in the individual level, as the distributions of the elderlies visiting doctor are barely affected by the changes in non-need variables.

5 Conclusions

Elderly people are the greatest consumers of health care services. By 2030 they will account for over 30% of the EU population. Even nowadays, they experience stronger inequities in the access to the health care system than the rest of the population. The importance of the problem of the inequal access to health care was already raised in the Constitution of the WHO (adopted in 1946), which declared that: “the highest attainable standard of health is one of the fundamental rights of every human being without distinction of race, religion, political belief, economic or social condition".

We show that for elderly people there exists often pro-rich inequity in access to healthcare. Nevertheless, similar patterns are present in the data for the younger generations which suggests that this effect is orthogonal to the dichotomy between these two groups. We also find that the inequity phenomenon affects more the situation on an individual in a distribution of individuals, not the whole distributions.

The further research should pay more attention in simultaneous analysis of the health care usage variables, as one might expect some degree of correlation or comovement between them.

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A Appendix

Table A.1: Add caption

Variable	Type	Mean	Observations
Health variables			
Doctor visits	Count	6.86	62086
Hospital stay	Dummy	0.16	62653
Activities of Daily Living	Dummy	0.10	62714
Instrumental Activities of Daily Living	Dummy	0.05	62714
Number of chronic diseases	Count	1.16	62634
Depression	Dummy	0.10	61023
Recall of words	Dummy	0.24	60961
Smoke at present time	Dummy	0.18	62776
Drinking behaviour	-	-	62707
2 - high consumption	Factor	-	17751
1 - mediocre consumption	Factor	-	19643
0 - no or low consumption	Factor	-	25313
Vigorous activities	Dummy	0.49	62718
Self-perceived health	-	-	62724
very good	Factor	-	16140
good	Factor	-	39967
poor	Factor	-	6617
Socioeconomic variables			
Month	12 dummies	-	58134
Employment	Dummy	28.5	58134
Income	Deciles	-	58134
Age	Continuous	66.3	58134
Education	-		
education - none	Factor	-	2461
education - primary	Factor	-	9105
education - lower secondary	Factor	-	10916
education - upper secondary	Factor	-	22244
education - higher	Factor	-	13408
Marital status			
marital - couple	Factor	-	41369
marital - noncouple	Factor	-	9123
marital - widowed	Factor	-	7642
Household size			
household size - 1 person	Factor	-	12099
household size - 2 people	Factor	-	33713
household size - 3 people	Factor	-	7358
household size - 4+ people	Factor	-	4964