The Effect of Business Cycles on Socioeconomic Inequity in Health-care Usage Among Elderly Europeans*

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1 Introduction

One of the most striking developments in modern societies is the ever-increasing ageing of the population. For a large part this can be explained by the advancements in health-care and medicine, which are both important factors that contribute to the increase in average life expectancy. The other side of the coin is that for these extra years in life expectancy, the expenditures for health-care increase disproportionally.

A principal challenge of health care policy is to ensure equity in the distribution of the help that is provided. Two kinds of deviations from a profile which is 'fair' are coined to be vertical and horizontal inequity. To illustrate the vertical type, a relevant policy problem is how much of a given amount of fund to allocate to the treatment of devastating diseases, say cancer and Aids. It is difficult to tell objectively that one of the problems is more or less important from the other. An answer is to be found from the inherent architecture of norms and

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values that a specific society possesses. The second type of inequity considers cases in which there are two individuals who have the same health problem (say Aids), but are not treated equally, for example because one of them is wealthy and has the necessary funds to access expensive health recourses (e.g. specialist treatment), from which the more indigent parts of society are excluded. These kind of problems involve horizontal inequity, which comprises that individuals who have the same needs, receive equal treatment. For example, a wealthy and a poor individual should receive the same amount of help, if they suffer from the same health problem.

One of the major challenges in society is handling the diseases that come with a population that ages. Therefore, in this report, our objective is to combine the previously mentioned issues to motivate that health-care for the elderly should be centric in the analysis of health-care distribution, as perhaps this subgroup of the population is the most susceptible to (in)equity of use of health-care. We will look at this problem from two aspects. Firstly, the inequity in health-care usage will be examined in the context of socioeconomic status.

It is widely known that elderly cope with diseases such as dementia and Alzheimer (from hereon collectively referred to as dementia) notably. Dementia has a disproportional large effect on an individuals live, and as the individual progresses into later stages of dementia the general tendency is that the individual becomes less independent, and more and more dependent on others, such as personal care by their children or professional care in nursing homes. This reveals a specific form of potential inequity in health-care usage related to socioeconomic status: if an individual is no longer able to independently ask, seek, and obtain the health-care that they need, this will inevitably lead to inequity in health-care use. For example, if an individual is diagnosed with dementia but lives in a nursing home, or is surrounded by children that can provide support, it is more likely that this person will get the health-care that she needs. On the other hand, if someone that is diagnosed with dementia lives alone, secluded from society, it is likely that they 'miss out on the health-care they need as they are no longer to arrange such health-care for themselves. If a society strives for equity in health-care use this is a large societal challenge that has to be addressed.

In previous research inequity in health-care use has been explained by income. In this report, we hypothesize that another driving factor of inequity in health-care usage is the social network of an elderly individual, proxied by the number of children of the individual. This leads to our general research question: the goal of this research is to assess the socioeconomic inequities in health-care use among elderly Europeans. We assess this potential inequity by looking at income, as this is customary in the existing literature, and we examine the effect of an individuals social network, as this might provide a novel (potential) insight in the mechanics behind inequity in health-care usage of the elderly.

The second aspect that will be examined is the relationship between this inequity

due to socioeconomic factors and the economic conditions. Health-care expenditure shows an ever increasing trend over time. However, interestingly, this growth has diminished after the recent financial crisis. As health-care expenditure is strongly related to the usage of health-care, this observation suggests that the usage of health-care has been altered, possibly due to the worsened economic conditions. This raises the question whether economic conditions, which can be proxied by business cycles, influence the usage of health-care (even though it is likely to not influence the need for health-care). More specifically, the change in health-care usage, could affect the (socioeconomic) inequity in health-care usage. On these grounds, we incorporate the additional economic factor in our analysis and aim at investigating the relationship between health-care behaviour in response to businnes cycles and the effect of economic conditions on the socioeconomic inequity in health-care usage.

In addition to the previous mentioned, we aim to study, in more detail, whether these effects differs from country to country within Europe. In particular, we hypothesize that different patterns of inequity between southern European countries and northern European countries exist as we believe that for both groups of countries the social network of an elderly individual will make sure that the individual gets the health-care that they need, but that the way that this health-care is delivered differs. Furthermore, we expect that in southern European countries there is a tendency to provide the health-care to the individual 'within the family. This implies that there would be an inequity gap, in the direction that elderly with a large social network will receive less professional (i.e. measured) health-care. On the other hand, for northern Europe we hypothesize that it is more customary to seek professional care if an elderly becomes less independent. That is, the tendency exists of not directly providing health-care for parents but instead seeking professional care, for example in the form of a nursing home. We want to test these hypothesis using horizontal inequity (HI) indices for health-care usage.

In order to analyze the issues posed in this section, we make use of horizontal inequity indices, which are based on the usage and need of health-care. While health-care need should be estimated, the usage of health-care is observed. The operationalization of the health-care usage and the used explanatory variables for the estimation of health-care need are explained in the subsequent section. In the third section, deals with model selection, estimation of parameters and computation of the horizontal inequity index.

2 Data

The data are obtained from the SHARE database, which contains panel data for demographic variables, health and health behaviour related variables, socioeconomic variables and economic indicators for 4 waves.

2.1 Definition of Health-care Usage

In order to assess inequity in health-care use, a measure for an individuals use of health-care as well as the individuals need of health care is needed. Combining this information enables us to quantify the extent of inequity and the socioeconomic factors relating to this inequity. However, measuring health-care use is not trivial as most respondents are probably not able to (monetarily) quantify their health-care use. Even though some costs are directly observed by the individual, such as costs for medicine, other costs may be more obfuscated, e.g. the cost of a doctors visit, especially if this is covered by health insurance and the respondent does not have to pay the bill.

Given the above-mentioned, it seems more reasonable to look at a proxy for health-care use. In the literature, the number of visits to the general practitioner or medical specialist is often used as such a proxy. The SHARE dataset, however, contains many other potential proxies, for example, whether an individual visited the hospital in the last 12 months, or the number of chronic diseases an individual has. Both variables are likely to influence the usage of health-care. However, it might be difficult to combine them in a sensible way to quantify the (monetary) use of health care. Is the chronic disease expensive to treat, or not? Was the hospitalization for a minor health issue, or for an extensive surgery? That is, combining these measures into a single factor such that this factor acts as a valid proxy for the need of health care is a challenge that we have to leave for further research. As such, we stick to what is frequently done in the existing literature and take the number of doctor visits as a proxy for use of health care.

2.2 Explanatory and Control Variable Selection

When selecting the explanatory variables, we distinguish between several types of variables. As we intend to measure the need for health-care my means of a statistical model, variables that may influence the need for health-care are included. A logical choice for this type of variables is then health and health behaviour related variables. We select as many of these variables, such as self-perceived health, number of chronic diseases, smoking/drinking behaviour, from the SHARE dataset as possible. We also account for difficulty in activities/sports, as these could be related to health-care issues such as injuries. Furthermore, we include variables related to functional limitations; these are likely to be correlated with the health of individuals. Not all health related variables are used. Variables with a large percentage missing values are excluded from the analysis to preserve a large number of total observations.

Next to these variables, we select non-need related variables to account for differences in socioeconomic status of the individuals. Moreover, we control for income level as previous research shows that this variable explains the inequity in health-care use. Braveman et al. (2005) argue that, even though income and

education are likely to be correlated, they are not interchangeable in health related models; the correlation is not strong enough to proxy on another. As the education level of an individual may have an effect on the choices one makes, this variable is included as well.

The SHARE dataset contains information pertaining to family circumstances as well, which is of interest in the analysis pf inequity due to the social network of elderly. Even though having relatives cannot influence the need for health, it is possible that it influences the usage of health-care if family members take care of each other. This information is exploited by including the number of children, the number of grandchildren and marital status in the model.

To analyse the effect of economic conditions, we select the variable GDP growth to proxy this. Lastly, as health-care need is likely to differ over age and gender, we control for these variables.

2.3 Transformation of Variables

Based on the variable selection criteria mentioned in the previous subsection, many variables are selected to be included in the model. The manner in which the data is measured, where individuals are asked questions regarding many aspects of health, enforces this issue even more. Including many variables in the model is likely to result in multicollinearity and a loss of efficiency. Furthermore, the interpretation of the explanatory variables becomes very difficult when, for example, 8 activity related variables are included in the model. For these reasons, we decide to make use of data reduction to create a parsimonious model.

In the literature, datasets are reduced mainly based on Principal Component Analysis (PCA). However, as our dataset predominantly contains ordinal and nominal variables, PCA is not the appropriate technique to use (Linting, Meulman, Groenen, & Van Der Koojj, 2007). Therefore we choose to combine closely related variables that are measured in the same fashion, by including their individual specific average in the model, in stead of each variable separately. This way, the variables ActivityDifficulty (measures how much difficulty the respondent experiences in daily activities), Recall (proxies the memory-related capabilities of a respondent) and Muscle (proxies the motoric skills of a respondent) are created.

3 Methodology

3.1 Model Selection

Variables which quantify the extent of health-care consumption include visits to a doctor in a given amount of time (year), visits to a specialist, etc. Typically, these variables are observed as counts, and therefore econometric models in-

volving counting data provide a good starting points. The simplest such model assumes a Poisson Process for doctor visits, hence in a given amount of time the distribution of visits y_i is given by

$$\mathbb{P}[y_i = y, x_i] = e^{-\lambda}\frac{\lambda^y}{y!}. \tag{1}$$

In such a model the conditional variance of visits is equal to the conditional mean. However, empirics show *over-dispersion*, e.g. the conditional variance exceeds the mean. Count models based on the negative binomial distribution provide more flexibility and have been used frequently in previous research. This approach results if λ is assumed to be Gamma distributed, while given λ, (1) holds. For example Munkin and Trivedi (2007) consider a model of this type, with:

$$\begin{aligned} \lambda &\sim \Gamma(\phi_i, \nu_i), \\ \phi_i &= \exp(x_i'\beta), \\ \nu_i &= \exp(x_i'\beta)/\sigma^2 \end{aligned} \tag{2}$$

where $\nu, \sigma^2 > 0$ are parameters to be estimated. This model incorporates the possibility of over-dispersion as the conditional expectation and variance are $\mathbb{E}[y_i|x_i] = \exp(x_i'\beta)$ and $Var[y_i|x_i] = (1+\sigma^2)\mathbb{E}[y_i|x_i]$.

A salient feature of health use data is that zero observations proliferate. Indeed, visits to a doctor have an occasional nature, and in a typical cross-section the share of non-visits dominates. In a seminal article Pohlmeier and Ulrich (1995) solve this challenge, by considering the decision to visit a doctor, and the subsequent process of consuming health care once a doctor is visited as a two part decision making process. As they explain a principal agency relation plays a prominent role as a cause for this dichotomy: when considering whether to visit a doctor, an individual seeking treatment is in the main decision making role, however, once he is treated, it is the mainly the doctor who determines which treatment is suitable and to which extent it is provided (in this decision he will take into account his personal interests). Based on these considerations, the authors propose a hurdle model providing room to describe the two decision phases separately. Moreover, after comparing their hurdle model to a simple model of the Negative Binomial type, they find that the first considerably improves estimation results, and that failing to treat the phases separately, leads to serious misspecification problems.
The hurdle model consists of the components:

$$\begin{aligned} \mathbb{P}[y_i = 0|x_i] &= F(x_i'\beta_1, \sigma_1^2) \\ y_i|y_i > 0 &\sim N_i|N_i > 1, \end{aligned} \tag{3}$$

where the functional form of F can be for example of a logit, probit type, and N_i is a negative binomially distributed random variable:

$$N_i \quad \sim \quad NegBin(\exp(x_i'\beta_2), \sigma_2^2). \tag{4}$$

Importantly, the parameters (β_1, σ_1^2) describing the contact probability and the parameters (β_2, σ_2^2) describing the health usage conditional on contact are allowed to be different. By dis-tangling the decision phases involving the contact and the subsequent treatment, the model proves successful in describing the large fraction of zero observations, while accounting for the nonzero values simultaneously.

3.2 Estimation of Parameters

The analysis is performed with the hurdle model as described in the previous section. With the selected socioeconomic explanatory and control variables, the health-care usage is estimated for each individual per country. In order to examine the socioeconomic inequity due to income and social network, horizontal inequity indices are computed. A description of the the manner in which this statistic is computed can be found in the next subsection.

The absolute value of the difference of actual usage and estimated need is computed for all observations, which is defined as the individual inequity proxy. After this, per country, the relationship between inequity and economic conditions is estimated by regressing the individual inequity proxy on GDP growth. A fixed effects estimator is used to account for the possible individual (fixed) effects in the data.

3.3 Calculating Horizontal Inequity

We can use concentration curves to investigate the inequality and calculate the health inequity from this. The concentration curve is a plot of the rank of a socioeconomic rank, for example based on income or number of children, against the medical use rank, for example based on the number of doctor visits in the last year. In an equal world, the concentration curve would be a straight line from the bottom left to the top right corner at a 45 degree angle. Any deviations illustrate an inequality in favor of high values of the socioeconomic status if the line is above the 45 degree line and in favor of small values if it is below the 45 degree line. The concentration index measures this and is then defined as the area between the concentration curve and the 45 degree line.

However, this is not necessarily inequity. For that, we follow Wagstaff and Van Doorslaer (2002) and calculate both the concentration index using the observed medical use and the medical need. The need is the fitted value from our model where the non need variables are set to reference values. If we define our model

as $f(x_{it}, z_{it})$ with x_{it} the need variables and z_{it} the non-need variables. If we then also define y_{it} as the medical use, and $C(y)$ as the function yielding the concentration index, the health inequity is then given by the following equation.

$$HI = C(y_{it}) - C(f(x_{it}, \tilde{z})), \tag{5}$$

where $\tilde{z}$ are the reference values for the non need variables. If the health inequity is positive, this indicates inequity in favor of larger values of the socioeconomic variable. For more information, see for example O'Donnell et al. (2008).

4 Results

We start by visually exploring the relation between health care behaviour of individuals and the business cycle. Expressing health use in terms of number of doctor visits annually, we depict aggregate behaviour with respect to this quantity in Figure 1. The empiric cdf $\hat{P}[y_{i,t} \leq k]$ of the the number of visits $y_{i,t}$ is considered. For each year t, three bars are juxtaposed, which correspond to the empiric cumulative probabilities for $k = 0, 5, 10$. For example, the first bar shows the probability that no doctor visit occurs, and the second bar shown the probability that 5 or less visits have been made. To place the resulting numbers in context with the business cycle, we added two indicators of recessions to the graph: the CEPR recession indicator for the Euro-Area business cycle is displayed by means of greyly shaded areas, covering the time frame where recession were present accourding to the index. Additional insight is supplied by OECD GDP growth data for the EU area, constructed as a weighted avarage of 28 European Countries.

The most salient feature which is visible, is a steady decline of the $\hat{P}[y_{i,t} \leq k]$ for both $k = 5$ and $k = 10$, starting around 2009, which suggest that the probability mass is gradually shifting towards more frequent visits, which may be induced economic deterioration, but the relation seems to be lagged in time as the main economic downfall occurred around 2009. In particular, this seems to be conflicting with the result of Ruhm et al, as the recession precipitates induces consumption of health-care. To reconcile the findings, we note that a time lag in the relation seems to be present, i.e. increase of health-care usage is delayed. It is not difficult to gather some intuition for the existence of a lagged relation: when the crisis erupts, due to losses of jobs of households members, reduction of wages, and deterioration of wealth resources, burden on households increases to earn enough to sustain living condition of the family, which per-ultimately (with a time lag) induces psychological problems involving stress, burnout, etc.

Unfortunately, the SHARE data does not have been sample in the years 2008 and 2009, and it would be of pertinent interest to know what happend to health behaviour in these two crucial years.

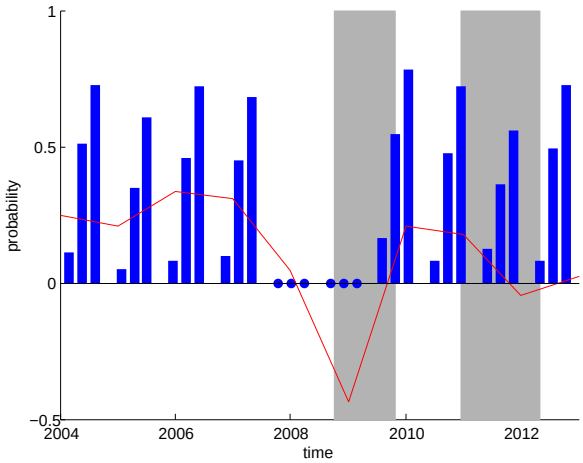

Figure 1: Empiric CDF of doctor visits by elderly Europeans in relation with business cycle measures for the EU area. In red OECD gdp growth for the European Area is shown (divided by 10 to fit in figure frame).

Next, we investigate change in behaviour on the individual level. For each individual who is contained in the sample in year t and $t+1$, we compute the change $\Delta y_{i,t} = y_{i,t+1} - y_{i,t}$ of the number of visits to a doctor, as well as the percentage change $g_{i,t}$ of gdp growth (measure of the extent of acceleration/deterioration of economic activity) as a proxy for business cycle vacillations. We sort the resulting pairs $(\Delta y_{i,t}, g_{i,t})$ (gathered over i and t) in four equally large groups based on the value of $g_{i,t}$ and then take the bottom 25% groups to represent behaviour in recessions, and the top 75% group to represent behaviour in expansions. Figure 2 shows the empiric cumulative density functions of $\Delta y_{i,t}$ for the recession and the expansion groups. The difference between the densities is marked: for expansions the distribution is concentrated more to the right compared to recession, moreover, the recession distribution is slightly skewed to the left, while the expansion distribution is slightly skewed to the rights. These findings suggests that people tend to visit the doctor more often after econometric improvements and less frequently after downturns. In particular, these findings are consistent with the results of Ruhm et al, and are in contrast with the discussion of Figure 5. We emphisize that the current exposition is based on analysis by tracking the behaviour on a single individual through time, while figure 1 was based on aggregate behaviour.

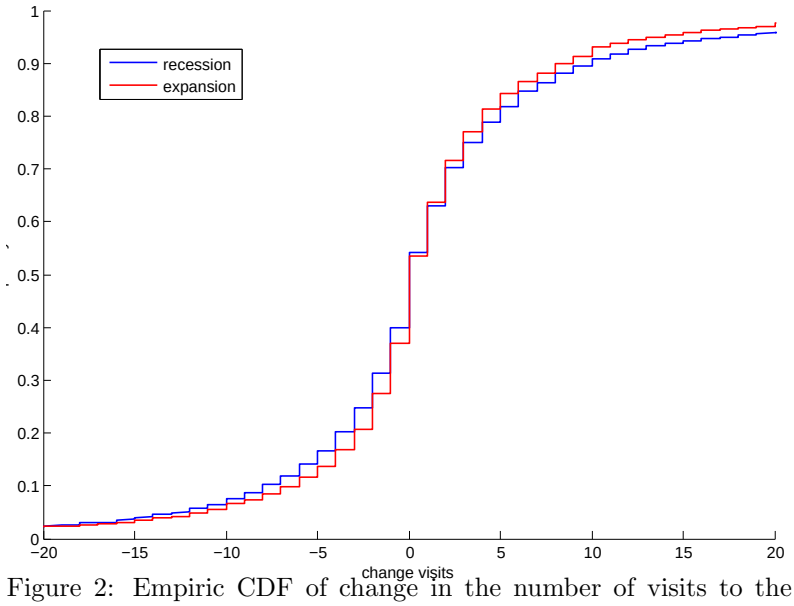

Figure 2: Empiric CDF of change in the number of visits to the doctor for recession and expansions.

The previous discussion sheds light on the first question of interest involving change in behaviour of elderly Europeans in relation with the business cycle. Next, we address how the extent of inequity relates to economic conditions.

Figure 3 shows the estimated HI indices per country for income and number of children. From the figure, we can see that HI for the number of children varies (HI_{child}) between -0.17 and 0.07. This implies that there is indication of inequity in health-care related to the number of children. Here, a negative value of HI_{child} indicates that people with more children tend to make less use of health-care than people with more children. The relative differences in HI_{child} between countries form a pattern: the results show positive HI_{child} indices for North-European countries, while the index tends to be lower for South- and East-European countries. This result is very intuitive as the analysed countries differ substantially in culture which causes differences in the manner in which the elderly are taken care of by their relatives. In particular, in South- and East-European countries, it is common that children take care of their parents for a long time. This is related to the fact that, while in North-European countries children move out when they come off age, this is not the case for East- and South-European countries. This discrepancy between countries contributes to the fact that, in East- and South-European countries, the elderly tend to make less use of health-care when they have more children. For North-European countries, the opposite applies.

Moreover, Figure 4 shows the HI indices per country for income (HI_{income}). As compared to the HI_{child} indices, this index is larger for all countries except

Table 1: Table HI

	HI Child	**HI Income**
Austria	-0.00472115	0.04114461
Slovenia	0.0472954	-0.02694226
Luxembourg	0.07162048	-0.00395248
Sweden	0.07185175	0.02421527
Estonia	0.07693716	0.02140878
France	0.08620079	-0.02232337
Switzerland	0.09155401	0.06779489
Netherlands	0.10281142	0.01915964
Spain	0.10862163	-0.08530023
Belgium	0.12369126	0.02230767
Czech Republic	0.13473144	-0.01034697
Germany	0.15435353	0.01236574
Denmark	0.18569724	0.0084503
Italy	0.19454007	-0.17368408

Austria. In fact, with the exception of Austria, the index is positive for all countries. This indicates that there is inequity in health-care due to income differences, which is pro-rich. These results are significantly different from the results found by Van Doorslaer, Koolman & Jones (2004). In that paper, far less indication of inequity was found; the estimated HI_{income} indices are much less for GP visits, but also for medical specialist visits compared to our results. Of course, this difference could be caused by various methodological factors. However, the aspects that could cause the difference in results may be the fact that our analysis focuses on elderly, the fact that Van Doorslaer et al. makes a distinction between GP and specialist visits and that we make use of more recent data. This implies that, for instance, the difference in results may imply that the inequity is larger for elderly or has become larger over time.

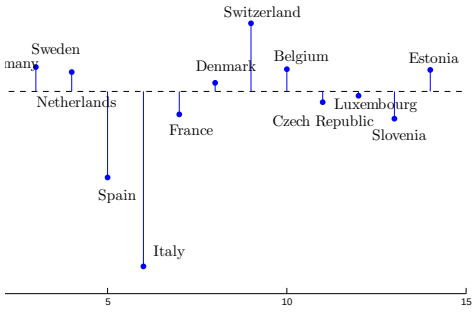

Figure 3: HI for number of children, per country

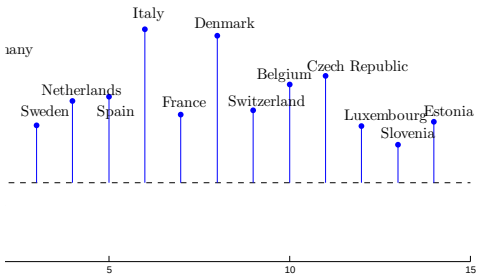

Figure 4: HI for income, per country

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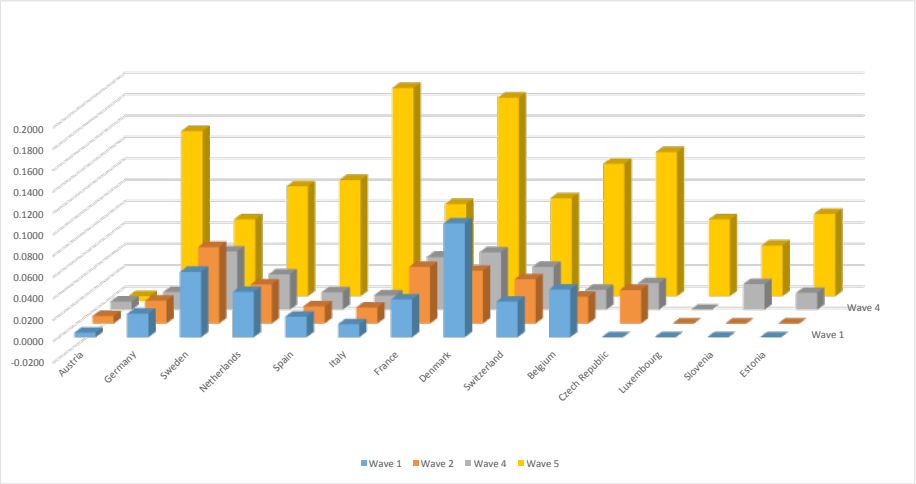

Figure 5: Horizontal Inequity for Income per wave.

The figure below shows the HI for Income over all waves. Here we can see that the socioeconomic inequity in health-care due to income has increase greatly the last couple of years (wave 5 corresponds to 2013, while wave 4 corresponds to 2011). This may be due to changes in policy regarding health-care of which we are unaware.

HI.pdf

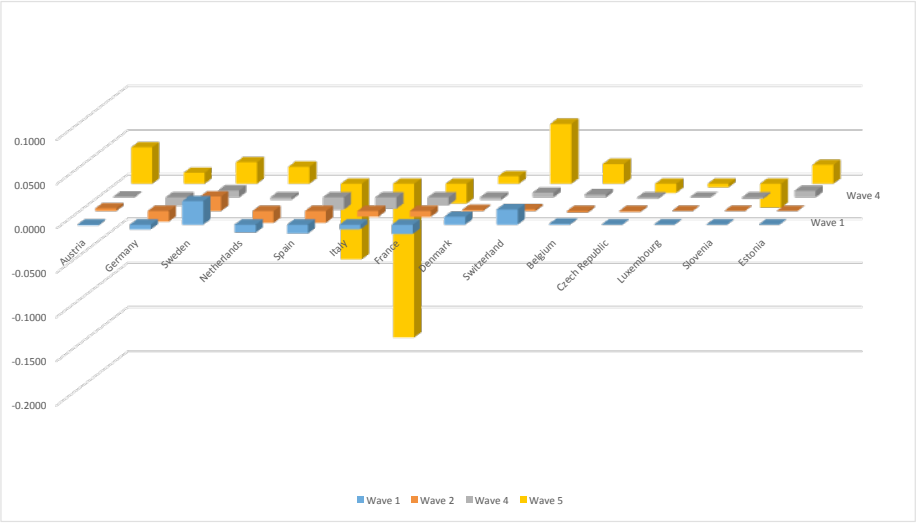

Figure 6: Horizontal Inequity for Children per wave.

Figure 5 depicts HI_{child} for all waves. This statistic is fairly constant over time for most countries. The inequity differences between Southern/Eastern countries and Northern countries observed in wave 5 are significantly more apparent than other waves. This might indicate that the effect of children is related to the economic environment of the countries. It is well-known that Spain and Italy are struggling with financial issues.

Table 2: HI for Income per Country

	Wave 1				Wave 2			Wave 4			Wave 5	
	HI	**C_need**	**C_use**		**C_need**	**C_use**	**HI**	**C_need**	**C_use**	**HI**	**C_need**	**C_use**
Austria	0.0042	-0.0220	-0.0178	0.0069	-0.0609	-0.0540	0.0076	-0.0186	-0.0110	-0.0047	0.0118	0.0165
Germany	0.0219	-0.0764	-0.0545	0.0214	-0.0480	-0.0266	0.0167	-0.0441	-0.0275	0.1544	-0.0407	-0.1950
Sweden	0.0611	-0.0508	0.0103	0.0715	-0.0566	0.0149	0.0547	-0.0404	0.0143	0.0719	-0.0022	-0.0741
Netherlands	0.0423	-0.0279	0.0144	0.0367	-0.0737	-0.0370	0.0332	-0.0626	-0.0294	0.1028	-0.0128	-0.1156
Spain	0.0193	-0.0586	-0.0393	0.0160	-0.0769	-0.0609	0.0164	-0.0234	-0.0071	0.1086	-0.0303	-0.1390
Italy	0.0122	-0.0851	-0.0730	0.0149	-0.0926	-0.0777	0.0135	-0.1018	-0.0883	0.1945	-0.0668	-0.2614
France	0.0352	-0.0594	-0.0242	0.0529	-0.0603	-0.0074	0.0494	-0.0699	-0.0205	0.0862	0.0001	-0.0861
Denmark	0.1066	-0.0898	0.0168	0.0493	-0.1074	-0.0581	0.0538	-0.0577	-0.0038	0.1857	-0.0328	-0.2185
Switzerland	0.0334	-0.0247	0.0087	0.0414	-0.0794	-0.0380	0.0401	-0.0711	-0.0310	0.0916	-0.0112	-0.1027
Belgium	0.0446	-0.0893	-0.0446	0.0250	-0.0816	-0.0566	0.0186	-0.0679	-0.0493	0.1237	-0.0266	-0.1503
Czech Republic	-	-	-	0.0314	-0.0923	-0.0609	0.0248	-0.0607	-0.0359	0.1347	-0.0403	-0.1750
Luxembourg	-	-	-	-	-	-	-	-	-	0.0716	-0.0162	-0.0878
Slovenia	-	-	-	-	-	-	0.0240	-0.1183	-0.0943	0.0473	-0.0148	-0.0621
Estonia	-	-	-	-	-	-	0.0159	-0.0318	-0.0159	0.0769	-0.0145	-0.0914

Table 3: HI for Child

	Wave 1			Wave 2			Wave 4			Wave 5		
	HI	C_need	C_use	HI	C_need	C_use	HI	C_need	C_use	HI	C_need	C_use
Austria	-0.0010	-0.0034	-0.0044	0.0030	-0.0628	-0.0598	0.0007	-0.0386	-0.0379	0.0411	-0.0199	-0.0611
Germany	-0.0053	-0.0096	-0.0149	-0.0122	0.0164	0.0041	-0.0095	0.0037	-0.0058	0.0124	-0.0097	-0.0220
Sweden	0.0264	-0.0411	-0.0147	0.0164	-0.0134	0.0030	0.0078	0.0130	0.0208	0.0242	-0.0050	-0.0292
Netherlands	-0.0091	-0.0091	-0.0182	-0.0136	-0.0024	-0.0160	-0.0028	0.0175	0.0147	0.0192	-0.0112	-0.0304
Spain	-0.0100	0.0369	0.0269	-0.0133	0.0530	0.0398	-0.0140	0.0616	0.0477	-0.0853	0.0252	0.1105
Italy	-0.0053	0.0539	0.0486	-0.0065	0.0699	0.0635	-0.0130	0.0894	0.0764	-0.1737	0.0698	0.2435
France	-0.0106	-0.0214	-0.0320	-0.0067	0.0112	0.0045	-0.0088	-0.0003	-0.0091	-0.0223	-0.0013	0.0210
Denmark	0.0089	-0.0150	-0.0062	0.0012	-0.0102	-0.0089	-0.0029	0.0552	0.0522	0.0085	-0.0071	-0.0155
Switzerland	0.0171	-0.0466	-0.0295	0.0020	-0.0345	-0.0325	0.0052	0.0141	0.0193	0.0678	-0.0308	-0.0986
Belgium	0.0010	-0.0124	-0.0115	-0.0018	-0.0106	-0.0124	0.0032	-0.0377	-0.0344	0.0223	-0.0087	-0.0310
Czech Republic	-	-	-	-0.0012	0.0184	0.0172	-0.0015	0.0232	0.0217	-0.0103	0.0083	0.0187
Luxembourg	-	-	-	-	-	-	-	-	-	-0.0040	0.0033	0.0073
Slovenia	-	-	-	-	-	-	-0.0017	0.0287	0.0270	-0.0269	0.0114	0.0383
Estonia	-	-	-	-	-	-	0.0073	0.0064	0.0137	0.0214	-0.0018	-0.0232

GDP Growth.pdf

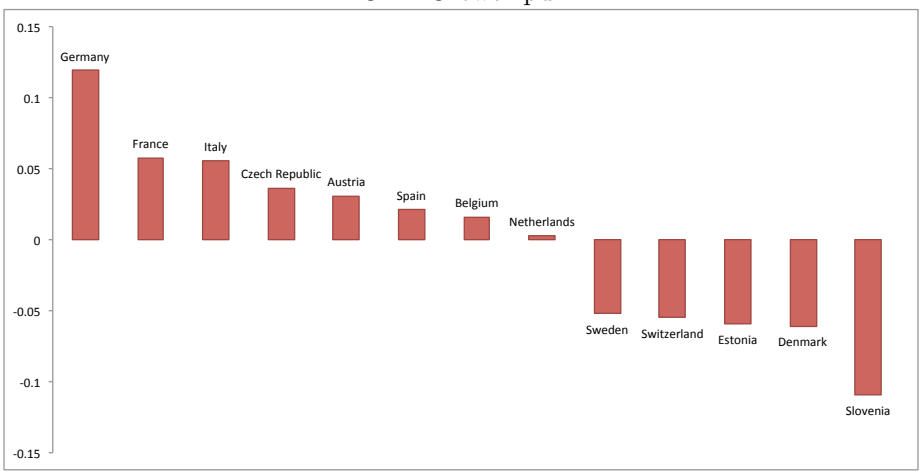

Figure 7: Effect GDP Growth on Individual Inequity proxy.

From Figure 7, it is clear that Scandinavian countries are similar and show a negative relationship between GDP growth and Individual Inequity proxy. This implies that in bad economic times, the difference between usage and need is larger. Hence, in these countries, this might indicate an increase in inequity.

5 Conclusion

In this report we have assessed the extent of socioeconomic inequities in health care use among elderly Europeans. We have assessed this inequity on the basis of two factors: income of an elderly individual and the size of the social network of an individual. In addition, we have examined these effects per country to assess whether there are geographical differences in health-care use inequity across Europe.

Our initial results are as follows: First of all we find strong evidence for inequity of health care usage among the elderly, based on income. That is, in general

we find a positive HI indices per country for income. In other words, this implies that the higher the income of an individual, the more health-care she uses, standardised for the other explanatory variables in our model. This is in line with the outcomes of other research on inequity in relation to income.

Secondly, we examine the inequity of health-care use explained away by the size of the social network of an individual. The results that we find are that southern European countries, together with eastern European countries, have a negative HI indices for size of social network. For northern European countries, however, we find the opposite that they have positive HI indices for size of social network. One potential explanation for this finding could be the difference in culture.

Lastly, the effect of economic conditions on inequity in health-care are different for each country. Furthermore, we examined whether the previously found conclusions also exist in other waves. Surprisingly, in terms of income, the HI has changed drastically over time. We observe large indices in wave 5, but this is not the case for the other waves, which may be due to policy changes of which we are not aware. Yet, inequity due to differences in social network is a promising topic for further research.

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