Econometric Game 2016

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April 8, 2016

1 Introduction

Our last paper emphasized the importance of equity in distribution of health services in European countries. However, a static analysis may neglect meaningful phenomena observed in health behaviour dynamics. Now we investigate the interplay of the elderly health care behaviour and business cycle conditions to examine whether exogenous circumstances influent individuals. Moreover we take a deep insight into the relation between the macroeconomic situation and the socioeconomic inequity in health care use.

Business cycle may have a noticeable influence on both, public and private health care. First of all, because of revenues shrinkage in downturn times, countries may reduce expenditures in all sectors, Stuckler, Basu, Suhrcke, Coutts, and McKee (2009). It may influent health care availability and optimality of health services distribution. What is more, recession may cause savings in socially relevant sectors. On the other hand, some evidence prove countercyclical government expenditure. Lane (2003) suggest that countries often apply a classical Keynesian approach trying to stimulate economy in recession. Because health care is one of the most important sectors from the social point of view, it often take advantage of such aid.

Moreover, financial crisis in years 2008-2010 might cause a significant structural break in terms of health care availability. Karanikolos, Mladovsky, Cylus, Thomson, Basu, Stuckler, Mackenbach, and McKee (2013) remarks that rises in patient charges might have a noticeable impact on health care usage especially for poorer individuals, what may directly influent inequity. The main idea of our analysis is to compare situation before and after the subprime crisis to investigate whether it had an observable impact on health care sector.

Health care systems in European countries differ substantially regarding aspects that may influent the extent to which health care utilisation is associated with socioeconomic characteristics, given the need for such care, such as: user charges in the public sector, the importance of the private sector, payment systems for doctors, which in some cases may create incentives to provide more extensive treatment to the better-off. For example, the existence of a large private sector where doctors are mainly paid fee-for-service may lead to large differences in utilisation by income because richer individuals are better able to afford private care and are also more likely to be insured against the costs of such care, and so they are more likely to opt for private care in order to side-step waiting lists.

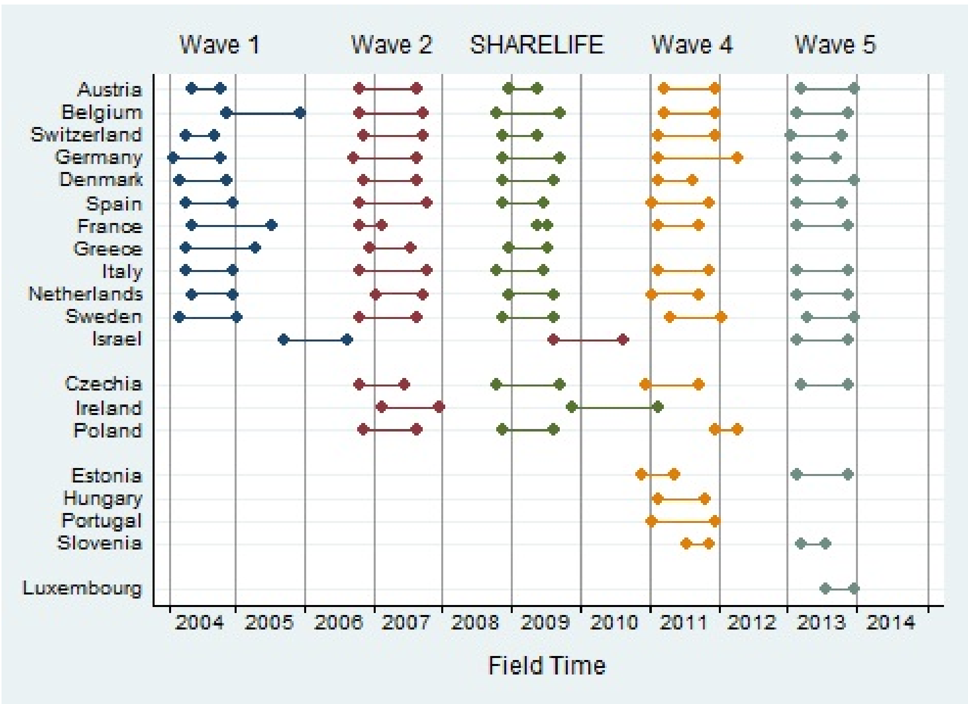
Last but not least, individual heterogeneity remains unobservable in a cross-section approach, Bago d'Uva, Jones, and Van Doorslaer (2009). Due to panel data models there is an unique opportunity to improve a quality of estimates covering such an inter-individual variation.

The paper is structured as follows. Section 2 describes the data. Section 3 presents models used to asses an impact of business cycle and financial crisis on health care across European countries. Results are presented in Section 4 and the last Section contains some concluding remarks.

2 Data

We employ the data from the 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. We use the panel data from 4 waves, no: 1, 2, 4 and 5. Figure 1. presents each country wave time overview. What can be seen, surveys in one wave were completed in different years in a few cases (e.g. compare Belgium and Austria in wave 1). What is more not all the countries participated in each of the 4 waves (e.g. Poland was present only in waves 2 and 4, Luxemburg only in wave 5). Also, SHARE follows rigorous procedural guidelines and programs, hence without going into particulars we can assume that all waves did not differ significantly in terms of the structure of the questionnaire or the mode of conducting the survey.

Figure 1: Realization of survey waves.



We keep the set of socioeconomic and health variables the same as in our previous analysis. Recoding of the variables also remains unmodified. From two variables describing healh care use only one had been choosen (number of doctor visits). For estimation purposes, we decided to exclude observations, if their number for a given year and a given country is lower than 100. Finally, to have a possibility of comaprison a situation before and after the crisis, we examined only the countries with Waves realized in both periods (before and after the crisis).

Furthermore, we use the macroeconomic indicators from the OECD database: employment rate, GDP annual growth, current total health care expenditure as share of GDP, public health care expenditure as share of GDP, dummy for years before crisis, dummmy for well-developed health care and intereraction between GDP growth and before crisis dummy. The 'before crisis' period refers to the data from the first two waves (2003-2007), whereas the 'after crisis' term to the waves 4 and 5 (2011-2013).

3 Influence of macroeconomic factors on inequity in health care use.

The analysis had been performed in 2 age subsamples. Retired group includes people, who are older than an effective retirement age in their country. Non-retired group consists of younger individuals.

To answer second research question we estimate HI indexes per each tuple of country and year (again, we estimate separately models for retired and non-retired subsamples) . Because we need one estimate per one tuple then we decide to use conventional methodology described in Bago d'Uva, Jones, and Van Doorslaer (2009) to estimate HI. Taking those values as a measure of inequity in healthcare accessibility we check how they change in time due to economic conditions. To estimate $\hat{y}$ we use Poisson model. This model gives consistent results with hurdle model, which is more computionaly complicated and hard to estimate for some of subsamples. To get estimates of HI index in periods before and after crisis we average (using weights) the HI estimates for years in given periods.

Figure 2. presents a comaprison of HI concentration indices in selected European countries before and after crisis. As can be seen, in almost every examined country there was a significant change in health care use inequity after the subprime crisis. In France and Spain there is a switch from pro-rich to pro-poor inequity. Moreover, in 6 out of 13 analyzed countries HI index fall after the crisis, but health care use inequity remained pro-rich. In Belgium, Denmark and German-speaking part of Switzerland post-crisis inequity rises. Concluding, there is no universal rule describing a direction changes in health care usage equity relative to income as a result of the last financial crisis. Changes in inequities seem to have a country specific foundation. To compare means of HI indices after and before crisis for non-retired people see Figure A.1 in Appendix.

Figure 2: Mean of HI index before and after the crisis.

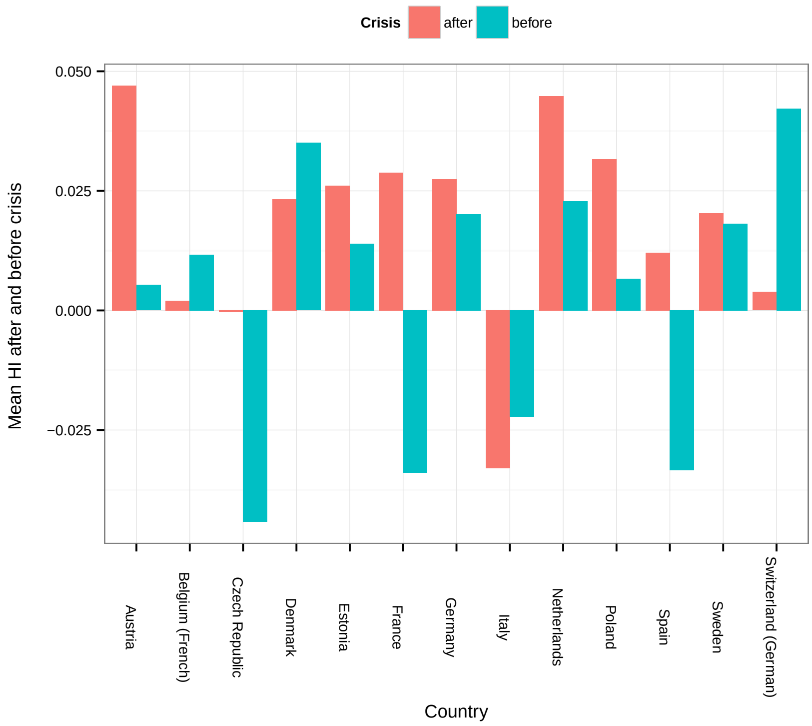
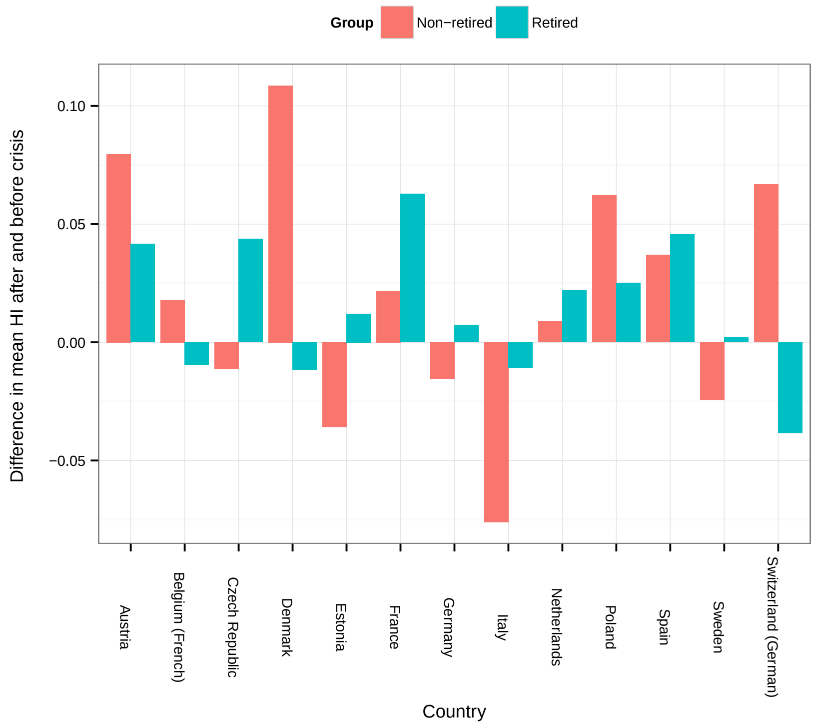


Figure 3. shows the difference in weighted means of the level of horizontal inequity in access to the health care before and after the recent financial and economic crisis. We report these statistics for two groups: retired and non-retired people. There are 13 countries for which we have data coming from at least one pre- and post-crisis wave.

Firstly, we find significant changes in average values of the horizontal inequity index before and after the crisis. However, the observed variation is not consistent across countries. In most cases we observe an increase in disproportional concentration on the relatively richer individuals either in retired or non-retired group. Only for Italy we obtained higher pro-poor inequity in use of the health care among both age groups. The greatest shift in favor of the better-off non-retired individuals can be seen in Denmark and Austria, whereas in case of retired individuals in France and Spain. Also, we conclude that usually differences in means among retired and non-retired are not similar in terms of magnitude and direction. Particularly, we estimated harmonious changes for retired and non-retired in Austria, France, Italy, Netherlands, Poland and Spain.

Figure 3: Difference in mean HI index before and after the crisis.



To answer a question about macroeconomic causes of HI index variation an OLS regression have been performed. Table 1. shows a summary of the results for retired group. We investigate, what are the effects on the magnitude of horizontal inequity among retired of (consecutively): GDP growth, crisis occurrence, presence of a strong public health care system, the amount of total health care expenditure (as a % of GDP), the amount of public health care expenditure (as a % of GDP) and employment. Also, we control for interactions between GDP growth and the occurrence of a crisis. The latter is a dummy variable, which is equal to 1 for the waves 1 and 2 (before the crisis) and to 0 otherwise. Developed public health care is a dummy equal 1 if the ratio of the share of public health care spending in GDP to the percentage of total heath protection expenditure in GDP is higher than 85%. Finally, GDP growth and developed public health care are statistically significant at 5% level. Share of total health care expenditure in GDP is statistically significant at 10% level.

Our results show, that the presence of strong public health care system increases the expected value of absolute horizontal inequality by 0.026 *ceteris paribus*. Also, all other variables held constant, one percentage point of GDP growth increases the expected disproportion in health care use by 0.005. Next, we obtained the positive effect of the high share of total spending on health protection in GDP on the endogenous variable.

The performed OLS analysis comes down to two main conclusions. Firstly, the low R squared measure indicates, that we cannot sufficiently well explain the studied variation of the horizontal inequity in health care use. Therefore there is a need for further investigation, that will identify other factors accounting for variation in the inequity index. Secondly, we estimate that the economic growth is related with the increase in horizontal inequality among retired elderly.

Table 1: OLS regression of absolute HI index on macroeconomic variables (standard errors in parenthesis).

	OLS
Constant	0,038
	(0,026)
GDP Growth	0,005*
	(0,002)
Before crisis	0,012
	(0,009)
Devoloped public health care	0,026*
	(0,011)
Total health care (%GDP)	$0,006^{\circ}$
	(0,004)
Public health care (%GDP)	-0,006
	(0,004)
Employment rate	-0,001
	(0)
Growth x Before crisis	-0,004
R^2	0.18
Adj. R^2	0.08
Num. obs.	68
RMSE	0.02

$\circ$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

4 Relation between health care behavior and business cycle.

In this section we investigate the potential differences in an individual demand for health services of the elderly with respect to the changes of business cycle. The construction of the data allows us directly to evaluate the effect of possible structural change in the economic environment on the individual number of visiting a doctor. Out of 4 waves of the questionnaire two have been collected in the period directly prior to the financial crisis 2008-2009, whereas the rest provide the information about the elderlies‘ behavior after this period. We do not have at our disposal any data from the period of the crisis, which one might perceive as a significant drawback in the context of modeling the business cycle issues. Nevertheless, this are the the crisis periods when usually the level of uncertainty is highly increased, which in turn might produce more noise in the data. Moreover, the adjustment processes connected with converging to the new equilibrium point might result in the relationships between variables which has only a temporary character and will vanish in a long run.

Therefore we test the null hypothesis that the structural change in the economic environment has no impact on the demand of health.

4.1 Estimation strategy

We use the standard approach in estimating the individual‘s demand for the health care, assuming that a conditional mean of the number of visiting doctor among the individuals could be approximated by a known function $g(\cdot|\cdot)$ that depend on a vector of covariates. We focus our attention on the need variables, which we have discussed to the previous paper, as they serve for identification of inequity effects. Nevertheless we control also for the need variables in order to obtain the estimates connected with the inequity among the elderly. Due to the nature of data we control also for a country-specific dummies[1] as well as for year effects where applicable. The main attention is focused on the effects for elderly, which is why we restrict our sample to cover only the individuals that are older than the country-specific effective retirement age reported by OECD. Moreover, we require they to be not younger than that threshold in each wave. This is of high importance, because including individuals who change their status during the sample period pose a thread on the credibility of estimates. An individual who was a part of labor force before crisis and has retired after was exposed to a structural break which might affect strongly their demand for health.

Testing the null hypothesis described in the last section requires a comparison between the (expected) individual‘s behavior of the respondent before and after the crisis. We distinguish two kinds effects. Firstly we estimate the marginal effect of a need variable on the conditional mean before the crisis which is in turn subtracted from the same effect but calculated for the sample interviewed after 2009:

$$\hat{\beta}_i = \frac{\partial g(\cdot|\cdot)}{\partial x_{it,NEED}}|_{post-crisis} - \frac{\partial g(\cdot|\cdot)}{\partial x_{it,NEED}}|_{pre-crisis} \tag{1}$$

This approach is to some extent similar to a difference-in-difference approach. However, the elements of the difference are estimated on separate samples, which allows to relax the parallel trends assumption. Moreover we gain on the efficiency of estimation, because in case of our data interacting the pre-post crisis dummy variable with the rest of covariates leads to enormous collinearity problems[2]. The standard errors are taken by application of panel bootstrap. As all of the estimators we employ in our research are asymptotically normal, the results of bootstrap seem reasonable.

Another challenges come from the characteristics of our data. It is a strongly unbalanced panel, where the definition of a time variable is ambiguous. On the one side, the year variable is available, but on the other the time structure is strongly related to the wave of a questionnaire. We find it more reasonable to set the time dimension of a panel to the number of a wave because it results in more individuals that have reported in consecutive years. The potential effect in time trends is eliminated by including time dummies (where applicable).

The next issue concern the unbalance property of the data set, which is subject to strong attrition. About 50% of individuals are observed only once. Therefore we divide our research into two parts. Firstly we drop each observation that does not participate in each wave in order to obtain balanced panel. The analysis on balanced panel is more appealing econometrically but is subject to a strong selection bias if one wants to refer the results to the whole population. Secondly we estimate the effects on the whole sam-

[1]We do not consider countries separately but focus on the average effects for the whole European region.

[2]The same applies if we interact year dummies with the rest of variables in the specification. Any reasonable set of interactions leads to enormous amount of collinearity, which in turn causes strongly biased estimates. To some degree it is connected with the features of data, mainly the large number of qualitative covariates. That is why we find it infeasible to estimate the effects for consecutive years. Instead, we focus on the pre-post crisis differences, which offer additionally an attractive economic interpretation.

ple, controlling additionally for the number of waves they participated in. This way of controlling for sample selection clearly does not rule out each sources of bias, but allows us to obtain reasonable estimates. However, in the case of balanced panel we are able to make comparisons between the same individuals in two subsamples which is not the case when considering unbalanced panel.

We estimate the outcome of interest using pooled OLS, linear fixed effects, linear random effects, pooled poisson and pooled poisson fixed effects estimators. Each of them has both strengths and weaknesses. OLS require the weakest assumptions and provides the best linear approximation to the underlying conditional expectation. However, it is not possible to account for the unobserved heterogeneity among the individuals which is the main advantage of using panel data. Fixed effects allows the unobserved individual effects to be correlated with other regressors, but it does not allow for time-varying variables. The need variables in our paper in definition are not constrained to be time-invariant, however the variation is weak for some of them. This in turn also may lead to biased estimation. Furthermore, random effects linear estimator is consistent provided that unobserved heterogeneity is not correlated with covariates. The last assumption is should be considered rather as a strong one. All of the previously mentioned estimators provide only a linear approximation for the conditional expectation. In our case the dependent variable is a count, so one may expect poor performance of linear estimation. That is why we apply also nonlinear models that achieve identification of parameters (and therefore the marginal effects) of interest via distributional assumption. This kind of assumptions are also perceived as strong, but in the case of the number of visiting doctor they are widely used in the literature(Riphahn, Wambach, and Million, 2003).

Finally some light should be on the nature of marginal effects we use to estimate the outcome of interest. The marginal effects from the linear regressions are individual-constant so they do not differ with respect to the covariates. The effects calculated from nonlinear likelihood methods in turn differs with respect to the features of an individual. It is advantageous while considering the balanced sample, as it allows to introducing more individual heterogeneity in the outcome of interest. Nevertheless, in the unbalanced case when we compare different individuals it might introduce some bias. Moreover, the marginal effects from models controlling for the unobserved heterogeneity are not directly corrected for the elderly-special effect. However, the unobserved heterogeneity is reflected in the estimated model parameters, so for some extend the marginal effects control for the unit effects. It occurs at least on average, hence it is suitable for our approach.

4.2 Balanced sample

Here we present the results of estimation on the balanced sample. The sample size of balance panel is more than 5 times smaller than in the unbalanced case.

Table 2: Estimation results on the balanced sample

	OLS	FE	RE	PP	PFE
	1	2	3	4	poiss
age	0.009	0.012	0.009	0.005	0.002
			education		
lower sec.	-0.562	-0.553	-0.562	-0.605	-0.080

none	-0.311	-0.300	-0.311	-0.350	-0.041
primary	-0.546	-0.538	-0.546	-0.601	-0.072
higher sec.	-0.335	-0.327	-0.335	-0.394	-0.055
			marital status		
noncouple	0.388	0.388	0.388	0.475	0.092
widow	-0.008	-0.020	-0.008	0.184	0.026
			household size		
2	0.331	0.321	0.331	0.505	0.085
3	0.510	0.481	0.510	0.540	0.087
3+	-0.033	-0.083	-0.033	0.079	0.038
			income deciles		
2	0.123	0.127	0.123	0.347	0.047
3	-0.238	-0.243	-0.238	-0.023	-0.010
4	0.375	0.372	0.375	0.437	0.061
5	0.360	0.374	0.360	0.440	0.070
6	1.178	1.178	1.178	1.191*	0.168*
7	1.076	1.078	1.076	1.045	0.140
8	0.299	0.307	0.299	0.401	0.068
9	-0.323	-0.288	-0.323	-0.310	-0.045
10	0.038	0.121	0.038	0.169	0.036
			employment		
unemployed	-0.577	-0.622	-0.577	-0.671	-0.087
			gender		
female	-0.334	-0.338	-0.334	-0.245	-0.041
N	16888	16888	16888	16888	16888

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
where OLS, FE, RE, PP and PFE stand for pooled OLS, linear fixed effects, linear random effects, pooled poisson and poisson fixed effects regression respectively.

The results on the balanced sample favor the null hypothesis of no effect on the expected number of visiting doctor caused by the potential structural change in economic environment caused by the crisis. No coefficient is statistically significant. This means that the elderly visit the doctor with the same frequency in the pre and post crisis period with respect to the nonneed characteristics. The results show that the level of inequity has not changed. As it is described previously, each of the estimator might suffer from certain drawback. That is why obtaining strongly robust to the choice of specification results strongly support our interpretation.

Although the results obtained on the balanced panel are strong and unambiguous, it is hard to refer them to the population values. Regardless of possible attrition effects which are not accounted for in this case, one should expect that the individuals who respond willingly to the questionnaire differ with respect to some characteristics. Neither the difference in sample size speaks for the balanced sample results.

4.3 Unbalanced sample

Here we present the results for the unbalanced sample.

Table 3: Estimation results on the unbalanced sample

	OLS	FE	RE	PP
	1	2	3	4
age	0.016	0.016	0.016	0.011
		education		
lower sec.	-0.443*	-0.443*	-0.443*	-0.441***
none	-0.935**	-0.935*	-0.935*	-0.713***
primary	-0.584**	-0.584**	-0.584**	-0.588***
higher sec.	-0.349	-0.349	-0.349*	-0.364***
		marital status		
noncouple	0.793**	0.793**	0.793**	0.609***
widow	0.114	0.114	0.114	0.111***
		household size		
2	0.775**	0.775**	0.775**	0.674***
3	1.140**	1.140**	1.140**	0.830***
4+	1.343***	1.343***	1.343***	1.058***
		income deciles		
2	0.095	0.095	0.095	0.158
3	-0.066	-0.066	-0.066	-0.011
4	0.271	0.271	0.271	0.306**
5	0.095	0.095	0.095	0.168**
6	0.577	0.577*	0.577*	0.574***
7	0.263	0.263	0.263	0.324
8	0.004	0.004	0.004	0.062
9	0.238	0.238	0.238	0.286
10.	0.500	0.500	0.500	0.481
		employment		
unemployed	0.323	0.323	0.323	0.327*
		gender		
female	-0.055	-0.055	-0.055	-0.020
N	108687	108687	108687	108687

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
where OLS, FE, RE, PP stand for
pooled OLS, linear fixed effects, linear random
effects, pooled poisson regression respectively.

Here the qualitative interpretation of the results is different. According to them the demand for the health services has changed significantly after the crisis with respect to two need variables: the education and household size. The less than tertiary educated elderlies visit doctor on average rarelier than they used to do before the crisis, with respect to the highest educated individuals. On the other hand the opposite effects is capture for households other than single. The effects are moderately weak, as the strongest amounts to more or less one visit at the doctor. However, they suggests that the level of inequity might have increased after the crisis. Once again the results are robust to the estimator.

Additionally, the need variables with respect to which individuals have changed their demand for health services might shed some light on the selection process and therefore provide some evidence on possible bias in balanced sample estimation. The significant variables here are the education and household size. One might expect that these variables are also predictive for the process of attrition, which is ruled out in the balanced panel case. Therefore we suggest that the results from the unbalanced sample estimation are probably closer to the population values.

Hence we found some evidence that the degree of inequity with respect to the access to the health care has changed after the crises. However, this interpretation is not causal, rather reflects some correlation and comovement of health care inequity and business cycle processes.

4.4 Macro - perspective

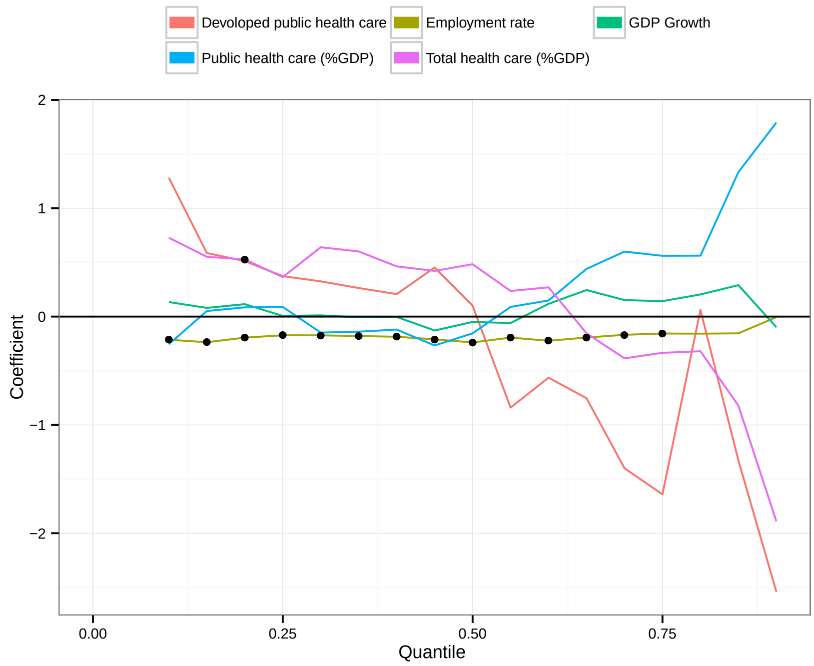
To get insight into how macroeconomic conditions could affect patterns in healthcare usage we also use simple macro-perspective approach. We average the number of doctor visits to the level of country and year. Then we try to explain variability in mean usage of doctor visits using OLS regression. Due to small sample size we cannot use more sophisticated methods in this perspective. Results of estimations are shown in Table 2 (we model only data for retired people). We can see that the only macro factor that is affecting healthcare usage in employment rate, which could mean that better economic conditions are correlated with less-frequent use of healthcare.

Table 4: OLS regression of average number of doctor visits on macroeconomic variables (standard errors in parenthesis).

	OLS
Constant	18,258***
	(2,782)
Public health care (%GDP)	0,206
	(0,448)
Total health care (%GDP)	0,011
	(0,393)
Developed public health care	-0,136
	(1,18)
GDP Growth	0,004
	(0,161)
Employment	-0,184***
	(0,048)
R^2	0.22
Adj. R^2	0.16
Num. obs.	68
RMSE	0.02

However this is only effect for mean, and in further analysis we investigate the influence of macro variables on different quantiles of healthcare usage distribution using quantile regression, Koenker (2006). The results of modelling are shown on Figure 4. The sign of effect of variables are different in low and high quantiles. However the only variable that is significant for most of quantiles is employment rate, which is always negative, which is in line with results from OLS modelling. To compare results of modelling for non-retired individuals see Figure A.2 in Appendix.

Figure 4: Coefficients of quantile regression for retired group.



Dots shows statistical significance of coefficient

5 Conclusions

Changing economic conditions influent the government's budget expenditure, hence also the public health spending. For instance, in 2013, the health spending as a share of GDP was 8.9% in the OECD countries. Between 2000 and 2009 average growth in health expenditure reached 3.8%, however it grounded to halt in the wake of the global financial and economic crisis. Evolution of health care system impacts the situation of individual consumers, limit or extend the set of available alternatives or causes a shift in their behaviors.

Secondly, we aimed to analyze the relation between the direction and scale of socioeconomic inequity and economic conditions. Countries did not exhibit consistent variation in horizontal inequity in health care use, as we compared it before and after the crisis. We were not able to explain sufficiently well the variation in the HI index or in the number of medical doctor visits using macro variables. However, we found statistically significant relation between the HI index and GDP growth ratio and the presence of developed public health care system. What is more, the regression of the medical doctor visits revealed highly significant value of employment. Further research should be conducted concerning other factors, which can explain the larger share of variation in the scale of horizontal inequity in healthcare use.

In this paper we investigated the possible change in the degree of inequity among the elderly in European countries. Taking advantage of the panel micro data we estimated models both on the balanced and unbalanced subsamples. The evidence from the data suggest that the average household with certain characteristics has changed the demand for the health care with respect mainly to their education and household size. The magnitude of the effects is rather moderate. Moreover, although the estimates might be subject to some severe econometric issues, they turned out to be strongly robust with respect to the estimation strategy.

References

Bago d'Uva, T., A. M. Jones, and E. Van Doorslaer (2009): "Measurement of horizontal inequity in health care utilisation using European panel data," *Journal of health economics*, 28(2), 280–289.

Karanikolos, M., P. Mladovsky, J. Cylus, S. Thomson, S. Basu, D. Stuckler, J. P. Mackenbach, and M. McKee (2013): "Financial crisis, austerity, and health in Europe," *The Lancet*, 381(9874), 1323–1331.

Koenker, R. (2006): "Quantile regresssion," *Encyclopedia of Environmetrics.*

Lane, P. (2003): "Business cycles and macroeconomic policy in emerging market economies," *International Finance*, 6(1), 89–108.

Riphahn, R. T., A. Wambach, and A. Million (2003): "Incentive effects in the demand for health care: a bivariate panel count data estimation," *Journal of applied econometrics*, 18(4), 387–405.

Stuckler, D., S. Basu, M. Suhrcke, A. Coutts, and M. McKee (2009): "'The public health effect of economic crises and altermative poliocy responses in Europe: An empirical analysis," *The Lancet*, 374, 315–323.

A Appendix

Figure A.1: Mean of HI index before and after the crisis.

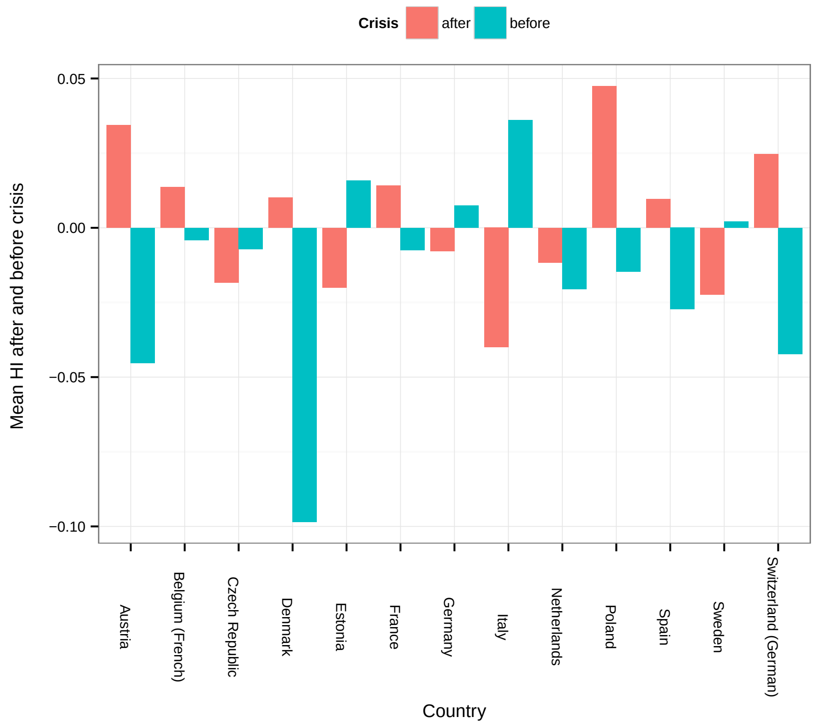


Figure A.2: Coefficients of quantile regression for non-retired group.