# Business Cycle and Policy Determinants of Socioeconomic Inequity in Healthcare

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**Abstract**

We examine the extent of horizontal inequity present in the accessibility of healthcare in 18 European countries using 2004-2013 data from the Survey of Health Aging and Retirement in Europe (SHARE), a cross-national panel database including data on health, socioeconomic status, and social and family networks of individuals. In particular, we estimate the impact of a variety of socioeconomic, demographic and health factors on an individual's annual contacts with a doctor. We explore the extent to which these measures are impacted by the business cycle and whether public health expenditure can mitigate any resulting increases in inequity. To account for unobserved heterogeneity in health, we focus on a Latent Component Model (LCM) to ultimately derive a measure for need for healthcare that is based on an individual's health status. We use this measure to construct a horizontal inequity index for each country and plot concentration curves. We find that downturns lower healthcare usage directly and also exacerbate the impact of income on usage, lowering equity. In tension with Gerdtham & Ruhm (2006), we find that posterior probability of being healthy is higher under expansions than contractions. Furthermore, the elasticity of demand for the healthy is higher than the ill. Most countries become more pro-rich during contractions as the poor are not insulated from income loss, but some become more pro-poor during crises, likely due to an increase in the social safety net. We find that while it has little effect during expansions, a higher share of public health spending means that economic contractions do not force individuals to decrease healthcare usage by as much as they would under a more highly privatized system.

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

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)."

# Contents

# 1 Introduction

Most European health care systems aim at ensuring an equitable distribution of health care, where (horizontal) equity is defined as equal use for equal need (Van Doorslaer et al., 2004). In other words, under socioeconomic (horizontal) equity, health care use should be equal for individuals of similar health needs - regardless of differences in socioeconomic status (SES). This study uses four waves of the Survey of Health Aging and Retirement in Europe (SHARE) from 2004 to 2013, a cross-national panel database including data on health, socioeconomic status, and social and family networks of individuals in 18 European countries, to create measures of health care need and usage across individuals of different socioeconomic status. Combining with data gathered from the OECD Composite Leading Indicators on economic contractions, we then explore to what extent these measures are impacted by the business cycle - does the disparity between rich and poor expand as the economy contracts and to what extent are these changes mitigated by the share of health expenditures that are public in each country.

Given the strengths of LCM in terms of accounting for unobserved heterogeneity in individuals' health needs and our findings in Case A, the LCM for doctor contacts ($hc002\_$) is our preferred specification. We use it to compute a unified measure of an individual's healthcare demand. By standardizing income and recomputing this measure, we obtain a measure for demand of individuals absent the impact of income, i.e. "need" for healthcare. This need measure for each individual is used to compute measures of horizontal inequity for each of the 18 countries in the sample and concentration curves.

We find that downturns lower healthcare usage directly and also exacerbate the impact of income on usage, lowering equity. Contracy to the results of Gerdtham & Ruhm (2006), we find that the posterior probability of being healthy is higher under expansions than contractions. The elasticity of demand for the healthy is higher than the ill. Most countries become more pro-rich during contractions as the poor are not insulated from income loss, but some become more pro-poor during crises, likely due to an increase in the social safety net. We find that while it has little effect during expansions, a higher share of public health spending means that economic contractions do not force individuals to decrease healthcare usage by as much as they would under a more highly privatized system.

These analyses can be used to make policy recommendations to European health care systems that will improve socioeconomic equity in health care access. For example, for many countries, it appears that the expansion of public healthcare expenditures during bad times - an explicitly countercyclical policy - would mitigate the extent to which healthcare usage skews towards pro-rich horizontal inequity.

# 2 Modeling Healthcare Demand

The main challenge to modeling healthcare demand and thus being able to measure "need" for services is the fact that true health status and thus main determinants of true healthcare need are almost certainly unobserved, despite the wealth of data in the SHARE sample. This unobserved heterogeneity threatens to bias the estimates and prevents identification in an OLS or standard non-linear settings. Further, such methods cannot distinguish between the extensive and intensive margins of healthcare demand. Many low levels of healthcare demand manifest as "zeroes" in the dataset, and we would like to be able to distinguish these outcomes from strictly positive counts of medical treatment. For outcomes that take on a count form, such as the number of doctor contacts ($hc002\_$), we can turn to an established literature to help solve this problem. Deb & Trivedi (1997) show that given the assumption that negative health events, following which individuals decide whether to seek treatment, are rare events, we are justified in viewing counts of utilization as a poisson random variable, which is a subset of the negative binomial distribution, with $\alpha = 0$, the dispersion parameter. However, healthcare utilization data is frequently thought to display overdispersion (some people never seek treatment - some people seek too much treatment), which suggests a negative binomial with positive dispersion, $\alpha > 0$. The Hurdle Method (TPM) has been used by many researchers (Pohlmeier 1995, Jimenez-Martin 2002, Deb & Trivedi 1997, 2002) to account for both the intensive and extensive margins of healthcare consumption and the fact that healthcare decisions can be seen as a two-step process. However, Deb & Trivedi (1997, 2002) argue that the Latent Component Model (LCM) is better suited to modeling healthcare decisions; our results from Case A favoured the LCM in comparison to TPM. As a result, our analysis focuses on LCM.

## 2.1 Latent Component Model

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

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

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

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

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

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

# 3 Data

Data for this paper come from the first, second, fourth, and fifth wave of Survey of Health Aging and Retirement in Europe (SHARE), which were gathered between 2004 and 2013. The data represent a cross-national panel database of 104,056 unique individuals from 18 European countries. [2] Because we are studying the effects of socioeconomic inequities in healthcare among elderly Europeans, we initially keep only data observations that represent individuals who are at least 50 years old. After dropping 1,140 observations for individuals younger than 50 years old, we cleaned dataset comprises 101,434 unique individuals and 178,065 total observations.

## 3.1 Adjustments to SHARE Data

This section outlines adjustments made to SHARE data, particularly to categorical data. Our approach to choosing controls was to include as many measures of health, access to health care, and socioeconomic status as possible. Variables were only excluded if there were multiple variables that were likely to be highly collinear. In these cases, we would choose a single variable that best encompassed the information with the fewest missing observations.[3]

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

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

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

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

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

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

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

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

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

- Marital Status: Under the assumption that couples who live together have similar health outcomes and access to health - whereas the correlation between couples who do not live together is less clear - "mar_stat"

[2] Note that not every individual is in each wave of the dataset. 49.37% of individuals were surveyed once, 33.81% were surveyed twice, 8.60% were surveyed three times, and 8.21% were surveyed four times.

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

is reclassified into whether the individual lives with his or her significant other.

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

Building on this set of socioeconomic, demographic, and health variables, we add a collection of business cycle and policy measures, also from the SHARE data. While we generally try to incorporate as much data on macroeconomic indicators as available, we cannot incorporate as much annual data in our model on 2008-2009, because we do not have individual-level data in our dataset from these years. Business cycle measures include GDP per capita, GDP growth, employment rates, and an indicator of whether there was a contraction in the prior twelve months. Slight adjustments and rescaling was done to the following variables:

- GDP per capita: We divided GDP per capita, which is normalized in 2005 PPP-adjusted US dollars, by 1000 for consistent interpretation in thousands of dollars.

- National employment rates: We divide national employment rate to rescale from percentage points.

- Indicator of recession within the previous 12 months: Using OECD data on peaks and troughs for leading macroeconomic indicators (e.g. GDP and industrial production) for each country in our dataset, we created an indicator of whether each country experienced any economic contraction within the previous 12 months for each month in our data. [4]

To analyze healthcare policy, we use the provided SHARE data to construct a measure of the share of health expenditure coming from the public sector:

- Publicly provided share of total per capita health expenditures: we divide the public health expenditures "hexp3" by total health expenditures "hexp4" to obtain the share of publicly provided per capita health expenditures. Following Gerdtham and Ruhm (2006), we can interpret an increase in the share of public health expenditures as a strengthening of the social insurance system.

## 3.2 Summary Statistics

The 2004-2013 SHARE data contains individuals from 18 European countries. Table 1 gives the number of individuals from each country in the data used for analysis. Tables 2-5 gives overall summary statistics for all variables used in this data set.

[4]OECD Composite Leading Indicators data is publicly available at http://www.oecd.org/std/leading-indicators/oecdcompositeleadingindicatorsreferenceturningpointsandcomponentseries.htm.

Table 1: Number of Individuals By Country & Wave

| Country | Wave 1 | Wave 2 | Wave 4 | Wave 5 |
|---|---|---|---|---|
| Austria | 1,546.00 | 1,172.00 | 5,137.00 | 4,164.00 |
| Belgium | 3,671.00 | 3,067.00 | 5,153.00 | 5,508.00 |
| Czech Republic | | 2,734.00 | 5,953.00 | 5,598.00 |
| Denmark | 1,596.00 | 2,520.00 | 2,215.00 | 4,045.00 |
| Estonia | | | 6,690.00 | 5,671.00 |
| France | 3,032.00 | 2,843.00 | 5,640.00 | 4,364.00 |
| Germany | 2,930.00 | 2,523.00 | 1,561.00 | 5,521.00 |
| Hungary | | | 2,996.00 | |
| Greece | 2,652.00 | 3,052.00 | | |
| Italy | 2,493.00 | 2,911.00 | 3,519.00 | 4,614.00 |
| Luxembourg | | | | 1,590.00 |
| Netherlands | 2,841.00 | 2,607.00 | 2,721.00 | 4,077.00 |
| Poland | | 2,414.00 | 1,712.00 | |
| Portugal | | | 2,010.00 | |
| Slovenia | | | 2,710.00 | 2,903.00 |
| Spain | 2,343.00 | 2,176.00 | 3,490.00 | 6,320.00 |
| Sweden | 2,984.00 | 2,702.00 | 1,945.00 | 4,487.00 |
| Switzerland | 942 | 1,418.00 | 3,635.00 | 2,947.00 |
| Total | 27,030.00 | 32,139.00 | 57,087.00 | 61,809.00 |

Given the sparseness of macroeconomic data available in the provided SHARE data, we downloaded the OECD Composite Leading Indicators, which indicates turning points in the business cycle for 33 OECD countries - including all 18 countries in the SHARE data. For each country and each month that SHARE interviews were conducted, we code a binary variable "contract_12mo" that equals 1 if the country had a business contraction within the twelve months prior to that month and 0 if the country did not. Figures 1-3 graph this indicator over time, giving a visual representation of the business cycle in each country. However, note that SHARE data was not collected for every country each month. To indicate this, we have shaded the portion of each country's graph that has SHARE data.

Note that Luxembourg only has SHARE data during expansionary times, while Portugal and Slovenia only have SHARE data during contractionary times. As a result, for these three countries, we cannot make comparisons on the effect of changes in the business cycle on health care expenditures. Thus, observations from these countries are not included in the analysis. However, these three countries represent a fairly small proportion of the data. The final data set includes 168,852 observations.

# 4 Methods

## 4.1 Doctor Contacts

Because for binary measures, like the variable $hc012\_$, measures like LCM that control for unobserved heterogeneity are unavailable, we proceed by examining only the count data for doctor contacts.We begin

Table 2: Summary Statistics: Wave 1

| A. Factors Affecting Health Needs | | | | | | |
|---|---|---|---|---|---|---|
| | Mean | Std. Dev. | Min | Max | Obs | NA |
| Age | 65.0788 | 10.11601 | 50 | 104.3 | 27030 | 0.00% |
| Mobility Index | 0.48984 | 0.8993554 | 0 | 4 | 26870 | 0.59% |
| | NA | Percent | | | | |
| Female | 0.00% | 54.25% | | | | |
| Ever Smoked | 0.50% | 47.20% | | | | |
| Has Chronic Disease | 0.56% | 59.69% | | | | |
| | NA | Great | Fair | Poor | | |
| Self-Reported Physical Health | 0.52% | 29.96% | 39.66% | 29.86% | | |
| | NA | None | Elementary | Middle | High | College |
| Education | 1.56% | 5.76% | 28.20% | 18.07% | 26.50% | 19.90% |
| | NA | Not Depressed | Low | Mid | High | |
| Depression | 2.70% | 23.33% | 58.46% | 13.83% | 1.68% | |
| | NA | Underweight | Normal | Overweight | Obese | |
| BMI | 24.72% | 1.03% | 29.66% | 31.94% | 12.65% | |
| | NA | Below | Above | | | |
| Recall | 2.10% | 64.69% | 35.31% | | | |
| | NA | Consume little | Consume lot | | | |
| Alcohol Consumption | 0.57% | 47.94% | 51.49% | | | |
| | NA | Low | Middle | High | | |
| Strenuous Activities | 0.56% | 41.76% | 23.07% | 34.61% | | |
| **B. Access to Health Care** | | | | | | |
| | Mean | Std. Dev. | Min | Max | Obs | NA |
| Doctor Visits | 6.499626 | 9.72335 | 0 | 98 | 26718 | 1.15% |
| **C. Socioeconomic Status Indicators** | | | | | | |
| | Mean | Std. Dev. | Min | Max | Obs | NA |
| Income Percentile | 5.425305 | 2.866204 | 1 | 10 | 27030 | 0.00% |
| Household Size | 2.160895 | 0.9774411 | 1 | 9 | 27030 | 0.00% |
| | NA | Percent | | | | |
| Live with Significant Other | 0.29% | 71.38% | | | | |
| | NA | Retired | Employed | Unemployed | Permanently Sick/Disabled | Homemaker |
| Current Job Situation | 1.10% | 49.50% | 27.40% | 3.10% | 3.30% | 15.80% |
| **D. Macroeconomic Indicators** | | | | | | |
| | Mean | Std. Dev | Min | Max | Obs | NA |
| Public Share of Health Expenditures | 73.10% | 8.23% | 58.39% | 83.55% | 11 | 7 |
| Employment Rate | 66.58% | 6.90% | 57.56% | 77.40% | 11 | 7 |
| GDP per Capita | 31.47636 | 3.857588 | 25.1096 | 37.771 | 11 | 7 |
| GDP Growth Rate | 2.9 | 1.136662 | 1.2 | 5.1 | 11 | 7 |

Table 3: Summary Statistics: Wave 2

| A. Factors Affecting Health Needs | | | | | | |
|---|---|---|---|---|---|---|
| | Mean | Std. Dev. | Min | Max | Obs | NA |
| Age | 65.42943 | 10.02486 | 50 | 104.3 | 32139 | 0.00% |
| Mobility Index | 0.5392929 | 0.9413633 | 0 | 4 | 32016 | 0.38% |
| | NA | Percent | | | | |
| Female | 0.00% | 54.62% | | | | |
| Ever Smoked | 1.00% | 46.90% | | | | |
| Has Chronic Disease | 0.42% | 59.54% | | | | |
| | NA | Great | Fair | Poor | | |
| Self-Reported Physical Health | 0.36% | 26.65% | 37.12% | 35.87% | | |
| | NA | None | Elementary | Middle | High | College |
| Education | 2.60% | 4.05% | 26.81% | 17.49% | 28.52% | 20.53% |
| | NA | Not Depressed | Low | Mid | High | |
| Depression | 2.80% | 23.91% | 57.48% | 14.01% | 1.80% | |
| | NA | Underweight | Normal | Overweight | Obese | |
| BMI | 27.29% | 1.16% | 26.74% | 31.05% | 13.76% | |
| | NA | Below | Above | | | |
| Recall | 1.80% | 61.55% | 38.45% | | | |
| | NA | Consume little | Consume lot | | | |
| Alcohol Consumption | 1.10% | 51.41% | 47.49% | | | |
| | NA | Low | Middle | High | | |
| Strenuous Activities | 1.11% | 42.56% | 23.54% | 32.80% | | |
| B. Access to Health Care | | | | | | |
| | Mean | Std. Dev. | Min | Max | Obs | NA |
| Doctor Visits | 6.749001 | 9.389631 | 0 | 98 | 31793 | 1.08% |
| C. Socioeconomic Status Indicators | | | | | | |
| | Mean | Std. Dev. | Min | Max | Obs | NA |
| Income Percentile | 5.455255 | 2.866816 | 1 | 10 | 32138 | 0.00% |
| Household Size | 2.211394 | 1.053279 | 1 | 14 | 32139 | 0.00% |
| | NA | Percent | | | | |
| Live with Significant Other | 0.71% | 71.41% | | | | |
| | NA | Retired | Employed | Unemployed | Permanently Sick/Disabled | Homemaker |
| Current Job Situation | 2.50% | 51.40% | 27.00% | 2.60% | 3.90% | 12.70% |
| D. Macroeconomic Indicators | | | | | | |
| | Mean | Std. Dev | Min | Max | Obs | NA |
| Public Share of Health Expenditures | 75.79% | 8.15% | 59.12% | 86.32% | 13 | 5 |
| Employment Rate | 66.87% | 7.45% | 54.47% | 77.94% | 13 | 5 |
| GDP per Capita | 33.21678 | 7.663433 | 15.153 | 43.3778 | 13 | 5 |
| GDP Growth Rate | 4.092308 | 1.470522 | 2 | 6.9 | 13 | 5 |

Table 4: Summary Statistics: Wave 4

| A. Factors Affecting Health Needs | | | | | | |
|---|---|---|---|---|---|---|
| | Mean | Std. Dev. | Min | Max | Obs | NA |
| Age | 66.31574 | 10.00983 | 50 | 103.9 | 57087 | 0.00% |
| Mobility Index | 0.5789706 | 0.9720792 | 0 | 4 | 56749 | 0.59% |
| | NA | Percent | | | | |
| Female | 0.00% | 55.90% | | | | |
| Ever Smoked | 2.20% | 44.80% | | | | |
| Has Chronic Disease | 0.57% | 64.92% | | | | |
| | NA | Great | Fair | Poor | | |
| Self-Reported Physical Health | 0.54% | 22.53% | 34.65% | 42.29% | | |
| | NA | None | Elementary | Middle | High | College |
| Education | 2.52% | 2.87% | 18.64% | 18.85% | 32.91% | 24.22% |
| | NA | Not Depressed | Low | Mid | High | |
| Depression | 3.27% | 18.70% | 59.55% | 16.45% | 2.04% | |
| | NA | Underweight | Normal | Overweight | Obese | |
| BMI | 36.56% | 0.83% | 22.87% | 26.10% | 13.66% | |
| | NA | Below | Above | | | |
| Recall | 2.70% | 56.53% | 43.47% | | | |
| | NA | Consume little | Consume lot | | | |
| Alcohol Consumption | 1.26% | 54.70% | 44.04% | | | |
| | NA | Low | Middle | High | | |
| Strenuous Activities | 1.26% | 44.48% | 22.22% | 32.03% | | |
| **B. Access to Health Care** | | | | | | |
| | Mean | Std. Dev. | Min | Max | Obs | NA |
| Doctor Visits | 6.74541 | 9.784945 | 0 | 98 | 56318 | 1.35% |
| **C. Socioeconomic Status Indicators** | | | | | | |
| | Mean | Std. Dev. | Min | Max | Obs | NA |
| Income Percentile | 5.474031 | 2.869315 | 1 | 10 | 57087 | 0.00% |
| Household Size | 2.157496 | 1.014547 | 1 | 12 | 57087 | 0.00% |
| | NA | Percent | | | | |
| Live with Significant Other | 1.62% | 68.32% | | | | |
| | NA | Retired | Employed | Unemployed | Permanently Sick/Disabled | Homemaker |
| Current Job Situation | 2.40% | 57% | 25.90% | 3.20% | 3.60% | 7.90% |
| **D. Macroeconomic Indicators** | | | | | | |
| | Mean | Std. Dev | Min | Max | Obs | NA |
| Public Share of Health Expenditures | 76.03% | 7.02% | 63.60% | 86.68% | 16 | 2 |
| Employment Rate | 66.01% | 7.16% | 55.43% | 79.35% | 16 | 2 |
| GDP per Capita | 35.59114 | 10.03616 | 21.0851 | 54.5507 | 16 | 2 |
| GDP Growth Rate | 1.7375 | 1.642711 | -1.8 | 5 | 16 | 2 |

Table 5: Summary Statistics: Wave 5

| A. Factors Affecting Health Needs | | | | | | |
|---|---|---|---|---|---|---|
| | Mean | Std. Dev. | Min | Max | Obs | NA |
| Age | 67.06032 | 10.01937 | 50 | 103.5 | 61809 | 0.00% |
| Mobility Index | 0.5326184 | 0.9699695 | 0 | 4 | 61637 | 0.28% |
| | NA | Percent | | | | |
| Female | 0.00% | 55.36% | | | | |
| Ever Smoked | 1.40% | 45.70% | | | | |
| Has Chronic Disease | 0.38% | 63.61% | | | | |
| | NA | Great | Fair | Poor | | |
| Self-Reported Physical Health | 0.25% | 25.28% | 36.72% | 37.74% | | |
| | NA | None | Elementary | Middle | High | College |
| Education | 1.82% | 4.59% | 16.17% | 18.45% | 32.56% | 26.41% |
| | NA | Not Depressed | Low | Mid | High | |
| Depression | 2.96% | 21.43% | 59.32% | 14.59% | 1.71% | |
| | NA | Underweight | Normal | Overweight | Obese | |
| BMI | 34.94% | 0.83% | 24.62% | 26.54% | 13.08% | |
| | NA | Below | Above | | | |
| Recall | 2.87% | 53.55% | 46.45% | | | |
| | NA | Consume little | Consume lot | | | |
| Alcohol Consumption | 0.28% | 52.34% | 47.38% | | | |
| | NA | Low | Middle | High | | |
| Strenuous Activities | 0.26% | 43.13% | 22.18% | 34.43% | | |
| B. Access to Health Care | | | | | | |
| | Mean | Std. Dev. | Min | Max | Obs | NA |
| Doctor Visits | 6.889173 | 9.845159 | 0 | 98 | 61023 | 1.27% |
| C. Socioeconomic Status Indicators | | | | | | |
| | Mean | Std. Dev. | Min | Max | Obs | NA |
| Income Percentile | 5.477244 | 2.869363 | 1 | 10 | 61809 | 0.00% |
| Household Size | 2.102542 | 0.9315675 | 1 | 12 | 61809 | 0.00% |
| | NA | Percent | | | | |
| Live with Significant Other | 1.13% | 69.26% | | | | |
| | NA | Retired | Employed | Unemployed | Permanently Sick/Disabled | Homemaker |
| Current Job Situation | 2.50% | 56.80% | 26.80% | 2.80% | 3.40% | 7.70% |
| D. Macroeconomic Indicators | | | | | | |
| | Mean | Std. Dev | Min | Max | Obs | NA |
| Public Share of Health Expenditures | 77.91% | 6.11% | 66.06% | 87.60% | 13 | 5 |
| Employment Rate | 67.76% | 7.06% | 55.57% | 79.55% | 14 | 4 |
| GDP per Capita | 43.02704 | 16.19855 | 25.8234 | 91.0476 | 14 | 4 |
| GDP Growth Rate | 0.3214286 | 1.580739 | -1.7 | 4.3 | 14 | 4 |

Figure 1: Contractions over time (a)

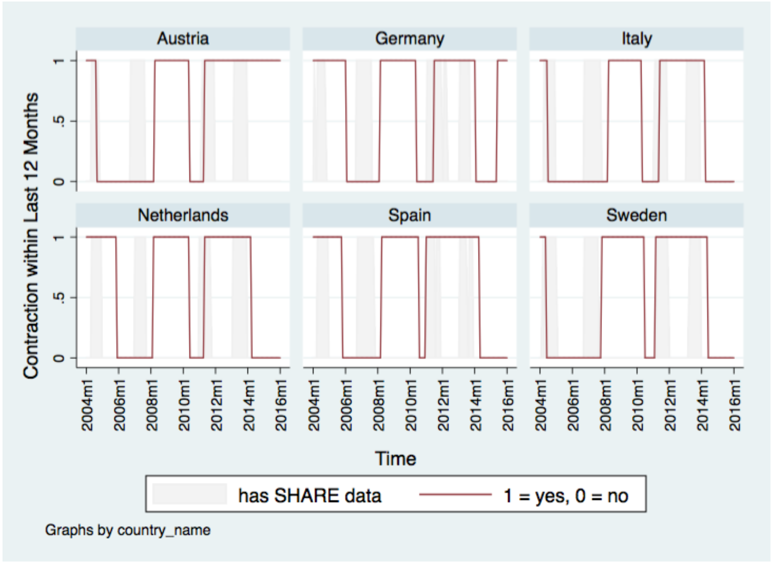



Figure 2: Contractions over time (a)

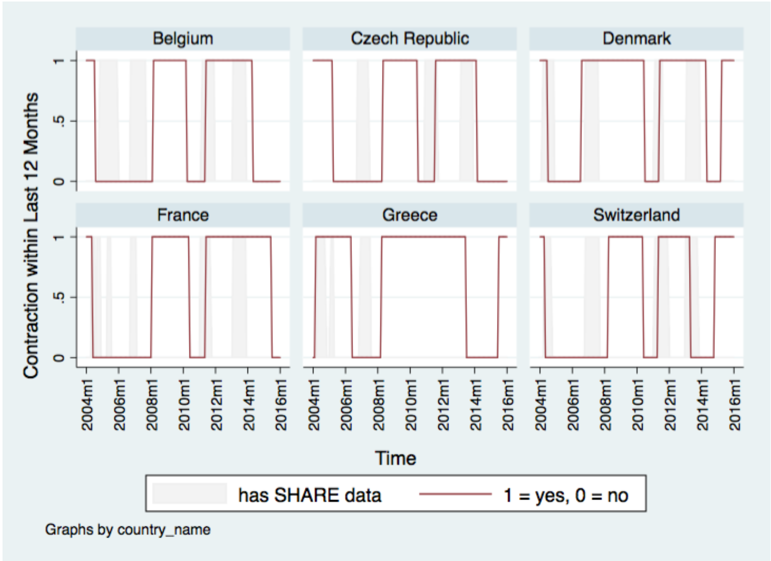
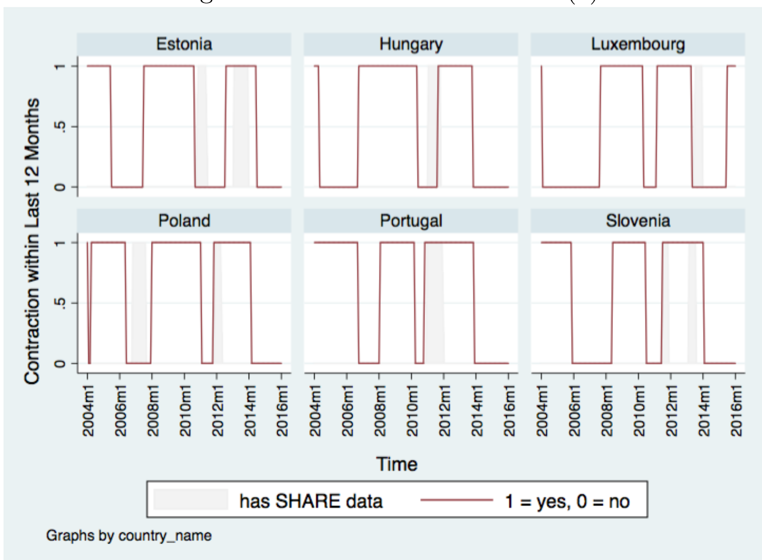


Figure 3: Contractions over time (a)




analysis of ($hc002\_$) with LCM using the variables discussed above. We interact income with the indicator for the presence of a contraction. We use country fixed effects to account for unobserved heterogeneity across countries. This can help adjust for factors like the structure of national healthcare institutions or cultural attitudes towards healthcare and treatment. We also use month of interview and year to compute two sets of time fixed effects. This accounts for seasonal variation in health, which, given that recall of medical experiences is likely to be imperfect and some health measures are sensitive to the date of interview, could otherwise bias results. Similarly, it is highly likely that there are time trends in healthcare utilization by year. Errors are clustered by household to account for correlation in the outcomes of family members living together (and sharing the same income). All sets of fixed effects and clustered standard errors are retained across all subsequent specifications. It is important to note that we have reason to believe that fixed effects are consistently estimated in this application. While Deb & Trivedi (2012) discuss the problems surrounding the estimation of fixed effects in non-linear models, we have far more data than their rough rule of thumb of $T \geq 8$; even Hungary has well over 1000 observations. We also run the model separately for contractionary periods and expansionary periods to enable us to calculate the posterior probabilities of individuals being healthy and unhealthy under each condition. This gives a business cycle-based estimate of the extent to which *healthcare need* may be driven by macroeconomic dynamics.

The previous specification allows analysis of how the business cycle moderates the impact of income on healthcare utilization. We are further interested in to what extent this relationship can be mitigated by public healthcare expenditure. To investigate this, we interact our measure of the share of healthcare expenditure that is public with both income and the interaction of income and contractions.

## 4.2 Equity Measures

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

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

Using this measure of need and the actual utilization as a measure of usage, we proceed to compute standard horizontal inequity measures found in the literature. We create horizontal inequity (HI) indices for each country with available data during two business cycle periods - contraction and expansion - by setting the contraction dummy to zero or one in our predictions. Note that while each individual to be compared is not "the same" per se, their health status is, and we consider the analysis that follows a lower bound on the inequity present in our data. Adjusting for all characteristics would only inflate the inequity measures by further attributing this variation to the "fairness" measure rather than actual use, as argued by Van Doorslaer (2004).

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

Finally, we calculate a horizontal inequity index $HI = C_m - C_n$. When $HI$ is positive (negative ) then the current distribution of healthcare use is pro-rich (pro-poor). Table 8 shows an $HI$ index for each country based along with confidence intervals for each country. We do this separately for contraction conditions and expansion conditions. We then can compute the difference in $HI$ between contrationary and expansionary periods for each country. We use a parametric bootstrap method with 1,000 repetitions to estimate confidence intervals around our LCM estimates. The bootstrap assumes that the parameters estimated in the LCM regression are distributed according to a multivariate normal distribution with means and covariances given by the estimation process. Each bootstrap iteration is conducted in two steps. First, we randomly draw a new vector of coefficients from the estimated distribution. Second, we use these new coefficients to generate new predicted values of healthcare usage, again at the mean value of the income variable. This results in 1,000 predicted values of $Need_i$, which we use to calculate the 2.5 and 97.5 percentile values of the horizontal inequity index under each condition and the difference between them.

# 5 Results & Discussion

## 5.1 Business Cycle Analysis

The first two columns of Table 6 present the results of the LCM incorporating business cycle and healthcare policy controls, with the contraction indicator interacted with income. Based on these results, we see that socioeconomic factors are statistically significant determinants of demand for doctor contacts. Those with post-secondary education demand significantly (1% level) more healthcare whether healthy or ill; those with higher secondary demand more when healthy (5%). This makes sense - the more educated are more likely to pursue precautionary health measures before their status deteriorates. Women are also significantly more likely (1%) to get healthcare when healthy - this coincides with the results of Deb & Trivedi (1997) and Cartwright, Hu, & Huang (1992), who argue that men put off treatment (like prevention) until they are quite ill. The share of health spending by the public sector increases doctor visits by the ill at the 1% level, but the impact for the healthy is not significant. This may at first seem surprising (given that the government foots the bill, people would be more likely to seek treatment) but is likely due to institutional details like additional rationing present under more public-concentrated systems. Growth does not have a significant effect for either class. Usage amongst the healthy is higher (1% level) when per capita income is higher, which makes sense for the "luxury" of precautionary treatment. However, among the ill, it is higher when employment is higher - in a better economy, we would generally expect higher health care usage, and even though a lot of these elderly people may not longer be in the job market, they likely base economic expectations on national macroeconomic aggregates like employment.

The impact of income is significant and positive during a contraction at the 1% for both the ill and the healthy - evidence that inequity is present during downturns. The significance of the interaction term at the 1% and 5% level respectively shows that income becomes more of a factor during downturns - equity worsens, as displayed in Table 7. The impact during an expansion is significant only for the healthy: given need (health status), income does not play a significant role in whether individuals can pursue healthcare. The impact of contraction on the healthy is insignificant and small for both healthy and ill.

These results indicate that the European elderly adjust their healthcare behavior in response to business cycle conditions and offer a first pass at the role of such conditions in shaping equity. Generally speaking, we find that economic conditions and socioeconomic conditions have a more profound impact on the healthy than the ill. This accords strongly with the fact that we expect the elasticity of demand for healthcare to be higher among the healthy than the ill by virtue of necessity. A final point is that the posterior probability of being healthy is higher under expansions than contractions, which is in tension with Gerdtham & Ruhm (2006) who argue that health outcomes are worse during good economic times.

We can draw three substantive conclusions about the reaction of healthcare demand to economic conditions. First, there is some evidence that economic conditions impact utilization for both the healthy and ill. Second, while the presence of contraction seems to lower preventative care for the healthy, for both classes, a substantial effect occurs through its interaction with income. That is, a contraction exacerbates the impact of income on healthcare utilization, lowering equity. Third, throughout the results, it is clear that the elasticity of healthcare usage is higher for the healthy (preventive care) than for the ill. Likewise, better educated individuals are more likely to pursue preventive care.

Table 6: Sensitivity of Demand to Socioeconomic Factors, Business Cycles, & Policy

| | Business Cycle | | Business Cycle & Policy | |
|---|---|---|---|---|
| | LCM (healthy) | LCM (ill) | LCM (healthy) | LCM (ill) |
| Female | 0.061*** | 0.010 | 0.061*** | 0.009 |
| | (0.006) | (0.017) | (0.006) | (0.017) |
| Primary Schooling | 0.006 | -0.015 | 0.007 | -0.014 |
| | (0.015) | (0.034) | (0.015) | (0.034) |
| Lower Secondary | 0.015 | -0.021 | 0.015 | -0.020 |
| | (0.015) | (0.037) | (0.015) | (0.037) |
| Higher Secondary | 0.030** | 0.050 | 0.032** | 0.052 |
| | (0.015) | (0.036) | (0.015) | (0.036) |
| Post-Secondary | 0.083*** | 0.114*** | 0.084*** | 0.116*** |
| | (0.015) | (0.037) | (0.015) | (0.037) |
| Income | 0.005*** | 0.006 | -0.024 | 0.002 |
| | (0.002) | (0.005) | (0.019) | (0.060) |
| $Income \times Contraction$ | 0.006*** | 0.012** | -0.011 | 0.017 |
| | (0.002) | (0.006) | (0.023) | (0.072) |
| Contraction | -0.035*** | -0.019 | -0.179 | -0.820* |
| | (0.013) | (0.041) | (0.154) | (0.483) |
| GDP (thousands) | 0.019*** | 0.008 | 0.024*** | 0.024** |
| | (0.003) | (0.009) | (0.004) | (0.010) |
| Growth | 0.000 | 0.004 | 0.002 | 0.008 |
| | (0.003) | (0.010) | (0.003) | (0.010) |
| Employment | 0.001 | 0.026*** | -0.002 | 0.017 |
| | (0.002) | (0.005) | (0.002) | (0.006) |
| Pubshare | 0.127 | 1.488*** | -0.319 | 0.636 |
| | (0.121) | (0.363) | (0.202) | (0.631) |
| $Pubshare \times Income$ | | | 0.038 | 0.006 |
| | | | (0.024) | (0.078) |
| $Pubshare \times Contraction$ | | | 0.190 | 1.060* |
| | | | (0.199) | (0.626) |
| $Pubshare \times Income \times Contraction$ | | | 0.023 | -0.007 |
| | | | (0.030) | (0.093) |
| $\pi_{Contraction}$ | 0.794 | 0.206 | 0.794 | 0.206 |
| $\pi_{Expansion}$ | 0.826 | 0.174 | 0.826 | 0.174 |
| K | 165 | | 171 | |
| N | 174,283 | | 174,283 | |
| LL | -482366.12 | | -482342.75 | |

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

Table 7: Interaction Effects for Business Cycles

| | Healthy | Ill |
|---|---|---|
| Effect of Income | | |
| Contraction | 0.011*** | 0.018*** |
| Expansion | 0.005*** | 0.006 |
| | | |
| Effect of Contraction | -0.001 | 0.045 |

*** indicates significance at the 1% level, ** at the 5%, and * at the 10%. Effects are calculated at the mean of income (5.5, given decile coding) and the mean of public spending, 0.767.

**Robustness Checks**

As noted above, individuals appear in the data up to four times (once per wave). However, over half of the individuals only appear in the data at a single point in time. Therefore, one might be concerned that our results are being driven by compositional effects, as individuals who appear in the data only once by definition will only appear during either a contraction or an expansion. As a robustness check, we therefore re-estimate our specification using only observations for individuals who appear in the dataset during both an expansion and a contraction. Our conclusions are not sensitive to this change.

## 5.2 Equity Measures

Table 8 displays the horizontal inequity index (HI) for each of the 15 countries with available data during both contractions and expansions. Of the 15 countries, 8 countries experiene horizontal inquity that favors the rich during both contractionary and expansionary times. Of these 8 countries, four of them (Austria, the Netherlands, Switzerland, and Poland) are significantly more pro-rich during contractions, which suggests a particularly undesirable form of horizontal inequity that harms poor elderly citizens in these countries.

During contractions, all (HI) measures are positive, or "pro-rich", except for Italy and Greece. Figure 6 shows that the HI measures range from -0.023 (Italy) to 0.043 (Austria) during recessionary times. The estimated values are significant at the 1% level for all except Spain, which is significant at the 10% level. While it is difficult to interpret the differences across countries, this is at worst suggestive evidence of a pro-rich bias in the vast majority of European countries studied. Greece's case is interesting - it likely reflects the government's run-up of fiscal spending prior to the financial crisis (all Greece data is pre-crisis).

During expansions, more countries are "pro-poor" (HI$<$0), either due to the fact that the poor make their budgets stretch to include a higher percentage of healthcare expenditure or the government can afford to better protect them. Figure 6 emphasizes that in particular, 4 of the 15 countries (Spain, France, Belgium, and the Czech Republic) are pro-poor during expansions, but become pro-rich during recessions, strengthening our previous hypothesis. The estimates range from -0.035 (Italy) to 0.038 (Denmark). All but France are significant at the 1% level.

Now, we can turn to a measure of the cyclicality - the difference of HI betweeen contractionary and expansionary periods for each country. The majority of estimates are positive, indicating that countries become more pro-rich during contractions - the poor, due to lower buffer stocks of precautionary spending, or because their incomes are more volatile, are less able to afford the healthcare that they need. Some HI changes, however, (Germany, Denmark, Greece, Hungary, and Estonia), are negative, indicating a movement towards pro-poor. This is indicative of social safety nets increasing to support the poor during downturns. All but Sweden's differences are significant at the 1% level. It is interesting that while these countries show a relative movement towards pro-poor, most remain pro-rich in both periods, as shown in Figure 6. Sweden is an interesting case - its HI does not change - suggesting the poor are fully insulated from economic fluctuations.

Figure 4 and Figure 5 present the two sets of concentration curves for the country with the most positive change, France (0.035), and most negative, Hungary (-0.044) The left panels represents expansions and the right contractions. The blue dots represent cumulative actual healthcare use by income decile, the red dots represent the cumulative estimated need by income decile, and the 45-degree line represent the relationship that would hold under "equality". Similar figures were computed for all countries but were omitted for brevity.

Table 8: Horizontal Inequity Index by Country and Conditions

| | Contraction | | | Expansion | | | Difference (Contraction-Expansion) | | |
|---|---|---|---|---|---|---|---|---|---|
| Country | HI | 0.025 pctl | 0.975 pctl | HI | 0.025 pctl | 0.975 pctl | HI | 0.025 pctl | 0.975 pctl |
| Austria | 0.043*** | 0.040 | 0.046 | 0.014*** | 0.011 | 0.016 | 0.029*** | 0.028 | 0.031 |
| Germany | 0.016*** | 0.013 | 0.020 | 0.021*** | 0.019 | 0.024 | -0.005*** | -0.007 | -0.003 |
| Sweden | 0.033*** | 0.029 | 0.037 | 0.033*** | 0.030 | 0.036 | 0 | -0.002 | 0.002 |
| Netherlands | 0.017*** | 0.014 | 0.020 | 0.011*** | 0.008 | 0.014 | 0.006*** | 0.004 | 0.008 |
| Spain | 0.002* | 0.000 | 0.005 | -0.018*** | -0.020 | -0.016 | 0.02*** | 0.019 | 0.022 |
| Italy | -0.023*** | -0.025 | -0.020 | -0.035*** | -0.037 | -0.033 | 0.012*** | 0.011 | 0.014 |
| France | 0.034*** | 0.031 | 0.038 | -0.001 | -0.003 | 0.002 | 0.035*** | 0.034 | 0.037 |
| Denmark | 0.019*** | 0.014 | 0.024 | 0.038*** | 0.034 | 0.042 | -0.019*** | -0.022 | -0.016 |
| Greece | -0.017*** | -0.021 | -0.011 | -0.009*** | -0.013 | -0.004 | -0.008*** | -0.009 | -0.006 |
| Switzerland | 0.015*** | 0.012 | 0.018 | 0.003*** | 0.000 | 0.006 | 0.012*** | 0.010 | 0.014 |
| Belgium | 0.007*** | 0.005 | 0.010 | -0.023*** | -0.025 | -0.021 | 0.03*** | 0.029 | 0.032 |
| Czech Rep | 0.007*** | 0.004 | 0.010 | -0.005*** | -0.007 | -0.002 | 0.012*** | 0.010 | 0.013 |
| Poland | 0.037*** | 0.036 | 0.039 | 0.01*** | 0.009 | 0.012 | 0.027*** | 0.027 | 0.028 |
| Hungary | -0.015*** | -0.018 | -0.013 | 0.028*** | 0.026 | 0.031 | -0.044*** | -0.044 | -0.043 |
| Estonia | 0.02*** | 0.017 | 0.023 | 0.028*** | 0.026 | 0.031 | -0.008*** | -0.009 | -0.007 |

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

## 5.3 Policy Analysis

The third and fourth columns of Table 6 repeat the analysis conducted above for business cycle measures with the addition of interactions of the public share of health expenditure with income and the contraction dummy, and a full interaction with both income and contraction. This allows us to study whether public health expenditure can mitigate the shift towards pro-rich inequity during economic downturns. The results for the impact of education and gender are qualitatively identical to those discussed earlier, so are not repeated here. Now, per capita GDP has a significant effect on health usage for both healthy and ill, significant at the 1% level for the healthy, as before, and the 5% level for the ill. Employment to longer has a significant impact on either class. As before, our posterior probabilities during contractions and expansions are at odds with the findings of Gerdtham & Ruhm (2006).

We can now turn to the impact of policy on inequity. We can calculate the degree to which income impacts healthcare demand during both good and bad times - shown in Table 9. For the healthy, income increases healthcare utilizations during both periods (at the 1% level), which makes sense with their higher elasticity. With the ill, the impact is only significant (at the 1% level) during contractions. During good times, the ill are able to afford to keep their healthcare utilization high, even if poor, in accordance with their relative inelasticity of demand.

We are interested in the impact that public policy can have on this relationship. First, public health expenditures increase healthcare usage during contractions for both the healthy and ill at the 1% and 10% level significantly. During expansions, the effect is not significant (and negative for the healthy) - their behaviour is less contingent on whether their spending is subsidized by the government. Looking at the

Figure 4: Concentration Curve for France

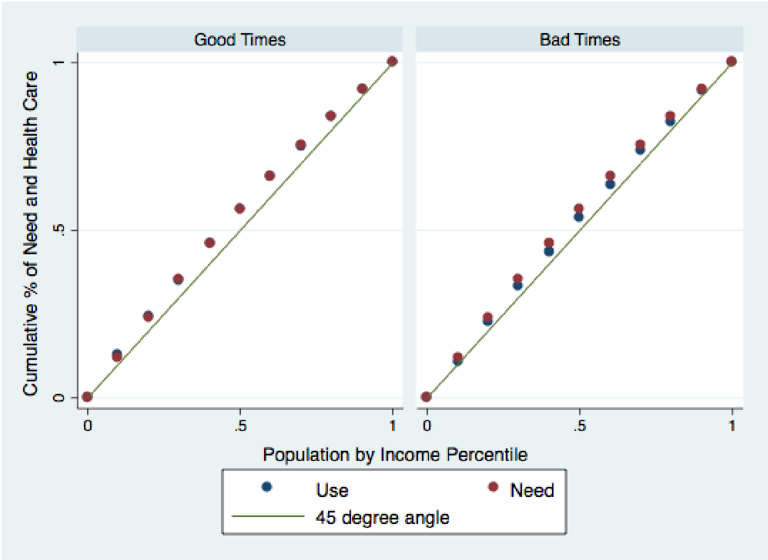



Figure 5: Concentration Curve for Hungary

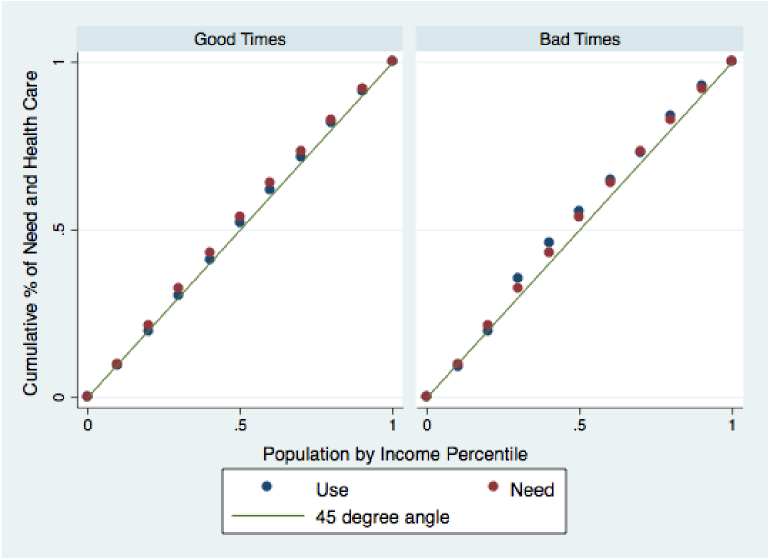
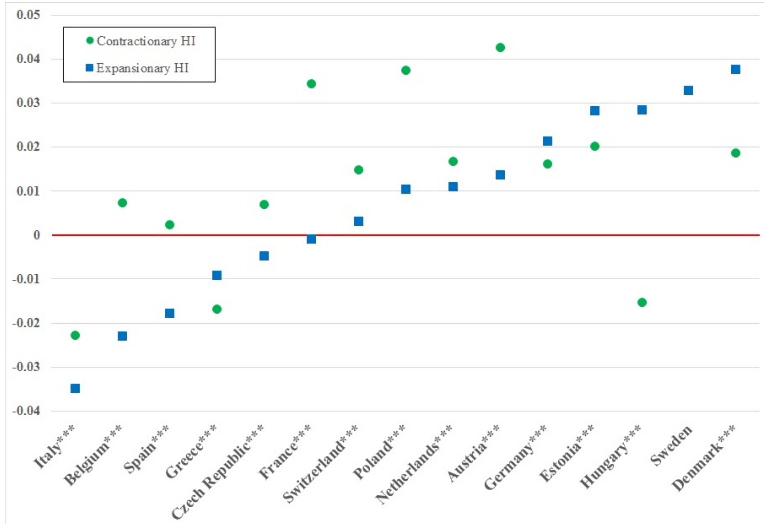



Table 9: Interaction effects for Public Policy Analysis

| | Healthy | Ill |
|---|---|---|
| Effect of Income | | |
| Contraction | 0.011*** | 0.018*** |
| Expansion | 0.005*** | 0.007 |
| | | |
| Effect of Public Share | | |
| Contraction | 0.203* | 1.691*** |
| Expansion | -0.113 | 0.668 |

*** indicates significance at the 1% level, ** at the 5%, and * at the 10%. Effects are calculated at the mean of income (5.5, given decile coding) and the mean of public spending, 0.767.

Figure 6: Horizontal Inequity (HI) During Contractions and Expansions By Country




interactions, during expansions, there is no significant impact of public health expenditure on the relationship between usage and income. Troublingly, the coefficients are actually positive - suggesting that higher public spending worsens equity - but thankfully this is not significant. During contractions, the impact of public share of expenditures is significant and positive on health usage at the 1% level for healthy and the ill at the 1% level. This suggests that on average, more public health spending means that economic contractions do not force individuals to decrease healthcare usage by as much. Spending has a negative effect on the relationship between income and healthcare usage during contractions, but it is not statistically significant.

# 6 Conclusion

We find that controlling for accurate measures of need, business cycles have a significant direct impact on healthcare usage. They also have an indirect effect working through widening of inequity, with income become a more important determinant of healthcare usage during downturns. We find that the healthy have a more elastic demand for healthcare (preventive in nature) than the ill, meaning that they are more likely to cut back during bad times. The more educated and women, other important socioeconomic indicators, are also more likely to pursue care while healthy. A final point is that the posterior probability of being healthy is higher under expansions than contractions, which is in tension with Gerdtham & Ruhm (2006) who argue that health outcomes are worse during good economic times. In general, the results are highly significant. Most countries become more pro-rich during contractions as the poor are not insulated from income loss, but some become more pro-poor during crises, likely due to an increase in the social safety net. The differences are highly significant. We find that while it has no significant effect during expansions, a higher share of public health spending means that economic contractions do not force individuals to decrease healthcare usage by as much as they would under a more highly privatized system.

These analyses can be used to make policy recommendations to European health care systems that will improve socioeconomic equity in health care access. For example, for many countries, it appears that the expansion of public healthcare expenditures during bad times - an explicitly countercyclical policy - would mitigate the extent to which healthcare usage skews towards pro-rich horizontal inequity.

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