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Abstract

Objectives with the health care system often include equity considerations. One objective is equal treatment for equal need. In this paper we explain the sources of income-related inequality in utilization of health care services in Funen County, Denmark, by linking survey data to register based data. A decomposition of the concentration index was used to explain the sources of overall income-related inequality in utilization. The decomposition approach suggests that health care is in general equally distributed in Denmark when need based variables are controlled for. However, this overall result is a consequence of a number of off-setting effects from different types of health care and a complicated pattern of various explanatory variables.

Keywords: health care, utilization, concentration index, inequality, decomposition

JEL classification: D20, D31, I10, I12

1. Introduction

The concentration index has become the standard method of estimating the degree of income-related inequality in utilization of health care (van Doorslaer et al., 2000), van Doorslaer et al., 1992). It is well known that there are inequalities in use of some types of health care. Lately, there has also been an increased focus on the sources of this inequality (van Doorslaer, Koolman, and Jones, 2004; van Doorslaer, Masseria and the OECD Health Equity Research Group Members, 2004). In several studies decompositions of concentration indices have been used to investigate the contributions to the magnitude of the inequality (Clarke, Gerdtham and Connelly, 2003; van Doorslaer and Koolman, 2004; van Doorslaer, Koolman and Jones, 2004; van Doorslaer, Masseria and the OECD Health Equity Research Group Members, 2004; Wagstaff, van Doorslaer and Watanabe, 2003). Furthermore, the decomposition approach can also be used to directly standardize for need (Gravelle, 2003). The principle for most studies of health care utilization is that people in equal need should be treated equally (Culyer, 1993; van Doorslaer et al., 2000). Therefore, need has to be taken into account when calculating concentration indices for equitable distributions. Excluding the contributions from need-based variables is equivalent to directly standardizing the concentration index for need (Gravelle, 2003).[1]

The present paper follows the lines of Clarke, Gerdtham and Connelly (2003) and Wagstaff, van Doorslaer and Watanabe (2003) and applied in Lauridsen et al. (2005). In Wagstaff et al. a multivariate regression approach was used for a decomposition of background characteristics. The regression approach assisted a decomposition of the single characteristic's impact on income-related inequality in health into 1) its regressive impact on the variation in health, and 2) the impact due to income-related inequality in the characteristic itself. In Clarke et al. a concentration index of health inequality was decomposed separately by health dimension and subgroup. The decomposition by dimension was a weighted average of concentration indices for each dimension (with the relative share of the aggregate health as weights). In Lauridsen et al. the decomposition by dimension from Clarke et al. was merged with the regression approach from Wagstaff et al. The concentration index was decomposed into the different dimensions of health summing up the index and the effect on health from different socio-economic characteristics.

In the present study the decomposition approach from Lauridsen et al. (2005) was applied on health care services. The concentration index for income-related inequality in health care utilization was decomposed into contributions from six different types of health care and from various explanatory variables including age, gender, health status, income, education, occupation, marital status and life style variables. The paper adds to existing literature by measuring health care utilization in monetary terms by using register-based data, and by including types of health care and explanatory variables that have not been included in previous studies.

2. Data

The data set used for the analysis is a combination of survey data and registers. 5,000 people living in Funen County, Denmark aged 16-80 were drawn from The Centralised Civil Register to participate in a health survey on health status, health behavior and socio-economic background. The sample was stratified with respect to municipalities, and the respondents have been weighted by the reciprocals of their selection probabilities (not taking internal non-response into account). The data were gathered through telephone interviews that took place in the period from October 2000 through April 2001 (Gundgaard and Sørensen, 2002).

The survey data were merged with data from individual level computerized registers including all somatic hospital visits, visits in the primary health care sector and prescription medicine in 2000 and 2001. Health care services were measured as the costs of the services and approximated by prices, charges or fees. Using registers to extract information on health care utilization makes it possible to obtain exact information about the health care services for a long period. The registers also make it possible to distinguish between types of health care that have normally not been included in previous studies: physiotherapy and prescription medicine. The health care services have been measured in monetary terms. The advantage of using a common unit of measurement is different types of services can be added together. Furthermore, the different services are weighted by the importance: A visit is not just a visit. Check-ups, for example, are weighted less than surgical treatments. Nevertheless, the charges and fees used are only crude approximations of the quality.

The hospital visits were extracted from Funen County Patient Administrative System (FPAS), which includes records on all inpatient stays, ambulatory and emergency room visits. Each hospital admission was described by an estimated charge based on the 2002 Danish case mix system of Diagnosis Related Groups (DRGs). The case mix system covers inpatient hospital stays, whereas ambulatory and emergency room visits are described by a similar, but a more simple system. Capital costs are not included in the case mix system. All charges were adjusted to 2003 price level for hospital treatments.

The visits in the primary health care sector were extracted from The Registry of Public Health Insurance. This registry includes all partly or fully reimbursed health services in the primary health care sector, i.e. from the general practitioners, physiotherapists, dentists and specialists. Each service is described with a reimbursement fee. As considerable co-payment exists for health care services from the dentist and the physiotherapist these fees have been adjusted to get the total amounts (reimbursement + co-payment).[2] Expert judgments were used to adjust the dentist fees to the average level of Funen dentist fees[3], whereas the relevant physiotherapist fees where adjusted by dividing the reimbursement fees with the proportion of reimbursement.[4] General practitioners are partly financed through capitation (about one third of GP income), and the GP reimbursement fees were scaled up by this amount. All reimbursement fees were inflation adjusted to 2003 by the price index for physicians and physiotherapists. Medicine was from Odense University Pharmacoepidemiologic Database (OPED). This database consists of all prescription refunds from Funen County. Each purchase of reimbursed medicine from a pharmacy in Funen County is described by a pharmacy retail price including VAT.[5] Medicine used at hospitals is included in the hospital charges. Furthermore, the database does not contain information on over-the-counter-medicine and prescription medicine not entitled to reimbursement (Hallas, 2001).[6] The pharmacy retail prices were inflation adjusted to 2003 level by the index for pharmaceutical products and equipment.

The ranking variable for the concentration index was income and this variable was defined as personal gross income from the previous year (gross of tax and deductibles) and measured as a categorical variable with 17 categories. The respondents were ranked according to their income category. Within the categories the respondents were ranked randomly.

To follow the practice from the literature the logarithm was taken of income to diminish the skewness for the inclusion of income as an explanatory variable in the regression models (van Doorslaer and Koolman, 2004; van Doorslaer, Koolman and Jones, 2004; van Doorslaer, Masseria and the OECD Health Equity Research Group Members, 2004).[7]

Other explanatory variables included age, gender, health status, socio-economic and lifestyle variables. Age and gender were described by categorical age and gender groups. Health status was measured at an interval scale using Danish EQ-5D TTO values. The scale takes values from 1 (perfect health) to 0 (dead). However, some respondents have negative values indicating health states worse than dead (Brooks, 1996a; Brooks, 1996b; Dolan, 1997; Wittrup-Jensen et al., 2001).[8]

Socio-economic variables were represented by dummy vectors for educational, occupational level and marital status. Lifestyle was characterized by dummy variables of being daily smoker, having a high weekly intake of alcohol (more than 21/14 units of alcohol for men/women), a daily intake of fruits and vegetables, and a sedentary lifestyle.

Due to non-response not all 5,000 people participated. 1,578 people were not interviewed for the health survey as they refused to participate, were not found, or were not able to participate for some other reason. This results in a survey of 3,422 respondents and an external response rate of 68 percent. However, not all the respondents answered all the relevant questions and had to be excluded from the study. As is common, income is a sensitive question that some people abstain from answering. Furthermore, people were also excluded due to lack of response to the questions regarding health. For the socio-economic and socio-demographic determinants missing answers were categorized in residual categories (like "other type of education" or "other type of job") in order to maintain people in the sample. The final working samples then consists of 2,915 respondents. This is equivalent to response rates of 58 percent.

Descriptive response/non-response analysis showed that the working sample is representative with respect to socio-demographic characteristics (Gundgaard and Sørensen, 2002). However, for almost all the types of health care the respondents use less health care than the non-respondents (although the proportion of users is about the same in the two groups).[9]

3. Modelling

As shown in Kakwani, Wagstaff and van Doorslaer (1997) the concentration index C can be estimated by the convenient OLS regression

$$2\sigma^2\left(\frac{y_i}{\mu}\right) = \alpha + \beta R_i + \varepsilon_i, \tag{1}$$

where y_i/μ is the relative consumption of health care services for individual i, R_i is the fractional income rank based on weights (the reciprocals of selection probabilities normalized to the sample size), and σ^2 is the variance of the fractional income rank. Then the OLS coefficient of the relative rank, $\hat{\beta}$, is equivalent to C.

For the purpose of decomposing C by income, need-standardizing variables, socio-economic and life style determinants it is assumed that health care is linked to these K determinants through a regression model:

$$y_i = f\left(\beta_I \ln x_{Ii} + \sum_Z \beta_Z x_{Zi} + \sum_S \beta_S x_{Si} + \sum_L \beta_L x_{Li}\right). \tag{2}$$

If (2) is a linear regression model then the concentration index can be decomposed as:

$$C = \frac{\beta_I \mu_I}{\mu} C_I + \sum_Z \frac{\beta_Z \mu_Z}{\mu} C_Z + \sum_S \frac{\beta_S \mu_S}{\mu} C_S + \sum_L \frac{\beta_L \mu_L}{\mu} C_L + \frac{1}{\mu} CG_\varepsilon \qquad (3)$$

where μ is the mean of y, and μ_k, β_k and C_k the mean, the regression coefficient and the concentration index of the kth determinant, respectively (Wagstaff, van Doorslaer and Watanabe, 2003). The decomposition is made up of two components: 1) The predicted concentration index, which is a deterministic component equal to the weighted sum of concentration indices of the K regressors, where the weight of x_k is simply the elasticity of y with respect to x_k. 2) A residual component, which is the generalized concentration index for ε, and reflects the income-related inequalities in health care that cannot be explained by variation in income.

If the link between health care and the K determinants is modeled as a non-linear regression model, which is normal for skewed data and data with a high share of zero-observations, then the relation in (3) no longer holds. However, a linear relationship can be approximated by the partial effects from a non-linear model (van Doorslaer, Koolman and Jones, 2004).

When aggregate health care is additively composed of health care from different sectors, which will be the case if health care is measured in monetary terms, then the concentration index for y can also be decomposed as a weighted average:

$$C = \sum_j w_j C_j \ , \qquad (4)$$

where C is the concentration index for y, C_j is the concentration index for sector j, and w_j is a weight attached to the jth sector and estimated as $w_j = \mu_j/\mu$, with μ_j and μ being the means of y and y_j respectively (Clarke, Gerdtham and Connelly, 2003). Each of the C_js can be decomposed as in (3). Substituting (3) for each sector into (4) gives:

$$\begin{aligned} C &= \sum_j w_j C_j = \sum_j w_j \left[\frac{\beta_{jI} \mu_I}{\mu_j} C_I + \sum_Z \frac{\beta_{jZ} \mu_Z}{\mu_j} C_Z + \sum_S \frac{\beta_{jS} \mu_S}{\mu_j} C_S + \sum_L \frac{\beta_{jL} \mu_L}{\mu_j} C_L + \frac{1}{\mu} CG_{\varepsilon j} \right] \\ &= \sum_j \frac{\beta_{jI} \mu_I}{\mu} C_I + \sum_{j,Z} \frac{\beta_{jZ} \mu_Z}{\mu} C_Z + \sum_{j,S} \frac{\beta_{jS} \mu_S}{\mu} C_S + \sum_{j,L} \frac{\beta_{jL} \mu_L}{\mu} C_L + \sum_j \frac{1}{\mu} CG_{\varepsilon j} \end{aligned} \qquad (5)$$

The betas can be estimated from sector specific regression models for health care utilization (Lauridsen et al., 2005). This decomposition contains contributions from six different types of health care and from various explanatory variables including age, gender, health status, income, education, occupation, marital status and life style variables.

The concentration index is standardized for need by estimating the augmented partial concentration index as in Gravelle (2003). This is equivalent to the horizontal inequity index in van Doorslaer, Koolman and Jones (2004). Gravelle (2003) suggests a direct standardization of the need based variables by excluding their contributions from the decomposition.[1]

$$HI = C - \sum_{j,Z} \frac{\beta_{jZ}\mu_Z}{\mu} C_Z \qquad (6)$$

It is not obvious whether or not the generalized concentration index should count as a contribution to the concentration index or the standardizing component. According to Gravelle (2003) both approaches are consistent estimates of the augmented concentration index. The present paper follows the style of van Doorslaer, Koolman and Jones (2004) and includes the generalized concentration index in *HI*.

4. Estimation

As is normal for health care data, the distribution is highly skewed to the right and have many zero-consumption-observations (Lipscomb et al., 1998; Manning, 1998). To deal with the problem of zero-consumption observations, a two-part regression model (TPM) is used to predict the level of health care consumption for each individual. The TPM consists of a logistic regression model to predict the probability of having non-zero consumption (part 1), and a semi-log linear regression model to predict the level of consumption given non-zero consumption (part 2). The dependent variable is log transformed to remove the skewness of the distribution, and the predicted values of log consumption are then retransformed using the smearing estimator (Manning, 1998). The advantage of using a TPM is that the probability of using health care services and the level of health services consumed for consumers are described by different functions as it is most likely not the same mechanisms that determine the barriers of starting to consume as the amount of health care consumed for people who are already consumers.

To approximate a linear model, partial effects for each of the variables included in the TPM were estimated using treatment effects. For each of the dummy variables the average partial effects were computed for the respondents who possessed the characteristic (van Doorslaer, Koolman and Jones, 2004; Wooldridge JM, 2002). For the continuous variables the average effects were computed by approximating the slope by predicting consumption for the observed values with small numbers added and subtracted to these values (van Doorslaer, Koolman and Jones, 2004).

To draw inference on the regression models and the *HI* the non-parametric bootstrap method was used with 1000 replications. The bootstrap method was adapted to reflect the stratified sampling with respect to municipalities. Within each municipality a 1000 resampled data sets were constructed with the sizes of the original municipal sample sizes. Adding the data sets from each of the municipalities together resulted in 1000 stratified resampled data sets. With such a large number of replications a few resampled data sets had “extreme” observations such as categorical variables with empty categories (17 resampled data sets could not be used). The bootstrapping was carried out for a little more than 1000 replications and the first 1000 usable resamples were used. All computations were repeated on each of the resampled data sets and the variability was used to obtain standard errors and confidence limits.

5. Results

Table 1 shows descriptive statistics and concentration indices and t-statistics for aggregate health care and for each of the health care sectors. Mean aggregate health care is estimated to DKK 18,102 for the two year period. The concentration index for aggregate health care utilization is estimated to -0.136 and is statistical significant indicating that health care is concentrated among the lower income groups. The biggest contributor is hospital visits with 64 percent of aggregate health care, and the concentration index for hospital visits constitute about 90 percent of the index value. The concentration indices for GP services and prescription medicine indicate that GP services and prescription medicine are also distributed unevenly with a concentration among the lower income groups. Dental treatments on the other hand are concentrated among the higher income groups. The concentration indices for physiotherapy and specialist treatment are not statistically significant.

Table 1. Descriptive statistics and concentration indices of aggregate health care and in each of the health care sectors.

	Mean(DKK)[a]	Std (DKK)	C	t-value[b]	Weight	Contrib	Contribpct
Hospital	11502	47490	-0.191	-4.33	0.635	-0.121	89.353
GP	1639	1826	-0.105	-8.94	0.091	-0.010	7.012
Physio	395	2243	-0.052	-0.86	0.022	-0.001	0.836
Specialist	578	1732	-0.048	-1.49	0.032	-0.002	1.127
Dentist	1680	1537	0.102	10.61	0.093	0.009	-6.969
Medicine	2307	5399	-0.092	-3.68	0.127	-0.012	8.641
Aggregate	18102	50079	-0.136	-4.60	1.000	-0.136	100.000

Notes: Data weighted by the reciprocals of their selection probabilities.
[a]Health care costs for a two year period, DKK.
[b]t-statistics from the regression model (formula (1)).

Table 2 shows descriptive statistics, concentration indices and t-statistics for each of the explanatory variables from the regression analysis shown in formula (2). The concentration index applied on income reduces the index to a Gini-coefficient. However, to follow the practice from the literature the natural logarithm has been taken of income to reduce the skewness of the income distribution, and the concentration index then represents the Gini-coefficient of the logarithm of income. Income inequality is one source of income-related inequality in health care utilization. Males and females aged 31-45 and 46-60 are significantly better off than the rest of the age groups with respect to income, while males and females aged 61-70 and 71-80 are significantly worse off than the rest of the age groups indicating that income is highest for the middle aged.

Table 2. Descriptive statistics and concentration indices for each of the 36 explanatory variables

	Mean[a]	Std	C	t-value[b]
ln(income)	11.986	0.770	0.034	135.35
Male (31-45)	0.147	0.354	0.462	19.03
Male (46-60)	0.149	0.356	0.436	17.96
Male (61-70)	0.057	0.231	-0.088	-2.03
Male (71-80)	0.032	0.176	-0.286	-4.87
Female (16-30)	0.110	0.313	-0.481	-16.52
Female (31-45)	0.157	0.364	0.089	3.61
Female (46-60)	0.124	0.329	0.014	0.50
Female (61-70)	0.062	0.240	-0.426	-10.37
Female (71-80)	0.036	0.187	-0.508	-9.35
Low education	0.650	0.477	-0.008	-1.06
Medium education	0.148	0.355	0.327	13.13
Other education	0.138	0.345	-0.576	-23.51
Skilledworker	0.145	0.353	0.237	9.29
White-collarworker	0.307	0.461	0.347	23.61
Selfemployed	0.043	0.203	0.555	11.25
Assisting spouse	0.005	0.069	-0.192	-1.24
Housewife	0.014	0.118	-0.607	-6.86
Apprentice	0.015	0.122	-0.551	-6.41
Student	0.103	0.305	-0.708	-24.72
Retired	0.188	0.391	-0.371	-17.54
Unemployed	0.021	0.144	-0.338	-4.67
Other job	0.061	0.24	0.119	2.84
Cohabitant	0.146	0.354	0.063	2.43
Separated	0.007	0.085	0.129	1.03
Divorced	0.053	0.224	0.079	1.74
Widowed	0.047	0.212	-0.321	-6.72
Alone	0.192	0.394	-0.374	-17.99
Other	0.002	0.042	0.138	0.54
Daily smoker	0.357	0.479	-0.022	-1.54
High alcohol	0.103	0.304	0.023	0.72
Vegetables, cooked	0.294	0.456	0.022	1.34
Vegetables, raw	0.286	0.452	0.048	2.83
Fruit	0.595	0.491	-0.011	-1.21
No exercises	0.103	0.305	-0.069	-2.18
EQ-5D score	0.896	0.155	0.013	7.35

Notes: Weighted by the reciprocals of their selection probabilities
[a]Max,min for ln(income): (10.127,13.561) for EQ-5D score: (-0.266,1) for all other variables: (0,1)
[b]t-statistics from the regression model (formula 1)

Low education (short or no education) is distributed among the lower income classes whereas medium education (post secondary education but not university degree) is distributed more amongst the higher income classes. With respect to occupational status, the skilled workers, white-collar workers and self-employed are distributed among the higher income classes, whereas the rest of the occupational groups are distributed among the lower income groups.

When it comes to the lifestyle variables the concentration indices for smoking and excessive alcohol consumption are not statistical significant (but present the expected signs, however). Daily consumption of raw vegetables is distributed among the higher income groups, and daily consumption of fruit and a lifestyle without physical exercises are distributed among the lower income classes.

The concentration index for health status (the EQ-5D score) is positive and significant indicating that good health is concentrated among the higher income classes.

Table 3. Partial effects of the two-part-models for health care consumption.

	Hospital	GP	Physiotherapy	Specialist	Dentist	Medicine	Aggregate
ln(income)	859.8	-10.3	136.6*	89.3*	342.4***	55.1	1908.5**
Male (31-45)	-2284.4	17.6	-13.2	1.3	200.7	236.5**	-638.8
Male (46-60)	-497.8	-32.2	-180.6	67.5	709.2***	1610.5***	3147.7*
Male (61-70)	4655.0	341.7	66.7	190.6	453.6**	3794.6***	6160.3
Male (71-80)	18610.6*	1371.0***	-88.8	251.9	-11.2	7382.6***	21893.3***
Female (16-30)	3552.7*	1401.5***	28.2	181.7***	52.3	336.4***	5798.8***
Female (31-45)	-977.0	738.0***	-11.2	140.2	422.8***	745.2***	4283.3***
Female (46-60)	-2386.8	743.8***	177.9	246.2**	873.7***	3262.8***	8750.3***
Female (61-70)	-10767.1	791.5***	237.7	260.1*	459.1***	6789.1***	9051.8**
Female (71-80)	-989.7	1949.8***	769.2	958.1***	121.9	10922.1***	30712.8***
Low education	-1819.0	50.0	-81.7	-115.7	193.4	-1018.3	-335.4
Medium education	-2856.7	-131.3	100.8	-165.6	317.0*	-981.1*	-816.5
Other education	-4189.5	75.4	-298.9	-157.0	171.1	-637.3	-1377.3
Skilled worker	-98.4	-17.1	73.7	-216.4***	-58.3	-86.4	149.7
White-collar worker	639.3	-87.6	105.8	-108.6	-20.6	35.2	484.7
Selfemployed	4306.6	-78.9	216.4	-58.4	183.0	-112.1	3052.9
Assisting spouse	-2011.0	-877.1	700.5	-396.1	-74.6	-1705.6*	-5291.6
Housewife	6336.3	439.2	319.5	233.0	647.0*	2282.6	9385.6*
Apprentice	3284.9	160.1	404.6	210.7	-25.2	298.3	3428.3
Student	682.8	-188.4	82.4	0.5	-59.4	164.8	-5.1
Retired	19912.9***	250.4	518.5***	36.5	-3.0	3025.7***	14442.8***
Unemployed	11685.9	520.8	435.9	-27.9	309.5	1908.1*	14459.9**
Other job	5219.4*	-159.0	116.6	13.3	-4.6	-249.4	3343.0
Cohabitant	-1959.3	-38.5	-37.0	-114.5	-105.7	-313.0***	-2226.2**
Separated	-7035.8	1022.8*	250.8	-61.5	-593.5*	-1349.1	-5131.9
Divorced	5716.0	332.9	-458.0*	-101.8	-43.9	541.6	4156.6
Widowed	-7440.7	237.9	-676.2**	-387.1**	26.7	114.4	-5920.6
Alone	-2310.7	-122.1	48.8	-85.2	-247.0***	-75.2	-2941.2***
Other	-10074.8**	618.8	-530.1***	-553.7***	-609.1	-110.9	-5797.5
Daily smoker	1203.8	5.0	-86.6	-91.2	-70.6	-547.5**	-725.3
High alcohol	-821.8	-233.8**	-76.5	-49.4	-1.5	310.6	724.0
Vegetables, cooked	1322.9	160.4*	-88.4	-1.9	-11.2	472.3	1709.1
Vegetables, raw	1866.5	70.6	23.2	87.6	64.4	24.6	1811.6*
Fruit	4761.8***	225.8***	-34.0	58.2	109.8	451.8*	4682.8***
No exercises	1884.1	89.3	153.4	-21.1	-211.9*	727.3	1771.5
EQ-5D score	-33593.7***	-3290.0***	-1529.8***	-912.0***	-584.5***	-7067.7***	-47976.1***

Notes: Bootstrapped SE to indicate significance.
***Indicates coefficient estimates significantly different from zero at the 1 percent level.
**Indicates coefficient estimates significantly different from zero at the 5 percent level.
*Indicates coefficient estimates significantly different from zero at the 10 percent level.

In Table 3 the average partial effects are shown for all the explanatory variables for each of the seven TPMs. The TPMs can be interpreted as reduced form demand functions for health care. For (log of) income the partial effects are positive and significant only for dental services and aggregate health care. For the rest of the sectors the partial effects are statistically insignificant at a 5 percent level of significance.

Age and gender are important in some of the sectors. For aggregate health care women consume statistically more than the reference group of male 16-30. This effect is increased for the higher age groups. The pattern is similar for prescription medicine and GP visits. For hospital contacts, however, age and gender do not seem to matter in a model when health status is controlled for.

Education, marital status and occupational status are of little importance with the exception of being retired, which does have a positive influence on health care utilization in some of the sectors.

The life style variables like smoking and alcohol consumption do not seem to have an influence on health care consumption as could have been expected. However, their influence probably works through a lower health status, which is controlled for by the EQ-5D score. The partial effect of the EQ-5D score is negative and significant for aggregate health and for all the health care sectors at a 1 percent level of significance.

The overall decomposition of the concentration index is presented in Table 4. Summing all the contributions from different sectors and various explanatory variables result in the predicted concentration index. This is equivalent to the first four terms on the right hand side of formula (5). The generalized concentration index is estimated as the residual term (the difference between the observed and predicted concentration index). The generalized concentration index is relatively small as most of the inequality is explained by the explanatory variables. However, for some of the health care sectors the generalized concentration is rather big. One reason for this is that the generalized concentration index consists of unexplained variation as well as the approximation error from the linear approximation. Positive contributions increase the size of the inequality and negative contributions decrease the size of inequality (or increase inequality in favor of the lower income groups). The biggest contributors to the concentration index come from (log of) income, health status and being retired.

In Table 5 the contributions are categorized into types of variables according to formula (2). The need based variables consist of the age and gender dummies and the EQ-5D health status variable. The HI index is estimated as all the categories added together excluding the need variables, but including the error term (the generalized concentration index). Bootstrapping standard errors have been computed to indicate statistical significance. When standardizing for need, the income-related inequality for aggregate health care is no longer statistically significant. However, for prescription medicine and dentistry significant inequality in favor of the higher income groups emerges, and in the hospital sector we see that the inequality in favor of the lower income groups is still significant.

Tabel 4. Decomposition of C: Contribution from each health care sector and explanatory variable in percent of predicted concentration index[a].

	Hospital	GP	Physiotherapy	Specialist	Dentist	Medicine	Aggregate
ln(income)	18.14	-0.22	2.88*	1.88*	7.23***	1.16	31.08
Male (31-45)	-7.95	0.06	-0.05	0.00	0.70	0.82**	-6.41
Male (46-60)	-1.65	-0.11	-0.60	0.22	2.35***	5.34***	5.56
Male (61-70)	-1.19	-0.09	-0.02	-0.05	-0.12	-0.97*	-2.44
Male (71-80)	-8.68	-0.64***	0.04	-0.12	0.01	-3.44***	-12.84**
Female (16-30)	-9.60*	-3.79***	-0.08	-0.49**	-0.14	-0.91***	-15.01***
Female (31-45)	-0.70	0.53***	-0.01	0.10	0.30***	0.53***	0.76
Female (46-60)	-0.22	0.07	0.02	0.02	0.08	0.29	0.26
Female (61-70)	14.41	-1.06***	-0.32	-0.35*	-0.61***	-9.08***	2.98
Female (71-80)	0.93	-1.84***	-0.73	-0.90***	-0.11	-10.30***	-12.95
Low education	0.50	-0.01	0.02	0.03	-0.05	0.28	0.77
Medium education	-7.09	-0.33	0.25	-0.41	0.79*	-2.43*	-9.22
Other education	17.05	-0.31	1.22	0.64	-0.70	2.59	20.49
Skilled worker	-0.17	-0.03	0.13	-0.38***	-0.10	-0.15	-0.71
White-collar worker	3.49	-0.48	0.58	-0.59	-0.11	0.19	3.08
Selfemployed	5.27	-0.10	0.26	-0.07	0.22	-0.14	5.45
Assisting spouse	0.09	0.04	-0.03	0.02	0.00	0.08	0.20
Housewife	-2.79	-0.19	-0.14	-0.10	-0.28*	-1.00	-4.51
Apprentice	-1.39	-0.07	-0.17	-0.09	0.01	-0.13	-1.84
Student	-2.56	0.71	-0.31	0.00	0.22	-0.62	-2.56
Retired	-71.06***	-0.89	-1.85***	-0.13	0.01	-10.8***	-84.72***
Unemployed	-4.29	-0.19	-0.16	0.01	-0.11	-0.70*	-5.44
Other job	1.95	-0.06	0.04	0.00	0.00	-0.09	1.84
Cohabitant	-0.92	-0.02	-0.02	-0.05	-0.05	-0.15*	-1.20
Separated	-0.33	0.05	0.01	0.00	-0.03	-0.06	-0.37
Divorced	1.21	0.07	-0.10	-0.02	-0.01	0.12	1.27
Widowed	5.76	-0.18	0.52**	0.30**	-0.02	-0.09	6.29
Alone	8.50	0.45	-0.18	0.31	0.91***	0.28	10.27
Other	-0.13	0.01	-0.01	-0.01	-0.01	0.00	-0.14
Daily smoker	-0.49	0.00	0.03	0.04	0.03	0.22	-0.17
High alcohol	-0.10	-0.03	-0.01	-0.01	0.00	0.04	-0.10
Vegetables, cooked	0.44	0.05	-0.03	0.00	0.00	0.16	0.62
Vegetables, raw	1.30	0.05	0.02	0.06	0.04	0.02	1.49
Fruit	-1.55	-0.07	0.01	-0.02	-0.04	-0.15	-1.81
No exercises	-0.68	-0.03	-0.06	0.01	0.08	-0.26	-0.95
EQ-5D score	-20.76***	-2.03***	-0.95***	-0.56***	-0.36***	-4.37***	-29.04***
Pred.CI	-65.25***	-10.68***	0.25	-0.71	10.11***	-33.72***	-100.00***

Notes: Bootstrapped SE to indicate significance.
[a]The contributions have been multiplied by -1 to maintain the original signs of the contributions.
***Indicates coefficient estimates significantly different from zero at the 1 percent level.
**Indicates coefficient estimates significantly different from zero at the 5 percent level.
*Indicates coefficient estimates significantly different from zero at the 10 percent level.

As could be expected (log of) income contributes positively to income-related inequality. However, this is not the case for GP services where income contributes negatively. Except for dental treatments the need based variables exhibit a negative contribution to inequality in all health sectors. That is, controlling for need the size of the inequality diminishes. The socio-economic variables and life style variables contribute positively in some sectors and negatively in others, and there is no clear pattern.

Tabel 5. Decomposition of C: Contribution from each health care sector and explanatory variable

	Hospital	GP	Physiotherapy	Specialist	Dentist	Medicine	Aggregate
Decompositions in each sector separately							
Income	0.031	-0.003	0.143*	0.064*	0.084***	0.010	0.034
Need	-0.060*	-0.106***	-0.132***	-0.072***	0.024***	-0.187***	-0.075***
Socio-econ	-0.080***	-0.018	0.003	-0.018	0.008	-0.109***	-0.066***
Lifestyle	-0.002	0.000	-0.001	0.003	0.001	0.000	-0.001
Error	-0.080*	0.022*	-0.064	-0.024	-0.016*	0.194***	-0.028
Obs. C	-0.191***	-0.105***	-0.052	-0.048	0.102***	-0.092***	-0.136***
HI	-0.131***	0.001	0.080	0.024	0.078***	0.095***	-0.061*
Weighted by contribution							
Income	0.020	0.000	0.003*	0.002*	0.008***	0.001	0.034
Need	-0.038*	-0.01***	-0.003***	-0.002***	0.002***	-0.024***	-0.075***
Socio-econ	-0.051***	-0.002	0.000	-0.001	0.001	-0.014***	-0.066***
Lifestyle	-0.001	0.000	0.000	0.000	0.000	0.000	-0.001
Error	-0.051*	0.002*	-0.001	-0.001	-0.001*	0.025***	-0.028
Obs. C	-0.121***	-0.010***	-0.001	-0.002	0.009***	-0.012***	-0.136***
HI	-0.083***	0.000	0.002	0.001	0.007***	0.012***	-0.061*

Notes: Bootstrapped SE to indicate significance.
***Indicates coefficient estimates significantly different from zero at the 1 percent level.
**Indicates coefficient estimates significantly different from zero at the 5 percent level.
*Indicates coefficient estimates significantly different from zero at the 10 percent level.

6. Discussion

For this study a health survey was merged with various individual level computerized registers to give a more precise measure of health care consumption than the self-reported number of visits you often find in health surveys. The analysis showed that lower the income groups consume a bigger share the health care services than the higher income groups. After standardization for age, gender and health status there is no significant horizontal inequity for aggregate health care use at a 5 percent level of significance. This suggests that the Danish health care system is not in general inequitable in terms of horizontal inequity. In two sectors, however, a different picture emerges. For specific types of care the least advantaged have a lower share of the prescription medicine and dental treatments than expected. In the hospital sector, on the other hand, the need based variables cannot explain the high concentration of hospital treatment among the lower income groups.

The decomposition analysis showed that health care inequality is a diversified matter, and an overall measure of income-related inequality may be too crude to measure health care inequality for specific purposes. Policies combating inequalities in health care might not show any changes in the overall index if decreases in inequality in one type of health care are offset by increases in another. Therefore, it is relevant to know the sources of health care inequality.

Lifestyle variables were included as explanatory variables in this study as it is well documented that smoking, alcohol habits, and diet and activity patterns have a big influence on health (Ferrucci et al., 1999; McGinnis and Foege, 1993; Oguma et al., 2002; Paffenbarger Jr. et al., 1993). The life style variables, however, did not seem to contribute significantly to inequality, at least not directly. Although lifestyle behavior is sometimes rooted in firmly cemented cultural habits, the possibilities of health policy initiatives might still have better chances of altering lifestyles than socio-economic and socio-demographic conditions.

In van Doorslaer, Masseria and the OECD Health Equity Research Group Members (2004) health care services are measured by the number of visits extracted from household surveys in 21 OECD countries. They found significant pro-poor income-related inequality in inpatient hospital care and GP visits in Denmark. When standardizing for need the inequality vanished for hospital care, but not for GP visits, whereas in the present study the inequality vanished for GP visits but not for hospital care. For dental visits there is agreement between the two studies. Both found income-related inequality in dental care in favor of the higher income groups, with or without standardization. For specialist treatment there is a serious deviation between this study and other studies. The present study found no significant inequality in specialist care. When standardizing for need significant inequality for specialist treatment is found in most countries, including Denmark.

The survey data made it possible to gather information on variables, like self-perceived health status that can normally not be found in registers. The use of survey data, however, limited the size of the population, which could have been considerably bigger, had the data only consisted of registers. The use of survey data also caused non-response. The non-response analysis suggested that the non-respondents had a higher level of health care consumption than respondents. The survey data were gathered through telephone interviews. This means that people too weak to have a telephone conversation obviously are not included in the study. This could be one explanation for the higher level of health care consumption among the non-respondents for most types of health care. The income variable was taken from the health survey. Income is a sensitive question and a large fraction of the respondents were reluctant to answer that question. 485 respondents were left out of the analysis due to missing observations with respect to income.[10]

The study covers only somatic hospital treatment and services that are subject to partial or complete reimbursement by the Public Health Insurance. For most types of health care there is no co-payment (although private for-profit supply of some health care services does exist). For dentistry, however, a considerable share of the services is not reimbursed at all, and these services are not included in the database. If income-related inequalities exist they are most likely bigger for the kind of services the patients have to pay for. Therefore, the concentration index for dentistry is certainly a conservative estimate.

For medicine only prescription medicine in the primary health care sector entitled to reimbursement is in the database. In addition, prescription medicine bought from pharmacies outside Funen County, medicine used in hospitals, and illegal purchases of medicine over the internet are not covered by the database either (medicine used in hospitals is included in hospital charges).

The health care data were limited to two years (2000 and 2001). The longer the period is, the smaller is the problem of zero consumption data and random fluctuations. However, the health status indicators are point estimates, and will be less valid as standardization variables for health care consumption taken place too long before or after the time of the interview.

As a proxy for need for health care EQ-5D values were used. Health status as a proxy for need for health care services is common in the literature (Van der Heyden et al., 2003; van der Meer, van den Bos and Mackenbach, 1996, van Doorslaer et al., 2000; van Doorslaer, Masseria and the OECD Health Equity Research Group Members, 2004). Health status is not always a good proxy for need for health care. Some products are taken for the preventive effect. Furthermore, when treatment cures the illnesses the need for health care is not accounted for by the health status indicators, which might show good or perfect health as a result of the treatment. For dental care the health status variables seem to be particular inappropriate as general health status cannot be expected a good proxy for dental health status. If preferable the EQ-5D score could be excluded from the need component in formula (6).

7. Conclusion

The decomposition approach suggests that health care is in general equally distributed in Denmark when need based variables are controlled for. The overall result is a consequence of a number of off-setting effects from different types of health care and a complicated pattern of various explanatory variables. The analyses show that decompositions can be useful when using concentration indices to estimate income-related inequality in health care. Different health care sectors contribute to inequality in aggregate health care to a varying degree. Therefore, decompositions contribute with information about the importance of the different health care sectors and off-setting effects, that would otherwise have been missed in the aggregate data.

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Notes

1. In the literature the terms ’direct’ and ‘indirect’ standardization are used in different ways. Here the approach from Gravelle is used.
2. About 18 percent of all health care expenditures in Denmark are financed directly by the patients.
3. For dentistry the size of the co-payment is attributable to the specific service and varies between 35% and 100%. Expert judgments were used to get a more accurate description of the price level of the different services as there is no clear relationship between the reimbursements and the full prices.
4. For physiotherapy the co-payment is the same percentage for all the services, 61%, although some patients are exempt from co-payment.
5. For prescription medicine the co-payment follows the individual at a decreasing rate, such that large-scale consumers of medicine face a lower percentage of co-payment.
6. Prescription medicine such as oral contraceptives, benzodiazepines and certain antibiotics is not entitled to reimbursement.
7. As an explanatory variable income was treated as a continuous variable by using midpoints.
8. Only five people had negative scores and they were included in the sample.
9. Presumably a group of people is missing from the survey due to bad health and is expected to have a higher level of consumption of health care, than what we see among the respondents. A comprehensive non-response analysis will be carried out in a separate article.
10. The income variable from the health survey has been validated against income from national registers and there are no signs of important differences between the observed income and the income from registers.

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