Measurement Issues in Subsidy Provision - A Case Study of Switzerland

Master of Science Quantitative Economics (M1)
Measurement Issues in GDP, Poverty and Inequality

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Abstract: In this paper, I investigate the impact of a doctor visit subsidy on income distribution, poverty, and healthcare utilization in Switzerland, using microdata from the easySHARE 9.0.0 dataset. My analysis focuses on the Swiss sub-sample of the Survey of Health, Ageing and Retirement in Europe (SHARE), which provides harmonized panel data for individuals aged 50 and above. I begin by examining the determinants of doctor visit frequency through an OLS model, accounting for demographic and health-related characteristics while carefully avoiding bad controls and endogeneity bias. I then simulate a €10 per-visit subsidy, first assuming no behavioral response and later incorporating demand elasticity to account for price sensitivity. My results show that the subsidy modestly reduces poverty and inequality, particularly benefiting older, lower-income, and less healthy individuals. While the subsidy leads to a modest 8% increase in average doctor visits under the behavioral response scenario, its redistributive effects remain limited. Specifically, the change in poverty rates is negligible, and inequality indicators such as the Atkinson and Theil indices decline only marginally. Overall, the subsidy has a small but directionally progressive effect, offering higher relative benefits to lower-income and less healthy individuals. However, due to the flat structure of the transfer and its limited magnitude, its impact on reducing poverty is minor.

Key-words: Measurement Issues, Health Subsidies, Switzerland, Econometric Applications

1. Introduction

This analysis is based on the easySHARE version 9.0.0 of the Survey of Health, Ageing and Retirement in Europe (SHARE), which harmonises nine waves of longitudinal data collected across more than 25 European countries and Israel. The easySHARE dataset simplifies the full SHARE data for training and teaching purposes and maintains a subset of key variables. For this paper, I subsequently will focus on the Swiss sub-sample. SHARE respondents are selected using a stratified, probability-based sampling method, with adjustments for nonresponse and differential attrition over time. The dataset is representative of the population aged 50 years and older living in private households in Switzerland.[1] All data are collected through computer-assisted personal interviews (CAPI), and harmonised across countries and waves. To begin the empirical analysis, I present summary statistics for key socio-demographic and economic variables in the following section.

Descriptive Overview of the Swiss SHARE Sample

The variables I selected for the descriptive analysis are of continuous, discrete, and categorical data nature. I focused on the main socio-demographic variables (gender, age (at reporting), employment status and household

[1] See `https://share-eric.eu` for documentation on SHARE sampling design.

income) and further included years of education as well as the self-perceived health status, which capture long-run socioeconomic background and are one of the key determinants of both income and health. Age (age), years of education (eduyears_mod), household income (*thinc_m*), and household size (hhsize) are therefore treated as continuous variables, although in practice household size takes on integer values only. Gender is captured as a binary indicator variable (female = 1, male = 0). Employment status and self-rated health (sphus) are categorical variables with mutually exclusive, unordered categories. I present the latter in a relative frequency format across survey waves to illustrate changes in the sample's composition over time. As I want to analyze cross-country variances in household income longitudinal later on, the tables are separated for each variable per wave.

Wave	Obs	Mean	SD	Min	Max
1	995	64.28	11.26	29.4	95.8
2	1498	64.68	10.73	33.4	98.2
3	1324	66.28	10.55	29.3	100.2
4	3784	64.96	10.51	30.4	101.7
5	3048	66.51	10.02	33.7	97.4
6	2803	68.38	9.84	30.6	99.6
7	2402	69.99	9.57	37.8	100.5
8	2095	70.63	9.83	32.6	99.3
9	1844	71.86	9.36	36.9	100.7

Table 1: Age

Wave	Obs	Mean	SD	Min	Max
1	707	11.08	4.60	1	25
2	1441	11.29	4.63	1	25
3	1214	11.28	4.63	1	25
4	3481	8.57	5.31	0	25
5	2825	8.67	5.33	0	25
6	2608	8.69	5.35	0	25
7	2239	8.73	5.34	0	25
8	1962	8.73	5.47	0	25
9	1732	8.63	5.51	1	25

Table 2: Years of Education

Wave	Obs	Mean	SD	Min	Max
1	997	0.55	0.50	0	1
2	1498	0.56	0.50	0	1
3	1324	0.57	0.49	0	1
4	3784	0.55	0.50	0	1
5	3048	0.55	0.50	0	1
6	2803	0.55	0.50	0	1
7	2402	0.55	0.50	0	1
8	2095	0.54	0.50	0	1
9	1844	0.55	0.50	0	1

Table 3: Female (Dummy)

Wave	Obs	Mean	SD	Min	Max
1	996	52178.03	48949.57	24.06	466756.5
2	1489	54053.28	66893.31	5.77	662811.1
3	0	–	–	–	–
4	3778	69530.77	57104.52	0.15	659488.2
5	3029	60034.58	44211.69	53.84	737836.1
6	2795	54282.69	41030.22	3.75	511863.1
7	754	50250.71	38633.60	110.61	272283.1
8	2084	51369.86	34975.03	16.08	389323.8
9	1840	57238.57	76059.15	25.81	2264857.2

Table 4: Household Income (EUR)

Wave	Obs	Mean	SD	Min	Max
1	997	1.98	0.90	1	7
2	1498	2.10	0.99	1	6
3	1324	2.02	0.89	1	6
4	3784	2.12	0.94	1	10
5	3048	2.07	0.85	1	7
6	2803	1.98	0.79	1	7
7	2402	1.90	0.74	1	7
8	2095	1.87	0.75	1	7
9	1844	1.82	0.73	1	7

Table 5: Household Size

Wave	Ret.	Empl.	Unemp.	Disab.	Homem.	Other
1	45.8	40.0	1.5	3.3	9.3	0.0
2	41.1	41.8	1.8	2.6	11.7	1.1
3	–	–	–	–	–	–
4	44.7	42.2	1.6	2.1	8.5	1.0
5	50.2	38.7	1.1	1.9	7.6	0.5
6	54.8	34.3	0.9	1.7	7.3	0.9
7	59.3	28.9	0.9	2.0	7.7	1.2
8	63.3	27.6	1.0	1.8	5.2	1.0
9	69.9	22.3	0.9	1.6	4.7	0.6

Table 6: Employment Status (in %)

Wave	Excellent	Very Good	Good	Fair	Poor
1	14.7	27.0	42.3	13.1	2.9
2	15.4	30.3	36.7	13.6	4.0
3	11.4	24.5	41.1	18.9	4.1
4	12.4	30.7	39.4	14.5	3.0
5	11.4	29.0	42.6	14.1	2.9
6	9.9	29.1	41.9	15.6	3.4
7	9.6	25.5	42.8	17.4	4.6
8	9.8	29.5	41.1	15.7	4.0
9	9.0	27.6	43.3	16.3	3.9

Table 7: Self-Rated Health (in % of respondents)

Tables 1 - 7 present the evolution of key demographic and economic variables across the nine waves of the panel. As expected in an ageing cohort, mean age increases steadily from 64.3 years in wave 1 to 71.9 years in wave 9, reflecting the panel's longitudinal nature. The gender composition remains stable over time, with a consistent female share of approximately 54–57%. A noticeable structural shift appears in educational attainment: while the mean years of education center around 11 in waves 1–3, they drop to approximately 8.6 from wave 4 onward.

This likely results from a refreshment of the sample with older cohorts who might have completed schooling under earlier education systems. Household income displays substantial variability both within and across waves. Notably, wave 3 reports no income data. According to the data set documentation, this omission stems from wave 3 being a retrospective "SHARELIFE" wave, which focused on life histories meaning many regular panel variables such as household income and employment status have not been asked for in this wave and explain their absence. Across other waves, a clear upward trend in retirement is visible, increasing from 46% in wave 1 to nearly 70% in wave 9, while employment correspondingly declines. Self-reported health remains fairly stable over time, though positive ratings ("excellent" or "very good") decline slightly, while "fair" and "poor" increase, which is consistent with ageing. Household size also decreases gradually, from 2.1 in wave 2 to 1.8 in wave 9, possibly reflecting typical life transitions like widowhood or children leaving home.

2. Comparative Analysis - Switzerland, France and Italy

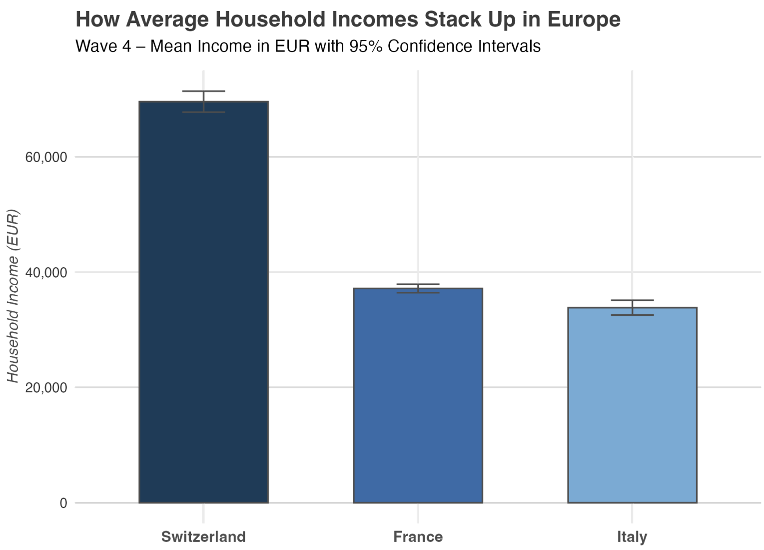

Figure 1: Average Household Income in Switzerland, France, and Italy (Wave 4)

Country	Obs	Mean	SD	SE	$CI_{0.95}$ Lower	$CI_{0.95}$ Upper
France	5846	37,143.88	28,314.83	370.33	36,418.04	37,869.72
Italy	3488	33,819.13	38,825.13	657.39	32,530.64	35,107.62
Switzerland	3778	69,530.77	57,104.52	929.05	67,709.83	71,351.71

Table 8: Household Income Comparison – Wave 4

In the analysis of cross-country household income, I focus on the fourth wave of the dataset, as it offers the highest number of valid income respondents for France and Switzerland, and the third highest for Italy. This makes it particularly suitable for a cross-country comparison. The other two countries were selected due to their geographic closeness and deep economic and cultural links with Switzerland. In wave 4, Switzerland reports the highest average household income (€69,531), followed by France (€37,144) and Italy (€33,819). The 95% confidence intervals for all three countries are non-overlapping: This suggests that the differences in income levels are statistically significant, allowing us to confidently rank the three countries in terms of average household income with Switzerland first, France second and Italy in the third place.

3. Determinants for Doctoral Visits - Metrics for Switzerland

In this section, I analyse the determinants of doctor visit frequency in Switzerland, limiting the data set to Swiss respondents only. The dependent variable is $hc002\_mod$, which records the number of times an individual has seen or talked to a medical doctor in the last 12 months, excluding hospital stays. The sample is restricted to complete cases on relevant covariates to ensure comparability and robustness of results.

The choice of explanatory variables is grounded in economic theory and informed by the SHARE data documentation. The final model includes gender, age, household income, education years, chronic illness status, functional limitations (IADL), and employment status (specifically retired and disabled). These covariates were selected to balance explanatory power with the need to avoid biased estimation due to bad controls, omitted variable bias, or reverse causality. Including household income and years of education can be justified by their conceptual roles as pre-set and enabling factors in behavioural models of health services. Higher income may facilitate better access to healthcare, while education may enhance health literacy and navigation of the healthcare system. While concerns over endogeneity and bad controls are valid—particularly if income is affected by current health status - I mitigate this risk by treating income as a proxy for long-term socioeconomic status, which is arguably more stable. Furthermore, the Swiss healthcare system offers universal coverage and capped out-of-pocket costs significantly to 10% (International Citizens Insurance 2023), meaning the marginal effect of income is likely muted.

To further test the income relationship more carefully, I also ran an alternative model using the logarithm of income ($log(thinc\_m + 1)$) to better capture the diminishing marginal effect of income on healthcare use. However, both AIC and BIC values favoured the logged income model, but the log specification yielded a notably lower R-squared (0.064) (See Appendix). This reduction in explained variance reflects how income's raw scale absorbs more variation, not necessarily that the logged model fits worse. Given this, and the interpretative clarity of the linear income term, I retain the untransformed income variable in the final model. Since my goal is explanatory accuracy I will use the raw income model for my baseline specification as including logged household income led to loss of data and lower explanatory power.

The final model includes gender, age, household income, education years, chronic illness status, functional limitations (IADL), and employment status (retired and disabled), while excluding potentially endogenous or statistically insignificant predictors such homemaker status or smoking status.

$$\begin{aligned} \text{hc002\_mod}_i &= \beta_0 + \beta_1 \text{female}_i + \beta_2 \text{age}_i + \beta_3 \text{thinc\_m}_i + \beta_4 \text{eduyears\_mod}_i \\ &+ \quad \beta_5 \text{chronic\_mod}_i + \beta_6 \text{iadla}_i + \beta_7 \text{retired}_i + \beta_8 \text{disabled}_i + \varepsilon_i \end{aligned}$$

Variable	**Estimate**	**Std. Error**	**t value**	**Pr(> $\|t\|$)**	
Intercept	1.6330	0.5024	3.251	0.00115	**
Female	0.6378	0.1275	5.004	0.00000	***
Age	0.0234	0.0077	3.058	0.00223	**
Household Income	-0.000000869	0.000001246	-0.698	0.48537	
Years of Education	0.0038	0.0079	0.478	0.63288	
Chronic Illness (dummy)	1.4270	0.0548	26.062	0.00000	***
IADL Limitations	-0.2289	0.0594	-3.857	0.00012	***
Retired	0.5950	0.1661	3.583	0.00034	***
Disabled	9.1790	0.4718	19.457	0.00000	***
Observations					19,795
R-squared					0.2352
Adj. R-squared					0.2349
Residual Std. Error					8.754
F-statistic					760.8 (p-value < 2.2e-16)

Note: Dependent variable is number of doctor visits (hc002_mod). $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table 9: OLS Regression - Determinants of Doctor Visits in Switzerland

Interpreting the results, gender is a significant predictor: women report approximately 0.64 more visits per year than men, holding other variables constant. Age also shows a positive association, albeit of modest magnitude, with each year increasing visits by roughly 0.023. This aligns with expectations that healthcare needs increase with age.

Chronic illness is by far the strongest driver of doctor visits. Individuals with at least one chronic condition visit doctors 1.43 times more per year, on average, than those without. Functional limitations (IADL) are significantly and negatively related to the number of visits. This suggests that those who struggle with daily activities may face physical or logistical barriers to accessing ambulatory care.

Among employment statuses, being retired is associated with 0.60 additional visits per year, which may reflect both age and greater time availability. Disability status has the largest effect, with disabled individuals making more than 9 additional visits annually compared to their non-disabled peers—likely reflecting both medical necessity and institutional interactions with the healthcare system.

While education and income are statistically insignificant in this model, their inclusion is theoretically justified and helps avoid omitted variable bias, especially if they correlate with health-seeking behaviour. The model explains about 23.5% of the variation in doctor visit frequency, which is within a reasonable range for cross-sectional health utilization models, particularly given the unobserved heterogeneity in health needs and preferences. I still have to acknowledge that the non-logged household income might be soaking up a lot of variance - especially if income should correlate with health, chronic conditions, or age, ehich might be the case with this underlying panel data.

4. Health Subsidy Analysis Without behavioural Responses

4.1. Simulation of a Subsidy on Individual Income

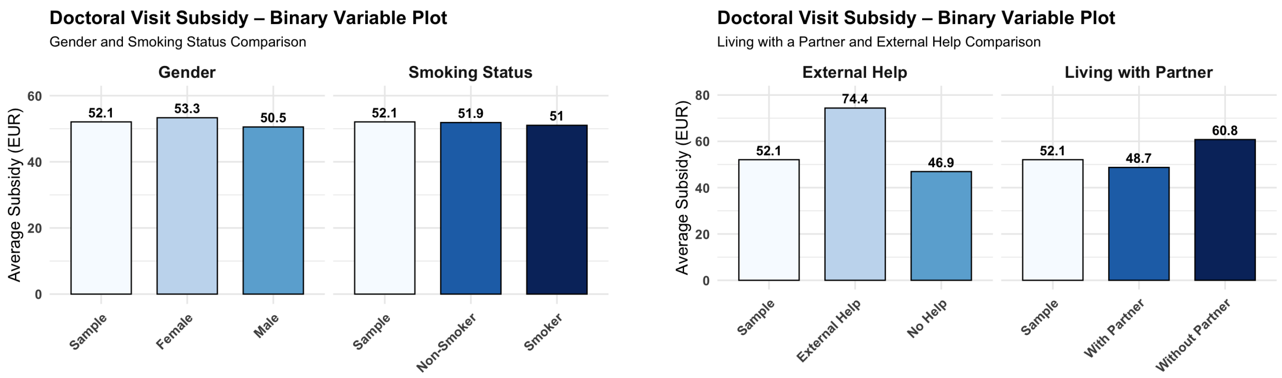

Figure 2: Average Subsidy by Binary Subgroup Characteristics (EUR)

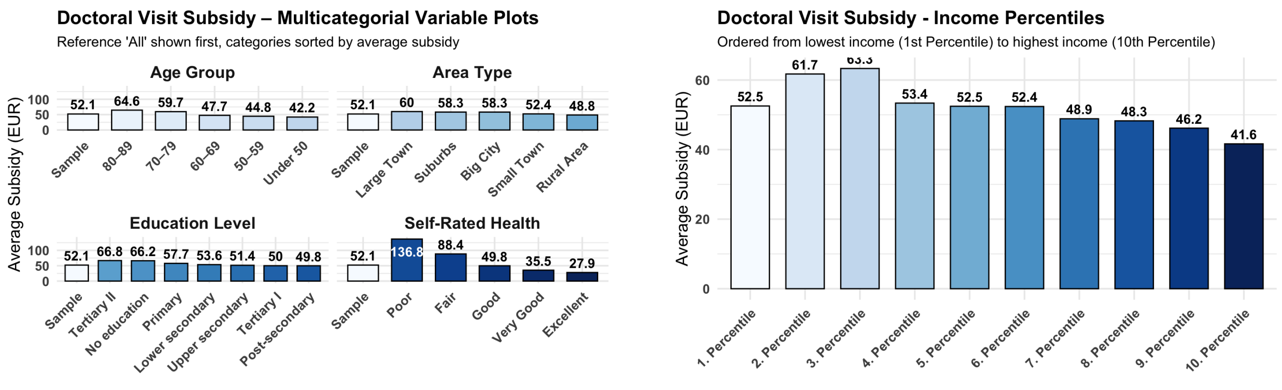

Figure 3: Average Subsidy by Multicategorial Subgroup Characteristics (EUR)

In this scenario, we simulate a policy that grants each individual a €10 subsidy per doctor visit, without observable change in individuals behaviour - different from what we would usually observe in health insurance markets from Public Economics point of view, where adverse selection might occur, as modeled in Einav and Finkelstein (2011). Since the income variable in SHARE (*thinc_m*) is measured at the household level and assigned to all household members in the survey, I compute the total household subsidy by summing individual doctor visits within each household. I then divide the household subsidy equally among all household members, and add this per-capita subsidy to each individual's household income. That gives a consistent baseline (*thinc_m*) for all household members and a per-person share of the household subsidy, which is added to *thinc_m*, providing consistency for individual-level analysis while respecting the shared nature of income in the data. However, therefore we have to make a strong assumption, which is that everyone shares the subsidy in the household equally, implying that people do not longer posses their "own" subsidy in isolation, but are instead pooled and shared in the household. This is a trade-off I take into account for the fact that we have no further variables that would let us help to compute the individual income share in the household. The household-level subsidy is computed as

$$S_i = \frac{10 \cdot V_{h(i)}}{N_{h(i)}} \tag{1}$$

with S_i be the subsidy assigned to individual i, $V_{h(i)}$ be the total number of doctor visits by all individuals in household h(i) and $N_{h(i)}$ be the number of individuals in household h(i). The adjusted income writes as follows

$$I_i^{\text{adj}} = I_i + S_i \tag{2}$$

with I_i^{adj} be the adjusted income after applying the subsidy, I_i be the initial household net income assigned to individual i (i.e., *thinc_m*) and S_i be the subsidy assigned to individual i.

Given that, I find that the average individual in a household receives €52.10 in additional income due to the subsidy, implying the average number of doctor visits with 5.21 times a year across the population, adjusted per household member. This is higher than expected from the average of 4 doctor visits per person, because individuals share in the household's total visits. Some individuals with few or no visits still benefit if other members visited the doctor frequently. This approach reflects the shared nature of income and benefits in the household. To better understand the distribution of the subsidy across relevant subgroups, I evaluate the average subsidy by binary and multicategorical characteristics, including age group, gender, self-perceived health status, income percentile, living situation, education, and area of residence approximately:

Individuals living without a partner benefit substantially more from the subsidy than those living with a partner, likely reflecting a greater need for formal healthcare services among those without close at-home support. Similarly, individuals who receive external help from others report the highest average subsidy, while those without help report below-average gains. Gender differences are minimal (€53.3 for women vs. €50.5 for men), and smoking status shows virtually no effect differences.

Concerning age groups, the subsidy increases monotonically with age. Individuals aged 80 - 89 receive on average €64.6, significantly above the sample average of €52.1, while those under 50 receive only €42.2. This development supports the notion that older individuals utilise more healthcare services and therefore benefit more from the policy.

In regards to education, there is a slight U-shaped pattern in subsidy distribution across education levels. Those with no education and those with tertiary II education receive the highest subsidies. The lowest subsidies are observed for post-secondary and tertiary I educated individuals. This may reflect differing health-seeking behaviours, occupational histories, or health statuses across education groups.

Further, Self-rated health status is strongly predictive of subsidy magnitude. Individuals in poor health receive on average €136.8, compared to just €27.9 for those reporting excellent health. This wide disparity highlights the policy's inherently progressive nature in terms of health status: the worse one's health, the greater the financial benefit received.

Subsidy levels vary across residential environments, though the differences are smaller. Individuals in large towns receive the highest average subsidy, while those in rural areas receive the least, possibly due to differential access to healthcare infrastructure.

Finally, the subsidy appears slightly progressive when examined across income percentiles. The lowest three income percentiles receive the highest average subsidies (peaking at €65.3 for the 3rd percentile), while the top percentiles benefit least, with the 10th percentile receiving just €41.6. This suggests the subsidy provides relatively more financial support to lower-income individuals, which could contribute to modest reductions in income inequality.

Overall, the distributional analysis between sub-groups demonstrates that the subsidy disproportionately benefits older, sicker, and lower-income individuals. This aligns with usual normative goals of equity in healthcare access and social protection, even in the absence of behavioural responses.

4.2. Subsidy Impact on Poverty in Switzerland

To find the impact of the subsidy on poverty I will make use of the at-risk-of-poverty measure (AROP), defined by Eurostat, which is set at 60% of the national median income Eurostat (2023). To assess the poverty effects of the subsidy, I computed the relative poverty threshold as 60% of the median pre-subsidy household income. Then I created binary indicators identifying whether each individual falls below this threshold before and after the subsidy. Finally, I calculated the overall poverty rates using these indicators to quantify the change in poverty induced by the policy. This yields the results in Table 10.

	Poverty Rate Before	**Poverty Rate After**	**Change in Poverty**
Rate	27.60%	27.52%	-0.08%

Table 10: Poverty Rate Before and After Subsidy

The introduction of a €10-per-visit subsidy has only a marginal effect of 0.08% on overall poverty decrease in the Swiss sample. While the average value of the subsidy is €52.10 per person per year, this amount is relatively small compared to the level of the poverty threshold. As a result, the policy does not meaningfully lift a large share of the population above the threshold, but it can still affect individuals who are just marginally below it. This result is consistent of what I would expect of a subsidy that mostly profited those with high healthcare needs: the policy effectively acts as a small, conditional transfer that modestly improves their income.

4.3. Measuring Redistributive Effects of A Subsidy

To evaluate how the subsidy affects income inequality, I compute two of the standard measures that have been discussed in class: the Atkinson index, the and the Theil-Indices (Theil-T, as well as Theil-L index). These indices allow me to quantify distributional changes before and after the simulated introduction of a €10 subsidy per doctor visit. As they all three satisfy the four core axioms of inequality measurement presented in the course - anonymity, population principle, relative income, and the Pigou-Dalton transfer principle - they are well suited for this analysis.

Measure	**Before Subsidy**	**After Subsidy**	**Change**
Theil-T Index (GE(1))	0.332	0.328	-0.0040
Theil-L Index (GE(0))	0.283	0.283	-0.0006
Atkinson Index ($\varepsilon = 1$)	0.282	0.279	-0.0029

Table 11: Inequality Measures Before and After Subsidy (Switzerland Sample)

The **Atkinson index** is particularly useful because it is normative: its inequality aversion parameter ε reflects societal preferences toward inequality. I set $\varepsilon = 1$, giving greater sensitivity to changes at the lower end of the income distribution. The index can be interpreted as the share of total income that society would be willing to give up to achieve perfect equality without reducing overall welfare. In my results, the Atkinson index decreases from 0.282 to 0.279 after the subsidy - a modest change of approximately 0.29 percentage points. For context, the UNDP (2024) reports a value of 0.18 for Switzerland in 2022 with $\varepsilon = 1$ (OWID 2024). My higher estimate might be consistent with the demographic skew in my sample, which consists of individuals between 64 and 72 on average (depending on each wave), likely featuring more pronounced inequality than the general population.

To complement this, I also compute the **Theil-T (GE(1))** and **Theil-L (GE(0))** indices. The Theil-T is more sensitive to disparities at the top of the distribution, while Theil-L emphasises the bottom tail. Both indices decreased slightly: Theil-T from 0.332 to 0.328 (0.004) and Theil-L from 0.283 to 0.283 (0.0006). These changes confirm that the redistributional effect of the subsidy is modest but consistent in direction - income inequality falls slightly in both the upper and lower parts of the distribution.

Given the structure of the subsidy - universal yet correlated with poor health and age - this outcome is expected. While the policy is not progressive in the fiscal sense, it ends up being indirectly redistributive, as those with lower incomes and worse health tend to have higher doctor visit rates and thus benefit more.

5. Health Subsidy Analysis With a behavioural Response

5.1. Model and Set-Up

In line with the majority of the health economics literature, I model behavioural responses to the subsidy using a revealed preference framework. This approach simulates changes in demand based on observed utilization patterns and empirically estimated price elasticities. As discussed in Skriabikova, Pavlova, and Groot (2010), this method benefits from grounding in actual consumer behaviour, though it also inherits limitations: it does not reveal underlying motivations and makes causal interpretation difficult due to potential unobserved confounders.

While stated preference methods - such as discrete choice experiments - can help explore counterfactual policies ex ante, they are rarely applied in the context of out-patient[2] physician services due to concerns over predictive validity. Consequently, I proceed with an elasticity-based simulation of behavioural change, using an empirically grounded price elasticity of demand. The logic is straightforward: when the out-of-pocket cost of a doctor visit decreases from €30 to €20 due to the subsidy, individuals adjust their demand based on their sensitivity to price. This behavioural adjustment is driven by the price elasticity of demand (ε).

Based on the RAND Health Insurance Experiment, Manning et al. (1987) estimate an elasticity of approximately -0.2 for out-patient care. Similarly, Chernew et al. (2008) report values in the range of -0.15 to -0.30 across different demographic groups. Further support comes again from the meta-analysis by Skriabikova, Pavlova, and Groot (2010), which synthesizes 46 studies on out-patient physician services and finds that the largest share (35%) report elasticity values between 0.1 and 0.5, suggesting moderate but non-negligible price sensitivity. The same study identifies consumer income as the most frequently cited determinant of price elasticity, as mentioned in 39% of reviewed studies (Skriabikova, Pavlova, and Groot 2010, p. 2716), further validating the application of moderate elasticity assumptions in this context.

Accordingly I apply a standard elasticity of -0.2 to estimate the change in doctor visits and recalculate the individual-level subsidies accordingly. My elasticity measure builds on Allen (1934)'s Arc Elasticity in demand concept and rewrites in our context as

$$\widehat{V}_i = V_i \cdot \left(1 + \varepsilon \cdot \frac{P\text{after} - P_{\text{before}}}{\frac{P_{\text{after}} + P_{\text{before}}}{2}}\right) \tag{3}$$

[2]Throughout this context, out-patient care refers to medical services that do not require an overnight stay in a hospital.

with $\hat{V}_i$ being the change in absolut visits, V_i as observed number of visits, $P_{\text{before}} = 30$, $P_{\text{after}} = 20$ and $\varepsilon = -0.2$ as justified elasticity value. This yields us the results in Table 12.

Metric	**Before Subsidy**	**After Subsidy**
Average Doctor Visits per Person	4.02	4.34
Change in Visits	+0.32 (+8%)	
Average Individual Income (€)	35,035.30	35,067.47
Income Gain (€)	+32.17 (+0.09%)	

Table 12: Impact of Subsidy on Doctor Visits and Income (with behavioural Response)

This leads to an estimated increase in doctor visits of approximately **8%**. Specifically, average utilization rises from 4.02 to 4.34 visits per person, an increase of 0.32 visits. This behavioural response constitutes the central effect of the subsidy: individuals react to lower out-of-pocket costs by modestly increasing their use of medical care.

While secondary to the behavioural effect, I also compute the corresponding change in income, using the same per-capita allocation approach as in section 4.1. Under this assumption, both household income and the total subsidy are equally distributed across all household members. The behavioural response increases the average per-person income from 35,035.30 to €35,067.47, representing a gain of €32.17 or 0.09%. This is a minor increase, reflecting the marginal boost in utilization driven by price responsiveness.

In sum, this simulation illustrates that applying a moderate, empirically grounded elasticity leads to a measurable **8% increase in utilization**, with a modest accompanying rise in individual income. It reinforces the idea that demand for health care is price-sensitive, and even moderate subsidies can influence behaviour in economically meaningful ways.

5.2. Discussion

The subsidy can be classified as progressive. Although the monetary amount - €10 per doctor visit - is flat for everyone, its relative impact is greater for lower-income individuals, who experience a higher proportional increase in income. In my simulation, the average income gain per person was €32.17, or roughly 0.09%. This uniform euro amount represents a larger share of income for those at the bottom of the distribution compared to those at the top. Moreover, as I obtained that health care utilization trends in section 4.1 tend to be higher among older, less healthy, and lower-income individuals, it means that these groups benefit more from the subsidy in practice. Since the subsidy is distributed equally within households (on a per-capita basis), and households with greater medical needs tend to have higher total visit counts, the redistributive effect is reinforced. This interpretation is supported by inequality metrics: the Atkinson index decreases slightly (from 0.2823 to 0.2795), as do the Theil-T and Theil-L indices. While these changes are modest, they indicate a small reduction in income inequality, consistent with a progressive transfer mechanism.

In summary, even though the subsidy is uniform in nominal terms, it delivers proportionally larger benefits to lower-income individuals and contributes to a reduction in income inequality - therefore, it is progressive in both relative and distributional terms.

References

Allen, R. G. D. (June 1934). "The Concept of Arc Elasticity of Demand: I". In: *The Review of Economic Studies* 1.3, pp. 226–229. ISSN: 1467-937X. DOI: 10.2307/2967486. URL: http://dx.doi.org/10.2307/2967486.

Chernew, Michael et al. (Apr. 2008). "Effects of Increased Patient Cost Sharing on Socioeconomic Disparities in Health Care". In: *Journal of General Internal Medicine* 23.8, pp. 1131–1136. ISSN: 1525-1497. DOI: 10.1007/s11606-008-0614-0. URL: http://dx.doi.org/10.1007/s11606-008-0614-0.

Einav, Liran and Amy Finkelstein (Feb. 2011). "Selection in Insurance Markets: Theory and Empirics in Pictures". In: *Journal of Economic Perspectives* 25.1, pp. 115–138. ISSN: 0895-3309. DOI: 10.1257/jep.25.1.115. URL: http://dx.doi.org/10.1257/jep.25.1.115.

Eurostat (2023). *Glossary: At-risk-of-poverty rate*. Accessed: 2025-04-20. URL: https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Glossary:At-risk-of-poverty_rate.

International Citizens Insurance (2023). *Switzerland Health Care System*. https://www.internationalinsurance.com/health/systems/switzerland.php. Accessed: 2025-04-20.

Manning, Willard G. et al. (1987). "Health Insurance and the Demand for Medical Care: Evidence from a Randomized Experiment". In: *The American Economic Review* 77.3, pp. 251–277. ISSN: 00028282. URL: http://www.jstor.org/stable/1804094 (visited on 04/21/2025).

OWID (2024). *Income Inequality - Atkinson Index (UNDP)*. Accessed: 2025-04-21. URL: https://ourworldindata.org/grapher/income-inequality-atkinson-index-undp?time=latest.

Skriabikova, Olga, Milena Pavlova, and Wim Groot (June 2010). "Empirical Models of Demand for Out-Patient Physician Services and Their Relevance to the Assessment of Patient Payment Policies: A Critical Review of the Literature". In: *International Journal of Environmental Research and Public Health* 7.6, pp. 2708–2725. ISSN: 1660-4601. DOI: 10.3390/ijerph7062708. URL: http://dx.doi.org/10.3390/ijerph7062708.

UNDP (2024). *Human Development Report 2023–24: Breaking the Gridlock: Reimagining Cooperation in a Polarized World*. New York: United Nations Development Programme.

A. Appendix - OLS Regression: Logged Income Approach

Variable	Estimate	Std. Error	t value	Pr(> |t|)
Intercept	1.0454	0.8670	1.206	0.22792
Female	0.7823	0.1380	5.670	< 0.001 ***
Age	0.0335	0.0085	3.956	< 0.001 ***
Log(Income + 1)	-0.0288	0.0591	-0.487	0.62626
Years of Education	0.0197	0.0085	2.303	0.02129 *
Chronic Illness (dummy)	1.4786	0.0641	23.060	< 0.001 ***
IADL Limitations	-1.5255	0.1075	-14.196	< 0.001 ***
Retired	0.5306	0.1780	2.981	0.00288**
Disabled	9.7710	0.4958	19.707	< 0.001 ***
Observations				16,823
R-squared				0.06425
Adj. R-squared				0.06381
Residual Std. Error				8.725 (df = 16,814)
F-statistic				144.3 (p-value < 2.2e-16)

Table 13: OLS Regression - Doctor Visits with Log Income (Switzerland)

Note: Dependent variable is number of doctor visits (hc002_mod). $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Model	AIC	BIC
Baseline Model	142,078.9	142,157.8
Log Income Model	120,637.5	120,714.8

Note: Lower AIC and BIC values indicate better model fit. The log income model has lower values despite a lower R^2, suggesting improved parsimony.

Table 14: Model Fit Comparison: Baseline vs. Log Income Specifications