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User charges and their impact on planned and unplanned hospital use: evidence from Portugal

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Abstract: Predicted values for individual's expected costs related to emergency department visits and primary care unit (PCU) appointments are constructed using Portuguese survey data. These are used in regressions of count data and binary dependent variable models to identify the partial effect of user charges on (1) yearly emergency department visits and (2) the probability that an individual has an appointment at a PCU in a year. User charges are found to reduce both types of use. Individuals with chronic conditions are less impacted. No evidence is found to suggest that individual's income levels influence their sensitivity to user charges.

Keywords: Health Economics, Access, Healthcare Barriers, User Charges, Emergency Department, Primary Care Unit

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1 – Introduction

One of the most pressing issues in more developed countries is the availability of healthcare. In the past few decades, state provision of healthcare has become increasingly relevant, with many people coming to depend on it. However, the sustainability of public healthcare systems has been called into question – how these systems should be financed is the key issue. Importantly, there are clear concerns regarding how a healthcare system that is only indirectly funded by tax revenues could generate issues of moral hazard – having the system be free of charge at point of use seems likely to prompt excessive uses in comparison to a system where individuals pay for each usage, *ceteris paribus* (not to say that private health insurance systems are not immune to moral hazard). One possible solution is introducing user charges, where individuals pay a small fee in exchange for access to a service.

Recent changes to the Portuguese national healthcare system, or *Serviço Nacional de Saúde* (SNS), aiming to make it more "just and inclusive", have reduced the number of services that carry a user charge: consultations and complementary diagnostic and therapeutic exams prescribed in the context of primary healthcare provision are now exempt (DRE 2020). This is part of a broader effort to improve the system and better guarantee universal coverage. Given these reforms, it is now particularly relevant to determine what role the abolition of user charges could have in reaching this goal – is there evidence to suggest that user charges are barriers to healthcare access? At first glance, it seems clear that user charges, which raise prices, should reduce hospital visits. We will focus our attention in this paper on the impact of user charges on hospital use, while also considering the impacts of other expenses. This analysis will be supported by repeated cross-section survey data collected in Portugal.

Four econometric models will be estimated, two for each type of hospital use: emergency department and primary care unit. The dependent variables will be yearly emergency department visits by individuals and the probability of an individual having an appointment at a primary care unit over the course of a year, being regressed using count data and binary dependent variable models, respectively. The key independent variables are constructed – they are predictions of what individuals expect to be the costs related to hospital visits.

Overall, the results show user charges as having negative effects on hospital use. Each additional unit of user charges is associated with a reduction of 3.37% for emergency department visits. Individuals with chronic health conditions are impacted only by 1.19%. The marginal effect of user charges on primary care unit appointments could not be satisfactorily identified. User charge exemptions have a very strong positive impact on either usage: they are associated with an increase in yearly emergency department visits of 58.41%, and an increase in the probability that an individual has an appointment at a primary care unit by the multiple 2.25. Individuals with chronic conditions are once again less sensitive to these changes. No evidence is found to suggest that an individual's wealth impacts their sensitivity to the effects of user charges.

2 – Literature review

The main problems regarding how healthcare systems are financed are shared with most organisations: difficulties in raising funds amidst high costs. User fees, on paper, seem to solve both problems: they increase revenues (although only by a very small amount) while reducing costs, due to fewer uses (Canadian Foundation for Healthcare Improvement 2014). Does this hold in practice?

RAND's Health Insurance Experiment (HIE) attempted to compare the relative benefits between a healthcare system that featured cost sharing measures and one that was free at point of use, considering the differences in overall use, appropriateness of care, quality of care and consequences for health (RAND Corporation 2006). It randomly allocated participants to various healthcare schemes, including free care. It found that, compared to participants with free care, those with cost sharing made one to two fewer physician visits annually and had 20% fewer hospitalisations (*Ibid*). Specifically, participants ended up initiating healthcare less often – once started, cost sharing had only modest effects on use (*Ibid*). In as far as appropriateness and quality of care, cost sharing reduced in roughly equal amounts effective and ineffective uses: the proportion of inappropriate hospitalisations (23%) and inappropriate antibiotic use was the same for all participants (*Ibid*). The study also does not find significant differences in quality of care. In what concerns health, cost sharing overall did not reduce it, but it did reduce the health of the poorest participants. For this group, free care resulted in better outcomes for 4 out of the 30 health conditions measured, namely a 10% reduction in mortality for participants with hypertension and a lower prevalence of serious symptoms (*Ibid*). The study does note, however, that participants with cost sharing saw some benefits: they worried less about their health and had fewer days with their activities restricted (such as due to seeking medical care) (*Ibid*).

The HIE supports the notion that user charges reduce use globally. It also provides evidence in favour of user charge exemptions for the poor, something that the SNS has in place already. But the longer-term impact is still unclear. A paper by Tamblyn et al. studied the impact of cost sharing in poor (defined as being welfare recipients) and elderly persons (Tamblyn, et al. 2001). It found that this resulted in both groups reducing their consumption of essential and less essential drugs (with a slightly larger fall on those that were less essential), but the rate of serious adverse events linked to reductions in the use of essential drugs almost doubled in both the elderly (5.8 per 10,000 person-months to 12.6) and poor (14.7 to 27.6). Emergency department visit rates rose as well, by 14.2 per 10,000 person-months in the elderly and by 54.2 in the poor (*Ibid*). The authors note that no such adverse consequences arose due to the reduction in less essential drugs (*Ibid*). Essentially, the attempt to curb costs by imposing cost sharing on these groups resulted in them using the healthcare system more intensely, due to being discouraged from using their needed medication. Increased user charges appear to be correlated with increased emergency department use.

While there is some evidence for an overall decline in use resulting from user charges, the precise effects on people depends on their income groups. Evidence from the Saskatchewan province of Canada, cited by Stoddart, Gl et al. shows that its user charge resulted in a decrease in annual per capita use of physician services by 6-7% (Stoddart, et al. 1993). However, among poorer individuals, there was an 18% reduction – some of this decrease was offset by increased use of physician services by richer individuals (*Ibid*). User charges may increase certain groups' consumption of healthcare services. This may be due to hospitals being less used by others – and therefore more available than before to a group that does not suffer greatly by user charges. Here, user charges disproportionately impact the poor and a case could be made for an exemption for them. One problem that this poses is that it implies that richer individuals can be expected to increase consumption if user charges are higher, which damages the appeal from the potential of user charges to reduce use. This is possibly due to user charges reducing other costs by more than the amount they get charged – for example, the time spent in waiting rooms. It is possible that a joint policy of exemptions for the poor and charges on the rich would not result in the latter raising consumption.

There is a consensus that universal health coverage necessarily requires healthcare access to be free at the point of use. The main goal is to prevent financial troubles for those who are less wealthy but, nonetheless, require medical attention – user charges, therefore, serve as an obstacle towards achieving universal health coverage. Under this view, healthcare systems should be exclusively supported by compulsory prepayments – for example, through taxation or social security premiums (WHO 2013).

The above findings suggest some important hypotheses. First, the idea that user charges have a particular impact on individuals with chronic conditions, tending to raise their use of emergency departments – we would expect user charges on emergency department visits to have a weaker impact on individuals with chronic conditions. Second, the notion that user charges will impact the poor more than the rich; perhaps even to the extent that poorer individuals will reduce their usage of hospital services while wealthier individuals will increase theirs – we should expect to see user charges decreasing hospital use for poorer individuals, with a weaker reduction on the use of wealthier individuals, if not an increase.

3 – Data

3.1 – Collection process

The statistical analysis will be based on a dataset of repeated cross-section data, composed of surveys conducted in 2013, 2015, 2017, 2019, 2020 and 2021. Given that some of the variables do not have values for all years, the econometric models will use only observations from 2020 and 2021. The questions in each survey are similar, with only minor variations. They cover numerous topics regarding access to healthcare. Specifically, the data from 2021 comprises 1,269 interviews, all to residents in mainland Portugal who are at least 15 years old. For 2021, the selection of the interviewees was done through quota sampling, a non-probabilistic sampling method; it is possible that some bias is present, and this is worth considering for the results. Sub-groups were chosen based on: region (7 groups); habitat (5); gender (2); age (6); education (2), applied to men; and occupation (2), applied to women. The random route method was not applied, but interviewers were given instructions such that they distributed their interviews throughout each location. Interviews were conducted in person and privately at each individual’s residence, based on an established list of questions. The 2021 survey is representative of previous years’ surveys.

3.2 – Description of variables used

Variable	Definition	Type
em_freq	Total number of yearly visits to the emergency department at a hospital by an individual.	Discrete
went_pcu	Indication of whether someone had an appointment at a primary care unit over the past year.	Binary
uc_exempt	Exemption status of individuals from user charges. Exemptions apply to all types of use, emergency department and primary care unit, by assumption.	Binary
uc_em_cleaned and uc_pcu_cleaned	Original data for user charges on last use of hospital service: "em" refers to the cost of the last emergency department visit and "pcu" to the last appointment at a primary care unit. Cleaning process dropped the observations which had values indicating no data ("999" values) and also cut the zero values for observations where *uc_exempt* = 0.	Continuous
trpt_em_cleaned, presc_em_cleaned, trpt_pcu_cleaned and presc_pcu_cleaned	Original data for expenses incurred in the context of the last hospital service used: "trpt" refers to transportation expenses, "presc" to the cost of prescribed medication, and "em" and "pcu" to expenses related to the last emergency department visit and appointment at a primary care unit, respectively.	Continuous
uc_em, uc_em_expected, trpt_em, presc_em, uc_pcu, uc_pcu_expected, trpt_pcu and presc_pcu	Main regressors, constructed by generating predictions following a regression of the cleaned data. The estimation method used was Stepwise OLS. When relevant, negative predicted values were set to "0". The "_expected" suffix for the user charge variables indicates a further transformation to these two variables: where the observation has uc_exempt = 1, the value of uc_em/uc_pcu was changed to "0".	Continuous
age	The individual's age, given in years.	Discrete
alcohol_consumption	Frequency of consumption of alcoholic beverages. 9 levels. Used as a proxy for health condition.	Binary (set of 9)
chronic	Indication of whether someone has a chronic health condition.	Binary
distance_to_em	Distance, in metres, an individual needs to travel to reach a hospital's emergency department.	Continuous
economic_status	Set of dummy variables indicating the individual's income – specifically, the difficulty in meeting expenses. Possible values: easy, somewhat easy, somewhat difficult, and difficult. The base value will be set to "somewhat easy".	Binary (set of 4)
education	An individual's level of education: (1) at least undergraduate from a university; (2) degree from a polytechnic institution; (3) attended 1 or 2 without being awarded a degree; (4) secondary education; (5)	Binary (set of 8)

	completed 9th grade; (6) completed 6th grade; (7) primary education; (8) incomplete primary education or illiterate.	
female	Dummy variable for the individual's sex.	Binary
health_self_assessment	Indication of an individual's own perception of his/her health. 5 possible values.	Binary (set of 5)
household_nr	Number of people who live in the same household as the individual.	Discrete
region	Region where the individual lives: (1) Norte Litoral; (2) Grande Porto; (3) Interior; (4) Centro Litoral; (5) Grande Lisboa; (6) Alentejo; (7) Algarve.	Binary (set of 7)
municipality	Municipality where the individual lives, out of 278.	Binary (set of 278)
profession	The individual's profession: (1) Self-employed; (2) Works for someone else; (3) Unemployed; (4) Retired; (5) Stay-at-home; (6) Student.	Binary (set of 6)
y****	Indicates year observation was taken from: 2013, 2015, 2017, 2019, 2020, 2021.	

Table 1: Descriptions of each of the variables and their type.

Table 1 presents the descriptions of the relevant variables from the dataset, taken from the survey questions. The dependent variables to be used are: *em_freq* and *went_pcu*. The main independent variables are: *uc_exempt*, *uc_em_SW_expected* and *uc_pcu_SW_expected*. The latter two give expected user charge expenses by individuals, one for each type of hospital use. The other independent variables of interest are estimates for expected transportation and prescribed medication expenses for each type of hospital use. Table 2 presents the descriptive statistics, where observations were restricted to 2020 and 2021. A table with the descriptive statistics for the dataset's full set of observations will be included in the Appendix.

Variable	Obs.	Mean	Std. Dev.	Range
em_freq	2,469	0.352	0.930	[0,15]
went_pcu	2,540	0.476	0.500	{0,1}
uc_exempt	2,444	0.441	0.497	{0,1}
age	2,540	46.393	18.323	$[15,94] \cap \mathbb{Z}$
chronic	2,540	0.273	0.446	{0,1}
distance_to_em	2,385	9358.532	10131.06	[0,120000]
female	2,540	0.530	0.499	{0,1}
household_nr	2,540	2.807	1.240	$[1,9] \cap \mathbb{Z}$

Table 2: Descriptive statistics for each variable. Observations were restricted to those from 2020 and 2021.

3.3 – Variable cleaning process

Certain binary variables – such as *uc_exempt*, *went_pcu* and *chronic* – presented their data in terms of yes/no or 1/2; they were accordingly converted to 1/0. It was necessary to remove "missing" values for certain variables, in most cases denoted by "99" or "999". This was the case for the variables related to the costs of hospital visits and *alcohol_consumption*.

4 – Methodology

4.1 – Regression strategy

This paper will attempt to identify the impact of user charges and related variables on emergency department and primary care unit visits. Two sets of models will be used, one for models with *em_freq* as the dependent variable, and another with *went_pcu*. Models with *em_freq* will be estimated using Pooled OLS, Negative Binomial and Zero-Inflated Negative Binomial regressions. The latter two will both use NB2. Models with *went_pcu* will use regression methods for binary dependent variables – in this case, the Linear Probability Model and the Logistic model. The demand functions of the two types of hospital use will be estimated in the models to follow. We will assume the same functional form for both types of hospital use: Q1 is a function of P1, P2 and Y, where Q1 is the quantity demanded of a type of hospital service; P1 and P2 are the costs of Q1 and its alternative, composed of user charges, transportation expenses, and costs of prescribed medication; and Y is the individual's income.

4.2 – Construction of the expenses variables

The variables for the expenses to be used are all constructed. This was necessary because data on expenses were not reported when individuals did not make use of hospitals. Further, these values were known after the individual decided to go to the hospital and are likely not the same as the costs they anticipated in their decision-making process. To investigate the impact of costs on use, predictions were made from the data available by estimating models with the expenses as the dependent variables – not only were more observations made available for the analysis, but the predictions are hoped to better represent what individuals expected to pay *a priori*. The dependent variables were: *uc_em_cleaned*, *trpt_em_cleaned*, *presc_em_cleaned*, *uc_pcu_cleaned*, *trpt_pcu_cleaned*, *presc_pcu_cleaned* – user charges, transportation, and prescribed medication expenses on each type of use. Besides the changes described in the cleaning process, a further change was done to both user charge variables before the models were estimated: when individuals had user charge exemptions, the value was removed from the variable. This was done because it was assumed that the process that determines whether an individual is exempt from user charges is different from that which determines what user charges an individual expects to pay. In this way, many "zero" observation were removed that are assumed to not be generated by the latter process and the resulting predictions should be more useful. Once the user charge predictions were generated, another transformation was applied to the data – where individuals had indicated that they were exempt from user charges, their user charge prediction changed to be zero. A final transformation was applied to all constructed variables, replacing negative values with "zero" values when present.

A number of different estimation methods were used to try to find the predictions that were most highly correlated with the cleaned data: OLS, Tobit type two (with censoring at 0) and Stepwise OLS. OLS produced the highest levels of correlation, but SW was a close second, while also being much more parsimonious. SW estimates will be used in the analysis as a result. More detailed information on how these variables were constructed is available in the Appendix, including the variables used to construct the variables used as well as the alternatives that were discarded. Histograms of the distributions of the original data and the predicted variables (both those that were selected and discarded) are also presented there. Table 3 presents the descriptive statistics of the cleaned data and the predicted variables generated by Stepwise OLS.

Variable	Obs.	Mean	Std. Dev.	Range
uc_em_cleaned	1,612	6.909	9.899	[0,80]
uc_pcu_cleaned	1,790	3.953	5.121	[0,51]
trpt_em_cleaned	2,716	2.590	6.064	[0,80]
presc_em_cleaned	2,663	13.708	25.374	[0,500]
trpt_pcu_cleaned	2,948	1.322	3.219	[0,40]
presc_pcu_cleaned	3,086	14.201	21.244	[0,250]
uc_em	2,540	16.929	4.482	[12.067,47.664]
uc_pcu	2,540	6.527	4.675	[4.141,46.417]
uc_em_expected	2,444	9.375	8.998	[0,46.523]
uc_pcu_expected	2,444	3.576	4.848	[0,45.791]
trpt_em	2,385	5.263	3.950	[0,28.114]
presc_em	2,540	23.962	6.731	[2.952,59.067]
trpt_pcu	2,385	1.904	1.216	[0.752,7.075]
presc_pcu	2,540	19.990	8.035	[0,85.422]

Table 3: Descriptive statistics for cleaned data and predictions generated from it.[1]

These constructed variables have a number of clear limitations. Extreme values are not estimated well – these are assumed to be randomly determined, and, consequently, not considered when individuals decide to go to a hospital, as they are not costs individuals can be expected to predict. Determining the accuracy of the predicted variables is difficult, especially considering the biased nature of the original data: it comes from individuals who used hospital services and reported their expenses – those who decided against going do not report any data on costs. If this decision was motivated by the costs themselves, then we can expect the original data to be biased downward – in this case, only expenses that did not prevent uses of hospital services were reported. The predictions are likely to be biased downward as a result. It would, however, be difficult to avoid this problem. It is hoped that the overall, “true”, trend is represented.

[1] NOTE: Cleaned data statistics are from whole dataset, while the predictions are based on the observation set used in the analysis (those from 2020 and 2021). A table with the descriptive statistics for the dataset’s full set of observation will be included in the Appendix.

4.3 – Interaction terms

To support the analysis, a few interaction terms were created to identify particular effects on certain types of individuals. Interaction terms *uc_em_chronic*, *uc_pcu_chronic* and *exempt_chronic* will be used to see what the particular effect of user charges are when individuals suffer from chronic health conditions. Dummy variables from *economic_status* will be similarly used to study the particular impact of user charges on individuals of varying incomes. The interactions created are: *uc_em_easy*, *uc_pcu_easy*, *exempt_easy*, *uc_em_somewhatdifficult*, *uc_pcu_somewhatdifficult*, *exempt_somewhatdifficult*, *uc_em_difficult*, *uc_pcu_difficult* and *exempt_difficult*. Value "somewhat easy" is not included as it is the selected base value of *economic_status*.

4.4 – Equations of models to be estimated

Each model aims at estimating the demand function for each type of hospital service. Prices for each type are included in all models. The variables used are predictions which are assumed to reflect individuals' expectations of prices. Each individual is assumed to consider the prices of the two types of hospital service before deciding on which one to use. Two models for each type are used – one to observe the effect of exemptions (user charges as a whole) and another to observe the marginal impact of an additional euro in user charges. The expected price of a hospital visit is assumed to be the sum of user charges, transportation expenses and costs of prescribed medication. Models with *uc_exempt* assume that individuals either do or do not have user charges while models with *uc_***_expected* allow individuals' user charge expenses to vary, with a range of [0,47.664] for emergency department visits and [0,46.417] for primary care unit appointments.

Given the nature of this task, the results for the marginal effects of user charges are likely to have very serious limitations, but we feel that this is at least a good effort in answering an important question: if user charges are to be used, what level should they be set at? That said, we expect the most reliable results to be those from *uc_exempt*.

The two models for *em_freq* are:

$$(1)\ em\_freq = \beta_0 + \beta_1 uc\_em\_expected + \beta_2 trpt\_em + \beta_3 presc\_em + \beta_4 uc\_pcu\_expected + \beta_5 trpt\_pcu + \beta_6 presc\_pcu + \beta_7 uc\_em\_chronic + \beta_8 uc\_em\_easy + \beta_9 uc\_em\_somewhatdifficult + \beta_{10} uc\_em\_difficult + \mathrm{X}\beta$$

$$(2)\ em\_freq = \beta_0 + \beta_1 uc\_exempt + \beta_2 trpt\_em\_SW + \beta_3 presc\_em\_SW + \beta_4 trpt\_pcu\_SW + \beta_5 presc\_pcu\_SW + \beta_6 exempt\_chronic + \beta_7 exempt\_easy + \beta_8 exempt\_somewhatdifficult + \beta_9 exempt\_difficult + \mathrm{X}\beta$$

Those for *went_pcu* are:

$$(3)\ went\_pcu = \beta_0 + \beta_1 uc\_pcu\_SW\_expected + \beta_2 trpt\_pcu\_SW + \beta_3 presc\_pcu\_SW + \beta_4 uc\_em\_expected + \beta_5 trpt\_em\_SW + \beta_6 presc\_em\_SW + \beta_7 uc\_pcu\_chronic + \beta_8 uc\_pcu\_easy + \beta_9 uc\_pcu\_somewhatdifficult + \beta_{10} uc\_pcu\_difficult + \mathrm{X}\beta$$

$$(4)\ went\_pcu = \beta_0 + \beta_1 uc\_exempt + \beta_2 trpt\_pcu\_SW + \beta_3 presc\_pcu\_SW + \beta_4 trpt\_em\_SW + \beta_5 presc\_em\_SW + \beta_7 exempt\_chronic + \beta_8 exempt\_easy + \beta_9 exempt\_somewhatdifficult + \beta_9 exempt\_difficult + \mathrm{X}\beta$$

$X\beta$ represents the set of control variables. $\mathrm{X_i} = \{y2021, age, alcohol\_consumption, chronic, economic\_status, education, female, household\_nr, profession, region\}$. No suitable instrument was found, motivating the inclusion of these variables. The endogeneity issue that is likely present around the user charge variables should be greatly diminished.

5 – Results

5.1 – Estimated models

Below are the tables of results for all eight models.[2] The estimates for certain variables not directly relevant to the analysis will reported in the appendix.

[2] Statistical significance: *** at 1%, ** at 5%, * at 10%.

y = em_freq	1		2	
	OLS	NB2	OLS	NB2
uc_em_expected	-0.00836**	-0.0342**	-	-
	(0.00422)	(0.0144)	-	-
uc_exempt	-	-	0.112*	0.460**
	-	-	(0.0595)	(0.183)
trpt_em	-0.00547	-0.0274*	-0.00547	-0.0283*
	(0.00363)	(0.0149)	(0.00362)	(0.0149)
presc_em	0.00526	0.0112	0.00491	0.0111
	(0.00593)	(0.00832)	(0.00597)	(0.00854)
uc_pcu_expected	0.00623	0.0203	-	-
	(0.00561)	(0.0209)	-	-
trpt_pcu	-0.0255	-0.0670	-0.0248	-0.0663
	(0.0232)	(0.0500)	(0.0233)	(0.0497)
presc_pcu	-0.00199	-0.00343	-0.00187	-0.00337
	(0.00339)	(0.00809)	(0.00338)	(0.00822)
chronic	0.405***	0.936***	0.447***	1.31***
	(0.0754)	(0.138)	(0.0728)	(0.155)
easy	-0.0760	-0.226	-0.120**	-0.652**
	(0.108)	(0.259)	(0.0585)	(0.302)
somewhatdifficult	0.190**	0.462***	0.0642	0.241
	(0.0802)	(0.153)	(0.0466)	(0.168)
difficult	0.147	0.384**	0.205***	0.638***
	(0.0929)	(0.192)	(0.0786)	(0.248)
uc_em_chronic	0.00242	0.0223**	-	-
	(0.00526)	(0.0108)	-	-
uc_em_easy	-0.00350	-0.0312	-	-
	(0.00714)	(0.0233)	-	-
uc_em_somewhatdifficult	-0.00723	-0.0139	-	-
	(0.00487)	(0.0128)	-	-
uc_em_difficult	0.00317	0.0153	-	-
	(0.00622)	(0.0153)	-	-
exempt_chronic	-	-	-0.0497	-0.385*
	-	-	(0.103)	(0.199)
exempt_easy	-	-	0.0351	0.417
	-	-	(0.130)	(0.393)
exempt_somewhatdifficult	-	-	0.128	0.217
	-	-	(0.0979)	(0.224)
exempt_difficult	-	-	-0.0465	-0.210
	-	-	(0.125)	(0.299)
Fixed effects	Yes	Yes	Yes	Yes
R2/Pseudo R2	0.0817	0.0611	0.0811	0.0605
Obs.	2,254	2,254	2,254	2,254

Table 4: Estimated coefficients for models 1 and 2, from OLS and NB2.

y = em_freq	1		2	
	NB2	Excess zeroes	NB2	Excess zeroes
uc_em_expected	-0.0482	-0.0124	-	-
	(0.0660)	(0.0912)	-	-
uc_exempt	-	-	0.319	-0.185
	-	-	(0.416)	(0.967)
trpt_em	0.0185	0.0688	0.00168	0.0729
	(0.0500)	(0.0729)	(0.0418)	(0.0713)
presc_em	0.00837	-0.0114	-0.00151	-0.0598
	(0.0140)	(0.0258)	(0.00888)	(0.0578)
uc_pcu_expected	0.0565	0.0421	-	-
	(0.0637)	(0.0617)	-	-
trpt_pcu	-0.0760	-0.0277	-0.107	-0.122
	(0.136)	(0.295)	(0.119)	(0.390)
presc_pcu	-0.0383***	-0.0950***	-0.0253	-0.112
	(0.0149)	(0.0275)	(0.0164)	(0.0639)
chronic	0.336	-1.08	0.401	-15.1***
	(0.239)	(0.445)	(0.586)	(3.23)
easy	-0.508	-0.475	-0.497	0.472
	(0.528)	(0.912)	(0.736)	(1.40)
somewhatdifficult	0.259	-0.321	0.256	0.0364
	(0.544)	(0.934)	(0.245)	(0.505)
difficult	0.212	-0.280	0.703*	0.103
	(0.742)	(1.40)	(0.409)	(0.881)
uc_em_chronic	0.00415	-0.0529	-	-
	(0.0279)	(0.0694)	-	-
uc_em_easy	0.0107	0.0766	-	-
	(0.0791)	(0.126)	-	-
uc_em_somewhatdifficult	-0.000981	0.0190	-	-
	(0.0481)	(0.0825)	-	-
uc_em_difficult	0.0200	0.00234	-	-
	(0.0417)	(0.0799)	-	-
exempt_chronic	-	-	0.0820	13.7***
	-	-	(0.484)	(3.47)
exempt_easy	-	-	-0.0170	-1.36
	-	-	(0.896)	(2.02)
exempt_somewhatdifficult	-	-	0.0178	-0.598
	-	-	(0.430)	(1.47)
exempt_difficult	-	-	-0.574	-1.19
	-	-	(0.501)	(1.71)
Fixed effects	Yes		Yes	
Obs.	2,254		2,254	

Table 5: Estimated coefficients for models 1 and 2 from ZINB.

y = went_pcu	3		4	
	LPM	Logit	LPM	Logit
uc_pcu_expected	0.00332	0.0144	-	-
	(0.00375)	(0.0279)	-	-
uc_exempt	-	-	0.184***	0.813***
	-	-	(0.0355)	(0.169)
trpt_pcu	-0.0285***	-0.153***	-0.0287***	-0.155***
	(0.00978)	(0.0496)	(0.00975)	(0.0497)
presc_pcu	0.00316	0.0165	0.0034*	0.0175
	(0.00197)	(0.0109)	(0.00199)	(0.0109)
uc_em_expected	-0.00838***	-0.0394***	-	-
	(0.00201)	(0.0107)	-	-
trpt_em	0.000602	0.00386	0.000902	0.00514
	(0.00268)	(0.0129)	(0.00267)	(0.0130)
presc_em	0.00188	0.00937	0.00135	0.00736
	(0.00214)	(0.0110)	(0.00215)	(0.0112)
chronic	0.231***	1.16***	0.309***	1.41***
	(0.0290)	(0.151)	(0.0366)	(0.181)
easy	-0.0618	-0.321	-0.0382	-0.214
	(0.0472)	(0.234)	(0.0366)	(0.198)
somewhatdifficult	0.0291	0.177	0.0417	0.200
	(0.0272)	(0.152)	(0.0299)	(0.150)
difficult	0.102***	0.552***	0.135***	0.653***
	(0.0349)	(0.197)	(0.0470)	(0.223)
uc_pcu_chronic	0.00687	0.0242	-	-
	(0.00605)	(0.0294)	-	-
uc_pcu_easy	0.00103	0.00640	-	-
	(0.00873)	(0.0455)	-	-
uc_pcu_somewhatdifficult	-0.000811	-0.0171	-	-
	(0.00378)	(0.0289)	-	-
uc_pcu_difficult	0.00116	0.00799	-	-
	(0.00531)	(0.0318)	-	-
exempt_chronic	-	-	-0.107**	-0.352
	-	-	(0.0449)	(0.234)
exempt_easy	-	-	-0.0440	-0.169
	-	-	(0.0642)	(0.315)
exempt_somewhatdifficult	-	-	-0.0381	-0.181
	-	-	(0.0450)	(0.226)
exempt_difficult	-	-	-0.0538	-0.150
	-	-	(0.0593)	(0.310)
Fixed effects	Yes	Yes	Yes	Yes
R2/Pseudo R2	0.2203	0.1773	0.2244	0.1794
Obs.	2,311	2,311	2,311	2,311

Table 6: Estimated coefficients for models 3 and 4, from LPM and Logit

5.2 – Interpretation of results and statistical tests

5.2.1 – Yearly emergency department visits

Model 1 model attempts to show the marginal impact of additional units (here, euros) of user charges on yearly emergency department visits at the individual level, while Model 2 considers instead the impact of user charge exemptions. As the dependent variable is best suited to count data models, the most relevant results are from NB2. At first glance, ZINB does not appear to be a very good fit, indicated by the fact that the variables employed are not, generally, statistically significant in the inflate/excess zeroes portion. A Vuong test outputs a test statistic of 4.33, with a p-value close to zero. This strongly suggests that there are excess zeroes present in the dependent variable, *em_freq*.

Variable *uc_em_expected* – which is composed of predictions of what individuals expect to pay in user charges – is used to estimate the marginal effect of additional units of user charges. It has a negative estimated coefficient under all three estimation methods, but only OLS and NB2 show it as statistically significant – at 5% in both. ZINB does not indicate that user charges are statistically significant in reducing the probability that an observation is generated by the excess zeroes process. OLS indicates that, on average, *ceteris paribus*, one additional euro of user charges is associated with a reduction in yearly emergency department visits of 0.00836. NB2 presents an IRR of 0.9663, indicating that additional euros are associated with a reduction in 3.37% in yearly visits. In other words, if an individual visits the emergency department 10 times in a year, a user charge increase of 10€ will be expected to, on average, *ceteris paribus*, decrease his visits by a third, down to around 7.

Variable *uc_exempt* considers the impact of user charge exemptions on yearly emergency department visits. It is statistically significant at 10% under OLS and at 5% under NB2. The OLS estimate associates exemptions with a 0.112 increase in yearly emergency department visits, while the NB2 estimate of 0.460 associates exemptions with an increase by the multiple 1.5841, or an increase of 58.41%, in both cases on average, *ceteris paribus*. Given that the mean value of *em_freq* in the observation set used in these regressions was 0.352, the OLS and NB2 values are similar (OLS is essentially indicating an average change of 33.3% at the mean), and not unreasonable – a 58.41% increase on all *em_freq* values would result in an average of 0.558 visits a year.

The expenses variables are predictions of what individuals expect to pay. User charges on primary care unit appointments are not statistically significant by themselves in Model 1. The variables for expected transportation expenses in primary care unit appointments and expected prescribed medication expenses for emergency department visits, *trpt_pcu* and *presc_em*, are not statistically significant in models 1 and 2. Consequently, these results provide us with no evidence to suggest that *uc_pcu*, *trpt_pcu* and *presc_pcu* individually have marginal effects different from zero.

Expected transportation expenses for emergency department visits, *trpt_em* are statistically significant at 10% under NB2, but not at all under OLS. ZINB also does not show any statistical significance. Though NB2 results are more reliable due to it fitting the data better than OLS, 10% significance is small. Models 1 and 2 present estimated coefficients of 0.0274 and 0.0283, respectively, under NB2. One additional euro in expected emergency department transportation expenses are associated with reduction in yearly emergency department visits of 2.71% in model 1 and 2.80% in model 2 (essentially the same).

Expected primary care unit prescribed medication costs, *presc_pcu*, are statistically significant at 1% under ZINB, in both the count data and excess zeroes portions. This indicates that an additional euro in expected prescribed medication costs is associated with a decrease in yearly visits of 3.76%. Each additional euro is also associated with a reduction of

10.1% in the probability that a given observation is generated by the excess zeroes process. This result is strange – we would expect primary care unit prices to increase emergency department visits, assuming that the two are competing options for individuals. It is possible that costs for prescribed medication are very similar in both types of hospital service. Given this, increases in expected costs would reduce both types of hospital use. If this is the case, it may also explain why the other two estimation methods show no statistical significance – costs are not an important factor for individuals as they are not avoidable and are perceived as being very similar in either case.

Tests for joint significance for Model 1 (following the NB2 regression) indicate that *uc_em*, *trpt_em* and *presc_em* are jointly significant at 1% (p-value of 0.0089); and *uc_pcu*, *trpt_pcu* and *presc_pcu* are not jointly significant even at 10% (p-value of 0.3299). We may take this to mean that the price of going to the emergency department (the sum of user charges and transportation and prescribed medication expenses) is highly statistically significant in explaining the individual's decision to demand emergency department visits. The price of the alternative (primary care unit appointments), however, is not. This may reflect the unplanned nature of typical emergency department visits.

Chronic conditions are statistically significant at 1% in all cases in Models 1 and 2, except for: Model 1 ZINB, both count data and excess zeroes; and Model 2 ZINB, under count data. OLS associates them with an increase of 0.405 and 0.447 in Models 1 and 2, respectively. Models 1 and 2 disagree on NB2 estimates, however, presenting IRRs of 2.55 and 3.71, respectively – increases in yearly visits of of 155% and 271%. This is probably due to a bias in *chronic*, likely because both *uc_em_expected* and *uc_pcu_expected* were constructed, among other variables, using *chronic* – these three have significant multicollinearity between each other. As suggested by Wooldridge in (Wooldridge 2013) (page 149), this multicollinearity could be making it difficult to uncover the partial effect of each variable, splitting the impact of *chronic* between *chronic*, *uc_em_expected* and *uc_pcu_expected* in Model 1, and between *chronic* and *uc_exempt* in Model 2. Then, the Model 2 estimate could be seen as underestimating the impact that having a chronic condition has on an individual's emergency department use.

The large estimated impact of *chronic* leads us to expect a strong result in the interaction between it and *uc_em_expected*. The interaction with user charges is statistically significant at 5% under NB2, with an estimated coefficient of 0.0223. The interaction with *uc_exempt*, *exempt_chronic* is significant at 10% under NB2, with an estimated coefficient of -0.385; and at 1% in the excess zeroes portion of ZINB, with an estimate of 13.7. The values of interactions must be added to the general impact of user charges or exemptions for the full impact on the particular type of individual: user charges have an overall IRR of .9881 ($e^{0.0223-0.0342}$) in individuals with chronic conditions; they are expected to reduce their yearly visits by 1.19% with each additional euro in user charges. This value is less than half the value for the average individual of 3.37%. The overall IRR for exemptions on individuals with chronic conditions is 1.0779 ($e^{0.460-0.385}$), indicating an average, *ceteris paribus*, increase of 7.79% – much lower than the overall impact of 58.41%. As for the excess zeroes, the overall IRR is 0.2466 ($e^{13.7-15.1}$), indicating that the probability of being an excess zero of observations which have chronic conditions and exemptions (all individuals with chronic conditions should be exempt) is lower by 75.3%. These results show that individuals with chronic conditions are less sensitive to changes in user charges. This fits with the notion that their demand for hospital services is relatively more inelastic. It is worth nothing, though, that the result for *exempt_chronic* is not very reliable: all individuals with chronic conditions have user charge exemptions – it is unclear what the regressions are capturing, since it cannot compare these results to individuals with chronic conditions but no exemptions.

Different levels of income, proxied by the dummy variables *easy*, *somewhatdifficult* and *difficult* (indicating the individual's self-assessment of how easily their household meets overall costs, not only hospital expenses) show some statistical significance: *easy* at 5% under OLS and NB2 in Model 2; *somewhatdifficult* at 5% under OLS and 1% under NB2, both in Model 1; *difficult* at 5% under NB2 in Model 1, 1% under OLS and NB2 under Model 2, and 10% in Model 2's ZINB count data portion. But, these results are not very intuitive and likely suffer from bias – lower levels of income are associated with increased emergency department visits. This is the well-known link between less wealth and worse health. To try to tackle this bias, Model 1's regression was repeated including variable *health_self_assessment* – this resulted in the estimates for dummy variables *somewhatdifficult* and *difficult* to increase, becoming closer to zero, but still negative. Including *health_self_assessment* is not enough. No suitable control is available to correct this endogeneity issue – hence, *health_self_assessment* was omitted from the main results as it would cause more endogeneity issues than it would solve (due to poor health leading to increased uses of both emergency departments and primary care units). The bias in these variables would also lead to questionable results in the interactions but, in any case, they are not statistically significant at 10%. The p-values of the interactions remain above 0.1 even when *health_self_assessment* is added to the regression, additionally.

5.2.2 – Probability of having an appointment at a primary care unit

Models 3 and 4 considers the impact of user charges on the probability that an individual has an appointment at a primary care unit over the course of a year. The predictions used (constructed using Stepwise OLS) show that the unit change of user charges does not have a statistically significant effect on primary care unit use. Further, the estimated coefficients are positive – a counterintuitive outcome. This result is highly sensitive to the method used in the construction of the predictions of individual expectations of costs – the use of a different estimation method (such as normal OLS or Tobit), or a different selection of variables, can easily result in statistically significant estimates and reverse the sign of the estimates. Given this, it is difficult to reject the null hypothesis of no effect. Economic theory would suggest that there should be a negative impact, but evidence is unclear. Repeating the regressions with alternative constructions results in estimated coefficients of *uc_pcu_expected* that are more negative than the ones in Table 6, and with statistical significance (10% for OLS, 1% for Tobit). We may tentatively accept that additional euros of user charges are associated with at least a negative impact, but these variables are difficult to trust. In any case, none of the constructed variable variants have an especially significant economic effect.

User charge exemptions are rather more impactful. Both LPM and logit show *uc_exempt* with statistical significance at 1%. LPM associates exemptions with increasing the probability that *went_pcu* = 1 by, 0.184 or 18.4% (note: probability falls linearly by 0.00882), while logit associates exemptions with multiplying the probability by 2.25, a 125% increase. Logit shows the exemption variable as being the most important of the expense variables, having an 8 times larger (in absolute value) impact than single euros of transportation expenses on primary care unit appointments.

The variable *trpt_pcu* is statistically significant at 1% in all four cases. The estimates do not seriously change between Models 3 and 4: the LPM estimates are -0.0285 and -0.0287 while the logit estimates are -0.153 and -0.155. Considering the average of the two, LPM associates additional euros in *trpt_pcu* with a decrease of 2.86% in the probability that *went_pcu* = 1, while logit associates additional units with a multiplication of that probability by 0.8573 (14.27%). Under logit, *trpt_pcu* has the greatest importance of the unit cost variables (of course, it is much weaker than *uc_exempt*).

Expected costs of prescribed medication on primary care units are only statistically significant under LPM in Model 4, and only at 10%. The estimated coefficient is 0.0034 – additional euros in costs are associated with an increase in the probability that *went_pcu* = 1. This result is too imprecise to be trusted and has little economic significance. Variables *trpt_em* and *presc_em* do not have any statistical significance in Models 3 and 4.

The expected user charges on emergency department visits are statistically significant at 1% in all four estimation methods, with negative coefficients: -0.00838 under LPM and -0.0394 under logit. A confusing result – it may be a sign that the Stepwise estimates are improperly constructed. These negative coefficients may be picking up the impact of the "true" expected user charges on primary care unit use, leading *uc_em_expected* to be biased downward due to the likelihood of there being a large degree of correlation between the two types of user charges. That said, if we assume that these results are accurate, they serve as an indication that emergency department visits and primary care unit appointments are complements.

The *chronic* variable is statistically significant at 1% in all four cases, being associated with increases in the probability of success. Model 3 has estimated coefficients of 0.231 under LPM and 1.16 under logit, while Model 4 has 0.309 and 1.41. These slight differences are likely due to the same causes discussed in the section for *chronic* in the emergency department visit models. The only interaction term with *chronic* that is statistically significant is *exempt_chronic* under LPM, at 5%. Model 4 had an LPM chronic estimate of 0.309, indicating a 30.9% increase in the probability that *went_pcu* = 1. Exemptions had an impact of raising this probability by 18.4% under LPM. The coefficient on *exempt_chronic* of -0.107 indicates that exemptions will have a smaller impact on individuals with chronic conditions – exemptions will raise the probability of *went_pcu* = 1 by 7.7% instead. But, as before, this result is unreliable as, in the data, everyone with a chronic condition was exempt.

Finally, the variables indicating wealth: only *difficult* is statistically significant, and at 1%. The same problem emerges – positive coefficients, likely due to poorer individuals having worse health. None of the interaction terms are statistically significant and including *health_self_assessment* in the regression does not change matters much.

5.2.3 – Closing remarks

Some interesting results came to light. The user charge predictions had clear limitations from the start, though it was hoped that interesting insights would emerge. Exemptions and unit changes have at times contradictory results – especially in Models 3 and 4, where there was very limited evidence for *uc_pcu_expected* having an effect different than zero, but where *uc_exempt* had a strong estimated effect. This suggests that user charges may have a non-linear impact – perhaps the existence of user charges itself discourages hospital use but, at least in the range of the data available (where values of user charges are relatively contained), unitary increases have a smaller impact. This could be estimated by adding a variable that takes on the value of 0 when the observation has user charges at "0" (this would not coincide with *uc_exempt*, as non-exempt individuals may use services that have no associated user charge), and "1" otherwise. The problem with these estimates, however, is that the lowest value estimated is around 0.55, with zero values added once the data from *uc_exempt* was copied over – it is unclear what constitutes a "zero" value in *uc_em_expected* and *uc_pcu_expected*. Regardless, we tested this by generating a variable that is "0" when user charges are less than 0.6, and 1 otherwise, and repeating the regressions with it. This variable was not statistically significant, and the user charge constructed variables lost statistical significance – we lack evidence to reject the null hypothesis of no non-linear effects. Despite this, the notion of there being a non-linear effect remains appealing.

The strong impact of expected transportation expenses was interesting. In Models 1 and 2, unit increases were correlated with decreases of 2.71% of *em_freq* and were the strongest factor after *uc_exempt* in Models 3 and 4. These are highly important costs that governments cannot easily change by law – policymakers will struggle to improve healthcare coverage without tackling transportation problems; the best solutions may involve setting up expensive infrastructure. Politically, it would probably be less popular than abolishing user charges.

Expected prescribed medication had weak impacts in general – this may be due to individuals not perceiving a significant difference between these costs in emergency department or in primary care units; in this case, it would not be considered when deciding between visiting an emergency department or having an appointment at a primary care unit, as both would have the same expected value. It would make sense for this to be the case – if the individual would go to either place with the same problem, it is natural to assume that the solution prescribed would be the same. Overall hospital usage may be influenced by medication costs, but not usage of emergency departments and primary care units.

Finally, there were disappointing results for the economic status dummy variables. It was hoped that they would reinforce or contradict some of the finding discussed in the Section 2. Instead, insufficient evidence was found to identify the impact of wealth on sensitivity to user charges – if there is any at all. It is unclear whether this was due to the lack of an adequate treatment of the endogeneity problems, the limitations of the constructed variables or because in fact there is no particular effect of wealth on this.

6 – Conclusion

User charges were found to have clear negative effects on hospital use in emergency departments, but unclear effects in primary care units. Furthermore, even when statistically significant, these effects are small at the individual level. One-euro increases in user charges on emergency department use were found to reduce yearly visits by 3.37% for the average individual and by 1.19% for individuals with chronic conditions. No evidence was found to reject the null hypothesis that an individual's income influences the impact user charges have on them. User charge exemptions were found to increase yearly visits by 58.41%. Visits by individuals with chronic conditions were found to only increase by 7.79%, indicating a more inelastic demand for healthcare from them. No evidence was found to suggest that user charges on primary care unit use impacted yearly emergency department visits.

User charges on primary care unit use were found to reduce the probability that an individual has an appointment over the course of a year. Exemptions were found to increase this probability by 18.4% following an OLS regression. A logistic regression reported that exemptions increased this probability by the multiple 2.25, or by 125%. Only OLS found evidence for a particular effect of exemptions on individuals with chronic health conditions: they raise the probability in question by only 7.7%. Marginal effects of additional euros of user charges were studied, but no strong evidence was found to allow for the precise impact to be identified. No evidence was found, once more, to suggest that income levels impact the sensitivity of individuals to user charges.

The results partly agree with the expectations regarding the demand functions for each type of hospital use. Costs related to the type of hospital use under analysis had negative coefficients when statistically significant. Costs of using the other type of service had very little statistical significance in all models, though they usually had positive estimated coefficients. The main exception was that user charges on emergency department visits was associated with an increase in the probability that *went_pcu* = 1. That said, it is unclear from this whether emergency department visits and primary care units are complements or substitutes. This result for user charges may be due to incorrect methodology and incorrectly constructed predictions, or even due to bias. Not enough evidence was found either way.

Bibliography

Cameron, A. Colin, and Parvin K. Trivedi. 2005. *Microeconometrics - Methods and Applications.* New York: Cambridge University Press.

Cameron, A. Colin, and Pravin K. Trivedi. 2009. *Microeconometrics Using Stata.* Stata Press.

Canadian Foundation for Healthcare Improvement. 2014. "Myth: User fees ensure better use of health services." *Journal of Health Services Research & Policy* (Sage Publications, Inc.) 19 (2): 121-123. Accessed September 10, 2021. https://www.jstor.org/stable/26751463.

DRE. 2020. "Decreto-Lei n.º 96/2020." *Diário da República.* November 4. Accessed September 20, 2021. http://www.acss.min-saude.pt/wp-content/uploads/2016/09/DL_96_2020.pdf.

Fundação Francisco Manuel dos Santos. n.d. *SNS: consultas, internamentos e urgências - Continente: Pordata.* Accessed 11 12, 2021. https://www.pordata.pt/Portugal/SNS+consultas++internamentos+e+urg%c3%aancias+++Continente-159-3649.

RAND Corporation. 2006. "The Health Insurance Experiment." *RAND Corporation research brief series.* California. Accessed September 11, 2021. https://www.rand.org/content/dam/rand/pubs/research_briefs/2006/RAND_RB9174.pdf.

Stoddart, G.L., M.L. Barer, R.G. Evans, and V. Bhatia. 1993. "Why not user charges? The real issues." *HPRU* (Centre for health services and policy research, University of British Columbia) (93:12D).

Tamblyn, R., R. Laprise, J. A. Hanley, M. Abrahamowicz, S. Scott, N. Mayo, J. Hurley, et al. 2001. "Adverse events associated with prescription drug cost-sharing among poor and elderly persons." *JAMA* 285 (4): 421-429. Accessed September 21, 2021. https://doi.org/10.1001/jama.285.4.421.

WHO. 2013. "Arguing for Universal Health Coverage." *World Health Organisation.* Accessed December 9, 2021. https://www.who.int/health_financing/UHC_ENvs_BD.PDF.

Wooldridge, Jeffrey M. 2013. *Introductory Econometrics - A Modern Approach.* South-Western, Cengage Learning.

Appendix I – Table of descriptive statistics for the full set of observations

Variable	Obs.	Mean	Std. Dev.	Range
em_freq	7,194	0.5252989	1.502206	[0,50]
went_pcu	5,848	0.5803694	0.4935407	{0,1}
uc_exempt	7,370	0.4134328	0.4924825	{0,1}
uc_em_cleaned	1,612	6.909	9.899	[0,80]
uc_pcu_cleaned	1,790	3.953	5.121	[0,51]
trpt_em_cleaned	2,716	2.590	6.064	[0,80]
presc_em_cleaned	2,663	13.708	25.374	[0,500]
trpt_pcu_cleaned	2,948	1.322	3.219	[0,40]
presc_pcu_cleaned	3,086	14.201	21.244	[0,250]
uc_em_SW	5,058	12.661	7.248	[0.552,47.664]
uc_pcu_SW	5,058	5.029	4.026	[0.679,46.417]
uc_em_SW_expected	4,924	5.454	7.895	[0,47.664]
uc_pcu_SW_expected	4,924	2.178	3.452	[0,46.417]
trpt_em_SW	4,568	4.262	3.622	[0,28.114]
presc_em_SW	7,572	14.401	12.379	[0,114.622]
trpt_pcu_SW	4,568	1.491	1.181	[0.014,7.075]
presc_pcu_SW	5,058	15.373	9.337	[0,85.422]
age	7,572	45.78975	18.11133	$[15,97] \cap \mathbb{Z}$
alcohol_consumption	5,058	6.695532	11.80833	$[1,9] \cap \mathbb{Z}$
chronic	5,058	0.2643337	0.4410214	{0,1}
distance_to_em	7,082	6178.754	9022.985	[0,120000]
female	7,572	0.5334126	0.4989153	{0,1}
health_self_assessment	3,795	2.261397	0.8380599	$[1,5] \cap \mathbb{Z}$
household_nr	7,572	2.944929	1.296187	$[1,9] \cap \mathbb{Z}$

Appendix II – Construction of the predicted values

We focused on three estimation methods when constructing candidates for the predictions to be used in the main analysis. These methods were OLS, Tobit type II (with censoring at 0) and Stepwise OLS. Each cleaned variable was regressed on a specific set of variables three times, once for each estimation method. The set of regressors was chosen per cleaned variable, remaining the same for each estimation method. The only difference is in Stepwise OLS, which was set to cut out the variables that were not statistically significant at 5%. The list of variables used in OLS and Tobit is presented in the table below:

Constructed variable	Dependent variable and regressors used
uc_em_OLS and uc_em_tobit	**Dependent variable:** uc_em_cleaned **Regressors:** female age y2021 y2020 y2019 y2017 y2015 household_nr municipality profession chronic
trpt_em_OLS and trpt_em_tobit	**Dependent variable:** trpt_em_cleaned **Regressors:** distance_to_em female age y2021 y2020 y2019 y2017 y2015 household_nr municipality profession chronic
presc_em_OLS and presc_em_tobit	**Dependent variable:** presc_em_cleaned **Regressors:** y2021 y2020 y2019 y2017 y2015 household_nr alcohol_consumption municipality profession age female education
uc_pcu_OLS and uc_pcu_tobit	**Dependent variable:** uc_pcu_cleaned **Regressors:** female age y2021 y2020 y2019 y2017 y2015 household_nr municipality profession chronic
trpt_pcu_OLS, trpt_pcu_tobit	**Dependent variable:** trpt_pcu_cleaned **Regressors:** distance_to_em female age y2021 y2020 y2019 y2017 y2015 household_nr municipality profession chronic
presc_pcu_OLS, presc_pcu_tobit	**Dependent variable:** presc_pcu_cleaned **Regressors:** y2021 y2020 y2019 y2017 y2015 household_nr alcohol_consumption municipality profession age female education

The next table presents the variables that were not omitted by Stepwise OLS:

Constructed variable	Regressors used
uc_em_SW	profession4, municipality239, y2021, y2020, y2019, municipality175, municipality182, municipality102, municipality8, municipality46, municipality11, municipality39, municipality112, municipality163, municipality190, profession2, municipality196, chronic, municipality132
trpt_em_SW	distance_to_em, municipality41, municipality278, y2021, y2020, y2019, municipality14, municipality90, municipality8, municipality115, chronic, municipality183, municipality45
presc_em_SW	y2021, y2020, y2019, municipality243, municipality67, municipality237, municipality165, municipality155, municipality190, municipality186, profession4, municipality145, education2, age, municipality183, municipality167, municipality15
uc_pcu_SW	municipality167, age, y2021, y2020, y2019, municipality36, municipality182, municipality102, municipality158, municipality107, municipality109, municipality196, chronic, municipality112, municipality163, municipality168, municipality67
trpt_pcu_SW	distance_to_em, municipality9, municipality89, y2021, y2020, y2019, municipality153, municipality157, municipality7, chronic, municipality155, municipality183, municipality47, municipality195, municipality186, municipality40, municipality182, municipality264, municipality68, municipality187, municipality13, municipality189, municipality168, municipality177, municipality14, municipality41, municipality35, municipality152, municipality188
presc_pcu_SW	y2021, y2020, y2019, municipality248, municipality155, municipality63, municipality201, age, municipality229, municipality270, alcohol_consumption8, municipality67, municipality190, municipality167, profession10, municipality182, municipality8, municipality192

Table 7: Regressors used to construct the predicted values for each of the expenses variables, using Stepwise OLS.

As stated in the main text, Stepwise OLS estimates were selected due to retaining a good degree of correlation with the cleaned data while being much more parsimonious and, hence, minimising the number of observations lost. Tables 8 and 9 present the descriptive statistics of the three constructed variables and others. Table 10 presents the correlations between predictions for each expense variable and the cleaned data for each estimation method. This considers only the observation set used in the regressions conducted to estimate the coefficients.

Expenses related to emergency department use:

Type		Variable	Obs.	Mean	Std. Dev.	Range
User charges:	Original:	uc_em_cleaned	1,612	6.909	9.899	[0,80]
	Estimates:	uc_em_OLS	5,058	12.527	7.442	[0,48.922]
		uc_em_tobit	5,058	10.051	9.462	[0,52.906]
		uc_em_SW	5,058	12.661	7.248	[0.552,47.664]
	Expected costs:	uc_em_SW_expected	4,924	5.454	7.895	[0,47.664]
Transportation:	Original:	trpt_em_cleaned	2,716	2.590	6.064	[0,80]
	Estimates:	trpt_em_OLS	4,568	4.176	3.937	[0,27.812]
		trpt_em_tobit	4,568	2.135	4.194	[0,33.055]
		trpt_em_SW	4,568	4.262	3.622	[0,28.114]
Prescribed medication:	Original:	presc_em_cleaned	2,663	13.708	25.374	[0,500]
	Estimates:	presc_em_OLS	5,058	19.349	12.972	[0,114.267]
		presc_em_tobit	5,058	15.556	15.917	[0,114.309]
		presc_em_SW	7,572	14.401	12.379	[0,114.622]

Table 8: Variables for expenses related to emergency department use, including cleaned raw data and constructed variables.

Expenses related to primary care unit use:

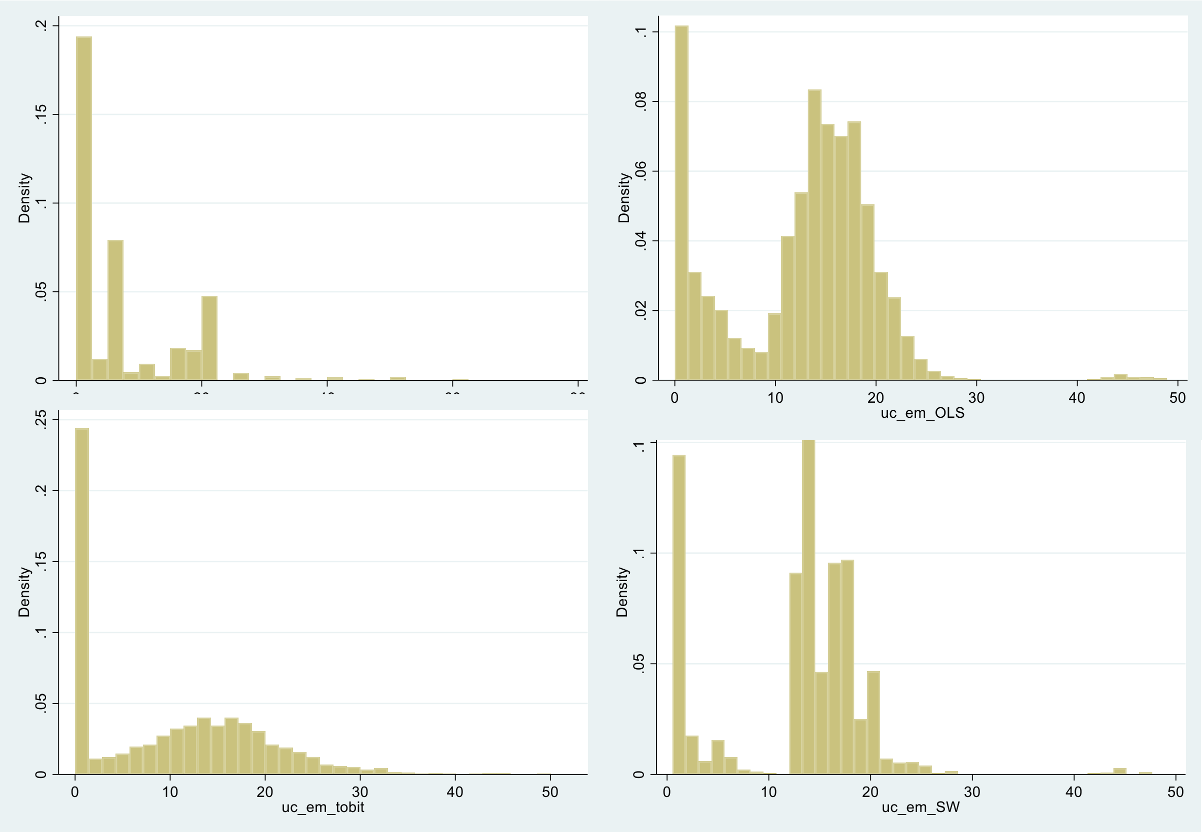
Type		Variable	Obs.	Mean	Std. Dev.	Range
User charges:	Original:	uc_pcu_cleaned	1,790	3.953	5.121	[0,51]
	Estimates:	uc_pcu_OLS	5,058	5.063	4.108	[0,46.408]
		uc_pcu_tobit	5,058	4.572	4.647	[0,46.884]
		uc_pcu_SW	5,058	5.029	4.026	[0.679,46.417]
	Expected costs:	uc_pcu_SW_expected	4,924	2.178	3.452	[0,46.417]
Transportation:	Original:	trpt_pcu_cleaned	2,948	1.322	3.219	[0,40]
	Estimates:	trpt_pcu_OLS	4,568	1.540	1.275	[0,7.370]
		trpt_pcu_tobit	4,568	0.340	0.886	[0,10.178]
		trpt_pcu_SW	4,568	1.491	1.181	[0.014,7.075]
Prescribed medication:	Original:	presc_pcu_cleaned	3,086	14.201	21.244	[0,250]
	Estimates:	presc_pcu_OLS	5,058	15.184	9.919	[0,87.823]
		presc_pcu_tobit	5,058	11.070	12.201	[0,95.355]
		presc_pcu_SW	5,058	15.373	9.337	[0,85.422]

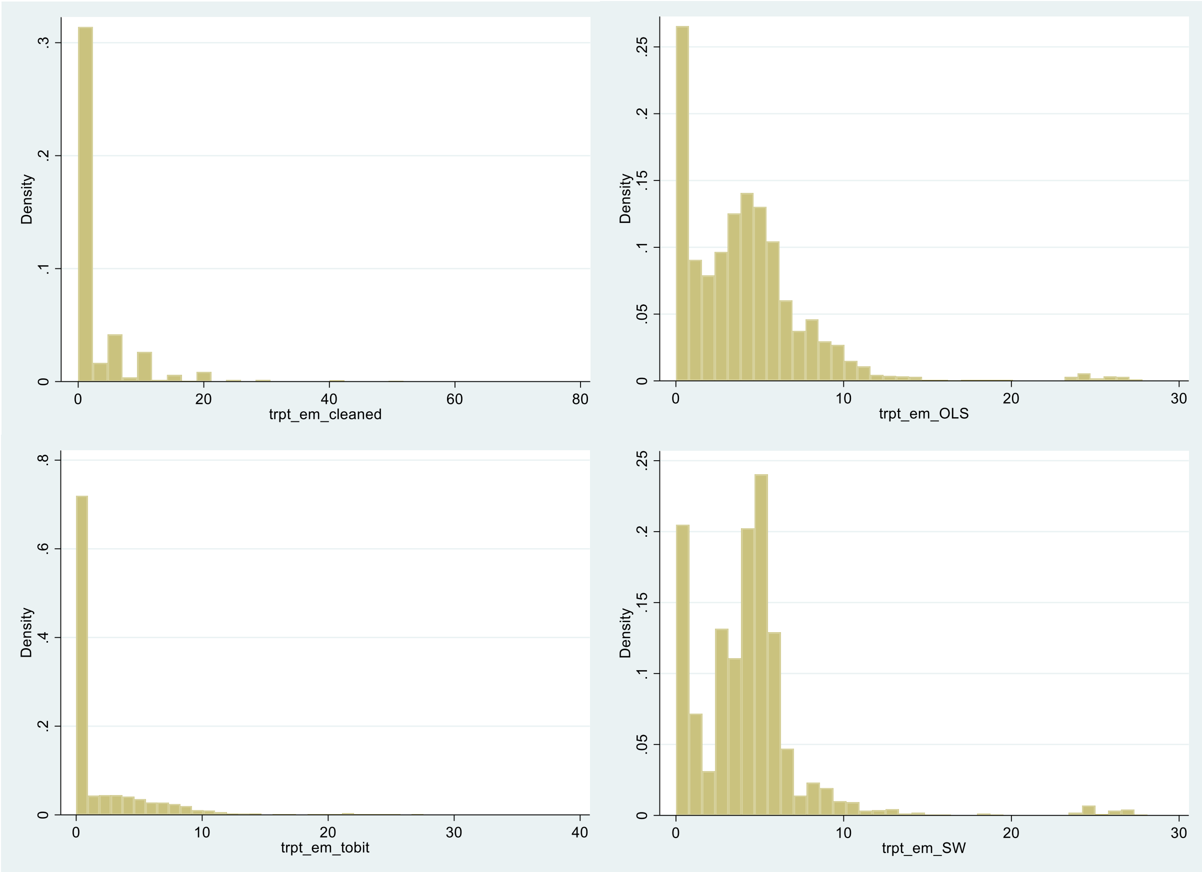
Table 9: Variables for expenses related to primary care unit use, including cleaned raw data and constructed variables.

Estimation method	Variable to be predicted					
	Emergency department			Primary care unit		
	uc	trpt	presc	uc	trpt	presc
OLS	0.7568	0.5407	0.5987	0.6545	0.4327	0.5383
Tobit	0.7311	0.4649	0.5717	0.6303	0.2885	0.5261
Stepwise OLS	0.7324	0.4919	0.5687	0.6366	0.3946	0.5037

Table 10: Correlations between estimates for each of the expenses variable and for each estimation method used. Observation set is that used in each particular regression.

Histograms of the cleaned data and the three different predictions are presented below. Though useful in checking how accurate the predictions were, ultimately, the decision to select the Stepwise OLS estimates was based on the degree of correlation, rather than on how similar the distributions look: it is probable that if the original data were unbiased, its distribution would be significantly different. Therefore, even if the distribution of a constructed variable matched the cleaned data's distribution perfectly, this would not be a guarantee that the predicted values were any good – the original distribution may be wrong.

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.2
.3
0
20
40
60
80
trpt_em_cleaned
Density
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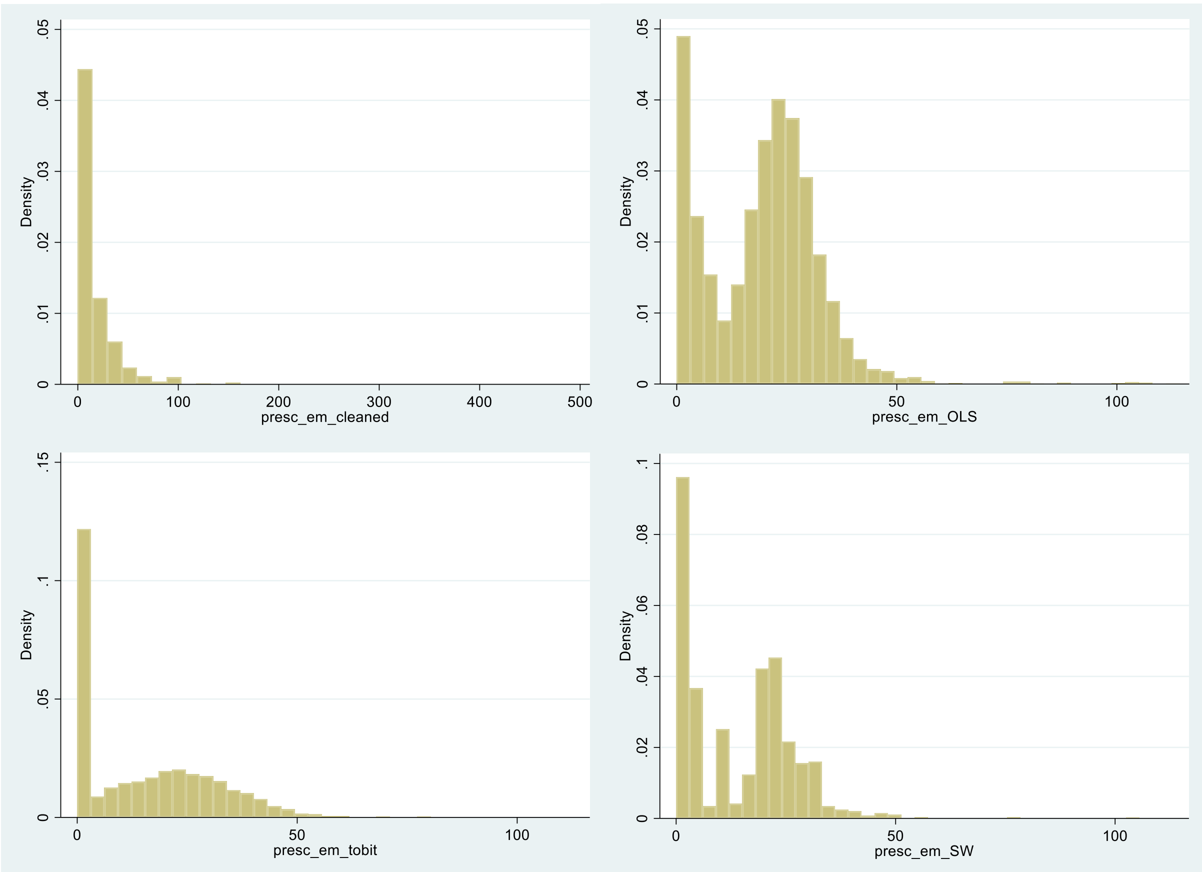
.05
.1
.15
.2
.25
0
10
20
30
trpt_em_OLS
Density
0
.2
.4
.6
.8
0
10
20
30
40
trpt_em_tobit
Density
0
.05
.1
.15
.2
.25
0
10
20
30
trpt_em_SW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.03
.04
.05
0
100
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300
400
500
presc_em_cleaned
Density
0
.01
.02
.03
.04
.05
0
50
100
presc_em_OLS
Density
0
.05
.1
.15
0
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100
presc_em_tobit
Density
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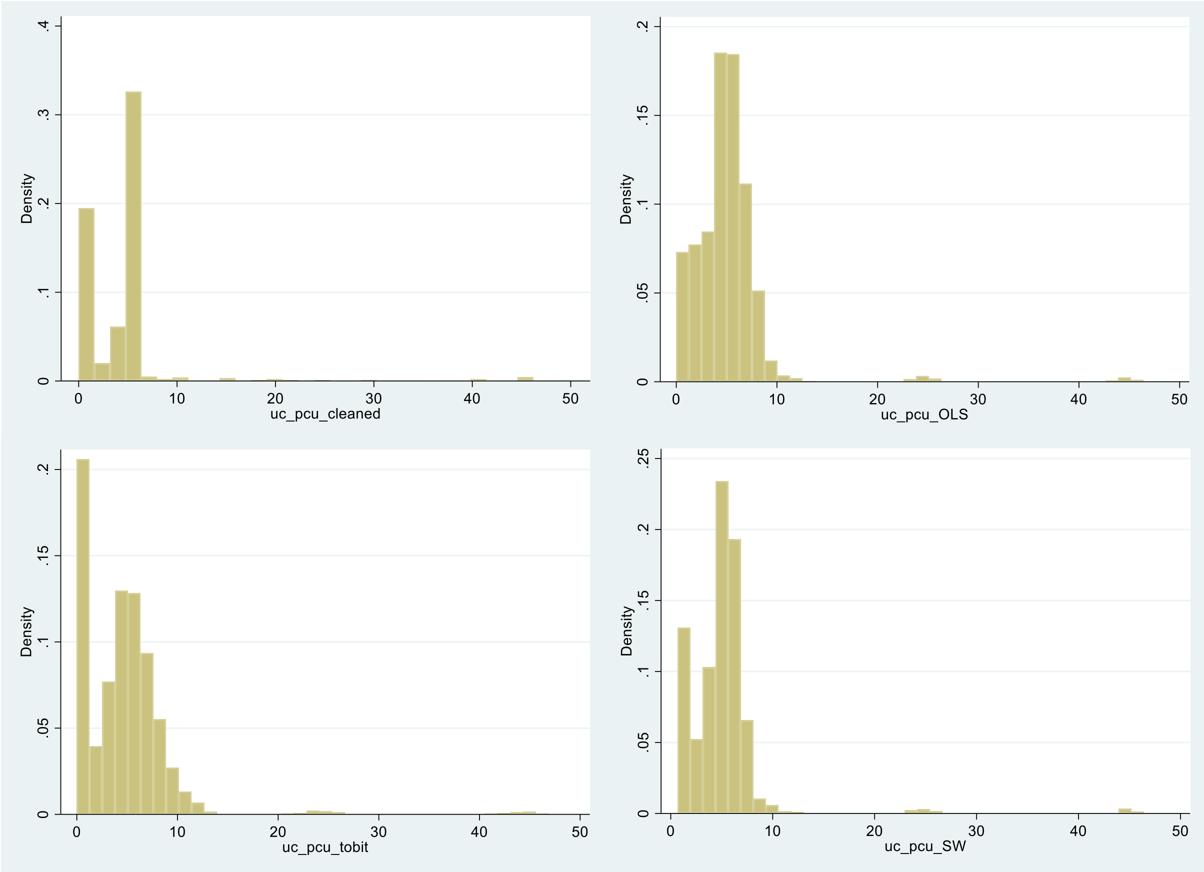
.02
.04
.06
.08
.1
0
50
100
presc_em_SW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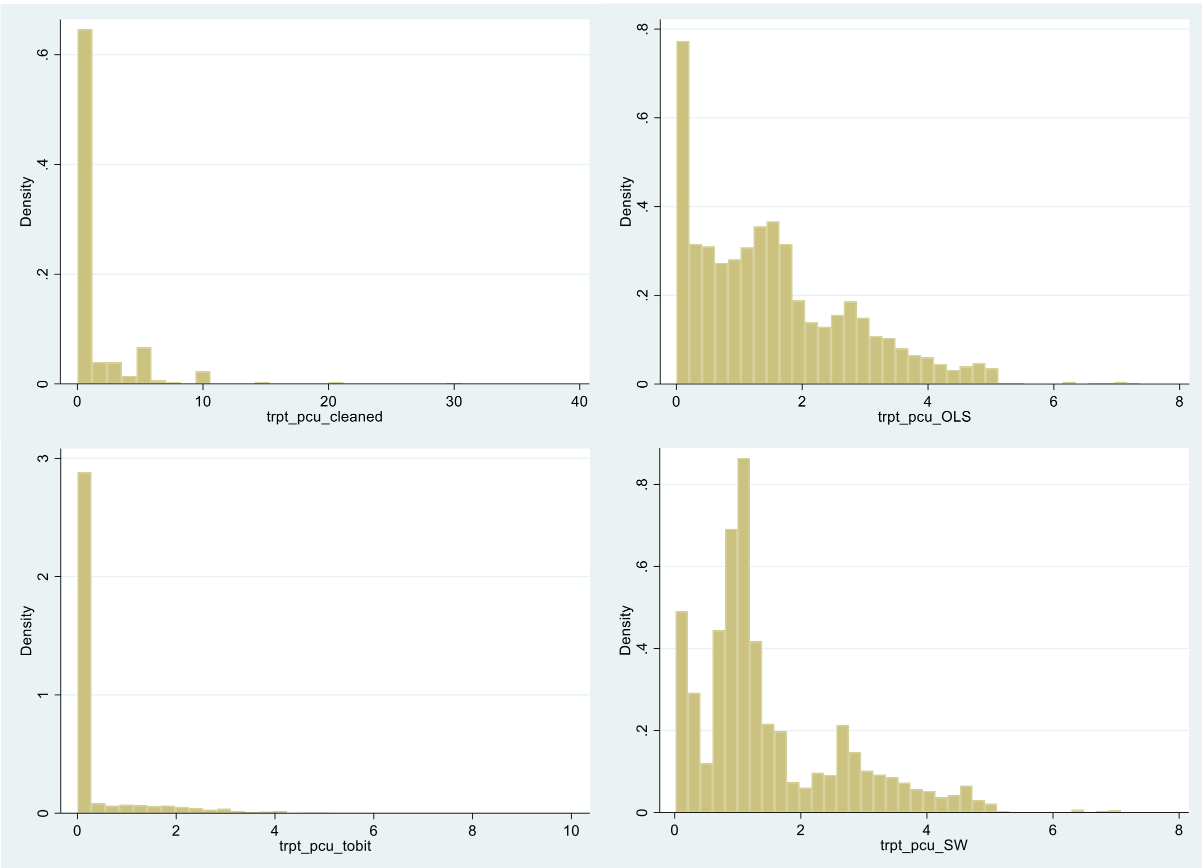
uc_pcu_cleaned
Density
uc_pcu_OLS
Density
uc_pcu_tobit
Density
uc_pcu_SW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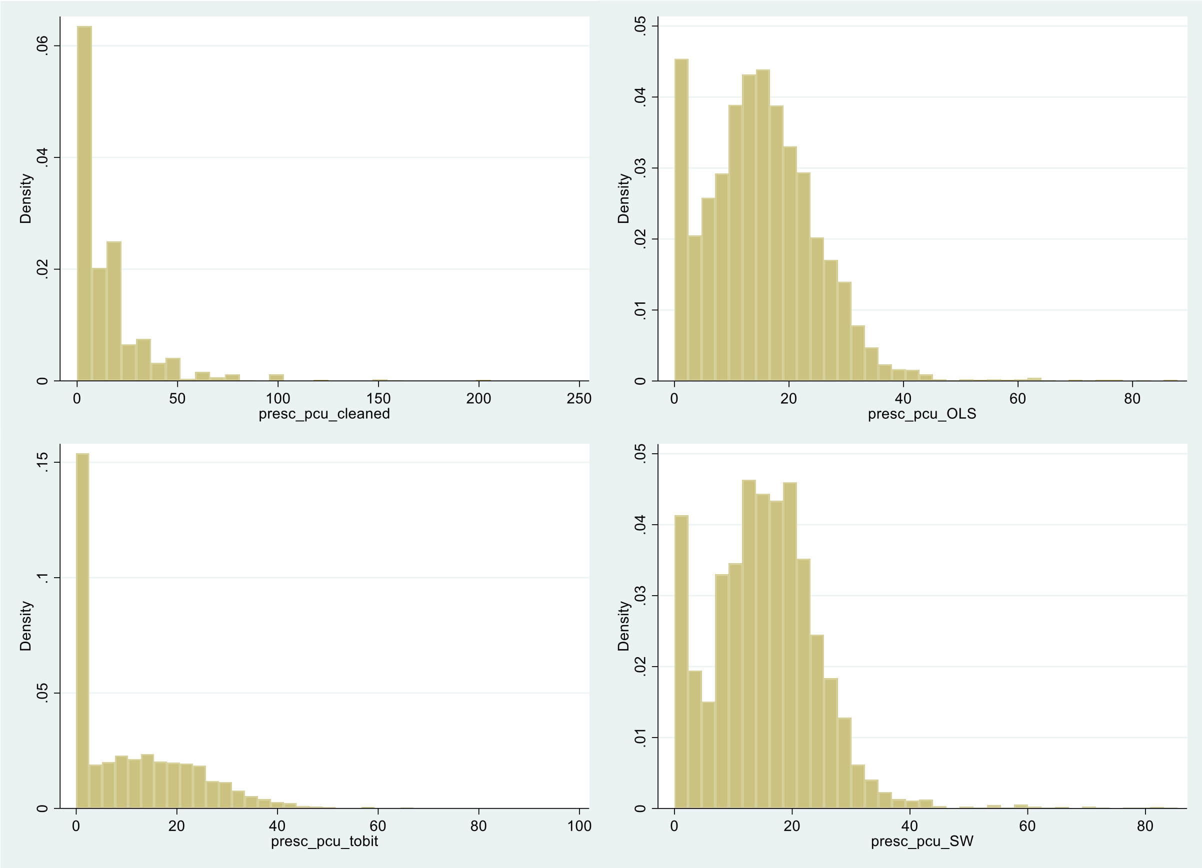
Density
trpt_pcu_OLS
Density
trpt_pcu_tobit
Density
trpt_pcu_SW


Density
presc_pcu_cleaned
presc_pcu_OLS
presc_pcu_tobit
presc_pcu_SW

Appendix III – Verification of assumptions

OLS – Models 1 and 2[3]

The model is linear in its parameters. A non-probabilistic sampling method was used, which may imply bias due to not employing random sampling. Further, the expenses variables are predictions – each observation is therefore not independent of each other. There is no perfect collinearity, with dummy variables set such that this is avoided.

There are likely problems with endogeneity. We cannot guarantee that the zero conditional mean assumption holds in this case. The user charge variables in either model are likely correlated with omitted variables. For example, user charges on emergency department use may be correlated with the quality of healthcare provided at any given location. This may be captured by the municipality dummy variables, but perhaps not completely. One vector which is not considered is the correlation with government spending – as it is a source of revenue in itself – which in turn is correlated with the resources available to public hospitals. The estimated coefficient may be biased through absorbing these effects, and others.

OLS would be unbiased if the above assumptions held. Since they cannot all be confirmed, we also cannot confirm that OLS is unbiased in this case.

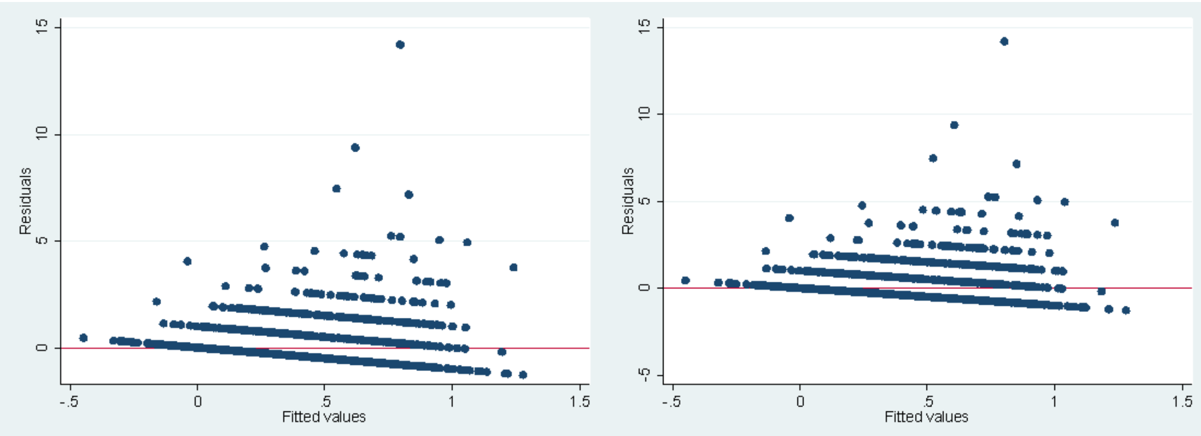
There is certainly a problem with heteroskedasticity; as stated, the expenses variables are predictions – variance cannot be constant here. Furthermore, survey data was used, which itself requires corrections to the standard errors. A Breusch-Pagan test conducted on models 1 and 2 confirms the presence of heteroskedasticity:

[3] The discussion on the OLS assumptions is based on material from (Wooldridge 2013).

	Model 1	Model 2
Test Statistic	915.2	907.36
P-value	0	0

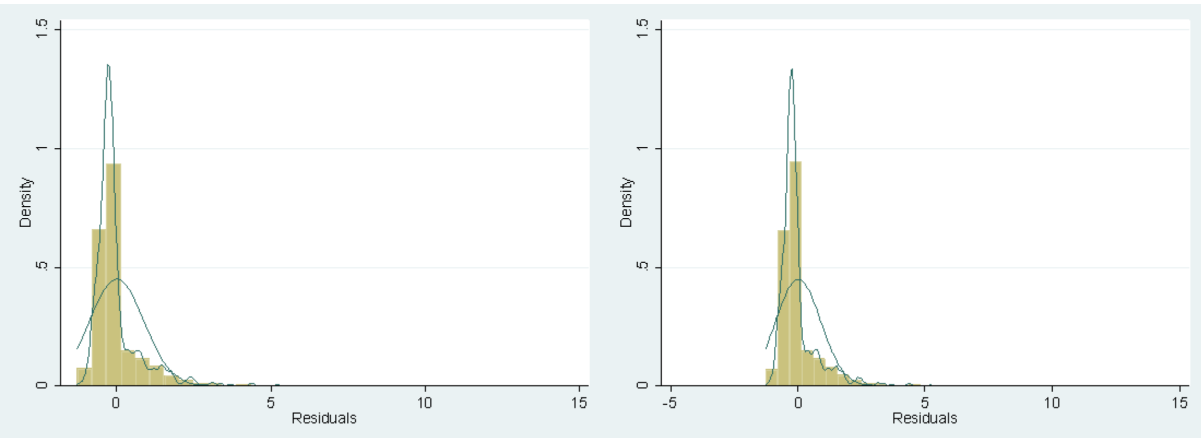
Table 1: Results of Breusch-Pagan tests for heteroskedasticity on models 1 and 2.

The standard errors in the estimated regressions were adjusted, taking into account each observation’s probability weight in the survey.



Figures 1 and 2: Shapes of heteroskedasticity for models 1 (left) and 2 (right).

The above graphs show the predicted errors on the y-axis and the fitted values of the explanatory variables on the x-axis. It illustrates the shape of the heteroskedasticity on each model – in this case, there is a significant trend for it to increase as the fitted values increase.



Figures 3 and 4: Distributions of estimated residuals overlayed on standard normal distribution for models 1 (left) and 2 (right).

For correct inference, we also require that the error term be independent of the regressors and normally distributed. As previously established, the error term is likely correlated with the independent variables. As for its distribution, the histogram above plots the predicted residuals over a standard normal distribution. From this, we can see that the error term distribution features substantially higher kurtosis than the normal distribution and is also slightly positively skewed. A Jarque-Bera test for normality confirms this impression:

	Model 1	Model 2
Test Statistic	190000	190000
P-value	0	0

Table 2: Results of Jarque-Bera tests for normal distribution of the estimated residuals, for models 1 and 2.

In either case, we can safely reject the null hypothesis that the error term is normally distributed. Due to the large sample size used, we can, however, invoke the central limit theorem and say that the error term is approximately normally distributed. Due to endogeneity, we cannot be certain that the OLS estimators will follow a normal distribution as well.

Count Data Models – 1 and 2 (NB2 and ZINB)[4]

The count data models used are the Negative Binomial and Zero-Inflated Negative Binomial. The dependent variable, *em_freq*, takes on only non-negative, discrete values. Further, there are a large number of zeroes and the distribution has a fairly long right tail – the data at first glance appears to fit a Negative Binomial/Poisson-Gamma mixture distribution. Consequently, the standard Poisson model assumption of equidispersion seemed to be too restrictive and NB2 was chosen instead, making the assumptions that the variance is a quadratic function and that the mean parameterisation is $\mu = \exp(x'B)$. Supporting this

[4] The discussion on the assumptions of the count data models used is based on material from (Cameron and Trivedi, Microeconometrics - Methods and Applications 2005)

decision is the result of a test for overdispersion on each model – model 1 has a test statistic of 341.60 and model 2 has 345.22; the null hypothesis that the variance is equal to the mean can be safely rejected.

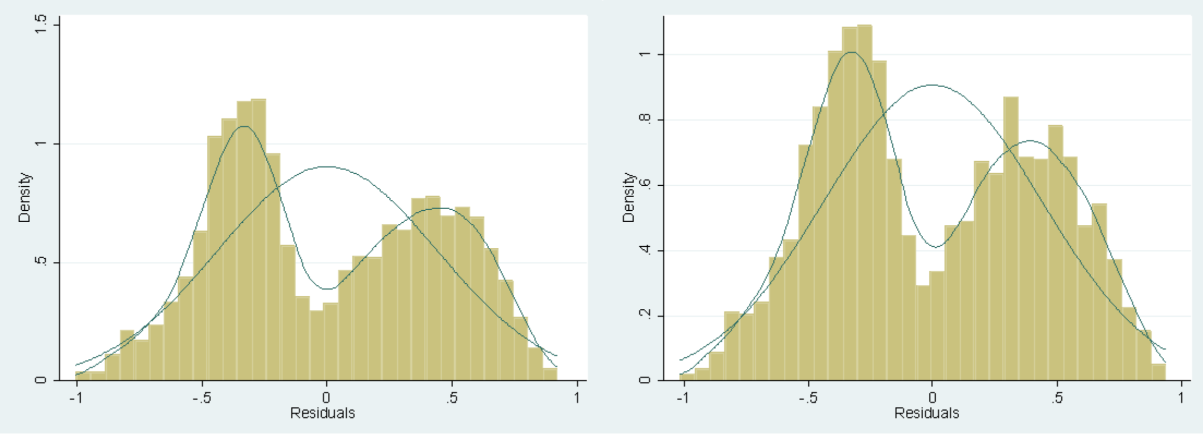
ZINB was considered as well as, firstly, there is a particularly large proportion of zeroes in the data (74.4%) and, secondly, it seems plausible that there is a separate process that determines whether someone goes to the emergency department at all, in addition to a process that, given that the person goes to an emergency department, determines how often said person will go in a year. Whether this proves to be the case will be discussed alongside the interpretation of the coefficients.

Binary Outcomes Models – 3 and 4 (LPM and Logitistic Model)

The Linearly Probability Model estimations for 3 and 4 have linear parameters. As before, the random sampling assumption is violated due to the survey sampling method employed. Perfect collinearity is avoided. Endogeneity concerns are still present, but the controls implemented should be enough to greatly minimise its magnitude. Even so, we cannot be sure that the LPM estimators in this case are unbiased.

On top of heteroskedasticity due to the inclusion of constructed variables, LPM is in fact inherently heteroskedastic. The standard errors, as before, have been corrected using the survey probability weights for each observation.

The residuals once again were tested for normality:



Figures 5 and 6: Distributions of estimated residuals overlayed on standard normal distribution for models 3 (left) and 4 (right).

	Model 3	Model 4
Test Statistic	137.6	126.4
P-value	1.3E-30	3.5E-28

Table 3: Results of Jarque-Bera tests for normal distribution of the estimated residuals, for models 3 and 4.

The residuals are similarly distributed to the normal distribution, but not quite. Invoking the central limit theorem, we can say that they are approximately normally distributed and carry out inference on this basis.

As for the Logistic Model, the assumptions of a binary dependent variable and no perfect multicollinearity are satisfied. As already mentioned, there may be endogeneity and an attempt has been made to correct it through including controls in the regression.

Appendix IV – Full tables of results

Variable	Model 1			Model 2			Model 3		Model 4	
	OLS	NB2	ZINB	OLS	NB2	ZINB	LPM	Logit	LPM	Logit
#1										
uc_em_expected	-0.0084	-0.0342	-0.0482				-0.0084	-0.0394		
	0.0042	0.0144	0.066				0.002	0.0107		
trpt_em	-0.0055	-0.0274	0.0185	-0.0055	-0.0283	0.0017	0.0006	0.0039	0.0009	0.0051
	0.0036	0.0149	0.05	0.0036	0.0149	0.0418	0.0027	0.0129	0.0027	0.013
presc_em	0.0053	0.0112	0.0084	0.0049	0.0111	-0.0015	0.0019	0.0094	0.0014	0.0074
	0.0059	0.0083	0.014	0.006	0.0085	0.0089	0.0021	0.011	0.0022	0.0112
uc_pcu_expected	0.0062	0.0203	0.0565				0.0033	0.0144		
	0.0056	0.0209	0.0637				0.0038	0.0279		
trpt_pcu	-0.0255	-0.067	-0.076	-0.0248	-0.0663	-0.1072	-0.0285	-0.1532	-0.0287	-0.1554
	0.0232	0.05	0.1362	0.0233	0.0497	0.119	0.0098	0.0496	0.0098	0.0497
presc_pcu	-0.002	-0.0034	-0.0383	-0.0019	-0.0034	-0.0253	0.0032	0.0165	0.0034	0.0175
	0.0034	0.0081	0.0149	0.0034	0.0082	0.0164	0.002	0.0109	0.002	0.0109
uc_em_chronic	0.0024	0.0223	0.0042							
	0.0053	0.0108	0.0279							
uc_em_easy	-0.0035	-0.0312	0.0107							
	0.0071	0.0233	0.0791							
uc_em_somewhatdifficult	-0.0072	-0.0139	-0.001							
	0.0049	0.0128	0.0481							
uc_em_difficult	0.0032	0.0153	0.02							
	0.0062	0.0153	0.0417							
y2021	0.0414	0.2015	0.0829	0.0767	0.299	0.2162	-0.0825	-0.4145	-0.0578	-0.2955

	0.0562	0.1326	0.3386	0.0505	0.1252	0.2103	0.0258	0.1348	0.0234	0.1215
age	-0.0037	-0.0123	0.0071	-0.0037	-0.0126	-0.0053	0.0028	0.014	0.0028	0.0139
	0.0025	0.0056	0.0189	0.0025	0.0056	0.0174	0.0011	0.0057	0.0011	0.0057
alcohol_co~2	0.0463	0.087	0.4123	0.0473	0.0926	0.2658	0.0934	0.4937	0.0939	0.4883
	0.0828	0.2679	0.4814	0.0829	0.2682	0.5079	0.0531	0.2707	0.0535	0.2744
alcohol_co~3	0.0787	0.3037	0.0442	0.0785	0.3077	-0.1258	-0.0164	-0.0826	-0.0162	-0.0807
	0.0571	0.2059	0.4494	0.0572	0.2063	0.6012	0.0372	0.1942	0.0371	0.1948
alcohol_co~4	0.0543	0.2788	0.1751	0.0528	0.2762	-0.1054	0.0552	0.2808	0.0566	0.2872
	0.0529	0.1862	0.5318	0.0528	0.1856	0.6265	0.0349	0.175	0.035	0.1753
alcohol_co~5	0.0828	0.2783	0.118	0.0866	0.2877	0.2053	0.0228	0.109	0.0263	0.1231
	0.0591	0.1821	0.379	0.0591	0.1816	0.4238	0.0361	0.1806	0.0358	0.1812
alcohol_co~6	0.2526	0.7257	0.5242	0.2507	0.7224	0.5646	-0.0126	-0.0511	-0.0164	-0.08
	0.1488	0.3071	0.7711	0.1488	0.309	0.6281	0.0549	0.2795	0.0554	0.2857
alcohol_co~7	0.1523	0.5182	0.3408	0.1533	0.523	0.2107	0.077	0.3882	0.0757	0.3782
	0.0823	0.1994	0.4962	0.0823	0.1999	0.3375	0.0369	0.1857	0.0368	0.1855
alcohol_co~8	0.2002	0.5642	0.4711	0.1984	0.5612	0.3687	0.1447	0.735	0.1408	0.7237
	0.1003	0.2024	0.3933	0.1002	0.2043	0.3	0.0463	0.2561	0.0461	0.2564
alcohol_co~9	0.111	0.333	0.248	0.1098	0.333	0.2659	0.0727	0.3597	0.0711	0.3523
	0.0617	0.1606	0.4602	0.0615	0.1608	0.4104	0.0314	0.1576	0.0312	0.1571
chronic	0.4053	0.9362	0.336	0.4474	1.3124	0.4015	0.2309	1.159	0.3094	1.4094
	0.0754	0.1379	0.2391	0.0728	0.1551	0.5863	0.029	0.1507	0.0366	0.1808
easy	-0.076	-0.2261	-0.508	-0.1199	-0.6523	-0.4966	-0.0618	-0.3209	-0.0382	-0.2143
	0.1077	0.2591	0.5281	0.0585	0.3021	0.7358	0.0472	0.2336	0.0366	0.1983
somewhatdifficult	0.1902	0.4616	0.259	0.0642	0.2406	0.256	0.0291	0.1768	0.0417	0.2
	0.0802	0.1526	0.5441	0.0466	0.168	0.2447	0.0272	0.1522	0.0299	0.1499
difficult	0.1471	0.3836	0.2123	0.2054	0.638	0.7034	0.1018	0.5522	0.1345	0.653
	0.0929	0.1924	0.7417	0.0786	0.2477	0.409	0.0349	0.197	0.047	0.2225

education											
	2	0.2653	0.7996	0.056	0.2621	0.7814	0.334	0.1988	0.9618	0.1953	0.9535
		0.198	0.4212	0.9347	0.1973	0.4178	0.423	0.1128	0.5191	0.1135	0.5248
	3	-0.0735	-0.3109	-0.8516	-0.0814	-0.3113	-0.3666	-0.0176	-0.0911	-0.0172	-0.0883
		0.0962	0.3833	0.9055	0.0968	0.3867	0.3646	0.0779	0.4375	0.0781	0.4424
	4	0.0134	-0.0241	0.1657	0.0141	-0.0165	-0.0555	0.0492	0.2457	0.0474	0.234
		0.0542	0.1875	0.282	0.0541	0.1878	0.1959	0.0357	0.1836	0.0357	0.1859
	5	-0.0408	-0.2222	0.1293	-0.0421	-0.2152	-0.2612	0.0439	0.2008	0.0401	0.1879
		0.071	0.2248	0.3857	0.0713	0.2258	0.242	0.0389	0.1984	0.0389	0.2008
	6	-0.0642	-0.3038	-0.3952	-0.0652	-0.2928	-0.3233	0.0204	0.063	0.009	0.0228
		0.0726	0.2217	0.405	0.0732	0.2218	0.2518	0.0447	0.2251	0.0448	0.2261
	7	-0.0177	-0.1532	-0.2732	-0.0191	-0.1371	-0.1685	0.0397	0.1806	0.0313	0.1522
		0.0842	0.2345	0.4376	0.0849	0.2353	0.2465	0.045	0.2289	0.045	0.2309
	8	-0.31	-0.898	-1.0583	-0.3117	-0.8958	-0.8795	-0.0294	-0.1707	-0.0291	-0.1709
		0.1159	0.336	1.1557	0.116	0.3351	0.3692	0.0623	0.3541	0.0619	0.3509
female		0.0368	0.1134	0.173	0.0358	0.1118	0.1513	0.0903	0.4477	0.0868	0.437
		0.0406	0.1066	0.1524	0.0404	0.1063	0.1782	0.0215	0.1081	0.0214	0.1081
household_nr		0.0106	0.0554	0.0675	0.0114	0.0566	0.0454	0.0184	0.0922	0.0182	0.0922
		0.0162	0.0415	0.0794	0.0162	0.0415	0.0816	0.0088	0.0449	0.0088	0.045
profession											
	2	0.0037	0.0341	-0.0714	-0.0061	0.0041	0.0882	-0.0074	-0.0431	-0.0218	-0.1051
		0.0541	0.2037	0.6303	0.0542	0.2044	0.6102	0.0349	0.1703	0.035	0.172
	3	-0.0587	-0.1531	0.0006	-0.0674	-0.1792	0.0727	-0.0321	-0.1976	-0.0472	-0.2483
		0.0817	0.244	0.3858	0.0821	0.2458	0.3763	0.0458	0.2225	0.0461	0.2246
	4	0.0381	0.2088	0.1723	0.0238	0.1733	0.2369	0.0346	0.1689	0.016	0.082
		0.0937	0.2539	0.714	0.0936	0.2551	0.6834	0.0448	0.2235	0.045	0.2253

	5	-0.0937	-0.1003	0.0595	-0.0956	-0.1035	-0.0399	0.0692	0.4389	0.0628	0.4073
		0.1237	0.345	0.824	0.1239	0.3493	0.7489	0.0539	0.3014	0.054	0.305
	6	0.0282	0.0413	0.1061	0.0214	0.0249	0.1661	0.0072	0.0566	-0.0114	-0.0198
		0.1268	0.3155	0.5285	0.1265	0.3174	0.405	0.0597	0.2955	0.0602	0.3
region											
	2	0.0236	0.0844	0.0697	0.0188	0.0681	0.046	-0.1336	-0.7027	-0.1371	-0.7198
		0.1042	0.1984	0.2468	0.1036	0.198	0.2349	0.0376	0.1925	0.0375	0.1929
	3	-0.0579	-0.0887	0.0152	-0.0555	-0.0969	-0.0308	-0.1887	-0.9848	-0.1881	-0.9838
		0.0982	0.2009	0.2792	0.098	0.1997	0.2529	0.0369	0.1895	0.0369	0.19
	4	0.1489	0.3173	0.373	0.1434	0.2974	0.3154	-0.1519	-0.7684	-0.1527	-0.7857
		0.1017	0.1841	0.3217	0.1012	0.183	0.1999	0.0375	0.197	0.0374	0.1963
	5	-0.1164	-0.2791	-0.2643	-0.1093	-0.2673	-0.2921	-0.1758	-0.8899	-0.1665	-0.8563
		0.0819	0.1754	0.2019	0.0821	0.1755	0.2142	0.0322	0.1661	0.0323	0.1673
	6	-0.0746	-0.153	-0.2186	-0.0722	-0.1519	-0.2377	-0.2035	-1.0441	-0.2032	-1.0432
		0.098	0.2549	0.3275	0.0978	0.2537	0.299	0.0514	0.259	0.0514	0.2595
	7	-0.1872	-0.8047	-0.7847	-0.1813	-0.7383	-0.7143	-0.3692	-2.0275	-0.3688	-2.0184
		0.0985	0.3639	0.3791	0.1037	0.3546	0.4488	0.052	0.3137	0.0476	0.2955
uc_exempt					0.1118	0.4601	0.3189			0.1844	0.8132
					0.0595	0.1828	0.4161			0.0355	0.1692
exempt_chronic					-0.0497	-0.3854	0.082			-0.1074	-0.3518
					0.1031	0.1986	0.4842			0.0449	0.2343
exempt_easy					0.0351	0.4173	-0.017			-0.044	-0.1688
					0.1297	0.3927	0.8956			0.0642	0.3153
exempt_somewhatdifficult					0.1279	0.2167	0.0178			-0.0381	-0.1814
					0.0979	0.2237	0.4303			0.045	0.2264
exempt_difficult					-0.0465	-0.2097	-0.574			-0.0538	-0.1501

				0.1249	0.299	0.5009			0.0593	0.3099
uc_pcu_chronic							0.0069	0.0242		
							0.0061	0.0294		
uc_pcu_easy							0.001	0.0064		
							0.0087	0.0455		
uc_pcu_somewhatdifficult							-0.0008	-0.0171		
							0.0038	0.0289		
uc_pcu_difficult							0.0012	0.008		
							0.0053	0.0318		
_cons	0.3165	-1.2072	-0.4118	0.2034	-1.6757	-0.3233	0.2858	-1.0003	0.1565	-1.618
	0.2151	0.4735	0.571	0.202	0.4755	0.5932	0.0934	0.476	0.0898	0.4627
/lnalpha		0.7285	-0.8585		0.7373	0.0262				
		0.1103	0.4532		0.1104	0.7218				
inflate										
uc_em_expected			-0.0124							
			0.0911							
trpt_em			0.0688			0.0729				
			0.0729			0.0713				
presc_em			-0.0114			-0.0598				
			0.0258			0.0578				
uc_pcu_expected			0.0421							
			0.0617							
trpt_pcu			-0.0277			-0.1217				
			0.2955			0.3901				
presc_pcu			-0.095			-0.1122				
			0.0275			0.0639				

uc_em_chronic	-0.0529			
	0.0694			
uc_em_easy	0.0766			
	0.1259			
uc_em_somewhatdifficult	0.019			
	0.0825			
uc_em_difficult	0.0023			
	0.0799			
y2021	0.056	0.0665		
	0.5562	0.5554		
age	0.0433	0.0333		
	0.0269	0.026		
alcohol_co~2	0.4883	0.4982		
	0.8735	0.9624		
alcohol_co~3	-0.5165	-1.3045		
	0.8784	2.7236		
alcohol_co~4	-0.3382	-1.2494		
	0.9627	2.5746		
alcohol_co~5	-0.4163	-0.3365		
	0.7082	1.1345		
alcohol_co~6	-0.3525	-0.5475		
	1.2414	1.6329		
alcohol_co~7	-0.3201	-0.9122		
	0.9571	1.2307		
alcohol_co~8	-0.1121	-0.5666		
	0.8694	1.0152		
alcohol_co~9	-0.1587	-0.1366		
	0.8246	1.1681		

chronic		-1.0802	-15.1209	
		0.4447	3.228	
easy		-0.4748	0.472	
		0.912	1.4031	
somewhatdifficult		-0.3212	0.0364	
		0.9344	0.5049	
difficult		-0.2802	0.1033	
		1.4034	0.881	
education				
	2	-2.0624		
		5.0494		
	3	-1.7456		
		4.0717		
	4	0.4173		
		0.5236		
	5	0.7223		
		0.6476		
	6	-0.1842		
		0.758		
	7	-0.2515		
		0.8136		
	8	-0.5228		
		2.8287		
female		0.1034	0.1205	
		0.2978	0.5371	
household_nr		0.0336	-0.0219	

			0.1445			0.227				
profession										
2			-0.2208			0.1913				
			0.9892			1.7628				
3			0.254			0.7029				
			0.5995			1.2762				
4			0.0581			0.2704				
			1.1051			1.7712				
5			0.4583			0.2659				
			1.3904			2.5269				
6			0.0696			0.3346				
			0.8451			1.0718				
uc_exempt						-0.1845				
						0.9674				
exempt_chronic						13.6698				
						3.4711				
exempt_easy						-1.3566				
						2.0237				
exempt_somewhatdifficult						-0.598				
						1.4666				
exempt_difficult						-1.19				
						1.7064				
_cons			0.3892			2.3401				
			1.0801			1.969				
Observations	2254	2254	2254	2254	2254	2254	2311	2311	2311	2311