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Abstract:
The paper estimates the effect of the abolition of user charges for outpatient care (30 CZK/1.2 EUR) in 2009 on the demand for ambulatory doctor visits in the Czech Republic. The reform applied only to children, which enabled us to take the difference-in-differences approach. Children constitute a treatment group, whereas adults serve as a control group. Besides the treatment effect, we control also for a number of personal characteristics using a micro-level data (EU-SILC). We estimate two models: Multinomial logit (MNL) and Zero-inflated negative binomial (ZINB). The effect of the abolition of user charges on the number of doctor visits proved insignificant suggesting that either the demand for this type of care is indeed inelastic, user charges were set too low or the people have not changed their behavior yet. On the contrary, we found that personal income, the number of

household members and sex significantly influence the number of visits to the doctor. Two robustness checks using restricted samples confirms the results.

Keywords: co-payments, outpatient care, Czech Republic, natural experiment, Zero-inflated negative binomial (ZINB) model, Multinomial logit (MNL) model

JEL: D04, I18

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1 Introduction

In many countries, governments have been increasing the rate of private participation on heath care expenses. The Czech Republic is not an exception. In 2005 general government expenditure amounted to 87.5 % of the overall spending on healthcare, in 2009 the share decreased to 83.6 % (UZIS 2012). A number of reforms have been introduced in recent years which includes transformation of hospitals into private entities, which started in 2003; or the introduction of user charges for healthcare services which was introduced in January 2008. In 2008, three types of user charges were introduced: CZK 30 for physician visits during which a clinical examination was carried out; CZK 30 for every item on a drug prescription; CZK 60 for each day of inpatient care; CZK 90 for emergency service. The latter reform received a wide discussion. Advocates argued that user charages would have a desired effect and patients would, as a result, decrease overutilization of healthcare services. On the contrary, opponents argued that in the Czech Republic (CR), the introduction of user charges would not have a significant effect on the demand for health-care services because such a demand is not very price-elastic. Others claimed that user charges should not be applied to at least some vulnerable groups, because their utilization of health-care services is minimal and user charges could have a detrimental and inequitable effect on their health status as supported by Gertler & Gaag (1990), Trivedi *et al.* (2010), Lundberg *et al.* (1998) or Tamblyn *et al.* (2001). As a result, in April 2009 user charges on physician visits were abolished for children up to 18 years of age and a cap on copayments for the elderly (over 65) decreased from CZK 5,000 to CZK 2,500.

The first studies to assess effectiveness of user charges include Gruber & Foundation (2006), Manning *et al.* (1987) or Newhouse & Group (1993) who use data from the US social experiment - the Rand Health Insurance Experiment (HIE). All of these studies consistently find that, in the short term, user charges that are too low do not reduce excessive care and user charges that are too high can result in avoiding necessary health-care. They also show that for a person of average health and with average income, a reasonable level of user charges does not have a negative influence on ones health status. Saltman *et al.* (1997) however argue that these effects of cost-sharing arrangements may be valid only in the US and studies performed in other countries could come up with different results.

As far as later studies are concerned, user charges on physician visits were found not to reduce demand for health-care services in South Korea (Kim *et al.*, 2005) and in France (Chiappori *et al.*, 1998). Other studies come up with mixed results. In Japan (Kan & Suzuki, 2010), the effect of increased copayments for physician visits was found to be negative and statistically significant only for a two-year panel, but the effect was not clear for data acquired for longer periods. This phenomenon was interpreted as a transitory effect. In Belgium, Cockx & Brasseur (2003) found negative effects of increased user charges on the demand for three types of physician services (GP office visits, GP home visits, specialist visits), in disaggregation however the effect was insignificant for men visiting GP offices and for women visiting a specialist. In Germany, Winkelmann (2004) found that increase in user charges for drug prescription fulfilled its purpose of reducing the number of outpatient doctor visits. However, as Augurzky *et al.* (2006) and Schreyögg & Grabka (2010) found out, further

German reforms which introduced user charges for the first doctor visit in each quarter in 2004, failed to reduce the number of physician visits. Significance and the effect of user charges thus depend on its amount, frequency of payment, type and characteristics of each country.

The effect of user charges in the Czech Republic has been estimated only by Zapal (2010) so far who, however, relies on proxies for doctor visits and quite a restricting assumption. Zapal (2010) estimated the effect of user charges on the number of children's physician visits in the Czech Republic proxying the number of doctor visits by the number of drug prescriptions under the assumption that there is a fixed probability of generating prescriptions during a doctor visit. The author detects a positive and significant effect of user charges only if March 2009 (one month before the reform) is used as a pre-reform period, i.e. there is only a timing effect because some visits (e.g. preventive care) might have just been postponed, resulting in fewer visits prior to the reform and more visits after it.

Except for Kim *et al.* (2005) who carried out a conditional-on-use analysis, all of the cited research papers investigate the effect of user charges on doctor visits using the Difference-in-Differences methodology. In the Czech environment, Zapal (2010) takes advantage of the co-payment exemption for children introduced in 2009 where children's drug consumption is used as a treatment group and drug consumption among adults serves as a control group. He employs the Ordinary Least Squares (OLS).

We will contribute to this stream of research and analyze the effects of user charges on the number of outpatient visits in the Czech Republic. We will estimate the effect of the 2009 abolition of user charges for children and thus carry out a natural experiment. Children will constitute a treatment group, whereas the rest of the population will serve as a control group As opposed to Zapal (2010), however, we will use the micro-level data on the number of doctor visits made by individuals during 12 previous months, as obtained from the EU-SILC survey. Moreover, a larger time period (February 2008 to May 2010) gives us a possibility to eliminate a timing effect of postponed utilization of health-care services. Last but not least, due to distributional properties of the dependent variable (number of doctor visits), we will avoid the OLS and use the Multinomial logit and Zero-inflated negative binomial models which provide a better fit to the data. The analysis covers the area of the city of Prague only because co-payment arrangements are different outside Prague. Furthermore, there is believed to be hardly any spillover of patients from Prague to other regions. Our research questions are: (1) Did the abolition of outpatient user charges have a significant effect on the demand for outpatient doctor visits of the members of the treatment group; (2) How do individual characteristics such as sex, income etc. affect the demand for healthcare services?

If the the number of children physician visits increased after the abolition of user charges in 2009, the introduction of regulatory fees would be effective. We however found an insignificant effect using either model, i.e. the number of children's outpatient visits (treatment group) did not significantly change after the abolition of regulatory fees. We further discovered that the probability of visiting a doctor increases for women and decreases with personal income and the number of household members. We also carry out two robustness checks. In the first one we exclude the elderly (over 65) from the control group because of the decrease in the cap on co-payments, which may slightly underestimate the result. This robustness check revealed consistent results with the previous analysis which suggests that the decrease of the out-of-pocket payment limit for the elderly did not significantly influence the probability of health-care utilization. In the second robustness check, we restricted the control group to individuals aged 18-26 finding out consistent results in terms of the treatment effect. However, all individual characteristics turned insignificant suggesting even a higher level of consistency between control and treatment groups.

The paper is organized as follows: Section 2 introduces the dataset, Section 3 explains theoretical underpinnings, Section 4 presents and discusses results of the analysis and Section 5 concludes and provides motivation for further research.

2 Data

The data come from the Czech Statistical Office (CZSO), the EU-SILC survey which is an annual survey of household income and living conditions and includes data on health related variables, such as the number of doctor visits during 12 previous months, health status, and respondent characteristics associated with the tendency of health-care utilization (age, sex, educational level, marital status, employment status, household income per year, number of children in a household etc.). Approximately 12,000 households (approx. 30,000 people) are interviewed annually sometime between February and May in the Czech Republic. (Mysikova, 2011)

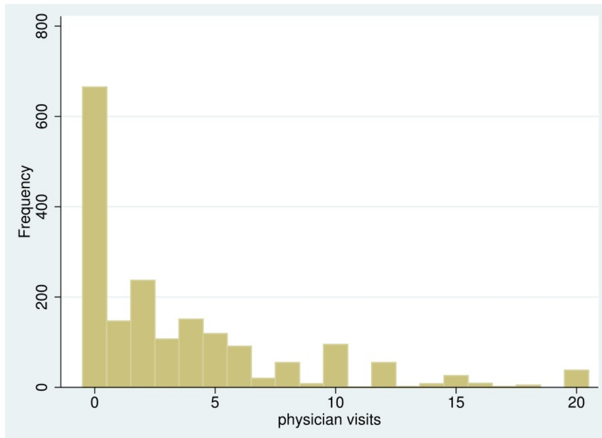
Our sample covers only two years of observations (2009, 2010) because information regarding utilization of health services was not included in earlier surveys. From the overall sample, we excluded all people living outside Prague because the data for the whole country could be contaminated by the fact that other regional governments except Prague reimbursed the adults for co-payments in all regional hospitals (but not others) during the observed period. Not being able to distinguish whether the patient took advantage of reimbursement could influence our estimated results. We further restricted the sample such that the reference period of all respondents analyzed is either prior to the reform or after it. Lastly, we truncate our sample at 20 visits. The final dataset covers 97.3 % of the whole set and includes 1,841 individuals, 281 children and 1,560 adults. The proportion of children and adults stays consistent with the overall sample

2.1 Dependent variable

The dependent variable *visits* denotes the number of physician visits made by an individual during 12 previous months. Frequency distribution in Figure 1 indicates a rapidly decreasing tail and suggests that the distribution is not normal.

The maximum number of visits is 99, however only 2.7% of respondents exceed 20 visits. We suppose that some of the high values may be results of measurement errors, others may be brought about by the elderly (over 65) who more often visit doctors. Truncation at 20 visits gets rid of these erroneous observations as well as it considerably removes a potential bias stemming from a decreased cap on out-of-pocket contributions for the elderly introduced in

Figure 1. Frequency distribution - visits



2009. In other words, we assume that a greater number of visits (made mostly by the elderly and chronically ill) is refunded and so these individuals are not included into the analysis.

2.2 Independent variables

Besides the desired interaction term, there are other independent variables which are likely to influence the number of outpatients visits. Variable *female* is a dummy taking on the value of 1 for a female and 0 for a male. The mean reveals that our sample contains approximately the same number of men and women. We expect a positive effect of this variable.

Variable *p_income* denotes household income per year divided by the number of household members. This variable takes on a wide range of values and its minimum is very low. The impact of this variable may be two-fold: (a) With increasing income, the number of doctor visits decreases because people's life-style is better (they buy better food, shoes, mattress etc.) and so is their health status. However, a low number of doctor visits for high income individuals may also be caused by high opportunity costs of going to the doctor and not working; (b) With increasing income the number of doctor visits may grow because money spent on health-care expenses becomes unimportant. The final effect depends on which of these two effects overweighs.

The number of household members (*members*) takes on values from 1 to 7. We suppose a negative influence of this variable, for with increasing number of household members, an individual no longer cares so much about one's health due to lack of time.

Summary statistics of all variables is provided in Table 1. Table A.1 shows a correlation matrix.

3 Methodology

3.1 Difference-in-Differences (DiD) approach

The abolition of user charges for children's outpatient visits in 2009 constitutes a natural experiment with children's physician visits being the treatment group and physician visits for

Table 1. Summary statistics

Variable	Mean	Std. Dev.	Min.	Max.	Median
female	0.528	0.499	0	1	1
visits	3.539	4.533	0	20	2
members	2.806	1.211	1	7	3
reform	0.382	0.486	0	1	0
dummy_child	0.153	0.36	0	1	0
interaction	0.062	0.241	0	1	0
p_income	191014.582	140161.259	32040	1579988	156089.7

the rest of the population being the control group.

The idea of the DiD is based on the comparison of the average change in physician visits for the treatment group (children) before and after the reform with the average change in physician visits for the control group. If we compared pre-reform and post-reform periods for the treatment group only, the results could be contaminated by trends, which are not related to the reform.

To find the effects of the reform, we estimate a model of the form:

$$\begin{aligned} \text{visits}_i = \; & \beta_0 + \beta_1 \text{reform}_i + \beta_2 \text{dummy\_child}_i + \beta_3 \text{interaction}_i + \beta_4 \text{female} \\ & + \beta_5 \text{members} + \beta_6 \text{p\_income} + \varepsilon_i \end{aligned} \tag{1}$$

where i's, $i \in 1, \dots N$, denote individuals. Variable *visits* reflects the number of doctor visits for person i. *Reform* is a dummy variable representing the period after the reform. Variable *dummy_child* is a dummy variable that takes the value of 1 for respondents younger than 18 and 0 otherwise. In other words, it denotes the treatment group, i.e. group on which the reform had an effect. The *interaction* term equals to $reform \times dummy\_child$, that takes the value 1 for children (members of the treatment group) and the period after the reform. Variable *female* takes the value of 1 if the respondent is a woman. Variable *members* denotes members of the household and variable *p_income* stands for personal income of an individual i.Parameter ε_i is the error term.

We are particularly interested in the estimate of β_3, because it gives us the net treatment effect which measures the change in physician visits for a child caused by the abolition of user charges – it is the DiD estimator. If positive, the number of doctor visits in the treatment group rises relative to the number of visits in the control group.

3.2 Multinomial logit model (MNL)

The dependent variable (the number of physician 'visits' during last 12 months) is a nonnegative integer and thus its distribution is not normal, which results in the OLS estimate being inefficient.

We therefore employ the Multinomial logit model, setting the base outcome to zero number of physician visits:

$$p_{ij} = Pr(y_i = j \mid y_i = 0) = \frac{Pr(y_i = j)}{Pr(y_i = j) + Pr(y_i = 0)} = \frac{exp(x_i'\beta_j)}{1 + exp(x_i'\beta_j)} \tag{2}$$

where j is one of the m alternatives (jth physician visit). p_{ij} is the probability that the outcome for an individual i is the alternative j, conditional on the vector of regressors x_i. $y_i = j$ if the outcome is the jth alternative. Probability p_{ij} has to satisfy two conditions: (i) $0 < p_{ij} < 1$, (ii) $\sum_{j=1}^{m} p_{ij} = 1$.

We get the estimation results of equation 1 for all m alternatives. A positive coefficient $\hat{\beta}_3$ for the jth visit means that when the interaction term equals 1, we are more likely to choose an alternative j than zero doctor visits during 12 previous months.

For MNL model, independence of irrelevant alternatives (IIA) is important. It follows from the assumption that disturbances are independent and homoscedastic (Greene & Zhang, 2003). It requires that the odds ratio, ratio of probabilities for any two alternatives for a particular observation (in our case $\frac{\pi_{ij}}{\pi_{i0}}$), are independent of other alternatives. In other words, adding or deleting another alternative (for example pth alternative, where $p = 1, \ldots, m;\ p \neq j$) does not affect the relative odds $\frac{\pi_{ij}}{\pi_{i0}}$ (Wooldridge, 2002). We will check this using the Hausman test (Hausman & McFadden, 1984).

3.3 Zero-inflated negative binomial (ZINB) model

For the distribution of the dependent variable *visits* is skewed and contains a large proportion of zeros, we additionally use a count data model, specifically the Zero-inflated negative binomial model. We assume that the main result, i.e. the effect of user charges on the demand for doctor visits, will be consistent with the results from the MNL regression.

The Zero-inflated negative binomial model contains two submodels, because it assumes that zero values of the dependent variable are generated from two different processes (Long *et al.*, 2006). (i) A respondent was not ill over the year and therefore he did not visit a doctor ("Not Always Zero group") and (ii), a respondent was ill, but still did not visit a physician ("Always Zero group").

The first model is negative binomial and models the count process of (i)"Not Always Zero group", i.e. how often respondents visit a physician. The second process is modeled by a logit model for binary data to model the probability of being in the (ii) "Always Zero group", i.e. the respondent is ill but he does not visit a doctor. The probability of visiting a doctor is then expressed as a combination of the two models.

ZINB model has a density of (Cameron & Trivedi, 2009):

$$f(y) = \begin{cases} f_1(0) + \{1 - f_1(0)\}\, f_2(0) & if\ y = 0 \\ \{1 - f_1(0)\}\, f_2(y) & if\ y \geq 1 \end{cases} \tag{3}$$

And conditional mean

$$E(y \mid x) = \{1 - f_1(0 \mid x_1)\} \times exp(x_2\beta_2) \tag{4}$$

where $f_1(.)$ is a density of the count process (NB) and $f_2(.)$ is a density of the binary process (logit). If the binary process takes on a value of 0, with a probability of $f_1(0)$, then $y = 0$. If the binary process takes on a value of 1, with a probability of $f_1(1)$, then y takes on the count values 0,1,2,... from the count density $f_2(.)$. And $1 - \mathrm{f}_1(0 \mid \mathrm{x}_1)$ is the probability that the binary process equals 1.

4 Empirical results

4.1 Multinomial Logit (MNL) model

We estimate Equation 1 and set zero visits as the base category. The results of the analysis are presented in Table 3.

The model passes the IIA assumption at the 0.01 level of significance in all cases (Table 2).

Table 2. Hausman tests of IIA assumption (N=1841)

Ho: Odds are independent of other alternatives.

Omitted	chi2	df	P>chi2	evidence
1	0.000	28	1.000	for Ho
2	0.000	28	1.000	for Ho
3	0.000	28	1.000	for Ho
4	0.000	27	1.000	for Ho
5	0.000	27	1.000	for Ho
6	0.000	27	1.000	for Ho
7	0.000	26	1.000	for Ho
8	0.000	27	1.000	for Ho
9	0.000	26	1.000	for Ho
10	0.000	26	1.000	for Ho
11	0.000	25	1.000	for Ho
12	0.000	27	1.000	for Ho
13	0.000	26	1.000	for Ho
14	0.000	26	1.000	for Ho
15	0.000	26	1.000	for Ho
16	0.000	26	1.000	for Ho
17	0.000	26	1.000	for Ho
18	0.000	26	1.000	for Ho
20	0.000	26	1.000	for Ho

Table 3. Multinomial Logit (MNL) Model

visits		Coef.	RRR	P>|t|
0		(base outcome)		
1	reform	-0.634	0.530	0.002
	dummy_child	-4.222	0.015	0.000
	interaction	1.007	2.738	0.483
	female	0.424	1.527	0.029
	members	-0.143	0.867	0.086
	p_income	1.95×10^{-8}	1.000	0.974
	_cons	-0.515	.	0.106
2	reform	-0.705	0.494	0.000
	dummy_child	-3.121	0.044	0.000
	interaction	-0.513	0.599	0.646
	female	0.660	1.935	0.000
	members	-0.181	0.834	0.011
	p_income	-4.90×10^{-7}	1.000	0.398
	_cons	0.066	.	0.812
3	reform	-0.565	0.568	0.014
	dummy_child	-19.266	-4.29×10^{-9}	0.993
	interaction	17.058	2.56×10^{7}	0.994
	female	1.095	2.990	0.000
	members	-0.249	0.780	0.009
	p_income	-6.00×10^{-7}	1.000	0.460
	_cons	-0.821	.	0.029
4	reform	-0.606	0.545	0.003
	dummy_child	-3.029	0.048	0.000
	interaction	-15.628	1.63×10^{-7}	0.995
	female	1.039	2.825	0.000
	members	-0.339	0.712	0.000
	p_income	-6.45×10^{-8}	1.000	0.917
	_cons	-0.301	.	0.346
5	reform	-0.795	0.451	0.000
	dummy_child	-3.160	0.042	0.000
	interaction	-15.242	2.40×10^{-7}	0.995
	female	1.031	2.804	0.000
	members	-0.432	0.649	0.000
	p_income	4.27×10^{-9}	1.000	0.995
	_cons	-0.254	.	0.462
6	reform	-1.019	0.361	0.000
	dummy_child	-3.621	0.027	0.000
	interaction	-14.526	4.92×10^{-7}	0.996
	female	1.056	2.876	0.000
	members	-0.560	0.571	0.000
	p_income	-3.10×10^{-6}	1.000	0.023
	_cons	0.413	.	0.342
7	reform	-0.561	0.570	0.245
	dummy_child	-18.585	8.49×10^{-9}	0.997
	interaction	0.534	1.705	1.000
	female	1.136	3.115	0.019
	members	-0.767	0.464	0.001
	p_income	-4.69×10^{-7}	-0.280	0.779
	_cons	-1.322	.	0.081
8	reform	-0.642	0.526	0.038
	dummy_child	-2.755	0.064	0.008
	interaction	-15.381	2.09×10^{-7}	0.997
	female	0.910	2.485	0.002
	members	-0.700	0.497	0.000
	p_income	-1.03×10^{-6}	1.000	0.391
	_cons	-0.190	.	0.697
9	reform	-1.092	0.336	0.185
	dummy_child	-19.312	4.10×10^{-9}	0.998
	interaction	0.991	2.694	1.000
	female	1.053	2.866	0.154
	members	-0.347	0.707	0.278
	p_income	5.08×10^{-8}	1.000	0.982
	_cons	-3.087	.	0.008
10	reform	-0.642	0.526	0.008
	dummy_child	-18.920	6.07×10^{-9}	0.993
	interaction	0.581	1.787	1.000
	female	1.163	3.199	0.000
	members	-0.558	0.572	0.000
	p_income	-3.99×10^{-7}	1.000	0.624
	_cons	-0.218	.	0.570
11	reform	-17.310	3.04×10^{-8}	0.998
	dummy_child	-18.777	7.00×10^{-9}	0.999
	interaction	17.383	3.54×10^{7}	0.999
	female	17.509	4.02×10^{7}	0.999
	members	-0.763	0.466	0.443
	p_income	-5.95×10^{-6}	1.000	0.715
	_cons	-18.912	.	0.997
12	reform	-0.255	0.775	0.398
	dummy_child	-2.923	0.054	0.005
	interaction	-15.574	1.72×10^{-7}	0.997
	female	0.982	2.669	0.001
	members	-0.741	0.477	0.000
	p_income	-1.19×10^{-5}	1.000	0.000
	_cons	1.472	.	0.019
13	reform	0.384	1.468	0.790
	dummy_child	-2.326	0.098	1.000
	interaction	0.662	1.938	1.000
	female	-0.002	0.998	0.999
	members	-16.410	7.46×10^{-8}	0.989
	p_income	-2.69×10^{-5}	1.000	0.247
	_cons	17.537	.	0.989
14	reform	0.175	1.192	0.809
	dummy_child	-18.553	8.76×10^{-9}	0.998
	interaction	-0.074	0.928	1.000
	female	2.316	10.135	0.032
	members	-0.721	0.486	0.031
	p_income	-2.21×10^{-8}	1.000	0.016
	_cons	-0.358	.	0.845
15	reform	-0.540	0.583	0.208
	dummy_child	-18.701	7.56×10^{-9}	0.996
	interaction	0.537	1.711	1.000
	female	1.092	2.981	0.011
	members	-0.787	0.455	0.000
	p_income	-5.93×10^{-6}	1.000	0.058
	_cons	-0.030	.	0.971
16	reform	-1.848	0.158	0.085
	dummy_child	-18.589	8.45×10^{-9}	0.997
	interaction	2.260	9.585	1.000
	female	-0.488	0.614	0.506
	members	-1.335	0.263	0.002
	p_income	-2.6×10^{-5}	1.000	0.010
	_cons	3.775	.	0.027
17	reform	0.188	1.207	0.895
	dummy_child	-19.067	5.24×10^{-9}	0.999
	interaction	-0.006	0.994	1.000
	female	0.346	1.413	0.810
	members	-0.606	0.546	0.339
	p_income	-2.79×10^{-5}	1.000	0.159
	_cons	0.073	.	0.983
18	reform	-0.365	0.694	0.692
	dummy_child	-18.737	7.29×10^{-9}	0.998
	interaction	0.307	1.359	1.000
	female	0.936	2.550	0.309
	members	-0.628	0.534	0.152
	p_income	-5.84×10^{-7}	1.000	0.862
	_cons	-2.930	-3.866	0.048
20	reform	-1.108	0.330	0.005
	dummy_child	-19.409	3.72×10^{-9}	0.995
	interaction	1.053	2.866	1.000
	female	1.500	4.481	0.000
	members	-0.408	0.665	0.006
	p_income	-9.27×10^{-6}	1.000	0.003
	_cons	-0.127	.	0.864

Measures of fit of the model are provided in Table 4.

Table 4. Measures of Fit for MNL model

Log-Lik Intercept Only:	-4031.924	Log-Lik Full Model:	-3614.483
LR(114):	834.882	Prob>LR:	0.000
McFadden's R^2:	0.104	McFadden's Adj R^2:	0.069
AIC:	4.079	AIC*n:	7508.966
BIC:	-5559.261	BIC':	22.178
BIC used by Stata:	8228.868	AIC used by Stata:	7494.966

Pseudo (McFadden's) R^2 equals[1] 0.104 which suggests that the log-likelihood of the fitted model significantly improves compared to the model with intercept and no regressors. The like is also revealed by the LR test.

The sign of the coefficients of the interaction term varies for different alternatives, it is however always strongly insignificant. To check whether the coefficient of the variable *interaction* is indeed insignificant in the model as a whole, we perform the Wald test, which determines joint significance over all sets of alternatives. Results are provided in Table 5.

Table 5. Wald test of joint significance

**** Wald tests for independent variables (N=1841)
Ho: All coefficients associated with given variable(s) are 0.

	chi2	df	P>chi2
reform	40.524	19	0.003
dummy_child	114.499	19	0.000
interaction	0.715	19	1.000
female	78.046	19	0.000
members	99.896	19	0.000
p_income	45.683	19	0.001

We cannot reject the null hypothesis that the interaction term is zero, i.e. the overall effect of this variable is statistically insignificant. In other words, members of the treatment group (children) did not significantly change the probability of visiting the doctor more after the abolition of user charges.

Table 5 further reveals that coefficients of the remaining variables - *female*, *members*, *p_income* - are statistically significant even at 0.01 significance level in the model as a whole. They are thus important determinants of the demand for physician visits.

As obvious in Table 3, coefficients of the variable *members* are negative in all sets of regressions, which suggests that with increasing number of household members, we are less likely to go to the doctor at least once than not to go there at all (zero visits). Relative risk ratio (RRR), which is defined as $\frac{Pr(y_i = j)}{Pr(y_i = 0)} = exp(x_i'\beta_j)$, in the first set of results, for

[1]Pseudo R^2 is defined as

$$\tilde{R}^2 = 1 - \frac{\mathrm{L_{fit}}}{\mathrm{lnL_0}} \tag{5}$$

where $\mathrm{lnL_0}$ is the log-likelihood of an intercept-only model, and $\mathrm{L_{fit}}$ is the likelihood of the fitted model.

example, reveals that an increase in the number of household members by one leads to a change in the relative risk of choosing one doctor visit by 0.867, i.e. with more household members a patient more probably does not visit a doctor at all than visits once, which is consistent with our initial assumption.

The coefficients of the variables *female* and *p_income* are not always significant. But when they are significant, the effect of sex (female) is positive, which is consistent with our initial expectations that women have more appointments with a doctor than men; and that of personal income is negative indicating that with increasing personal income, an average patient more probably chooses not to visit a doctor at all than visit at least once. This suggests that the first effect overweighs, i.e. with increasing income people may be healthier or have high opportunity costs to often visit a doctor.

4.2 Zero-inflated Negative Binomial (ZINB) Model

We again estimate Equation 1. Estimation results are provided in Table 6.

Table 6. Zero-inflated Negative Binomial (ZINB) Model

Number of obs = 1841
Non-zero obs = 1176
Zero obs = 665
LR $\chi^2(6)$ = 58.49
Prob> χ^2 = 0.0000

visits	**Coef.**	**Std. Err.**	**z**	**P>|z|**	**[95% Conf.**	**Interval]**
count process = neg. binomial						
reform	-0.0116038	0.0589792	-0.20	0.844	-0.127201	0.1039934
dummy_child	-0.2339358	0.2696446	-0.87	0.386	-0.7624296	0.2945579
interaction	-0.5123555	0.6721009	-0.76	0.446	-1.829649	0.8049381
female	0.1920095	0.0564243	3.40	0.001	0.0814198	0.3025991
members	-0.1231691	0.0231478	-5.32	0.000	-0.168538	-0.0778002
p_income	-7.02×10^{-7}	1.78×10^{-7}	-3.94	0.000	-1.05×10^{-6}	-3.53×10^{-7}
_cons	1.911219	0.0830703	23.01	0.000	1.748404	2.074033
inflation model = logit						
reform	1.224747	0.2434943	5.03	0.000	0.7475071	1.701987
dummy_child	4.355646	0.3872761	11.25	0.000	3.596599	5.114693
interaction	-0.5858195	0.6910387	-0.85	0.397	-1.940231	0.7685916
female	-1.251901	0.218099	-5.74	0.000	-1.679367	-0.8244345
members	0.4824235	0.0870107	5.54	0.000	0.3118855	0.6529614
p_income	5.80×10^{-7}	5.68×10^{-7}	1.02	0.307	-5.33×10^{-7}	1.69×10^{-6}
_cons	-3.202891	0.4157973	-7.70	0.000	-4.017838	-4.017838
lnα	-0.4192716	0.0788312	-5.32	0.000	-0.573778	-0.2647652
α	0.6575256	0.0518336			0.5633929	0.7673861

Likelihood-ratio test of $\alpha = 0$: $\bar{\chi}^2(01) = 1437.06$ Pr$\geq \bar{\chi}^2 = 0.0000$
Vuong test of zinb vs. standard negative binomial: z = 6.90 Pr>z = 0.0000

Significant ln α suggests overdispersion which proves that the ZINB is appropriate. Moreover, the LR test of Vuong, which compares the ZINB model to the standard NB model, indicates that the ZINB model should be preferred to the NB regression model even at 1 % significance level. Moreover, the likelihood-ratio statistics of 58.49 which has χ^2 distribution with p-value<0.0001 reveals that the full model fits significantly better than an empty model.

The estimated coefficient $\hat{\beta}_3$, i.e. the interaction term, is insignificant in both parts of

Table 6. This analysis again confirms that user charges did not reduce the number of outpatient doctor visits. Specifically, the abolition of user charges did not significantly change the utilization of doctor visits in the "Not Always Zero group" (first part of the Table 6). And, the odds of being in the "Always Zero group" (those who avoid health-care services even if ill) compared to the "Not Always Zero group" did not significantly change after the abolition of user charges (second part of Table 6).

The coefficients of individual characteristics are all statistically significant at 0.01 significance level in the NB model. The interpretation of the estimated coefficients in the first part of Table 6 is such that when, for example, the number of household members increases by one, the expected change in the variable visits is by 0.88 (decrease), holding other variables constant (ceteris paribus). By including an interaction term of dummy_child and the number of household members, we additionally tested whether the number of household members influences children and adults in the same way finding out no significant difference either under MNL or ZINB.

Furthermore, being a woman increases the expected visits by 1.21, as opposed to men (ceteris paribus). And one-unit increase in personal income[2] decreases the expected visits by 0.99.

The second part of the regression expresses the probability of being in the "Always Zero group" relative to the "Not Always Zero group". The results reveal that being a woman decreases the odds of being in the "Always Zero group" by exp 0.29. In other words, in the female part of the population the zero values are less likely generated by the fact that a woman is ill and does not visit a doctor. If the number of household members increases by one, the odds that the respondent is in the "Always Zero group" increases by 1.61. In other words, the number of household members increases the probability that zeros are generated by the fact that the sick do not go to a doctor. The coefficient of personal income is not statistically significant.

4.3 Robustness check

In Tables 7 and 9, we check whether our previous results are robust to the exclusion of the elderly (over 65) - whose cap on co-payments decreased in 2009 - from the control group. We again employ the MNL and ZINB models.

The main results are consistent with our previous estimates. The coefficients of the interaction term are statistically insignificant in all regression sets in the MNL model as well as in the ZINB model. Thus, we verified that the abolition of user charges did not have a significant effect on the number of doctor visits even if the elderly were excluded from the control group. It is believed that the decreased protective limit may have rather significantly influenced the number of drug prescriptions or utilization of health-care services above 20 outpatient visits.

Individual characteristics are jointly significant over all sets in the MNL model, which is also consistent with the results from the previous analysis. The only difference is the direction of the effect of personal income which varies across sets (when significant). Previously the

[2]The coefficients of *p_income* is small because the values of the input variable are high.

Table 7. Zero-inflated Negative Binomial (ZINB) Model

Number of obs = 1471
Non-zero obs = 837
Zero obs = 634
LR $\chi^2(6)$ = 30.89
Prob> χ^2 = 0.0000

visits	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
count process = neg. binomial						
reform	0.0282441	0.0768556	0.37	0.713	-0.1223901	0.1788784
dummy_child	-0.0518715	0.2917086	-0.18	0.859	-0.6236098	0.5198669
interaction	-0.6443572	0.7171472	-0.90	0.369	-2.04994	0.7612254
female	0.3774727	0.0759816	4.97	0.000	0.2285515	0.526394
members	-0.0402803	0.0309676	-1.30	0.193	-0.1009756	0.0204151
p_income	-2.32×10^{-7}	2.10×10^{-7}	-1.10	0.270	-6.44×10^{-7}	1.80×10^{-7}
_cons	1.229487	0.1258047	9.77	0.000	0.9829142	1.47606
inflation model = logit						
reform	1.632956	0.4134258	3.95	0.000	0.8226566	2.443256
dummy_child	4.785042	0.5255265	9.11	0.000	3.755029	5.815055
interaction	-1.025958	0.784059	-1.31	0.191	-2.562685	0.5107696
female	-1.34776	0.2692444	-5.01	0.000	-1.875469	-0.8200504
members	0.4681187	0.1266468	3.70	0.000	0.2198956	0.7163418
p_income	3.51×10^{-7}	6.97×10^{-7}	0.50	0.614	-1.01×10^{-6}	1.72×10^{-6}
_cons	-3.51157	0.7443763	-4.72	0.006	-4.970521	-2.052619
$\ln\alpha$	-0.1971178	0.0960659	-2.05	0.040	-0.3854034	-0.0088321
α	0.8210939	0.0788791	0.6801762	0.9912068		

Likelihood-ratio test of $\alpha = 0$: $\bar{\chi}^2(01) = 956.32$ Pr $\geq \bar{\chi}^2 = 0.0000$
Vuong test of zinb vs. standard negative binomial: z = 5.78 Pr>z = 0.0000

Table 8. Wald test of the joint significance of variable *interaction* for MNL regression

**** Wald tests for independent variables (N=1471)
Ho: All coefficients associated with given variable(s) are 0.

	chi2	df	P>chi2
reform	28.055	18	0.061
dummy_child	106.312	18	0.000
interaction	0.754	18	1.000
female	85.133	18	0.000
members	32.642	18	0.018
p_income	33.059	18	0.016

coefficient of personal income was always negative. In the ZINB model, this coefficient became insignificant. It may be caused by the fact that pensioners live in small households and thus have higher fixed costs. Furthermore, the elderly also belong to the poorer segment of the population. For all these reasons, the variable personal income plays an important role in the previous analysis. Put differently, the elderly are believed to be responsible for the significance of this variable in the main analysis.

We also re-estimated both models when only individuals between 18-26 years of age were included into the control group. In terms of the treatment effect, the results were consistent with both the main analysis and the robustness check without the elderly. Since such age restriction in the control group makes the treatment and control groups even more alike, all individual characteristics turned insignificant both under MNL and ZINB (results are availale on request with the authors).

Table 9. Multinomial Logit (MNL) Model

	visits	Coef.	RRR	P>|t|
0		(base outcome)		
1	reform	-0.7274083	0.4831596	0.001
	dummy_child	-4.254504	0.0142001	0.000
	interaction	1.101006	3.00719	0.443
	female	0.4056609	1.500294	0.047
	members	-0.1483331	0.8621439	0.104
	p_income	-7.73×10^{-8}	0.9999999	0.911
	_cons	-0.4357008	.	0.236
2	reform	-0.7700284	0.4629999	0.000
	dummy_child	-3.175116	0.0417892	0.000
	interaction	-0.4405858	0.6436593	0.694
	female	0.6902056	1.994126	0.000
	members	-0.2087742	0.8115785	0.007
	p_income	-7.01×10^{-7}	0.9999993	0.288
	_cons	0.2337235	.	0.467
3	reform	-0.5412123	0.5820422	0.032
	dummy_child	-19.25928	4.32×10^{-9}	0.993
	interaction	17.06951	2.59×10^{7}	0.994
	female	1.21175	3.359358	0.000
	members	-0.1537765	0.8574636	0.160
	p_income	-2.27×10^{-7}	0.9999998	0.796
	_cons	-1.370618	.	0.003
4	reform	-0.5597447	0.5713549	0.016
	dummy_child	-2.949192	0.052382	0.000
	interaction	-15.82488	1.34×10^{-7}	0.995
	female	1.311516	3.711798	0.000
	members	-0.1300549	0.8780472	0.194
	p_income	5.48×10^{-7}	1.000001	0.409
	_cons	-1.447525	.	0.000
5	reform	-0.7122904	0.4905194	0.009
	dummy_child	-2.983747	0.0506029	0.000
	interaction	-15.62748	1.63×10^{-7}	0.996
	female	1.234299	3.435969	0.000
	members	-0.1898804	0.827058	0.102
	p_income	7.00×10^{-7}	1.000001	0.335
	_cons	-1.565682	.	0.001
6	reform	-0.7000893	0.496541	0.028
	dummy_child	-3.222165	0.0398687	0.002
	interaction	-15.24547	2.39×10^{-7}	0.997
	female	1.158744	3.185929	0.000
	members	-0.4135138	0.6613224	0.003
	p_income	-1.47×10^{-6}	0.9999985	0.295
	_cons	-0.8126441	.	0.165
7	reform	-0.3290354	0.7196175	0.582
	dummy_child	-18.74952	7.20×10^{-9}	0.997
	interaction	0.2880594	1.333837	1.000
	female	1.273131	3.572018	0.041
	members	-0.4955632	0.6092277	0.074
	p_income	9.22×10^{-7}	1.000001	0.522
	_cons	-2.785668	.	0.005
8	reform	-0.6475239	0.52334	0.096
	dummy_child	-2.565418	0.0768871	0.014
	interaction	-15.75953	1.43×10^{-7}	0.997
	female	0.9816943	2.668975	0.009
	members	-0.4652494	0.6279784	0.007
	p_income	6.65×10^{-7}	1.000001	0.507
	_cons	-1.509572	.	0.015
9	reform	-18.40279	1.02×10^{-8}	0.997
	dummy_child	-19.76431	2.61e-09	0.998
	interaction	18.30374	8.90×10^{7}	0.999
	female	1.947381	7.010301	0.084
	members	-0.004833	0.9951786	0.990
	p_income	6.87×10^{-7}	1.000001	0.799
	_cons	-4.881679	.	0.006
10	reform	-0.4308218	0.6499747	0.177
	dummy_child	-18.98428	5.69×10^{-9}	0.994
	interaction	0.3722241	1.450958	1.000
	female	1.92924	6.884277	0.000
	members	-0.2216751	0.8011756	0.115
	p_income	1.25×10^{-6}	1.000001	0.094
	_cons	-2.625781	.	0.000

	visits	Coef.	RRR	P>|t|
12	reform	-0.3789355	0.6845898	0.401
	dummy_child	-2.288792	0.1013889	0.032
	interaction	-16.14215	9.76×10^{-8}	0.997
	female	0.8306949	2.294913	0.063
	members	-0.7307653	0.4815403	0.001
	p_income	-0.0000101	0.9999899	0.006
	_cons	0.6916038	.	0.473
13	reform	16.4381	1.38×10^{-7}	0.995
	dummy_child	12.52069	273946.2	0.999
	interaction	-15.09604	2.78×10^{-7}	0.999
	female	15.91488	8161025	0.993
	members	-15.57658	1.72×10^{-7}	0.985
	p_income	-0.0000174	0.9999826	0.283
	_cons	-14.86946	.	0.996
14	reform	-0.5300392	0.5885819	0.675
	dummy_child	-19.27107	4.27×10^{-9}	0.998
	interaction	0.3871189	1.472732	1.000
	female	17.5669	4.26×10^{7}	0.995
	members	0.1034415	1.108981	0.819
	p_income	-0.000035	0.999965	0.037
	_cons	-17.06541	.	0.995
15	reform	-0.8150981	0.4425959	0.184
	dummy_child	-19.10457	5.05×10^{-9}	0.997
	interaction	0.8261248	2.284449	1.000
	female	1.229327	3.418928	0.046
	members	-0.6321987	0.5314221	0.020
	p_income	-8.40×10^{-6}	0.9999916	0.068
	_cons	-0.4388168	.	0.731
16	reform	-17.74951	1.96×10^{-8}	0.997
	dummy_child	-19.93515	2.20×10^{-9}	0.999
	interaction	18.06774	7.03×10^{7}	0.999
	female	0.1568753	1.16985	0.917
	members	-0.5337495	0.5864021	0.401
	p_income	-0.0000356	0.9999644	0.055
	_cons	1.74162	.	0.594
17	reform	-16.39864	7.55e-08	0.997
	dummy_child	-19.47735	3.48×10^{-9}	0.999
	interaction	16.27627	1.17×10^{7}	0.999
	female	16.72296	1.83×10^{7}	0.996
	members	0.2125168	1.236787	0.773
	p_income	-0.0000465	0.9999535	0.154
	_cons	-16.38989	.	0.996
18	reform	-0.6778462	0.5077093	0.582
	dummy_child	-18.84817	6.52×10^{-9}	0.999
	interaction	0.6578419	1.930621	1.000
	female	1.235738	3.440918	0.316
	members	-0.5962441	0.5508768	0.289
	p_income	-3.17×10^{-7}	0.9999997	0.940
	_cons	-3.491177	.	0.094
20	reform	-0.8083443	0.4455952	0.112
	dummy_child	-19.45494	$3.55e\times10^{-9}$	0.996
	interaction	0.7426352	2.101466	1.000
	female	1.795484	6.02239	0.002
	members	-0.2040279	0.8154396	0.335
	p_income	-8.79×10^{-6}	0.9999912	0.035
	_cons	-1.589434	.	0.170

5 Conclusion

This paper investigates the effect of the abolition of user charges on the demand for ambulatory doctor visits. It analyses the EU-SILC micro-level data from 2009 and 2010 surveys. The setup enabled us to carry out a natural experiment where children constitute a treatment group and the rest of the population serves as a control group. The analysis limits itself to the area of the city of Prague. Not only are the systems in the city of Prague and outside of it different, but due to such a restriction we avoid a spillover effect. In other words, it is believed that hardly any Prague citizen would go to a hospital outside Prague, but it is quite common visa versa.

Two estimation methods were used: the Multinomial logit model which estimated the probability of a change in the number of physician visits made by a member of the treatment group (children) after April 2009; and the Zero-inflated negative binomial model which expressed the probability of visiting a doctor as a combination of two submodels assuming that the zero number of doctor visits are generated by two different processes - (i) a respondent was not ill and therefore did not visit a doctor ("Not Always Zero group"); (ii) a respondent was ill, but still did not visit a physician ("Always zero group ").

Results of both models consistently show an insignificant effect of the abolition of user charges on the number of doctor visits, i.e. the probability of visiting a doctor among the members of treatment group (children) did not significantly change when user charges were abolished. Our results are consistent with a number of previous papers, e.g. Kim *et al.* (2005), Chiappori *et al.* (1998), Zapal (2010), etc. Sex, personal income and the number of household members all have a significant effect on the demand for outpatient care - the number of household members and personal income decrease the probability of visiting a doctor multiple times suggesting that richer people have considerable opportunity costs of visiting a doctor and the bigger the household is, the less its members care about their health. Being a woman increases the probability, suggesting that women care about their health more than men.

Results of ZINB model further reveal that the odds of being in the "Always Zero group" compared with the the "Not Always Zero group" does not significantly change for the treatment group after the introduction of co-payments. In other words, relative probability of avoiding healthcare among members of the treatment group did not significantly change when user charges were abolished.

Assuming that a decreased cap (introduced also in April 2009) on co-payments for the elderly may have an effect, we carried out a robustness check excluding the elderly from the sample. The results are however consistent with the previous analysis. The only difference brought about by the robustness check was the effect of personal income, which proved not to be an important determinant when the elderly were excluded. It is assumed to be caused by the fact that the elderly usually live in smaller households and are a poorer part of the population with proportionately higher fixed costs.

Besides, we also restricted the control group to the population aged 18-26. In terms of the treatment effect, the results both under MNL and ZINB are consistent with the previous analyses and the robustness check without the elderly. However, all individual characteristics turned insignificant because such a restriction made control and treatment groups even more alike.

When carrying out this analysis, we could not distinguish between emergency and ordinary visits due to data availability. Being able to analyze such disaggregated data, we would additionally find whether the people in the Czech Republic are sensitive in terms of the structure of user charges. In other words, we may find that it pays off for some to wait a day or two before they go to a doctor. This serves as a motivation for further research.

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Appendix

Table A.1. Correlation matrix

	sex	visits	members	reform	dummy_child	interaction	p_income
sex	1.00000						
visits	0.1620	1.00000					
members	-0.0530	-0.2861	1.00000				
reform	-0.0486	-0.0961	0.0765	1.00000			
dummy_child	-0.0253	-0.3088	0.3576	0.0203	1.00000		
interaction	-0.0325	-0.1962	0.2386	0.3265	0.6054	1.00000	
p_income	-0.0367	-0.0563	-0.1379	0.0309	-0.0956	-0.0516	1.00000

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