Charles University in Prague

Faculty of Social Sciences
Institute of Economic Studies

BACHELOR THESIS

The Effect of the Introduction of Fee-For-Service on the Demand for Outpatient Care

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Declaration of Authorship

I hereby proclaim that I wrote my bachelor thesis on my own under the leadership of my supervisor and that the references include all resources and literature I have used.

Furthermore, I declare that I have not used this thesis to acquire another academic degree.

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Abstract

The thesis estimates the effect of the 2008 introduction of regulatory fees for outpatient visits by using 2009 health reform, abolition of co-payments for children, as a natural experiment. To estimate this effect we use micro-level data from EU-SILC survey and two different econometric models — Multinomial logit (MNL) and Zero-inflated negative binomial (ZINB). As co-payments for examination were abolished only for children, we use children as a treatment group and adult part of the population as a control group in difference-in-differences approach. We found an insignificant effect, i.e. introduction of user charges was ineffective in reducing number of doctor visits in Czech Republic. Another important result from this analysis is the significant role of the socio-economic characteristics, associated with the tendency of health-care utilization.

JEL Classification	I18, H51, C13, I11, H31, H75
Keywords	co-payments/regulatory fees, cost-sharing, doctor visits, Czech health-care system, natural experiment, difference-in-differences approach, Zero-inflated negative binomial (ZINB) model, Multinomial logit (MNL)

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Abstrakt

Bakalářská práce hodnotí efekt zavedení regulačních poplatků na návštěvnost u lékaře s použitím reformy zdravotnictví 2009, zrušení poplatků pro děti, jako přirozeného experimentu. K odhadu tohoto efektu používáme mikro-data z šetření EU-SILC a dva různé ekonometrické modely – Multinomial logit (MNL) a Zero-inflated negative binomial (ZINB). Jelikož poplatky za vyšetření u lékaře byly zrušeny pouze pro děti, použijeme děti jako treatment skupinu a dospělou část populace jako control skupinu v metodě difference-in-differences. Zjistili jsme nevýznamný efekt, tj. zavedení poplatků v České republice nebylo účinné při snižování počtu návštěv u lékaře. Dalším důležitým závěrem z naší analýzy je významná role některých charakteristik jednotlivce, spojených s tendencí využívání zdravotních služeb.

Klasifikace JEL	I18, H51, C13, I11, H31, H75
Klíčová slova	regulační poplatky, spoluúčast pacientů, návštěvy u lékaře, Český systém zdravotní péče, přirozený experiment, metoda tzv. rozdílu v rozdílech, zero-inflated negative binomial model, Multinomial logit model

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Acronyms

DiD Difference-in-differences

ZINB Zero-inflated negative binomial

MNL Multinomial logit

CZSO Czech Statistical Office

EU-SILC European Union-Statistics on Income and Living Conditions

CR Czech Republic

PPP Purchasing Power Parity

OLS Ordinary least squares

IIA Independence of irrelevant alternatives

NB Negative binomial

LR Likelihood-ratio test

GP General Practitioner

Bachelor Thesis Proposal

Author	Pavlína Žílová
Supervisor	PhDr. Jana Votápková
Proposed topic	The Effect of the Introduction of Fee-For-Service on the Demand for Outpatient Care

Zásady pro vypracování:

Zavedení regulačních poplatků bylo důležitou součástí reformy zdravotnictví, která v České republice nabyla účinnosti 1. ledna 2008. Tento reformní krok byl přijat za účelem omezení nadměrného plýtvání finančních prostředků ve zdravotnictví a nadužívání zdravotních služeb ze strany pacientů. V své práci se blíže zaměřím na jeden druh poplatků, a to na poplatky za návštěvu u lékaře.

V úvodu své práce budu specifikovat fungování poplatků v České republice, jejich vývoj a důvody zavedení. Dále poukážu na zkušenosti s poplatky v zahraničních systémech zdravotnictví a na méně či více důležitou roli proměnných (věk, pohlaví, vzdělání, příjem v rodině, rodinný stav, zaměstnání, počet dětí a členů domácnosti a sebehodnocení zdravotního stavu) na počet návštěv u lékaře. V další části bude následovat analýza vlivu zavedení regulačních poplatků na poptávku po zdravotních službách, konkrétně po ambulantní péči. V závěru práce provedu diskuzi k zjištěným výsledkům.

Současný stav poznání, můj přínos:

V různých státech, kde funguje veřejně financovaný systém zdravotnictví, jsou poplatky za ambulantní péči zaváděny kvůli rostoucím výdajům na zdravotnictví. Tento růst je dán stárnutím populace a lepšími technologickými možnostmi. Studie na toto téma byly již vydány v mnoha zahraničních zemích. Například v jedné studii z USA (Trivedi *et al.*, 2010) bylo zjištěno, že většího efektu ze zavedení poplatků bylo dosaženo na území s nižšími příjmy a nižším vzděláním. Pro nízkopříjmové jedince a jedince se špatným zdravím, existuje velký negativní účinek na zdraví po zavedení poplatků (Gruber & Foundation, 2006). Starší pacienti mohou být také více citliví na zavedení poplatků, protože mají nižší příjmy a také většinou horší zdravotní stav (Trivedi *et al.*, 2010). Tedy hlavní charakter regulačních poplatků je jejich výše. Zavedení poplatků, které jsou příliš velké, mohou vést k vyhýbání se potřebné zdravotní péči, ale na druhou stranu, příliš nízké poplatky nevedou k efektivnímu využívání péče.

Proto se ve své práci zaměřím na zodpovězení otázek, zda (1) po zrušení poplatků pro děti došlo k významnému nárůstu návštěv u lékaře a tedy zavedení poplatků mělo odstrašující efekt (2) charakteristiky jednotlivce významně ovlivňují poptávku po zdravotní péči. Pro analytickou část použiji mikrodata z šetření EU-SILC, které provádí Český statistický úřad a aplikuji metodu difference-in-differences. Jako závislou proměnnou zvolím počet návštěv u lékaře (praktického a specialisty, s výjimkou zubaře a očního lékaře) a jako nezávislé proměnné vyberu tři charakteristiky jednotlivce – pohlaví, osobní příjem a počet členů domácnosti.

Od 1.1.2008 byly stanoveny regulační poplatky ve výši 30 Kč za návštěvu lékaře a položku na receptu, 60 Kč za každý den pobytu v nemocnici a dalších zdravotnických zařízeních (lázně, léčebny a další) a 90 Kč za pohotovostní službu. Regulační poplatky jsou určitou formou spoluúčasti a jejich funkce je snížit nadměrnou

poptávku po zdravotní péči. V roce 2009 byly zrušeny poplatky pro děti za návštěvy u lékaře, vyjma logopeda a psychologa. V metodě difference-in differences proto zvolím jako kontrolní skupinu dospělou část populace nad 18 let, pro kterou žádná změna nenastala a jako treatment skupinu stanovím děti, které poplatky za návštěvy u lékaře po dubnu 2009 již neplatí, tedy:
$\text{visits}_i = \beta_0 + \beta_1 \text{post}_i + \beta_2 \text{dummy\_child}_i + \beta_3 \text{interaction}_i + \beta_4 \text{X}_i + \varepsilon_i$ kde visits_i je závislá proměnná, tedy počet návštěv u lékaře pro osobu i. dummy_child_i indikuje, zda osoba i patří do treatment skupiny. post_i označuje, zda se jedná už období po zrušení poplatků pro děti. X_i obsahuje různé závislé proměnné uvedené výše. β_3 měří průměrný efekt regulačních poplatků. Pokud je teda β_3 kladné, poptávka po ambulantní péči u treatment skupiny vzrostla po zrušení poplatků vzhledem k poptávce u kontrolní skupiny.

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Author Supervisor

Chapter 1

Introduction

In many countries, governments have introduced cost-sharing in their health-care system because of increasing public spending on health-care. In the health system with patient cost-sharing, the people pay a fraction of the actual cost and therefore their awareness of the cost of health-care should increases. In other words, the purpose of this measure is to make consumers more cost-conscious and reduce unnecessary demand for utilization of health services. Furthermore, cost-sharing generates additional revenues to the system and decreases public expenditure on health-care.

In Czech Republic, solidarity and equity are important in the health system and, therefore, public health spending has substantially increased over the past 13 years, as in other OECD countries. Specifically, the value of total public health expenditure per capita adjusted to PPP increased with some fluctuations from 815 US$ (approximately CZK 16,000) in 1995 to 1,415 US$ (approximately CZK 27,000) in 2007 (OECD 2011b). Reasons for this increase are advancing technological possibilities in health system and a demographic change, especially ageing of the population. The former reason increases total cost through new drugs against incurable diseases. The latter generates bigger total demand for health-care because of more and more costly visits made by the elderly. This is supported by Riley & Lubitz (2010) who showed that most of the health-care expenditure is incurred in the last year of life.

Increasing costs on health-care led, among others, to the introduction of co-payments into the Czech health-care system to increase its efficiency. In January 2008 regulatory fees on doctor visits, emergency care and pharmaceuticals were established to put pressure on patients to deter over-utilization of health-care services. This policy measure received a wide discussion among general public and politicians and became a subject of considerable interest. This policy change wanted to partly shift health-care expenditure from public to private resources. Some argued that patients would, as a result, also use fewer outpatient services. On the contrary, opponents argued that in Czech Republic (CR), introduction of co-payments would not have significant effect on the demand for health-care services. When not successful, we should not apply it at least to some vulnerable groups, because their utilization of health-care services is minimal and co-payments could have a detrimental and inequitable effect on their health status. As a result of the discussion, in April 2009 co-payments on physician visits were abolished for children. Rationality of this decision is supported by the study of Gertler & Gaag (1990), which found out that the introduction of regulatory fees for children is more deterrent than for the rest of the population.

The thesis estimates the effect of the 2008 introduction of user charges for outpatient visits by using 2009 health reform, abolition of co-payments for children, as a natural experiment. In other words, we will study whether the abolition of outpatient user fees for children had significant positive effect on the demand for physician visits. We employ a difference-in-differences approach where children from Prague represent treatment group and the rest of the population in Prague represents a control group. The results are estimated by the multinomial logit (MNL) and zero-inflated negative binomial (ZINB) models. The data come from the Czech Statistical Office (CZSO)[1]. We also carry out a robustness check where we excluded the elderly (over 65) from the control group because in April 2009 another change occurred; limit on health expenses for people over 65 decreased from CZK 5,000 to CZK 2,500, which may slightly underestimate the result.

Our research questions are: (1) Did the introduction of outpatient regulatory fees have a significant effect on children (treatment group)? (2) How do the individual characteristics such as sex, income etc. affect the demand for health-care?

The additional analysis, which re-estimated the MNL regression using three levels of the dependent variables (non-visitor, occasional visitor and frequent visitor), aims to find the effect of the regulatory fees on the poor health people by assuming that frequent-visitor is the one with poor health.

If the abolition of co-payments for physician visits made by children significantly increased the number of physician visits in 2009, the introduction of regulatory fees would be found effective in its purpose. We however found an insignificant effect with using both models (MNL and ZINB), i.e. number of children's outpatient visits (treatment group) did not significantly change after the abolition of regulatory fees. With re-estimated MNL model we additionally found out that co-payments also did not also significantly change the probability of visiting a doctor by the people with poor health status (frequent-visitors). We further

[1]Available on request at: Czech Statistical Office (CZSO 2005-2010)

discovered that the probability to visit the doctor more increases for women and decreases with personal income and number of household members.

The 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 the utilization of health-care.

The thesis is organized into eight chapters. In the next one, we investigate the history of cost-sharing and provide the overview of major issues related to it. Chapter 3, The Czech Health-Care System, describes how the Czech health-care system is financed. Literature review follows in chapter 4. The fifth chapter explains Methodology, models and approach that we will use. Chapter 6, Data, gives the descriptive statistics and introduces variables used in the regressions. In chapter 7 – Results – we present the estimation results. Finally, in chapter Conclusion, we discuss the results, provide motivation for further research and conclude the thesis.

Chapter 2

History of cost-sharing and the overview of major issues

Since the end of last century cost containment arrangements of health-care expenses have worldwide shifted from focusing on providers (supply side arrangements) to focusing on patients (demand side arrangements). This shift means a change from macroeconomic cost control tools and solidarity goals to microeconomic efficiency goals. The governments stopped focusing on budget caps in the health system financing and cost-sharing became the subject of interest.

In recent years these important microeconomic instruments were mainly being introduced because of enormous moral hazard as well as increasing costs for health-care. Cost-sharing solves primarily the former because it reduces over-utilization of health-care services and risky behavior of patients. At the same time it shifts health-care expenses from public to private and, moreover, it provides additional revenues, which partly compensate increasing costs.

We can find cost-sharing in many countries in the form of co-payments, co-insurance, deductibles or a combination of these possibilities. Ros *et al.* (2000) assert that because patients pay a percentage of the costs in case of co-insurance and full costs sum up to a ceiling in case of deductibles, these forms should be used if exact price of a health service is known, i.e. in case of pharmaceuticals. The overview of forms of cost-sharing valid in 2010 in the EU countries and change in health system in the EU since 1990 is presented in Table A.1. There we can see a relationship between the type of health-care service (inpatient, outpatient, and medication utilization) and the form of cost-sharing.

Tambor *et al.* (2011) find relation between type of financing (insurance-based, tax-based) and existence of cost-sharing. Specifically, quality is an important social value in a tax-based health system and, therefore, cost-sharing, which generates inequality, is not often used. However, if cost-sharing is used in a tax-based funding system, exemptions of vulnerable groups (e.g. children, low income people etc.) from paying charges are common.

In most countries there are four vulnerable groups that are generally exempted from cost-sharing: low income, children, elderly and people with poor health. Rationality of this exemption is confirmed by a couple of studies. Trivedi *et al.* (2010) assert that the effect of cost-sharing is greater in areas with low income levels and poor health conditions. Lundberg *et al.* (1998) support the hypothesis claiming that patients with poor health or the low income are more price-sensitive. Tamblyn *et al.* (2001) examine effects of cost-sharing drug prescriptions for the elderly and they detect significant reductions in use of essential drugs. According to these studies, cost-sharing may cause undesirable reduction in utilization of health-care services and cause deterioration of health status of the low income and chronically ill.

Apart from exemption of some groups, another way to protect these vulnerable groups is to establish income-based limits on health expenses or a fixed cap on total health-care costs.

There also exist some health-care services, e.g. maternity and preventive services that are often excluded from patient cost-sharing. These exclusions are justified by the fact that cost-sharing may contribute to the under-utilization of recommended preventive care, which is supported by Solanki & Schauffler (1999), who investigate the relationships between the utilization of recommended preventive services and different forms of patient cost-sharing.

Another issue connected with user charges is that if government introduces co-payments on one type of health-care services, it decreases demand for this services but it may increase demand in another (substitute) sector. Specifically, Anis *et al.* (2005) found that older patients had fewer prescriptions filled out after the introduction of cost-sharing but they increasingly visited hospitals. Some further evidence shows that co-payments for ambulatory services decrease doctor outpatient visits, but increase hospital inpatient visits and, as a result, the co-payments increase overall costs and they may be self-defeating. Helms *et al.* (1978) found this effect especially significant for vulnerable groups in a California co-payment experiment, which lasted for six quarters from July 1971 to December 1972, where the co-payments for doctor visits was set to one dollar for each of the first two office visits in a month. Davis & Russell (1972) further confirm this assertion finding out that substitution of outpatient care with inpatient care actually occurs in response to a relative price change.

Chapter 3

The Czech Health-Care System

The Czech health-care system has undergone many changes since the Second World War. Until the Velvet revolution (1989), the communist regime funded health-care through taxation. Government managed and controlled all decisions related to the health-care system, because health-care was fully financed by the state budget.

In 1992 a new health-care system, based on market principles was created. Competition and private property became major features of the new system, which was independent from the government. Health-care system was reformed radically, compulsory insurance was established and many insurance companies emerged. All citizens contributed to the health insurance budget by part of their income – except for children, students, pensioners, women on maternity leave, unemployment etc., for which health insurance was covered by the state. Later on, most health establishments, except for larger hospitals, were privatized.

This change in financing of health-care from the taxation-based system to the insurance based system did not guarantee absolute efficiency but it brought positive developments and supported the process of democratisation, which was a great progress at that time (Medveď *et al.* 2005). Quality of the system improved and patients gained universal access to the sufficient level of health-care.

The Czech health insurance system is administered by eight health insurance companies since March 2011, when the health insurance fund MEDIA merged with the largest health insurance company, the General Health Care Insurance Company. The main functions of insurance companies are to collect contributions and pay for health services.

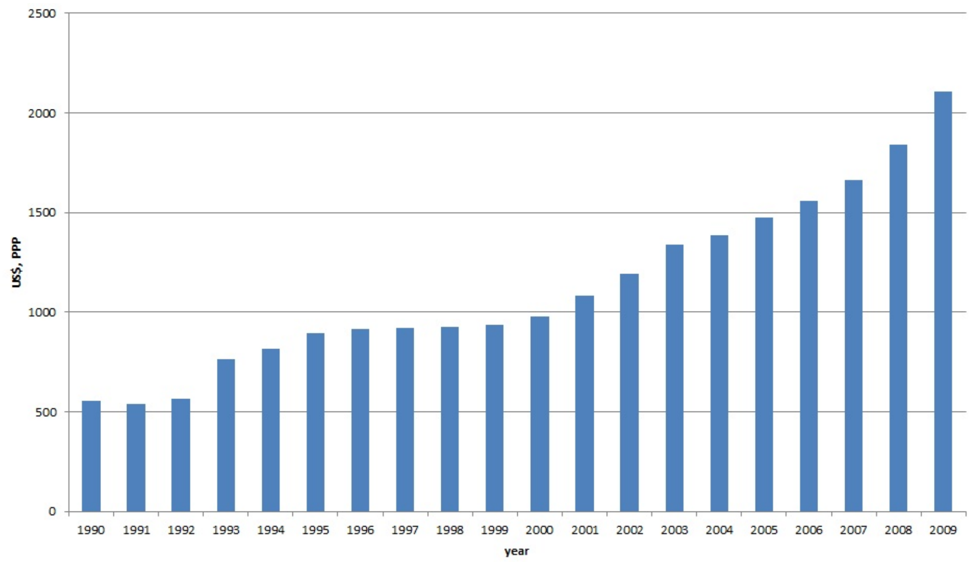
Another important change in the Czech health-care system, the introduction of co-payments in 2008, was a very controversial topic and it was accompanied by much disagreement. This measure was, similar as in other countries, introduced in the CR because of deemed overuse of health-care services. Czech patients had an average of 14.8 contacts with a physician in 2005, which was twice more than the Western European average (Riphagen *et al.* 2005). As we can see in Figure 3.1, total health expenditure per capita continued to rise and therefore government wanted to reverse this trend.[1]

The chosen policy option wanted to reduce the number of excess doctor visits and included cost-sharing imposed on the patients. The aim of this change was to decrease health-care expenditures by assuring that the people visit physician only if they really need it. Three values of co-payments were introduced[2]:

- CZK 30 for physician visits during which a clinical examination was carried out.
- CZK 30 for every drug prescription (for one item on prescription).

[1]Data are available on OECD (2011c)
[2]For more information: http://www.mzcr.cz/Odbornik/.

Figure 3.1: Total health expenditure per capita in the CR



- CZK 60 for each day of inpatient care.
- CZK 90 for emergency service.

Revenues from regulatory fees remain in budget of the particular health-care facility as an additional income.

At the same time, a limit on health-care expenses, a so called protective limit, was introduced at CZK 5,000 per year. Only co-payments in the amount of CZK 30 and surcharges for prescriptions count into it.

Since the beginning of 2009 all regions except for Prague, started to reimburse co-payments in regional hospitals. It was a part of the pre-election promise of the Czech Social Democratic Party in the elections to the regional councils. In 2010, reimbursements in regional hospitals was canceled, as a result of objections of the European Commission, which considered this behavior discriminatory. Pražmová & Dušek (2011) found that regions spent in total CZK 480.7 mil. on the reimbursements of regulatory fees.

Additional health-care reform came into force 1 April 2009, when children were exempted from paying co-payments for a physician visit, except for psychologist and speech therapist visits. Decrease in protective limit from CZK 5,000 to CZK 2,500 for children and patients over 65 years of age was another change that this reform brought.

Latest changes in the Czech health-care system were introduced in December 2011 and January 2012. Co-payment for one day of hospitalization was increased from CZK 60 to CZK 100 and a regulatory fee for an item on a prescription was abolished – patients now have to pay CZK 30 for the whole prescription, not for an item on it.

Figure 3.2: Public expenditure as percentage of total expenditure on health in the Czech Republic

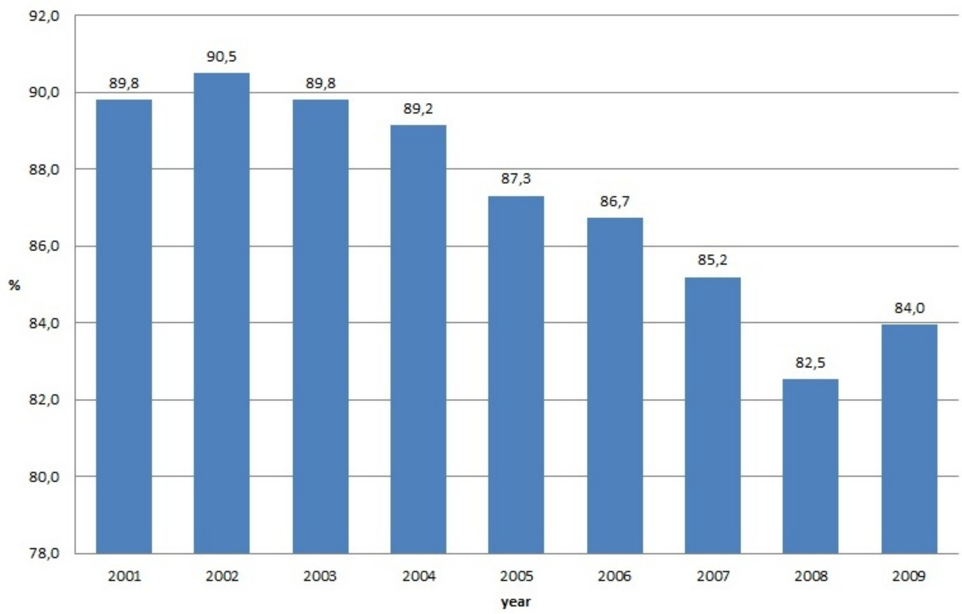


Figure 3.2 shows that the introduction of co-payments in 2008 probably decreased the share of public health-care expenditure by 2.7 percentage points.[3] After 2009 the share of public expenditure in the total expenditure on health started to rise again, but the share of public expenditure did not reach such high values as before the reform of 2008. It is assumed that reimbursement

[3]Data are available on OECD (2011a)

by regions and the abolition of children's outpatient co-payments partly caused this increase.

Chapter 4

Literature review

Most of the first studies investigating the effect of cost-sharing use data from the social experiment named the Rand Health Insurance Experiment (HIE) which took place in the USA. It started in 1974 and families who enrolled in it were observed over five years. Families were randomly assigned to the different levels of patient co-insurance in order to allow the researchers to estimate nexus between the level of cost-sharing and demand for health-care services. One research paper that used data from this experiment is Gruber & Foundation (2006). The study answers several questions concerning how large should co-insurance be and how effects of level of co-insurance vary by patients characteristics such as health status and income. They find that co-insurance rate that are too low do not lead to declines in excessive care. On the contrary, too high co-insurance rate can result in avoiding necessary health-care. The results show that for a person of average health and with average income, co-insurance in a health plan does not have a negative influence on his or her health status. "The one clear negative impact on health occurs only for those who are at high medical risk, particularly if they are also of lower income." (Gruber & Foundation 2006)

Other research that works with the data from the HIE are Manning *et al.* (1987) and Newhouse & Group (1993). Both studies confirm results of Gruber and Foundation (2006). Specifically, the studies show that 25% co-insurance rate implies nearly 20% reduction in the health-care expenditures and no adverse impact on health status among patients.

On the contrary, the criticisms of the HIE experiment (Saltman *et al.* 1997) argue that the effects of cost-sharing arrangements may be valid only in the US and studies performed in other countries could come up with different results. Rosen *et al.* (2011) point out that some characteristics of HIE may limit its generalizability.

We could divide later studies depending on what type of cost-sharing is analysed – charges on inpatient care, outpatient care or pharmaceuticals. Ong *et al.* (2003), Martikainen *et al.* (2007), and O'Brien (1989) investigate effect of increasing or decreasing co-payment on the consumption of various drugs. Ong *et al.* (2003) find no significant effect of co-payment increases on the use of antidepressants, anxiolytics, and sedatives in Sweden. Different results are shown in two other above mentioned studies – fees on prescriptions are effective in reducing consumption of some drugs in Finland (Martikainen *et al.* 2007) and in England (O'Brien 1989).

The effect of co-payments on physician visits was investigated in South Korea (Kim *et al.* 2005) and in France (Chiappori *et al.* 1998). Both studies found that cost-sharing is not functioning well enough in reducing the demand for health-care. Kim *et al.* (2005), who analysed data from the National Health and Nutrition Survey conducted in 1998 by the Korean Ministry of Health and Welfare, found out that demand for ambulatory services is costresistant. In case of France, Chiappori *et al.* (1998) claim that introduction of 10% co-payment rate did not have an influence on the participation rate in GP office visits.

Other studies dealing with the same issue have mixed results. Kan & Suzuki (2010) estimated the effect of an increase in the co-insurance rate in 1997 on the frequency of physician visits in Japan. The effect of this reform was found to be negative and statistically significant for a two-year data but the effect was not clear for data acquired from longer periods. Therefore authors concluded that patients are not very price sensitive within the 10-20 percent range of co-insurance rate. The sign of results from two-year data could be seen only as a transitory effect. In Belgium, Cockx & Brasseur (2003) came also to mixed conclusions. Specifically, they found negative effects of increased co-payment in 1994 in Belgium 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 specialist.

In Germany, however, Winkelmann (2004) found that increase in co-payments fulfilled its purpose. Winkelmann (2004) estimates the effect of increased co-payments for drug prescriptions on the number of doctor visits. This change became effective in July 1997 and co-payments increased up to 200%. Winkelmann's study relies on data from the German Socioeconomic Panel (GSOEP) using a four-year sample with 40,000 observations. Results show that the 1997 reform effect is negative and significant, and doctor visits are reduced by 10% on average.

It is followed by other studies that investigate further changes in the German health system. Augurzky *et al.* (2006) and Schreyögg & Grabka (2010) examined German health reform of 2004, in which co-payment for the first doctor visit in each quarter was introduced. These two studies came to the same finding that co-payments of 2004 failed to reduce the number of physician visits in Germany. From this literature survey we can conclude that significant and desired effect of co-payments depends on its amount, frequency of payment and characteristics of each state. Therefore not all the studies agree on the effect of co-payment.

The above mentioned studies differ in methods employed. Ong *et al.* (2003), a Swedish study of drug utilization, uses Box-Jenkins autoregressive, integrated moving-average time-series modeling methods which enabled them to determine a model that fits best the time series data. Other two studies that estimate effects of cost-sharing on utilization of pharmaceuticals using time-series data employed segmented regression analysis (Martikainen *et al.* 2007) and seemingly unrelated regression (O'Brien 1989). Most of the cited research papers which investigate the effect of cost-sharing on doctor visits use DiD method, only the South Korean experiment uses conditional-on-use analysis. Advantage of the DiD method is its ability to filter out effects of other possible changes which are not caused by the health reform.

4.1 Czech Studies investigating the effect of co-payment

There are not many studies investigating the effects of co-payment in Czech Republic, which is probably caused by the short time period when co-payments is in effect and unavailability of adequate data.

One important study examining the effect of co-payment in the Czech Republic is Zapal (2010), who estimates the effect of co-payments on the number of children's physician visits in the Czech Republic proxying the number of doctor visits by the number of drug prescriptions. The data on drug consumption are obtained from Prague pharmacies. This proxy can be used because the author supposes a fixed probability of generating prescriptions during a doctor visit. Zapal takes advantage of the co-payment exemption for children of 2009 and employs the DiD methodology. Children's drug consumption is used as a treatment group and drug consumption among adults as a control group. Using neither the ordinary least squares (OLS) model nor poisson and negative binomial (NB) models, he did not find any effect of co-payments on children's demand for health-care services . The only positive and significant effect was detected if March 2009 was used as a pre-reform period. However it is considered as timing effect, because some of outpatient visits made by children (for example preventive care) were postponed last month before the reform and the data therefore show an increase in doctor visits after the abolition of co-payments.

We will contribute to this stream of research by analysing effects of co-payments on number of outpatient visits in the Czech Republic. As opposed to Zapal (2010), we will use micro-level data on the number of doctor visits made by individuals during 12 previous months. This dataset is obtained from the EU-SILC experiment. Moreover, larger time period used in our analysis (February 2008 to May 2010) gives us possibility to eliminate timing effect of postponed utilization of health-care services and possible seasonal effects (allergies etc.), which could contaminate our results. Last but not least, we will use different models (Multinomial logit and Zero-inflated negative binomial), which provide a better fit to our data than the OLS, poisson and NB models.

Chapter 5

Methodology

This chapter introduces Difference-in-differences methodology and used econometric models, Multinomial logit and Zero-inflated negative binomial.

5.1 Difference-in-Differences (DiD) approach

The abolition of co-payments for children's outpatient visits in 2009 constitutes a natural experiment with one treatment and one control group, which will enable us to assess the effect of user charges introduced in 2008. Our data sample met criteria that are neccesary to adopt the framework of natural experiment. We have available data before and after the health reform of 2009 and we suppose that control group is equally influenced by any general trends as the treatment group (Kawaura & La Croix (2010), Meyer (1994) and Rosenzweig & Wolpin (2000)). Furthermore, all children are exempted from paying co-payments for doctor visits, without discrimination.

Our sample includes respondents from all age range which makes it possible to divide our sample into two subsamples. The first one consists of children and the second comprises the rest of the population. Co-payment rates for doctor visits of the latter subsample did not change during the observed period and therefore we might employ the Difference-in-differences technique. The former group constitutes our treatment group and the latter is our control group.

The idea of DiD approach is based on the comparison of the average change in physician visits for children (treatment group) before and after reform with the average change in physician visits for other subsample (control group). If we compared pre-reform and post-reform periods only for treatment group, result 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

$$\text{visits}_i = \beta_0 + \beta_1 \text{post}_i + \beta_2 \text{dummy\_child}_i + \beta_3 \text{interaction}_i + \beta_4 \text{X}_i + \varepsilon_i \tag{5.1}$$

where i's denote individuals. Variable *visits* reflects the number of doctor visits for person i. β_0 is a *intercept.* *Post* is a the dummy variable representing period after the reform. Variable *dummy_child* is a dummy variable that takes the value of 1 for respondents aged<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 is equal to *post* × *dummy_child*, that takes the value 1 for children (members of the treatment group) after reform. Vector X_i represents set of all individual characteristics for individual i (personal income, sex and number of household members). Parameter ε_i is the error term.

The parameter of our interest is the estimate of β_3, because it gives us the net treatment effects. This estimate measures the change in physician visits for a child caused by the abolition of the co-payments – it is the DiD estimator. If it is positive, the number of doctor visits in the treatment group rises relative to the number of visits for adults (control group) after the abolition of co-payments for children's oupatient visits.

5.2 Multinomial logit model (MNL)

The dependent variable (the number of physician visits during last 12 months) have the nonnegative integer nature and its distribution does not follow normal distribution (Figure 6.1). The estimation by Ordinary least squares (OLS) model is therefore inappropriate.

At a starting point, we employ the Multinomial logit model. (Cameron & Trivedi 2009) defines the MNL model as a probability that is equal to

$$p_{ij} = \frac{exp(x_i'\beta_j)}{\sum_{l=0}^{m} exp(x_i'\beta_l)}, \qquad j = 0, \ldots, m \tag{5.2}$$

where j is one of the m alternatives (in our case, 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. Probability p_{ij} has to satisfy the following two conditions: $0 < p_{ij} < 1$, $\sum_{j=1}^{m} p_{ij} = 1$

We set the base outcome to be the zero number of physician visits, because it is the most frequent alternative. Then the MNL model changes

$$p_{ij} = Pr(y_i = j \mid y_i = 0) = \frac{Pr(y_i = j)}{Pr(y_i = j) + Pr(y_i = 0)} = \frac{exp(x_i'\beta_j)}{1 + exp(x_i'\beta_j)} \tag{5.3}$$

where $y_i = j$ if the outcome is the jth alternative.

We get the estimation results of equation 5.1 for all m alternatives. A positive coefficient of interaction ($\hat{\beta}_3$) for the jth visit means that with increasing value of the regressor (i.e. when it takes value of 1) we are more likely to choose an alternative j than 0 (0 = no doctor visits during 12 previous months).

An important assumption of the MNL model is the independence of irrelevant alternatives (IIA). This limitation follows from the assumption that disturbances are independent and homoscedastic (Greene & Zhang 2003). It tells us that the odds ratio, ratio of the choice probabilities for any two alternatives for a particular observation (in our case $\frac{\pi_{ij}}{\pi_{i0}}$), are independent of the other alternatives. It means that adding or deleting another alternative (for example pth alternative, where $p \epsilon 1, \ldots, m;\ p \neq j$) does not affect the relative odds $\frac{\pi_{ij}}{\pi_{i0}}$ (Wooldridge 2002). We will check this assumption using the Hausman-type test. The idea of this test is to compare two sets of estimates, one is the full set of choices and another is the restricted subset of choices. If the null hypothesis holds, both sets are consistent and IIA assumption is satisfied. Under the alternative hypothesis, the restricted subset of choices will lead to inconsistent parameter estimates, it means that the odds ratio ($\frac{\pi_{ij}}{\pi_{i0}}$) will change with eliminating the pth alternative and therefore IIA would not be satisfied. The test statistic for the Hausman test is

$$q = (\hat{\beta}_s - \hat{\beta}_f)'[\hat{V}_s - \hat{V}_f]^{-1}(\hat{\beta}_s - \hat{\beta}_f) \sim \chi^2_m \tag{5.4}$$

where s indicates the estimators based on the restricted subset and f denotes the estimator based on the full set of choices (Baltagi 2008).

In addition we estimate how co-payments for doctor visits affected frequency in which health-care services are used (Shen &

Zuckerman 2005). We employ again the MNL model but for reduced number of alternatives. We separate the number of visits into three levels (non-visitors, occasional visitors = 1–5 visits, and frequent visitors = 6–20 visits). This categorical variable and the MNL model allow us to investigate whether the introduction of co-payments for outpatient visits significantly changes the odds of being a frequent visitor or an occasional visitor as opposed to a non-visitor. In this part, we assume that more doctor visits (6–20) is more likely to reflect chronic illness or need of health-care services (poor health status), as in the study Shen & Zuckerman (2005). This approach is important because each group of people with different health status could respond to the introduction of co-payments in a different way, and we can estimate how regulatory fees affect frequent-visitors, i.e. people with poor health status.

5.3 Zero-inflated negative binomial (ZINB) model

Distribution of the variable *visits* is skewed and contains a large proportion of zeros (Figure 6.1). We therefore additionally use a model for count data, specifically Zero-inflated negative binomial model, which handles data with excess zeros problems by assuming that zero outcomes are generated from two distinct processes. The possibility of the distinction between two processes extends our analysis against previous MNL model because now we are able to focus on the process of generation of excessive outcomes. We, however, assume that the main result, i.e. the effect of co-payments on the demand for doctor visits, will be consistent with result from the MNL regression.

Cameron & Trivedi (2009) highlight that the starting point for analyses of counts is the Poisson distribution with the probability mass function

$$Pr(Y = y) = \frac{e^{-\mu}\mu^y}{y!} \qquad y = 0, 1, 2, \ldots \tag{5.5}$$

where $\mu_i = exp(x_i'\beta)$

We will however immediately shift to the negative binomial (NB) model which overcomes the problem of overdispersion ($Var(y) \neq E(y) = \mu$), which we encounter under poisson model. Specifically, in our sample the average number of visits per year is 3.539381, and the variance is 20.54858, more than 5 times larger than mean, so variance of y_i exceed its mean (Table 6.4). Furthermore, we will extend the NB model into a zero inflated alternative because the data has 36.12% zeros which violates the prediction of lower probability of a zero count under the standard NB than is observed in our sample.

ZINB analysis assumes two distinct processes that arrive at a zero outcome. Long *et al.* (2006) define that "there are two latent (i.e. unobserved) groups. An individual in the *Always zero group* has an outcome of 0 with probability of 1, whereas an individual in the *Not Always zero group* might have a zero count, but there is non-zero probability that she has a positive count".

In our case, we can also assume that zero values are due to two different processes:
(1) Some respondent was not ill over the year and, therefore, he did not visit a doctor.
(2) Some respondent was ill but still did not visit a physician.
In the first case, if the respondent was ill, he would go to the doctor and it will be then a count process, a non-zero probability

of a positive count. The latter group is characterised as *Always zero group*. Although its members were ill, they did not go to the physician. In this case, we assume that such an individual has an outcome of 0 with probability of 1.

The ZINB analysis is carried out in three steps Long *et al.* (2006):
(1) Membership into the latent group is modelled.
(2) Counts for those in *Not Always zero group* are modelled.
(3) Observed probabilities as a mixture of the probabilities for the two groups are computed.
For the first step of the analysis logit model is used, which indicates the probability of being in the *Always zero group*. The second step is modeled using a NB model and it determines the probability of each count (including zeros).

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

$$f(y) = \begin{cases} f_1(0) + \{1 - f_1(0)\}\, f_2(0) & if\ y = 0 \\ \{1 - f_1\,(0)\}\, f_2\,(y) & if\ y \geq 1 \end{cases} \tag{5.6}$$

And conditional mean

$$E(y \mid x) = \{1 - f_1(0 \mid x_1)\} \times exp(x_2 \beta_2) \tag{5.7}$$

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 variable equals 1.

5.4 Robustness check

As a robustness check we will exclude the elderly (over 65) from the control group to eliminate the effect of decreased protective limit on health expenses for people over 65 years.[1] This change came into force in April 2009, simultaneously with the abolition of co-payments for children's doctor visits. Even though it is believed that a decreased limit on co-payments is not likely to significantly affect the result, because we do not assume to reach the limit by any individuals in our sample, where the value of the dependent variable is reduced up to 20 visits[2], we will check this alternative specification, as well. We will again employ the MNL and ZINB models.

[1]Sample hereby will be reduced from 1,841 to 1,471 observations.
[2]This reduction of the sample is described in more detail in the section 6.1.1.

Chapter 6

Data

This thesis employs data from the EU-SILC survey. It is collected in 27 European Union countries and 5 other states (Switzerland, Croatia, Norway, Turkey and Iceland). The EU-SILC is an annual survey of household income and living conditions, which includes data on health related variables such as number of doctor visits during the previous 12 months, health status and respondent characteristics associated with the tendency of health-care utilization such as age, sex, educational level, marital status, employment status, self-reported health, household income per year, number of children in a household etc.

In Czech Republic (CR) the SILC project started in 2005, after joining the EU. The data is collected by the CZSO. Approximately 12,000 households participate in this survey each year in CR. The people are interviewed from February to May of each year.

For our study we use only two years of observations (2009, 2010) because information regarding utilization of health services was not included in earlier surveys. From the sample we excluded all people living outside of Prague because the data for the whole country could be contaminated. Specifically, other regional governments except Prague reimbursed co-payments in all regional

hospitals during the observed period and not being able to distinguish whether the adult patient took advantage of reimbursement could influence our estimated result. We further limited the sample to two interview periods:
(1) From February to March 2009 referring to the period of health-care utilization with co-payments (i.e. February 2008–March 2009).
(2) From April to May 2010 referring to the period of health-care utilization without co-payments for children's outpatient visits (i.e. April 2009–May 2010).

Removed interview periods refer to the utilization of physician visits during the mixed period, with the co-payments as well as without the co-payments, which could contaminate our results.

6.1 Data description

Definitions of chosen variables for our regression are presented in Table A.2.

If we look at Table 6.1, we can see that the subsample of children and subsample of adults are not of the same size. Subsample of adults is almost six times bigger because the data are collected at household level and there is a higher number of adults than children under 18 years, and also Czech population contains approximately six times more adults than children.

Table 6.1: Number of children and adults in the sample

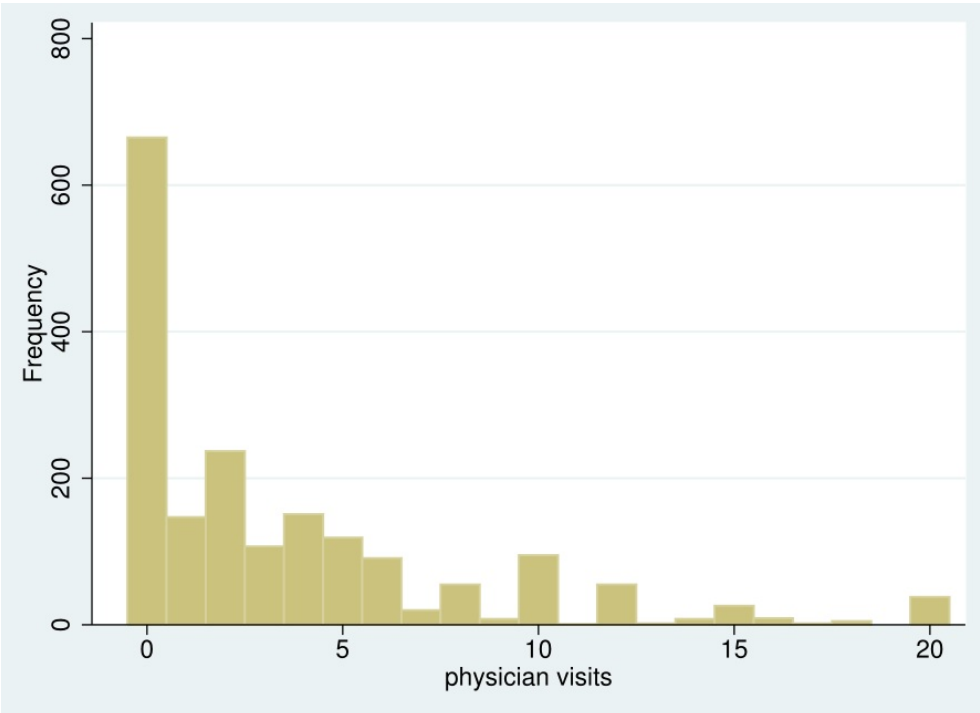
dummy_child	**Freq.**	**Percent**
0	1,610	85
1	282	15
Total	1,892	100

6.1.1 Dependent variable

Dependent variable *visits* denotes the number of physician visits made by an individual during 12 previous months. Observed period refers to the utilization of physician visits from February 2008 to May 2010.

Distribution plot of variable *visits* is shown in Figure 6.1. A histogram indicates a rapidly decreasing tail and distribution does not follow normal distribution.

Figure 6.1: Distributional graph



Summary statistics of the variable *visits* is presented in Table 6.2.

Table 6.2: Summary statistics of variable *visits*

Subsample	Variable	Mean	Standard deviation	Max	Cumulative Frequency up to 20 visits	Proportion of zeros(%)
full sample	visits	4.567	8.584	99	97.30	35.15
children	visits	0.33	1.868	25	99.65	93.26
adults	visits	5.309	9.071	99	96.89	24.97

The distribution of our dependent variable for the full sample has a long right tail. Only 2.7% exceed 20 visits and the maximum value of visits is 99 (Table 6.2). The proportion of zeros is 35.15%. If we compare health-care utilization for children and adults, subsample of children have 93.26% zero observations for outpatient visit as opposed to adults (24.97%). This is partly because children are mostly healthier part of the population and moreover the subsample of adult population contains almost 30% of elderly (Table A.3), who more often visit doctors. Other difference between these two subsamples is maximum value of variable *visits*, for children the maximum is 25 visits and for adults it is 99 visits (Table 6.2). We suppose that some high values of variable *visits* are errors in measurement. Therefore we decided to reduce our sample up to 20 visits, which constitute still 97.3% of full sample as we can see in Table 6.2. Not only does this elimination remove the fact that children are the healthier part of the population, making the control and treatment groups the same which is an important prerequisite for the DiD, but it also considerably removes the potential contamination of the results stemming from a decreased cap on out-of-pocket contributions for the elderly. In other words, we assume that greater number of visits to the doctor (made mostly by the elderly and chronically ill) are refunded and so these individuals are not included into the analysis.

After this elimination, the dataset contains 1,841 individuals, 281 children and 1,560 people aged ≥ 18 (adults). The proportion of children and adults stays consistent with the overall sample.

Summary statistics for the observed individuals and for all variables are in Table 6.3.

Dependent variable, number of physician visits per year (*visits*), takes on the values ranging from 1 to 20, as we mentioned

Table 6.3: Summary statistics of all variables

Variable	Mean	Std. Dev.	Min.	Max.	Median
sex	1.528	0.499	1	2	2
visits	3.539	4.533	0	20	2
members	2.806	1.211	1	7	3
post	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

above. The mean is low because this variable has a high proportion of zeros and first ten values account for over 89% of our sample. Table 6.4 summarizes physician visits in detail. The median of 2 is smaller than the mean of 3.5, indicating the skewness of the data. The skewness has to be zero for symmetrically distributed data. The value here of 1.71 indicates right skewness. Furthermore, the value of kurtosis for normally distributed data is 3. The value of 5.73 reflects that the tails are thicker than those of normal distribution.

Table 6.4: Summary statistics of variable *visits* in detail

Number of observations	1841
Median	2
Mean	3.539381
Standard Deviation	4.533055
Variance	20.54858
Skewness	1.705345
Kurtosis	5.729843

Table A.4 shows a correlation matrix of all variables that gives us pairwise correlation.

6.1.2 Independent variables

Besides the desired interaction term, there are other variables which are likely to influence the number of outpatients visits.

Data exist for these variables for all of 1,841 sample individuals, there are no missing values.

- The variable *sex* takes on the values 1 for male and 2 for female and, according to the mean, our sample contains approximately the same number of men and women. We assume that women visit physician more often than man, because they have to visit gynecologist and take care of themselves more than men, therefore we expect a positive sign of the coefficient.

- The 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 unusually low. Impact of this variable may be two-fold:
  (1) With increasing income, the number of doctor visits decreases because the people have a better lifestyle (buy better quality food, shoes, mattress etc.) and therefore they should have a better health status. However, a low number of doctor visits for high income individuals may also be caused by high opportunity costs of doing so and not working.
  (2) With increasing income number of doctor visits may grow because money spent on health-care expenses becomes unimportant with increasing income.

  The final effect depends on which of these effects overweights.

- Number of household members (*members*) takes on values from 1 to 7 and we suppose that the number of members has a negative influence on health-care utilization because we assume that with increasing number of household members or rather with increasing number of children, a member no longer cares so much about his health.

- Variables *post*, *dummy_child* and *interaction* are related to the effect that we are interested in, i.e. the effect of co-payments on the demand for outpatient care. These variables are described in more detail in the section 5.1.

Chapter 7

Results

In this chapter we show estimation results of three different models. All of them are estimated using the STATA software.

7.1 Multinomial Logit (MNL) model

We regress number of physician visits on an intercept, post, dummy_child, interaction, sex, members and p_income.[1]

$$\begin{aligned} \text{visits}_i = \; & \beta_0 + \beta_1 \text{post}_i + \beta_2 \text{dummy\_child}_i + \beta_3 \text{interaction}_i + \beta_4 \text{sex} \\ & + \beta_5 \text{members} + \beta_6 \text{p\_income} + \varepsilon_i \end{aligned} \tag{7.1}$$

Zero number of visits is set to be the base category. The results of the analysis are presented in Table 7.1. We show estimated coefficients, relative-risk ratio (RRR)[2] and p-values. The relative risk ratio is the probability that outcome is the jth alternative relative to the probability that outcome is zero number of visits (base alternative).

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[1] We estimated also other models with more or different variables, but based on Likelihood-ratio (LR) test, we chose this model as the most appropriate.

[2] RRR=$\dfrac{Pr(y_i = j)}{Pr(y_i = 0)} = exp(x_i'\beta_j)$

Table 7.1: Multinomial Logit (MNL) Model

visits		Coef.	RRR	P>|t|
0		(base outcome)		
1	post	-0.634	0.530	0.002
	dummy_child	-4.222	0.015	0.000
	interaction	1.007	2.738	0.483
	sex	0.424	1.527	0.029
	members	-0.143	0.867	0.086
	p_income	1.95×10^{-8}	1.000	0.974
	_cons	-0.938	.	0.025
2	post	-0.705	0.494	0.000
	dummy_child	-3.121	0.044	0.000
	interaction	-0.513	0.599	0.646
	sex	0.660	1.935	0.000
	members	-0.181	0.834	0.011
	p_income	-4.90×10^{-7}	1.000	0.398
	_cons	-0.594	.	0.101
3	post	-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
	sex	1.095	2.990	0.000
	members	-0.249	0.780	0.009
	p_income	-6.00×10^{-7}	1.000	0.460
	_cons	-1.916	.	0.000
4	post	-0.606	0.545	0.003
	dummy_child	-3.029	0.048	0.000
	interaction	-15.628	1.63×10^{-7}	0.995
	sex	1.039	2.825	0.000
	members	-0.339	0.712	0.000
	p_income	-6.45×10^{-8}	1.000	0.917
	_cons	-1.340	.	0.002
5	post	-0.795	0.451	0.000
	dummy_child	-3.160	0.042	0.000
	interaction	-15.242	2.40×10^{-7}	0.995
	sex	1.031	2.804	0.000
	members	-0.432	0.649	0.000
	p_income	4.27×10^{-9}	1.000	0.995
	_cons	-1.285	.	0.006
6	post	-1.019	0.361	0.000
	dummy_child	-3.621	0.027	0.000
	interaction	-14.526	4.92×10^{-7}	0.996
	sex	1.056	2.876	0.000
	members	-0.560	0.571	0.000
	p_income	-3.10×10^{-6}	1.000	0.023
	_cons	-0.643	.	0.261
7	post	-0.561	0.570	0.245
	dummy_child	-18.585	8.49×10^{-9}	0.997
	interaction	0.534	1.705	1.000
	sex	1.136	3.115	0.019
	members	-0.767	0.464	0.001
	p_income	-4.69×10^{-7}	-0.280	0.779
	_cons	-2.459	.	0.021
8	post	-0.642	0.526	0.038
	dummy_child	-2.755	0.064	0.008
	interaction	-15.381	2.09×10^{-7}	0.997
	sex	0.910	2.485	0.002
	members	-0.700	0.497	0.000
	p_income	-1.03×10^{-6}	1.000	0.391
	_cons	-1.100	.	0.096
9	post	-1.092	0.336	0.185
	dummy_child	-19.312	4.10×10^{-9}	0.998
	interaction	0.991	2.694	1.000
	sex	1.053	2.866	0.154
	members	-0.347	0.707	0.278
	p_income	5.08×10^{-8}	1.000	0.982
	_cons	-4.140	.	0.010
10	post	-0.642	0.526	0.008
	dummy_child	-18.920	6.07×10^{-9}	0.993
	interaction	0.581	1.787	1.000
	sex	1.163	3.199	0.000
	members	-0.558	0.572	0.000
	p_income	-3.99×10^{-7}	1.000	0.624
	_cons	-1.381	.	0.009
11	post	-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
	sex	17.509	4.02×10^{7}	0.999
	members	-0.763	0.466	0.443
	p_income	5.08×10^{-8}	1.000	0.715
	_cons	-36.421	.	0.997
12	post	-0.255	0.775	0.398
	dummy_child	-2.923	0.054	0.005
	interaction	-15.574	1.72×10^{-7}	0.997
	sex	0.982	2.669	0.001
	members	-0.741	0.477	0.000
	p_income	-1.19×10^{-5}	1.000	0.000
	_cons	0.490	.	0.533
13	post	0.384	1.468	0.790
	dummy_child	-2.326	0.098	1.000
	interaction	0.662	1.938	1.000
	sex	-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	17.539	.	0.989
14	post	0.175	1.192	0.809
	dummy_child	-18.553	8.76×10^{-9}	0.998
	interaction	-0.074	0.928	1.000
	sex	2.316	10.135	0.032
	members	-0.721	0.486	0.031
	p_income	-2.21×10^{-8}	1.000	0.016
	_cons	-2.674	.	0.305
15	post	-0.540	0.583	0.208
	dummy_child	-18.701	7.56×10^{-9}	0.996
	interaction	0.537	1.711	1.000
	sex	1.092	2.981	0.011
	members	-0.787	0.455	0.000
	p_income	-5.93×10^{-6}	1.000	0.058
	_cons	-1.122	.	0.290
16	post	-1.848	0.158	0.085
	dummy_child	-18.589	8.45×10^{-9}	0.997
	interaction	2.260	9.585	1.000
	sex	-0.488	0.614	0.506
	members	-1.335	0.263	0.002
	p_income	-2.6×10^{-5}	1.000	0.010
	_cons	4.263	.	0.037
17	post	0.188	1.207	0.895
	dummy_child	-19.067	5.24×10^{-9}	0.999
	interaction	-0.006	0.994	1.000
	sex	0.346	1.413	0.810
	members	-0.606	0.546	0.339
	p_income	-2.79×10^{-5}	1.000	0.159
	_cons	-0.273	.	0.946
18	post	-0.365	0.694	0.692
	dummy_child	-18.737	7.29×10^{-9}	0.998
	interaction	0.307	1.359	1.000
	sex	0.936	2.550	0.309
	members	-0.628	0.534	0.152
	p_income	-5.84×10^{-7}	1.000	0.862
	_cons	-3.866	-3.866	0.059
20	post	-1.108	0.330	0.005
	dummy_child	-19.409	3.72×10^{-9}	0.995
	interaction	1.053	2.866	1.000
	sex	1.500	4.481	0.000
	members	-0.408	0.665	0.006
	p_income	-9.27×10^{-6}	1.000	0.003
	_cons	-1.626	.	0.092

The model passes the IIA assumption at the 0.01 level of significance (Table 7.2), therefore the model can be used for our data. In one case, the Hausman statistic is negative. It means that the estimated model does not meet asymptotic assumptions of the test and test statistic is not computable. However, Hausman & McFadden (1984) assert that a negative test statistics is a supportive evidence for null hypothesis (IIA is not violated), therefore, IIA assumption holds in all cases.

The first measure of fit of the model is the log-likelihood $(-3614, 4829)$ (Table 7.3), that does not have a meaning in itself, however it can be used in comparison of models, often it is used in comparison of nested models. Also based on this value, we chose the final model (equation 7.1).

Table 7.2: 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	3	—	—
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

The second measure of fit, pseudo (McFadden's) R^2 that is defined as (Cameron & Trivedi 2009)

$$\tilde{R}^2 = 1 - \frac{\mathrm{L_{fit}}}{\ln \mathrm{L_0}} \tag{7.2}$$

Table 7.3: 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

where $\ln L_0$ is the log-likelihood of an intercept-only model, and L_{fit} is the likelihood of the fitted model. Pseudo R^2 is equal to 0.104 (Table 7.3) and denotes the improvement of log-likelihood of the fitted model to the model with intercept and no regressors.

As we can see in Table 7.3, the overall model is significant at the 0.01 level of significance because LR(114) = 834.88. This LR with p-value<0.0001 tells us that our model as a whole fits significantly better than the intercept-only model.

Other important measures of fit of models are Akaike's information criterion (AIC) and the Bayesian information criterion (BIC). Formulas for AIC and BIC statistics are as follows (Cameron & Trivedi 2009):

$$\text{AIC} = \text{-2lnL+2k} \tag{7.3}$$

$$\text{BIC} = \text{-2lnL+klnN} \tag{7.4}$$

where the quantities 2k and klnN are penalties for the model size. For better fit of the model, we want smaller values of the statistics. In our case, BIC = 8228.868 and AIC = 7494.966 (Table 7.3). These criterions could be used to compare models with different regressors and thus determine which model is preferred.

The sign of the coefficients of interaction varies, but coefficient is always insignificant at 0.99 confidence interval because |t|<P is bigger than 0.01 in all 18 sets of regression estimates. To check the insignificance of the variable *interaction* in the whole model,

we perform Wald test, which determines the joint significance of interaction over all sets of alternatives (Table 7.4).

Table 7.4: Wald test of the joint significance of variable *interaction*

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

	chi2	df	P>chi2
post	40.524	19	0.003
dummy_child	114.499	19	0.000
interaction	0.715	19	1.000
sex	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 interaction term is 0 and therefore the overall effect of interaction is clearly statistically insignificant. So we find that co-payments have no significant effect, i.e. children (treatment group) did not significantly change the probability of physician visits after the abolition of user charges.

If we perform the Wald test for variables *sex*, *members*, *p_income* (Table 7.4), we find that all three variables are overall statistically significant at 0.01 significance level and thus they are important determinants of the demand for physician visits.

As we can see in Table 7.1, signs of the coefficients of variable *members* are negative in all sets of regressions and because these coefficients show the effect of independent variable on each category relative to the base category, we know that with increasing number of household members we are less likely to choose one or two or more visits than zero. For example if we look at the RRR in the first set, increase in the number of household members by one leads to a change in the relative risk of choosing one doctor visit than the zero doctor visit by 0.867, i.e. with increasing household members a patient more probably does not visit a doctor at all than visits once. This result confirms our assumptions. The signs of the coefficients of variables *sex* and *p_income* vary across different sets, but always if coefficients are significant, sex has a positive sign and p_income has a negative sign, thus indicating that women more likely choose more visits than men, which is consistent with our expectations. On the contrary, with increasing personal income, patient more probably chooses not to visit a doctor at all than visit once, twice or more. This suggest that the first effect overweighs, i.e. with increasing income people more likely have a better health status and high opportunity costs to often visit a doctor.

7.2 Multinomial Logit (MNL) Model for Categorical Outcome

In Table 7.5 we re-estimate the regression using three levels of the dependent variables to investigate whether the introduction of co-payments for outpatient visits significantly change the status of individual to be a frequent-, occasional- or non-visitor. Furthermore, we estimate how regulatory fees affect people with poor health status by assuming that frequent-visitor is chronically ill. The Multinomial logit model can be used, because IIA assumption is again satisfied at the 0.01 level of significance (Table 7.6).

The main result is consistent with the previous analysis – coefficients of interaction are statistically insignificant at 0.01 level of significance in all sets of regressions. The abolition of co-payments appears to have no significant effect on the change of the odds of being a frequent visitor or an occasional visitor as opposed to a non-visitor. Therefore, co-payments neither significantly affect the probability of visiting a doctor by people with good health status (non-visitors, occasional visitors) nor by people with a poor health status (frequent visitors).

Table 7.5: Multinomial Logit (MNL) Model for Categorical Outcome

visits	**Coef.**	**RRR**	**z**	**P>|z|**
0	(base outcome)			
1				
post	-0.6673595	0.5130615	-5.17	0.000
dummy_child	-3.436006	0.032193	-10.42	0.000
interaction	0.0643608	1.066477	0.10	0.916
sex	0.8035997	2.233567	6.37	0.000
members	-0.2481352	0.7802544	-4.59	0.000
p_income	-2.18×10^{-7}	0.9999998	-0.55	0.582
_cons	0.4689675	.	1.74	0.083
2				
post	-0.710389	0.491453	-4.64	0.000
dummy_child	-3.88869	0.0204722	-6.50	0.000
interaction	-11.75062	7.88×10^{-6}	-0.03	0.975
sex	1.084413	2.957703	7.25	0.000
members	-0.6046005	2.957703	-9.04	0.000
p_income	-2.63×10^{-6}	0.5462927	-3.83	0.000
_cons	0.7557359	0.9999974	2.26	0.024

Table 7.6: Hausman tests of IIA assumption (N=1841)

Ho: Odds are independent of other alternatives.

Omitted	**chi2**	**df**	**P>chi2**	**evidence**
1	0.000	1	1.000	for Ho
2	0.144	6	1.000	for Ho

Table 7.7: Wald test of the joint significance of variable *interaction*

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

	chi2	df	P>chi2
post	31.146	2	0.000
dummy_child	140.948	2	0.000
interaction	0.012	2	0.994
sex	59.596	2	0.000
members	81.994	2	0.000
p_income	15.729	2	0.000

The coefficients of individual characteristics are jointly significant at 0.01 significance level and also have the same sign as in the previous analysis (Table 7.7). We therefore conclude that the individual characteristic variables significantly influence the number of physician visits. The number of household members and personal income have a negative effect on the probability of becoming occasional or frequent visitor relative to a non-visitor. Women more likely change the status to become an occasional or frequent visitor relative to a non-visitor.

Table 7.8: Variety of measures of fit

Log-Lik Intercept Only:	-1967.706	Log-Lik Full Model:	-1611.428
LR(12):	712.556	Prob>LR:	0.000
McFadden's R^2:	0.181	McFadden's Adj R^2:	0.170
AIC:	1.773	AIC*n:	3264.856
BIC:	-10460.021	BIC':	-622.340
BIC used by Stata:	3328.109	AIC used by Stata:	3250.856

7.3 Zero-inflated Negative Binomial (ZINB) Model

This section presents results of the Zero-inflated negative binomial model. This model contains two submodels, because ZINB model assumes that zero values of the dependent variable are generated from two different processes.[3] The first model is negative binomial to model the count process of "Not Always Zero group", i.e. how often respondents visit a physician. The second process is modelled by a logit model for binary data to model the probability of being in the "Always Zero group", i.e. the respondent is ill but he does not visit a doctor. The probability of visiting a doctor is, however, expressed as a combination of the two models.

The estimated results of performed model in Table 7.9 show overdispersion expressed by significant $\ln\alpha$. It again proves that

[3] Some respondent was not ill over the year and therefore he did not visit a doctor "Not Always Zero group" and on the contrary, some respondent was ill, but still did not visit a physician "Always Zero group".

Table 7.9: Zero-inflated Negative Binomial (ZINB) Model

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

visits	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
visits						
post	-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
sex	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	1.719209	0.118809	14.47	0.000	1.486348	1.95207
inflate						
post	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
sex	-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	-1.95099	0.4591403	-4.25	0.000	-2.850888	-1.051091
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

using ZINB is more convenient than Poisson model. Moreover the LR test of Vuong which compares the ZINB model to the standard NB model indicates that the ZINB model is favored to the NB regressin model, with one-sided p-value<0.0001.

If we look at the key coefficient $\hat{\beta}_3$ in both part of Table 7.9, we see that estimates are insignificant. This analysis therefore confirms our above mentioned results about inefficiency of co-payments to reduce the number of outpatient visits. The introduction of regulatory fees did not significantly change the expected utilization of doctor visits in “Not Always Zero group” (first part of the table 7.9). Moreover, odds of being in “Always Zero group” (avoidance of health-care even if respondent is ill) compared with the “Not Always Zero group” does not significantly change after the introduction of co-payments (second part of the table 7.9).

The likelihood-ratio statistics of 58.49 which has χ^2 distribution with p-value<0.0001 (Table 7.9) tells us that our full model fits significantly better than an empty model, because we can reject null hypothesis that all of the coefficient in both models are simultaneously equal to zero, so at least one of coefficients is not equal to zero and therefore our model is better than the intercept-only model.

Table 7.10: Variety of measures of fit

Log-Lik Intercept Only:	-4274.462	Log-Lik Full Model:	-3921.659
LR(12):	705.606	Prob>LR:	0.000
McFadden's R^2:	0.083	McFadden's Adj R^2:	0.079
AIC:	4.277	AIC*n:	7873.317
BIC:	-5884.668	BIC':	-615.390
BIC used by Stata:	7956.088	AIC used by Stata:	7873.317

The predictors of individual characteristic variables in the part of the NB model are all statistically significant at 0.01 significance level. The expected change in log(visits) when the number of household members increases by one is -0.1231691 holding other variables constant (ceteris paribus). In other words, with one member increase, the expected number of doctor visits decreases by $\exp(0.1231691) = 1.13107567$. Furthermore a woman have an expected log(visits) of 0.1920095 higher than man, ceteris paribus. And one-unit increase in p_income[4] decreases the expected log(visits) by 7.02×10^{-7}.

The second part of the regression (logit) shows probability of being in "Always Zero group" (respondent is ill, but does not visit a doctor) relative to the "Not Always Zero group".

- The log odds of being in "Always Zero group" decreases by 1.251901 for woman compared to a man. In other words, for women applies that, the zero values are less likely generated by the fact that the woman is ill, but does not visit a doctor.

[4]Coefficients of *p_income* is small because of high values of the variable *p_income*.

- If a number of members increases by one, the odds that the respondent would be in "Always Zero group" increases by exp(0.4824235) = 1.61995708. In other words, with increasing number of household members, respondent's zero values are more likely to be generated from the process that the ill patient does not visit a doctor.

- The coefficient of p_income is not statistically significant at 0.01 level. With a change in personal income, the odds of being in "Always Zero group" compared with the "Not Always Zero group" does not significantly change.

7.4 Robustness check

In Tables 7.11 and 7.12, we check whether our previous results could be underestimated because the value of the protective limit for the elderly decreased. We therefore excluded the elderly (over 65) from the control group to eliminate the effect of the changed protective limit. We again employed the MNL and ZINB models

The main results remain the same suggesting that our previous results are robust with respect to the decreased cap on copayments for the elderly. The coefficients of interaction 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 copayments did not have significant effect on number of doctor visits even if as control group we define adults without pensioners. It is likely that the decreased protective limit could significantly influence the number of drug prescriptions or utilization of health-care services above 20 outpatient visits.

Further, each individual characteristic variable is jointly significant over all sets in the MNL model, which is consistent with the results from the previous analysis. The only difference is the signs of the coefficient of p_income which varies accross different sets, where the coefficient is significant. Previously the coefficient of p_income was always found with a negative sign.

In ZINB model we found out that the coefficient of p_income became insignificant. Personal income is not an important determinant of health-care utilization in a sample without the elderly part of the population. It can be caused by the fact that pensioners have a more price-sensitive demand for physician visits, therefore, the variable *p_income* plays an important role in the previous sample, where there are respondents from all age ranges and pensioners are responsible for the significance of this variable.

Table 7.11: Zero-inflated Negative Binomial (ZINB) Model

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

visits	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
visits						
post	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
sex	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	0.8520142	0.172863	4.93	0.000	0.5132089	1.190819
inflate						
post	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
sex	-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	-2.16381	0.7863709	-2.75	0.006	-3.705069	-.6225514
$\ln\alpha$	-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 7.12: Multinomial Logit (MNL) Model

visits		Coef.	RRR	P>|t|
0		(base outcome)		
1	post	-0.7274083	0.4831596	0.001
	dummy_child	-4.254504	0.0142001	0.000
	interaction	1.101006	3.00719	0.443
	sex	0.4056609	1.500294	0.047
	members	-0.1483331	0.8621439	0.104
	p_income	-7.73×10^{-8}	0.9999999	0.911
	_cons	-0.8413617	.	0.072
2	post	-0.7700284	0.4629999	0.000
	dummy_child	-3.175116	0.0417892	0.000
	interaction	-0.4405858	0.6436593	0.694
	sex	0.6902056	1.994126	0.000
	members	-0.2087742	0.8115785	0.007
	p_income	-7.01×10^{-7}	0.9999993	0.288
	_cons	-0.4564821	.	0.259
3	post —	-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
	sex	1.21175	3.359358	0.000
	members	-0.1537765	0.8574636	0.160
	p_income	-2.27×10^{-7}	0.9999998	0.796
	_cons	-2.582368	.	0.000
4	post	-0.5597447	0.5713549	0.016
	dummy_child	-2.949192	0.052382	0.000
	interaction	-15.82488	1.34×10^{-7}	0.995
	sex	1.311516	3.711798	0.000
	members	-0.1300549	0.8780472	0.194
	p_income	5.48×10^{-7}	1.000001	0.409
	_cons	-2.759042	.	0.000
5	post	-0.7122904	0.4905194	0.009
	dummy_child	-2.983747	0.0506029	0.000
	interaction	-15.62748	1.63×10^{-7}	0.996
	sex	1.234299	3.435969	0.000
	members	-0.1898804	0.827058	0.102
	p_income	7.00×10^{-7}	1.000001	0.335
	_cons	-2.799981	.	0.000
6	post	-0.7000893	0.496541	0.028
	dummy_child	-3.222165	0.0398687	0.002
	interaction	-15.24547	2.39×10^{-7}	0.997
	sex	1.158744	3.185929	0.000
	members	-0.4135138	0.6613224	0.003
	p_income	-1.47×10^{-6}	0.9999985	0.295
	_cons	-1.971388	.	0.009
7	post	-0.3290354	0.7196175	0.582
	dummy_child	-18.74952	7.20×10^{-9}	0.997
	interaction	0.2880594	1.333837	1.000
	sex	1.273131	3.572018	0.041
	members	-0.4955632	0.6092277	0.074
	p_income	9.22×10^{-7}	1.000001	0.522
	_cons	-4.058798	.	0.004
8	post	-0.6475239	0.52334	0.096
	dummy_child	-2.565418	0.0768871	0.014
	interaction	-15.75953	1.43×10^{-7}	0.997
	sex	0.9816943	2.668975	0.009
	members	-0.4652494	0.6279784	0.007
	p_income	6.65×10^{-7}	1.000001	0.507
	_cons	-2.491266	.	0.003
9	post	-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
	sex	1.947381	7.010301	0.084
	members	-0.004833	0.9951786	0.990
	p_income	6.87×10^{-7}	1.000001	0.799
	_cons	-6.82906	.	0.007
10	post	-0.4308218	0.6499747	0.177
	dummy_child	-18.98428	5.69×10^{-9}	0.994
	interaction	0.3722241	1.450958	1.000
	sex	1.92924	6.884277	0.000
	members	-0.2216751	0.8011756	0.115
	p_income	1.25×10^{-6}	1.000001	0.094
	_cons	-4.555021	.	0.000
12	post	-0.3789355	0.6845898	0.401
	dummy_child	-2.288792	0.1013889	0.032
	interaction	-16.14215	9.76×10^{-8}	0.997
	sex	0.8306949	2.294913	0.063
	members	-0.7307653	0.4815403	0.001
	p_income	-0.0000101	0.9999899	0.006
	_cons	-0.1390911	.	0.908
13	post	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
	sex	15.91488	8161025	0.993
	members	-15.57658	1.72×10^{-7}	0.985
	p_income	-0.0000174	0.9999826	0.283
	_cons	-30.78434	.	0.994
14	post	-0.5300392	0.5885819	0.675
	dummy_child	-19.27107	4.27×10^{-9}	0.998
	interaction	0.3871189	1.472732	1.000
	sex	17.5669	4.26×10^{7}	0.995
	members	0.1034415	1.108981	0.819
	p_income	-0.000035	0.999965	0.037
	_cons	-34.63231	.	0.995
15	post	-0.8150981	0.4425959	0.184
	dummy_child	-19.10457	5.05×10^{-9}	0.997
	interaction	0.8261248	2.284449	1.000
	sex	1.229327	3.418928	0.046
	members	-0.6321987	0.5314221	0.020
	p_income	-8.40×10^{-6}	0.9999916	0.068
	_cons	-1.668144	.	0.309
16	post	-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
	sex	0.1568753	1.16985	0.917
	members	-0.5337495	0.5864021	0.401
	p_income	-0.0000356	0.9999644	0.055
	_cons	1.584744	.	0.706
17	post	-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
	sex	16.72296	1.83×10^{7}	0.996
	members	0.2125168	1.236787	0.773
	p_income	-0.0000465	0.9999535	0.154
	_cons	-33.11285	.	0.996
18	post	-0.6778462	0.5077093	0.582
	dummy_child	-18.84817	6.52×10^{-9}	0.999
	interaction	0.6578419	1.930621	1.000
	sex	1.235738	3.440918	0.316
	members	-0.5962441	0.5508768	0.289
	p_income	-3.17×10^{-7}	0.9999997	0.940
	_cons	-4.726915	.	0.098
20	post	-0.8083443	0.4455952	0.112
	dummy_child	-19.45494	$3.55e\times10^{-9}$	0.996
	interaction	0.7426352	2.101466	1.000
	sex	1.795484	6.02239	0.002
	members	-0.2040279	0.8154396	0.335
	p_income	-8.79×10^{-6}	0.9999912	0.035
	_cons	-3.384918	.	0.025

Table 7.13: 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
post	28.055	18	0.061
dummy_child	106.312	18	0.000
interaction	0.754	18	1.000
sex	85.133	18	0.000
members	32.642	18	0.018
p_income	33.059	18	0.016

Chapter 8

Conclusion

This thesis investigates the effect of regulatory fees on physician visits. We used micro-level data from 2009, 2010 EU-SILC surveys. The abolition of co-payments on children's doctor visit effective since April 2009 enabled us to carry out a natural experiment. As co-payments of CZK 30 for examination were abolished only for children, they constituted our treatment group. The rest of the population served as a control group in the difference-in-differences approach. Besides the effect of the 2009 reform, we claim that the two groups are the same. The analysis limits itself to the area of Prague.

The health reform of 2009 was enacted as a result of discussion between supporters and opponents of the Czech regulatory fees, where opponents claimed that regulatory fees imposed on the vulnerable groups could be deleterious and cost-sharing could significantly decreased the number of necessary doctor visits.

Firstly, the thesis employed the Multinomial logit model to estimate the probability of the change in the number of physician visits made by children (members of the treatment group) after April 2009. We found an insignificant effect, i.e. the probability of utilization of children's outpatient visits did not significantly change when user charges were abolished. The results thus did not prove opponents' claims about the detrimental effect of cost-sharing on necessary health-care utilization. Our result is however consistent with the findings of a lot of studies discussed, e.g. Kim *et al.* (2005), Chiappori *et al.* (1998) etc., who estimated the effect of cost-sharing on the number of outpatient visits.

Another important result from this analysis is the role of the socio-economic characteristics, associated with the tendency of health-care utilization. We investigated how the characteristics such as sex, personal income and number of household members affect demand for health-care. All these variables proved to be significant determinants of the demand for physician office visits at 0.99 confidence interval. The number of household members and personal income have a negative effect on the probability of visiting a doctor. In other words, with increasing personal income, patient more probably choose not to visit doctor at all than visit once or more. It could be caused by lack of time to visit a doctor and considerable opportunity costs connected with increasing income. When there are more household members, it is assumed that patient more probably choose not to visit doctor at all than visit once or more, as well. A member no longer cares so much about his health with increasing number of household members. Estimated coefficients of variable sex have positive signs, it means that women more likely choose more visits than men, which is consistent with our expectations that women take care of their health more than men.

Furthermore, we re-estimated the MNL regression using three levels of the dependent variables to investigate whether introduction of co-payments for outpatient visits significantly change the status of individual to be a frequent-, occasional- or non-visitor.

This additional analysis aimed to finding out how regulatory fees affect individuals with a poor health status by assuming that frequent-visitor is the one with poor health. From this analysis we can conclude that introduction of the co-payments did not also significantly change the probability of visiting a doctor by people with poor health status (frequent visitors). The main results are consistent with our previous analysis. The effect of regulatory fees proved not to be significant and individual characteristics reveal a statistically significant effect on the number of outpatient visits.

As the second econometric technique we used Zero-inflated negative binomial model. It served as extension of our previous analysis by that it handles data with excess zeros problems and we are therefore able to focus on the process of generation excessive zero outcomes. This model contains two submodels (negative binomial and logit), because ZINB regression assumes that zero values of the dependent variable are generated by two different processes: (1) some respondent was not ill over the year and therefore he did not visit a doctor ("Not Always Zero group") (2) some respondent was ill, but still did not visit a physician ("Always zero group "). The probability of visiting a doctor is, however, expressed as a combination of the two models. This analysis confirms our above mentioned results about inefficiency of co-payments to reduce the number of outpatient visits. Also the results concerning the effects of the individual characteristics we confirmed. Moreover, odds of being in "Always Zero group" compared with 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 avoidance of health-care when a member of the treatment group is ill did not change after the abolition of regulatory fees.

We also carried out a robustness check for our found results. We excluded the elderly from the control group to eliminate a potential effect of decreased protective limit on health expenses for people over 65 years. This change came into force from April 2009 together with the abolition of co-payments for children's doctor visits. The results confirm the assumed robustness of the results. We found an insignificant effect of co-payments, as in the previous results. The only difference in the results of the robustness check is the coefficient for the variable p_income, which proved not to be an important determinant of health-care utilization in a sample without elderly part of the population. It is assumed that pensioners cause significance of this variable in the overall sample, probably because their demand for health-care is more price sensitive.

Overall, we conclude that introduction of co-payments on outpatient visits did not significantly affect utilization of health-care. This result is consistent with Zapal's (2010) finding. The insignificant results may be caused by limits in the design of the copayments scheme in the Czech health-care system.

However, we acknowledge that analysing the effect of co-payments for outpatient visits without distinguishing between emergency and ordinary visits is a limitation. Such disaggregated data was, however, not available.

The thesis has some recommendations for further research. Another analysis should use panel data with extended observed period and more observations. This data were not available when this thesis was completed and thus it serves as a motivation for further research. Moreover effect of another individual characteristic should be also accounted for in further research.

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Appendix

Table A.1: The overview of major changes in patient cost-sharing in the EU from 1990 to 2010.

Country	Major changes in patient cost-sharing for physician's and hospital services since 1990.
Austria	Periodic increases in existing patient cost-sharing. New fees were introduced in 1996/1997/2001 for GPs' and specialists' services. From these, the out-patient clinic fee was withdrawn in 2005 due to administrative costs and public resistance.
Belgium	No essential changes in the patient cost-sharing mechanism but constantly increasing patient fees. The increase was slow until 1993, but in 1994, patient cost-sharing obligations raised dramatically (∼50%) followed by periodic increases in fee levels.
Bulgaria	Patient cost-sharing was introduced in 2000 with the establishment of social health insurance. The fee levels are periodically adjusted with the increase of the minimum salary in the country. Patient cost-sharing is questioned due to informal payments.
Cyprus	No essential changes in the patient cost-sharing. Only periodic increases in the fee levels.
Czech Republic	Patient cost-sharing for physician and hospital services was implemented in 2008.
Denmark	No obligatory patient cost-sharing. No changes.
Estonia	Co-payments for physician's services were introduced in 1995–2002, together with co-insurance for only few hospital services. In 2004, co-payments for visits to GPs were abolished (except for home visits) while fees for hospital stay were introduced.
Finland	No essential changes in patient cost-sharing. Only periodic increases in co-payment fees.
France	Patient cost-sharing was re-introduced in the 1990s. Prior to 2004, it was mainly in the form of co-insurance (constantly increasing) during the last two decades. Since 2004, new co-payments have been introduced in addition to co-insurance.
Germany	Patient cost-sharing for hospital services was introduced prior to 1990 and was fluctuating during the years. In 1994, fees for hospital care were made uniform (health insurance law). Patient cost-sharing for physician's services was introduced in 2004.
Greece	Traditionally, no patient cost-sharing, except for out-patient hospital visits without referrals. However, widely spread informal patient payments, according to some estimations, 36% of patients in public hospitals pay informally.
Hungary	Patient cost-sharing (co-payments) was introduced in 2007 in a context of widely spread informal payments. It met a strong public opposition and was abolished in 2008 after a referendum by the same government that introduced it.
Ireland	Only periodic increases in the fee levels paid by those who do not have medical card and thus, are not eligible for exemptions (∼70% of the population after 2001 when those aged ≥70 years received also entitlement to a medical card).
Italy	Patient cost-sharing for visits to specialists was introduced in 1990. Attempts to introduce patient cost-sharing for hospital services in 1989 and for emergency services in 1994 have failed due to public discontent.
Latvia	Patient cost-sharing (co-payments) was first introduced in 1995. Patient fees are regularly updated and extended. There are concerns among the public and health-care providers about the negative effects of patient cost-sharing.
Lithuania	No patient cost-sharing for physicians' and in-patient hospital services, except for fees for GPs' home visits, visits to specialists without referrals and some diagnostic services (legislation 1991). Little public support for patient cost-sharing.
Luxembourg	No essential changes in the patient cost-sharing (co-insurance). Only, constantly increasing fees.
Malta	No patient cost-sharing. There are policy perceptions that patient cost-sharing could help to reduce unnecessary care.
Netherlands	Patient cost-sharing (co-insurance and co-payments for specialists' and hospital services) was introduced in 1997 and then abolished in 1999. In 2008, obligatory patient cost-sharing for specialist's and hospital care was re-introduced as deductibles.
Poland	No patient cost-sharing. No changes. Prolonged discussions on possible introduction of patient cost-sharing but still no actual policy plans also due to the existence of informal patient payments.
Portugal	Patient cost-sharing was introduced in 1982 and abolished after the 1986 elections mainly because it was thought to contravene the constitution. After the constitution was changed, patient cost-sharing was re-introduced in 1992.
Romania	No patient cost-sharing. Plans to introduce fees. However, widely spread informal patient payments.
Slovakia	Patient cost-sharing (co-payments) was introduced in 2003 and abolished in 2006, even though it is suggested that formal payments by patient might have helped to reduce the informal patient payments.
Slovenia	Patient cost-sharing (co-insurance) was introduced in 1992 after changes in the health insurance legislation. At the same time, voluntary private insurance for covering cost-sharing obligations was implemented, and neutralized the effects on demand.
Spain	No patient cost-sharing. Government attempted to introduce patient cost-sharing in 1991, but failed due to public opposition.
Sweden	No essential changes in the patient cost-sharing mechanism. Only periodic increases in the co-payment fee levels by each municipality in accordance with limits set by the government.
UK	No patient cost-sharing. No changes. Discussions on the potential role of patient cost-sharing.

(Source of the Table: Tambor *et al.* (2011))

Table A.2: Definitions of variables

variable name	variable label
sex	sex of respondent (1=man, 2=woman)
visits	number of physician visits during last 12 months
members	number of household members
post	dummy for period when copayments were abolished for children
dummy_child	dummy for respondents aged 0-17
interaction	interaction term = post $\times$ dummy_child
p_income	personal income per year = $\frac{\text{household income per year}}{\text{number of household members}}$

Table A.3: Frequency of variable *age* in the subsample *adults* aged 65+

Age	Freq.	Cumulative percent
65	33	77.27
66	32	79.25
67	18	80.37
68	27	82.05
69	22	83.42
70	24	84.91
71	19	86.09
72	13	86.89
73	16	87.89
74	16	88.88
75	17	89.94
76	14	90.81
77	14	91.68
78	14	92.55
79	17	93.60
80	21	94.91
81	17	95.96
82	15	96.89
83	12	97.64
84	10	98.26
85	8	98.76
86	4	99.01
87	3	99.19
88	3	99.38
89	3	99.57
90	7	100.00
Total	1,610	

Table A.4: Correlation matrix

	sex	**visits**	**members**	**post**	**dummy_child**	**interaction**	**p_income**
sex	1.00000						
visits	0.1620	1.00000					
members	-0.0530	-0.2861	1.00000				
post	-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