Essays on Cost-Containment Measures in Health Care

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Dissertation

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Abstract

The topic of this dissertation is cost-containment measures in health care and their effects on various aspects of a patient's behavior. The dissertation consists of three chapters.

In the first chapter I assess the ability of gatekeeping restrictions within insurance plans to control the utilization of medical care through their influence on the choice of the initial provider. Empirical results are based on individual-level utilization panel data from the 2001-2006 US Medical Expenditure Panel Survey. I find only small differences between the types of initial provider chosen by individuals enrolled in gatekeeping and non-gatekeeping plans. Further, within gatekeeping plans, 21 percent of patients self-refer to specialists. Taken together, these findings imply that the intended cost-containment of gatekeeping - restriction of the utilization of specialist care - is surprisingly weak.

The second and third chapters make use of a unique natural experiment - a policy change that implemented patient cost-sharing in the Czech Republic starting in 2008. In the second chapter, my coauthor and I investigate the effects of the introduction of lump sum copayments on the utilization of prescription drugs by elderly patients. We find that after the introduction of copayments the number of prescriptions filled decreased by 29%. At the same time, however, total expenditures on prescription drugs dropped only in the first quarter of the postintroduction period and then returned to previous levels. This was partially due to behavioral responses of patients and physicians: a strategic shift of prescription purchases to the time immediately before the introduction of the reform, prescribing more packages on one prescription and an upward shift in the price composition of prescribed drugs.

In the third chapter, we complement the analysis by looking at the effects of the partial reversal of this policy, when regional governing bodies started to reimburse copayments for prescription drugs in the selected (region-owned) pharmacies. Using matched individual level data on the location of visits and prescription fillings, we analyzed how the variation in the prescription drugs' prices implied by copayment affected an individual's choice of pharmacy. Using both non-parametric and parametric estimation techniques, we find a significant shift in patients' preferences towards reimbursing pharmacies. We also identified main drivers of the shift which include monetary cost (proxied by number of prescriptions), type of physician, and distance as a measure of opportunity cost of time.

Chapter 1

Gatekeeping - An Open Door to Effective Medical Care Utilization?

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Abstract

We assess the ability of health insurance plans with gatekeeping restrictions to control the utilization of medical care through their influence on the choice of the initial provider. Empirical results are based on the individual-level utilization panel data from the 2001-2006 U.S. Medical Expenditure Panel Survey. We find only small differences between the initial provider chosen by individuals enrolled in gatekeeping and non-gatekeeping plans. This, together with the fact that within gatekeeping plans, 21 percent of patients self-refer to specialists, implies that the intended cost-containment effect of gatekeeping - restricting the utilization of specialty care - is surprisingly weak.

1.1 Introduction and motivation

Many health insurance companies in the US try to contain costs by influencing the behavior of enrollees as to the specifics of how they demand medical care. This linking of health insurance with medical care provision frequently takes the form of managed care, and is implemented as a complex set of requirements and incentives for both patients and physicians. One rarely challenged cornerstone of managed care is gatekeeping - the requirement that a primary care physician (PCP)[1] coordinates a patient's treatment and provides referrals to specialists, hospitals or other medical care. The intended purpose of gatekeeping is to ration access to more costly specialty care to patients who really need it, and to maintain treatment of less severely ill patients with the less costly PCP. In this paper, we use panel data to evaluate whether gatekeeping actually works as intended and to shed some light on patterns of subsequent care by examining patient and physician behavior in gatekeeping and non-gatekeeping situations.

As health care costs continue to escalate, it has become progressively more imperative for health insurance companies to find effective ways to control costs while not significantly degrading patient outcomes. To this end, a large body of empirical literature has attempted to quantify the effects of managed care (Miller and Luft 1997; Miller and Luft 2002; Garrido, Zentner, and Busse 2011) and, more specifically, gatekeeping (Pati et al. 2005; Deb and Trivedi 2009) on medical care utilization. The results so far have been inconclusive.

This lack of conclusive findings arises from two methodological problems, both of which this paper addresses. First, previous work routinely uses aggregate data on total utilization of medical care in a given time period. Looking at the end point, i.e., total use, of an often multi-layered care process tells us little about the effect of gatekeeping, which by design should manifest itself most strongly at the beginning, by influencing which practitioner the patient chooses as their initial contact provider (ICP).[2] Second, previous studies fail to address the problem of self-selection, i.e., the fact that enrollees who prefer direct access to specialty care because of their anticipated health care needs should prefer to opt for plans without gatekeeping restrictions.

To address the end point/aggregate data issue, we use detailed, individual-level panel

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[1]By primary care physician we mean family doctors and general practitioners, who provide primary care services for patients in both gatekeeping and non-gatekeeping programs.

[2]Initial contact provider categories as defined in this paper are: PCP, specialist, non-MD, hospital, and emergency room (ER).

data from the 2001-2006 U.S. Medical Expenditure Panel Survey, in which we can distinguish not only each episode of illness, but within a given episode, the pattern of initial and subsequent provider contact. To our knowledge, use of this design is unique in the literature. To deal with the self-selection problem, we take advantage of a quasi-natural experiment within our data by identifying the impact of gatekeeping in a sub-sample of respondents whose enrollment choice between gatekeeping and non-gatekeeping insurance plans was driven by factors external to their health care demand - the choice of insurance plans provided by their employer.

Our main finding is intuitively surprising and has profound implications for health insurance design. Contrary to previous studies, we find no economically significant difference between the initial contact provider (ICP) choices of individuals enrolled in gatekeeping versus non-gatekeeping plans. Even though one would predict fewer self-referrals to specialists (and a consequent higher number of PCP visits for patients in gatekeeping) our results show only slight differences, which are partially explained by self-selection. Therefore, we conclude that gatekeeping does not effectively influence patient behavior through its presumed main operating channel, i.e., restricting direct access to specialty care. The implication of these findings for the insurance industry is that gatekeeping has minimal impact on health care costs.

While the above finding is provocative, it is not the entire gatekeeping story. What if gatekeeping via other mechanisms, such as patient and physician incentives, influences the specifics of whether a patient utilizes primary care or the broad spectrum of specialist care accessible after the ICP? We address this issue by analyzing patterns of medical care after initial contact for both gatekeeping and non-gatekeeping plans. We find that contact with different types of ICP imply distinctly different patterns of future care (e.g. utilization rates after an initial hospitalization are much higher than after an initial contact with a PCP). However, conditional on the same type of ICP, we find no differences between the utilization measures of gatekeeper versus non-gatekeeper patients, with the following important exception. Gatekeeper patients are 25 percent more likely to be referred by their PCP to a specialist than non-gatekeeper patients who use a PCP as an ICP. This result continues to support the main finding that gatekeeping does not reduce specialty care.

Following these hints of unexpected interactions within the gatekeeping model, we delve further into the nuances of gatekeeping's impact on patient and physician behavior. We analyze the effectiveness and appropriateness of referrals by PCPs as compared to

self-referrals, with a focus on gatekeeping plans. We find that PCP-referred patients more severe illnesses (as proxied by the probability of further hospitalization) than self-referred patients. Therefore, in keeping with expectations, it appears that within gatekeeping plans, PCPs do retain the healthier patients, referring only the more severely ill patients to specialty care. On the other hand, a sizeable 21 percent of patients with gatekeeping do self-refer mainly for conditions that are recognizable and less severe, but still suitable for specialty care even when they may must pay out of pocket. This efficiency shift in the composition of self- and PCP- referred patients within gatekeeping plans should be taken into account by policy makers, especially when combining gatekeeping with referral incentives for physicians.

1.2   Managed care, gatekeeping and health care utilization

1.2.1   Theoretical approaches

The idea behind managed care (MC) is to design measures that affect the demand and supply sides of health care systems in order to limit increasing medical care utilization and, consequently, rising health care expenditures. If one aims to analyze how the design of these measures specifically affects the demand side, the key requirement is to understand the decision-making process underlying the demand for health care at the individual level. Two broad categories of models attempt to tackle this problem. One line of reasoning, initiated by the Grossman (1972) seminal model views the demand for health care solely as an outcome of the agent's own utility maximization, where health enters the agent's utility as valuable capital, and demand for health care is derived the same way as for any other investment. The other line of thought, represented by Zweifel (1981),is a principal-agent approach, which assumes that demand for health care is determined by the physician who, due to an informational advantage, acts as an effective agent for a patient.

The model that best fits a general understanding of the decision-making process underlying health care demand is a combination of the above approaches. Based on the episodic model of care developed by Stoddart and Barer (1981) and applied by Pohlmeier and Ulrich (1995) and Holmes and Deb (1998), one can model this process as having two parts, with each part better explained by one of the models. In the first stage, it is

the patient who decides whether to visit a physician at all and, specifically, what type of provider he wants to contact first. This decision can be satisfactorily captured by a Grossman-type model because it is based on the patient's optimization with respect to his budget constraints and supply-side restrictions. On the other hand, after first contact, the patient (for practical purposes) delegates decisions about the future course of treatment to the physician, who then, in line with Zweifel's model, determines further medical care utilization based on both clinical reasons and his own financial incentives.[3] Various mechanisms of managed care are targeted to affect both of these stages. This paper focuses particularly on gatekeeping, which at the first stage restricts provider choice, and then affects the further course of treatment through referral policies.

The standard rationale for introducing gatekeeping into MC is based on moral hazard in its standard interpretation by Arrow (1963) and Pauly (1968). According to moral hazard theory, people with insurance (i.e. people who do not face the real price of the provided health services at the time they use them) tend to demand more services than they otherwise would without insurance. The gatekeeping role of the PCP in this context would lie in rationing access to specialty care only to patients who need it to reduce unnecessary medical interventions, thus controlling costs.

This cost-containment function of gatekeeping is one of two fundamental arguments put forward by Scott (2000), the other being the informational advantage of the PCP over the patient. Naturally, one would expect the PCP to be better informed about the appropriate specialization of secondary care for a particular patient. On the other hand, a PCPs actions in terms of diagnosis, treatment and/or referral strongly affect the patient's welfare, but the patient is not fully aware of how much influence the PCP has or whether the PCP's action is appropriate in the particular situation. Therefore, the value of gatekeeping depends on the validity of the assumption that primary care can effectively substitute for more costly specialty and inpatient care.

From the theoretical point of view, however, the complexity of interaction between primary and secondary care makes this assumption seem oversimplified. Fortney et al. (2005) provide an overview of mechanisms that can lead to both substitutability and complementarity of primary and secondary care. Primary care can be seen as a substitute for secondary care if (1) it averts the need for specialist care by the prevention or early detection of illness; (2) by managing chronic illnesses, it prevents their evolution into more serious conditions treatable only at higher levels of expertise, or (3) by simply

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[3]For empirical evidence see e.g. Campbell et al. (2007).

restricting access through formal rules such as gatekeeping (Starfield 1994).[4] On the other hand, several possible mechanisms exist by which primary care acts as a complement to secondary care: by using services that are ancillary to primary care (like laboratory tests) or by detection of illnesses that must be treated through secondary care (like cancer). Therefore, we cannot predict the overall effect of gatekeeping as a policy aimed to increase use of primary care and we have to rely on analysis of real world examples to provide comprehensive insights into interactions with other regulatory mechanisms and, eventually, on effect on patient behavior.

1.2.2 Empirical findings

This paper contributes to a broad class of empirical investigation on the effects of managed care on utilization of medical services. Comprehensive reviews of this line of research are provided in Glied (2000), Miller and Luft (1997), Miller and Luft (2002) and recent results are summarized in Gaynor, Li, and Vogt (2007). As Glied points out, however, the concept of managed care incorporates many different combinations of the mechanisms used to manage health care provision and utilization. By using the broad categorization *health management organization* (HMO) versus *"other"* health care plans, many studies fail to take this aspect into account. So, it is not surprising that very little evidence exists on specifically how gate-keeping and corresponding provider access restrictions affect medical care utilization. Also, the problem of self-selection into health insurance plans is of great importance to this line of research. Naturally, people who prefer unrestricted access to specialist care because of their anticipated health needs should opt for plans without gatekeeping restrictions.[5] Therefore, if the authors of a particular study do not account for selection, they easily overestimate the effect of gatekeeping by capturing the effect of unobserved characteristics of enrollees rather than that of gatekeeping alone.

In the literature, researchers employ different techniques to deal with the problem of selection into particular insurance types. First, they avoid the issue altogether by taking advantage of various natural or randomized experiments and consecutive random assignment of enrollees. Martin et al. (1989) use a randomized trial to determine the

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[4]In their analysis of a mixed public-private health care system in Italy, Atella and Deb (2008) found that PCP, public specialists, and private specialist are indeed substitute sources of care.

[5]Glied (2000) claims that the results of the studies on selection, e.g.Hellinger (1995) suggest that managed care plans have 20-30 percent prior utilization advantage over indemnity plans.

effectiveness of a gatekeeping plan that imposes cost-containment incentives both on PCP (fundholding) and patient (100 percent copayment for self-referral), and find that it reduces the costs of ambulatory services by reducing specialist visits. For the second widely used technique, instrumental variable estimation, finding variables that are both good predictors of insurance choice and exogenous to further medical care utilization is difficult. Moreover, although this approach works well when the outcomes of interest can be modeled using linear regression methods, it is difficult to apply for utilization measures because of their count data character.[6]

Another option is to use latent factor models that parametrically account for selection on unobservables and then estimate the model using simulation based methods. This approach is taken in Deb and Trivedi (2009) and represents one of the few studies specifically examining the effect of gatekeeping and the physician network attributes of the health insurance plans on health care utilization. The authors define health insurance plans as bundles of three possible restrictions: (1) providers' network; (2) sign-up with PCPs, and; (3) out-of network costs coverage, and then estimate their effect on five fairly general measures of health care utilization. The study finds significant evidence of selection into managed care plans.[7] The authors find that if the plan requires a PCP sign-up, individuals have more contacts with non-physician providers and also undergo significantly more surgeries and hospital stays, a finding that the authors explain by a tendency of PCPs to diagnose new medical conditions requiring further treatment within the procedure of routine examinations.

The second line of relevant research is literature on the channels through which gatekeeping restrictions work. The first channel is through imposing constraints and incentives on physician referral behavior. Grembowski, Cook, and Patrick (1998) model the expected influence of managed care on physician referrals and health outcomes. Similarly to the previously cited Fortney et al. (2005), they point out that by reducing or delaying access to specialist services, MC can affect health outcomes in both positive and negative ways.[8] Forrest et al. (2002) present a descriptive overview of family physicians' referral decisions finding that apart from clinical reasons, patient pressure is a common determi-

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[6]See Mullahy (1997) for the nonlinear instrumental variable methods for count data models.

[7]In their complementary paper, Deb and Trivedi (2006) claim that this selection is based on socio-economic observables rather than health status.

[8]On the one hand, most medical problems can be diagnosed and treated appropriately in primary care (Donaldson et al. 1996). As more patients are allocated to PCPs to diagnose and treat, however, this can result in worse health outcomes due to misdiagnosis, inappropriate delay of referrals, or simple provision of lower quality of care than specialists would deliver (Kassirer 1994).

nants. Further, in one-third of cases, the referral was made during encounters other than office visits, which clearly undermines the cost-containment function of gatekeeping.

The other aim of gatekeeping is to restrict the widespread practice of self-referral as it has become a common route to specialty care. Analysis of the NAMCS survey of office-based physicians by Forrest and Reid (1997) found that 31 percent of specialists' new patients were self-referred. In attempting to evaluate the appropriateness of these self-referrals, the authors used hospitalization as a proxy for the severity of the illness and found that self-referred patients have a lower probability of hospitalization than patients referred by a physician, and therefore the appropriateness of self-referrals can be questioned. On the other hand, studies in specialized health care fields point to a positive effect of self-referral - see Swinkels et al. (2014) for the effects in physical therapy or Pollack et al. (2015) for lung and colorectal cancer.

A theoretically important tool to discipline patient behavior in order to contain costs is changing the out-of-pocket price of treatment, so that gatekeeping patients have higher co-payments or must even bear the full cost of the medical procedure if they decide to bypass the gatekeeper. Holmes and Deb (1998) examine the ways in which the costs of nonresidential mental health care depend on the choice of the initial provider and the level of cost sharing imposed on the patient. The results are consistent with an episodic model of demand. The out-of-pocket price significantly influences the patient's choice of the initial provider, but later utilization appears to be unrelated to the financial incentives that patients face. Pati et al. (2005) use MEPS data to look at the effect of managed care gatekeeping on overall health care costs. They find that mean per capita expenditures were approximately 6 percent lower for gatekeeping patients compared to indemnity plan patients, primarily due to lower out-of-pocket expenditures.

1.3   Methodology

We base our methodology on the episodic model of health care demand. We implement it in three steps corresponding to the three main stages prior to and during a medical care episode: choice of insurance plan, initial contact, and further course of treatment. The main questions we address are: (1) Does gatekeeping affect the choice of the initial contact provider? (2) Does this effect translate into further medical servicesutilization?

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1.3.1   Choice of insurance plan

Before the actual utilization, an individual decides whether and what kind of health insurance to purchase. In the US, generally, one is eligible for a publicly provided insurance (e.g. Medicare, Medicaid, or SCHIP); one can purchase private insurance through one's employer, insurance group or on the individual market; or can remain uninsured. In our study we focus on privately insured individuals, and analyze the impact of the more subtle decision concerning plans one with and without gatekeeping restrictions.

People decide by comparing their insurance options with their needs, including expected health care utilization, and financial constraints. While we do not model this stage of decision-making explicitly, we are aware that expected health needs are a possible source of selection bias in our estimation, as people with higher expected needs might be more willing to buy more generous coverage, which does not require a visit to gatekeeper.

1.3.2   Choice of initial provider

When a person becomes ill and seeks medical help, he has to decide what type of physician or medical care provider to contact first. This choice is influenced by his personal characteristics, previous experience (knowledge of doctors, expectations about quality of treatment), subjective evaluation of the severity of the illness, and the conditions and incentives embedded in his health insurance plan. This is also the stage of the patient's decision-making intended to be influenced by gatekeeping.

To quantify this influence, **a series of binomial logit models** is estimated for five basic initial provider choices - primary care physician, specialist, non-medical personnel, hospital and emergency care. We control for socio-demographic characteristics, employment characteristics, type of illness and, in particular, we introduce a dummy variable indicating whether the insurance that person holds has a gatekeeping condition. To deal with the endogeneity of gatekeeping status we estimate the model both on the full sample and on the sub-sample of respondents who, due to supply restrictions, did not their insurance type themselves. They are thus subject to gatekeeping requirements that should be unrelated to their individual preferences or expectations about their future health care utilisation (see e.g. Martin et al. (1989)). In our analysis, we focus on a sub-sample of covered respondents who were offered only one type of health insurance by their employer.

There are two implicit assumptions embedded in the application of this methodology.

First, we assume that people do not choose their job based on the type of health insurance it offers. There are apparent differences in the characteristics of firms that offer none, single, or a broader choice of health plans. Naturally, the question arises as to whether different firms attract employees with varying health care preferences that will later translate into different patterns of utilisation (we try to answer this question in the Results section). Second, we assume that people generally prefer employer-provided insurance to the outside option of purchasing individual coverage, and therefore, the restricted choice is binding for them. This is true mainly due to financial concerns, as in the US, employer provided insurance is much cheaper than individual coverage. Our data indicates that almost 90 percent of the respondents who were offered some plan through their employer accepted it, and 95 percent of those who rejected an employer plan are dependents on a family policy.

1.3.3 Further course of treatment

The episodic model of health care demand assumes that once the decision about the first point of contact has been made, a patient delegates most of his decision-making authority over the further course of treatment to the initial contact provider. This provider is then responsible for directing the patient through treatment either by directly providing care or through referrals. Nevertheless, a patient's characteristics still influence health outcomes because of their clinical importance or due to the patient's compliance with treatment.

Therefore, we develop our analysis of the ICP choice by focusing on how this choice affects the course of a patient's further treatment. The course of treatment is approximated using two measures - the probability of further encounters with different types of providers within the episode of treatment (extensive margin) and the number of medical care events within the episode of treatment by provider type(intensive margin). Control variables include socio-demographic characteristics, self-reported health status, and dummy variables for the most prevalent health conditions.

In our simple empirical model of the determinants of medical care utilization, the further course of treatment is assumed to depend on the actual choice of the initial contact provider. We also include the interaction of this choice with the gatekeeping restriction to separately estimate the utilization measures for patients with and without gatekeeping restriction who initially choose the same type of provider. This way, we

can identify whether any effect of gatekeeping stems from a source other than the initial provider choice.

In general, both measures of health care utilization are modeled through a density function f such as

$$P(Y_{ij} = y_{ij} \mid \boldsymbol{X}_i, d_i, p_{ik}) = f(\sum_k \alpha_k p_{ik} + \sum_k \delta_k p_{ik} d_i + \boldsymbol{X}'_i \boldsymbol{\beta}), \quad k = 1, \ldots, 5$$

where Y_{ij} denotes the utilization of services of provider type $j(j = 1, \ldots, 5)$ by individual i; $\boldsymbol{X}_i$ is the vector of independent explanatory variables; d_i is the binary indicator for the gatekeeping status; and p_{ik} are dummy variables indicating whether the provider of type k was the initial provider for individual i. The model of the probability of a further encounter is then specified as a simple logit model, while the number of visits to a particular type of provider, recorded as a non-negative integer count, is specified as a negative binomial-2 density to account for the excess number of zeros and over-dispersion.[9] We estimate the model on both the full sample and sub-sample with exogenous enrollment into health insurance plans so that we can assess the effect of self-selection into gatekeeping plans.

1.4 Data

1.4.1 General description

Data for the episode-level analysis are derived from the Household Component of the US Medical Expenditure Panel Survey (MEPS) for 2001 to 2006 (Panels 6, 7, 8, 9 and 10). These data are collected by the Agency for Health Care Research and Quality (AHRQ) and the National Center for Health Statistics by drawing a sample of households that participated in the previous year's National Health Interview Survey (NHIS) and then applying an overlapping panel design with five interviews occurring over a two-and-a-half year period. The sample is representative of the American civilian, non-institutionalized population with an oversampling of minorities.[10]

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[9]Encounters with different types of medical care providers are not mutually exclusive nor are they independent. A person with a severe condition would have a high probability of seeing more types of medical care providers in the course of his treatment. Therefore, one can consider estimating the equations for the utilization of different types of services as a system.

[10]For more information on MEPS survey design, see Cohen (1996), Cohen (1997b) and Cohen (1997a).

MEPS data contain detailed information on medical expenditures and utilization, demographic characteristics, employment characteristics, health insurance coverage, and the health status of individuals. Moreover, MEPS groups medical care events (e.g. office visits, in-patient visits, or emergency room admissions) into episodes of care based on self-reported medical conditions, which enables us to use the **treatment episode as the unit of analysis**. Basically, we draw an individual and his characteristics from the MEPS Full Year Consolidated Data File, connect him with all of his reported medical conditions from MEPS Medical Conditions File, and get detailed information about all the medical care events connected to these conditions from the series of MEPS Event Files. By connecting the treatment to a particular condition we avoid the problem of undetected multiple illness spells, which is the main pitfall of studies using aggregated utilization measures.[11] Also, we are able to detect the event that initiated the episode of care (at least within the time scope of a survey), which is crucial for our analysis of ICP choice.

In our analysis, we only consider medical care events identified as office visits, outpatient department visits, hospital inpatient stays, and emergency room visits.[12] Furthermore, we restrict our analysis to the first condition reported after June 1st of the first year of the panel survey (e.g. 2001 for respondents from Panel 6, 2002 for respondents from Panel 7, etc.). The main reason is to avoid the problem of left-truncation. Since we do not observe any condition-related event within the first five-month period, we can assume that we have identified the true beginning of treatment and that the first reported event also represents the first contact for that episode. By including only one episode of treatment for each respondent, we ensure that observations are independent. This approach also has drawbacks, however. We discard patients who do not report any medical care utilization, as well as those who were treated only within the first five months of the survey. This strategy introduces a source of selection bias into data, the magnitude of which will be discussed in the next sub-section. Also, the treatment episode might not have concluded by the end of the survey.

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[11]See Silva and Windmeijer (2001) for a detailed discussion of the problem of multiple illness spells.

[12]We thus discard dental visits and home health care, first because dental coverage is usually separate from general coverage and, second, because home health care applies to long-term and chronic conditions that generally last more than 2 years.

1.4.2   Sample construction

We focus on a sub-sample of non-elderly adults (ages 18-64) with private insurance only who have responded in all five interview rounds. The age restriction enables us to avoid selection bias originating in different age-specific insurance coverage opportunities: children are often covered by their parents' plans[13], and the elderly above the age of 64 are eligible for the publicly funded Medicare program. Also, these three groups have inherently different levels of medical utilization (unrelated to their specific insurance coverage) with children and the elderly tending to have higher medical care utilization than non-elderly adults. We further narrow the sample to employed (but not self-employed) individuals for whom we have information about employer characteristics. After dropping observations for which variables of interest were not defined, we are left with 18,809 individuals.

We then merge this sample with information about the first condition reported after June 1st, including the detailed characteristics of the ICP within this condition. This strategy resulted in omission of 6,020 respondents who did not report any medical care utilization (872 obs.), or for whom all episodes of medical care utilization began before June 1st (5,148 obs.). Thus, the final sample is 12,789 observations. Simple tabulation reveals that in the sample of dropped observations, we observe a significantly higher proportion of people with gatekeeping requirements. These are not the people who report no medical care utilization, however, as their distribution is the same across the two insurance types. Instead, respondents with gatekeeping restrictions tend to have fewer reported conditions in general and therefore a higher probability of reporting all medical care in the first five months of the survey.

1.4.3   Definition of variables

Insurance plans with gatekeeping restrictions

MEPS identifies the HMO and gatekeeper plans among privately covered individuals by asking a series of questions about the characteristics of the plan. First, the person is asked whether he is covered by an HMO. If the answer is negative, a follow-up question determines whether the person is in a gatekeeping plan other than an HMO. Consistent

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[13]Although young adults (students) are usually covered by their parents' insurance plans, they account only for 2.3 percent of the sample without choice of insurance. Also, the age division is standard in the literature.

with prior studies (Pati et al. 2005), we then define gatekeeping enrollees as those who responded "yes" either to the first or the second question. From our tabulations, 59 percent of the sample has insurance with gatekeeping restrictions and 41 percent of the sample has insurance without gatekeeping restrictions. We use the answers provided in the first round to avoid the issue of the reverse causation, i.e., influence of changed health status on the choice of insurance.

Medical care utilisation

The particular focus of this paper is on the first point of contact - i.e., the choice of ICP. We divide medical care providers into five categories – primary care physicians (PCP), specialists (SPEC), non-physician medical personnel (nonMD), hospitals (HOSP), and emergency rooms (ER). A physician was designated as a PCP if he or she was a general or family practitioner or general internist.[14] Any other medical field was designated as "specialist". Under non-physician medical personnel we include chiropractor, nurse, physician's assistant and other (undefined) non-MD providers.

Table 1.1 presents a summary of utilization measures by gatekeeping status. First, we present general summary measures of the number of conditions reported, as well as total numbers of visits to a particular provider, all as a total over the two years of the panel survey. In general, gatekeeping enrollees report fewer conditions and fewer non-MD encounters. With respect to other types of medical care utilization, we do not see a significant difference between gatekeeping and non-gatekeeping enrollees. We also report what we refer to as health indicators, i.e. responses concerning the individual's health status in the first round of interviews, which could predict further medical care utilization. We include dummies for good health[15], for physical limitations and smoking, and Body Mass Index (BMI). The comparison shows that a significantly lower percentage of gatekeeping respondents consider themselves to be healthy; other health indicators, however, do not appear to be correlated with the gatekeeping status.

The second part of Table 1.1 describes utilization within the first observed condition after June 1st, in terms of the ICP chosen as well as a summary of further utilization

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[14]Note that we did not include obstetricians/gynecologists in the category of PCP's but as specialists. Even so, this definition tends to overestimate PCPs in the non-gatekeeping plan and therefore any differences in PCP use between the two plans would be underestimated.

[15]This dummy was derived from the self-reported perceived health status variable ascertained in the first interview round, where we designated respondents who answered "excellent" and "very good" as healthy.

measures. A summary of the first encounter gives us the first insight into the question: "How does the gatekeeping requirement affect the choice of the initial contact provider?" Simple tabulation suggests that gatekeeping enrollees have a significantly higher probability of visiting a PCP and a lower probability of visiting a specialist as their first point of contact than non-gatekeeping enrollees. This difference is not as striking as one would expect, however, under such an explicit restriction: only 3 percentage points in the case of PCP and 3 percentage points in the case of specialist visits. Also, in terms of further utilization, gatekeeping and non-gatekeeping enrollees are very similar with the exception that gatekeeping respondents have on average more PCP visits in the course of their treatment.

Finally, we control for the particular conditions reported, which were chosen either due to their prevalence in the sample or due to the specific and predetermined course of treatment in terms of provider choice. These conditions are hypertension, upper respiratory infection, pregnancy, intervertebral disc dislocation, sprains and strains, wounds, other injuries, joint disorders, connective tissue disease, skin disorders, diabetes, neoplasm, lipid metabolism disorders, blindness, chronic pulmonary conditions, intestinal infections, and urinary calculus. Their prevalence among gatekeeping and non-gatekeeping respondents is summarized in Table 1.2.

Other covariates

Other covariates used in the estimation are summarized in Table 1.3. We divide them into two categories: socio-demographic and employment-related variables.

Socio-demographic characteristics include age, sex, race, years of education at the time of entering MEPS (top coded at 17), region of residence, urban status (whether the person resides in a metropolitan statistical area), marital status, family size (number of children), and the natural logarithm of family income. When compared to non-gatekeeping enrollees, gatekeeping enrollees are more likely to belong to a minority group (hispanic, black, or Asian), have fewer years of schooling, have a higher probability of living in a city, are less likely to be married, and have bigger families with more children.

Employment characteristics and the availability of health insurance through an employer are interesting variables because they are assumed to be determinants of

the choice of health plans, but should not affect gatekeeping enrollment. Employment characteristics include number of employees at the current job location, an indicator for being employed by a small company (1-10 employees), an indicator for firms with more locations, and union status. Furthermore, the MEPS includes information on whether or not the employer offers a health insurance plan, whether he provides a choice of plans or a single option; and whether the employee eventually holds insurance through his employer. Indeed, all these characteristics vary significantly by gatekeeping status, with gatekeeping enrollees having a higher probability of working in larger companies with a choice of health plans than non-gatekeeping enrollees.

1.5   Results

1.5.1   Choice of initial provider

We implement the methodology outlined in section 1.3.2 by restricting the sample to respondents who held a health insurance policy provided by their employer, which was the only option offered by the employer. We excluded respondents who at any time during the reference period acquired an additional health insurance policy, either as a policy holder (e.g. to cover special health care requirements) or as a dependent (e.g. within family coverage).

First, we check whether the sub-sample is systematically different from the full sample in terms of individual characteristics and health care utilization. In Table 1.3, panel (2), we summarize socio-demographic and employment-related characteristics. Our sub-sample consists of people who are slightly older and less educated than the average respondent, with a higher proportion of males. The ethnic and regional distributions, as well as marital status and family income are similar to the full sample. Respondents from this sub-sample typically work in firms with fewer employees but not in the smallest firms (with fewer than 10 employees). This finding is consistent with the observation that medium-sized firms usually offer health insurance coverage but with a limited choice of plans.

The main difference in health insurance between the full sample and sub-sample is that the sub-sample has a much lower share of gatekeeping enrollees (53 percent in the sub-sample compared to 61 percent in the full sample). This finding suggests that when people can choose their coverage type, they opt for a gatekeeping plan. Moreover, as shown in

Table 1.1, panel (2), respondents in the sub-sample have lower levels of general medical care utilization, with the exemption of primary care utilization. Summary characteristics of the first event within the selected medical condition shows that the ICP choice, as well as pattern of further utilization, is similar between the full sample and sub-sample. While in the full sample the main difference between the gatekeeping and non-gatekeeping enrollees is in the choice between PCPs and specialists in the sub-sample, the substitution occurs between PCPs and non-medical personnel.

Table 1.4 summarizes results from estimating a logit for the choice of ICP within the first medical condition that occurred after 6 months of monitoring for both full and sub-sample. We include two broad classes of exogenous covariates that influence the choice of the initial provider – condition indicators and demographic characteristics (sex, race/ethnicity, education, region, marital status, income, number of children, and self-perceived health status). The logit results for the full sample suggest that gatekeeping restrictions have a positive and statistically significant marginal effect on the probability of contacting a PCP (3.8 percentage points) and a negative, significant marginal effect on the probability of contacting a specialist (3.3 percentage points). On the other hand, estimates performed on the sub-sample indicate a weak, positive marginal effect of gate-keeping on the probability of first contact with a PCP (3.4 percentage points at 10 percent significance level), while having no statistically significant effect on the probability of con-tacting a specialist or any other type of providers. To put these results into perspective: the share of patients who self-refer themselves decreased from 24 percent to 21 percent for the full sample and remains at 22-23 percent for the subsample.

This finding is quite surprising because in most managed care settings with a gate-keeper, a person cannot go to a specialist without a referral from the primary care physi-cian. If they do go to a specialist, then the insurance will most probably not reimburse the expenses. However, as the publicly available data from MEPS do not include out-of-pocket payments of patients, it is not possible to check this implication empirically.

As for the estimated marginal effects of the other explanatory variables, condition indicators are, in general, very good predictors of initial provider choice. Also, they are similar both in sign and magnitude over the full sample and sub-sample. This finding is probably due to our choice of conditions with fairly standardized courses of treatment. Demographic characteristics, in general, do not seem to affect the probability of hospi-talization and have a relatively low effect on the probability of a PCP visit, but they are a significant predictor of choosing a specialist, non-medical personnel, or ER as the

ICP. This pattern also holds for the sub-sample, with the exemption of encounters with specialists, where the demographic variables lose their explanatory power and choice is primarily determined by the type of condition.

1.5.2 Course of further treatment

In this section, we explore further possible mechanisms of gatekeeping's indirect impact by analyzing the effect of ICP choice on patterns of further medical care utilization. The results of the simple model of further utilization, estimated on the full sample, are presented in Tables 1.6 - 1.10. Tables 1.6 and 1.6 summarize the average sample probabilities and numbers of encounters with a given type of provider during the episode of care conditional on the choice of ICP and gatekeeping status. Table 1.8 then contains the results of estimation of a logit model for the probabilities of an encounter, while Table 1.9 contains results of estimation of a negative binomial regression model for the number of encounters. In both tables, columns represent utilization outcomes of interest (probability and number of encounters with a given type of provider), while rows represent the marginal effects of binary indicators of initial provider status in interaction with the gatekeeping status of the respondent with a PCP contacted by a non-gatekeeping enrollee being the base category. Both types of models were estimated with and without additional covariates, corresponding to the first and second column within each provider category. We do not report the outcomes for other included covariates, but we comment on their significance in particular cases later.

The results of the estimation lead us to two basic conclusions: (1) we can observe distinctly different patterns of medical care utilization conditional on the choice of ICP; and (2) after controlling for ICP choice, gatekeeping requirements in general do not have any additional impact on further utilization, with a few exceptions. These results hold for both extensive and intensive utilization measures, are statistically significant, and are robust to the inclusion of other covariates.

More detailed analysis of utilization measures reveals other interesting patterns. PCP-initiated episodes of care have the lowest further utilization measures both in terms of probability and number of events. On the other hand, episodes initiated by a visit to a specialist have a high probability of continuing treatment by the specialist and also have an increased probability of ending in a hospital, which means that specialists see enrollees with more serious conditions.

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Two types of patients are induced to switch from secondary to primare care by the gatekeeping restriction. First, there are patients who do not need specialist care, and PCPs contain costs by keeping them within primary care. Second, there are patients who need to see a specialist for whom the initial visit to a PCP results in an immediate referral. In comparing gatekeeping and non-gatekeeping patients, we observe that gatekeeping patients have a significantly higher probability of referral to a specialist.[16] Thus, we can infer that the second type of patient prevails.[17] At this point, we cannot make any inference regarding the effectiveness of gatekeeping in such a setting, however, since these patients could be either those who would self-refer correctly and for whom the initial PCP visit was redundant, or patients who did not know the proper specialist and benefited from the screening provided by a PCP.

Episodes initiated by a visit to non-MD personnel have a very specific character. They lead to a high probability of continuing treatment by non-MD personnel with multiple visits (8 times more visits as compared to when the treatment was initiated by a PCP visit). From the data, we indicate that these are the episodes connected to specific chronic conditions with a standardized treatment procedure.[18]

If the episode starts with a hospital admission, the expected future medical care utilization is on average highest among the alternatives, which suggests that hospitalization can be used as a proxy for illness severity. Finally, emergency room visits often result in further treatment by specialists or hospitalisation, but there is no significant difference between the outcomes of gatekeeping and non-gatekeeping enrollees. Thus, we confirm that ERs do not provide after-hours care for patients with gatekeeping insurance plans, as is the case with uninsured patients.

Appropriateness of self-referral

Self-referral is a common path to specialist care. Based on our summary tabulations, 24 percent of non-gatekeeping and 21 percent of gatekeeping enrollees self-refer. The effectiveness and appropriateness of self-referral depends on the patient's ability to assess

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[16]Their probability of being referred to a specialist is 2.5 percentage points higher, which represents a 24.5 percent increase.

[17]This observation was confirmed by a repeated estimation on the sub-sample of respondents with exogenous choice of health insurance, for which we did not find significant effect of gatekeeping on ICP choice in the first stage. Consistently with our inference, we also did not find any difference in PCP-referral rates between gatekeeper and non-gatekeeper patients.

[18]Types of medical personnel contacted the most are chiropractors, nurses, technicians, physical therapists and psychologists. Conditions treated by non-medical personnel include intervertebral disc dislocation, connective tissue disease, and sprains and strains.

the severity of his condition and choose an appropriate provider type. Inspired by Forrest and Reid (1997), we try to evaluate the appropriateness by using a simple proxy for condition severity, i.e. hospitalization.

We re-estimate the logit model for the probability of hospitalization on the sub-sample of respondents who either have visited a PCP as the ICP and were then referred to a specialist or who have self-referred to specialist directly. First, we examined whether the probability of hospitalization varies by type of ICP. Our findings are consistent with the previous literature. In the simplest version of the model, i.e. estimation after controlling for individual-specific covariates (not presented in the table), respondents who self-referred to specialty care had a 4 percentage point lower probability of being hospitalized than respondents who were referred by a PCP. With a baseline hospitalization rate of 0.073 for PCP-referred patients, this corresponds to a 55 percent lower hospitalization rate.

Further, we add interaction terms in order to estimate separate effects for gatekeeping and non-gatekeeping enrollees. Table 1.10 summarizes the results of estimation both on the full sample of PCP-referred and self-referred patients, as well as exclusively on those who were defined as having no choice of insurance plan. We see that the difference in hospitalization rates is based on the difference among gatekeeping enrollees. While there is no significant difference in the hospitalization rates among non-gatekeeping enrollees, there is an almost 6 percentage point difference between the hospitalization rate of PCP-referred and self-referred within gatekeeping enrollees. For the sample of respondents without insurance choice,the difference increases to 9.4 percentage points, i.e. the chances of hospitalization for PCP-referred patients are 3.3 times greater than for the self-referred!

1.6   Concluding Remarks

The majority of current studies on the effectiveness of managed care evaluate the role of gatekeeping restrictions by estimating their effects on aggregate measures of health care utilization. This approach is questionable, however, because gatekeeping is primarily intended as a mechanism to reinforce the use of primary care physicians as initial contact providers. Taking advantage of individual-level panel data on medical care utilization from the 2001 - 2006 U.S. Medical Expenditure Panel Survey, we are able to isolate multiple effects of gatekeeping restrictions, including their influence on the choice of initial care providers and on the course of further treatment. We explore a quasi-natural

experiment in our data, arising from differences in the degree of choice of insurance plans employers offer their employees, to account for the effect of self-selection into gatekeeping plans.

Our main results are counterintuitive and genuinely surprising. The theory behind the concept of gatekeeping predicts fewer self-referrals to specialists and a corresponding increase in the number of primary care physician (PCP) visits for individuals with gatekeeping requirements as opposed to those enrolled in non-gatekeeper plans. Nevertheless, our results show only economically trivial (although statistically significant) differences. Probing more deeply, we see that most of the patients who were required to use their primary care physicians as initial contact providers wereb referred back to a specialist, i.e. they indeed needed specialty care. This finding, together with the fact that within gatekeeping plans, 21 percent of patients still self-refer to specialists, implies that the intended economic effect of gatekeeping, reducing utilization of specialty care, is surprisingly weak.

When we assess the appropriateness of self-referrals, we find that self-referred patients are less severely ill than patients who were referred to specialists by primary care physicians. Two mechanisms can explain these results. The first is the behavior of patients. While without gatekeeping restriction, patients with severe illnesses seem to distribute themselves randomly between PCP and specialist care, they seem to behave differently under the gatekeeping restriction. They self-refer mainly with regular and recognizable conditions that need specialist attention but which are only moderately severe, while with any other condition they visit their PCP. The second mechanism is the screening role of PCPs. As the first-contact provider, they are retaining less sick patients in a primary care setting while referring the more severely ill to specialty care. This tendency towards screening is generally incentivized in gatekeeping plans (by, for example, provisions that limit physician referral rates).

Therefore, it appears that gatekeeping operates through channels other than those typically assumed. It does not affect direct access to specialty care as much as it changes the composition of patients who self-refer and patients who are referred by a PCP. This has important implications for the designers of health insurance policies as it implies a differentiated effect of gatekeeping restriction on the agents within a health system. While behavior of patients seems to be only slightly modified, the incentives imposed on gatekeeping physicians could induce a higher efficiency of screening and treatment process.

Table 1.1: Summary of medical care utilisation measures for (1) the full sample and (2) the sub-sample of respondents with exogenous choice of health insurance plan by gatekeeping status

| | (1) Full sample | | | | (2) Sub-sample | | | |
| | non-gatekeeping | | gatekeeping | | non-gatekeeping | | gatekeeping | |
	mean	SE	mean	SE	mean	SE	mean	SE
General utilization								
# of conditions	3.93**	[0.04]	3.81**	[0.03]	3.79	[0.07]	3.69	[0.07]
total # of PCP visits	3.92	[0.10]	3.92	[0.07]	4.10	[0.24]	4.12	[0.16]
total # of SPEC visits	4.83	[0.11]	4.82	[0.11]	4.40	[0.21]	4.27	[0.22]
total # of nonMD visits	7.32***	[0.25]	6.24***	[0.18]	6.38	[0.40]	5.82	[0.41]
total # of HOSP visits	0.24	[0.01]	0.24	[0.01]	0.19	[0.01]	0.21	[0.02]
total # of ER visits	0.45	[0.01]	0.44	[0.01]	0.39	[0.02]	0.44	[0.03]
Health indicators								
healthy (0/1) [b]	0.66***	[0.01]	0.62***	[0.01]	0.63***	[0.01]	0.58***	[0.01]
limitations (0/1) [a]	0.07	[0.01]	0.08	[0.01]	0.07	[0.01]	0.08	[0.01]
BMI [a]	27.9	[0.08]	27.8	[0.07]	28.6	[0.16]	28.2	[0.15]
smoking [a]	0.20	[0.01]	0.19	[0.01]	0.21	[0.01]	0.22	[0.01]
First condition after June 1st								
First encounter								
PCP	0.43***	[0.01]	0.46***	[0.01]	0.44**	[0.01]	0.48**	[0.01]
specialist	0.24***	[0.01]	0.21***	[0.01]	0.23	[0.01]	0.22	[0.01]
nonMD	0.20	[0.01]	0.19	[0.01]	0.20**	[0.01]	0.17**	[0.01]
hospital	0.02	[0.01]	0.02	[0.01]	0.02	[0.01]	0.02	[0.01]
emergency	0.11	[0.01]	0.11	[0.01]	0.11	[0.01]	0.12	[0.01]
Further utilization								
# of PCP visits	0.82**	[0.02]	0.88**	[0.02]	0.97	[0.07]	0.93	[0.06]
# of SPEC visits	1.00	[0.03]	1.00	[0.03]	0.81*	[0.04]	0.91*	[0.04]
# of nonMD visits	1.28	[0.07]	1.15	[0.05]	1.3**	[0.14]	0.96**	[0.08]
# of HOSP visits	0.07	[0.01]	0.06	[0.01]	0.06	[0.01]	0.05	[0.01]
# of ER visits	0.15	[0.01]	0.15	[0.01]	0.15	[0.01]	0.14	[0.01]
N	5203		7586		1397		1576	

Note: The differences between gate and non-gatekeeping enrollees significant at the 1%, 5%, and 10% levels are denoted by ***, **, and *, respectively.
[a] The averages made over the sub-sample of respondents that were eligible and responded to the Self-Administered Questionnaire - approx. 87% of the sample.
[b] The averages made over the sub-sample of respondents who answered the question.

Table 1.2: Prevalence of selected health conditions by gatekeeping status

Conditions	non-gatekeeping		gatekeeping		
	mean	SE	mean	SE	t-stat
hypertension	0.03	[0.003]	0.04	[0.002]	−0.57
upper resp. infection	0.07	[0.004]	0.07	[0.003]	1.30
pregnancy$^{a)}$	0.04	[0.004]	0.05	[0.003]	−0.29
disc dislocation	0.05*	[0.003]	0.04*	[0.002]	1.87
sprains & strains	0.04	[0.003]	0.03	[0.002]	0.64
joint disorders	0.03	[0.002]	0.03	[0.002]	−0.66
connective tissue	0.03	[0.002]	0.04	[0.002]	−1.68
skin disorders	0.05	[0.003]	0.05	[0.002]	0.05
other injuries	0.02	[0.002]	0.03	[0.002]	−0.94
diabetes	0.01*	[0.001]	0.01*	[0.001]	−0.66
neoplasm	0.02***	[0.002]	0.01***	[0.001]	2.60
lipid metabolism	0.02	[0.002]	0.02	[0.002]	0.03
blindness	0.01	[0.002]	0.02	[0.001]	−1.06
chronic pulmonary cond.	0.02	[0.002]	0.02	[0.002]	0.19
intestinal infection	0.02	[0.002]	0.02	[0.002]	−1.70
urinary calculus	0.01	[0.001]	0.01	[0.001]	1.00
wounds	0.01	[0.002]	0.01	[0.001]	0.49

Note: The differences between gate and non-gatekeeping enrollees significant at the 1%, 5%, and 10% levels are denoted by ***, **, and *, respectively.
$^{a)}$ The prevalence calculated over the sub-sample of women.

Table 1.3: Socio-demographic and employment-related characteristics of (1) the full sample and (2) the sub-sample of respondents with exogenous choice of health insurance plan by gatekeeping status

| | (1) Full sample | | | | (2) Sub-sample | | | |
| | non-gatekeeping | | gatekeeping | | non-gatekeeping | | gatekeeping | |
	mean	SE	mean	SE	mean	SE	mean	SE
Demography								
age	41.8	[0.162]	41.9	[0.106]	43.5	[0.286]	43.7	[0.269]
male	0.44	[0.006]	0.43	[0.006]	0.51	[0.013]	0.50	[0.013]
years of education	13.68**	[0.034]	13.56**	[0.031]	13.32***	[0.067]	13.03***	[0.071]
- race/ethnicity dummies								
hispanic	0.09***	[0.004]	0.15***	[0.004]	0.10***	[0.008]	0.19***	[0.010]
black	0.11***	[0.004]	0.12***	[0.003]	0.11	[0.008]	0.12	[0.008]
white	0.77***	[0.006]	0.68***	[0.005]	0.77***	[0.011]	0.66***	[0.012]
asian	0.03***	[0.002]	0.04***	[0.002]	0.02*	[0.004]	0.03*	[0.005]
-region dummies								
northeast	0.12***	[0.005]	0.20***	[0.005]	0.11***	[0.008]	0.20***	[0.010]
midwest	0.31***	[0.006]	0.22***	[0.005]	0.31***	[0.012]	0.21***	[0.010]
south	0.40***	[0.007]	0.33***	[0.005]	0.45***	[0.013]	0.37***	[0.012]
west	0.16***	[0.005]	0.25***	[0.005]	0.14***	[0.009]	0.21***	[0.010]
urban status (0/1)	0.73***	[0.006]	0.85***	[0.004]	0.68***	[0.012]	0.82***	[0.010]
-marital status dummies								
married	0.67***	[0.006]	0.64***	[0.006]	0.65***	[0.013]	0.59***	[0.012]
divorced	0.12**	[0.004]	0.13	[0.004]	0.16	[0.010]	0.17	[0.010]
single	0.18	[0.005]	0.19**	[0.005]	0.16*	[0.010]	0.17	[0.010]
family size	2.87***	[0.019]	2.95***	[0.017]	2.82	[0.037]	2.83	[0.038]
log(income)	10.9	[0.010]	10.9	[0.007]	10.90*	[0.017]	10.86*	[0.015]
# of children	0.81**	[0.015]	0.85**	[0.013]	0.80	[0.019]	0.79	[0.028]
Employment								
# of employees	168.9***	[2.6]	186.2***	[2.2]	157.1	[4.7]	165.1	[4.6]
small firm (0/1)	0.17***	[0.005]	0.14***	[0.004]	0.15*	[0.010]	0.13*	[0.009]
more locations*a)* (0/1)	0.71**	[0.006]	0.73**	[0.005]	0.67	[0.013]	0.67	[0.013]
unionized*a)* (0/1)	0.16	[0.005]	0.17	[0.004]	0.20	[0.011]	0.17	[0.009]
offer insurance (0/1)	0.85***	[0.005]	0.88***	[0.004]	—	—	—	—
choice of plans (0/1)	0.49***	[0.008]	0.58***	[0.006]	—	—	—	—
hold insurance (0/1)	0.75***	[0.006]	0.78***	[0.005]	—	—	—	—

Note: The differences between gate and non-gatekeeping enrollees significant at the 1%, 5%, and 10% levels are denoted by ***, **, and *, respectively.
a) The averages made over the sub-sample that responded who answered the question.

Table 1.4: Estimation of the marginal effect of gatekeeping restriction on the probability of the choice of the initial provider, logit on (1) the full sample and (2) the sub-sample of respondents with exogenous choice of health insurance plan

	PCP				SPEC			
	(1)		(2)		(1)		(2)	
privGK	**0.038***	[0.009]	**0.034***	[0.019]	**-0.033***	[0.008]	**-0.016**	[0.017]
male	0.064***	[0.009]	0.046**	[0.020]	−0.033***	[0.008]	−0.021	[0.017]
hispanic	0.094***	[0.015]	0.148***	[0.031]	−0.001	[0.013]	−0.047*	[0.025]
black	0.021	[0.014]	0.058*	[0.032]	−0.000	[0.014]	0.006	[0.029]
years of educ	−0.008***	[0.002]	−0.006*	[0.004]	0.007***	[0.002]	0.003	[0.003]
NE	−0.056***	[0.012]	−0.063**	[0.029]	0.086***	[0.016]	0.051	[0.034]
MW	0.004	[0.012]	−0.029	[0.028]	0.016	[0.013]	−0.008	[0.028]
S	0.001	[0.012]	−0.022	[0.026]	0.066***	[0.013]	0.050*	[0.029]
married	0.013	[0.010]	0.044**	[0.022]	0.002	[0.010]	−0.019	[0.020]
log(income)	0.010	[0.007]	−0.006	[0.016]	0.037***	[0.006]	0.062***	[0.015]
# of children	0.005	[0.004]	0.012	[0.008]	−0.004	[0.003]	0.001	[0.007]
healthy	0.021**	[0.009]	−0.004	[0.019]	−0.020**	[0.008]	0.005	[0.019]
neoplasm	−0.116***	[0.029]	−0.065	[0.066]	0.342***	[0.038]	0.293***	[0.075]
diabetes	0.225***	[0.042]	0.395***	[0.069]	−0.130***	[0.025]	−0.138***	[0.047]
lipid metab.	0.167***	[0.031]	0.118*	[0.065]	−0.180***	[0.014]	−0.158***	[0.036]
blindness	−0.333***	[0.003]	−0.346***	[0.022]	0.204***	[0.036]	0.258***	[0.083]
hypertension	0.341***	[0.025]	0.386***	[0.046]	−0.163***	[0.013]	−0.185***	[0.023]
upper resp.	0.385***	[0.018]	0.348***	[0.036]	−0.194***	[0.007]	−0.206***	[0.013]
chron. pulm.	0.380***	[0.031]	0.332***	[0.059]	−0.213***	[0.010]	−0.236***	[0.014]
intestinal	0.258***	[0.035]	0.391***	[0.071]	−0.222***	[0.009]	−	−
urinary	−0.163***	[0.035]	−0.204***	[0.057]	−0.125	[0.033]	−0.122**	[0.060]
pregnancy	−0.266***	[0.013]	−0.266***	[0.046]	0.366***	[0.029]	0.351***	[0.082]
disc disloc.	−0.120***	[0.016]	−0.168***	[0.031]	−0.118***	[0.013]	−0.147***	[0.023]
sprain	−0.026	[0.021]	−0.086*	[0.044]	−0.123***	[0.015]	−0.135***	[0.031]
wounds	−0.147***	[0.027]	−0.120*	[0.062]	−0.203***	[0.016]	−0.193***	[0.035]
otherinj	−0.088***	[0.023]	−0.119**	[0.047]	−0.092***	[0.021]	−0.081*	[0.044]
joint	0.091***	[0.026]	0.084	[0.056]	−0.017	[0.022]	0.039	[0.050]
connect. tissue	0.008	[0.023]	−0.056	[0.045]	−0.012	[0.021]	0.045	[0.045]
skin disorder	0.028	[0.020]	−0.002	[0.043]	0.145***	[0.021]	0.113***	[0.044]
constant	0.346***	[0.075]	0.511**	[0.169]	−0.233***	[0.064]	−0.431***	[0.148]
Wald	1123	[0]	303	[0]	1002	[0]	221	[0]
pseudo R2	0.093		0.097		0.098		0.095	
N	12,789		2,973		12,789		2,927	

Note: Significance at the 1%, 5%, and 10% levels is denoted by ***, **, and *, respectively. Standard errors for coefficient estimates and p-value for Wald test are reported in brackets.

Table 1.5: (continued from previous page)

	NONMD		HOSP		ER	
	(1)	(2)	(1)	(2)	(1)	(2)
privGK	**-0.005** [0.009]	**-0.025** [0.019]	**-0.005** [0.003]	**-0.009** [0.006]	**0.002** [0.007]	**0.007** [0.011]
male	-0.077*** [0.008]	-0.086*** [0.016]	0.012** [0.006]	0.006 [0.010]	0.030*** [0.008]	0.042** [0.015]
hispanic	-0.102*** [0.012]	-0.106*** [0.023]	-0.005 [0.006]	0.015 [0.016]	-0.007 [0.010]	-0.024* [0.013]
black	-0.107*** [0.012]	-0.115*** [0.025]	0.015* [0.008]	0.001 [0.012]	0.067*** [0.013]	0.025 [0.019]
years of educ	0.007*** [0.002]	0.007*** [0.003]	-0.001 [0.000]	-0.000 [0.001]	-0.005*** [0.001]	-0.003 [0.002]
NE	-0.036*** [0.013]	-0.034 [0.031]	0.005 [0.008]	0.002 [0.017]	0.023* [0.012]	0.054* [0.027]
MW	-0.026** [0.012]	-0.009 [0.029]	-0.004 [0.006]	-0.006 [0.012]	0.009 [0.010]	-0.046* [0.024]
S	-0.073*** [0.010]	-0.078*** [0.023]	0.004 [0.007]	0.025 [0.023]	0.007 [0.010]	0.031 [0.021]
married	0.007 [0.011]	0.025 [0.023]	0.001 [0.005]	0.001 [0.008]	-0.021*** [0.005]	-0.027*** [0.007]
log(income)	-0.013** [0.006]	-0.024* [0.013]	-0.002 [0.002]	-0.006 [0.005]	-0.029*** [0.004]	-0.030*** [0.010]
# of children	-0.012*** [0.003]	-0.021*** [0.007]	0.001 [0.001]	-0.001 [0.003]	0.009*** [0.002]	0.008 [0.005]
healthy	0.010 [0.010]	0.004 [0.021]	-0.014*** [0.002]	-0.014** [0.004]	-0.002 [0.006]	0.005 [0.011]
neoplasm	-0.142*** [0.031]	-0.121* [0.065]	-0.015 [0.011]	— [—]	-0.110*** [0.009]	— [—]
diabetes	0.078* [0.044]	-0.135** [0.063]	-0.024*** [0.006]	— [—]	-0.115*** [0.006]	— [—]
lipid metab.	0.202*** [0.033]	0.221*** [0.072]	— [—]	— [—]	-0.116*** [0.004]	— [—]
blindness	0.386*** [0.035]	0.299*** [0.086]	0.024*** [0.007]	— [—]	-0.115*** [0.005]	-0.078*** [0.012]
hypertension	-0.093*** [0.024]	-0.097*** [0.046]	-0.016*** [0.006]	-0.008 [0.015]	-0.079*** [0.009]	-0.073*** [0.016]
upper resp.	-0.073*** [0.017]	-0.015 [0.039]	-0.024*** [0.003]	-0.022*** [0.007]	-0.091*** [0.005]	-0.077*** [0.009]
chron. pulm.	-0.104*** [0.029]	-0.030 [0.063]	-0.021*** [0.007]	-0.008 [0.020]	-0.049*** [0.016]	-0.061*** [0.010]
intestinal	-0.095*** [0.032]	-0.136* [0.066]	-0.009 [0.011]	-0.001 [0.0227]	0.041 [0.025]	-0.035 [0.022]
urinary	-0.137*** [0.045]	-0.197*** [0.058]	0.005 [0.021]	0.004 [0.052]	0.381*** [0.053]	-0.017 [0.033]
pregnancy	-0.017 [0.028]	-0.062 [0.079]	0.060*** [0.0022]	0.120 [0.082]	-0.082** [0.011]	0.400*** [0.096]
disc disloc.	0.383*** [0.020]	0.472*** [0.036]	-0.023*** [0.004]	-0.012 [0.012]	-0.060*** [0.010]	-0.064** [0.025]
sprain	0.050* [0.026]	0.101* [0.056]	— [—]	— [—]	0.134*** [0.021]	-0.055*** [0.014]
wounds	-0.184*** [0.029]	-0.176*** [0.061]	— [—]	— [—]	0.495*** [0.040]	0.144*** [0.041]
other inj	0.019 [0.031]	0.040 [0.066]	— [—]	-0.014 [0.015]	0.191*** [0.027]	0.380*** [0.079]
joint	0.047* [0.029]	-0.001 [0.061]	-0.024*** [0.004]	-0.004 [0.018]	-0.090*** [0.009]	0.155*** [0.048]
connect. tissue	0.121*** [0.027]	0.128** [0.056]	-0.024*** [0.005]	— [—]	-0.073*** [0.011]	-0.082*** [0.008]
skin disorder	-0.098*** [0.019]	-0.021 [0.048]	-0.022*** [0.004]	— [—]	-0.091*** [0.007]	-0.057*** [0.013]
constant	0.312*** [0.060]	0.431*** [0.134]	0.059*** [0.023]	0.039 [0.048]	-0.516*** [0.051]	-0.449*** [0.106]
Wald	852 [0]	254 [0]	134 [0]	39 [0.01]	978 [0]	246 [0]
pseudo R2	0.077	0.103	0.058	0.056	0.135	0.137
N	12,789	2,973	11,731	2,419	12,789	2,880

Note: Significance at the 1%, 5%, and 10% levels is denoted by ***, **, and *, respectively. Standard errors for coefficient estimates, and p-values for Wald test are reported in brackets.

Table 1.6: Probability of further visit conditional on the initial provider (in percentage points) - summary table

First event	probPCP gate	probPCP non-gate	probSPEC gate	probSPEC non-gate	probnonMD gate	probnonMD non-gate	probHIS gate	probHIS non-gate	probER gate	probER non-gate
PCP	29.15	27.48	12.59***	10.01***	12.28	11.99	1.67	1.13	2.10	1.75
specialist	7.28*	5.74*	52.56	51.65	14.07	15.41	6.91	7.39	1.73	1.97
nonMD	12.80	13.72	15.11	14.30	43.50	45.87	2.93	2.59	1.97	1.34
hospital	30.33	21.88	34.43	41.67	16.39	17.70	10.66	15.63	28.69**	42.71**
ER	21.72*	17.84*	19.72	21.73	13.22	14.49	8.97	9.72	8.15	9.89

Note: The differences between gate and non-gatekeeping enrollees significant at the 1%, 5%, and 10% levels are denoted by ***, **, and *, respectively.

Table 1.7: Number of further visit conditional on the initial provider - summary table

First event	probPCP gate	probPCP non-gate	probSPEC gate	probSPEC non-gate	probnonMD gate	probnonMD non-gate	probHIS gate	probHIS non-gate	probER gate	probER non-gate
PCP	0.615	0.600	0.318**	0.240**	0.392	0.402	0.019	0.014	0.025	0.019
specialist	0.137*	0.097*	2.09*	1.84*	0.609	0.801	0.075	0.075	0.021	0.021
nonMD	0.228	0.282	0.500	0.468	2.687	2.978	0.030	0.030	0.025	0.015
hospital	0.475	0.5	1.95	1.521	1.484	0.739	0.164	0.177	0.311**	0.5**
ER	0.440	0.401	0.609	0.760	0.911	0.912	0.092	0.122	0.099	0.129

Note: The differences between gate and non-gatekeeping enrollees significant at the 1%, 5%, and 10% levels are denoted by ***, **, and *, respectively.

Table 1.8: Probability of further visits at different types of providers - marginal effects of initial provider choice, given gatekeeping status, from logit estimation on the full sample of respondents.

The model is estimated using a full set of dummy variables indicating combined initial provider choice - gatekeeping status, with non-gate PCP as the baseline category. Marginal effects are evaluated at the mean of other covariates; standard errors are computed by delta method and presented in brackets. Coefficients by gatekeeping subgroups represent the marginal effect of being a gatekeeping enrollee for a given type of provider.

first contact	PCP		SPEC		nonMD		HOSP		ER	
	logit	logit + X[a]	logit	logit + X[a]	logit	logit + X[a]	logit	logit + X[a]	logit	logit + X[a]
PCP (base)	0.275	0.254	0.100	0.102	0.120	0.116	0.013	0.009	0.018	0.017
- PCP - gate	-0.017 [0.012]	0.011 [0.012]	0.026*** [0.009]	0.025*** [0.009]	0.003 [0.009]	-0.001 [0.009]	0.003 [0.004]	0.004 [0.003]	0.002 [0.004]	0.009** [0.004]
SPEC	-0.217*** [0.008]	-0.201*** [0.009]	0.416*** [0.020]	0.355*** [0.019]	0.034*** [0.013]	0.013 [0.012]	0.060*** [0.004]	0.031*** [0.003]	0.001 [0.005]	0.001 [0.005]
- SPEC - gate	0.015* [0.008]	0.017* [0.010]	0.009 [0.020]	0.013 [0.018]	-0.013 [0.013]	-0.012 [0.012]	-0.010 [0.012]	-0.006 [0.008]	-0.002 [0.005]	-0.004 [0.005]
nonMD	-0.138*** [0.009]	-0.128*** [0.010]	0.043** [0.020]	0.021* [0.018]	0.339*** [0.021]	0.263*** [0.012]	0.012* [0.008]	0.006 [0.007]	-0.004 [0.005]	-0.007** [0.005]
- nonMD - gate	-0.009 [0.018]	-0.008 [0.013]	0.008 [0.012]	0.009 [0.012]	-0.024** [0.020]	-0.017 [0.019]	0.005 [0.008]	0.003 [0.005]	0.006 [0.005]	0.006 [0.005]
HOSP	-0.056 [0.013]	-0.051 [0.014]	0.317*** [0.014]	0.246*** [0.012]	0.057 [0.040]	0.040 [0.036]	0.143*** [0.008]	0.066** [0.006]	0.331*** [0.007]	0.342*** [0.006]
- HOSP - gate	0.085 [0.043]	0.067 [0.042]	-0.072 [0.053]	-0.081 [0.048]	-0.013 [0.051]	0.000 [0.046]	-0.035 [0.042]	-0.024 [0.029]	-0.115 [0.057]	-0.12* [0.061]
ER	-0.096*** [0.059]	-0.078*** [0.057]	0.117*** [0.066]	0.099*** [0.061]	0.025 [0.046]	0.012 [0.015]	0.084*** [0.004]	0.074*** [0.032]	0.056*** [0.065]	0.065*** [0.060]
- ER - gate	0.039* [0.018]	0.030 [0.018]	-0.020 [0.020]	-0.019 [0.020]	-0.013 [0.017]	-0.015 [0.015]	-0.043* [0.023]	-0.004 [0.014]	-0.017 [0.014]	-0.015 [0.013]
Wald stat.	604	1130	1696	1860	1133	1584	259	823	522	625
pseudo R2	0.059	0.109	0.130	0.173	0.088	0.151	0.067	0.232	0.119	0.149

Note: Significance at the 1%, 5%, and 10% levels is denoted by ***, **, and *, respectively.

a) Vector of covariates X consists of age, sex, ethnicity, years of education, marital status, health status dummy, and dummies for illness types.

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Table 1.9: Number of further visits – marginal effects of initial provider choice and gatekeeping status from negative binomial regression on full sample

The model is estimated using a full set of dummy variables indicating combined initial provider choice - gatekeeping status, with non-gate PCP as the baseline category. Marginal effects are evaluated at the mean of other covariates; standard errors are computed by delta method and presented in brackets. Coefficients by gatekeeping subgroups represent the marginal effect of being a gatekeeping enrollee for a given type of provider.

first contact	PCP nbreg	PCP nbreg + X[a]	SPEC nbreg	SPEC nbreg + X[a]	nonMD nbreg	nonMD nbreg + X[a]	HOSP nbreg	HOSP nbreg + X[a]	ER nbreg	ER nbreg + X[a]
PCP (base)	0.602	0.486	0.240	0.153	0.319	0.282	0.014	0.007	0.019	0.011
- PCP - gate	0.013	0.023	0.077**	0.041**	−0.010	−0.011	0.004	0.005	0.006	0.004
	[0.044]	[0.043]	[0.027]	[0.018]	[0.067]	[0.051]	[0.004]	[0.004]	[0.005]	[0.005]
SPEC	−0.505***	−0.471***	1.597***	1.272***	0.399***	0.356***	0.061***	0.033***	0.002	−0.001
	[0.020]	[0.021]	[0.161]	[0.133]	[0.145]	[0.138]	[0.013]	[0.010]	[0.005]	[0.005]
- SPEC - gate	0.040*	0.025	0.250*	0.306**	−0.193	−0.163	−0.001	−0.002	−0.001	−0.003
	[0.023]	[0.023]	[0.150]	[0.136]	[0.156]	[0.154]	[0.013]	[0.007]	[0.006]	[0.005]
nonMD	−0.320***	−0.319***	0.228***	0.123**	2.576***	2.187***	0.015*	0.009	−0.004	−0.003
	[0.036]	[0.033]	[0.072]	[0.055]	[0.410]	[0.353]	[0.008]	[0.006]	[0.005]	[0.005]
- nonMD - gate	−0.054	−0.042	0.032	−0.006	−0.291	−0.113	0.001	0.001	0.010	0.009
	[0.036]	[0.033]	[0.076]	[0.056]	[0.324]	[0.326]	[0.008]	[0.006]	[0.007]	[0.008]
HOSP	−0.102	−0.041	1.281***	0.891***	0.338	0.328	0.163***	0.069**	0.481***	0.413***
	[0.160]	[0.190]	[0.361]	[0.228]	[0.298]	[0.280]	[0.052]	[0.028]	[0.094]	[0.087]
- HOSP - gate	−0.025	−0.091	0.430	0.279	0.744	0.809	−0.013	−0.007	−0.189**	−0.193**
	[0.172]	[0.205]	[0.645]	[0.397]	[0.795]	[0.807]	[0.073]	[0.040]	[0.085]	[0.081]
ER	−0.201***	−0.147**	0.519***	0.424***	0.508**	0.325*	0.108***	0.093***	0.110***	0.081***
	[0.063]	[0.066]	[0.143]	[0.119]	[0.208]	[0.176]	[0.027]	[0.024]	[0.025]	[0.021]
- ER - gate	0.039	0.017	−0.151	−0.102	−0.001	0.033	−0.030	−0.022	−0.030	−0.029
	[0.078]	[0.077]	[0.148]	[0.123]	[0.245]	[0.203]	[0.022]	[0.020]	[0.023]	[0.018]
Pseudo-likelihood	−9515	−9191	−12147	−11659	−11592	−11142	−2212	−1906	−1849	−1174
Wald stat.	340	1046	930	64915	453	1384	237	72451	601	67490

Note: Significance at the 1%, 5%, and 10% levels is denoted by ***, **, and *, respectively.
a) Vector of covariates X consists of age, sex, ethnicity, years of education, marital status, health status dummy, and dummies for illness types.

Table 1.10: Probability of hospitalisation - comparison of PCP-referred and self-referred respondents for (1) the full sample and (2) the sub-sample of people without choice of insurance

	(1) logit + $\mathbf{X}^{a)}$		(2) logit + $\mathbf{X}^{a)}$	
PCP non-gate	0.063		0.053	
SPEC non-gate	-0.011	[0.018]	-0.006	[0.039]
PCP gate	0.030	[0.025]	0.046	[0.065]
SPEC gate	-0.024	[0.018]	-0.045	[0.032]
pseudo R2	0.226		0.139	
N	3,424		692	
Gate only:				
PCP referred - self-referred	0.052***	[0 .016]	0.094**	[0.045]
pseudo R2	0.217		0.156	
N	1,952		364	

Note: Significance at the 1%, 5%, and 10% levels is denoted by ***, **, and *, respectively.
a) Vector of covariates X consists of age, sex, ethnicity, years of education, marital status, health status dummy, and dummies for illness types.

Chapter 2

Demand Side Cost-Sharing and Prescription Drugs Utilization: Evidence From a Quasi-Natural Experiment

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Abstract

In this chapter we investigate the effects of introduction of lump sum copayments on the utilization of prescription drugs by elderly patients. We make use of a unique dataset to analyze a policy change that implemented patient cost-sharing in the Czech Republic starting in 2008. After the introduction of copayments, the number of prescriptions filled decreased by 29%. At the same time, however, total expenditures on prescription drugs dropped only in the first quarter of the postintroduction period and then returned to previous levels. This was partially due to behavioral responses of patients and physicians: a strategic shift of prescription purchases to just prior to the introduction of the reform, prescription of more packages on one prescription and an upward shift in the price composition of prescribed drugs.

2.1 Introduction and Motivation

The rapid increase in utilization of health care and the corresponding rise in health expenditures over recent decades concern policymakers in most developed countries (OECD 2009). In the European context, rising health expenditures have often led to adoption of additional cost-containment strategies, mostly implemented within the framework of reforms to existing systems of universal health coverage. While some of these measures are aimed to regulate providers, those that target the demand (patient) side are more often the topic of public debate. By introducing higher patient out-of-pocket payments, policy makers aim to alter the attitudes of people towards their health, and to motivate them to take greater personal responsibility in utilization of health care.

The ultimate success and efficiency of cost-sharing measures, however, crucially depends on two main factors. First, universally applied cost-containment measures disproportionately affect vulnerable groups within a population (e.g. youth, elderly, chronically ill), but it is difficult to design adjustment mechanisms for their protection. Second, cost-sharing measures often trigger ex-ante unanticipated behavioral responses. Third, changes in utilization patterns may bear negative consequences for long-term health outcomes. Policy makers should be aware of these pitfalls, understand their implications, and take them into consideration in the process of reform design.

In this paper we investigate the effects of the introduction of lump-sum copayments on the demand for prescription drugs. We make use of the quasi-experiment of the recent nation-wide policy change that implemented patient cost-sharing in the Czech Republic in the form of copayments paid directly to providers/pharmacies at the point of service starting in 2008.[1] Just one year after the introduction of copayments, regional elections led to political changes that resulted in partial reversal of the reform, as regional governments began to reimburse copayments at region-owned facilities.[2] Interestingly, different regions decided to implement different forms of reimbursement, ranging from on-the-spot reimbursement to ex-post bank transfer. In addition, the timing of the implementation of reimbursement differed by region. We employ this rich exogenous variation in our analysis. The design of the policy change enables us to not only identify and quantify changes in patient behavior after introduction of the copayment, but also to evaluate how persistent the changes are over time. Our paper focuses on patients aged 64 and older.

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[1]Motivation for the reform as well as details of its implementation are described in MHCR (2008).

[2]For details on policy change see Zděnek (2011)

This is often the most vulnerable subgroup of a population, due to age-related health issues, higher prevalence of chronic illnesses and financial constraints due to limited job opportunities and relatively low state pensions in the Czech Republic[3].

Our results show that after the introduction of copayments, the number of prescriptions filled decreased by 29%. At the same time, however, we find that the total price of prescription drugs purchased dropped only in the first quarter of the post-introduction period and then returned to previous levels and, in some cases, prices tended to increase. We explore determinants of this seeming inconsistency and identify three important behavioral responses to the cost-sharing. First, we find evidence of strategic timing behavior, estimating that people stocked-up on their medications in advance by almost 50% of the monthly pre-reform level of prescriptions. Second, since the copayment was paid on a per prescription basis, the average number of packages per prescription increased by 14%. Finally, the price composition of drugs purchased changed as physicians started to prescribe more expensive drugs. We show that, while the segment of cheapest prescription drugs (less than 30 CZK per package) plummeted by 60% (23% in total price) , the segment of high-cost drugs (more than 300 CZK per package) grew by more than 6%.

We also analyze the effects of policy reversal. We found no level response to the start of reimbursement, however, we found an increase in the linear trend. This implies that while the reaction to the introduction of copayments was an immediate drop in consumption, people reacted to reimbursement by a gradual adjustment in utilisation. The magnitude of this effect is lower compared to the introduction of reform also because only a small subset of pharmacies owned by regional governments was reimbursing the copayments.

To analyse the effect further, we looked into the separate reactions of different age groups, finding that they were strikingly similar. The only difference can be traced in their further development - while younger cohorts gradually increased utilisation of drugs, patients 80+ remained at the post-reform levels. Many patients decided to forego those types of drugs that did not cause immediate worsening of their health (e.g. drugs for high cholesterol or diuretics, and life style maintenance drugs like immunostimulants, products against joint / muscle pain and analgesics). While this decision can be considered a rational outcome of individual cost-benefit analysis, long-term health effects (mainly due

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[3]According to the OECD (2011) the ratio of average pension to average net wage is 64% (for men). This is an average percentage among OECD countries, with Greece and Hungary having the highest and Ireland and Mexico the lowest pensions relative to their respective average net wage.

to decreased demand in the category of chronic treatment drugs) are yet to be determined. In general, our study confirms that even patients from the highly sensitive subpopulation of retired patients are willing to change their behavior in response to external stimuli, and that these changes have predictable patterns.

2.2 Literature Review

The seminal basis for the evaluation of the effects of the patient cost-sharing on both utilization of medical care and health outcomes is the results of the RAND Health Insurance Experiment (summarized in Manning et al. (1987) and Newhouse (1993)). In the late 1970s the US government funded a large scale social experiment in which participating families were randomly assigned to plans with different levels of copayments and deductibles. The main findings that are important for our study are that (1) cost-sharing matters and (2) the price sensitivity of drug utilization to prescription drug copayments is fairly strong.

With expansion of health maintenance organizations (HMOs) in the US and adoption of similar cost-containment measures in the health care systems of other countries, the literature evaluating these measures has expanded. Recently, much attention has been given to prescription drugs.[4] Goldman et al. (2004) and Landsman et al. (2005) both look at the outcomes of natural experiments in prescription drug coverage and confirm a significant elasticity with respect to price. They find that price elasticity differs with different types of drugs - from low elasticity of utilization of drugs treating chronic conditions (- 8% for antidepressants and - 10% for antihypersensitives) to higher elasticity of utilization of treatments for acute diseases (-45% for anti-inflammatory drugs and -44% for antihistamines). Both of these studies, however, were conducted on on samples of non-elderly patients.

Rice and Matsuoka (2004) review studies that focus on the elderly. Most of these studies used cross-sectional data to identify the effect of cost-sharing either directly on health outcomes (Kennedy and Erb 2002; Pilote et al. 2002) or on the degree of "appropriateness" of utilization of medical services (Tamblyn et al. 2001). Existing studies were designed as either cross sectional or simple before-and-after comparisons and did not allow the researchers to control for underlying trends in the utilization of drugs. As the one

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[4]Mainly in the context of information used to design of Medicare Prescription Drug Coverage (part D) within the US Medicare.

exception, Johnson et al. (1997) use the quasi-experimental design of comparing health status indicators of HMO enrollees who experienced an increase in drug copayments with enrollees of a different HMO who did not. They do not find any significant effect. Most recently, Chandra, Gruber, and McKnight (2010) used a natural experiment of changes in elderly patients' cost-sharing with variation both over time and across plans. They estimated the elasticities of prescription drug demand, and provide the first sound evidence of the existence of offset effects (specifically higher hospitalization rates), mainly for the sickest population, with chronic diseases.

The first academic study that quantified the effects of the 2008 health care reform in the Czech Republic was conducted by Zápal (2010). He exploits variation created by the April 2009 legislative waiver that abolished copayments for children aged 0-18 to measure the effect on utilization of health care. He used data on drug sales from a pharmacy as a proxy for the number of visits to a doctor, finding no effect of the reform. He also points out a strong strategic timing effect, with evidence suggesting that visits to a doctor were often postponed after the start of waiver. However, his dataset consists of data from only one Prague pharmacy and the length of the dataset is very limited. The same natural experiment has been utilized by Votapkova and Zilova (2012), who used data from the EU-SILC survey, to look at the change in the number of visits to a doctor in the year after copayments for children were abolished.

One year after the introduction of copayments in 2008, the Ministry of Health of the Czech Republic prepared a non-technical evaluation document, which was summarized in the March 2009 press release (MHCR 2009). They conclude that regulatory copayments brought yearly savings of 10 billion CZK which were used to finance the high-cost-treatment of severely ill patients. They also report a 30% drop in the number of (filled) prescribed items and a 21% drop in the number of purchased drug packages.

2.3   Institutional background

Prior to the reform, the Czech public health insurance system provided complete coverage. The level of cost-sharing by patients was very low (around 10% of total health care costs) and consisted solely of the supplementary payments for prescription drugs (i.e. no copayments).[5] Expenditures on prescription drugs and medical aids together

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[5]Within the Czech health insurance system, part of the price for a prescription drug is paid by an insurance company (reimbursement), and part by a patient (supplementary payments). The ratio varies

accounted for approximately 60 billion CZK paid from the public health insurance system per annum.[6] The estimated value of unused and expired drugs was between 4-10 billion CZK annually, i.e. 6 - 16 % of total expenditures on health care (MHCR 2008). Moreover, the Czech Republic had the highest number of physician visits per person in the EU, at an average of 13 visits per year (MHCR 2008). According to anecdotal evidence, some visits to a physician were undertaken solely to obtain a prescription. The Ministry of Health claimed that the system of drug prescription and reimbursement was inefficient and that without reform its financing would be unsustainable in the long term.

On August 21, 2007, the Czech Parliament approved reform of the health care system as part of its comprehensive reform of public finance. The main goal was to establish appropriate incentives on both demand and supply sides of the health care market, thereby controlling costs and enhancing the efficiency of the system as a whole. To achieve this goal, on January 1, 2008, the Ministry of Health of the Czech Republic introduced mandatory cost sharing in the form of lump-sum copayments for several types of health care services including physician office visits (30 CZK), each prescription for drugs (30 CZK), emergency room visits (90 CZK) and each day of hospitalization / institutional care (60 CZK). The patient was obliged to pay 30 CZK for each drug prescribed, regardless of the number of packages purchased. Prescription drugs fully paid for by the patient were not eligible for the copayment.

The main function of the copayments was intended to be regulatory and behavioral. Policymakers declared that the prescription copayment was intended to lower the total number of prescriptions, with particular focus on low-priced drugs also available for the over-the-counter purchase.[7] The additional resources in the system, coming either from savings or from the copayments themselves, were supposed to be used to improve treatment of high-severity illnesses and to finance high cost life-saving medications.

It is important to note that several other changes were made in the system of reimbursement of drugs from the universal health insurance. Value added tax (VAT) on drugs increased from 5% to 9%, effective from January 1, 2008. The reimbursement amounts from the insurance companies did not change, however, though there was a change in the regulation of profit margins of pharmacies on the prescribed drugs. These steps have prevented the VAT increase being directly reflected in the final price of the drug, i.e.,

with the price of the drug, with more expensive drugs being more generously reimbursed.

[6]The exchange rate was 24.942 CZK/EUR in 2008 and 26.445 CZK/EUR in 2009.

[7]Contrary to common practice in the US, some drugs can be both prescribed and sold over the counter in the Czech Republic.

VAT increase was mostly absorbed by the profit margins of pharmacies.

The introduction of patient cost-sharing became one of the main topics of the October 2008 election for regional councils, which took place in 13 of 14 regions of the country (excluding Prague). Newly established regional governments pledged to mitigate the effects of health reform on citizens by reimbursing the copayments for treatment in regional government-owned health centers/hospitals from their own regional budgets.[8] With respect to copayments on prescription drugs, 12 regions (excluding Zlinsky kraj and Prague) decided to reimburse copayments in pharmacies affiliated with the hospitals and medical centers owned by regional governments (in total 53 pharmacies of approximately 2400 in the country). Stredocesky kraj started to reimburse copayments on January 1, 2009, followed by the other 12 regions from February 2, 2009, while Prague (the largest region) never reimbursed copayments. This has resulted in great variation in the ratio of reimbursed copayments among the regions (for details on the reimbursement policies of individual regions see Table 2.1).

The institutional set-up of the reform and its reversal created sufficient variation to identify the causal effect of copayments on the utilization of prescription drugs. In particular, it allows us to shed light on the behavioral responses of patients (and physicians) to the introduction of copayments, and the effect of these responses on the efficiency of the new policies.

2.4 Data and Methodology

2.4.1 Data and sample construction

We use unique individual level panel data obtained from the major Czech public health insurance company, which currently covers approximately 64% of the population of the Czech Republic. The data spans 2006-2009, i.e. two years before the introduction of copayments, one year of their existence and one year after they began to be reimbursed in regional government-owned medical facilities.

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[8]Different regions decided to implement different types of reimbursement. For example in Stredocesky kraj the patient had to agree (verbally) with the reimbursement of copayment by the region, in Jihocesky kraj the patient had to sign an agreement that he obtained a gift from the regional government, while in Plzensky kraj the patient had to pay the copayment himself and then claim a reimbursement by post. Some regions only reimbursed selected types of copayments - for example Zlinsky kraj reimbursed ambulance copayments, but did not reimburse ER copayments, or copayments for prescription drugs.

Our sample consists of a balanced panel[9] of 332,724 enrollees older than 64, which represents 5% of all enrollees of the health insurance company and 29% of its enrollees older than 64 years of age. The insurance company that provided the data has historically served more than 77% of the elder population of the Czech Republic. The sample was randomly selected from all enrollees over 64. This allows us to claim that our results give a representative picture of the drugs utilization patterns among the elderly in all regions of the Czech Republic.

Our data provide information about all prescribed drugs, materials and medical aids that enrollees utilized throughout the period of coverage, including drugs provided at hospitals and physician's offices, and drugs purchased by prescription at pharmacies. For our analysis in this paper we focus on prescription drugs collected at pharmacies, because only these were affected by the introduction of copayments, and we disregard the drugs provided in hospitals and during other inpatient admissions.[10] Information in our dataset includes identification of the general type of drug (the first three digits of ATC nomenclature[11]), number of packages, date of purchase, identification of the physician who prescribed the drug, identification of the pharmacy and the final price of the drug.

We construct four utilisation measures: (1) number of prescriptions filled at pharmacies, (2) total price of purchased prescription drugs[12], (3) total number of packages of prescription drugs purchased, and (4) average number of packages per prescription. We then compute the total of each utilization measure for each cohort in each region, year and month, separately for males and females, which yields 46,977 observations in our final dataset.

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[9]Our dataset consist only of enrollees who were continuously insured by the designated health insurance company for the entire 4 years. In our analysis we thus do not consider people who changed insurers in the given time period, or who became deceased. Even though this might bias results, we argue this would be a downward bias due to generally higher utilisation levels in the last years of life, and thus our results provide a lower bound for the estimates.

[10]One could thus argue that part of the estimated effect was offset by an increase in the drugs provided in physician's offices and hospitals. Nevertheless, this form of provision accounts for only around 9% of all utilised drugs, the rest being prescriptions. Moreover, while the raw number of prescriptions dropped by 29% between 2007 and 2008, the amount of drugs provided by physicians grew by only 4%, which is less than the growth in the previous year (7%).

[11]The Anatomical Therapeutic Chemical (ATC) Classification System is used for the classification of drugs. It is controlled by the WHO Collaborating Centre for Drug Statistics Methodology (WHOCC).

[12]Regarding the total expenditure on purchased drugs, it is important to distinguish expenditures on the price of drugs and expenditures on copayments. In our analysis, we decided to omit the latter, as they are a simple multiplication of the number of prescriptions times 30, and their inclusion would distort information on the change in price composition of the purchased drugs.

2.4.2   Empirical approach

To quantify the magnitude of the causal effect of the introduction of copayments, we estimate the specification of the form:

$$
\begin{aligned}
\text{util}_{\text{crmy}} \quad = \quad & \alpha + \beta_1 \, \text{reform}_{\text{my}} + \beta_2 \, \text{reversal}_{\text{rmy}} + \\
+ \quad & \gamma_1 \, \text{trend}_{\text{my}} + \gamma_2 \, \text{trend\_after}_{\text{my}} + \gamma_3 \, \text{trend\_reverse}_{\text{my}} \\
+ \quad & \delta_1 \, \text{M}(-3)_{\text{my}} + \delta_2 \, \text{M}(-2)_{\text{my}} + \delta_3 \, \text{M}(-1)_{\text{my}} + \delta_4 \, \text{M}(1)_{\text{my}} + \delta_5 \, \text{M}(2)_{\text{my}} + \delta_6 \, \text{M}(3)_{\text{my}} \\
+ \quad & \rho \, \text{male}_{\text{rmy}} + \omega_1 \text{cohort} + \omega_2 \text{cohort}^2 + \theta_r + \phi_m + \epsilon_{\text{crmy}} \quad\quad\quad\quad (2.1)
\end{aligned}
$$

where util_{rmy} is selected utilization measure (in logs) for cohort c in region r, month m and year y, and $\text{reform}_{\text{my}}$ is a dummy variable indicating time after introduction of copayments (i.e. Jan 08 - Dec 09). Variable $\text{reversal}_{\text{rmy}}$ is zero for the period before the start of reimbursement, while afterwards it takes on the values of the share of copayments that were actually reimbursed in the given region (Jan/Feb 09 - Dec 09, reimbursement shares available in Table 2.1). Therefore, we interpret β_1 as the level percentage change in selected utilization measure after the introduction of copayments, and β_2 as additional percentage change after copayments started to be reimbursed by regional governments. We control for a linear trend in utilisation corresponding, for example, to ageing and increasing health care needs of our cohorts, as well as for possible changes in trends after both introduction and reversal of the policy.

We also account for the possible **strategic timing of drug purchases** (stockpiling). For the patients informed about the upcoming reform it would be optimal to put pressure on their physicians in order to shift all possible prescriptions to before the start of the reform. This would, however, imply a decrease in prescription activity in the period immediately after the introduction. We account for this possibility by introducing the dummy variables M(-3) - M(3) indicating separately three months before and after copayment introduction.[13] We wanted tocapture a persistent (robust) change in the utilization patterns, rather than a one-time shift in the timing of prescription collection. We also estimate an alternative specification without these controls, to demonstrate the importance of this phenomena and its effects on the evaluation of the reform.

Other control variables included are a quadratic polynomial of cohort (age in 2006), region and month fixed effects ω_c, θ_r and ϕ_m and a gender dummy. We cluster by regions,

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[13]The three month period was chosen based on visual inspection of data.

to allow both for autocorrelation and heteroskedasticity in residuals.[14]

We first estimate both standard and alternative specification without stockpiling dummies on the full sample. Then we use the standard specification to separately estimate effects for **different price categories** based on price per one package. The hypothesis is that with the increasing price of the drug the lump sum copayment represents smaller share of the total price and thus is less effective in regulation of usage. We have divided drugs into six categories: drugs priced 0 - 30 CZK (group of drugs targeted by the policy, as the copayment is higher than their price), 30 - 60 CZK, 60 - 100 CZK, 100 - 300 CZK, 300 -1300 CZK and more than 1300 CZK[15]. By tracking changes in the price composition of drugs, we can also detect whether the prescription behavior of physicians has changed (e.g. whether they prescribe fewer low-cost drugs and more high-cost drugs).[16]

Next, we estimate the regression separately for **different age groups** of patients, to describe how the patterns of utilisation change with rising age. We divided patients into 5 age groups: younger than 70, 70-74, 75-79, 80-84 and 85+. While the utilisation of prescription drugs might differ by age simply due to different health needs, in the absence of income age is the best proxy for the vulnerability, due to a relatively low level of retirement benefits and absence of other sources of income among the elderly population.

Finally, we want to assess whether the copayments affected consumption of different drug categories differently; in particular whether, in line with findings of Landsman et al. (2005), there was a different reaction with respect to acute treatment vs. chronic treatment drugs. Therefore, we estimate the regression separately for each of 82 available ATC groups (2nd level).[17]

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[14]We considered using GLS to account for autocorrelation and heteroskedasticity, however, estimated standard-errors were similar to the OLS estimation with clustering. Bertrand, Duflo, and Mullainathan (2004) explain the problems stemming from autocorrelation and heteroskedasticity in difference-in-difference estimates.

[15]Drugs costing more than 1300 CZK are the top percentile in the price distribution of drugs in 2006. In this category, therefore, we capture the trends in prescription of high-cost drugs.

[16]In a system in which more expensive drugs are usually fully reimbursed, physicians may opt more often to prescribe more expensive drugs, effectively lowering the total amount of payments that a patient has to make (supplementary payment for the drug plus lump sum copayment).

[17]We have excluded groups with fewer than 50 prescriptions, effectively omitting 12 categories.

2.5 Results

A basic description of the sample and of trends in the utilisation of prescription drugs in the period analyzed can be found in Figure 2.1 and Table 3.2. Table 3.2 provides additional information about the age, gender and regional composition of the sample and summary statistics of both important utilisation measures: the number of prescriptions and price of drugs purchased. Observed trends are in line with general intuition. There is an increasing percentage of women in older cohorts, consistent with the higher life-expectancy of women and thus higher probability of remaining in a balanced sample. The share of cohort categories on the total sample population remains constant over the years, indicating a fairly similar response of utilisation to reform. We observe substantial variation in utilisation across regions, with Prague as an outlier with the lowest number of prescriptions yet the highest price of drugs purchased per person. Nevertheless, at all levels of categorisation we can observe a drop in the number of prescriptions and number of packages after introduction of copayments.

Figure 2.1 depicts the evolution of different utilisation measures over time, and illustrates the direction and magnitude of changes after the implementation of copayments. We observe a peak in the total number of filled prescription items one quarter before introduction, while immediately after, these numbers dropped and remained at the lower levels for the next two years. On the other hand, the total price of prescription drugs purchased decreased only temporarily, and resumed growing at increasing rates afterwards. There is a discontinuous jump in the average number of packages per prescription, indicating that prescription of additional packages was a common behavioral response to the reform. Finally, we find that patients made fewer visits to pharmacies to fill prescriptions.

While there is an evident effect of the introduction of copayments, the question of how individual copayments interacted to cause this effect remains. In our supplementary analysis we found that the post-reform drop in the number of prescriptions (around 30%) can be ascribed to all three levels in the prescription process. Fewer patients visited a physician in general (-10%), and they made slightly fewer visits per person (-5%). Finally, fewer prescriptions were written at each visit (approx - 5-10%). Comprehensive analysis of these findings are provided in Appendix 1.

These observations were confirmed by the results of our estimation, summarized in Table 2.3. In panel A we show a robust 29 % level decrease in the **number of pre-**

scriptions filled in the post-introduction period.[18] After the start of reimbursement we observe an increasing trend in the number of prescriptions filled, corresponding to a gradual return of patients to their pre-reform utilisation patterns.

We would like to stress, however, the extent of the **stockpiling effect** and its implications for policy evaluation. Patients were well-informed about the timing of the reform and were able to take the opportunity to save money by asking their physicians to prescribe more drugs before its onset. According to our estimates, during the three months before introduction of reform people stocked up (cumulatively) almost 50% of the pre-reform monthly level of prescriptions, which almost perfectly corresponds to the relative drop in the first quarter after introduction. Comparing the results of two specifications in Table 2.3 panel A, we see that without accounting for the strategic timing we would overestimate the overall effect by 12.5%, i.e., by more than a third of its actual value.

While the quantity of prescriptions conveys information about patients' visits to physicians and changes vis-a-vis the reform, the **number of packages** is more indicative of actual drug utilization. In Table 2.3 panel C we report a 13% post-introduction drop in the number of packages purchased accompanied by significant decrease in growth (-0.3% a month). We detect an even higher stockpiling effect than by prescriptions, cumulatively at 55% of pre-reform values.

Stockpiling behavior motivated us to look at the evolution of the **number of packages per prescription**. We inferred that as the number of prescribed packages is not effectively limited, the rational response would be to increase it to the maximum extent possible given the expiration date. Indeed, we find a significant increase in the number of packages per prescription estimated at 16% (Table 2.3, panel D). After the start of reimbursement we observe a trend reversal (-0.2% per month), which leads us to infer that this behavioral response is fairly persistent over time. Estimates of the stockpiling effect confirm our assumption that patients both stocked up on prescriptions before the reform, and also obtained prescriptions for more packages.

Finally, we look at the **total price** of prescribed drugs. Estimates endorse the visual observation from the Figure 2.1, where, after accounting for the stockpiling effect and consequent offset in utilisation, neither reform nor reversal had a significant level effect on

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[18]We performed a robust check on our results using the subsample of prescriptions purchased by patients officially residing in different regions, to account for cross-region traveling after the introduction of reimbursement. Nevertheless, results for this subsample were similar to the aggregate results and we have not estimated a significant change in the proportion of out-of-region clients after the reform, or its reversal. For detailed results, please contact the authors.

the total price of prescribed drugs. Comparing columns (1) and (2) in panel B of Table 2.3 we see that accounting for stockpiling changed the sign of the estimated effect from a decrease (which was communicated by the Ministry in media) to an actual increase. Furthermore, we see that after introduction of copayments the trend became significantly steeper (+0.5% per month), and there was no change after the start of reimbursement.

2.5.1 Price composition of purchased drugs

Growing expenditures on a decreasing number of drug packages (and even lower number of prescriptions) present an interesting paradox, which leads to speculation that the price composition of the drugs prescribed changed. Therefore, we have categorized drugs with respect to their unit price (per package) and estimated the effect of copayments on each group separately. Figure 2.2 depicts the evolution of the number of prescriptions as well as total price of these drugs over time separately for each price group, together with the representation of the shares that each category represents. To simplify comparison, we present variables in logarithms, normalized by the log level in January 2006, i.e., as percentage differences from the initial value. Results of the estimation are summarized in Table 2.4, panels A-D.

The copayments should primarily affect prescription of cheaper drugs. Drugs priced lower than the copayment of 30 CZK should be particularly sensitive, because the patient would be better off to purchase them directly over-the counter. Although some lower priced drugs that are available only by prescription (e.g. antidepressants) exist, if they are fully paid for by the patient, the copayment does not apply. Indeed, our data confirm that the number of packages as well as total price of this group of drugs decreased discontinuously from the introduction of copayments. In Table 2.4, panel A we show that the number of prescriptions dropped by 61%. The start of reimbursement then seems to reverse the decreasing utilisation trend. [19]

Contrary to aggregate results, in this group the total price persistently dropped by almost 23% percent. This is less than the drop in the number of filled prescriptions, which can be explained by the 24% increase in the number of packages per prescription. We can thus conclude that for the category of drugs with a unit price under 30 CZK, the reform

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[19] One could argue, however, that a deeper drop was expected, as prescription of this group of drugs is irrational. We therefore performed a robustness check of this estimation using as dependent variable the total price for the prescription (because the prescription could be still rational if more than one package was prescribed). Results confirmed our intuition, with an estimated 88% drop.

had the intended effect of decreasing both utilization and expenditures on drugs from the perspective of public insurance. Nevertheless, we cannot infer anything about the amount of drugs purchased over the counter and related expenditures.[20] Moreover, even though drugs under 30 CZK represent around 20% of all packages sold, they constitute only 2-3% of the total price of prescription drugs purchased.

Within the category of cheaper drugs (under 300 CZK), we originally singled out drugs with a unit price between 30 and 60 CZK, as in this category the drug price corresponds to the copayment for prescription plus copayment for the physician visit. Yet, the results are very similar to the categories of 60-100 and 100-300, so we will comment on them together. We found a persistent drop in both the number of prescriptions filled (30% , 26% and 19%, respectively) and a smaller drop in the total price (12% , 12% , and 0%). This is, however, a much weaker response than in the category of the cheapest drugs. Reimbursement that began in 2009 primarily affected long-term trends, indicating that patients gradually returned to their pre-reform utilisation. In summary, in the broader category of drugs cheaper than 300 CZK, we confirm a discontinuous drop in utilization, consistent with the intentions of the reform. This broader category represents more than 90 % of total purchased packages, however, only 50 % of total price.[21] Yet the results are striking, because as numerous pharmecists have commented in the media, the reform did not effectively change the total purchase price for the patient, as the 30 CZK copayment was absorbed by the lower supplementary payment of the patient.

On the other hand, drugs with unit price higher than 300 CZK represent 50-60 % of total price of prescription drugs, and the total number of packages purchased in this group did not show any permanent decrease after the reform. Quite the opposite, for the drugs priced 300-1300 CZK, we estimate a 6% increase in the number of prescriptions in the period after reform accompanied by a significant increase in the trend. This translates into evolution of expenditures by 6% increase in total price after the start of reform and an additional 10% after reversal (and a continuing increasing trend). The increasing trend is even more pronounced in the category of drugs which represented the top 1% of prices in 2006, i.e. more expensive than 1300 CZK. Here we find an 18% increase in the number of prescriptions accompanied by almost 1.5 percentage points / month increase in the linear trend. The number of packages and total price of drugs follow very similar patterns. In both price categories no bundling effect is present.

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[20]These purchases are not recorded by the insurance company and therefore do not appear in our data
[21]After reform the ratios changed to slightly above 80 % and 40%, respectively.

The question arises as to whether the difference in evolution was caused by prescription of more expensive drugs within the same line of treatment or introduction of previously unavailable drugs. While the information about drug types is not detailed enough to identify newer drugs, we can say that after the reform physicians started to prescribe more expensive drugs within the same class of drugs.[22] In the price category of 300-1300 CZK the increase was driven mostly by drugs for treatment of cardiovascular diseases (approx 1/3 of all prescriptions in this price range), and urological drugs[23]. In the highest price category, on the other hand, the greatest increase was recorded for osteoporosis treatment, representing approximately 75% of drugs in this category. Other growing ATC categories included psychoanaleptics (antidepressants and anti-dementia drugs) and diabetes treatment, but these represented only a small share of drugs within respective ATC categories.

2.5.2 Changes in the utilisation of prescription drugs by age category

Our analysis of drug utilisation by age categories is motivated by the different health needs of individual age subgroups. Indeed, in Table 3.2 we see that patients older than 85 years fill almost 50% more prescriptions per person than patients younger than 70 years. Interestingly, however, the total price of their drugs only amounts to 90% of the bills of younger patients. Consequently, we ask whether these differences also imply different willingness and ability to cut down on utilisation.

General trends are illustrated in Figure 2.3[24] and estimation results are summarized in Table 2.5. In general, the magnitude of the discontinuous jump in utilisation measures after the introduction of copayments is very similar for all age groups and thus corresponds to overall values – 29% decrease in number of prescriptions and approximately 14% decrease in number of packages (with 14-18% increase in packages per prescription), with no significant change in the total price of drugs purchased. The largest difference can be noted for the category of people older than 85 - as they do not have a long-term

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[22] We approximated this by the entropy of the prescription choices between different drug types by the patient, and followed its mean value in time.

[23] Their upward trend, however, had already started in 2007 when most urological drugs were reclassified from the more expensive category due to a decrease in the pharmacy margin and, correspondingly, the total price.

[24] Again, we simplify comparison by expressing the variables of interest in logs and normalizing them by their value in January 2006

trend of increasing utilisation (approx 0.3% per month) and after reimbursement they do not tend to converge to the pre-reform levels, but rather stay at lower post-reform levels.

We were interested in identifying the main driver of the differences between age categories. First, we compared the price composition of the average "drug consumption basket" of different categories. However, we did not find significant differences. Therefore, we looked further into the utilisation of drugs from different treatment categories.

2.5.3 Effect of the reform on the utilisation of selected drug categories

We follow the Anatomical Therapeutic Chemical (ATC) classification system which has 14 main groups (1st level) with different pharmacological and therapeutic subgroups (2nd level). While in the dataset we observe 94 categories, for estimation we omitted 12 as having too few observations. For illustration of general pattern, we have chosen categories that had one of the ten greatest shares in total utilisation of at least one age group in at least one year. In Table 2.6 we report the share of the given category on the total number of prescriptions for all age groups, and their estimated change after the introduction of copayments.

The biggest share of all utilised prescription drugs in most age categories was for cardiovascular drugs (group C in ATC nomenclature). In terms of age structure, while for patients under 80 years after reform utilisation of these drugs dropped (ranging from -21% for lipid modifiers to -41% for vasoprotectives), for older patients the magnitude of the drop was only half of those numbers. We explain this by differences in the need for utilisation. These are maintenance drugs for treatment of chronic health conditions.

Our results indicate that at younger ages, when severe symptoms are unlikely to be observed, patients may choose to forego their medication. This becomes less and less sustainable at older ages, when symptoms are more likely to manifest. By way of contrast, a good example of a chronic treatment drug where cutting down on utilisation is not an option are drugs used to treat diabetes (A10). Indeed, in this category (see Table 2.6) we see only a modest drop in utilisation across the age categories.

On the other hand, in Table 2.7 we report the top 10 drug categories with the greatest utilisation drops after reform.[25] In line with common intuition, these are mostly so called

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[25]These categories were selected based on the drop estimated for the category of people younger than 70.

"life-style maintenance" drugs, where the decision to utilize the drugs lies primarily at the discretion of patients. Indeed, after introduction of copayments all age groups decided to lessen use of psycholeptics, vaccines, immunostimulants, medicines treating cough and cold, products against joint and muscular pain, and dermatological preparates.

2.6   Concluding remarks

In this paper we analyze the natural experiment of introducing small lump-sum copayments for health services in the Czech Republic. Our findings have several generalizable implications for policy makers considering similar measures. First, we find that patients approach reforms with reasonable foresight and adjust their behavior to mitigate the impact of reforms. In our example, patients not only prepare in advance by "stocking-up" on prescriptions few months before the introduction of reforms, but also exploit the weakness of the reform design where the fee is paid per prescription, not per package. This implies that policy makers should: 1) carefully construct the incentive structure of reform in the design stages (e.g. limit numbers of packages per prescription), and, 2) in the evaluation stage, be aware of strategic timing issues that can bias initial estimates of the effects.

While the introduction of copayments induced an almost immediate and massive response, the estimated effects of policy reversal are relatively small. None of the utilisation measures reacted by a level response, but rather by a trend adjustment back to the pre-reform values. The magnitude of this effect is also much lower compared to the response to introduction. This can be explained by the institutional set-up of reversal, when only a small subset of pharmacies owned by regional governments (around 52 pharmacies around the country) were effectively reimbursing the copayments.

We have also looked at whether the reform disproportionately affected the most vulnerable subgroups of the population, where we proxy vulnerability by age category. In younger cohorts patients were willing to cut down on their utilisation and lowered their demand for so called "life-maintenance" and chronic treatment drugs. On the other hand, in older cohorts the post-reform drop was more limited, indicating that these age-groups cannot forego treatment without severe health implications. One could therefore argue that the reform did not have an immediate negative effect on the health of elderly, as they have carefully considered which drugs they can and cannot afford to forego. There are, however, also possible negative implications. First, the elderly face a higher financial

burden of copayments, which in their case represent a non-negligible share of monthly expenditures (approx 4.5% based on Household Budget Survey statistics). Second, long term health outcomes may be negatively affected by under-utilisation of chronic treatment drugs, a consideration that can be confirmed only after the passage of time.

Appendix A

Even after analyzing the overall effect of the reform, one important policy question remains: Was the drop in the number of prescriptions filled the result of the copayment for the prescription drugs, or of the introduction of copayments in general and patients subsequently cutting down their visits to a physician?? How do these different types of copayments interact?

We have attempted to partially answer this question by matching data on prescriptions filled at pharmacies and visits to physicians. We identified the visits to physicians with associated prescriptions by personal ID, physician ID and date of visit in relation to the date of prescription filling (we have chosen max 15 days gap between the two, as this is the deadline provided in the law). Three types of episodes have been identified:

1. Visits to a physician with associated prescription

2. Prescription without associated visit to a physician: most likely these represent long-term prescriptions, as most are prescribed by the same provider and are filled at fairly regular intervals

3. Visits to a physician without associated prescription

For type 1 and 2 episodes we look separately at how many people visited a physician's office or pharmacy, respectively, in a given period and how many visits per person they made (both attributable primarily to the copayment for the visits) and how many prescriptions were written or filled per visit (impact of a copayment for prescription) both before and after introduction of copayments. For type 3 episodes we look at how the frequency of visits changed over time.

In Figure 2.4 we present results for the visits with associated prescriptions. We can see that there is a post-reform drop in the number of prescriptions (around 30%) which can be ascribed to all three levels in the prescription process. Fewer patients visit physicians in general (-10%), and they make slightly fewer visits per person (-5%). Finally, fewer prescriptions are written at each visit (approx - 5-10%). The magnitude of change varies significantly for different age groups, with the oldest category of patients having the greatest drop.

Results for episodes where prescriptions were filled without a previous visit to a physician (Figure 2.5) have a similar pattern, yet much greater magnitude (total drop around 40%, primarily driven by a lower number of patients making any visit to a doctor).

Again, the differentiation between age groups is only significant at last level - i.e. number of prescriptions filled per one pharmacy visit.

Interestingly, introduction of copayments did not change the patterns of the probability of at least one visit to a GP (Figure 2.6) or specialist (Figure 2.7) without an associated prescription being written (while with GPs the pattern is an increasing trend, in specialist visits we see seasonal fluctuations around the constant). Conditional on at least one visit, the non-prescription visits to a GP decreased consistently by 10% (without a hint of reversal), while specialist visits remained roughly the same.

Table 2.1: Overview of regional reimbursement policies.

Region	Start of reimbursement	Reimbursement of copay for drugs	Type of agreement	% of reimbursed copays	Number of reimbursing pharmacies
Praha	never	NO	NA	NA	NA
Stredocesky	1.1.2009	Yes	oral	95 %	5
Jihocesky	1.2.2009	Yes	written	70 %	7
Plzensky	1.2.2009	Yes	ex-post	25 %	3
Karlovarsky	1.2.2009	Yes	oral/written	63 %	1
Ustecky	1.2.2009	Yes	written	40 %	4
Liberecky	1.2.2009	Yes	written	51 %	2
Kralovehradecky	1.2.2009	Yes	oral/written	65 %	3
Pardubicky	1.2.2009	Yes	written	46 %	5
Vysocina	1.2.2009	Yes	written	60 %	5
Jihomoravsky	1.2.2009	Yes	written	65 %	4
Olomoucky	1.2.2009	Yes	written	65 %	3
Zlinsky	1.2.2009	NO	written	25 %	4
Moravskoslezsky	1.2.2009	Yes	written	45 %	8
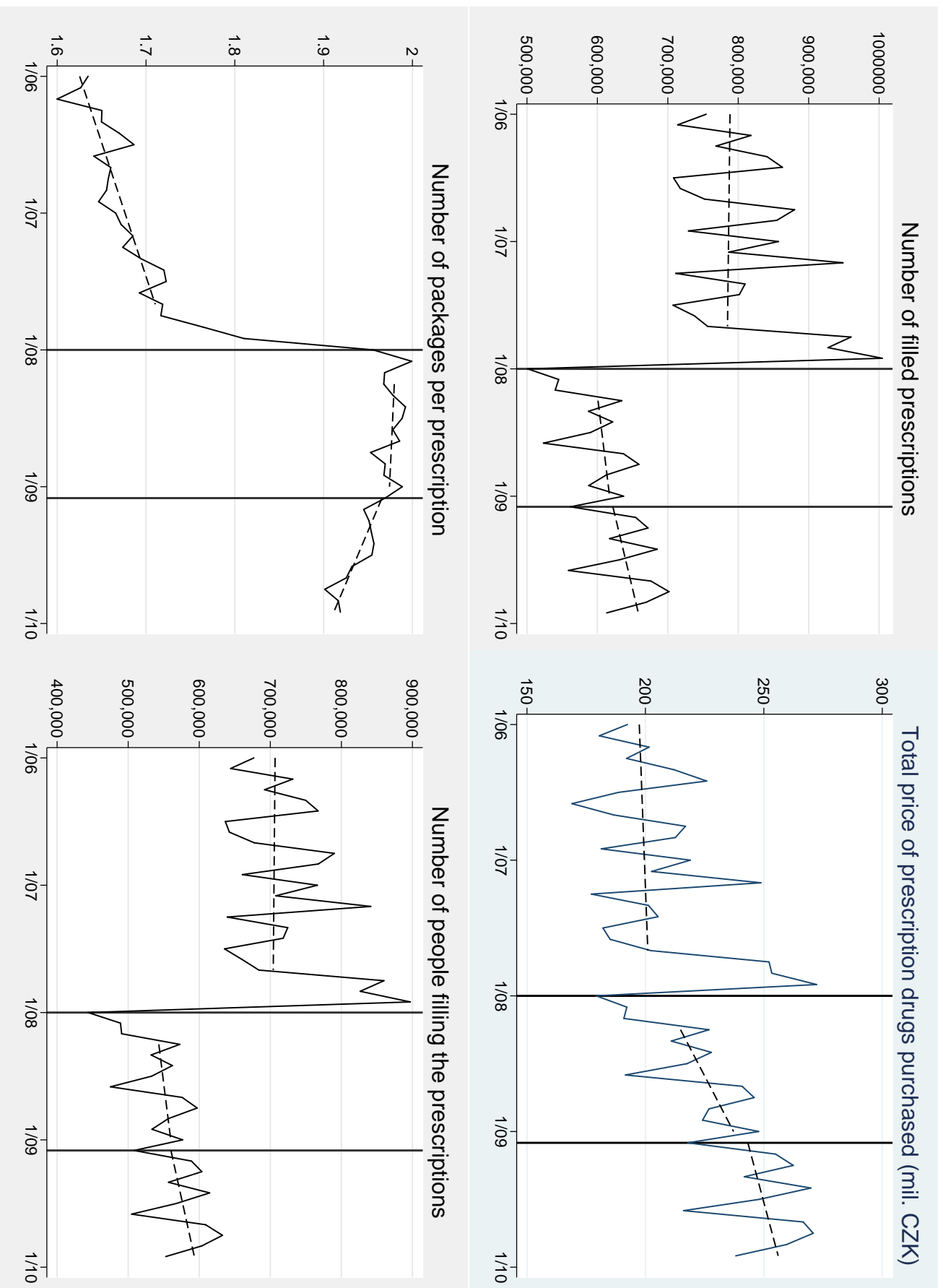
Figure 2.1: Overview of aggregate utilisation measures, including linear fit (reform - 1.1.2008, reversal - 1.2.2009)

Table 2.2: Summary statistics of the sample of patients purchasing prescriptions drugs over 2006-2009, by age category and NUTS.

Age group	% share of group on total	female (%)	Prescriptions (per person)				Expenditures (per person)			
			2006	2007	2008	2009	2006	2007	2008	2009
<70	40	57	24.6	26.3	19.1	21.1	7,140	7,840	7,990	9,330
70-74	23	61	30.3	32.4	23.0	25.1	7,980	8,810	8,820	10,240
75-79	20	65	34.1	36.0	25.2	27.0	7,930	8,720	8,560	9,860
80-84	12	71	36.1	37.5	26.2	27.4	7,330	8,950	7,790	8,620
85+	5	75	36.3	37.0	25.5	26.0	6,310	6,550	6,240	6830

Region	pharmacies	patients	Prescription (per person)				Price of purchased drugs (per person)			
			2006	2007	2008	2009	2006	2007	2008	2009
Praha	472	64,755	23.2	24.2	18.0	19.3	7,230	7,750	8,030	9,170
Stredocesky	269	50,015	24.1	25.1	18.3	19.7	5,330	5,800	5,840	6,800
Jihocesky	191	31,224	26.3	28.1	20.4	21.9	6,090	6,710	6,840	7,850
Plzensky	132	23,069	26.1	27.5	20.0	21.3	7,020	7,610	7,670	8,710
Karlovarsky	102	12,401	27.3	28.7	21.0	22.7	6,540	7,110	7,160	8,470
Ustecky	204	32,676	25.9	27.1	20.1	21.7	6,150	6,630	6,900	7,920
Liberecky	118	20,431	25.6	26.8	18.8	20.3	5,870	6,310	6,380	7,310
Kralovehradecky	149	25,915	26.5	27.9	20.4	21.9	6,860	7,250	7,520	8,560
Pardubicky	154	25,616	26.0	27.6	20.3	22.1	6,390	7,110	7,180	8,420
Vysocina	122	22,806	25.8	27.3	20,0	21.4	6,030	6,660	6,810	7,920
Jihomoravsky	361	46,834	28.7	30.1	21.3	22.7	7,400	8,150	8,330	9,300
Olomoucky	157	24,957	27.4	28.8	20.5	22.0	6,900	7,450	7,510	8,530
Zlinsky	160	26,228	28.1	29.8	21.1	22.6	6,490	7,160	7,280	8,290
Moravskoslezsky	302	34,918	28.8	30.5	21.7	23.7	7,030	7,760	7,840	9,200

Table 2.3: Effect of introduction and consequent reimbursement of copayments on the utilization of prescription drugs.

	A. Number of prescriptions		B. Price of drugs		C. Number of packages		D. Packages/prescription	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
Reform	-0.411***	-0.285***	-0.144***	0.014	-0.268***	-0.125***	0.143***	0.160***
	(0.017)	(0.021)	(0.018)	(0.023)	(0.016)	(0.020)	(0.005)	(0.006)
Reversal	0.030	-0.008	0.070**	0.019	0.039	-0.005	0.009	0.003
	(0.028)	(0.031)	(0.027)	(0.030)	(0.029)	(0.029)	(0.010)	(0.010)
Trend	0.003***	0.000	0.005***	0.001*	0.006***	0.002***	0.003***	0.002***
	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)
Trend_after	0.002	0.000	0.007***	0.005**	-0.002	-0.003**	-0.004***	-0.004***
	(0.002)	(0.000)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
Trend_reverse	-0.002	0.007**	-0.007***	0.003	-0.003	0.006**	-0.002**	-0.001
	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)	(0.001)	(0.001)
M(-3)		0.090***		0.130***		0.100***		0.010**
		(0.006)		(0.016)		(0.009)		(0.005)
M(-2)		0.100***		0.158***		0.133***		0.033***
		(0.018)		(0.018)		(0.018)		(0.004)
M(-1)		0.267***		0.330***		0.325***		0.058***
		(0.014)		(0.017)		(0.014)		(0.003)
M(+1)		-0.201***		-0.228***		-0.233***		-0.032***
		(0.023)		(0.030)		(0.023)		(0.006)
M(+2)		-0.017		-0.042*		-0.018		-0.001
		(0.017)		(0.022)		(0.017)		(0.004)
M(+3)		-0.200***		-0.229***		-0.200***		0.000
		(0.013)		(0.019)		(0.014)		(0.005)
R^2	0.941	0.942	0.937	0.938	0.938	0.939	0.350	0.353
N	46,977	46,977	46,977	46,977	46,977	46,977	46,977	46,977

Note: Each panel shows results of regressions of different dependent variables (in logs) under two specifications: (1) baseline regression controlling for level and trend effect of introduction of copayments and reversal; (2) regression with controlling for the timing effect 3 months before and 3 months after introduction of copayments. All regressions control for region, month and fixed effects, gender, as well as cohort effects (quadratic specification) ; SE are clustered on the level of regions. ***,** and * denote significance at 1%, 5% and 10% level; standard deviations are in the brackets

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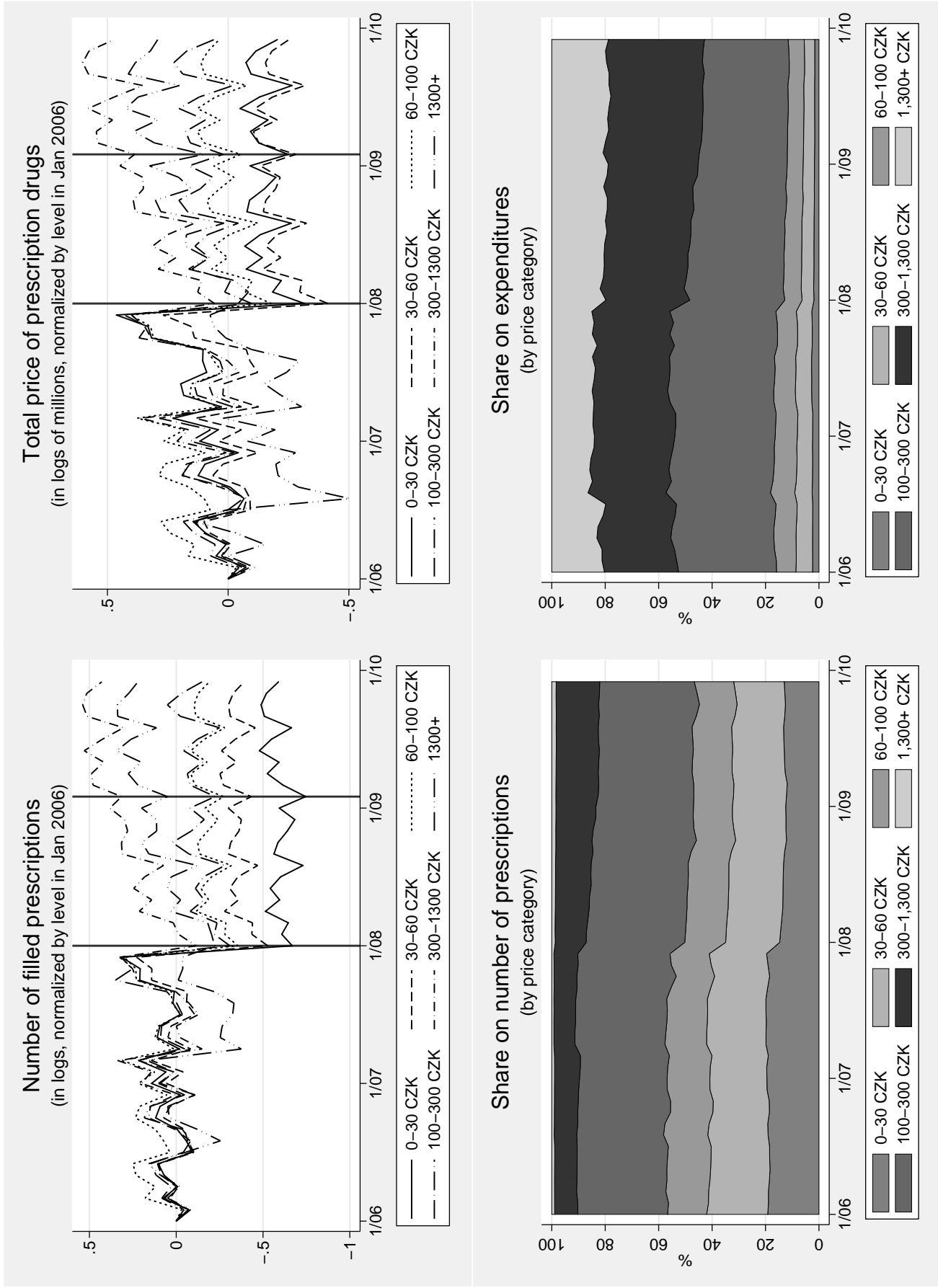
Figure 2.2: Evolution of total number of prescriptions, as well as of share on total number of prescriptions, by price per package.

Table 2.4: Effect of introduction and consequent reimbursement of copayments on the utilization of prescription drugs, by price category.

A. Total prescriptions (log)

	<30 CZK	30-60 CZK	60-100 CZK	100-300 CZK	300-1300 CZK	>1300 CZK
Reform	−0.608 ***	−0.296 ***	−0.261 ***	−0.186 ***	0.063 **	0.183 ***
	(0.030)	(0.024)	(0.021)	(0.015)	(0.027)	(0.016)
Reversal	−0.064	−0.012	0.007	−0.015	0.086 *	0.045
	(0.046)	(0.031)	(0.028)	(0.029)	(0.042)	(0.026)
Trend	0.003 ***	−0.001	−0.002 ***	0.001 **	0.003 **	−0.015 ***
	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)
Trend_after	−0.009 **	−0.001	0.000	−0.002	0.011 ***	0.026 ***
	(0.003)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
Trend_reverse	0.019 ***	0.005	0.007 ***	0.007 **	−0.002	0.000
	(0.004)	(0.003)	(0.002)	(0.002)	(0.003)	(0.002)
R-squared	0.921	0.927	0.933	0.939	0.928	0.733
N	45,430	45,540	44,145	45,626	41,924	33,169

B. Total price of purchased drugs (log)

	<30 CZK	30-60 CZK	60-100 CZK	100-300 CZK	300-1300 CZK	>1300 CZK
Reform	−0.228 ***	−0.119 ***	−0.115 ***	0.001	0.057 *	0.228 ***
	(0.024)	(0.023)	(0.020)	(0.017)	(0.031)	(0.024)
Reversal	−0.060	−0.024	0.025	0.012	0.099 **	0.006
	(0.040)	(0.025)	(0.025)	(0.029)	(0.043)	(0.031)
Trend	0.006 ***	−0.002 **	0.000	0.002 ***	0.007 ***	−0.002
	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)
Trend_after	−0.012 ***	−0.000	−0.002	−0.004 ***	0.005 ***	0.016 ***
	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
Trend_reverse	0.010 ***	0.004	0.007 ***	0.006 **	−0.001	0.000
	(0.003)	(0.002)	(0.002)	(0.001)	(0.003)	(0.002)
R^2	0.904	0.919	0.925	0.936	0.917	0.686
N	45,430	45,540	45,626	45,626	41,924	33,169

Note: Each panel shows coefficients for different dependent variable for different price ranges. All regressions control for region, month and fixed effects, gender, as well as cohort effects (quadratic specification) ; SE are clustered on the level of regions. ***, ** and * denote significance at 1%, 5% and 10% level, standard deviations are in the brackets
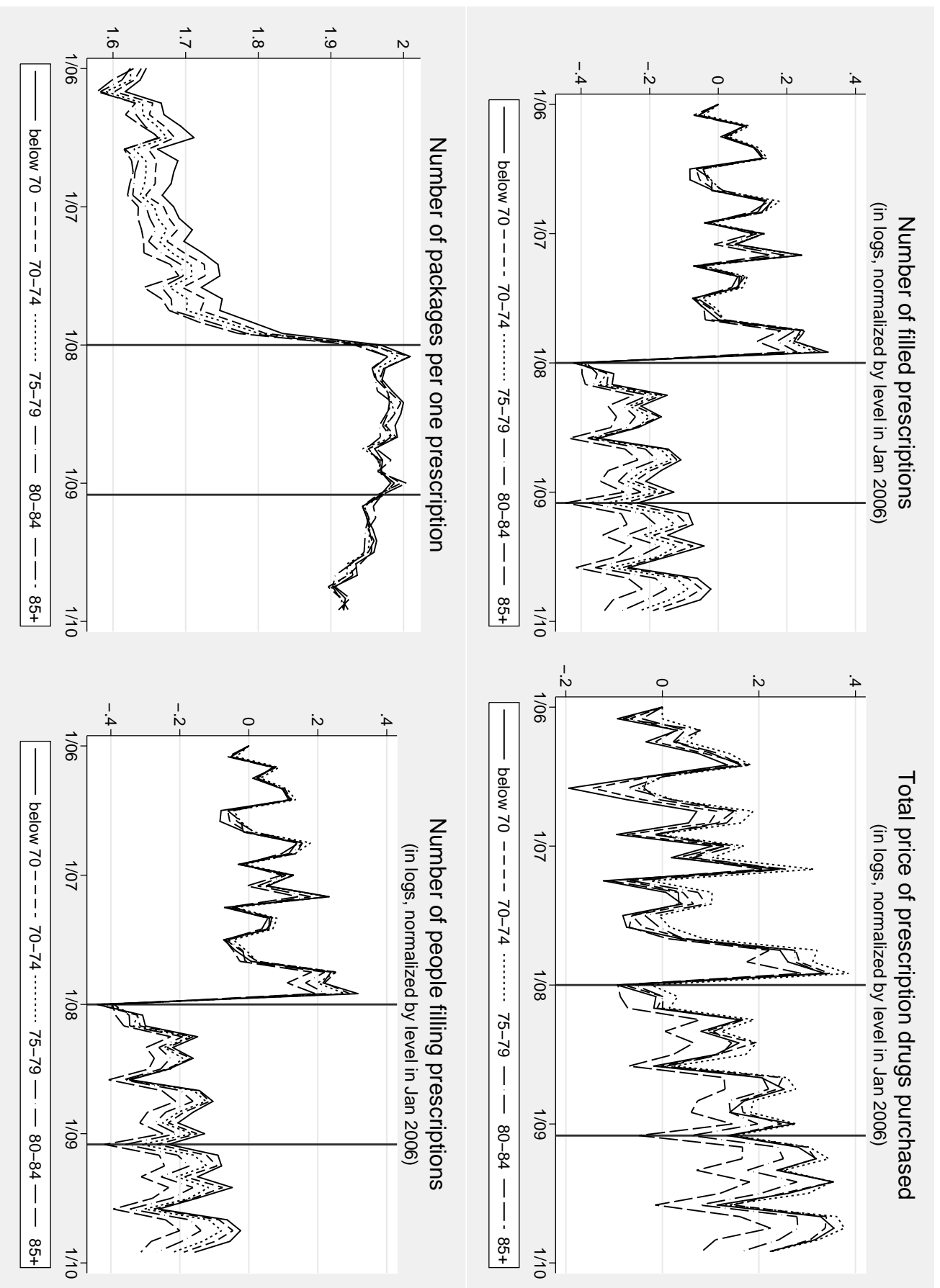
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Table 2.4: (cont) Effect of introduction and consequent reimbursement of copayments on the utilization of prescription drugs, by price category.

C. Total number of packages (log)

	<30 CZK	30-60 CZK	60-100 CZK	100-300 CZK	300-1300 CZK	>1300 CZK
Reform	-0.364 ***	-0.121 ***	-0.113 ***	-0.016	0.060 **	0.177 ***
	(0.026)	(0.024)	(0.020)	(0.016)	(0.027)	(0.021)
Reversal	-0.061	-0.021	0.016	0.008	0.120 ***	0.027
	(0.046)	(0.027)	(0.025)	(0.029)	(0.033)	(0.029)
Trend	0.007 ***	-0.001 *	0.000	0.005 ***	-0.001	-0.003 **
	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)
Trend_after	-0.012 ***	-0.002	-0.003	-0.007 ***	0.012 ***	0.015 ***
	(0.003)	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)
Trend_reverse	0.013 ***	0.004	0.007 ***	0.006 **	-0.000	0.001
	(0.004)	(0.003)	(0.002)	(0.002)	(0.003)	(0.003)
R^2	0.911	0.919	0.925	0.937	0.920	0.714
N	45,430	45,540	44,145	45,626	41,924	33,169

D. Number of packages per prescription (log)

	<30 CZK	30-60 CZK	60-100 CZK	100-300 CZK	300-1300 CZK	>1300 CZK
Reform	0.244 ***	0.175 ***	0.148 ***	0.170 ***	-0.004	-0.006
	(0.010)	(0.005)	(0.008)	(0.005)	(0.008)	(0.015)
Reversal	0.003	-0.010	0.009	0.023 *	0.034	-0.018
	(0.014)	(0.011)	(0.013)	(0.012)	(0.019)	(0.032)
Trend	0.004 ***	-0.000	0.002 ***	0.004 ***	-0.004 ***	0.012 ***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
Trend_after	-0.003 **	-0.001	-0.003 ***	-0.005 ***	0.001	-0.011 ***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
Trend_reverse	-0.006 ***	-0.001	0.001	-0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
R-squared	0.474	0.211	0.245	0.469	0.155	0.141
N	45,430	45,540	44,145	45,626	41,924	33,169

Note: Each panel shows coefficients for different dependent variable for different price ranges. All regressions control for region, month and fixed effects, gender, as well as cohort effects (quadratic specification) ; SE are clustered on the level of regions. ***,** and * denote significance at 1%, 5% and 10% level, standard deviations are in the brackets

Figure 2.3: Effect of introduction and consequent reimbursement of copayments on the utilization of prescription drugs, by age category.

Table 2.5: Effect of introduction and consequent reimbursement of copayments on the utilization of prescription drugs, by age category.

A. Total prescriptions (log)

	65-69	70-74	75-79	80-84	85+
Reform	-0.287 ***	-0.291 ***	-0.307 ***	-0.283 ***	-0.285 ***
	(0.022)	(0.020)	(0.018)	(0.016)	(0.031)
Reversal	-0.027	-0.018	-0.032	-0.014	0.017
	(0.034)	(0.034)	(0.035)	(0.031)	(0.039)
Trend	0.002 ***	0.002 ***	0.001 ***	0.001 *	-0.002 *
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
Trend_after	0.003	0.001	0.001	-0.002	-0.000
	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)
Trend_reverse	0.006 *	0.007 **	0.007 **	0.009 ***	0.005
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
R^2	0.946	0.959	0.965	0.966	0.866
N	9,408	6,720	6,720	6,720	17,409

B. Total price of purchased drugs (log)

	65-69	70-74	75-79	80-84	85+
Reform	0.016	0.013	-0.017	0.041 **	0.003
	(0.020)	(0.019)	(0.022)	(0.015)	(0.049)
Reversal	-0.003	0.007	0.001	0.015	0.042
	(0.031)	(0.026)	(0.027)	(0.026)	(0.053)
Trend	0.003 ***	0.003 ***	0.004 ***	0.002 ***	-0.002 *
	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)
Trend_after	0.007 ***	0.006 ***	0.005 **	-0.000	0.006 *
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
Trend_reverse	0.002	0.002	0.002	0.008 **	0.002
	(0.003)	(0.002)	(0.003)	(0.003)	(0.006)
R^2	0.889	0.904	0.935	0.937	0.833
N	9,408	6,720	6,720	6,720	17,409

Note: Each panel shows coefficients for different dependent variable for different price ranges. All regressions control for county and month fixed effects, as well as the average age of patients; SE are clustered on the level of regions. ***,** and * denote significance at 1%, 5% and 10% level, standard deviations are in the brackets

Table 2.5: (cont) Effect of introduction and consequent reimbursement of copayments on the utilization of prescription drugs, by age category.

C. Total number of packages (log)

	65-69	70-74	75-79	80-84	85+
Reform	−0.148 ***	−0.142 ***	−0.150 ***	−0.122 ***	−0.108 ***
	(0.019)	(0.018)	(0.017)	(0.015)	(0.032)
Reversal	−0.008	−0.004	−0.020	0.003	−0.002
	(0.026)	(0.030)	(0.030)	(0.029)	(0.039)
Trend	0.005 ***	0.004 ***	0.004 ***	0.003 ***	−0.001
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
Trend_after	−0.002	−0.003 **	−0.003 **	−0.006 ***	−0.003 *
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
Trend_reverse	0.005 **	0.006 **	0.007 **	0.008 ***	0.005
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
R^2	0.942	0.956	0.961	0.964	0.857
N	9,408	6,720	6,720	6,720	17,409

D. Number of packages per prescription (log)

	65-69	70-74	75-79	80-84	85+
Reform	0.139 ***	0.149 ***	0.158 ***	0.162 ***	0.177 ***
	(0.005)	(0.005)	(0.004)	(0.005)	(0.011)
Reversal	0.019	0.014	0.012	0.017	−0.018
	(0.011)	(0.011)	(0.010)	(0.012)	(0.012)
Trend	0.003 ***	0.003 ***	0.002 ***	0.002 ***	0.001 ***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Trend_after	−0.005 ***	−0.004 ***	−0.004 ***	−0.004 ***	−0.003 ***
	(0.000)	(0.001)	(0.001)	(0.001)	(0.000)
Trend_reverse	−0.001	−0.001	−0.001	−0.001	−0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
R^2	0.898	0.891	0.892	0.829	0.197
N	9408	6720	6720	6720	17409

Note: Each panel shows coefficients for different dependent variable for different price ranges. All regressions control for county and month fixed effects, as well as the average age of patients; SE are clustered on the level of regions. ***, ** and * denote significance at 1%, 5% and 10% level, standard deviations are in the brackets

Table 2.6: Changes in utilisation of selected drug categories after introduction of copayments, by age categories.

ATC	Description	% share on total consumption					Estimated change in # of prescriptions				
		<70	70-74	75-79	80-84	85+	<70	70-74	75-79	80-84	85+
A - Alimentary tract and metabolism											
A02	Drugs for acid related disorders	2.6	2.5	2.7	2.9	3.2	-0.135	-0.152	-0.145	-0.087	-0.040§
A10	Drugs used in diabetes	4.7	4.1	4.1	1.3	1.7	-0.117	-0.129	-0.147	-0.091‡	-0.040§
B - Blood and blood forming organs											
B01	Antithrombotic agents	5.1	5.8	6.1	6.3	6.3	-0.312	-0.282	-0.272	-0.247	-0.172
C - Cardiovascular system											
C01	Cardiac therapy	2.8	4.1	5.3	6.6	8.0	-0.110	-0.088	-0.066‡	-0.038§	0.082‡
C03	Diuretics	5.4	5.7	6.3	6.8	7.5	-0.123	-0.112	-0.135	-0.102	-0.087†
C04	Peripheral vasodilators	2.0	2.6	3.1	3.8	4.6	-0.177	-0.129	-0.126	-0.053§	-0.068§
C05	Vasoprotectives	3.6	4.0	4.3	4.6	4.8	-0.207	-0.216	-0.197	-0.224	-0.082†
C07	Beta blocking agents	7.3	6.8	6.3	5.7	4.8	-0.129	-0.110	-0.126	-0.092	-0.012§
C08	Calcium channel blockers	5.3	5.2	4.9	4.7	4.3	-0.091	-0.083	-0.075	-0.040§	-0.005
C09	Agents acting on the renin-angiotensin system	11.0	10.3	9.8	9.3	8.5	-0.033†	-0.029	-0.041‡	-0.020	0.020
C10	Lipid modifing agents	6.2	5.4	4.4	3.1	1.8	-0.088	-0.104	-0.091	-0.079†	-0.103§
M - Musculo-skeletal system											
M01	Anti-inflammatory and antirheumatic products	5.5	5.3	5.2	5.1	4.9	-0.265	-0.223	-0.257	-0.239	-0.129
N - Nervous system											
N05	Psycholeptics	2.7	2.7	2.8	3.2	3.8	-0.674	-0.782	-0.808	-0.778	-0.467
N06	Psychoanaleptics	2.7	3.0	3.3	3.7	3.9	-0.063†	-0.027§	-0.079	-0.040	0.016
R - Respiratory system											
R03	Drugs for obstructive aerial disease	2.6	2.6	2.4	2.1	1.9	-0.077†	-0.078†	-0.091	-0.067‡	0.051‡

Note: Drug categories were chosen as top 10 categories used at least by one age group. Dependent variable is the number of packages, all regressions control for county and month fixed effects and control for stockpiling; SE are clustered on the level of regions. Estimates are all significant at 1% level, if not stated otherwise († - at 5%, ‡ - at 10%, § - not stat. significant).

Table 2.7: Drug categories with greatest utilisation drop (# of packages) after introduction of copayments.

ATC	Description	<70	70-74	75-79	80-84	85+
J07	Vaccines	-0.816	-0.837	-0.810	-0.636	-0.311§
N05	Psycholeptics	-0.674	-0.782	-0.808	-0.778	-0.467
M02	Topical products for					
	joint/muscular pain	-0.635	-0.573	-0.532	-0.434	-0.224
R05	Cough and cold preparations	-0.569	-0.565	-0.533	-0.413	-0.127§
D08	Disinfectants	-0.444	-0.374	-0.337	-0.440	0.007§
L03	Immunostimulants	-0.418	-0.279	-0.297	-0.082§	0.172§
N02	Analgesics	-0.383	-0.343	-0.311	-0.321	-0.201†
D01	Antifungals	-0.369	-0.265	-0.282	-0.183	0.056‡
B01	Antithrombotic agents	-0.312	-0.282	-0.272	-0.247	-0.172
H03	Thyroid therapy	-0.309	-0.277	-0.314	-0.261	-0.084†
M01	Anti-inflammatory and					
	antirheumatic products	-0.265	-0.223	-0.257	-0.239	-0.129
D06	Antibiotics (dermatological)	-0.252	-0.222	-0.247	-0.151	-0.022§
D07	Corticosteroids	-0.225	-0.123	-0.184	-0.117†	0.020§
C05	Vasoprotectives	-0.207	-0.216	-0.197	-0.224	-0.082†

Note: Categories were chosen by the drop estimated for the age category of people younger than 70. Dependent variable is number of packages, all regressions control for county and month fixed effects and adjust for stockpiling; SE are clustered on the level of regions.
Estimates are all significant at 1% level, if not stated otherwise ($\dagger$ - at 5%, $\ddagger$ - at 10%, $\S$ - not stat. significant).
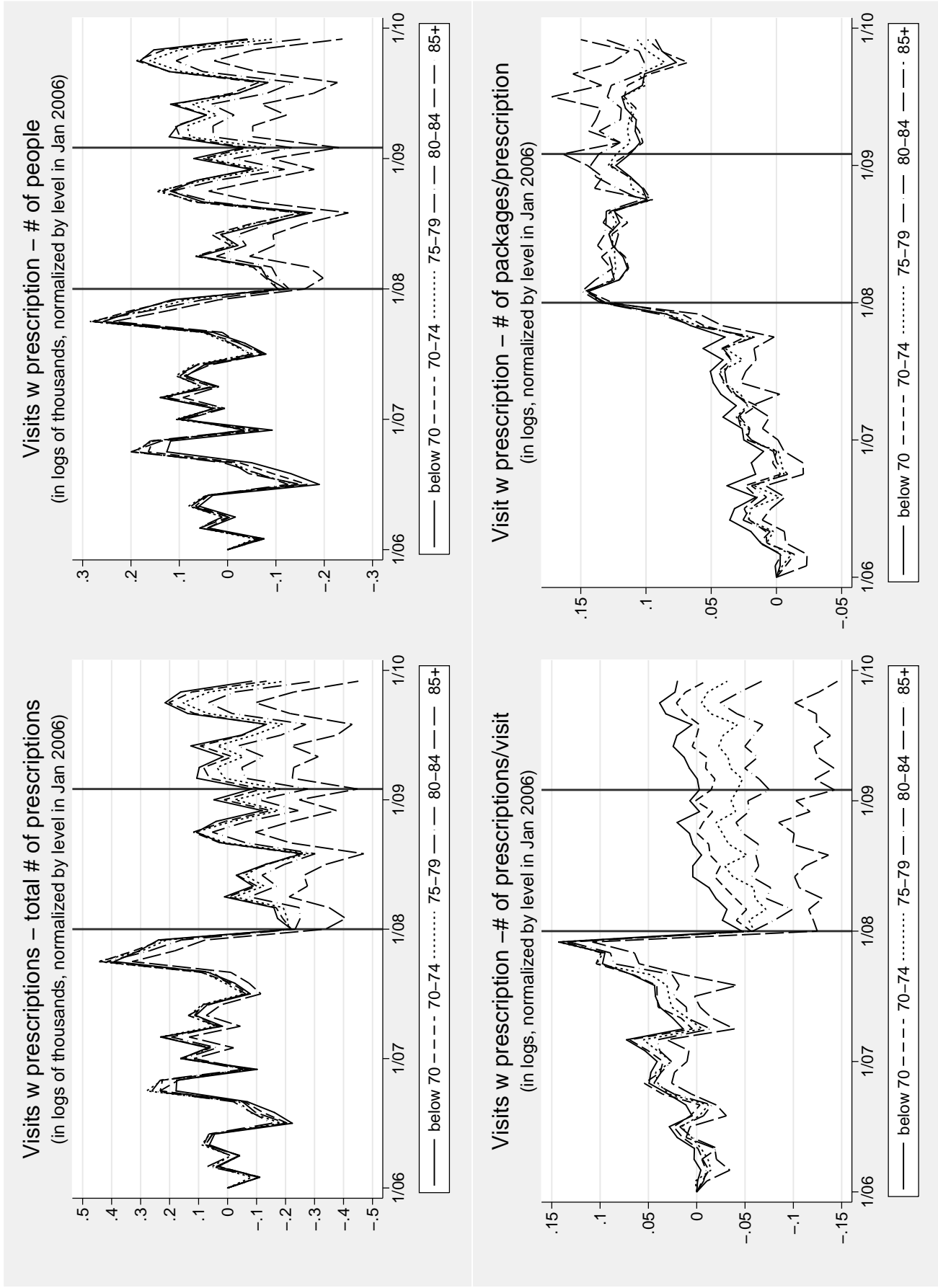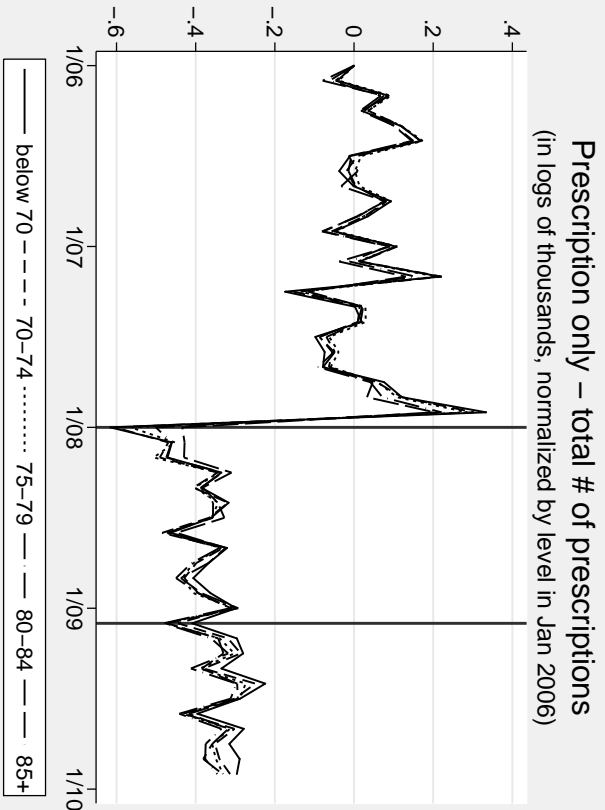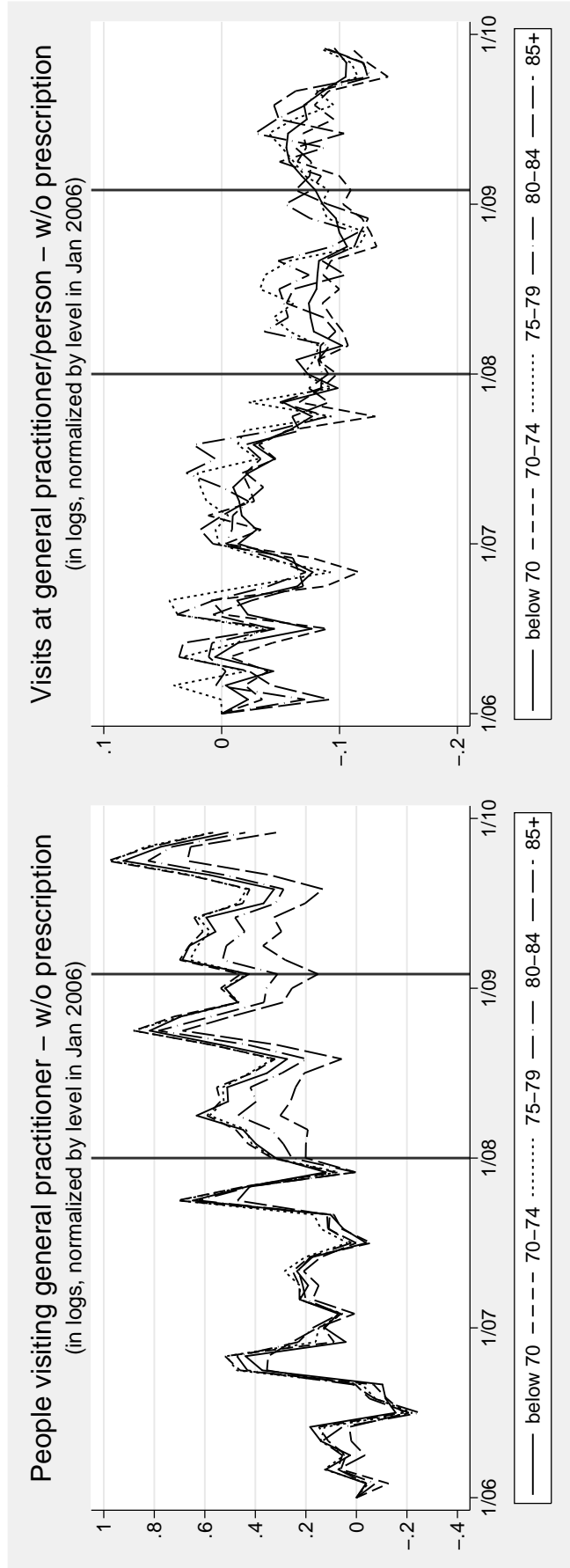
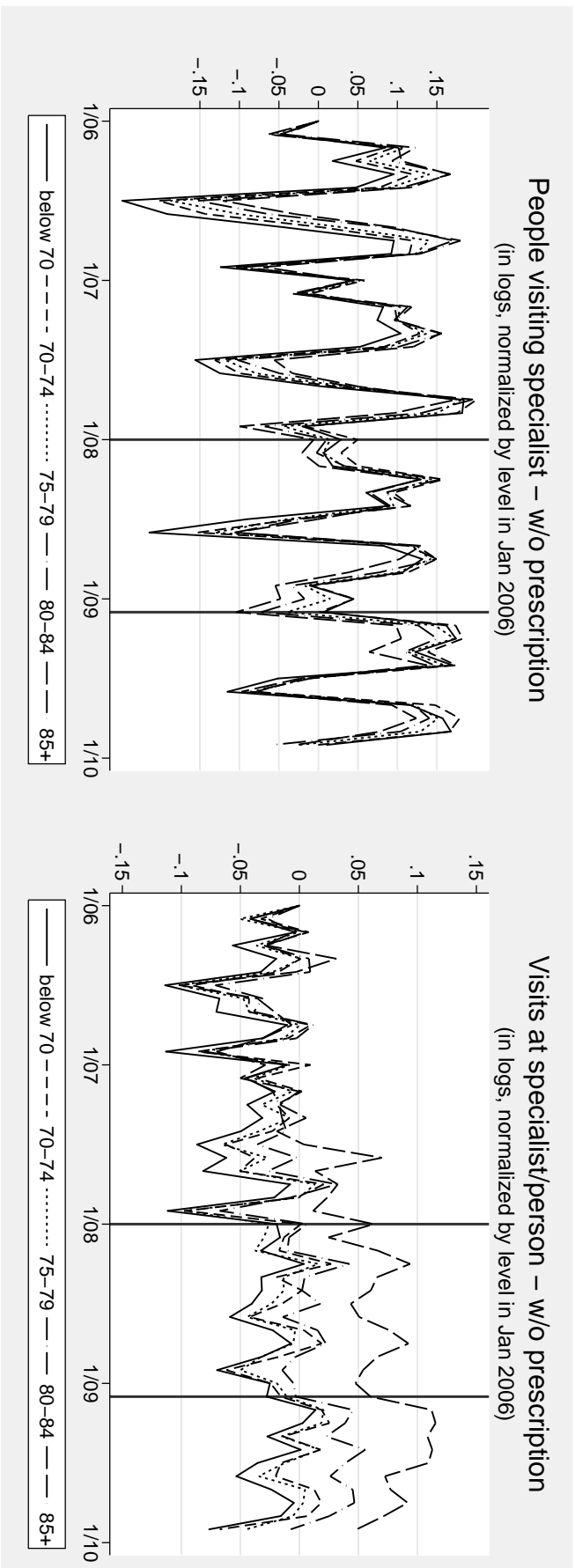**Figure 2.4:** Visits to a physician with associated prescription.
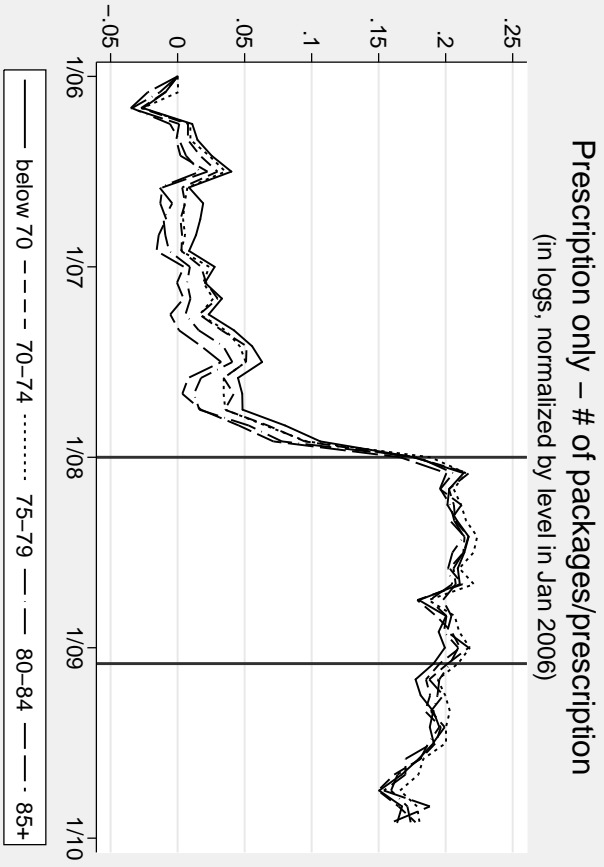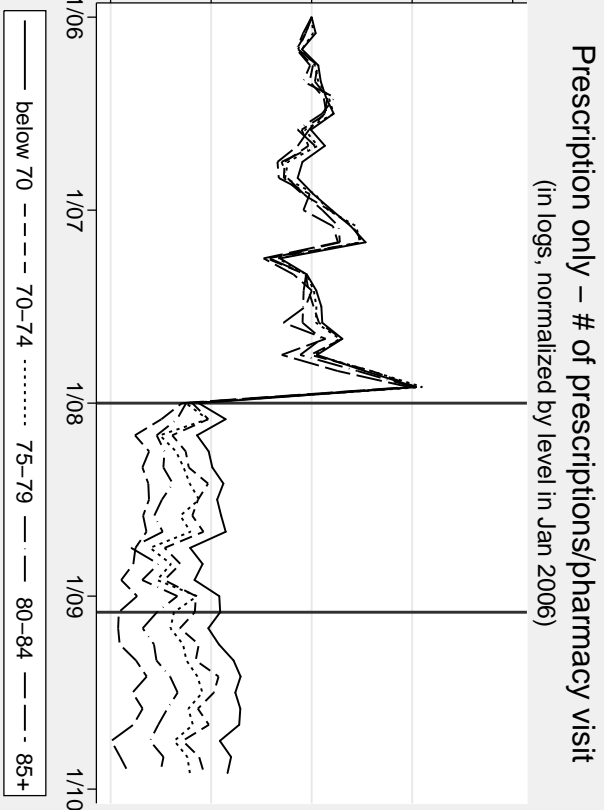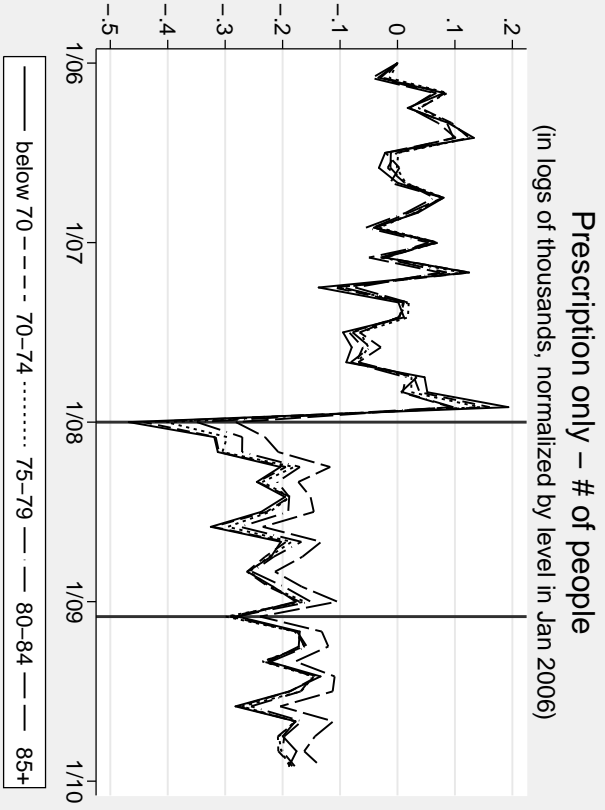
Figure 2.5: Prescriptions filled at a pharmacy, without a related visit to a physician.

64

Figure 2.6: Visits to a general practitioner without associated prescriptions.

65

Figure 2.7: Visits to a specialist without associated prescriptions.

Chapter 3

Effect of User Fee Reimbursement: The case of the Czech Republic

Eva Hromádková[†], František Kopřiva[‡] and Michal Zděnek[§]

Abstract

In this chapter, we study the extent and determinants of the behavioral response to cost-sharing in health care. We make use of unique patient level data that cover the introduction and partial reversal of patient cost-sharing in the Czech Republic, where regional governing bodies started to reimburse copayments for prescription drugs in the selected (region-owned) pharmacies. We analyze how the resulting variation in the prescription drugs' prices affected an individual's choice of pharmacy. Using both non-parametric and parametric estimation techniques, we find a significant shift in patients' preferences towards reimbursing pharmacies. We also identified main drivers of the shift which include monetary cost (proxied by number of prescriptions), type of physician, and distance as a measure of opportunity cost of time.

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3.1 Introduction and Motivation

Literature on patient cost-sharing in health care focuses primarily on its effect on utilization measures, deriving implications for both financial sustainability of the systems as well as health status implications for patients. These aggregate effects result from individual behavioral changes triggered by different aspects of cost-sharing working interactively. Therefore it is difficult to predict the outcomes of particular reforms if we do not understand all the individual incentive mechanisms at work.

In this paper, we decided to focus on one specific mechanism of behavioral response – choice of pharmacy based on the price of a drug. We look at whether small differences in drug prices implied by a user fee affect a patient's preference for individual pharmacies. Choice of pharmacy is a decision made after the visit to a physician, and as such is fairly autonomous and not affected by other features of the health care system (such as fees for an inpatient visit). Although it does not provide a direct measure of the utilization change, it serves as a clear signal of how strongly even small incentives can alter patients' behavior.

While most studies look at the effect of introduction of copayments, or explore exogenous differences in copayments levels, we make use of a reversal of copayment policy. In the Czech Republic, only one year after a substantial 2008 health care reform that introduced copayments for health services, governing bodies in selected regions started to reimburse copayments for prescriptions in the region-owned pharmacies. This situation created a unique set-up of a reform and its subsequent partial reversal.

In this paper, we use an extensive dataset of individual physician-pharmacy visits to identify the effect of the reimbursement. Figure 3.1 illustrates why the use of individual data is crucial for our analysis: Looking at aggregated data (panel A) a researcher would conclude that the start of reimbursement did not reverse the effects of introduction of copayment. This was also the general finding regarding the effect of reversal in the Chapter 2 of this dissertation (Hromadkova and Zdenek 2013). However, if one considers that the reimbursement took place only in a few selected pharmacies and look at the prescription filling at pharmacy level (panel B), the effect of reimbursement is striking, as the number of prescriptions filled in reimbursing pharmacies almost doubled.

We estimate the effect of reimbursement both by non-parametric and parametric methods. In the first step, we compare patients' preferred pharmacies before and after the start of reimbursement. We find that in 2009 (year of reimbursement) almost 3-times

more patients switched from a non-reimbursing to a reimbursing pharmacy. Also, the preference for reimbursing pharmacies, measured as their ranking by number of visits, significantly increased, while the preference for other types of pharmacies decreased.

In the parametric estimation, we restrict our sample to the prescriptions where the prescribing physician is located at the same building as a pharmacy, so that a patient has a natural baseline choice for prescription filling. We estimate the probability that a patient will visit this local pharmacy conditional on its reimbursement status and find a significant 5% increase in the probability of visits at reimbursing pharmacies, accompanied by a similar decrease at non-reimbursing pharmacies, with pharmacies in the non-reimbursing cities serving as a control for common market trends.

For those patients who choose not to fill a prescription in the local non-reimbursing pharmacy, we find that the probability of choosing a (distant) reimbursing pharmacy has almost doubled. We identified several factors that significantly affect the magnitude of the effect - type of prescribing physician as a proxy for the severity of illness, number of prescriptions as a direct measure of savings from reimbursement and, finally, distance to reimbursing pharmacy as a measure of opportunity costs of time. We believe that our results will inform the public discussion on health care financing and the role of patients' incentives.

3.2 Literature review

The first comprehensive evaluation of the relationship between the patients' cost-sharing level, their subsequent utilisation of health care services and final health outcomes was performed in the mid-1970s within the framework of the RAND Health Insurance Experiment and later summarized in Newhouse (1993). This study found a significant yet modest response of medical care utilization to the co-payments, in general with no detrimental effects on health and further medical care use. The sensitivity of drug utilization to prescription drug copayments, however, was fairly strong when compared to other types of copayments.

In our study, we focus on the effect of cost-containment measures targeted at prescription drugs. In early studies on this topic, Nelson, Reeder, and Dickson (1984) examined the introduction of a drug copayment in South Carolina's Medicaid program. They found that the change was associated with a statistically significant reduction in usage of drugs which, according to Reeder and Nelson (1985), could result in worsening of health and

extensive use of medical care. This field of literature gained further attention with the introduction of the Medicare D supplement for the prescription drug coverage. Goldman et al. (2004) and Landsman et al. (2005) in their analysis of the natural experiments mostly within US system, confirm a significant elasticity with respect to price and type of drugs, with higher elasticity of utilization of treatments for acute diseases.

Recent research has confirmed that increased cost-sharing may be associated with offsetting increases in other forms of care. Gaynor, Ho, and Town (2015) claim that after increases in drug copayment, rises in spending on outpatient care offset 35% of the savings from reduced prescription drug use. The effect seemed to be even more pronounced in the population of elderly and chronically ill. Chandra, Gruber, and McKnight (2010) find evidence that increased prescription drug and office visit copayments caused offsetting increases in hospitalizations in elderly patients who had been diagnosed with chronic diseases such as diabetes, hypertension, and hyperlipidemia. Similarly, Trivedi, Moloo, and Mor (2010) find that increased copayments for ambulatory care for elderly patients were associated with increased rates of hospitalizations. On the other hand, Chandra, Gruber, and McKnight (2014) do not find offseting effects for the sample of low-income enrollees in the Massachusetts Commonwealth Care program.

Offset effects are a particular concern if psychological biases cause patients to overvalue the immediate cost of a copayment relative to expected future health benefits (Baicker, Mullainathan, and Schwartzstein 2012). We believe we can measure the extent of this bias by their reaction to the partial reversal of the nation-wide health care reform, initiated in the Czech Republic in 2008 (MHCR 2008). Zapal (2010) and Votapkova and Zilova (2012) analyzed the effect of the reform on t children's health care utilization of . They used the difference-in-difference approach, based on the waiver that abolished co-payments of any kind for children up to 18 years of age.

With a sample population similar to ours, Kalousova (2014) uses the Survey of Health Ageing and Retirement in Europe (SHARE) to examine the effects of copayments on health care utilization of elderly Czechs. According to her results, the reform was as- sociated with lower probability of primary care visit, but no change in probability of hospitalization. Finally, Krutilová and Yaya (2012) analyze impact of this change in out-of-pocket payments on households. Importantly for our research, they find that the presence of pensioners and elderly in a household was the factor which increased the over- all burden the most and led to catastrophic payments. Thus we can identify the elderly as a vulnerable subgroup in terms of their income with a higher probability of behavioral

response.

Our previous paper Hromadkova and Zdenek (2013) we have identified a strong effect of introduction of copayments on the utilisation of prescription drugs. The estimated effect of the reversal, however, has been very small due to the aggregation of the data on the regional level. The share of the

3.3   Institutional background

As one of the measures targeting the cost-containment, starting January 1, 2008 the Ministry of Health of Czech Republic introduced mandatory cost sharing in the form of copayments for all types of health care services: physician office visits (30 CZK), item on the prescription for drugs (30 CZK), emergency room visits (90 CZK) and each day of hospitalization / institutional care (60 CZK). Patients paid 30 CZK for each item (type of drug) on the prescription, regardless of the number of packages purchased. The main function of the copayments was intended to be regulatory and behavioral. In the case of prescription copayment, the declared intention of policymakers was to lower the total number of prescriptions, with particular focus on low-priced drugs also available for the over-the-counter purchase.

The introduction of patient cost sharing initiated heated public debate and became one of the main topics of the 2008 elections to regional governments that took place in 13 out of 14 regions of the country.[1] Political opposition to the incumbent government achieved a decisive victory and newly established regional governments declared official pledge to alleviate the effects of health reform on citizens by reimbursing the copayments for treatment in municipality-owned health centers / hospitals from their own regional budgets. The regional government in Stredocesky kraj started to reimburse the copayments on January 1, 2009, followed by the other 12 regions on February 2, 2009. Prague has never started to reimburse copayments. Different regions decided to implement different type of reimbursement, e.g. in Stredocesky kraj the verbal agreement of patients was sufficient, in Jihocesky kraj a patient must sign anagreement that he obtained "gift" from the municipality, while in Plzensky kraj a patient had to pay the copayment himself and then claim the reimbursement by post. Also, some regions only reimbursed selected types of copayments. This has resulted in great variation in the ratio of reimbursed

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[1]The exception was the capital city ofPrague, which has legal status of both a city and a region. For historical reasons, however, only city council elections take place in Prague and these were held in 2006.

copayments among the regions (for details on the reimbursement policies of individual regions see Table 3.1).

With respect to copayments on the prescription drugs, most regions with the exception of Zlinsky kraj and Prague decided to reimburse copayments in pharmacies affiliated with the region-owned hospitals or medical centers. This, however, triggered reaction in the neighboring pharmacies, which reportedly faced plummeting demand. Effectively, copayments were reimbursed in 50 region-owned pharmacies out of almost 2400 registered public pharmacies in the Czech Republic, representing around 3.5% of filled prescriptions.

3.4 Data and methodology

3.4.1 Methodology

In the analysis, we focus on how the decision-making of patients with respect to filling prescriptions changed with the introduction of copayment reimbursement. Copayments affect all the stages of physician-patient-pharmacy interaction. First, they affect the patient's decision to seek medical help. Second, they influence the prescription habits of physicians, as we have pointed out in Hromadkova and Zdenek (2013). Finally, they might affect the patient's decision where to fill or purchase the prescription, in a situation when some pharmacies reimburse copayments and others do not. In our study, we are effectively focusing on the last step. In the simplified form, the decision of which pharmacy to use to fill a prescription is a cost-minimisation in which patients weight the convenience of the purchase (distance, ease of access, personal preferences) against the utility of purchase. Thus, if we assume that convenience can be proxied by distance from the decision point, the reimbursement policy will affect those at the margin between going to a more distant pharmacy and receiving reimbursement, or going to a closer pharmacy and paying the copayment.

We first take a non-parametric approach to this question by looking at the changes in the type of preferred pharmacies by reimbursement status over the time. For each patient and each year, his preferred pharmacy is identified as the one with highest frequency of visits.[2] We restrict our analysis to those patients that live or fill their prescriptions in towns with at least one reimbursing pharmacy (for a list, see Table 3.1). For this subsample, we track the type of their most preferred pharmacy over time, with particular

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[2]In case of a tie, all of pharmacies with the same number of visits have the same ranking

focus on switching between types.

We then look at pharmacies in order to fully utilize information about the distribution of visits. Similarly to the first step, for each patient and year we create a ranking of pharmacies he has visited based on frequency of visits. Then, for each individual pharmacy, we collect the rankings from all patients and identify the pharmacy's most frequent ranking (mode of distribution of individual rankings). Finally, we calculate the mean of these modal rankings for three groups of pharmacies by reimbursement status (pharmacy in non-reimbursing town serving as a control, non-reimbursing pharmacy in reimbursing town and reimbursing pharmacy) together with its standard error.

In the context of the parametrical estimation, there are several issues we had to address when translating the theoretical concept into an empirical model. First was the choice of the starting point - i.e. location/address where the decision about the choice of pharmacy was made. While natural choice would be a the patient's home address, the data does not contain that information. Therefore, we consider the address of the prescribing physician and limit the analysis to cases when the prescription was filled the same day, thus maximizing the probability that the patient went directly from physician to pharmacy. The second issue is the relative difference between distances to reimbursing vs. non-reimbursing pharmacies (e.g. one might be located farther, but directly on the way home). We thus decided to establish a costless baseline - look only at the subsample of visits where physicians are located at the same address as a pharmacy.

The decision problem can then be formulated in two layers - first is **probability of visiting local pharmacy** (i.e. pharmacy located in the same building) given its reimbursement status, second is probability of visiting a distant reimbursing pharmacy conditional on the local pharmacy being non-reimbursing. We implement the first stage by estimating model using linear probability specification.[3]

$$P(GoLocal)_{it} \;\; = \;\; F(R_t, TR_i, PR_i, \mathbb{X}) + \epsilon_{it} \tag{3.1}$$

In the specification, we include the full set of interactions between the three main variables: R_t which has value 1 if the time of purchase t falls after the introduction of reimbursement in given region, TR_i which indicates whether the town in which patient i fills the prescription has at least one reimbursing pharmacy, and PR_i which has value 1 if the filling pharmacy reimburses copayments. We further control for patient's age and

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[3]We have reestimated model using logit specification; results were the same.

sex, monthly seasonality, town and drug-specific fixed effects as well as the number of prescriptions given during the visit.

Conditional on not choosing the pharmacy located in the same building as the physician and living in a city with at least one reimbursing pharmacy, a patient has a choice to fill his prescription either at a reimbursing or non-reimbursing pharmacy. This is formalized in the following specification using the above-defined set of variables.[4]

$$P(GoReimburse)_{it} \quad = \quad G(R_t, \mathbb{X}) + \mu_{it} \tag{3.2}$$

3.4.2 Data and sample construction

We use unique individual level panel data from the major Czech public insurance company which serves approximately 64% of the Czech population. The data spans the period 2006-2009, i.e., two years before the introduction of copayments, one year of their existence and one year after reimbursement by the municipalities began in the county-owned medical facilities. The basic sample consists of a balanced panel of 332,724 enrollees older than 65 years, which represents 5% of all enrollees of the health insurance company and 29% of enrollees older than 64. The insurance company covers more than 77% of the elderly population of the Czech Republic.

Data provide information about all medical care services that were billed to the insurance company, i.e. all medical care encounters (outpatient care, inpatient care, emergency room visits and medical transfers), as well as all prescribed drugs, materials and medical aids that patients utilized throughout the period of coverage. Data on prescribed drugs include drugs provided at hospitals and physician offices, as well as drugs purchased by prescription at pharmacies. For our analysis we focused on the prescription drugs collected at the pharmacies, because only these were affected by introduction of copayments. Information on medical care encounters includes ID and type of provider, type of medical service provided as well as billed price. Information on prescribed drugs includes identification of general drug type (first three digits of ATC nomenclature[5]), number of packages, date of purchase, identification of the physician that prescribed the drug, identification of the pharmacy and billed price of the drug.

We combined data on physician visits with data on prescribed drugs into one obser-

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[4]We have estimated both equations jointly, the results are similar.

[5]The Anatomical Therapeutic Chemical (ATC) Classification System is used for the classification of drugs. It is controlled by the WHO Collaborating Centre for Drug Statistics Methodology (WHOCC).

vation based on three criteria: individual ID, physician ID, and date of physician visit / purchase at a pharmacy. We attribute the prescription to the visit if it was filled within a two week window after. This way, three types of visits can be identified - visits with prescription, visits without prescription (check-ups) and prescriptions without visits.[6] We discarded data on visits without prescription as well as prescriptions without associated visit. Then we merged this dataset with the secondary data source - information on all medical care providers and pharmacies in the Czech Republic, retrieved from the publicly available databases of insurance companies and the State Institute of Drug Control.[7] Based on identification number, we were able to identify 78% of providers and 93% public pharmacies representing around 88% of all considered prescriptions, and used this information to locate the address physician office and pharmacy. We restricted the analysis to those cases where the pharmacy was located in a town with at least one reimbursing pharmacy (see Table 3.1). Finally, using an automated script procedure, we retrieved all the distances between the physician and pharmacy visited, as well as the distance to the closest reimbursing pharmacy.[8] We used this sample to run our non-parametric estimates.

As explained in the methodological section, in the parametric estimation we focus on the visits where (1) the physician is located in the same building (address) as a pharmacy and (2) prescription is filled on the same day, to minimize the subjective motives for prescription filling. This selection criterion leaves us with 30% of original number of visits. Summary characteristics of the sample year-by-year are presented in Table 3.2.

3.5 Results

3.5.1 Non-parametric estimation

In the first step, we look at the distribution of a patient's most preferred pharmacies by their reimbursement status in 2009, and its evolution over time. Results are summarized in the Figure 3.2 panel A. In the years before the start of reimbursement the share of patients that preferred a reimbursing pharmacy was stable at 25-26%, where approximately 3-4% corresponded to turnover, i.e. switching preferences from reimburs-

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[6]We assume these are long-term standing prescriptions for drugs for chronic treatment

[7]Contacts   on   all   (currently)   registered   pharmacies   can   be   found   at: http://www.sukl.eu/modules/apotheke/search.php

[8]We were using the application program interface of mapy.cz, the leading mapping server in the Czech Republic.

ing to non-reimbursing and vice versa. The situation changed in 2009 where the share of people who preferred a reimbursing pharmacy jumped to 31% and the flow of people switching from non-reimbursing to reimbursing pharmacy more than doubled, with the reverse flow remaining at its pre-reimbursement levels. This is the first indication that the introduction of reimbursement affected patients' decision making regarding the choice of pharmacy.

Further, we look closer at the individual pharmacies, track how their modal (most frequent) ranking changed over time and whether it was related to their reimbursement status in 2009. In Figure 3.2 panel B we present the mean of these modal rankings in time for three groups of pharmacies by reimbursement status (pharmacy in non-reimbursing town, non-reimbursing pharmacy in reimbursing town and reimbursing pharmacy) together with its standard error (calculated by bootstrapping). Mean modal rankings of the three types of pharmacies are not statistically significantly different from each other except in 2009, when reimbursing pharmacies suddenly become relatively most visited and the ranking of non-reimbursing pharmacies in reimbursing towns plummets. Modal rankings of pharmacies in non-reimbursing towns (which can be perceived as controls) become significantly worse than rankings of reimbursing pharmacies, but still significantly better than rankings of non-reimbursing pharmacies.

3.5.2 Parametric estimation

To understand the effect of copayments reimbursement on patient behavior, we first look at the change of probability of filling a prescription in a pharmacy located in the same building as the physician, conditional on whether this pharmacy reimburses copayments or not. Figure 3.3 summarizes the result, first presenting the aggregate share of visits calculated directly from data, then the marginal probability resulting from estimation of the empirical specification (3.1). Estimation confirms the story from the raw data: After the start of reimbursement and in the towns with existing reimbursing pharmacy, probability of filling a prescription in the local pharmacy that reimburses the prescription copayments rose by 4.8 pp., while the probability of filling the prescription in the local pharmacy that does not reimburse the prescription copayments dropped by 4.5 pp. In towns without reimbursing pharmacies, the probability of filling prescription in local pharmacy did not change significantly. Almost 5% of patients thus responded to the relatively small incentive of paying 30 CZK less and refrained from going to their preferred

pharmacy.

Building on the previous results, we were interested whether the patients did not choose a local non-reimbursing pharmacy due to the existence of another (perhaps more conveniently located) pharmacy or specifically due to possibility of reimbursement. We thus looked at the probability that conditional on not filling the prescription in the local non-reimbursing pharmacy, the actual pharmacy of choice was reimbursing. Again, as illustrated in Figure 3.4, raw data and estimates are in accordance; the estimated probability after the start of reimbursement jumped from 10% to 19%, i.e. almost doubled. This clearly indicates that the drop was primarily motivated by the reimbursement possibility.

We also estimated the two equations together in a Heckman style MLE estimation. While the significance and direction of the results remained, the estimated magnitudes were slightly smaller - approximately 4 ppt drop in the probability of going to local non-reimbursing pharmacy and 6 ppt rise in the probability of choosing a distant reimbursing pharmacy. [9] This was due to positive correlation between the unobservables determining the two choices.

3.5.3 Sensitivity to selected factors

There are several factors that should affect the probability to fill a prescription in a given pharmacy in interaction with reimbursement status. In our analysis we considered three of them and explored, whether they have shifted preferences in a predictable direction. The results of the estimation are visualized in Figures 3.5-3.7 and summarized in Table 3.3 (step 1 - filling locally) and 3.4 (step 2 - filling in reimbursing conditional on not filling locally).

The first determinant we consider is the **specialty of the physician** that prescribed the drug. Our starting hypothesis is that the specialisation is positively correlated with the severity of condition, and patients with more severe illness prefer to fill their prescriptions locally regardless of the reimbursement policy of the pharmacy. Indeed, as can be seen in Figure 3.5, change in preferences is much more pronounced for patients bringing a prescription from their primary care physician (PCP) than for patients with a prescription from a specialist. For the case of PCP prescriptions, there has been 9 ppt drop in probability of filling it in non-reimbursing local pharmacies. If the local pharmacy was

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[9] For the full results please consult the corresponding author (Eva Hromadkova).

reimbursing, however, the probability of filling a prescription there jumped by 23 ppt. at 75%. For the case of specialists' prescriptions, the direction of changes was the same, yet much smaller in the magnitude. As regards step 2, after start of reimbursement, probability of filling a prescription in a distantly located reimbursing pharmacy jumped to approximately 19%. This is a slightly higher increase for PCP prescriptions, due to slightly lower pre-reimbursement levels.

The second factor that we examined in detail was **number of prescription filled**. As the copayment is paid on a per prescription basis, our intuition is that patients with more prescriptions will be motivated to choose a reimbursing pharmacy due to substantial cost-saving. Again, as illustrated in Figure 3.6 data strongly confirm the intuition: While in the case of patients with one prescription there is almost no change in filling habits, with an increasing number of prescriptions, the probability of them being filled in local non-reimbursing pharmacy decreases (- 11 ppt for 5+ prescriptions) and probability of filling in a local reimbursing pharmacy increases (+ 8.3 ppt). Interestingly, this translates also into the step 2 decision. Although in all cases the probability of filling in a distant reimbursing pharmacy increases significantly after start of reimbursement, the magnitude is 7% for patients with 1 prescription as opposed to 14% for patients with 5+ prescriptions.

Finally, the third factor we considered was **distance of reimbursing pharmacy**. This serves as approximation of opportunity costs of time, when patients with a shorter trip are expected to be more willing to switch from a local non-reimbursing pharmacy to a distant reimbursing one. Following this logic, we have only estimated specification (3.2). Figure 3.4 illustrates the results summarized in Table 3.4 panel C: the probability of choosing a reimbursing pharmacy is highest if it is located at a distance smaller than 500m, which holds both for period before and after the start of reimbursement. Even though there was almost 19 ppt increase in this distance category, we observe the highest increase in the category of pharmacies approximately 1.5-2 km from the physician office, with further pharmacies having then lower and lower marginal increases in probability. The non-linear pattern of relationship between distance and probability of visit could be explained by several factors including the availability of public transport, or favorable location vis-a-vis home address which is not present in our dataset.

3.6 Concluding Remarks

Our results contribute to the line of research focusing on the utilisation of health care services by elderly patients. From a theoretical perspective, there are two plausible lines of reasoning for the effect on their behavior, going in the opposite direction. First, as these patients are older, weaker and more prone to chronic conditions, one can assume that their patterns of utilisation are driven by habit and thus are hard to change. On the other hand, their generally lower income and corresponding low opportunity cost of time imply stronger impact of financial incentives. We believe our findings indicate that the latter motivation prevails, as patients in our study respond quite strongly to the financial incentives created by the regional reimbursement policy. They shifted their preferences toward pharmacies which reimbursed the copayments, even in the cases when they had an outside option of visiting a conveniently located pharmacy within the same building as prescribing physician. We believe this is a strong indication that incentives in other aspects of utilisation might have very similar effect.
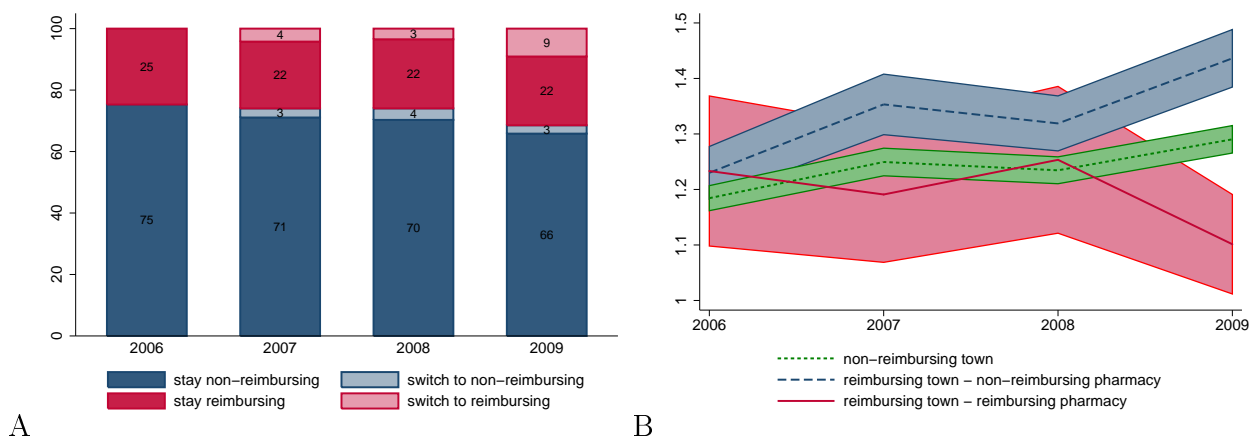
Tables and Figures
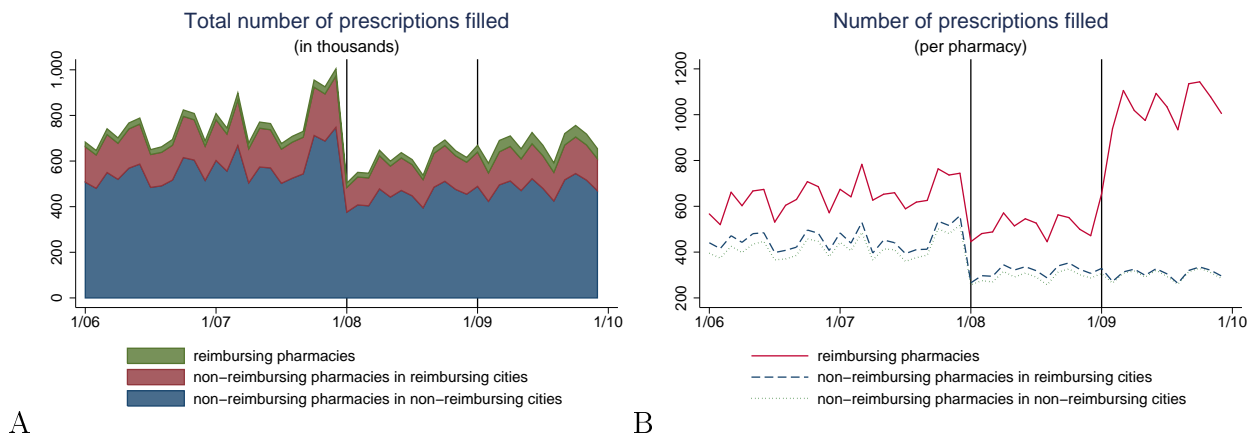
Figure 3.1: Total number of filled prescriptions (A) and average number of filled prescriptions by pharmacy (B), by reimbursement status

Note: Using sample of all filled prescriptions with identified physician visit, 14 663 451 observations.


Figure 3.2: Patients'most preferred pharmacies (A) and modal rankings of pharmacies (B), averaged within groups by reimbursement status and year

Note: Using sample of all filled prescriptions with identified physician visit, 14 663 451 observations.
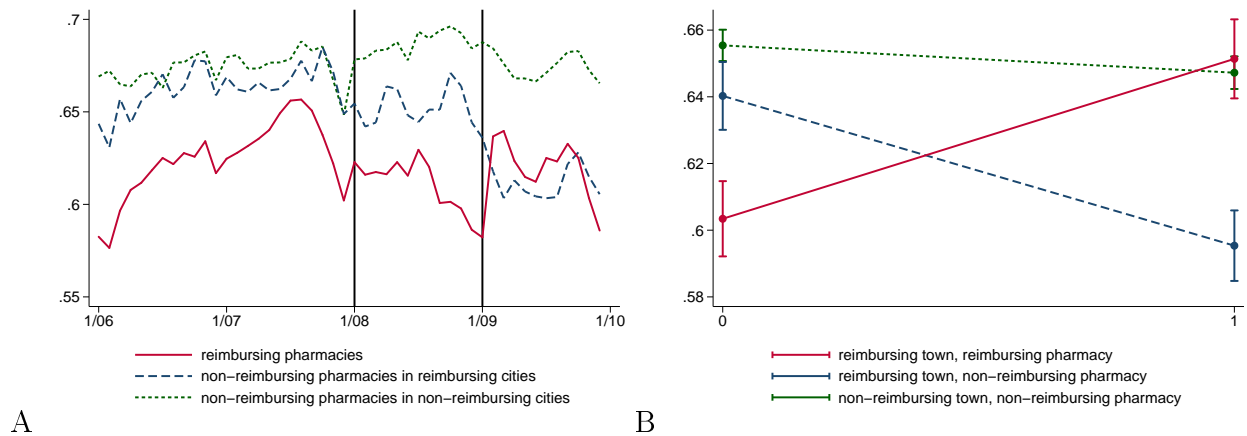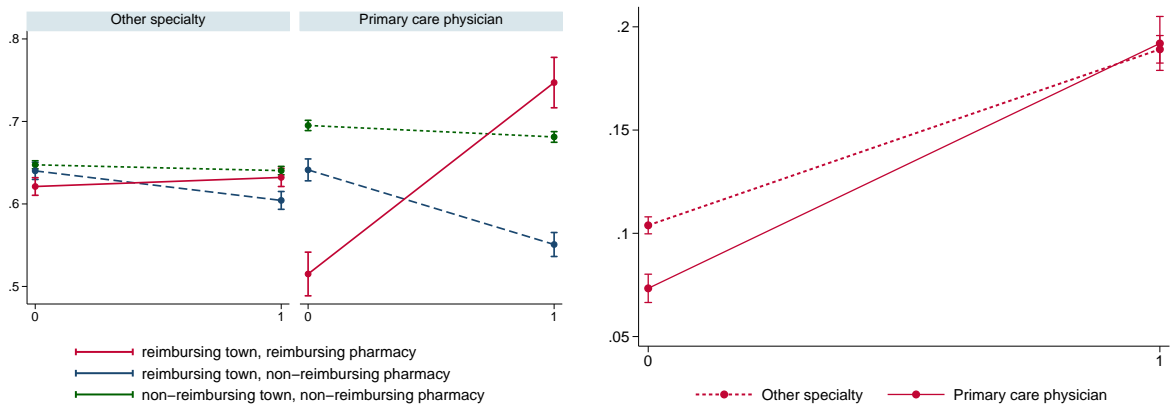
Figure 3.3: Probability of filling a prescription in the local pharmacy by pharmacy type - share calculated from data (A) and marginal probability resulting from estimation of empirical model (B).

Note: Using sub-sample of visits where there exists a pharmacy located at the same address as physician, and prescription was filled the same day as visit has been made, 4 440 667 observations.
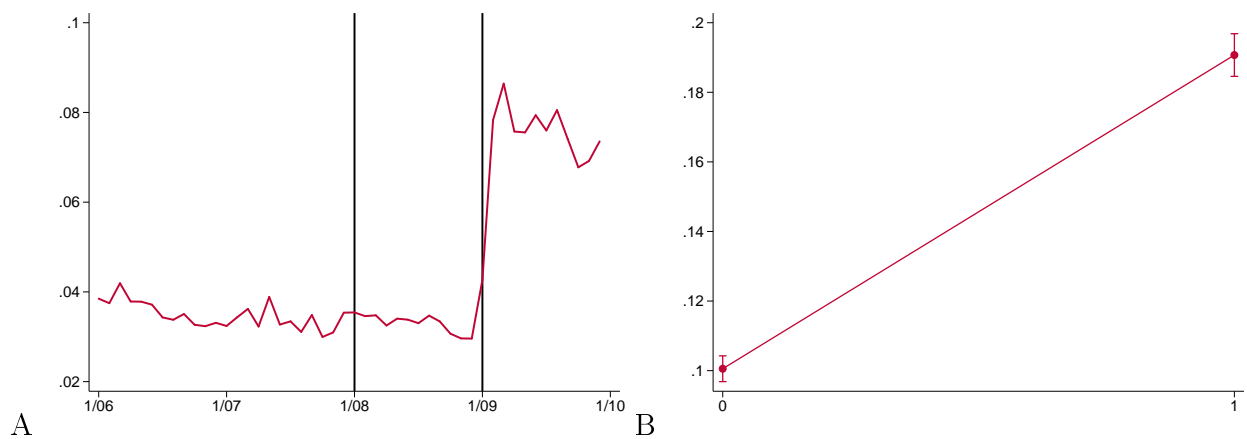
Figure 3.4: Probability of visiting distant reimbursing pharmacy conditional on not filling a local non-reimbursing pharmacy - share calculated from data (A) and marginal probability resulting from estimation of empirical model (B).

Note: Using sub-sample of visits where there exists a pharmacy located at the same address as physician, and prescription was filled the same day as visit has been made, 147 976 observations.
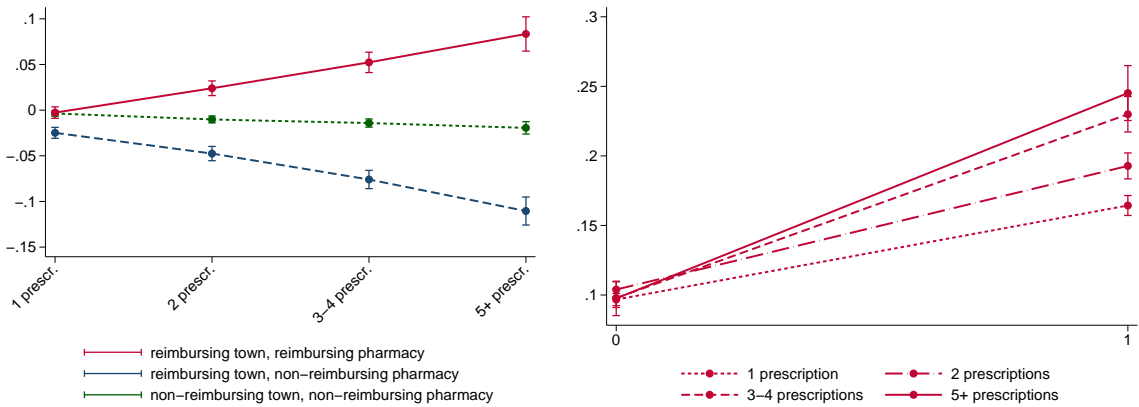
Figure 3.5: Probability of filling a prescription at the local pharmacy before and after start of reimbursement (A) and probability of filling prescription in distant reimbursing pharmacy, conditional on not filling it in the local non-reimbursing one (B), by pharmacy type and specialty of prescribing physician.

Figure 3.6: Marginal effect of start of reimbursement on the probability of filling a prescription at the local pharmacy (A) and probability of filling prescription in distant reimbursing pharmacy, conditional on not filling it in the local non-reimbursing one (B), by pharmacy type and number of prescriptions filled.
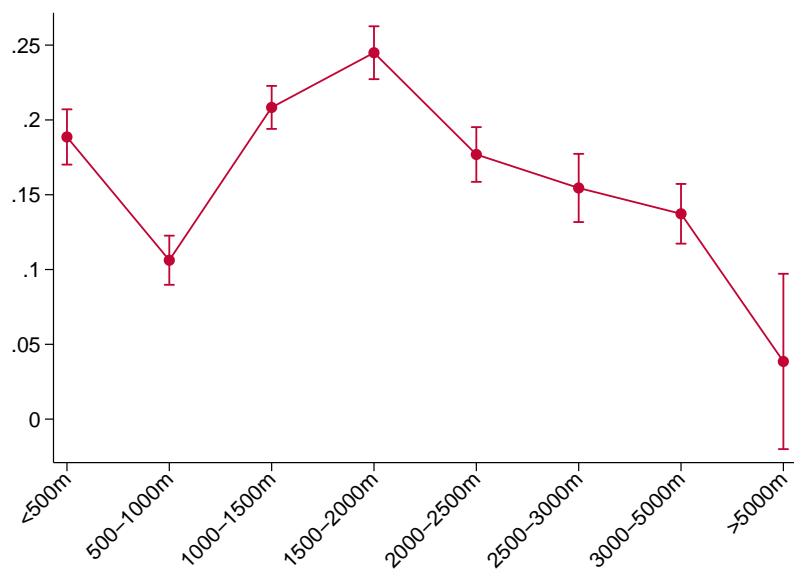
Figure 3.7: Marginal effects of start of reimbursement on the probability of visiting distant reimbursing pharmacy conditional on not filling a local non-reimbursing pharmacy, by distance to reimbursing pharmacy.

Table 3.1: Overview of regional reimbursement policies

Region	Start of reimbursement	Reimbursement of copay for drugs	Type of agreement	% of reimbursed copays (regions)	Reimbursing cities
Praha	never	NO	NA	NA	NA
Stredocesky	1.1.2009	Yes	oral	95%	Benešov, Kladno, Kolín, Mladá Boleslav, Příbram
Jihocesky	1.2.2009	Yes	written	70%	Prachatice, Písek, Strakonice, Tábor (2), České Budějovice, Český Krumlov
Plzensky	1.2.2009	Yes	ex-post	25%	Domažlice, Rokycany, Stod
Karlovarsky	1.2.2009	Yes	oral/written	63%	Karlovy Vary
Ustecky	1.2.2009	Yes	written	40%	Děčín, Most, Teplice, Ústí nad Labem
Liberecky	1.2.2009	Yes	written	51%	Liberec, Česká Lípa
Kralovehradecky	1.2.2009	Yes	oral/written	65%	Jičín, Náchod (2)
Pardubicky	1.2.2009	Yes	written	46%	Chrudim, Litomyšl, Pardubice, Svitavy, Ústí nad Orlicí
Vysocina	1.2.2009	Yes	written	60%	Havlíčkův Brod, Jihlava, Nové Město na Moravě, Pelhřimov, Třebíč
Jihomoravsky	1.2.2009	Yes	written	65%	Hodonín, Ivančice, Vyškov, Znojmo
Olomoucky	1.2.2009	Yes	written	65%	Prostějov, Přerov, Šternberk
Zlinsky	1.2.2009	NO	written	25%	NA
Moravskoslezsky	1.2.2009	Yes	written	45%	Frýdek-Místek, Havířov, Karviná, Krnov, Opava, Orlová, Stonava, Třinec

Table 3.2: Summary statistics of the sameday sample, by year

	2006	2007	2008	2009
# of patients	224,687	239,343	241,045	252,397
# of visits	1,012,402	1,181,183	1,066,806	1,180,276
% of men	36.6%	36.9%	37.5%	38.6%
average age	72.7	73.6	74.4	75.2
# of prescriptions per visit	2.11	2.19	2.04	2.06
average price per prescription	380	390	500	530
share of PCP visits	0.22	0.25	0.24	0.24
Share of patients by regions (in %)				
Praha	14.39	13.94	14.64	14.80
Stredocesky	8.84	8.71	8.43	8.20
Jihocesky	4.77	4.79	5.27	.38
Plzensky	5.35	5.66	5.70	6.02
Karlovarsky	3.11	3.26	3.09	2.95
Ustecky	7.88	7.82	7.53	7.152
Liberecky	3.94	3.85	3.84	3.74
Kralovehradecky	4.69	4.40	4.56	5.08
Pardubicky	5.51	5.65	5.89	5.73
Vysocina	6.75	6.78	6.91	6.88
Jihomoravsky	10.76	10.87	10.72	10.57
Olomoucky	6.64	7.02	6.71	6.96
Zlinsky	7.86	7.57	7.53	7.53
Moravskoslezsky	9.52	9.68	9.18	9.02

Table 3.3: Effect of start of reimbursement on the probability of going filling a prescription in the pharmacy located at the same address as provider

	Before		After		dy/dx	
	coef	SE	coef	SE	coef	SE
Baseline						
control	0.655	0.002	0.647	0.002	**-0.008**	0.001
non-reimbursing	0.639	0.005	0.594	0.005	**-0.045**	0.002
reimbursing	0.605	0.006	0.652	0.006	**0.047**	0.003
A) Physician type						
- PCP						
control	0.695	0.003	0.681	0.003	**-0.014**	0.002
non-reimbursing	0.641	0.007	0.552	0.007	**-0.090**	0.006
reimbursing	0.517	0.013	0.746	0.016	**0.226**	0.017
- specialist						
control	0.647	0.002	0.641	0.003	**-0.007**	0.001
non-reimbursing	0.639	0.005	0.603	0.006	**-0.036**	0.003
reimbursing	0.623	0.005	0.634	0.006	**0.011**	0.003
B) # of prescriptions						
- 1 prescription						
control	0.648	0.002	0.645	0.003	**-0.004**	0.001
non-reimbursing	0.629	0.005	0.604	0.006	**-0.025**	0.003
reimbursing	0.613	0.005	0.609	0.006	-0.003	0.003
- 2 prescriptions						
control	0.665	0.003	0.655	0.003	**-0.010**	0.002
non-reimbursing	0.641	0.006	0.593	0.006	**-0.048**	0.004
reimbursing	0.62	0.006	0.644	0.006	**0.024**	0.004
- 3-4 prescriptions						
control	0.674	0.003	0.660	0.003	**-0.014**	0.002
non-reimbursing	0.637	0.006	0.562	0.007	**-0.076**	0.005
reimbursing	0.614	0.007	0.666	0.007	**0.052**	0.006
- 5+ prescriptions						
control	0.675	0.004	0.655	0.004	**-0.019**	0.003
non-reimbursing	0.637	0.008	0.527	0.009	**-0.110**	0.008
reimbursing	0.593	0.009	0.676	0.010	**0.083**	0.009

Note: Using sub-sample of visits where there exists a pharmacy located at the same address as physician, and prescription was filled the same day as visit has been made, 4 440 667 observations.

Table 3.4: Effect of start of reimbursement on the probability of going filling a prescription in the pharmacy located at the same address as provider

	Before		After		dy/dx	
	coef	SE	coef	SE	coef	SE
Baseline	0.099	0.002	0.190	0.003	**0.091**	0.003
A) Physician type						
- PCP	0.073	0.003	0.191	0.007	**0.119**	0.007
- specialist	0.104	0.002	0.189	0.003	**0.085**	0.004
B) # of prescriptions						
- 1 prescription	0.968	0.002	0.164	0.004	**0.068**	0.004
- 2 prescriptions	0.104	0.003	0.192	0.005	**0.089**	0.005
- 3-4 prescriptions	0.098	0.003	0.230	0.006	**0.132**	0.007
- 5+ prescriptions	0.098	0.006	0.245	0.010	**0.148**	0.010
C) distance to closest reimbursing pharmacy						
<500	0.275	0.009	0.463	0.011	**0.189**	0.009
500-1000m	0.133	0.008	0.239	0.010	**0.106**	0.008
1000-1500m	0.087	0.006	0.295	0.009	**0.208**	0.007
1500-2000m	0.136	0.008	0.380	0.010	**0.245**	0.009
2000-2500m	0.150	0.006	0.328	0.010	**0.177**	0.009
2500-3000m	0.103	0.008	0.258	0.013	**0.155**	0.012
3000-5000m	0.200	0.009	0.338	0.012	**0.137**	0.010
>5000m	0.208	0.022	0.246	0.026	0.038	0.030

Note: Using sub-sample of visits where there exists a pharmacy located at the same address as physician, and prescription was filled the same day as visit has been made, 147 976 observations.

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