Journal Pre-proof

Policy implications of heterogeneous demand reactions to changes in cost-sharing: Patient-level evidence from Austria

Michael Berger, Eva Six, Thomas Czypionka

PII: S0277-9536(23)00845-6

DOI: https://doi.org/10.1016/j.socscimed.2023.116488

Reference: SSM 116488

To appear in: *Social Science & Medicine*

Received Date: 17 March 2023

Revised Date: 11 July 2023

Accepted Date: 29 November 2023

Policy implications of heterogeneous demand reactions to changes in cost-sharing: Patient-level evidence from Austria

Authors: Michael Berger[1,2*], Eva Six[3], Thomas Czypionka[2,4,*]

1) Department of Health Economics, Center for Public Health, Medical University of Vienna, Kinderspitalgasse 15/1, 1090 Vienna, Austria

2) Institute for Advanced Studies, Josefstädterstraße 39, 1080 Vienna, Austria

3) Research Institute Economics of Inequality, Vienna University of Economics and Business, Welthandelsplatz 1,1020 Wien Austria

4) London School of Economics and Political Science, Houghton Street, London, WC2A 2AE, UK

*Shared corresponding authorship
Michael Berger
email: michael.a.berger@meduniwien.ac.at

Thomas Czypionka
email: czypionk@ihs.ac.at

Keywords: Cost-sharing; price elasticity; healthcare service consumption; two-way fixed-effects difference-in-differences; entropy balancing;

JEL-Codes: C13; I18; L31;

Policy implications of heterogeneous demand reactions to changes in cost-sharing: Patient-level evidence from Austria

Keywords: Cost-sharing; price elasticity; healthcare service consumption; two-way fixed-effects difference-in-differences; entropy balancing;

JEL-Codes: C13; I18; L31;

Abstract: Cost-sharing is a prominent tool in many healthcare systems both for raising revenue and for steering patient behaviour. Although the effect of cost-sharing on demand for healthcare services has been heavily studied in the literature, researchers often apply a macro-perspective to these issues, opening the door for policy makers to the fallacy of assuming uniform demand reactions across a spectrum of different forms of treatments and diagnostic procedures. We use a simple classification system to categorize 11 such healthcare services along the dimensions of urgency and price to estimate patients' (anticipatory) demand reactions to a reduction in the co-insurance rate by a sickness fund in the Austrian social health insurance system. We use a two-stage study design combining matching and two-way fixed effects difference-in-differences estimation. Our results highlight how an overall joint estimate of an average increase in healthcare service utilization (0.8%) across all healthcare services can be driven by healthcare services that are deferrable (+1%), comparatively costly (+1.4%) or both (+1.6%) and for which patients also postponed their consumption until after the cost-sharing reduction. In contrast, we do not find a clear demand reaction for inexpensive or urgent services. The detailed analysis of the demand reaction for each individual healthcare service further illustrates their heterogeneity. Our findings provide useful insights for policy makers that even comparatively small changes to the costs borne by patients may already evoke tangible (anticipatory) demand reactions and help to better understand the implications of heterogeneous demand reactions across healthcare services for the use of cost-sharing as a policy tool.

Policy implications of heterogeneous demand reactions to changes in cost-sharing: Patient-level evidence from Austria

1 Introduction

Cost-sharing schemes are a common pillar in the financing of healthcare systems, in which they often fulfil a dual role. Decision makers frequently use them as a tool to alleviate the pressure on public healthcare budgets. Apart from generating revenue directly, cost-sharing is also a means to influence and steer the behaviour of patients to control demand for healthcare services and thereby deal with the problem of moral hazard (Robinson, 2002). For instance, in healthcare systems with comprehensive coverage through public schemes, patients are seldom aware of the true costs of healthcare services. Cost-sharing schemes can be a way of making patients internalize part of these costs. As the user charges levied from patients are essentially payments charged by providers at the point of delivery, they are a form of consumer price (Schokkaert and Van de Voorde, 2011). It is therefore imperative for policy makers to have a thorough understanding of the mechanisms behind the effects of cost-sharing.

Although the effects of cost-sharing in the form of user charges – both desired and undesired – are well-documented and extensively discussed in the literature (Barnieh et al., 2014; Kiil and Houlberg, 2014), researchers tend to approach the issue with aggregated measures. Early seminal contributions to the empirical investigation of the impact of cost-sharing on healthcare utilization include the work resulting from the RAND Health Insurance experiment (Manning et al., 1987; Newhouse et al., 1981). The results showed how rising levels of cost-sharing reduce the probability of healthcare utilization – with the greatest impact on low-income groups. More recent contributions still tend to take a bird's-eye perspective and investigate the effect of a (large-scale) introduction of user charges on healthcare services and do not differentiate between specific types of services, that is, diagnostics procedures and treatments (Jakobsson and Svensson, 2016a, 2016b; Schreyögg and Grabka, 2010; Van de Voorde et al., 2001). Other contributions try to move in closer, yet remain at a distance by picking arguably large fields of investigation. For instance, a considerable share of the current literature has been devoted to analysing the effects of cost-sharing components on prescription pharmaceuticals (García-Gómez et al., 2018; Gibson et al., 2005; Goldman et al., 2007). Other studies focus on specific medical specialities like mental health (Lambregts and van Vliet, 2018; Ndumele and Trivedi, 2011), or healthcare sectors like emergency care (Hsu et al., 2006; Mortensen, 2010; Sabik and Gandhi, 2016; Siddiqui et al., 2015), primary care (Johansson et al., 2019; Maynou et al., 2019) or outpatient care in general (Lee et al., 2017; Schellhorn, 2001), or span several healthcare service categories that correspond to different healthcare sectors (Ellis et al., 2017).

None of these studies differentiate between the precise types of services at the level of diagnostic procedures or treatments that are delivered. There is hence still a knowledge gap regarding the effect of changes in user charges on the demand for specific healthcare services, diagnostic procedures or treatments. To the best of our knowledge, the work related closest to the present study is the empirical investigation by Duarte (2012) on healthcare service specific price elasticities in the Chilean private insurance market, showing that consumers are more sensitive in their demand for elective procedures than for acute care. We draw from this previous evidence that where a specific healthcare service is located on the dimensions of price and urgency determines the elasticity of demand to consumer prices, i.e., user charges. In contrast to the acute/elective dichotomy used by Duarte (2012), we use the more broadly defined concept of urgency, which means that although some measures do not have to be taken immediately, the patient is unwilling to postpone them for long. By using the term urgency, we maintain higher flexibility by avoiding a strictly dichotomous interpretation.

The aim of this article is to present empirical evidence that demand reactions of specific diagnostic procedures and treatments (henceforth for simplicity referred to as *healthcare services*) to changes to a cost-sharing regime can be intuitively understood through the dimensions of costs and urgency. This can help policy makers to better gauge the impact of changes to a cost-sharing regime with respect to its efficacy in steering patient behaviour and raising revenue. Our empirical analysis investigates the demand reactions across a set of 11 healthcare services to a cost-sharing reduction by an Austrian sickness fund from 20% to 10% in 2016. We find that healthcare service utilization of its patients increased on average by 0.8% across all healthcare services. However, differentiating between cost and urgency categories demonstrates that the increase in healthcare demand is largely driven by services that are high cost (+1.4%), deferrable (+1%), or both (+1.6%). We further find that patients postponed their utilization of expensive and deferrable healthcare services until after the cost-sharing reduction. In contrast, for low cost and urgent healthcare services, we do not find a statistically significant demand reaction. The analyses of individual healthcare services further explores the heterogeneity between healthcare services in the dependency of their demand on price. We thereby add to the existing literature by providing insights for policy makers regarding the dual role of user charges as a steering and a financing tool as well as additional empirical evidence on the price elasticity of specific diagnostic procedures and treatments. When policy makers plan to introduce, abolish or alter the level of cost-sharing schemes, it is important to base the decision on precise estimates of the consequences with respect to the efficacy as tool for steering patients along a best-practice path and as a tool for raising revenue.

1.1 Cost-Sharing in the Austrian social health insurance system

The empirical evidence for our study comes from Austria. The Austrian healthcare system is of the Bismarckian type, with multiple sickness funds and near universal coverage. Insurees cannot freely choose among the different sickness funds, as assignment is determined by type and area of employment. Some sickness funds operate nationwide, while others operate exclusively within one of the nine federal states. For a detailed description of the fragmented organisation of the Austrian healthcare system, we refer interested readers to the latest Healthcare Systems in Transition article on Austria (Bachner et al., 2018).

Like all European countries with a healthcare system primarily financed by social health insurance (SHI) contributions, Austria applies cost-sharing schemes. Compared to the other SHI-financed EU member countries, Austria has a relatively high share of direct out-of-pocket payments by patients (OECD Statistics, 2018), although these OECD numbers also include payments outside the publicly funded healthcare system. Cost-sharing in Austria comes in various forms depending on the respective healthcare setting. All sickness funds demand co-payments for specific items such as pharmaceuticals or medical devices. While user charges for inpatient care are levied in the form of per diems and vary by federal state (between €12 and €19 per day in 2018, depending on the hospital and for a maximum of 28 days per year), cost-sharing for retail pharmaceuticals is a nationwide lump-sum co-payment (€6 in 2018) for each package in a prescription filled at a pharmacy.

Most importantly for the context of this study, cost-sharing in the outpatient sector is not uniform across sickness funds. Several sickness funds make use of their autonomy in requiring some form of cost-sharing from their insurees (Czypionka et al., 2019; Mossialos et al., 2017). Relevant for the present study are the sickness fund for public employees (*Versicherungsanstalt öffentlich Bediensteter*) which levies a co-insurance where patients are charged a fixed percentage of the costs for most outpatient healthcare services and the regional sickness funds (*Gebietskrankenkassen*) that cover nearly all private sector employees and do not apply outpatient cost-sharing. With the beginning of the second quarter of 2016, the nationwide sickness fund for public employees halved the general co-insurance rate from 20% to 10%, which provides the setting for our quasi-experimental study design.

Patients of the sickness fund for public employees receive a summary bill from the sickness fund at most once per month. Minor healthcare services (e.g., cerumen removal) are not billed directly as individual items. Rather, patients are billed with a lump-sum payment for each visit to a physician's office. Additionally, each 'first visit to the practice' within a month has a slightly higher fee. Co-insurance also applies in cases where there is no physician contact as long as it is an extra item reimbursable by the sickness fund, e.g., when renewing a prescription without a visit. Relevant to the context of our study, only diagnostic imaging, laboratory testing, and electrocardiographic and ergometric tests in outpatient settings show up directly on the patients' bills from the sickness funds.

An important aspect of this cost-sharing regime is that it does not affect physician reimbursement as such, thereby ruling out any effects through incentives for supplier-induced demand. In practice, the cost-sharing for most individual outpatient health care services is not too financially challenging for patients but can accumulate for patients with a higher disease burden. Exceptions from this cost-sharing for outpatient healthcare services are in place to protect vulnerable socioeconomic groups. Patients are exempt from the co-insurance if they are also exempt from the co-payment on prescriptions, which is waived for people under a certain income threshold (depending on the number of persons in the household and the presence of conditions that required elevated levels of medication). The co-payment for prescription pharmaceuticals is also waived if the staggered co-payments exceed 2% of the patient's annual net income or in case of certain infectious diseases. However, this does not affect the co-insurance component and is therefore not of direct relevance for our study. Lastly, outpatient healthcare services of children and minors insured with their parents are also exempt from the co-insurance.

2 Data

We utilise pseudonymised longitudinal patient-level routine data on healthcare service utilization provided by the Main Association of Social Security Institutions in Austria from the beginning of the second quarter of 2015 (Q2-2015) to the end of the second quarter of 2017 (Q2-2017). The dataset covers a total of 961,851 eligible patients with 2,264,052 healthcare service contacts. Children and minors insured with their parents are exempt from co-insurance in the intervention group. As the dataset does not include information on the insurance status of the patients, we removed patients aged 14 years or younger, as apprenticeships are possible from this age onwards in Austria and patients above that age could be insured directly. However, insurance coverage through parents is in practice possible up until the age of 27 years. As the service catalogues of reimbursed healthcare services differ between sickness funds, our data provider limited the dataset to three sickness funds to have as many comparable – in the sense of having the same definition and scope for reimbursement purposes across the sickness funds – healthcare services in the analysis as possible. In total, our data provider was able to identify 11 such comparable healthcare services suitable for our study design. The dataset contains all patients insured with the regional sickness funds of Salzburg and Upper Austria, and the nationwide sickness fund for civil servants. As the intervention group consists of patients of a nationwide sickness fund, the control group was chosen such that the two regional funds cover a patient population with similar characteristics the other regional sickness funds. We provide this background information concerning the generalizability in the electronic supplementary material of this article. It is important to note that the intervention and control group differ insofar as the intervention group is always confronted with a co-insurance component whereas the control group is not. However, as a constant co-insurance component likely only influences the level of the healthcare service consumption through a price effect, we argue that this does not impede our study design.

Patients in the sample were insured with one of the three sickness funds throughout the entire observation period and consumed at least one of the 11 comparable healthcare services, which are identified by their assigned unique identifier code in the catalogue of outpatient care services (*Katalog ambulanter Leistungen, KAL*). The list of comparable services and the corresponding number of contacts in the dataset as well as the fee paid per contact by sickness fund of the intervention group are presented in Table 1. The frequency of the different healthcare services in the dataset varies strongly, reaching from a few thousand (sonography of the intracranial vessels) to almost one million (routine electrocardiogram).

Healthcare service description	Number of contacts in dataset	Fees in 2016 (intervention group)	Cost-sharing reduction in absolute terms
Blood gas analysis	99,060	€55.70	€5.57
Cerumen removal	445,423	€10.68 – €18.57	€1.06 – €1.86
Electromyography	34,979	€51.99	€5.20
Incident-light microscopy	334,623	€2.79	€0.28
Nystagmus inspection	42,385	€10.68 – €18.57	€1.06 – €1.86
Removal of foreign bodies from the cornea, sclera or conjunctiva	19,572	€10.68 – €18.57	€1.06 – €1.86
Routine electrocardiogram (ECG)	950,153	€40.82	€4.08
Routine electroencephalography (EEG)	45,592	€59.42	€5.94
Sonography of the intracranial vessels	4,617	€55.81	€5.58
Sonography of the thyroid and parathyroid gland	167,731	€27.45	€2.75
Uroflowmetry	119,917	€19.50	€1.95
Sum	**2,264,052**		

The fees that physicians are reimbursed from the sickness fund for the relevant billing items that are not directly observed in the data are 'first visit to the practice' (€18.57) and 'additional visit to the practice' (€10.68). The patients' cost-sharing is 20% (before) and 10% (after) of the respective fee.

Table 1: Description, number of contacts and fee of the comparable healthcare services included in the dataset

The patients' count of episodes per healthcare service and quarter is our outcome variable of interest. We extend the panel with zero-observations, i.e., quarters in which patients do not have a specific service utilization to have a balanced panel that includes observations for each patient in every quarter. We further use patient-level data on sex and age contained in the dataset. The dataset does not include patient-level information on the socioeconomic status (SES), but empirical evidence suggests that deterrent effects of user charges are higher for vulnerable individuals such as low-income groups, the unemployed or those with chronic conditions (Johansson et al., 2019; Maynou et al., 2019). We therefore use a composite measure like Berger and Czypionka (2021) for the SES based on district characteristics of the patients' area of residence. The SES score is based on (i) the percentage of persons with only mandatory schooling in the labour force (Statistik Austria, 2016), (ii) the percentage of unemployed persons in the labour forces (Statistik Austria, 2019), and (iii) the average net income (Statistik Austria, 2016). For each variable, we divide the districts into quartiles. The higher the quartile, the worse a district ranks in the socioeconomic dimension. The SES score is simply the average of the three quartile ranks. The data required for the SES score was not available for one district in the federal state of Lower Austria, because it was merged into other districts after the study period. It was not possible to allocate the cases to new districts due to data limitations. We therefore excluded these patients from the sample. We further account for differences in the need for treatment by including the patients' total number of healthcare contacts over the entire observation period as a proxy variable for the individual burden of disease. Finally, an important limitation in the dataset is that it does not include information on patients who are exempt from cost-sharing and, therefore, would not react to a change in the cost-sharing regime. The summary statistics of the control variables used in our analysis before and after the matching procedure based on entropy balancing for the entire sample are reported in Table 3.

3 Methods

3.1 Classification of healthcare services

We classify the analysed healthcare services along the two decision-relevant dimensions of costs and urgency. This allows us to formulate two propositions for the demand reaction, which we use to guide our empirical analysis.

We distinguish between services that are urgent and whose consumption cannot be postponed by patient discretion and services that can be postponed. Here it is good to recall that 'urgent' is not restricted to emergency care services. A good example is an electromyography, which indicates that a neuromuscular disease is suspected, and although it does not need to be performed on the same day, a patient will normally seek timely clarification, while a foreign body in the eye requires immediate treatment. In case of an urgent medical condition, patients will likely not want to unnecessarily delay a needed test or procedure. The distinction is important because patients of the control group can postpone their health care consumption to the period after the reduction of the co-insurance rate. The incentives, i.e., the price, and possibilities for patients to do so differ between healthcare services. Healthcare services that can be easily postponed, like routine check-ups, will likely be differently affected by user charges – especially when they come in the form of co-insurance or staggered co-payments – than urgently required treatments or diagnostic measures. Along the same line of reasoning, we would expect user charges in the form of a co-insurance to have a larger impact on patient demand when the costs for a service are high as the amount covered by the patient increases proportionately. While patients' decisions are likely less affected by a co-insurance on low-cost services, co-insurance on high-cost services entails a higher trade-off with other forms of spending and may cause stronger demand reactions. Overall, we would expect a higher effect of a reduction of the co-insurance rate for cost-intensive, deferrable services on the demand for healthcare services.

Proposition 1: Price elasticity is highest for high-cost, non-acute healthcare services.

For non-urgent services, we would expect demand to decrease especially in the quarter preceding, and to increase in the quarter of the reduction in co-insurance due to patients forestalling their healthcare consumption. Again, we would also expect this effect to be stronger when the services in question are high-cost. Three healthcare services (electromyography, sonography of the thyroid and parathyroid gland, and blood gas analysis) are classified as `mix´, as these are urgent in the diagnostic phase for some conditions but can be postponed when they are used in follow-up exams.

Proposition 2: Demand for high-cost, non-acute healthcare services will be comparatively lower in the period leading up to the price shock and comparatively higher in the period of the price shock due to anticipatory postponement effects.

The classification of the 11 healthcare services in our analysis are provided in Table 2. We use the cost information provided in Table 1 and set the threshold for the cost classification at €25, which roughly corresponds to the median of the 11 comparable healthcare services. Note that this threshold is a crude measure for orientation purposes only. We can neither observe whether a patient considers a healthcare service expensive or not, nor is it necessary for the purpose of this analysis.

	Deferrable	Mix	Urgent
High Cost	Routine ECG Routine EEG	Blood gas analysis Electromyography Sonography of the thyroid and parathyroid gland	Sonography of the intracranial vessels
Low Cost	Cerumen removal Incident-light microscopy Uroflowmetry		Nystagmus inspection Removal of foreign bodies from the cornea, sclera or conjunctiva

Table 2: Classification matrix of the 11 healthcare services in the outpatient sector according to cost and urgency

3.2 Combining Matching and Two-way Fixed-effects Difference-in-differences

We estimate causal treatment effects under non-random assignment to the co-insurance regimes by using a combination of matching and two-way fixed-effects (TWFE) difference-in-differences estimation. The matching step makes the intervention and control group more similar with respect to the time-fixed observable control variables with the aim of thereby also making the two groups more comparable with respect to unobservable characteristics. A shared trend in the outcome variable between the two groups prior to the intervention is hence not just indicative for the success of the matching stage, but also a prerequisite for the validity of the quasi-causal interpretation of the estimation.

3.2.1 Entropy balancing

We lean on the approach by Everding and Marcus (2020), who combine matching via entropy balancing with subsequent difference-in-differences estimation. Entropy balancing is a multivariate reweighting method that directly aims for covariate balance by assigning a scalar weight to the observations in the control group such as to match the covariate distributions of the intervention and control group on the first and second moment. This has the advantage that it reduces the model dependence in the subsequent analyses compared to propensity score matching methods (Hainmueller, 2011). We use the user-written Stata programme "*ebalance*" (Hainmueller and Xu, 2013) to compute balancing weights with respect to sex, age, SES score and burden of disease in each service- or classification-specific subsample of patients (i.e. patients with at least one contact of the healthcare service in the observation period), as each healthcare service category and individual healthcare service has a distinct patient composition that is not well captured by weights calculated using the full sample. Table 2 presents the summary statistics of the joint estimation of the 11 healthcare services before and after the matching procedure where columns (4) and (5) present the standardised difference in means before and after the matching as a quality indicator for the matching procedure.

Variable	**Mean (treated)**	**Means (control)**		**Standardized difference**	
		Raw	EB	Raw	EB
	(1)	(2)	(3)	(4)	(5)
Female	0.487	0.527	0.487	-0.080	0.000
Age	57.980	55.217	57.980	0.154	0.000
Burden of disease	54.384	49.414	54.383	0.130	0.000
SES score	2.442	2.359	2.442	0.110	0.000
N	1,223,619		711,799		

Table 3: Summary statistics for the selected control variables before and after matching using entropy balancing (EB) in the full patient sample

3.2.2 Parallel trends

The validity of our identification strategy in our difference-in-differences estimation depends on a shared trend between the intervention and (weighted) control group absent the intervention. Figure 1 shows the trends in the quarterly outcome variable over the observation period for all healthcare services combined, the cost and urgency groups and their combinations after applying the entropy balancing weights. The trends of the individual healthcare services are presented in the supplement. We additionally check for this shared trend by regressing the quarterly weighted outcome variable on the time variable (quarters), the dummy variable signalling group affiliation (intervention versus control) and an interaction term of the two variables. As the interpretation of nonlinear difference-in-difference models is not trivial and depends on the functional form of the parallel trends assumption, we test under the assumption of a parallel trend in the natural scale of the outcome variable, such that the estimated treatment effect in the transformed scale of the nonlinear main regression model is the interaction effect (Barkowski, 2021). The linear model we use to check the parallel assumption in the natural scale of the outcome using fixed-effects (within) ordinary least squares (OLS) panel regression is given by

$$y_{i,t} = \beta_0 + \beta_1 D1_t + \cdots + \beta_3 D3_t + \beta_5 D5_t + \cdots + \beta_9 D9_t + \gamma POST_t$$

$$+\delta \left(D1_t * TREAT_i + \cdots + D3_t * TREAT_i + D5_t * TREAT_i + \cdots + D9_t * TREAT_i \right) + \epsilon_{i,t}$$

with $T-1$ dummies (as the quarter prior to the intervention, Q1-2016 is omitted) and where y denotes the healthcare consumption of individual *i=1,2,…,n* in period *t=1,2,…,9, POST is a variable that takes the value 1 for the quarters following the intervention and 0 otherwise, TREAT* takes the value 1 for individuals in the intervention group and 0 for individuals in the control group, and ε is the i.i.d. error term with $\epsilon_{i,t} \sim N(0, \sigma_\epsilon^2)$. The parallel trend assumption is violated when the coefficient on interaction term, δ, is statistically significant in the quarters prior to the intervention.

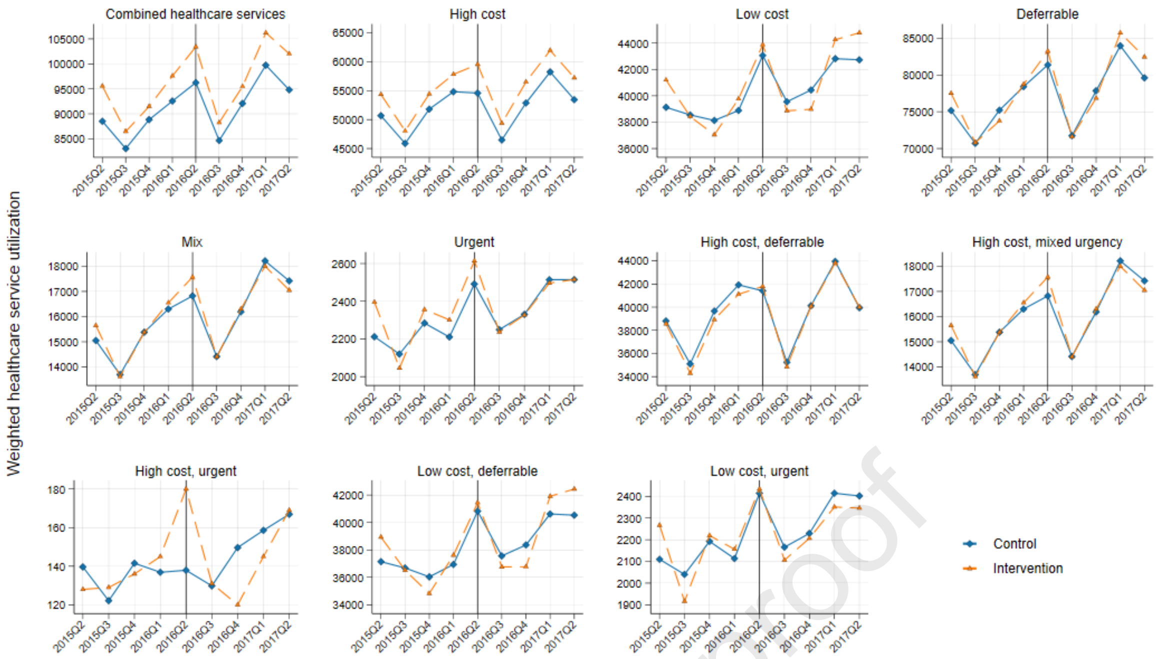

Figure 1: Pre-and post-intervention trends of the intervention and the weighted control group for the 11 healthcare services combined, the cost and urgency groups and their combinations in the four quarters before and after the reduction of the co-insurance rate.

3.2.3 Two-way Fixed-effects Difference-in-difference Regression

We then proceed to estimate a TWFE difference-in-difference model via conditional fixed-effects Poisson panel regression, which accounts for the nonnegative count outcome variable, using the weights obtained from the entropy balancing in the matching stage of the analysis and controlling for patient-level and time-fixed effects. The TWFE difference-in-difference model to test the demand reaction (*Proposition 1)* is given by:

$$y_{i,t} = \exp[\,\gamma POST_t \;+\; \delta\,(POST_t * TREAT_i) + \beta_1 D2_t + \cdots + \beta_9 D9_t], \qquad y \sim Poisson \quad (2)$$

While we control for time-fixed effects by including $T-1$ dummies (the first period, *D1,* is omitted), the conditional fixed-effects Poisson eliminates the time-invariant patient-fixed effects under the assumption the observations are independent. The coefficient of the interaction term, δ, captures the effect of the co-insurance rate reduction on healthcare utilization.

For anticipatory effects (*Proposition 2)*, we adapt our test for the assumption of parallel trends in equation (1), using Q1-2017 as the basis for comparison to avoid interference of seasonal fluctuations.

$$\begin{gathered} y_{i,t} = \exp[\, \beta_1 D1_t + \cdots + \beta_7 D7_t + \cdots + \beta_9 D9_t + \, \gamma POST_t \\ + \delta_1 D1_t * TREAT_i + \cdots + \delta_7 D7_t * TREAT_i + \cdots + \delta_9 D9_t * TREAT_i] \quad y \sim Poisson \end{gathered} \tag{3}$$

This procedure allows us to verify whether there has been a change in the trend of the intervention group leading up to the intervention as captured by the interaction term between the quarters of interest and the intervention dummy.

3.3 Sensitivity analysis

We test the plausibility of our estimated effect in the analysis via placebo regression. We truncate the panel up to the period of the actual intervention (Q2-2015 to Q2-2016) and signal the placebo intervention two quarters before the actual timing of the intervention (Q4-2015). By truncating the sample size, we circumvent the issue that persistent effects in combination with a large sample size may consistently yield statistically significant results also for placebo interventions before or after the actual intervention. We further estimate the regression model (2) for the demand reaction (*Proposition 1*) in the regression for the cost and urgency dimensions, as well as their combinations, using OLS estimation to assess the robustness of our results with respect to the functional form.

Another crucial aspect of our study results concerns the nature of the cost-sharing regime in the intervention group. Patients are usually billed retrospectively by the sickness fund. It is very likely that patients – especially those with few healthcare needs – are not aware of the actual fee when making the decision of using an outpatient healthcare service, though they may have some idea that some services (e.g., laboratory services, diagnostic imaging) are more expensive than other less elaborate procedures (e.g., cerumen removal). Patients could in principle inform themselves on the costs of the service prior to their appointment by looking up reimbursement fees for individual services, as the fee catalogues are available online. However, these may not be easily obtainable for laypersons and are additionally a somewhat cryptic read, as fees are expressed as points, which need to be converted into currency first. We therefore run the regression of the individual healthcare care services for the subsample of frequent healthcare utilisers as these patients are more likely aware of the costs of certain healthcare services and are conceivably more likely to be more price sensitive as the co-insurance rates add up and hence have a higher financial impact. We classify a patient as a frequent utiliser if the patient's total number of healthcare contacts is above the sample median of 39 healthcare contacts. Lastly, we account for possible sex-specific patterns in healthcare utilization of the individual healthcare services by running regression (2) separately for females and males.

4 Results

We start the presentation of our results with the general case of an *overall* effect of a joint estimation of all 11 healthcare services, moving on to the separate estimation of the impact of the cost-sharing reform along the cost and urgency dimensions separately and an estimation of the possible cost-urgency category combinations. Finally, we provide a short summary of the main estimation results for the individual healthcare services, which are provided in detail in the supplement.

Table 4 presents the results of the joint TWFE estimation for all healthcare services and the for the cost and urgency categories. In the joint estimation, the assumption of shared pre-trends between the control and intervention groups holds at least from visual inspection, although the formal procedure fails as due to the substantial size of the sample the negligibly small difference in the trends are statistically significant. We estimate that the cost-sharing reduction resulted in a roughly 0.8% increase in healthcare service utilization between all 11 healthcare services. We do not find a postponement effect for the overall estimate. Running the regression separately for the cost and urgency groups yields results in line with the expectations regarding the demand reaction (*Proposition 1)* and anticipatory effects (*Proposition 2)***.** While for the high cost group of healthcare services we estimate an increase in demand of 1.4% following the cost-sharing reduction, we do not observe a comparable effect in the low cost group. For the high-cost healthcare services, the intervention and control group follow similar pre-trends upon visual inspection, although also in this case the formal procedure highlights small statistically significant differences in the trends prior to the intervention, because of the large sample size. We observe a similar picture in line with the expectations when running the regressions for the different urgency groups, with an average increase in the demand for deferrable healthcare services by 1% and postponed utilisation in the quarter leading up to the intervention, with no clear and statistically significant patterns for the mix or high-urgency categories. The results are robust with regard to the placebo regression set-up.

Healthcare service category	All healthcare services				High cost healthcare services				Low cost healthcare services			
Matching method	Raw	Entropy balancing			Raw	Entropy balancing			Raw	Entropy balancing		
Regression method	Conditional Fixed-effects Poisson Regression	Weighted Conditional Fixed-Effects Poisson Regression		Weighted Fixed-Effects Ordinary Least Squares	Conditional Fixed-effects Poisson Regression	Weighted Conditional Fixed-Effects Poisson Regression		Weighted Fixed-Effects Ordinary Least Squares	Conditional Fixed-effects Poisson Regression	Weighted Conditional Fixed-Effects Poisson Regression		Weighted Fixed-Effects Ordinary Least Squares
Effect	Demand reaction	Demand reaction	Anticipatory reaction	Demand reaction	Demand reaction	Demand reaction	Anticipatory reaction	Demand reaction	Demand reaction	Demand reaction	Anticipatory reaction	Demand reaction
Sample	Full	Full	Full	Full	Full	Full	Full	Full	Full	Full	Full	Full
*POST*TREAT*	0.00321	0.00778*	n/a	0.00437***	0.00773*	0.0142**	n/a	0.00506***	-0.00285	-0.000919	n/a	0.000301
	(0.00268)	(0.00352)		(0.000755)	(0.00359)	(0.00472)		(0.000854)	(0.00387)	(0.00495)		(0.000776)
2016Q1*TREAT	n/a	n/a	-0.0101	n/a	n/a	n/a	-0.00897	n/a	n/a	n/a	-0.0106	n/a
			(0.00720)				(0.00956)				(0.0104)	
2016Q2*TREAT	n/a	n/a	0.00891	n/a	n/a	n/a	0.0248*	n/a	n/a	n/a	-0.0144	n/a
			(0.00735)				(0.00989)				(0.0104)	
N	8,656,659	8,655,849	8,655,849	8,655,849	5,877,504	5,876,982	5,876,982	5,876,982	4,932,117	4,931,730	4,931,730	4,931,730
N (intervention)	2,934,045	2,933,271	2,933,271	2,933,271	1,989,405	1,988,901	1,988,901	1,988,901	1,801,728	1,801,368	1,801,368	1,801,368
Linear parallel trends	No	No	No	No	No	No	No	No	No	No	No	No
Healthcare service category	Deferrable healthcare services				Mixed urgency healthcare services				Urgent healthcare services			
*POST*TREAT*	0.00398	0.00915*	n/a	0.00324***	-0.0105	-0.00925	n/a	-0.0000835	-0.00852	-0.0229	n/a	-0.00246
	(0.00277)	(0.00365)		(0.000690)	(0.00687)	(0.00720)		(0.00111)	(0.0172)	(0.0252)		(0.00249)
2016Q1*TREAT	n/a	n/a	-0.0166*	n/a	n/a	n/a	0.0268	n/a	n/a	n/a	0.0475	n/a
			(0.00752)				(0.0145)				(0.0507)	
2016Q2*TREAT	n/a	n/a	0.00183	n/a	n/a	n/a	0.0555***	n/a	n/a	n/a	0.0553	n/a
			(0.00767)				(0.0147)				(0.0492)	
N,	8,043,804	8,043,021	8,043,021	8,043,021	1,851,147	1,851,111	1,851,111	1,851,111	488,322	488,304	488,304	488,304
N (intervention)	2733237	2,732,481	2,732,481	2,732,481	840,150	840,114	840,114	840,114	147,123	147,114	147,114	147,114
Linear parallel trends	No	No	No	No	No	No	No	No	No	No	No	No

*p < 0.05, ** p < 0.01, ***p < 0.001; Heteroscedasticity robust standard errors in parentheses (clustered at the patient level)

Table 4: Results of the weighted conditional fixed-effects difference-in-difference Poisson regression for all healthcare services jointly and the cost and urgency categories

Turning to the regression results according to the different cost-urgency categories, we can see that for deferrable high-cost services, the co-insurance reduction resulted in a 1.6% increase in service utilisation. For the other cost-urgency categories we do not find a statistically significant effect. Regarding postponement effects, we do find statistically significant lower levels of healthcare service utilisation for the high-cost/deferrable category in the quarter leading up to the co-insurance reduction, and statistically significant higher levels of healthcare service utilisation in the high-cost/mixed and high-cost/urgent groups. The assumption of linear parallel trends holds only for two cost-urgency categories at the 5% significance level: deferrable and urgent high-cost healthcare services. The results of the TWFE difference-in-difference estimation for the demand reaction of five different cost-urgency-categories (*Proposition 1*), including the adapted pre-trend framework to test for anticipatory effects (*Proposition 2*) are presented in Table 5.

Healthcare service category	High cost/deferrable				High cost/urgent			
Matching method	Raw	Entropy balancing			Raw	Entropy balancing		
Regression method	Conditional Fixed-effects Poisson Regression	Weighted Conditional Fixed-Effects Poisson Regression		Weighted Fixed-Effects Ordinary Least Squares	Conditional Fixed-effects Poisson Regression	Weighted Conditional Fixed-Effects Poisson Regression		Weighted Fixed-Effects Ordinary Least Squares
Effect	Demand reaction	Demand reaction	Anticipatory reaction	Demand reaction	Demand reaction	Demand reaction	Anticipatory reaction	Demand reaction
Sample	Full	Full	Full	Full	Full	Full	Full	Full
*POST*TREAT*	0.00788*	**0.0161****	n/a	0.00367***	-0.0000557	0.00687	n/a	-0.000622
	(0.00386)	**(0.00521)**		(0.000783)	(0.0611)	(0.0974)		(0.00898)
2016Q1*TREAT	n/a	n/a	-0.0163	n/a	n/a	n/a	0.147	n/a
			(0.0106)				(0.204)	
2016Q2*TREAT	n/a	n/a	0.0121	n/a	n/a	n/a	0.356	n/a
			(0.0109)				(0.204)	
N	5,187,240	5,186,745	5,186,745	5,186,745	30,969	30,969	30,969	30,969
N (intervention)	1,710,252	1,709,775	1,709,775	1,709,775	9,117	9,117	9,117	9,117
Linear parallel trends	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Healthcare service category	Low cost/deferrable				Low cost/urgent			
*POST*TREAT*	-0.00254	-0.000192	n/a	0.000288	-0.00869	-0.0280	n/a	-0.00316
	(0.00389)	(0.00493)		(0.000763)	(0.0176)	(0.0255)		(0.00252)
2016Q1*TREAT	n/a	n/a	-0.0131	n/a	n/a	n/a	0.0466	n/a
			(0.0104)				(0.0512)	
2016Q2*TREAT	n/a	n/a	-0.0162	n/a	n/a	n/a	0.0347	n/a
			(0.0104)				(0.0494)	
N	4,686,606	4,686,237	4,686,237	4,686,237	462,483	462,465	462,465	462,465
N (intervention)	1,744,947	1,744,596	1,744,596	1,744,596	141,561	141,552	141,552	141,552
Linear parallel trends	No	No	No	No	Yes	No	No	No

*p < 0.05, ** p < 0.01, ***p < 0.001; Heteroscedasticity robust standard errors in parentheses (clustered at the patient level)
The results of the High cost/mix category are omitted as they correspond to the "Mixed urgency healthcare services" category in Table 4.

Table 5: Results of the weighted conditional fixed-effects difference-in-difference Poisson regression for the five cost-urgency categories

A summary of the results of the individual healthcare services, including results separated by the sexes and for frequent utilisers is provided in the supplement. The results highlight the heterogeneity of the demand reactions across the different healthcare services. While the demand reaction for routine electrocardiograms (+1.8%) is in line with expectations, we find a seemingly paradox statistically significant decrease in service utilisation (-7.9%) for nystagmus inspections, although the visual trends suggest that this is in fact related to an unexplained increase in service use in the control group. The demand reaction for Electromyography (+12.6%) is also in line with our expectations, but the assumption of linear parallel trends is not fulfilled. For other services, we do not find statistically significant demand reactions, suggesting that demand for these services is comparatively inelastic. The results are further robust to restricting the sample to frequent users as well as the placebo regression set-up. The results of the TWFE difference-in-differences regression, by and large, do not vary by sex.

5 Discussion

In this paper, we analyse the role of costs and urgency in the demand reaction of 11 different healthcare services to a reduction in the co-insurance rate. We find that halving the co-insurance rate from 20% to 10% led to an average increase in demand for the 11 healthcare services by 0.8%. However, detailed analyses show that this increase is driven by services that are deferrable (+1%) and comparatively high-cost (+1.4%), or both (+1.6%). For specific healthcare services, we find the strongest demand reaction for routine electrocardiograms (+1.8%), a deferrable and high-cost healthcare service.

Our findings suggest that patients in the intervention group postponed costly deferrable services in the quarter leading up to the co-insurance rate reduction as indicated either by comparative restraint in service consumption and/or excess consumption in the quarter of the intervention in the intervention group. However, although the coefficient estimates are roughly in line with the expectations, they are not always statistically significant at the 5%-level. We do not find any similar notable patterns of postponement for inexpensive services. This implies that the effect of a co-insurance – or even more generally user charges, though the effect of a fixed co-payment by design depends more on urgency rather than price – is not uniform across a spectrum of healthcare services and can hence not be generalised. Moreover, substitution effects between services are unlikely as all outpatient healthcare services are subject to the same reduction in the co-insurance rate and the relative prices between the different services do not change. However, as the cost-sharing for inpatient care and medication is unaffected, relative prices between these healthcare sectors change. Given the limited possibilities for substitution between healthcare sectors, we do not think that this impedes our study design.

We acknowledge some limitations to the interpretation of our study results. The lack of patient-level data on the SES is a crucial limitation with respect to policy conclusions. Policy makers need to understand potential differences in the demand-reaction of economically vulnerable groups to avoid prohibitive cost-sharing levels that create unmet need for treatment (Czypionka et al., 2019). It also reduces the accuracy of the matching procedure, which makes it harder to establish parallel trends in absence of the intervention. In combination with a small effect size, this is a major challenge in the empirical analysis. The small size of the identified effect, too, is not surprising considering that, firstly, patients who are exempt from the co-insurance could not be removed from the sample. These are part of the vulnerable populations who would likely have strong but undesirable demand reactions as they would not be able to afford a certain healthcare service. Secondly, the co-insurance rate was only reduced (with comparatively small absolute savings for patients between €0.3 and €6 in the sample of healthcare services, see Table 1) and not entirely abolished.

Patients in the intervention group were already used to having to co-pay for their healthcare service consumption, although many patients might not be aware of exact costs. We control for this possible information asymmetry by analysing the subsample of frequent utilisers for whom we expect better awareness of prices. Nevertheless, when the outpatient healthcare service in question is low-cost, the cost-sharing component might not matter for patients, whose status quo has been to have cost-share for outpatient healthcare services anyway. This is in line with a finding in the study by García-Gómez et al (2018), where individuals with prior access to free medicines decrease their pharmaceutical consumption following the introduction of a low co-payment of €1 compared to individuals who already paid a co-insurance. We argue that stronger change of the status-quo would also entail a more pronounced response in the patients' behaviour. The possibility that patients can be insured with multiple sickness funds simultaneously further complicates the issue. Insurance with multiple sickness funds is possible for persons with two or more (part-time) occupations or who run a side business next to a salaried job, as insurance is determined by the type of employment (public or private sector, self-employed, etc.) or employer (some large companies had their own SHI scheme at the time of the study). On average, one in 11 Austrian patients was insured with more than one sickness fund in 2018 (Main Association of Austrian Social Security Institutions, 2019), though this includes children who are co-insured with their parents. These patients can choose which sickness fund is billed by the healthcare service provider and typically avoid cost-sharing or opt for cost-sharing only in case this provides access to their preferred physician. Our data do not provide information whether patients are insured with multiple sickness funds, only which sickness fund covers the healthcare service fee. We expect only few patients to be insured with a sickness fund in the control and intervention group at the same time. As some physicians provide care only for the public-employee sickness funds some patients may choose this option to get quicker appointments, but this would only concern a small fraction of patients. A possible distortion of the estimated coefficient could hence go either way, but it is unlikely to substantially alter the results as the number of observations is sufficiently large. Lastly, we also cannot rule out the possibility that the unclear patterns in the trends stem from problems related to the quality of the data itself, as our dataset is based on the KAL-system which has only been instated in 2015. In the earlier phase of the roll-out, complete and comprehensive recording of data cannot be taken for granted.

Overall, our findings add to the understanding of cost-sharing as a policy tool. The finding that even small price changes elicit demand reactions is quite easily transferable to preventive services, which are non-urgent and easily deferrable by the patient. Taking into account that the propensity to seek preventive healthcare services is higher among patients with higher SES (see e.g. Burkert, Rásky, and Freidl 2012; de Waard et al. 2018; Schülein et al. 2017), tailored systems of cost-sharing for different patient groups could incentivise patients to seek care on a best-practice path to receive the right preventive service at the right time.

6 References

Bachner, F., Bobek, J., Habimana, K., Ladurner, J., Lepuschütz, L., Ostermann, H., Rainer, L., Schmidt, A.E., Zuba, M., Quentin, W., Winkelmann, J., 2018. Health Systems in Transition Austria Health system review.

Barkowski, S., 2021. Interpretation of Nonlinear Difference-in-Differences: The Role of the Parallel Trends Assumption. SSRN Electronic Journal. https://doi.org/10.2139/ssrn.3772458

Barnieh, L., Clement, F., Harris, A., Blom, M., Donaldson, C., Klarenbach, S., Husereau, D., Lorenzetti, D., Manns, B., 2014. A Systematic Review of Cost-Sharing Strategies Used within Publicly-Funded Drug Plans in Member Countries of the Organisation for Economic Co-Operation and Development. PLoS One 9, e90434. https://doi.org/10.1371/journal.pone.0090434

Berger, M., Czypionka, T., 2021. Regional medical practice variation in high-cost healthcare services: Evidence from diagnostic imaging in Austria. European Journal of Health Economics 22, 917–929. https://doi.org/10.1007/s10198-021-01298-w

Burkert, N., Rásky, É., Freidl, W., 2012. Social inequalities regarding health and health behaviour in Austrian adults. Wien Klin Wochenschr 124, 256–261. https://doi.org/10.1007/s00508-012-0164-7

Czypionka, T., Röhrling, G., Six, E., 2019. Can people afford to pay for health care? New evidence on financial protection in Austria, World Health Organization.

de Waard, A.-K.M., Wändell, P.E., Holzmann, M.J., Korevaar, J.C., Hollander, M., Gornitzki, C., de Wit, N.J., Schellevis, F.G., Lionis, C., Søndergaard, J., Seifert, B., Carlsson, A.C., 2018. Barriers and facilitators to participation in a health check for cardiometabolic diseases in primary care: A systematic review. Eur J Prev Cardiol 25, 1326–1340. https://doi.org/10.1177/2047487318780751

Duarte, F., 2012. Price elasticity of expenditure across health care services. J Health Econ 31, 824–841. https://doi.org/10.1016/j.jhealeco.2012.07.002

Ellis, R.P., Martins, B., Zhu, W., 2017. Health care demand elasticities by type of service. J Health Econ 55, 232–243. https://doi.org/10.1016/j.jhealeco.2017.07.007

Everding, J., Marcus, J., 2020. The effect of unemployment on the smoking behavior of couples. Health Econ 29, 154–170. https://doi.org/10.1002/hec.3961

García-Gómez, P., Mora, T., Puig-Junoy, J., 2018. Does €1 Per Prescription Make a Difference? Impact of a Capped Low-Intensity Pharmaceutical Co-Payment. Appl Health Econ Health Policy 16, 407–414. https://doi.org/10.1007/s40258-018-0382-x

Gibson, T.B., Ozminkowski, R.J., Goetzel, R.Z., 2005. The effects of prescription drug cost sharing: a review of the evidence. Am J Manag Care 11, 730–740.

Goldman, D.P., Joyce, G.F., Zheng, Y., 2007. Prescription drug cost sharing: associations with medication and medical utilization and spending and health. JAMA 298, 61–69. https://doi.org/10.1001/jama.298.1.61

Hainmueller, J., 2011. Entropy Balancing for Causal Effects: A Multivariate Reweighting Method to Produce Balanced Samples in Observational Studies. SSRN Electronic Journal. https://doi.org/10.2139/ssrn.1904869

Hainmueller, J., Xu, Y., 2013. ebalance: A Stata Package for Entropy Balancing. J Stat Softw 054.

Hsu, J., Price, M., Brand, R., Ray, G.T., Fireman, B., Newhouse, J.P., Selby, J. V, 2006. Cost-sharing for emergency care and unfavorable clinical events: findings from the safety and financial ramifications of ED copayments study. Health Serv Res 41, 1801–1820. https://doi.org/10.1111/j.1475-6773.2006.00562.x

Jakobsson, N., Svensson, M., 2016a. Copayments and physicians visits: A panel data study of Swedish regions 2003--2012. Health Policy (New York) 120, 1095–1099. https://doi.org/10.1016/j.healthpol.2016.07.010

Jakobsson, N., Svensson, M., 2016b. The effect of copayments on primary care utilization: results from a quasi-experiment. Appl Econ 48, 3752–3762. https://doi.org/10.1080/00036846.2016.1145346

Johansson, N., Jakobsson, N., Svensson, M., 2019. Effects of primary care cost-sharing among young adults: varying impact across income groups and gender. Eur J Health Econ 20, 1271–1280. https://doi.org/10.1007/s10198-019-01095-6

Kiil, A., Houlberg, K., 2014. How does copayment for health care services affect demand, health and redistribution? A systematic review of the empirical evidence from 1990 to 2011. The European Journal of Health Economics 15, 813–828. https://doi.org/10.1007/s10198-013-0526-8

Lambregts, T.R., van Vliet, R.C.J.A., 2018. The impact of copayments on mental healthcare utilization: a natural experiment. The European Journal of Health Economics 19, 775–784. https://doi.org/10.1007/s10198-017-0921-7

Lee, H.J., Jang, S.I., Park, E.C., 2017. The effect of increasing the coinsurance rate on outpatient utilization of healthcare services in South Korea. BMC Health Serv Res 17, 152–152. https://doi.org/10.1186/s12913-017-2076-8

Main Association of Austrian Social Security Institutions, 2019. Statistical Handbook of Austrian Social Security 2019 [Statistisches Handbuch der österreichischen Sozialversicherung 2019].

Manning, W.G., Newhouse, J.P., Duan, N., Keeler, E.B., Leibowitz, A., 1987. Health Insurance and the Demand for Medical Care: Evidence from a Randomized Experiment. Am Econ Rev 77, 251–277.

Maynou, L., Coll-de-Tuero, G., Saez, M., 2019. The effects of copayment in primary health care: evidence from a natural experiment. The European Journal of Health Economics 20, 1237–1248. https://doi.org/10.1007/s10198-019-01089-4

Mortensen, K., 2010. Copayments Did Not Reduce Medicaid Enrollees' Nonemergency Use Of Emergency Departments. Health Aff 29, 1643–1650. https://doi.org/10.1377/hlthaff.2009.0906

Mossialos, E., Czypionka, T., Cheatley, J., Thalmann, I., Polton, D., Jeurissen, P., Pfeil, W.J., Müller, R., Pöltner, W., Mosler, R., Hoffmann, W., Raupp, J., Duer, S., 2017. Efficiency Review of Austria's Social Insurance and Healthcare System: Volume 1: International Comparisons and Policy Options. London School of Economics and Political Science, London.

Ndumele, C.D., Trivedi, A.N., 2011. Effect of Copayments on Use of Outpatient Mental Health Services Among Elderly Managed Care Enrollees. Med Care 49, 281–286. https://doi.org/10.1097/MLR.0b013e31820399f6

Newhouse, J.P., Manning, W.G., Morris, C.N., Orr, L.L., Duan, N., Keeler, E.B., Leibowitz, A., Marquis, K.H., Marquis, M.S., Phelps, C.E., Brook, R.H., 1981. Some interim results from a controlled trial of cost sharing in health insurance. N Engl J Med 305, 1501–1507. https://doi.org/10.1056/NEJM198112173052504

OECD Statistics, 2018. Household out-of-pocket payments.

Robinson, R., 2002. User charges for health care. E. Mossialos, A. Dixon, J. Figueras and J. Kutzin (eds), Funding Health Care: Options for Europe.

Sabik, L.M., Gandhi, S.O., 2016. Copayments and Emergency Department Use Among Adult Medicaid Enrollees. Health Econ 25, 529–542. https://doi.org/10.1002/hec.3164

Schellhorn, M., 2001. The effect of variable health insurance deductibles on the demand for physician visits. Health Econ 10, 441–456. https://doi.org/10.1002/hec.630

Schokkaert, E., Van de Voorde, C., 2011. User Charges, in: The Oxford Handbook of Health Economics. https://doi.org/10.1093/oxfordhb/9780199238828.013.0015

Schreyögg, J., Grabka, M.M., 2010. Copayments for ambulatory care in Germany: a natural experiment using a difference-in-difference approach. The European Journal of Health Economics 11, 331–341. https://doi.org/10.1007/s10198-009-0179-9

Schülein, S., Taylor, K.J., Schriefer, D., Blettner, M., Klug, S.J., 2017. Participation in preventive health check-ups among 19,351 women in Germany. Prev Med Rep 6, 23–26. https://doi.org/10.1016/j.pmedr.2017.01.011

Siddiqui, M., Roberts, E.T., Pollack, C.E., 2015. The effect of emergency department copayments for Medicaid beneficiaries following the Deficit Reduction Act of 2005. JAMA Intern Med 175, 393–398. https://doi.org/10.1001/jamainternmed.2014.7582

Statistik Austria, 2019. Register-based Labour Market Statistics - Time series starting from 2009.

Statistik Austria, 2016. Wage Tax Statistics 2016.

Van de Voorde, C., van Doorslaer, E., Schokkaert, E., 2001. Effects of cost sharing on physician utilization under favourable conditions for supplier-induced demand. Health Econ 10, 457–471. https://doi.org/10.1002/hec.631

7 Supplement

Healthcare service	**Blood gas analysis**				**Cerumen removal**				**Electromyography**				**Incident-light microscopy**			
Matching method	Entropy balancing				Entropy balancing				Entropy balancing				Entropy balancing			
Regression method	Weighted Conditional Fixed-Effects Poisson Regression				Weighted Conditional Fixed-Effects Poisson Regression				Weighted Conditional Fixed-Effects Poisson Regression				Weighted Conditional Fixed-Effects Poisson Regression			
Sample	All patients	Female	Male	Frequent utilisers	All patients	Female	Male	Frequent utilisers	All patients	Female	Male	Frequent utilisers	All patients	Female	Male	Frequent utilisers
*POST*TREAT*	0.000968	0.0108	-0.0112	-0.0134	-0.0114	-0.0204*	-0.00555	-0.0168*	0.126*	0.111	0.146	0.147*	0.00439	0.0140	-0.00577	-0.00471
	(0.0149)	(0.0241)	(0.0188)	(0.0169)	(0.00689)	(0.0104)	(0.00921)	(0.00829)	(0.0588)	(0.0858)	(0.0791)	(0.0651)	(0.00819)	(0.0115)	(0.0116)	(0.0110)
N	567,675	265,401	302,274	363,456	2,449,179	1,242,504	1,206,675	1,162,629	270,585	162,558	108,027	170,919	2,245,734	1,297,872	947,862	838,854
N (intervention)	231,957	103,437	128,520	153,693	931,572	454,581	476,991	484,020	49,986	26,469	23,517	35,343	875,799	482,094	393,705	375,129
Linear parallel trends	No	No	No	No	No	No	No	No	No	No	Yes	No	No	No	No	No
Healthcare service	**Nystagmus inspection**				**Removal of foreign bodies from the cornea, sclera or conjunctive**				**Routine electrocardiogram**				**Routine electroencephalography**			
*POST*TREAT*	-0.0796**	-0.0919**	-0.0722	-0.106***	0.0644	0.0838	0.0372	0.0110	0.0183***	0.0189*	0.0192**	0.0243***	-0.0325	-0.0429	-0.0207	-0.0346
	(0.0253)	(0.0347)	(0.0369)	(0.0297)	(0.0874)	(0.122)	(0.119)	(0.110)	(0.00528)	(0.00793)	(0.00703)	(0.0059)	(0.0273)	(0.0381)	(0.0389)	(0.0310)
N	305,874	189,144	116,730	177,597	159,606	44,037	115,569	46,539	5,017,230	2,690,793	2,325,942	2,517,228	320,706	191,142	129,564	194,958
N (intervention)	114,597	66,825	47,772	71,469	27,747	10,512	17,235	11,934	1,657,827	842,220	815,607	921,681	103,266	58,185	45,081	68,148
Linear parallel trends	Yes	Yes	Yes	Yes	No	No	No	No	Yes	Yes	Yes	No	No	No	No	No
Healthcare service	**Sonography of the intracranial vessels**				**Sonography of the thyroid and parathyroid gland**				**Uroflowmetry**							
*POST*TREAT*	0.00687	0.120	-0.0730	0.0495	-0.00133	0.00295	0.00111	0.00367	0.0190	0.128	0.0146	0.00105				
	(0.0974)	(0.165)	(0.115)	(0.105)	(0.00764)	(0.00970)	(0.0124)	(0.0095)	(0.0130)	(0.0817)	(0.0130)	(0.0151)				
N	30,969	18,234	12,735	21,177	1,144,287	730,233	414,054	602,280	653,040	49,509	603,531	369,612				
N (intervention)	9,117	4,437	4,680	6,678	619,119	390,024	229,095	338,715	246,411	14,580	231,831	149,292				
Linear parallel trends	Yes	Yes	No	Yes	Yes	Yes	Yes	No	No	No	No	No				
*p < 0.05, ** p < 0.01, ***p < 0.001; Heteroscedasticity robust standard errors in parentheses (clustered at the patient level)																

Table S1: Results of the weighted conditional fixed-effects difference-in-difference Poisson regression for all healthcare services by subpopulations

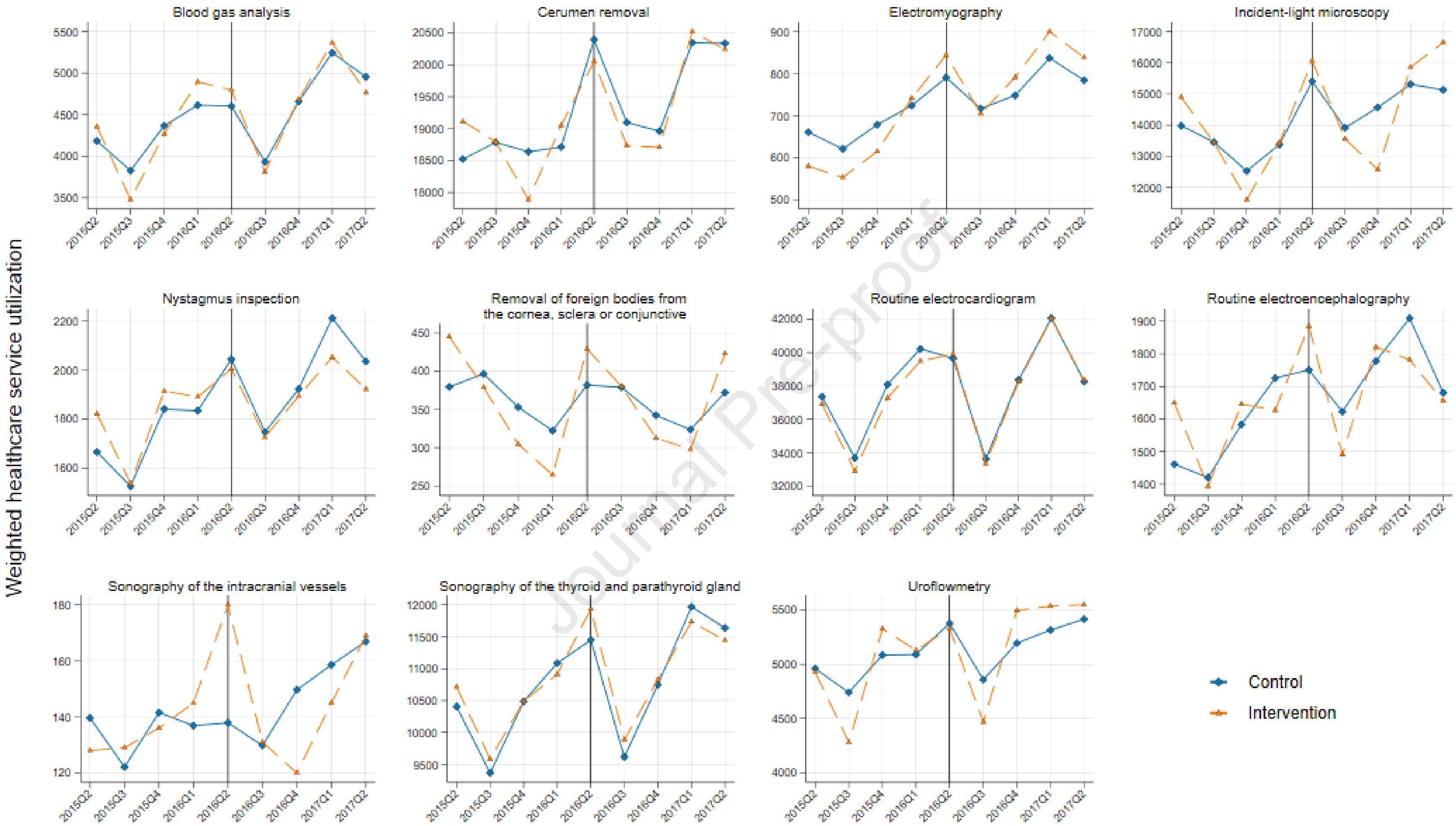

Figure S1: Pre-and post-intervention trends of the intervention and the weighted control group for the 11 healthcare in the four quarters before and after the reduction of the co-insurance rate.

Highlights

- Demand reactions to cost-sharing differ across treatments and diagnostic procedures
- We identify cost and urgency as two crucial dimensions for demand reactions
- Across-the-board estimation may be driven by reactions of few healthcare services
- Even small changes to cost-sharing can elicit tangible demand reactions