Devil in the Details

How urgency and costs influence the effects of cost-sharing on healthcare service consumption patterns

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Motivation

Cost-sharing schemes are a **common pillar** *in the financing of numerous healthcare systems*

- *Influence and steer* **patient behaviour** *by internalizing part of costs*
- *Instrument to generate* **revenue**

→ **Dual role** *in healthcare policy*

Imperative for policy makers to have a thorough understanding of the mechanisms behind the effects of cost-sharing

- *Knowledge healthcare service-specific price elasticity is crucial for* **policy makers** *in connection with the dual role of cost-sharing*
- *Possibility to steer patient behaviour along the* **best-practice path**

Background

Effects of cost-sharing (desired or undesired) **well-documented and extensively discussed** *in the literature (cf. Kiil & Houlberg, 2014)*

- *Previous studies often take a* **macro-perspective** *(e.g. Schreyögg & Grabka, 2010; Jakobsson & Svensson, 2016) or target* **specific healthcare sectors** *(Ellis et al., 2017)*

Few studies **differentiate** *between specific* **healthcare services**

- *Duarte (2012) is the work related the closest to our study (to the best of our knowledge)*
- *Empirical investigation of price elasticities in the Chilean private insurance market*
- **Main findings**
  - *Consumers' price elasticities vary by healthcare service*
  - *Consumers are more sensitive in their demand for elective procedures than for acute care*

Our study in a nutshell

Analysis of the demand reaction of **11 different healthcare services** *to a* **reduction in the co-insurance rate** *from 20% to 10% at beginning of Q2-2016 in* **Austria**

- *Near* **universal healthcare coverage**
- *Publicly-financed social health insurance (SHI) system with* **multiple sickness funds**
- **Quasi-experimental** *study design*

We add to the literature by

- *Formulating an* **intuitive framework** *to derive hypotheses that can be empirically tested and that may also aid policy makers in predicting policy effects*
  - *Backed by previous empirical findings (e.g. Duarte, 2012)*
- **Empirically test** *the direct impact of changes to a cost-sharing regime by estimating the price elasticity of a variety of healthcare services*

Data

We utilize a longitudinal pseudonymised patient-level dataset

- **Routine data** *on* **outpatient** *healthcare service consumption*
- *Dataset covers all insurees from three sickness funds*
- *Covered period: Q2-2015 to Q2-2017*
- *1,035,177 patients with 2,370,463 healthcare service contacts*

Outpatient service catalogues differ between sickness funds

- **11 comparable healthcare services** *analysed in our study*

Patient-level data on sex, age and healthcare service consumption (burden of disease) + district socio-economic status composite measure as additional controls

Methods
Healthcare service classification

Classification of services along **two dimensions**

- *Urgency*
- *Cost*

We expect to see the strongest reaction to price changes in healthcare services that are **deferrable** *and* **comparatively expensive**

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

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

Methods
Combining Matching and Difference-in-difference

Two-stage *estimation procedure (see Everding & Marcus, 2020)*

(I) Matching stage via **entropy balancing**

- *Multivariate reweighting method that matches covariate distribution on the 1st and 2nd moment → increases comparability of treatment and control group*
- *Stata package ebalance (Hainmueller & Xu, 2013)*
- *Balancing weights w.r.t. sex, age, socio-economic status and burden of disease*

(II) Regression stage via weighted-generalised linear model with Poisson distribution

$$log(Y_{i,t}) = \alpha_{i,t} + \beta_t\, post_t + \gamma_i\, treat_i + \delta_{i,t}\,(post_t * treat_i) + \theta_i C_i\, \varepsilon_{i,t}$$

Y … healthcare consumption, C … time-fixed controls

δ … interaction term, i.e. effect of co-insurance rate reduction

Methods
Sensitivity analysis

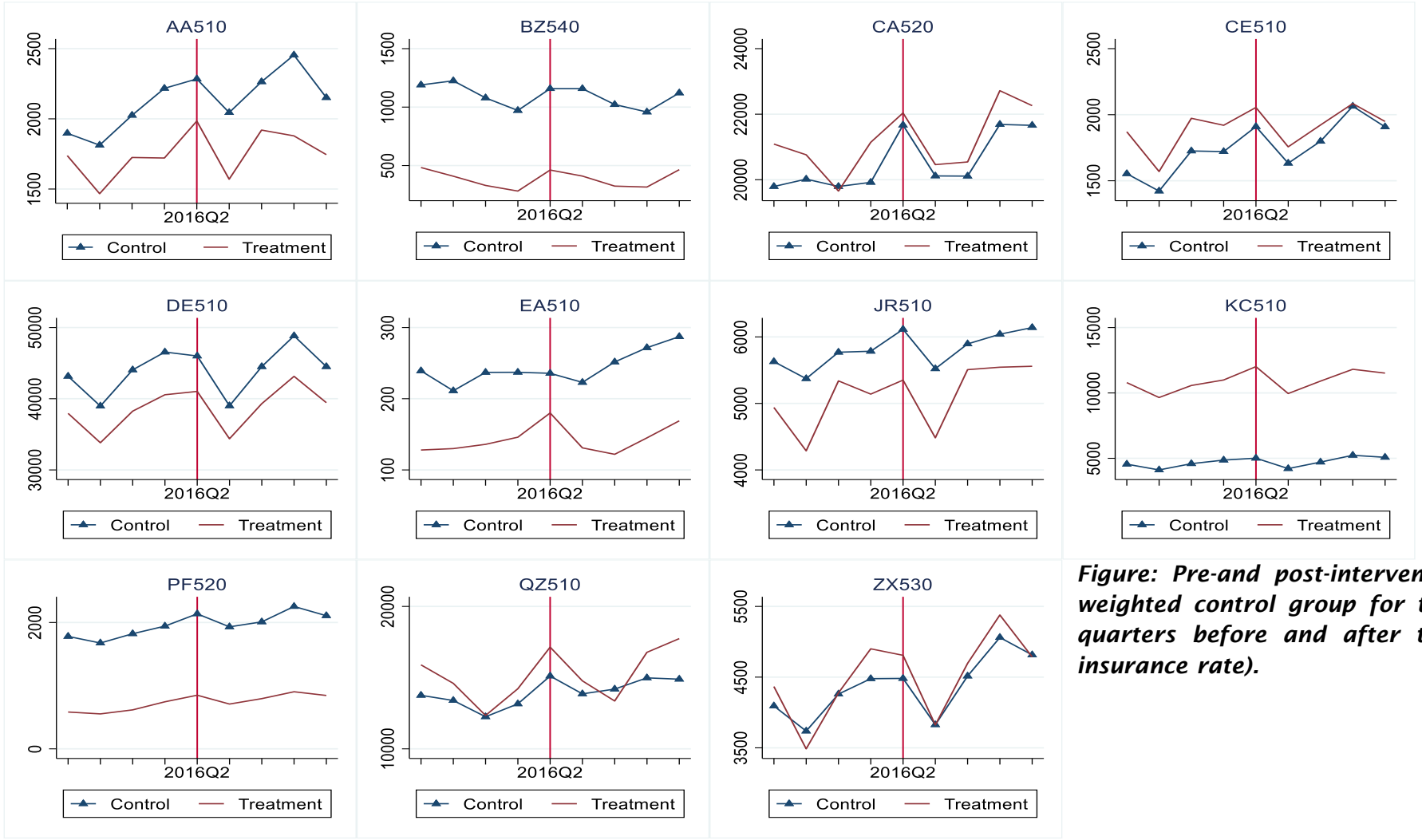
Validity *of DiD estimation depends crucially on* **shared pre-trends**

- *Visual and formal pre-trend analysis (Angrist & Pischke, 2008)*

Plausibility *that change in the co-insurance rate is the cause of the shift in demand*

- **Placebo regression** *with "treatment" signalled two quarters prior to actual treatment*

Pre- and post-intervention trends



Note

*Routine electroencephalography (**AA510**),*
*Removal of foreign bodies from the cornea, sclera or conjunctiva (**BZ540**),*
*Cerumen removal (**CA540**),*
*Nystagmus inspection (**CE510**),*
*Routine electrocardiogram (**DE510**),*
*Sonography of the intracranial vessels (**EA510**),*
*Uroflowmetry (**JR510**),*
*Sonography of the thyroid and parathyroid gland (**KC510**),*
*Electromyography (**PF520**),*
*Incident-light microscopy (**QZ510**),*
*Blood gas analysis (**ZX530**).*

The x-axes depict the number of (weighted) cases, the y-axes is the time dimension in quarters.

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

Results

Pre-trend analysis

- *7 out of 11 healthcare services pass* **formal** *test for shared pre-trend*
- *Only* **2 healthcare services** *show also* **well-behaved visual patterns**
- *Most pre-trends* **too volatile** *for DiD estimation*
- *Substantial variation in the number of observations as* **potential culprit**

DiD framework only suitable for **two healthcare services**

- *Routine electrocardiogram (DE510)*
- *Electromyography (PZ520)*

Results
Routine electrocardiogram (DE510)

Routine electrocardiogram

- *Low urgency, relatively high cost*
- *Small positive effect on demand (+1.4%)*
- *Effect statistically significant*

Healthcare service	**Routine electrocardiogram (DE510)**		
Regression Method	Generalised Poisson Regression	Weighted Generalised Poisson Regression	
Matching Method	Raw	Entropy Balancing	Entropy Balancing
Additional controls	✓	✓	✗
Time	0.0716*** (0.0012)	0.0751*** (0.0018)	0.0659*** (0.0013)
Treatment	0.0427*** (0.0018)	0.0473*** (0.0018)	0.0539*** (0.0019)
Time*Treatment	**0.0180*** ** (0.0021)	**0.0143*** ** (0.0023)	**0.0117*** ** (0.0022)
N	737,399	737,399	737,399
N (treated)	248,123	248,123	248,123
Log-Pseudolikelihood	-892,657.277	-904,991.171	-918,453.789

*p < 0.1, ** p < 0.05, ***p < 0.01
Heteroskedasticity robust standard errors in parentheses (clustered at the patient level)

Results
Electromyography (PZ520)

Electromyography

- *Mixed urgency, relatively high cost*
- *Minuscule positive effect on demand (+0.12%)*
- *Effect statistically* **not** *significant*
  - *Considerably* **smaller sample** *size*

Healthcare service	**Electromyography (PZ520)**		
Regression Method	Generalised Poisson Regression	Weighted Generalised Poisson Regression	
Matching Method	Raw	Entropy Balancing	Entropy Balancing
Additional controls	✓	✓	X
Time	0.0320*** (0.0036)	0.0348*** (0.0038)	0.0345*** (0.0038)
Treatment	0.0165*** (0.0071)	0.0189*** (0.0071)	0.0215*** (0.0072)
Time*Treatment	**0.0036** (0.0087)	**0.0012** (0.0088)	**0.0003** (0.0088)
N	31,927	31,927	31,927
N (treated)	5,884	5,884	5,884
Log-Pseudolikelihood	-34,107.755	-34,239.347	-34,259.48

*p < 0.1, ** p < 0.05, ***p < 0.01

Heteroskedasticity robust standard errors in parentheses (clustered at the patient level)

Results

Another service narrowly fails formal test, but is visually well-behaved

- *Sonography of the thyroid and parathyroid gland (KC510): Mixed urgency, high cost*
- *DiD result: demand increases by 2.7% in reaction to co-insurance reduction*

Additional hints *are found in the pre-trend graphs*

- *Routine EEG (AA510): Low urgency, high cost*
- *Pre-trend pattern suggests that patients postponed healthcare service consumption from Q1-2016 to Q2-2016*

DiD regressions for remaining services yield insignificant or paradox results

- *Reasons: group-specific seasonal patterns or spikes in consumption despite matching*

Discussion

Results show that even **minor changes** *to co-insurance cause reactions in demand*

- *Effect is not very pronounced given the small change of costs for patients (max. €6)*
- *Possibly stronger reaction if moving to or from zero cost-sharing (change to status-quo)*

Results are in line with **expectations** *derived from* **classification of healthcare services**

Limitations

Comparability *of treatment and control group*

- *Different patterns in healthcare consumption trends for some healthcare services*
- **Lack of data** *on patient characteristics reduces matching accuracy*
  - *Socio-economic status only derived from district characteristics*
- *Different levels of healthcare consumption between treatment and control group*

Difference in remuneration *between sickness funds for physicians could exacerbate outcome differences due to supplier-induced demand*

- *Physicians (unknowingly) react to price differentials (cf. Coey, 2015)*
- *Potential contributor to the difference in levels of healthcare service consumption between treatment and control group*

Limitations

Set of healthcare services *chosen due to* **comparability** *in definitions across sickness funds and may not be ideal*

- *The most expensive service in the sample is only €60*
- *Small price change likely contributes to weak findings*
- *Arguably idiosyncratic healthcare services*

Regional differences *in healthcare consumption due to medical practice variation additional potential source for distortion (cf. Berger & Czypionka, 2021)*

- *Number of cases often not large enough to allow sub-sample analysis*

Conclusion

We find evidence in our empirical analysis that the demand reactions of different healthcare services to changes in cost-sharing **vary along the dimension of urgency and cost**

- *Strongest reaction in expensive and deferrable services in the sample*

Relevant insights for policy makers *concerning dual role of cost-sharing*

- *Different demand reaction can be used for specific steering of patient behaviour and patient flows*
- *Postponement effects*

Concerns about the **quality of the data** *limits the strength of the results*

- *Unexplained differences in the consumption patterns* – **sample not well-behaved**
- *Lack of suitable control variables for better matching*

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