Drug Copayments, Child Outcomes, and Intra-family Spillovers

Jakub Červený* Boriana Miloucheva†

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Abstract

Reducing out-of-pocket costs of medication has been shown to lead to higher use initiation rates in childhood. Less is known, however, about the potentially asymmetric effects of increases in such costs, resulting from a loss in insurance coverage. This paper looks at the expiration of prescription drug copay waivers for children in Slovakia to investigate changes in pharmaceutical use resulting from increasing out-of-pocket costs. Leveraging age thresholds for copay waivers, this paper uses event study analyses to show that increases in out-of-pocket costs reduce prescription drug use, as well as average spending. Using a dataset capturing the universe of prescriptions filled between 2016–2018, we are further able to understand these effects among both chronic and non-chronic users. We trace the effects of these changes in prescription drug use to down-stream health consequences for children, as measured by GP visits and hospitalizations. Linking these data to social security records, we are further able to understand spillovers onto parental health and employment.

Keywords:
JEL Codes:

*Institute for Health Care Analyses, Ministry of Health of the Slovak Republic, Bratislava, Slovakia; e-mail: jakub.cerveny@health.gov.sk

†Center for Health and Wellbeing, Princeton University, Princeton, New Jersey; e-mail: bm6270@princeton.edu

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1 Introduction

Prescription drug use among children in Europe has been growing. Indeed, in Slovakia 99% of children have received at least one drug or vaccine by age 7. Given wide-spread use of prescription medication in this context, it is then important to think about drug use decisions beyond initiation. This paper serves to do just this, by addressing a set of interrelated research questions. The first focuses on whether prescription drug use and adherence changes for children when the out-of-pocket costs increase. Given this, we next demonstrate whether there are any health consequences resulting from these changes. In doing so, we speak to the literature investigating the potential moral hazard issues surrounding drug purchasing in a single-payer system. Finally, as young children are financially reliant on parents and guardians, we focus on the potential spillover of these changes to price onto other family members.

To address these questions, we leverage exogenous variation in insurance coverage generated by age cutoffs. Children aged 6 and over in Slovakia must pay the standard copay (described in more detail below) for all drugs consumed. We combine this empirical strategy with rich administrative data covering the universe of all pharmaceutical prescriptions filled between 2016 and 2018.

Our preliminary findings suggest that removal of copay waivers (and thus, increases in out-of-pocket costs) reduce pharmaceutical utilization by children, particularly among those who had chronic use prior to the policy. Leveraging parental data linkages, we then focus on the dimension of income heterogeneity. We find, consistent with prior expectations, that the children most affected by these cost changes originate from the lower two quartiles of the income distribution. Children in the bottom quartile see an almost 5.5% reduction in pharmaceutical use.

An important consideration is to understand the downstream consequences of these changes in pharmaceutical use. To the extent that these prescriptions were medically necessary, reductions in use may have harmful health consequences for children. Alternatively, concerns about moral hazard and low-benefit prescribing may suggest that these reductions in pharmaceutical drug purchases have little to now negative health consequences. Ongoing data linkages for this project will

allow us to identify visits to general practitioners and emergency rooms by the children in the analytic sample. In doing so, we will be able to speak to the broader consequences of this observed drug discontinuation. Finally, the existing family linkages

This paper builds on a large literature suggesting expanded coverage improves child pharmaceutical use (Schaller and Zerpa, 2019; Currie and Gruber, 1996; Currie et al., 2014; Furzer et al., 2023). With few exceptions (Kaplan and Zhang, 2014), this literature largely focuses on insurance gains rather than losses. We argue, however, that there is no ex-ante reason to believe that responses to insurance losses and gains would be symmetric.

We note that Slovakia provides a perfect case study to understand this issue for a number of reasons. First, losses in copayment waivers are untied to parental employment changes (Schaller and Zerpa, 2019), and are thus unlikely to suffer broader income effects. Second, these changes in insurance are not linked to broader insurance overhauls or other changes in insurance access. Finally, Slovakia provides a context of universal health coverage, allowing us to abstract from broader issues of healthcare provision and the potential for strategic care delays, as in the U.S context (Huh and Reif, 2017).

2 Institutional context

2.1 Health care insurance & subsidized care

Slovakia has universal health care coverage, citizens can choose between three nationwide health insurance companies; one state-owned, while the other two are private. All residents must have health insurance and are obliged to pay contributions. The state pays insurance for some citizens (children, students, mothers on maternity leave, the unemployed, etc.). Contributions amount to 14% of monthly income (4% paid by employee, the rest by employer). All treatments, procedures and pharmaceuticals are covered by the package, except some dental treatments. Insurance companies compete for patients mostly with benefit packages, which usually include better coverage of dental treatments, allowance for prescription

glasses or full coverage of copayments for children up to the age of 18.[1]

2.2 Pharmaceutical pricing and regulation

There is a dual setting of price and co-payments, determined by the Ministry of Health. The list of approved pharmaceuticals with prices and copayments is updated every month. There are no rules for setting over-the-counter (OTC) drug prices. The pricing of prescription medicines is subject to strict legislative regulation. The officially set price of the medicine is the price from the manufacturer or the importer that cannot be exceeded upon the initial sale of the medicine in the territory of Slovakia, or even upon subsequent sale of the medicine to the holder of a wholesale distribution license. All prescription medicines (with the exception of OTC, contraceptives, antismoking drugs, weight loss drugs, and homeopathic drugs) have set maximum prices that are published and may not be exceeded. For more information about pharmaceutical pricing and regulation in Slovakia, see for example Psenkova et al. (2017).

Three broad exceptions or limits for co-payments are in place. The first is a waiver for all children up to the age of 6, the second for retirees (based on retirement age, rather than on birth year), and finally disabled individuals. The first of these exceptions, for children under age 6, forms the basis of our empirical strategy, described in detail below. The 10€ limit for copayments applies to pharmaceuticals purchased within a calendar quarter (i.e. the sum of all co-payments within the quarter). All copayments exceeding the threshold are waived. The age criterion is evaluated at the first day of the calendar quarter.

3 Empirical Strategy

This paper aims to understand the consequences of increased drug costs on child utilization, subsequent health outcomes, and family spillovers.

[1] Coverage of copayments for children up until age 18 is only offered by 1 of the three insurance companies, which is dropped from the main analysis. The children covered by this insurance would not be considered as "treated" under our empirical strategy. We do, however, leverage this subpopulation in a robustness exercise where we consider them as an alternative control group.

Our empirical strategy exploits a unique feature of the health care system in Slovakia, where insurance fees and co-payments above the quarterly limit are covered by the state for children under the age of 6. This bureaucratic age cut-off is updated quarterly, meaning that children who turn 6 during the second quarter of a calendar year, for example, would no longer be covered by the state in the third quarter and onwards. This creates four treatment discontinuities in each calendar year, which occur on January 1st, April 1st, July 1st, and October 1st, and allows us to implement a staggered difference-in-differences (DiD) design.

3.1 Regression framework

The sharp cut-off occuring at the first day of the calendar quarter allows us to create control and treatment groups of similar children, different only in their co-payment scheme. The treatment group is formed by children, who just turn six years of age during three months preceding the first day of the calendar quarter, while the control group is formed by children who reach age of six half a year later. For example, for a cut-off occurring on April 1, 2016, all children born between January 1, 2010–April 1, 2010 lose their co-payment coverage, forming the treatment group. The control group for this cut-off consists of children who lose their coverage on October 1, 2016, born between July 1, 2010 and October 1, 2010. This allows us to compare pharmaceutical utilization for these children during six months preceding April 1, 2016 and for the following six months until October 1, 2016.[2] Given that the day of birth is nearly impossible to manipulate, we argue that the assignment is as good as random. Furthermore, we assume that the six-month gap in age between children in control and treatment groups should not give rise to any systematic bias resulting from differences in unobserved characteristics or medical needs. In principle, our empirical strategy is similar to

[2]Due to the fact that children losing their copayment coverage on October 1, 2016 are inevitably needed as a treatment group again, we deal with this issue by selecting children born between July 1, 2010–October 1, 2010 on even-numbered days to serve as a control group for April 1, 2016 cut-off, while children born on odd-numbered days between July 1, 2010–October 1, 2010 to serve as a treatment group for October 1, 2016 cut-off. A similar logic is applied to all other quarterly cut-offs during our observation period. This allows us to retain all relevant observations.

Huh and Reif (2017), who use event study and difference-in-difference frameworks to estimate effects of Medicare part D on mortality around the eligibility threshold by comparing 64-year and 66-year old individuals.

The effect of the policy is then estimated using a difference-in-differences setup, where the drug use is compared between control and treatment groups in pre- and post-periods. More formally, pharmaceutical utiliziation for an individual i in a month τ, where $\tau = -6, -5, \ldots, 5$ indexes months relative to coverage loss[3] is defined as:

$$E[Y_{i\tau} \mid X_{i\tau}] = \exp\left(\alpha_i + X'_{it}\beta + T_{i\tau}\rho + G_i\gamma + W_i\delta + \zeta_{it} + \epsilon_{i\tau}\right) \tag{1}$$

where $X_{i\tau}$ is a vector of observed individual characteristics, $G_i \in [0, 1]$ denotes the group assignment with 1 being the treatment group, $T_{i\tau} = I(\tau \geq 0)$ is an indicator for the post-treatment period, W_i is equal to interaction of the group and time indicators $T_{i\tau} \cdot G_i$, ζ_{it} captures the calendar time fixed effect[4] and $\epsilon_{i\tau}$ represents the error term. The main parameter of interest δ is the DiD estimate and captures the effects of how the outcome changes for the treated group in the post-period relative to the control group.

We focus on three outcomes of interest, including the prescription dosage, the number of packages filled, as well as the total price of the prescriptions (which will allow us to understand the extent to which parents may be substituting to cheaper alternatives). The age discontinuity in this context, is however, fully predicted by both parents and physicians. As a result, concerns may arise about strategic drug stockpiling just prior to a child's sixth birthday. To the extent that either parents or physicians do this, our estimates of the treatment effects would be biased upwards, suggesting larger potential declines in use which are in fact driven by pre-treatment changes in behaviour. Furthermore, the crucial assumption in the DiD framework is that pre-treatment trends between control and treatment groups are parallel. Figure 1 plots pharmaceutical utilization and provides graphical evidence of parallel trends. We also formally test this assumption by estimating the

[3]First month out of copayment coverage is indexed as 0.

[4]Use of prescription medications exhibits strong seasonal patterns. Flexible specification of calendar time effects for each year-month should capture this seasonal variation.

following event-study equation:

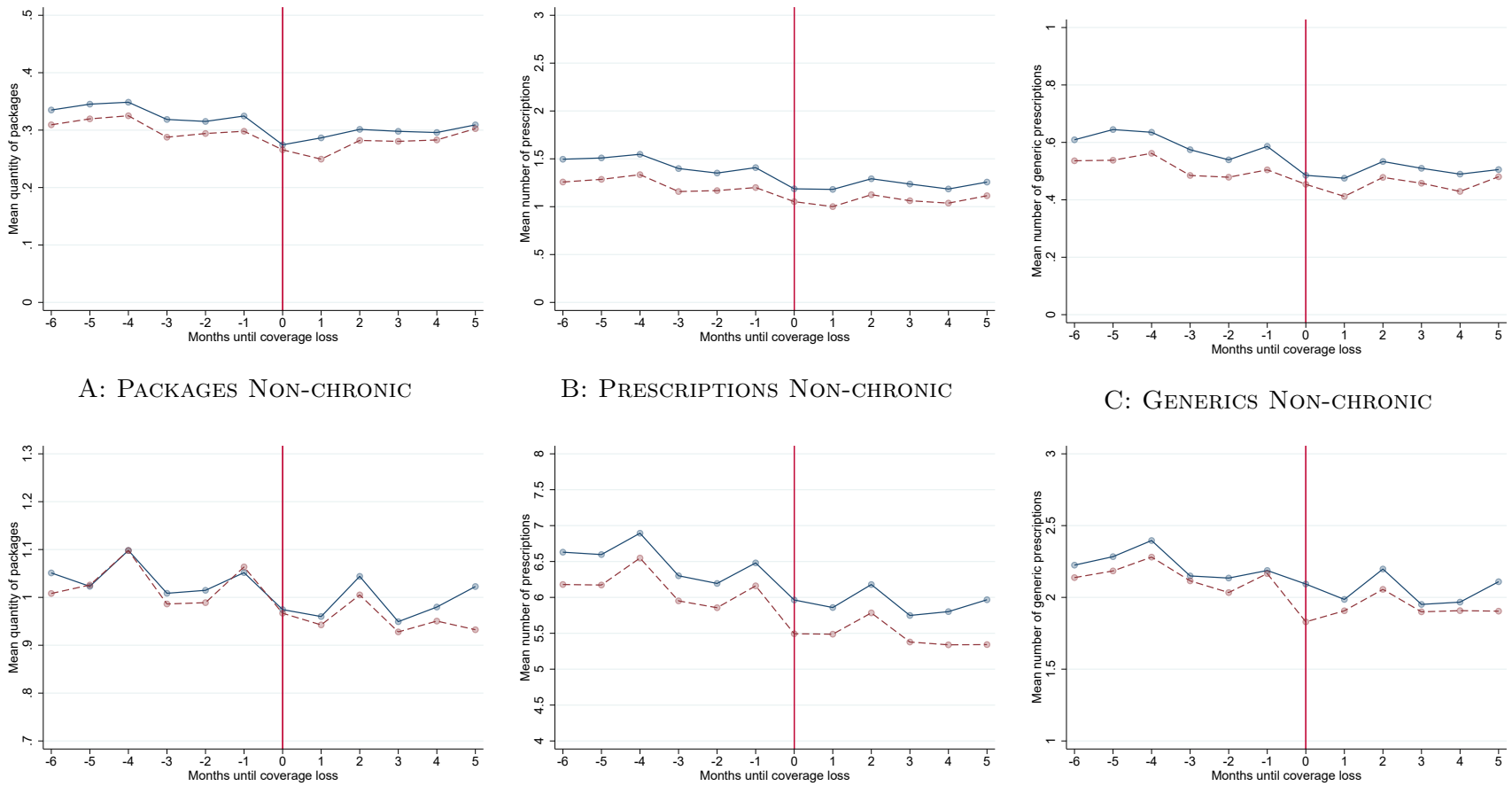
$$E[Y_{i\tau} \mid X_{i\tau}] = \exp\left(\alpha_i + X'_{i\tau}\beta + \sum_{\tau=-6,\tau\neq 0}^{5} \lambda_\tau \cdot G_i + \zeta_{it} + \epsilon_{i\tau}\right) \tag{2}$$

Due to the fact we are dealing with over-dispersed count data, containing significant amount of zeros for months with no pharmaceutical utilization, we estimate all regressions using zero-inflated negative binomial models.[5]

We also provide, in the appendix to this paper, the results from a more traditional regression discontinuity design, as in Equation 3, where the running variable used is MSL_i, which denotes months since coverage loss. Because of the grouped nature of implementation by quarter, the birthday of the child itself cannot be used as a running variable. This methodology allows us to compare children born just one month apart, landing on either side of the calendar-quarter discontinuity, but effectively receiving an additional quarter of copayment waivers. We note that our results are consistent when using both methods.

$$Y_i = \alpha_0 + \alpha_1 I[MSL_i \geq 0] + g(MSL_i) + \rho X_i + \epsilon_i \tag{3}$$

[5]We compare fit of the zero-inflated negative binomial model to a zero-inflated Poisson regression using a likelihood-ratio test, finding that the negative binomial model indeed provides a better fit.



A: Packages Non-chronic

B: Prescriptions Non-chronic

C: Generics Non-chronic

D: Packages Chronic

E: Prescriptions Chronic

F: Generics Chronic

Figure 1: Pharmaceutical Utilization Among Children

Notes: Solid lines represent control group, dashed lines treatment group. Vertical lines represent the first month out of coverage loss.

4 Data

Data on filled prescriptions between 2016–2018 is reported to the National Health Information Center by insurance companies on an annual basis. This dataset contains the universe of all prescriptions covered by universal health care insurance and contains rich information about the drug prescribed, the dosage (measured in a defined daily dose (DDD) form as well as in a unit number of packages), the associated ICD-10 code motivating the prescription, the price as well as copayment amounts. We link this data to information about the patients address at the zipcode level for each year of the data. This allows us to capture any potential mobility effects which may simultaneously occur around the child's birthday.[6] Finally, the data are linked with the birth register to obtain information on family linkages. This also allows us to observe annual family income. Due to the fact that children have to undergo compulsory vaccination against diphtheria, tetanus, pertussis and polio after reaching six years of age, we exclude pharmaceutical utilization records corresponding to the tetravalent vaccine deployed in Slovakia.

Between 2016–2018, approximately 180.3 million prescriptions were filled, averaging approximately 40 prescriptions per year for over 4.8 million individuals in the data. This data covers a substantial portion of the Slovak population, approximately 5.45 million individuals during this time period. We also include in our analysis individuals who were insured during the sample period, but did not redeem any pharmaceutical prescription. Rates of prescription drug use are higher than in the U.S and Canada, where estimates range between 41% in Canada[7] and 48% in the U.S[8] but appear to be in line with drug use across the E.U.[9] Since one of the insurance companies included full coverage of copayments for children up to the age of 18 in their benefit package, we exclude these individuals from our main analysis.[10] We also restrict our analysis to individuals who were insured for the full calendar year, in order to avoid capturing individuals who have either died or moved abroad. Importantly, individuals in the sample do not lose their insurance

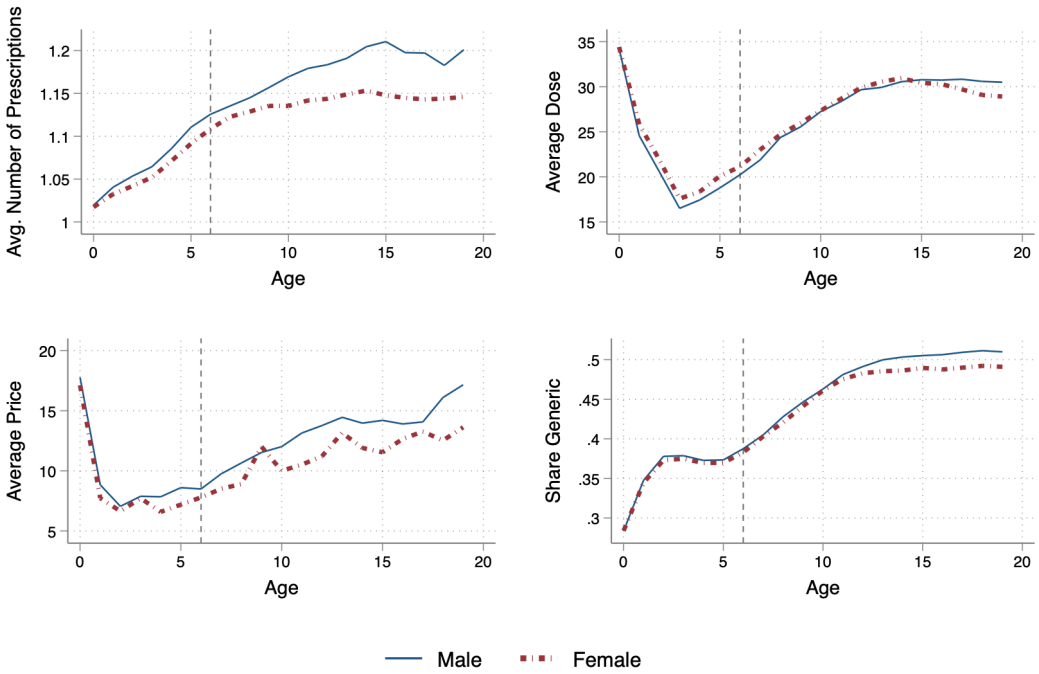
[6] This is particularly important in the context of concerns around school-starting and choice.

[7] https://www150.statcan.gc.ca/n1/pub/82-003-x/2014006/article/14032-eng.htm

[8] https://www.cdc.gov/nchs/fastats/drug-use-therapeutic.htm

[9] These statistics appear to be higher than self-reported figures provided by the European commission, suggesting a non-trivial amount of under-reporting of drug use. https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Medicine_use_statistics

[10] The market share of the respective insurance company is around 23%.



Excludes vaccines.

FIGURE 2: PHARMACEUTICAL USE THROUGHOUT CHILDHOOD

in the event of a job loss.

As discussed in section 2, both prices and copay amounts are determined by the Ministry of Health. Broadly, these drugs are relatively affordable, with copays for the most commonly prescribed drugs (Table 5) ranging from 0.44€to 7.35€. Children in Slovakia are not the top consumers of prescription drugs. Figure **??** plots average pharmaceutical use throughout childhood, excluding prescriptions for common childhood vaccinations (which comprise approximately 8% of pharmaceutical claims for children aged 0 to 19). Prescription drug use grows throughout childhood, continues to grow through adulthood (see Figure 1). Nevertheless, on average children tend to use some of the most costly drugs (see Figure 2). This further motivates our focus on their behavioural responses to cost changes.

Table 1: Prescription Use Before and After Copay Exemption

	Age 5	Age 6	Diff.	N
Number of prescriptions per month	2.78	2.13	0.64***	2548223
Packages collected per month	0.54	0.45	0.09***	2548223
Standardized doses per month	8.60	8.16	0.43***	2548223
Total drug price	4.98	4.08	0.90***	2548223
Total of out-of pocket copayments	1.02	0.97	0.04***	2548223
Chronic use (>=90 std. doses/year in ATC3 group)	0.19	0.19	-0.00	2548223
Share of cheapest alternatives	0.23	0.17	0.06***	2548223
Share of generics	0.09	0.09	0.00***	2548223
Median income	976.84	975.01	1.84***	2532685

5 Results

Table 2 presents results from DiD regressions. Columns (1)–(3) estimate the effect of copayments on total quantity of packages, columns (4)–(6) on number of prescriptions, while columns (7)–(9) on total quantity of generic prescriptions. We first estimate simple regressions only with the interaction term for treatment group and post period, then adding personal characteristics and finally also fixed effects for place of residence. We also split the estimation sample into non-chronic users and chronic users. Chronic user is defined as having 91 or more DDDs prescribed within a single anatomical therapeutic chemical category (ATC) during the 12-month observation period.[11] Panel A. presents results for non-chronic users, while Panel B. summarizes results for chronic drug users.

Looking at the estimates for non-chronic users, the estimated coefficients for monthly quantity of packages are small and not different from zero. Given that non-chronic users already have low utilization of prescription drugs, it is likely

[11] A similar criterion of 91 or more DDDs within an ATC category for children is used in risk equalization models in Slovakia and Netherlands, for classification of individuals into pharmaceutical cost groups (PCG). PCGs serve as an indicator for chronic use, where for example individuals meeting the required DDDs of insulin are categorized in the PCG for diabetes (Lamers and Vliet, 2003; van Kleef et al., 2018).

that vast majority does not even cross the 10€ per quarter threshold after which the copayments are fully covered until six years of age. It is therefore not surprising that there are no effects observed once they lose the coverage, since their out-of-pocket payments likely remain the same (i.e. below 10€ per calendar quarter). A similar result is observed for the total number of prescriptions. One of the possible mechanisms to mitigate increased costs associated with coverage loss is substitution to cheaper generic alternatives. Columns (7)–(9) investigate this scenario, finding a small increase in generic prescriptions in the full model with personal characteristics as well as time- and district-fixed effects. However, the point estimate is only significant at the 10% level.

Panel B. presents estimates for chronic users, finding that coverage loss is associated with $100 \times (\exp(-0.029) - 1) \approx -2.85\%$ decrease in quantity of packages redeemed. The result is statistically significant in all specifications of the model. A similar result is obtained when looking at the total number of prescriptions, finding that coverage loss is associated with approximately 1.3% decrease.

Table 2: Effects of Copayments on Pharmaceutical Utilization

	Packages			Prescriptions			Generic prescription	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A. Non-chronic users								
Treatment effect (δ)	0.007	0.005	0.004	−0.006	−0.005	−0.003	0.013	0.016
	(0.012)	(0.012)	(0.012)	(0.008)	(0.008)	(0.007)	(0.011)	(0.011)
Person-months	686,832	686,832	681,906	686,832	686,832	681,906	686,832	686,832
Individuals	57,236	57,236	56,829	57,236	57,236	56,829	57,236	57,236
Panel B. Chronic users								
Treatment effect (δ)	−0.029	−0.029	−0.028	−0.013	−0.014	−0.015	−0.005	−0.005
	(0.012)**	(0.012)**	(0.012)**	(0.007)*	(0.007)**	(0.007)**	(0.012)	(0.012)
Person-months	228,144	228,144	227,313	228,144	228,144	227,313	228,144	228,144
Individuals	19,012	19,012	18,943	19,012	19,012	18,943	19,012	19,012
Personal characteristics	No	Yes	Yes	No	Yes	Yes	No	Yes
Calendar time effects	No	Yes	Yes	No	Yes	Yes	No	Yes
Place effects	No	No	Yes	No	No	Yes	No	No

Notes: All models estimated using a zero-inflated Poisson regression. Zero counts modelled as logit. Robust standard errors clustered at the individual level in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.001$

5.1 Income heterogeneity

In the following section, we take our preferred specifications of the models and further split the estimation sample by quartiles of annual family income. Results are summarized in table 3. Looking at Panel A., the results reveal no significant effects for non-chronic users across all income quartiles. However, further splitting the sample according to annual family income reveals that the negative effect on quantity of packages is observed only for the two lowest income quartiles. The magnitude of the effect also increases to roughly 5.4% and 4.7% respectively. For the third and fourth income quartile we find no statistically significant effects. Clearly, the most vulnerable and affected by the coverage loss are low-income families, with annual income below 13,765€.

Table 3: Effects of Copayments on Pharmaceutical Utilization by Income Quartiles

	Q1 (1)	Q2 (2)	Q3 (3)	Q4 (4)
Panel A. Non-chronic users				
Packages	0.033	−0.007	0.013	−0.006
	(0.029)	(0.023)	(0.023)	(0.021)
Generic prescriptions	−0.009	0.033	0.025	0.020
	(0.025)	(0.021)	(0.021)	(0.021)
Person-months	121,992	163,128	165,249	231,537
Individuals	10,167	13,594	13,771	19,297
Panel B. Chronic users				
Packages	−0.055	−0.048	−0.001	−0.025
	(0.031)*	(0.023)**	(0.022)	(0.022)
Generic prescriptions	−0.035	−0.008	0.022	0.001
	(0.029)	(0.023)	(0.022)	(0.022)
Person-months	31,704	58,437	63,912	73,260
Individuals	2,642	4,870	5,326	6,105

Notes: Treatment effect estimate (δ) reported. All models estimated using a zero-inflated Poisson regression, including personal characteristics, calendar time and district fixed effects. Zero counts modelled as logit. Robust standard errors clustered at the individual level in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.001$

5.2 Robustness and Placebo Tests

In order to test robustness of our results, we estimate a placebo coverage loss occurring at five years of age. Treatment and control groups are composed similarly as in the main regressions. Since there is no change in copayment coverage, we would expect to find no difference in pharmaceutical utilization. Table 4 summarizes the results.

Table 4: Effects of Copayments on Pharmaceutical Utilization — Robustness Checks

	Packages (1)	Prescriptions (2)	Generic prescriptions (3)
Panel A. Non-chronic users			
Treatment effect (δ)	0.000	−0.023	−0.013
	(0.005)	(0.024)	(0.015)
Person-months	359,952	359,952	359,952
Individuals	29,996	29,996	29,996
Panel B. Chronic users			
Treatment effect (δ)	−0.016	−0.054	−0.015
	(0.017)	(0.097)	(0.057)
Person-months	123,516	123,516	123,516
Individuals	10,293	10,293	10,293

Notes: All models estimated using a zero-inflated Poisson regression, including personal characteristics, calendar time and district fixed effects. Zero counts modelled as logit. Robust standard errors clustered at the individual level in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.001$

6 Conclusion

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Appendix: Supporting Materials

Supporting Tables

Table 5: Most commonly used drugs (overall)

	Price (€)	Copay (€)	N
Antibacterials for systemic use	8.78	2.8	119991
Antihistamines for systemic use	7.88	2.88	87948
Vaccines	25.81	0.44	56413
Antibiotics and chemotherapeutics for dermatological use	6.25	2.66	39832
Drugs for obstructive airway diseases	16.45	3.53	20744
Ophthalmologicals	9.78	3.75	18959
Emollients and protectives	13.22	3.42	10597
Otologicals	11.93	3.73	9582
Nasal preparations	18.95	6.07	8879
Immunostimulants	32.29	7.35	7013

Sample of eligible children, average prices per standard package-dose.

Table 6: Most commonly used drugs amongst chronic users

	Price (€)	Copay (€)	N
Antihistamines for systemic use	5.7	2.59	139638
Drugs for obstructive airway diseases	10.66	1.02	81890
Emollients and protectives	6.36	1.44	60885
Nasal preparations	7.07	2.71	25574
Antiepileptics	12.63	1.11	17097
Other dermatological preparations	2.89	0.81	12291
Pituitary and hypothalamic hormones and analogues	100.52	5.85	6208
Antianemic preparations	5.21	1.8	3048
Corticosteroids, dermatological preparations	4.16	1.17	3033
Drugs used in diabetes	58	8.21	2817

Sample of eligible children with chronic use (>90 doses per ATC code-year), average prices per standard package-dose.

Table 7: Mean price, by drug class

	Price (€)	Copay (€)	Copay Share (%)	N
A:Alimentary tract and metabolism	84.72	9.85	22.17	12854
B:Blood and bloodforming organs	188.16	2.49	15.69	8553
C:Cardiovascular system	25.59	2.91	29.74	31642
D:Dermatologicals	8.16	2.36	34.4	5054
G:Genitourinary system and sex hormones	47.1	9.32	18.44	6366
H:Systemic hormonal preparations	250.88	4.49	8.83	2645
J:Antiinfective for systemic use	266.24	4.51	29.4	11083
L:Antineoplastic and immunomodulating agents	469.62	16.88	8.35	15064
M:Musculo-skeletal system	94.09	2.98	35.14	5539
N:Nervous system	31.35	1.76	14.69	34130
P:Antiparasitic products, insecticides, and repellents	6.55	1.64	24.89	246
R:Respiratory system	23.73	3.24	23.7	9070
S:Sensory organs	43.47	3.17	28.01	3525
V:Various	228.5	16.01	9.04	3555

Table 8: Most common chronic conditions by category, and average drug price

	Price (€)	Copay (€)	N
Diseases of the respiratory system	8.87	2.26	230536
Diseases of the skin and subcutaneous tissue	6.01	1.51	79242
Diseases of the nervous system	59.04	1.08	17372
Diseases of the blood and blood-forming organs	53.76	4.47	10614
Certain infections and parasitic diseases	3.69	1.09	8780
Mental, Behavioral and Neurodevelopmental disorders	31.93	1.26	8146
Endocrine, nutritional and metabolic diseases	123.4	15.94	7878
Diseases of the digestive system	16.21	2.63	6957
Diseases of the genitourinary system	46.25	1.65	5862
Congenital deformations & chromosomal abnorm.	21.97	2.56	3413

Sample of eligible children with chronic use (>90 doses per ATC code-year), average prices per standard package-dose.

Supporting Figures

Figure 1: Distribution of Drug Use by Birth Cohorts

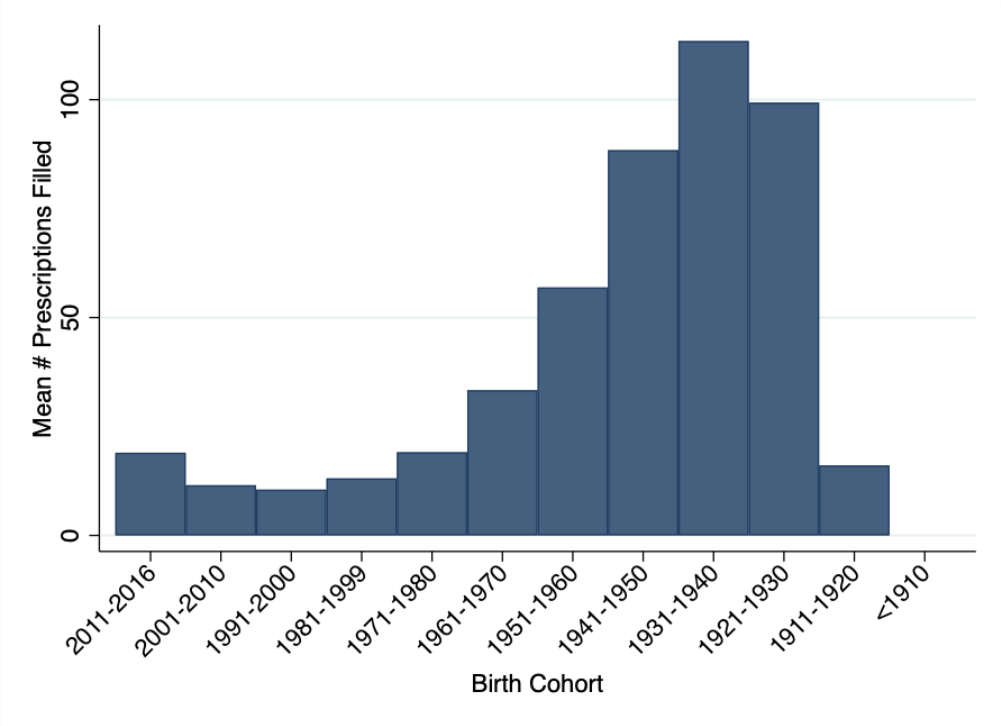

Figure 2: Distribution of Drug Costs by Birth Cohorts

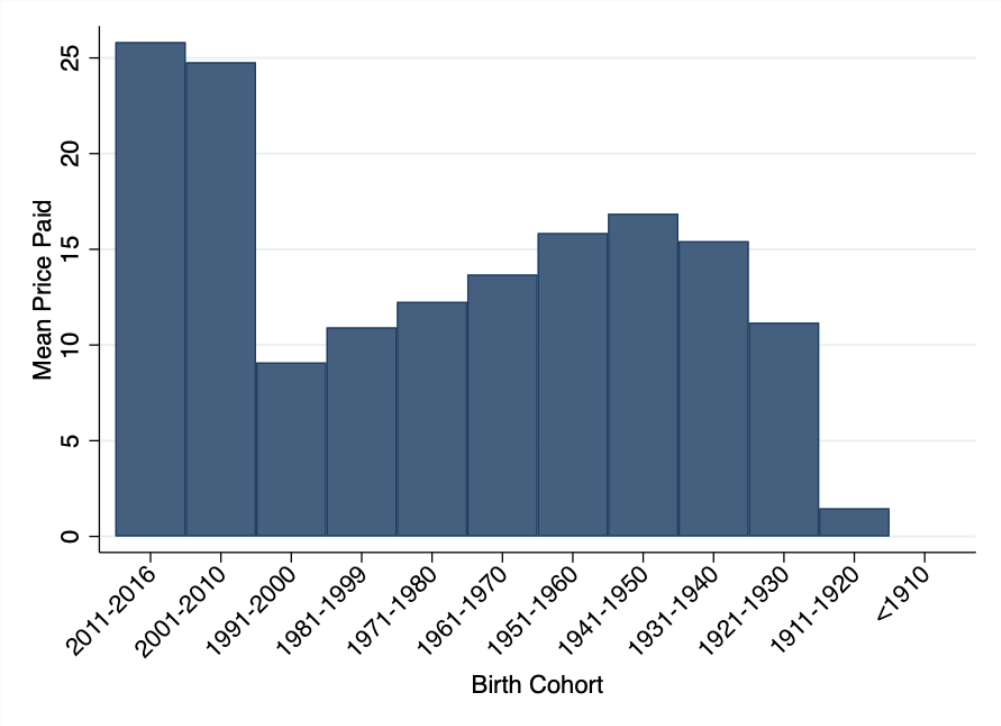

Figure 3: Regression Discontinuity Results for Number of Unique Prescriptions Filled

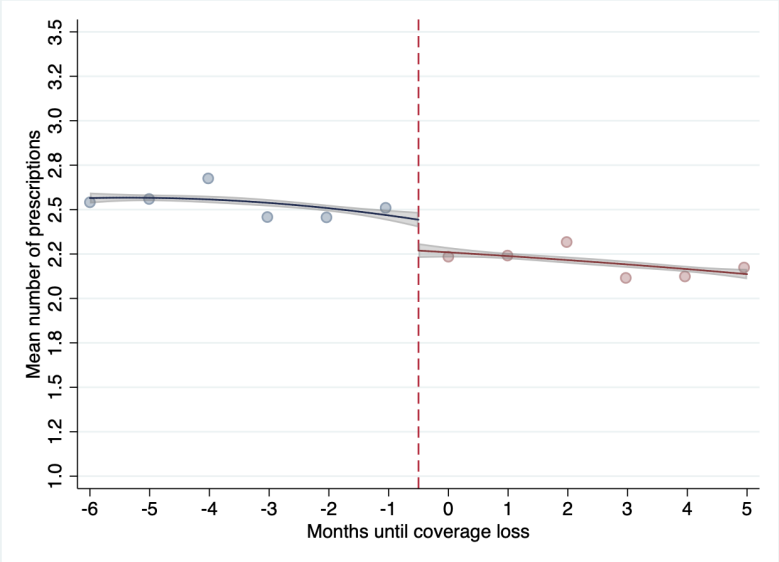

Figure 4: Regression Discontinuity Results for Number of Packages