Universal Subsidies in Pharmaceutical Markets: Lessons from Poland's Drugs 75+ Policy*

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Abstract

Widely used public policies fully subsidizing essential goods and services aim to improve access, but removing price signals may also produce distortions. We investigate this problem by leveraging Poland's Free Drugs for Seniors program, which provides free prescription medications to individuals above an age threshold, as a natural experiment. Using event studies, detailed administrative and survey data, we draw two main conclusions. First, the program improved access: medication consumption increased, particularly for higher-cost products, to some extent displacing cheaper alternatives. Second, the shift in consumption patterns increased public payer costs per dose of treatment. These findings highlight the challenges of subsidy programs that eliminate price signals, as they can alter demand in ways that improve access but undermine cost-effectiveness.

JEL Classification: I10, I13, I18

1 Introduction

Policymakers must continually navigate the delicate balance between improving access to medications and managing healthcare expenditures when designing drug reimbursement policies. The pharmaceutical market provides a particularly relevant context for exploring more general tension trade-offs between improved access and the fiscal costs associated with eliminating price signals in key markets. Public policies that remove price signals

* *Work in progress – please do not circulate.*

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by fully subsidizing essential goods and services are widely employed to promote welfare, improve access, and reduce inequality. Such interventions can inadvertently distort markets by encouraging unintended consumption choices and escalating fiscal costs.

Medications account for a substantial and growing share of healthcare expenditures worldwide, driven by aging populations, rising drug prices, and the increasing prevalence of chronic conditions. Across the European Union (EU), publicly financed medical products represent an average of 1.1% of GDP and 20% of total health spending. Policymakers are aware of these pressures, as evidenced by initiatives such as the Pharmaceutical Strategy for Europe and the Inflation Reduction Act in the United States, both aimed at reducing costs while ensuring broad access to life-saving treatments.

In the context of aging societies, drug subsidies for seniors, who account for a disproportionate share of medication use, are among the most debated policies in pharmaceutical markets. For many seniors, the cost of medication can be prohibitively expensive, leading to inadequate treatment and increased risk of serious health issues. Subsidizing medications presents a potential solution to this problem by enhancing accessibility and encouraging compliance with prescribed treatments. Moreover, the impact of these subsidies on seniors' broader financial well-being, including potential contributions to poverty alleviation, nutrition, and overall quality of life, remains an area of considerable uncertainty. Most governments employ partial subsidies, but several—including Italy, the UK, Spain, and Germany—provide certain medications free of charge to eligible populations. While such policies aim to improve adherence and financial security for vulnerable groups, they also remove price signals entirely, raising concerns about inefficiencies such as over-consumption or substitution toward higher-cost treatments.

In this paper, we assess the health and economic implications of medication subsidies in the context of Poland's free drugs for seniors program. Introduced in 2016, this policy provides free access to a subset of prescription medications for individuals aged 75 and older, and later expanded to cover almost all prescription medication and individuals 65 and older. Unlike systems characterized by voluntary enrollment or fragmented insurers, Poland operates a universal, single-payer healthcare system where the costs of pharmaceutical treatments are typically borne, in a large part, out-of-pocket by patients.

We examine the impacts of the program on pharmaceutical expenditures and demand allocation, focusing on two key questions. First, does removing out-of-pocket costs alter demand allocation, such as shifting consumption toward higher-cost medications or increasing overall utilization? Second, how does providing free medications influence overall expenditures of the public payer?

To address these questions, we leverage two critical features of the program. The first is the exogenous eligibility criterion, which grants free drug access to individuals above an age threshold. The second is the staggered inclusion of specific drugs into the program over time, which provides additional variation in treatment exposure. These institutional features allow us to apply rigorous causal inference methods to estimate the program's effects.

To study changes in the consumption of pharmaceuticals and the cost of the policy for the government, we utilize administrative data on sales of reimbursed drugs, which provide granular information on the quantity and value of monthly drug purchases for more than 4000 products between 2014 and 2024. We begin with event studies that compare trends in consumption between individuals above and below the eligibility age, allowing

us to track differential responses to the program over time. Furthermore, we implement a continuous difference-in-differences design, using pre-policy copayment levels as a measure of treatment intensity to identify how the program's full subsidy affected demand allocation. This approach captures heterogeneity in the policy's effects, particularly shifts in consumption toward higher-cost medications.

First, the program significantly increased consumption of reimbursed drugs, with an immediate rise of 7.5% that grew to 13% within 12 months of implementation, driven predominantly by increased use of higher-priced products. In addition to an overall growth in aggregate use of medication, we observe a decline in the use of cheaper alternatives, indicating a substitution toward pricier options. The effect was especially notable in markets with high price differential between cheap and expensive medication, suggesting that patient treat price as a quality signal.

Second, the substitution toward higher-cost medications increased the government's cost per dose of treatment. Expenditures rose not only due to higher overall consumption but also because the program shifted demand toward more expensive drugs, even when these offered no additional therapeutic benefits compared to cheaper alternatives. This highlights an unintended consequence of the policy: while improving access to medications through higher aggregate consumption, it also increased fiscal costs by encouraging a composition of demand that undermined cost-effectiveness.

This paper is related to three main strands of literature. First, we extend the evidence on demand elasticity for prescription drugs by examining a universal healthcare system with full subsidies. Prior studies, such as those by Dor and Encinosa (2010), Skipper (2013), Einav et al. (2018), and Dafny et al. (2022), have documented price sensitivity in medication consumption, with elasticity estimates ranging from -0.1 to -0.5. Much of this evidence is drawn from contexts like the Medicare Part D reform in the United States or the "donut hole" coverage gap, where individuals experience substantial increases in out-of-pocket costs. These settings often involve non-linear pricing structures and voluntary enrollment, producing distinct behavioral responses. Importantly, changes in price may have asymmetric impacts, as discontinuing therapy often carries different costs and consequences than initiating treatment. Furthermore, maintaining marginal out-of-pocket costs above zero, as is typical in most Medicare plans, can lead to very different fiscal outcomes compared to full subsidies.

By contrast, our study focuses on a single-payer system where eligibility is automatic and the price of medications falls to zero. This unique setting allows us to contribute new evidence to the literature on the price elasticity of prescription drugs, while also shedding light on unintended fiscal consequences, such as shifts in consumption toward higher-cost alternatives.

Second, we contribute to the growing literature on the health and financial impacts of drug subsidies. Research from the U.S., such as Kaestner et al. (2019) and Chandra et al. (2024), has demonstrated that the extent of cost-sharing under programs like Medicare Part D significantly affects medication adherence, hospitalizations, and even mortality. These findings underscore the critical role of drug subsidies in shaping health outcomes and financial well-being, particularly for vulnerable populations.

Third, we contribute to the broader debate on the efficiency of public subsidies. Our findings highlight potential inefficiencies, such as substitution toward more expensive treatments with no health benefits. This raises critical questions about the design of

subsidy programs: How can policies balance improving access with minimizing distortions in demand?

This paper contributes to the policy debate by showing that driving all medication costs to zero can improve access but also leads to potentially unintended consequences, such as substitution toward higher-cost alternatives with no added therapeutic value, which may be inefficient from the government's perspective. These findings suggest that more targeted approaches, such as subsidizing only the cheapest available medication, could enhance access while controlling fiscal costs and preserving efficiency.

The paper is structured as follows: Section 2 introduces the institutional setting and data used in the analysis; Section 3 and 4 present the empirical strategies and results for the analyses of household budgets and drug consumption respectively; Section 5 concludes.

2 Context and Data

Poland is the 5th biggest country in the European Union, after Germany, France, Italy and Spain. The population of Poland is shrinking and ageing, with the share of elderly (aged 65 or more) increasing by over 42% between 2012 and 2023 and catching up with the EU average of 21.3%. Despite improvement in the recent years, life expectancy at birth is below the EU average and there is a large gap between men and women. Table 3 in the Appendix presents some basic statistics on the country's economy and demographics compared to the EU27 average.

2.1 Poland's Health System

Like its European peers, Poland's health system is characterised by a virtually universal coverage with public health insurance. The right to healthcare is written in Article 68 of the Polish Constitution of 1997, with special weight put on the vulnerable parts of the population, including people with disabilities, pregnant women and the elderly. The public health insurance is provided through the National Health Fund (NFZ). Spending on the public health system amounted to almost 75% of total spending on health in Poland in 2022 and has been steadily increasing from 4.33% of GDP in 2012 to 5% in 2022 (OECD Data Archive).

The provision of a set of health services in predefined quantities, specified in 2009 by the Ministry of Health, is contracted by the NFZ through tenders. When demand for the publicly financed health services exceeds the contracted supply, their provision is managed via waiting lists. Patients can choose their provider and waiting times are published on a centralized platform.

The Polish public health insurance is characterized by substantial patient cost-sharing for reimbursed (outpatient) drugs, and the bulk of out-of-pocket health spending is devoted to pharmaceuticals. There is no cost-sharing for inpatient care nor for primary care and outpatient specialist care. Socioeconomic health inequalities remain one of the main health challenges in Poland (Sowada et al., 2019), and the subsidy program is a clear measure to alleviate the problem.

2.1.1 Drug Reimbursement Policy

The 2012 Reimbursement Act introduced strict price controls for reimbursed pharmaceuticals in Poland. Drozd and Michalska (2017) provide a thorough description of the policy. Following this reform, all reimbursed drugs have fixed manufacturer prices, set by the Minister of Health for a period of 2-3 years, through negotiations with the producer, and using both internal and external reference pricing[1]. The retail price is then augmented by fixed wholesaler and pharmacy margins. The list of reimbursed drugs and their prices is published bi-monthly by the Ministry of Health.

The reimbursement level of a particular drug for a specific patient depends on the condition the patient has been diagnosed with. There are three levels of percentage copays possible: 0, 30 and 50%, as well as fixed fee copays. In practice, the copay can be higher as the reimbursement level depends on the prices of close substitutes.

Drugs are organized into limit groups comprising of close substitutes (either the same active substance or similar mechanism of action and therapeutic effect). Reimbursement limits are defined at the level of a limit group and are related to the price of the cheapest drugs that comprise 15% of sales in the group. If the price of a given drug minus the percentage copay exceeds the reimbursement limit, the patient will have to pay this difference as well as the copay amount.

The reimbursement level is defined by the physician on the prescription and verified at the pharmacy. The NFZ conducts audits of healthcare providers and pharmacies, which include the verification whether reimbursement levels indicated on the prescriptions were in accordance with the current rules and the patient's diagnosis.

While there are no official guidelines on cost-effective prescribing, pharmacy margins are homogenous across drugs within a group, eliminating an incentive to privilege dispensing more expensive drugs, and pharmacists inform patients about available substitutes.

Drozd and Michalska (2017) show that after the 2012 reform, the NFZ pays less per dose, but subsidizes more drugs. The reform led to an increase in consumption of reimbursed drugs, and a shift towards more affordable substitutes.

2.1.2 The Drugs 75+ Program

In 2016 the Polish government introduced a change in the drug reimbursement policy, which allowed access to a subset of reimbursed drugs free of charge for people aged 75 and more. The policy is called LEKI 75+ (Drugs 75+ in English). In 2023, it was expanded to individuals 65+ and called Drugs 65+[2].

The design of the policy is simple: from 1st of September 2016, people aged 75 or more are fully reimbursed for drugs that are included on a list published by the Minister of Health on a bi-monthly basis, which constitute a subset of the full set of reimbursed drugs. To benefit from the program, patients have to present a prescription with a special

[1]Internal reference pricing: the price is affected by the prices of similar products on the market, and in particular the first generic entrant must be 25% cheaper than the branded product. External reference pricing: the Ministry of Health takes into consideration prices in the other EU and EFTA states (Sowada et al., 2019)

[2]Throughout the paper we will keep using the name Drugs 75+, although it covered also younger people later. In 2023, the program has also been extended to individuals 18 or younger, which we do not analyze in the paper.

annotation confirming their eligibility (drug reimbursement is tied to specific indications), issued by their primary care physician, and from 2021 also by specialists.

The list of drugs included in the Drugs 75+ program was defined based on three criteria: the relevance of the treatment for the targeted population, its safety and efficacy, and the pre-policy accessibility of the product.

The Drugs 75+ list has been extended over time. The first set of drugs established in 2016 consisted of treatments for hypertension, ischaemic heart disease, thromboembolism, asthma, chronic obstructive pulmonary disease, diabetes, depression and dementia, and accounted for 28.6% of products on the reimbursed drugs list. The list of products covered by the program was then gradually extended over the course of 2017 and in May 2018, an important extension included some cancer drugs and antibiotics, treatments for epilepsy and chronic obstructive pulmonary disease, opioids and heparins. In March 2021, the list was further extended to include more antiepileptics, corticosteroids and urological drugs. Since the 2018 extension, the program covered almost half of all the reimbursed drugs. The biggest expansion came in September 2023. At that point the program covered almost all products on the reimbursed drugs list. At this point also the eligibility extended to individuals 65 or older.

Figure 1 illustrates the evolution of the set covered by the program as well as the overall list of reimbursed drugs over the years 2014-2024. While, at the product level, there appears to be a lot of entries as well as exits, the situation is much less dynamic at the level of limit groups. Outside of the rare revisions of the reimbursed drugs list and the major extensions of the Drugs 75+ list, most product entry and exists are related to the changes in the composition of the limit groups.

2.2 Data on sales of reimbursed drugs

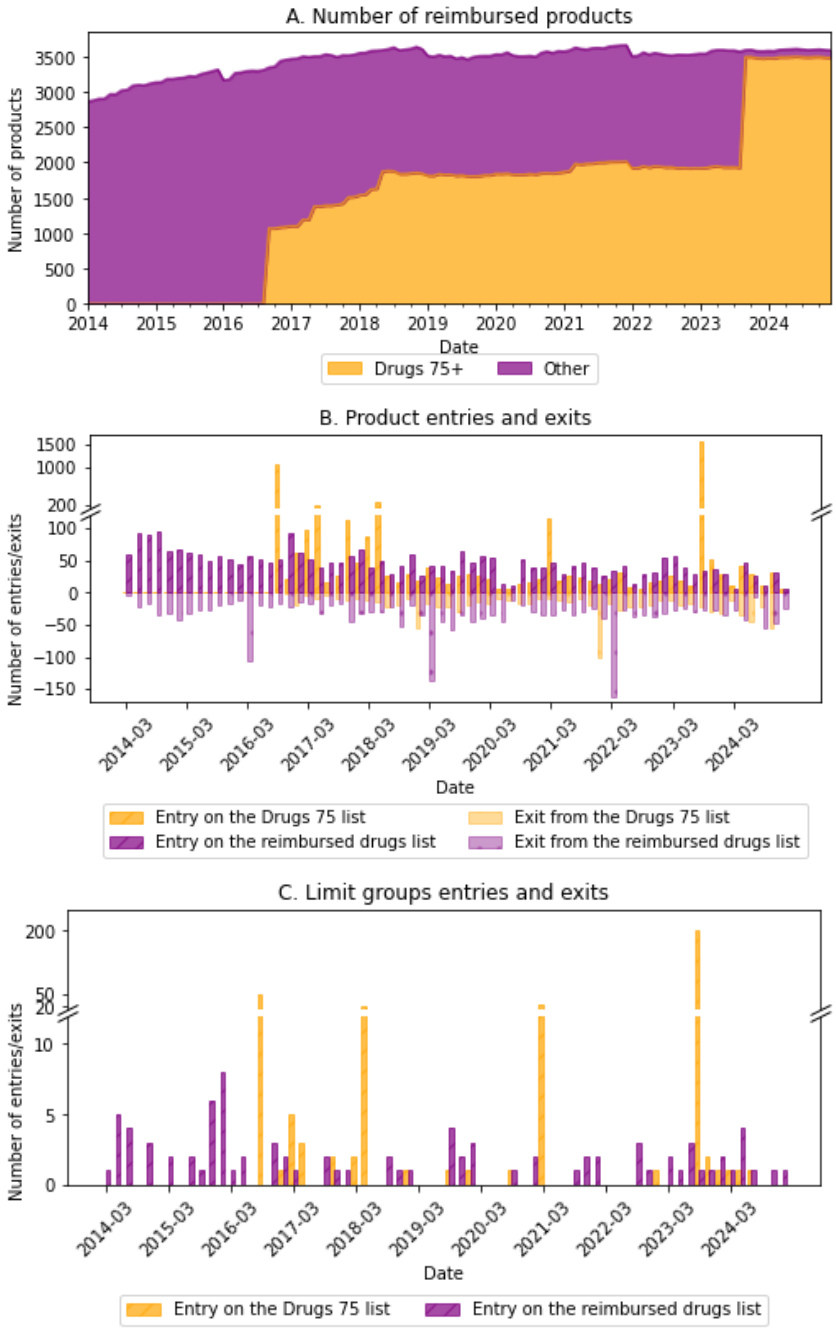
In our analysis, we use data on monthly sales of reimbursed drugs from 2014 to 2024 provided by the National Health Fund, a Polish government agency. The data contains information on the number of packages sold per product (at the EAN code level), the total OOP cost and the cost of reimbursement for the public payer. This data is further disaggregated by 5 years age groups.

We add more information at the product level using the official lists of reimbursed drugs, published every two months by the Ministry of Health, as well as the official registry of medical products from the E-Health Center. Using historical lists of reimbursed drugs, we are able to follow the evolution of the set of reimbursed drugs and of the set of the drugs covered by the Drugs 75+ program. Moreover, the lists contain the product and active substance names, limit groups, prices and out-of-pocket payment levels. From the registry, we take the ATC5 codes, package sizes, names of producers and countries of origin of the drugs in our set. Finally, we use also information on the Defined Daily Doses (DDD) published by the WHO.

Throughout this manuscript, we use the term *active substance* to refer to the main pharmacologically active component of a medication. The terms *active ingredient* and *molecule* are used synonymously in the literature. For clarity and consistency, we use *active substance* throughout all tables, figures, and analysis.

Table 1 presents an overview of the sales dataset. On average, the dataset contains sales data for 4142 products, organized into 372 limit group. There are on average 3.16

Figure 1: Evolution of the list of reimbursed drugs and drugs covered by the Drugs 75+ program, 2015-2022



Note: Panel A shows the total number of reimbursed drugs and those covered by the Drugs 75+ program, 2015-2024. Panels B and C show bimonthly product and limit group entries/exits. Data source: Ministry of Health, Poland, bi-monthly lists of reimbursed drugs.

products per active substance. The government-fixed manufacturer prices vary a lot, with the mean at $18 per product. The average product brings around $550 000 per year in sales and approximately $180 000 are paid out of pocket by the patients. The products

Table 1: Descriptive statistics of the reimbursed drugs sales dataset

	Mean	SD	Min	Max
Number of unique products	4141.91	203.44	3718.0	4362.0
Number of active substances	436.18	34.1	397.0	481.0
Number of limit groups	371.64	9.11	352.0	384.0
Government Price ($)	17.91	66.33	0.25	1909.09
Sales Value (mil. $)	0.55	1.71	0.0	103.92
Total OOP (mil. $)	0.18	0.54	0.0	15.65
75+ OOP (mil. $)	0.02	0.11	0.0	4.41
Total Reimbursement (mil. $)	0.5	1.65	0.0	103.18
75+ Reimbursement (mil. $)	0.17	0.83	0.0	85.0
Consumption (mil. su)	2.96	12.93	0.0	707.26

Note: Sales Value, OOP, Reimbursement, and Consumption are totals per year per product. Data source: National Health Fund, Poland, 2014-2024.

consumed by the seniors aged 75 and older are cheaper.

Table 2: Summary of Spending in 2015

	Less than 75	GEQ than 75
Monthly Per Capita		
Packages	0.707	3.123
Cost (USD)	4.988	18.54
Out of pocket (USD)	1.617	6.577

Note: This table reports monthly per capita consumption and spending on reimbursed drugs for two age groups in 2015, before the policy reform. Per capita values are calculated using the total population in each age group in 2015. Cost refers to total spending on reimbursed drugs; Out of pocket refers to patient payments. Data source: National Health Fund, Poland, 2015.

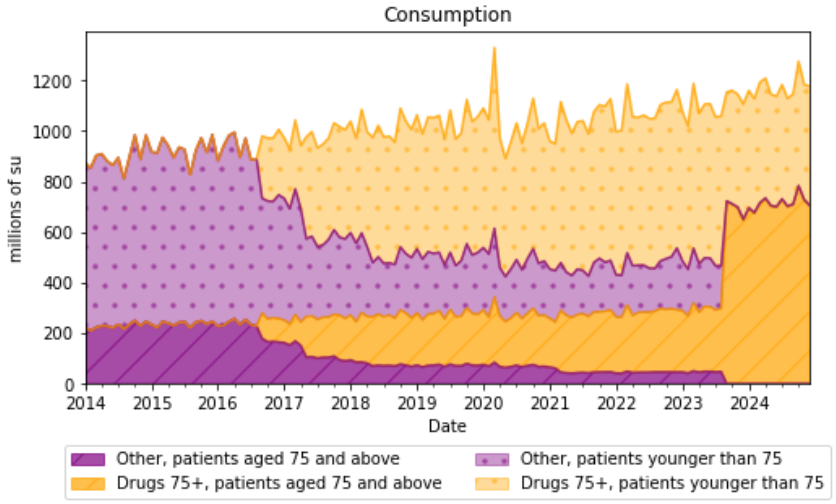
In Table 2 we present means of pre-reform measures of consumption of reimbursed drugs for the two age groups. The older part of the population consumed almost 4.5 times more reimbursed drugs and bore a proportionally higher out-of-pocket cost for them.

Figure 2 plots the consumption in standard units of reimbursed drugs both on the Drugs 75+ list and not, for the two age groups: below 75, and 75 and above. We can observe an overall increase in consumption of reimbursed drugs between 2014 and 2024 for the two age groups. The Drugs 75+ subset of products corresponds to the bulk of consumption of patients aged 75 and above, especially after the extensions of the list in 2017 and 2021. These products constitute also a large share of the consumption of the younger patients.

Figure 3 plots the value of sales of reimbursed drugs in the same four subgroups and paints largely the same picture. We observe an increase in the sales over the studied time period, and Drugs 75+ products account for the majority of sales among patients aged 75 and above. Among the younger population, however, these products account for slightly

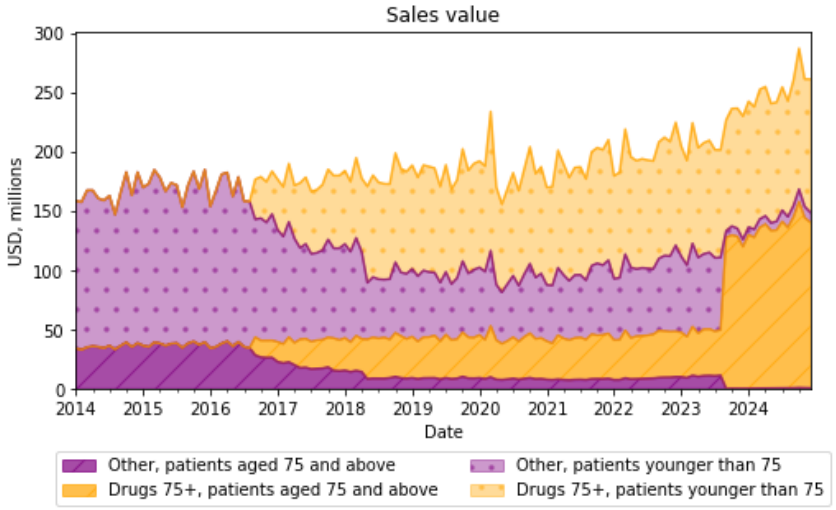
more than a half of the sales, suggesting that the other products consumed are relatively more expensive.

Figure 2: Consumption of reimbursed drugs in Poland 2014-2024, by subset and age group



Note: This figure shows the total number of units (packages) of reimbursed drugs consumed by age group and product subset, 2014-2024. The Drugs 75+ subset includes the 65+ extension from September 2023. Data source: National Health Fund, Poland.

Figure 3: Sales of reimbursed drugs in Poland 2014-2024, by subset and age group



Note: This figure shows the total sales value of reimbursed drugs by age group and product subset, 2014-2024. Data source: National Health Fund, Poland.

3 Impact on Consumption and Government Spending

3.1 Empirical Approach to Consumption Analysis

Our primary empirical strategy is an event study leveraging a natural experiment in which certain drugs were made free in a staggered manner, exclusively for individuals above the age threshold. To complement this, we employ a continuous difference-in-differences (DiD) approach (Callaway et al., 2024), which utilizes variation in pre-policy out-of-pocket prices. This design captures heterogeneity in the magnitude of price declines.

Baseline Specification The baseline specification is an event study that examines the inclusion of a product in the list of drugs reimbursed by the policy. This approach analyzes the temporal evolution of outcomes for individuals above the age threshold to those below. It assumes that, in the absence of the policy, trends would have evolved in parallel across these groups. The estimation equation is as follows:

$$Y_{ita} = \sum_{k \neq -2, k=-12}^{12} \delta_k \cdot \mathbf{1}(t - T_i = k) \cdot \text{Age\_Group\_Eligible}_{at} + \gamma_t + \lambda_{ia} + \epsilon_{ita}, \quad (1)$$

where Y_{ita} represents the outcome for product (or substance) i, at time t, and age group a. The model includes interaction terms between relative time indicators $\mathbf{1}(t - T_i = k)$ (where T_i is the time of inclusion of product i) and the dummy variable $\text{Age\_Group\_Eligible}_{at}$, which equals one for individuals who are eligible at a given expansion step. Specifically, people aged 75 or older became eligible at the first expansion in September 2016, while individuals aged 65 and over became eligible at the expansion in September 2023. Age group 60-64 serves as the control[3]. The coefficients δ_k capture the differential temporal impact of the policy on outcomes for eligible individuals relative to those who remain ineligible.

The pre-policy coefficients ($k < 0$) allow for pre-trends checks, providing partial validation of the empirical strategy. To account for potential anticipatory behaviors, the relative time dummy for two months prior to the policy is excluded from the estimation. This exclusion acknowledges that individuals might adjust their behavior in anticipation of the policy during the final month before its implementation. The lists of free medications are announced around 2 weeks before they can be first acquired at no cost.

We include product-by-age-group fixed effects (λ_{ia}) and time fixed effects (γ_t). Errors are clustered at the product-by-age-group level, consistent with the treatment definition. To address potential biases arising from staggered event timings, we complement this analysis with the robust methodology of Sun and Abraham (2021).

Outcomes of Interest Our primary analysis is conducted at the active substance level, where we aggregate all products containing the same substance to measure changes in overall demand. This level of aggregation is particularly informative, as it abstracts from

[3]Using age group 70-74 as control in the earlier expansion does not change the results

within-substance substitution patterns—which we examine separately—and focuses on changes in access to medication.

We examine three main outcomes: (i) the logarithm of the number of packages sold, (ii) the logarithm of the number of unique patients purchasing the substance, and (iii) the ratio of packages to patients, which allows us to see along which margin -intensive or extensive- patients adjust consumption. Each outcome is normalized by population size to control for demographic changes over time.

To ensure consistency across periods, we restrict the sample to substances that were continuously available with at least partial public subsidy throughout the 2015–2024 period.

Next, we assess within-substance substitution across products and examine changes in the government's cost per dose of treatment, applying a comparable empirical framework.

3.1.1 Continuous Difference in Differences in Out-of-Pocket Price

To explore the role of pre-policy costs in shaping the policy's impact, we complement the event study analyses with a form of a continuous difference-in-differences (DiD) approach. This method compares changes in consumption over time and across pre-policy out-of-pocket prices.

The analysis proceeds in two steps. First, we calculate the a DiD estaimte for each product. That is, a change in consumption for eligible vs control group, before and after the inclusion using a 12-month window on either side of its implementation. Next, we model these product-level differences as a function of the logarithm of the average pre-policy out-of-pocket price, employing both nonparametric (binscatter) and parametric (splines) methods. These methods allow us to examine how the policy's impact on consumption varies continuously with pre-policy price levels, providing insights into how changes in affordability drive medication use.

3.2 Consumption Results

Overall, the results demonstrate that the policy significantly increased medication consumption among seniors. The largest increases occurred for the most expensive medications, accompanied by declines in the consumption of cheaper substitutes. The shift toward higher-cost medications increased the treatment costs borne by the government.

3.2.1 Increase in Purchases

The policy was associated with a substantial increase in the purchase of medications covered under the new reimbursement scheme. Figure 4 offers a descriptive visualization, illustrating raw per capita consumption of eligible medications by age group. Prior to the first policy expansion (indicated by the first dashed line), consumption trends across age groups were broadly parallel, supporting the validity of the parallel trends assumption. Following the expansion, there is a clear and immediate increase in consumption among individuals aged 75–79. A similar pattern emerges for the 65–69 and 70–74 age groups after the second expansion (second dashed line), when these cohorts became eligible. These patterns provide suggestive evidence that the policy improved access to medication for older adults.

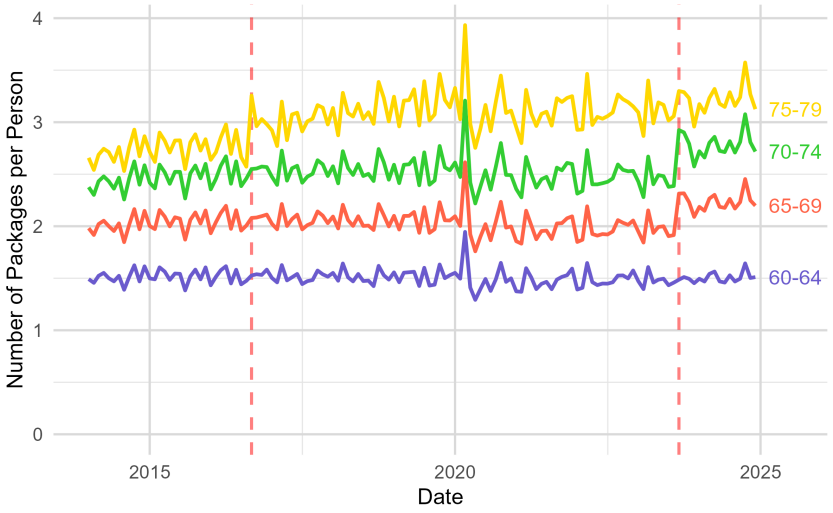


Figure 4: Medication Consumption per Person

Note: This figure shows the average number of packages of eligible medication purchased per person, by age group, over time. The denominator is the total population in each age group. The first dashed line marks the introduction of free medication for those aged 75 and over (September 2016), and the second dashed line marks the expansion to those aged 65 and over (September 2023). Data source: National Health Fund, Poland, 2014–2024.

To formalize this finding, Figure 5 presents the event study coefficients estimated from Equation 1. The pre-treatment coefficients for all outcomes are small and statistically indistinguishable from zero, supporting the validity of the parallel trends assumption. The only exception is the coefficient one month prior to the policy implementation, which shows a statistically significant 2% decline in patients and packages. This likely reflects anticipatory behavior, as individuals delayed purchases in expectation of obtaining free medication once the after the list was implemented.

Following the introduction of free medication[4], the number of patients increased by approximately 5% in the first month. This immediate response likely reflects pent-up demand and anticipatory behavior, as individuals postponed purchases in expectation of the policy. Patient counts continued to grow steadily over time, reaching a 7.5% increase after one year. The rise likely stems from a combination of factors: increased awareness of the policy's benefits, adjustments to chronic treatment plans, and evolving prescribing practices among healthcare providers adapting to the new reimbursement environment.

A similar pattern emerges in the volume of medications dispensed. The number of packages increased by 7.5% immediately following the policy, and continued to grow, reaching a 12.6% increase after one year. Importantly, we also observe a rise along the intensive margin: not only did more patients receive treatment, but the average number of packages per patient increased. In the long run, patients consumed approximately 5% more medication, suggesting that financial constraints had previously led to rationing or incomplete adherence to prescribed dosages. These findings demonstrate the policy's

[4]Defined as the date when the first product containing a given substance became available at zero cost

success in reducing financial barriers.

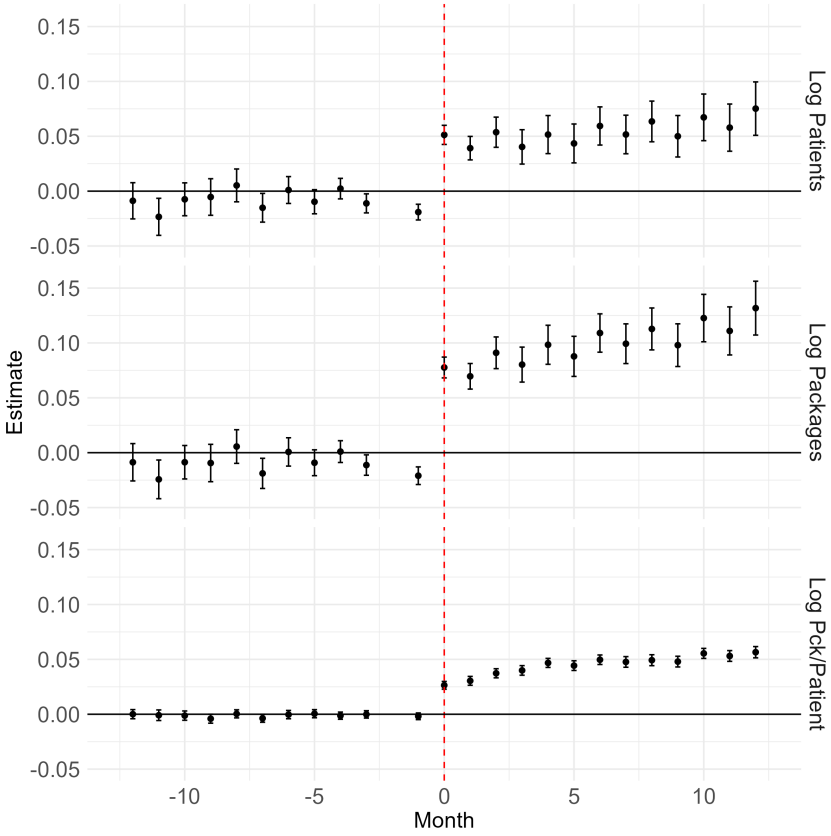


Figure 5: Event Study: Consumption

Note: This figure presents event study coefficients from Equation 1 for three outcomes: (1) the logarithm of the number of unique patients accessing the drug (Log Patients), (2) the logarithm of the number of packages purchased (Log Packages), and (3) the logarithm of the ratio of packages to patients (Log Packages/Patients). All outcomes (before logs) are calculated per capita to account for changing cohort sizes. Regressions include time and product-by-age-group fixed effects. Standard errors are clustered at the product-by-age-group level..

To ensure robustness, Figure 14 re-estimates the event study coefficients using the methodology of Sun and Abraham (2021), which accounts for potential biases from staggered treatment timing. The results align closely with the baseline event study, confirming the validity of our findings. Appendix analyses further explore medications subsequently excluded from the subsidy list, showing that consumption sharply increased upon inclusion but more gradually reverted to baseline after exclusion (Figure 15). Additionally, heterogeneity analysis by therapeutic use (Figure 17) reveals that the policy's largest effects were concentrated among high-cost, chronic-use medications such as dermatological, metabolism and blood related drugs, whose use may be easier to delay or avoid compared to acute medications like antibiotics, which are often required for immediate treatment. Finally, the heterogeneity analysis by age (Figure 19) reveals a similarity in treatment effects across all age groups above 75. In contrast, younger groups exhibit smaller effects on the extensive margin, with larger response in the intensive margin.

Interestingly, this policy incentivized individuals to visit primary care physicians. Consequently, the observed increase in drug consumption is driven not only by the fulfillment of previously unfilled prescriptions but also by new prescriptions generated from additional medical visits [5]. To evaluate the policy's impact on primary care visits, we compare the evolution in the number of visits among cohorts which become eligible at different times[6]. Cohorts are defined by birth month and year. To ensure comparability, we restrict the sample to individuals aged 72 to 77 around the time of the policy change. We then estimate the following event study regression:

$$\log(\text{visits}_{ct}) = \sum_{k=-18}^{18} \beta_k \cdot 1(\text{months to eligibility}_{ct} = k) + \gamma_c + \delta_t + \varepsilon_{ct}, \tag{2}$$

where $\log(\text{visits}_{ct})$ is the logarithm of the number of visits for cohort c in month t, and $1(\text{months to eligibility}_{ct} = k)$ are event-time indicators of months relative to eligibility. Eligibility timing varies across individuals: for those who turned 75 before the policy took effect, event time is defined relative to the policy introduction; for others, it is based on the month they turned 75. Cohort fixed effects (γ_c) control and time fixed effects (δ_t) are included. Standard errors are clustered at the cohort level. Figure 6 shows the results:

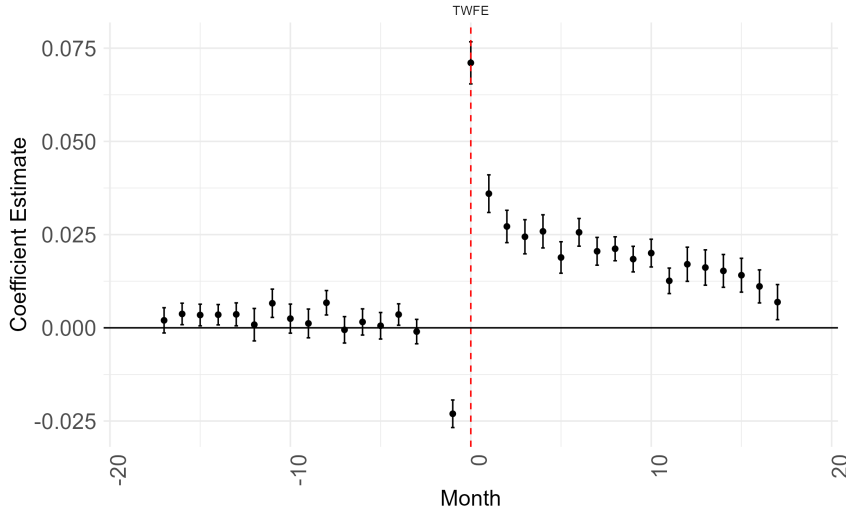


Figure 6: Event Study: Policy Impact on Visits to Primary Care Physicians

Note: This figure presents event study estimates of the policy's effect on primary care visits. The analysis is based on monthly visit counts at the cohort level, with cohorts defined by month-year of birth. The sample includes individuals who were 72 to 77 years old at the time of the policy change to ensure comparability. Event time is defined as the time of the policy implementation for those who had already turned 75 and as the month an individual turned 75 otherwise. The outcome variable is the logarithm of the number of visits. Regressions include time fixed effects cohort fixed effects. Standard errors are clustered at the cohort level.

[5] Visit to a physician is necessary to create a new prescription, but not to renew an existing one

[6] The visits data does not cover timeframe corresponding to the expansion including 65+, hence the focus on 75+

In the month prior to gaining eligibility, visits decline slightly—by approximately 2%. However, upon reaching eligibility, visits increase sharply by 7% and remain around 2% higher for at least a year. This sustained increase suggests that while primary care visits are nominally free, the reduction in the cost of subsequent treatment played a crucial role in encouraging individuals to seek medical attention. Beyond its direct impact on medication access, this policy likely generated positive spillover effects on health outcomes by prompting more frequent interactions with primary care providers. We investigate some of these in the appendix figure 16. It shows a short term increase in consumption of non-eligible medication mirroring the pattern of primary care visits.

The results regarding the consumption show the average effect across many medications, but this may hide key differences. If cost is the main barrier, the policy's impact should depend on how much affordability improved, which varies by how expensive the drug was before the policy. To test this, we examine how the policy's effect changes with pre-policy copays

3.2.2 Continuous Treatment Approach

We observe the largest increases in consumption for medications that had sizeable copays prior to the policy, with negligible, or even negative, effects for the cheapest medications.

The binscatter analysis (Figure 7) provides initial evidence that the policy's impact is greatest for medications that were previously less affordable. This method bins medications according to their pre-policy copay levels and calculates the average effect within each bin (Cattaneo et al., 2024). Medications with copays around $20 show a 27% increase in consumption, while the impact diminishes as copays decrease. Medications with near-zero pre-policy copays, which were already affordable, exhibit minimal changes in consumption.

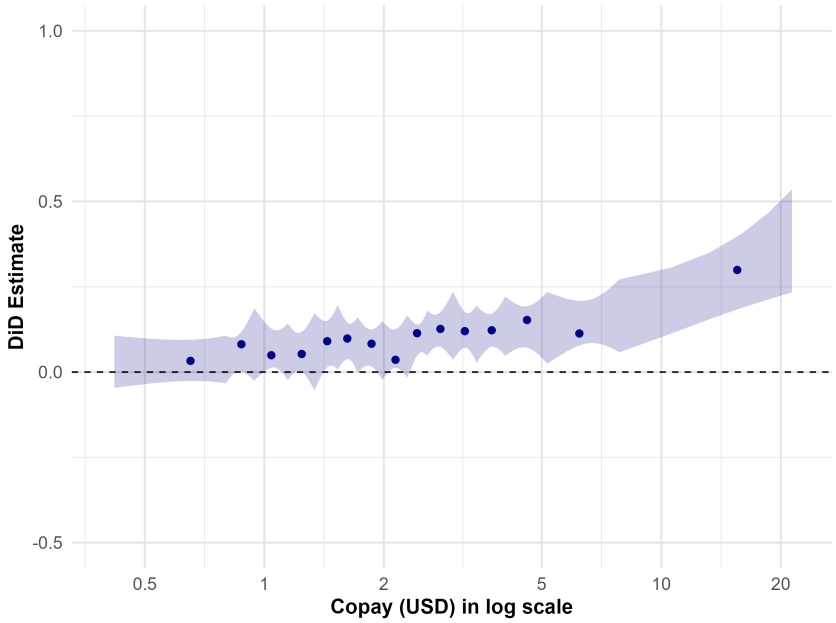


Figure 7: Consumption Change and Copay: Binscatter

Note: This figure presents a bin-scatter plot with a 95% confidence band, using optimal binning (Cattaneo et al., 2024). The plot is fitted to product-level time-difference estimates for the logarithm of packages per capita purchased. The X-axis represents the average pre-inclusion copay (in USD) on a logarithmic scale.

Figure 8 further validates these findings by using an adaptation of the continuous DiD method of Callaway et al. (2024) using the logharitm of pre-inclusion copays as the treatment intensity. The blue dots represent product-level differences-in-differences estimates, most of which are above zero, indicating that the majority of medications experienced increased consumption following the policy. The dashed line shows the average change of 11.2%. A linear fit suggests that a 1% increase in copay is associated with a 0.07% increase in the policy's effect. However, the relationship between pre-policy costs and treatment effects seems non-linear. The red spline, which flexibly captures this relationship, shows that the effect rises non-linearly with copay levels, highlighting that the largest impacts are concentrated among the most expensive medications. For cheaper medications, the spline remains below the average effect, such as a 4.4% increase at the 10th percentile copay ($0.82). In contrast, the highest effects are concentrated among previously cost-prohibitive medications, with a 18.5% increase at the 90th percentile ($6) and a 63% increase at the 99th percentile ($22).

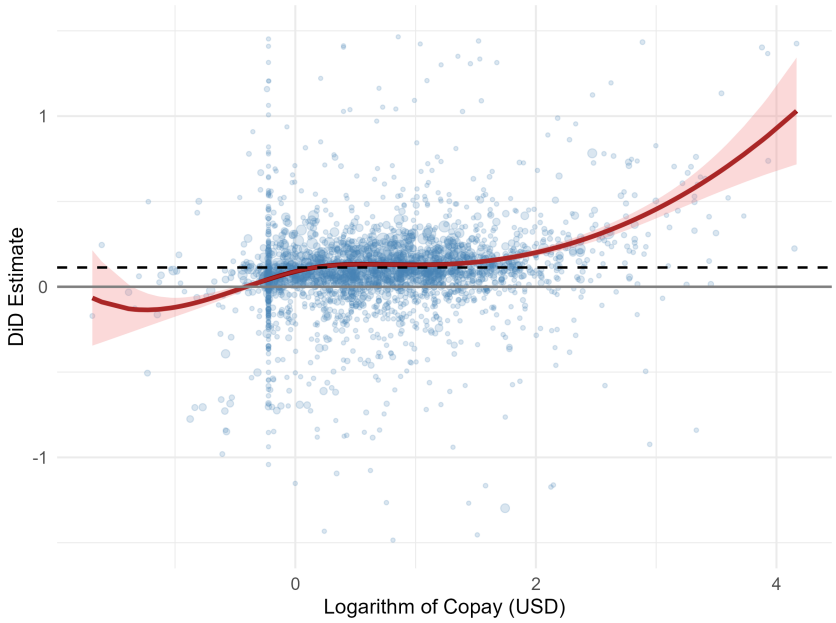


Figure 8: Continuous DiD in Copay

Note: This figure presents an adaptation of the continuous difference-in-differences method by (Callaway et al., 2024), which allows for treatment effects to vary with a continuous variable. The dots represent product-level pre-post change for the logarithm (plus one) of packages purchased, with dot size corresponding to the number of packages purchased by seniors pre-reform. The X-axis represents the logarithm of the average pre-inclusion copay (in USD). The dashed line indicates the average change, while the solid line is at 0. The red curve represents a cubic B-spline with 7 degrees of freedom fitted to the product-level changes, using pre-inclusion copay as the predictor. The spline is estimated with weighted least squares, where weights correspond to the number of packages purchased for each product pre reform. A 95% confidence interval is shown around the spline.

Figure 20 develops these findings in an event study framework, showing that both the average affect and this heterogeneity emerged only after the policy's implementation, with no evidence of pre-existing trends.

Interestingly, some products experienced a decline in consumption after the policy. This effect was particularly pronounced among the cheapest medications. It may reflect substitution effects across eligible medications, a possibility we investigate in the next section.

3.3 Analysis by the cheapest unit

Using heterogeneity of the effects by per-dose costs, we show substitution away from the cheapest medications to the more expensive substitutes.

To examine substitution effects, we first group all medications by their active substance—the chemical compound they share - dosage - and package size. Medications within the same group are considered perfect substitutes, as they provide the same medical effect. However, they may differ in terms of producer, branding (e.g., branded versus

generic), or packaging. In most cases, the majority or all insured products within a group were added to the list of free medications at the same time, although their prices varied. Customers can freely substitute across products with the same dosage, packaging and substance in the pharmacy, even if the subscription specifies a product brand.

Within each group, we categorize products based on their per-dose cost to the government into three categories: the cheapest, the most expensive, and those with intermediate prices. We then analyze changes in consumption for each of these groups to identify substitution effects. To ensure meaningful comparisons, we limit our analysis to categories where one drug had higher price throughout the time period

If seniors prefer higher-priced medications (e.g., branded options) and the policy removes out-of-pocket costs, we would expect a shift in consumption toward more expensive products, along with a decline in the use of cheaper substitutes. Beyond this substitution effect, the new demand generated by the policy may have been disproportionately directed toward higher-cost medications.

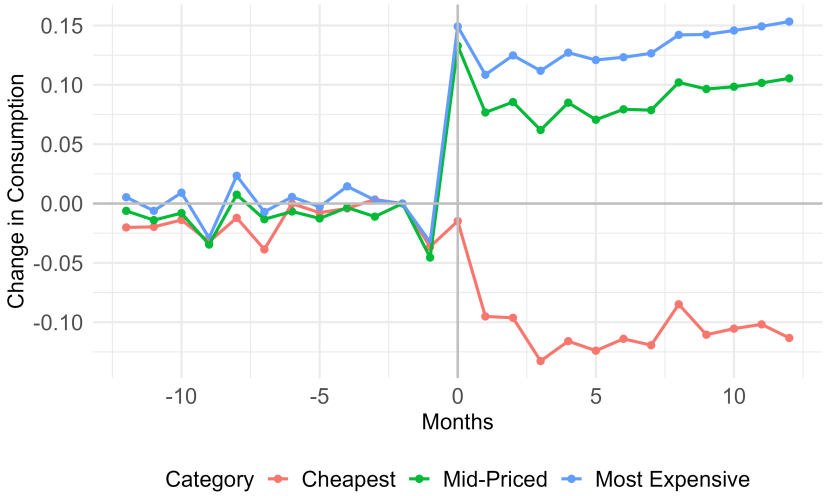


Figure 9: Consumption Changes by the Price per Dose of Treatment

Note: This figure presents changes in package consumption around the time of inclusion, compared to 2 months before inclusion, and relative to the oldest non-eligible group. Medications are categorized based on their relative price per dose within the same active substance.

The results confirm that the policy's impact is primarily driven by an increase in the consumption of more expensive substitutes. Figure 9 provides an intuitive visualization of these patterns, while Figure 10 formalizes them as an event study using Equation 1. The largest increase in consumption, between 10–15%, is observed for the most expensive medications. Mid-priced products experience a more moderate increase of around 5%-10%. In contrast, the consumption of the cheapest products declines by around 12%.

These results provide further evidence that, despite the medical equivalence of substitute products, individuals exhibit clear preferences among them. This behavior is suggestive of a perception that price serves as a signal of quality: even when the cost is fully subsidized, price differences appear to influence choice. Notably, this effect is observed only when price differentials across products are substantial.

In a heterogeneity analysis, we categorize substances into quartiles based on the ratio of the highest to the lowest price within each substance group. In the median quartile, the most expensive product is approximately 60% more expensive than the cheapest. Figures 21 and **??** in the appendix illustrate that substitution patterns emerge primarily in groups with larger price spreads. In the first quartile—where prices are closely aligned—all products experience an increase in usage. However, as the price differential increases across quartiles, we observe a consistent pattern: the cheaper products decline in use, while the more expensive ones gain market share.

This behavior is consistent with a model in which consumers interpret price as an indicator of quality and selectively switch to higher-priced products only when price differences are sufficiently large to convey a perceived quality distinction.

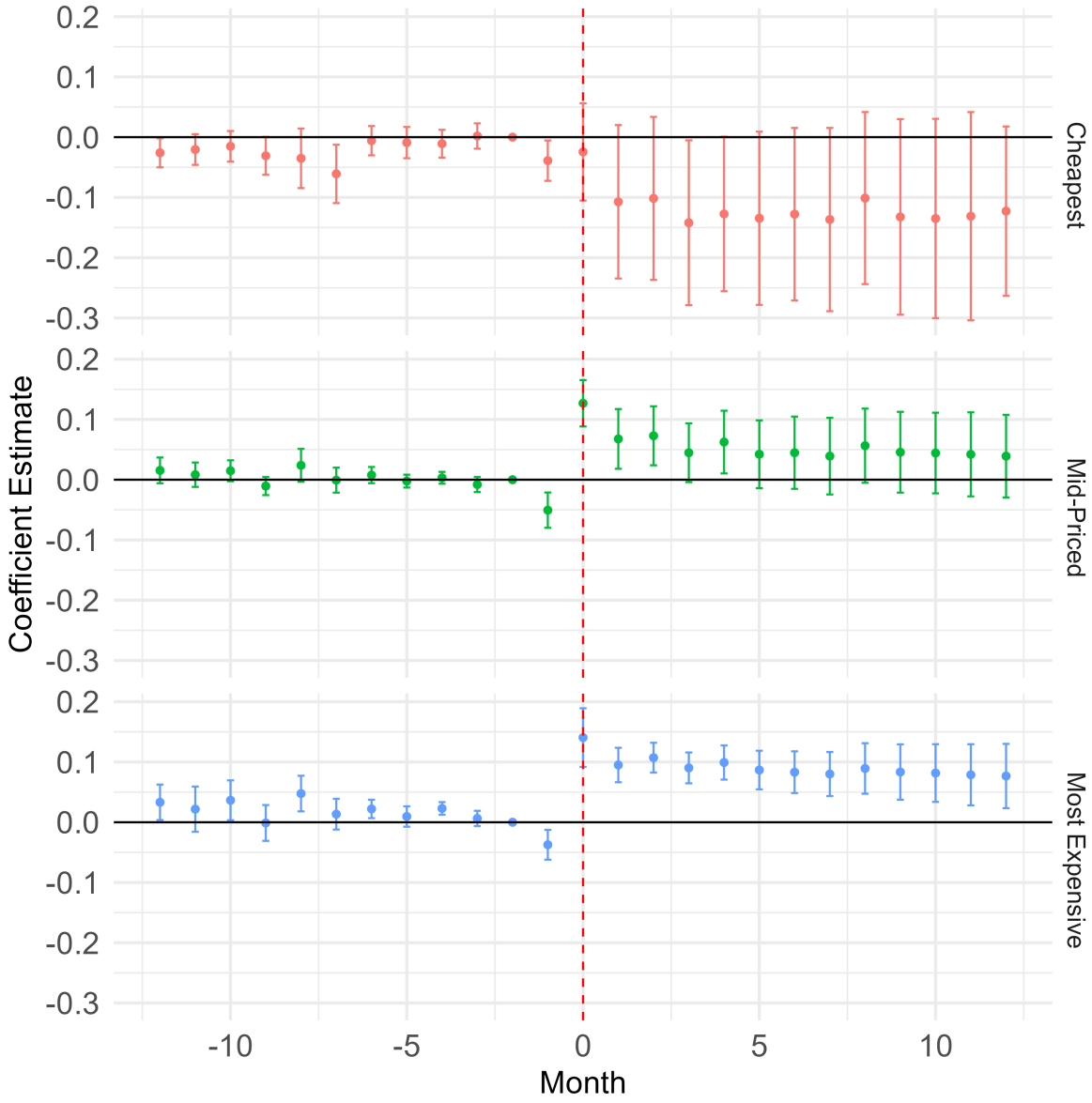


Figure 10: Event Study by the Price per Dose of Treatment

Note: This figure presents event study coefficients from Equation 1 with outcome being log of packages purchased per capita. Each drug is categorized based on its per dose price among all products with a given active substance. Regressions are weighted by purchases in reference period (-2) and include time and product by age group fixed effects. The errors are clustered at the product by age group level.

This substitution has important implications for policy design. While the full subsidy ensures that choosing between medications has no direct financial impact on seniors, it significantly alters the cost burden for the government. Specifically, the policy increases costs not only by raising overall consumption but also by might shift the demand toward more expensive options, despite identical clinical effects. These findings highlight a potential inefficiency in the policy design.

3.4 Cost of the treatment

The policy led to an increase in the average cost per dose of treatment for seniors by shifting consumption toward more expensive medications. The government's average cost per active substance is calculated as the total manufacturer cost of all packages purchased by a given age group within the substance-dosage-package size combination, divided by the total number of packages dispensed in this combination.

From the government's perspective, this metric captures the per-unit cost of fulfilling medically equivalent treatments, given that all products within a substance group are considered perfect substitutes in terms of therapeutic effect. An increase in this metric—driven by patient substitution toward higher-priced medications—is potentially undesirable from the payer's perspective, as it raises public expenditure without improving clinical outcomes.

We analyze this outcome using an event study design, where the dependent variable is the logarithm of the average price per treatment. The empirical specification follows Equation 1, but the unit of observation is the substance–dosage–packaging group rather than the individual product.

The pre-treatment event-time coefficients are close to zero, with the exception of a small uptick in the final month before implementation, likely reflecting anticipatory behavior. Following the policy change, we observe a steady increase in the average cost of treatment, reaching approximately 1% after one year. This trajectory reflects a clear shift in consumption away from lower-priced generics toward higher-priced alternatives, reinforcing the interpretation that perceived quality differentials—even among therapeutically equivalent products—play a role in patient behavior.

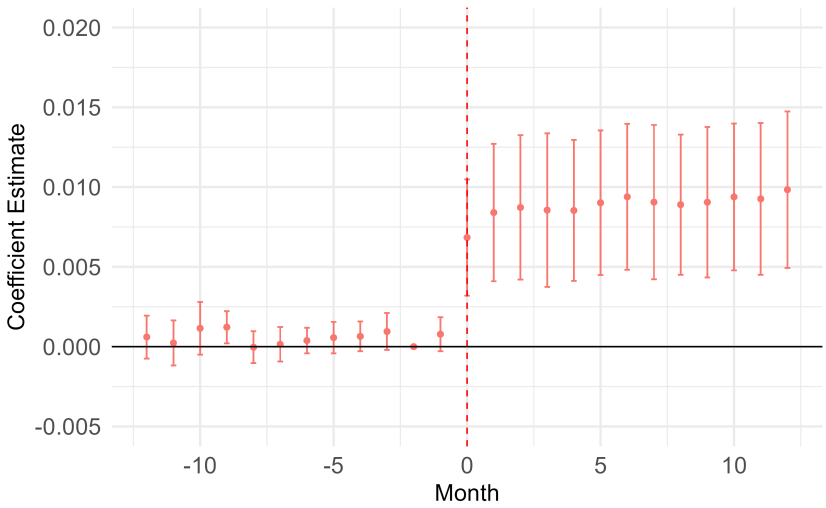


Figure 11: Event Study: Cost of Treatment

Note: This figure presents event study coefficients estimated from equation 1, where the outcome is the natural logarithm of the average price (paid by the government) per package in a combination substance-packaging-dosage. The unit of observation is the active substance. Regressions are weighted by purchases and include time fixed effects as well as combination-by-age-group fixed effects. Standard errors are clustered at the combination-by-age-group level.

The upward trend in treatment costs underscores a key consequence of the policy: while it successfully improved access to medications for seniors, it also shifted consumption patterns in ways that disproportionately increased government expenditures.

This pattern is particularly pronounced in groups where the price dispersion is largest, as shown in the heterogeneity analysis in Figure **??**, which stratifies categories by the ratio of the lowest to highest price. The effects in these groups are compounded through two mechanisms. First, as previously shown, substitution behavior is more prevalent when the price spread within a group is wider—patients are more likely to shift toward higher-priced products. Second, because the absolute price differences are larger in these groups, each instance of substitution contributes more substantially to the overall increase in average treatment cost. As a result, in the quartile with the highest price dispersion, we observe the largest increase in the average cost per treatment.

3.5 Global cost of the policy

Our analysis suggests that removing the price signal is inflating the cost of the policy. A simple back-of-the-envelope calculation can provide an estimate of the overall cost of the policy and the potential savings that could be achieved with a more efficient design.

Before the set of perfect substitutes K, composed from products $i = 1, 2, ..., k$, is included on the Drugs 75+ list, the government expenditure on partial reimbursement of the set K is equal to:

$$S_{0K} = \sum_{i \in K} q_{0i} \times (p_i^m - p_i^{oop})$$

and after being included on the list, the government covers the full price of these products:

$$S_{1K} = \sum_{i \in K} q_{1i} \times p_i^m$$

Then, we can write and decompose the cost of the policy as:

$$\begin{aligned} C_K &= \sum_{i \in K} [q_{1i} \times p_i^m - q_{0i} \times (p_i^m - p_i^{oop})] \\ &= \sum_{i \in K} \left[\underbrace{q_{0i} \times p_i^{oop}}_{\text{Pre-policy OOP}} + \underbrace{(q_{1i} - q_{0i}) \times p_i^m}_{\text{Full coverage of additional consumption}} \right] \\ &= \sum_{i \in K} \left[\underbrace{q_{0i} \times p_i^{oop}}_{\text{A. Pre-policy OOP}} + \underbrace{\gamma_i q_{0i} \times p_i^m}_{\text{B. New consumption}} + \underbrace{\Delta q_i \times p_i^m}_{\text{C. Reallocation}} \right] \end{aligned} \tag{3}$$

where q_{0i} corresponds to the counterfactual quantity consumed in the absence of the policy, and q_{1i} is the observed quantity. The total cost is a sum of three elements. First, the out-of-pocket payments of consumers buying drugs before the policy. This would be the simple ex-ante estimate of the policy's cost, holding consumer choices and quantities constant.

Then, the cost of fully covering the change in consumption due to the policy can be decomposed into two elements. One is the medication cost of consumers who were not buying before the policy, assuming they increase their consumption of the individual products proportionally (by a parameter $\gamma_i > 0$) to that of the pre-policy consumers. Finally, the remainder of the difference between the observed government expenditure and the counterfactual expenditure in the absence of the policy can be attributed to consumers switching to different substitutes (Δq_i at the level of a product can be positive or negative)[7].

In practice, to approximate the cost of the policy, we need to estimate the counterfactual quantities q_{01}. To do so, we extrapolate the pre-policy consumption trends taking into consideration the change in the composition of the given age group Namely, we calculate the number of patients buying each drug relative to the overall population in the given group age in the 12 months preceding the drug's inclusion on the Drugs 75+ list (or the start of eligibility of the 65-69 and 70-74 age groups for the September 2023 expansion)[8], allowing us to account for population changes and seasonality in our extrapolation. Similarly, we calculate the parameters γ_i using pre-policy monthly shares in the total consumption of each set of substitutes K.

Figure 12 shows the results of our calculation. The total height of the left-hand-side bar each year corresponds to the total government expenditure for the eligible drugs and age groups, as observed in our data. We decompose this amount into the counterfactual expenditure without the policy, which corresponds to the partial refund based on extrapolated pre-treatment consumption (solid orange area), $\sum_{i,K} \hat{q}_{i0} \times p_i^{oop}$, and the cost of the policy disaggregated into 3 parts as in Equation 3.

[7] We assume that the consumption with the policy q_{1i} can be written as $(1 + \gamma)q_{0i} + \Delta q_i$

[8] To abstract from possible anticipation effects, we look at the year starting 13 months before treatment, this way omitting the last month before treatment

On average, the Drugs 75+ policy doubles the government expenditure for the eligible drugs and age groups if we trust the pre-treatment extrapolation. The additional consumption induced by the policy accounts for less than 30% of the policy cost in 2017 to almost 38% in 2020 and increases from just above 50 million dollars in the first full year after its introduction to 364 million dollars. The reallocation of consumers relative to the pre-treatment period accounts for, on average, 7.5% of the total cost of the policy.

To gain an understanding of how much of the cost is driven by reimbursing more expensive medications, we consider an alternative policy design that incentivizes generic substitution.

In this scenario, we only manipulate the refund amounts for the observed sales, realized under the current policy (q_1)[9]. We consider a policy where the government covers only the price of the cheapest substitute, and either the entire eligible population buys the cheapest substitute or must cover the difference in price out of pocket.

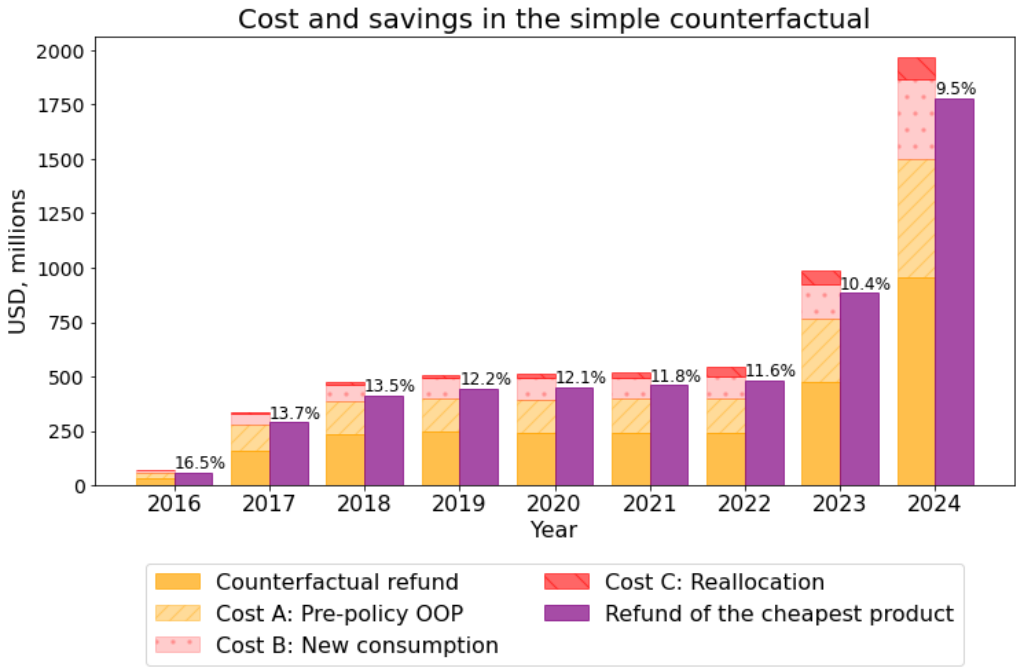


Figure 12: Observed and counterfactual government spending and cost decomposition

Note: This figure shows the observed (left-hand bars) and counterfactual (right-hand bars) government spending on eligible drugs and age groups. We decompose the observed spending into counterfactual expenditure without the policy (orange area) and the cost of the policy (as in Equation 3). The right-hand-side (purple) bars show the counterfactual scenario where only the cheapest substitute is fully covered. The numbers on top of the bars indicate the percent savings on the refund under the counterfactual policy (difference in the height of the two bars relative to the left-hand-side bar). Data source: National Health Fund, Poland, 2016–2024.

[9]To treat this issue more rigorously, we will estimate a structural model of demand and supply, allowing us to take into consideration changes in consumer choices under different counterfactual policies. The simple approach, on the other hand, allows us to calculate savings for all covered drugs. In contrast, the structural estimation requires us to focus on a limited number of drug classes.

The right-hand-side, purple bars in Figure 12 shows the results of our calculation[10]. Fully covering the price of the cheapest substitute could save 9.2% of the total government expenditure amounts on average, and 16.8% of the estimated cost, $660 million over the 2016-2024 period in total, and $186 million in 2024 alone. These savings, for example, could cover half of the cost of extending the policy to the 60-64 age group, even assuming a 15% increase in consumption due to the policy.

These aggregated figures conceal a large degree of heterogeneity in the composition of the estimated costs. In Figure 13, we present the estimated costs at the product level, aggregating brands with the same active substance, form, strength and packaging, for 2024, for a selected set of products. In products for which government spending is particularly high, the cost decomposition is similar to the overall figures, in particular the cost of new consumption. Still it is noticeable that the reallocation cost of Atorvastatin (20mg, 30 pills) is only half of that of Nebivololum (5mp, 28 pills). For some products, such as the antidiabetic combination Vildagliptinum and Metformine, over 90% of the cost comes from increasing (low) initial consumption. In contrast, the reallocation of consumption towards more expensive substitutes plays a very important role for the blood thinner Rivaroxaban (15mg, 14 pills).

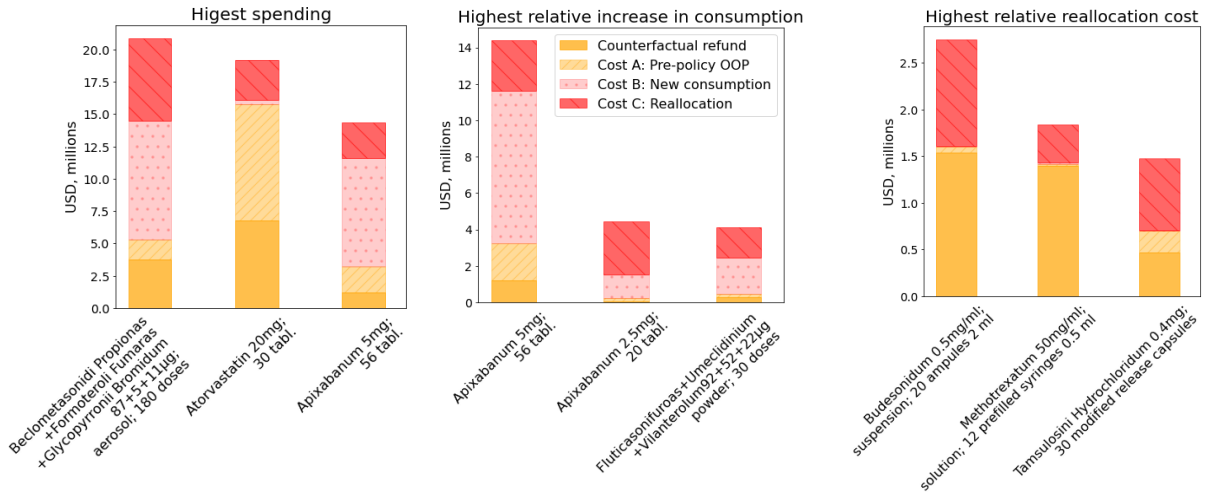


Figure 13: Product-level cost decomposition, 2024 data

Note: This figure shows the decomposition of government spending for selected high-cost drugs in 2024. For each product, the total bar is split into the counterfactual (pre-policy) out-of-pocket payments, additional consumption induced by the policy, and the cost due to reallocation toward more expensive substitutes, following the decomposition in Equation 3. Data source: National Health Fund, Poland.

[10]We underestimate the savings, as the realized refund does not account for the total sales value in the eligible population, as even with the policy, 3.5% of the sales value on average is covered by patient copays (e.g., due to prescriptions for indications not included on the Drugs 75+ list). Our counterfactual refund, on the other hand, is calculated based on the total consumption, including that of copaying patients

4 Conclusion

We leverage a unique natural experiment to learn about the consequences of providing full subsidies for prescription drugs within a universal healthcare system. Our analysis of Poland's Seniors Drugs program reveals two main findings. First, the program increased overall medication consumption at both intensive and extensive margin, particularly for higher-cost products, which displaced cheaper alternatives. Second, this shift significantly raised the government's per-dose treatment costs, underscoring the potential inefficiencies of subsidy designs that fully eliminate price signals. These findings advance the literature on the price elasticity of demand for prescription drugs by highlighting the behavioral responses to a zero-price regime in a universal healthcare context.

Our results also contribute to the broader debate on the design and efficiency of public subsidies. While full subsidies can successfully improve access and reduce financial vulnerability, they may also exacerbate fiscal pressures by incentivizing demand distortions, such as substitution toward higher-cost medications with no additional therapeutic value. These trade-offs are particularly critical for aging populations, where escalating healthcare expenditures place growing demands on public budgets.

The policy implications of our findings suggest that subsidy designs must balance equity, access, and efficiency. Policymakers could consider mechanisms such as reference pricing, or subsidies targeted specifically to cost-effective treatments. Retaining modest price signals can mitigate substitution effects while ensuring affordability for essential medications, thereby optimizing resource allocation and improving the overall efficiency of public healthcare expenditures.

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A Appendix

A.1 Additional information

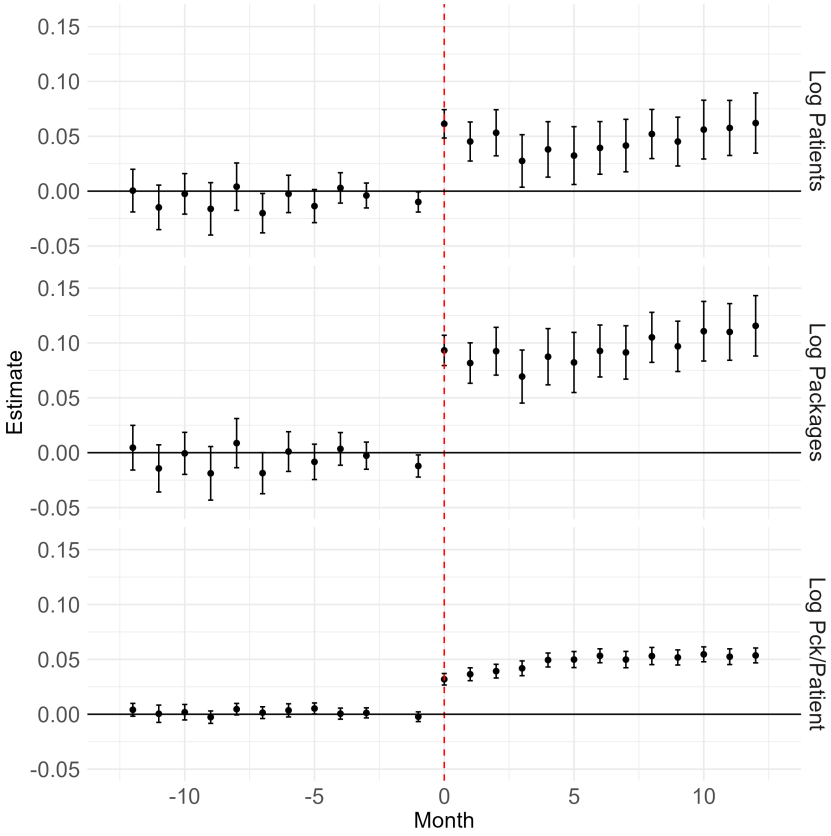

Figure 14: Event Study: Consumption (Sun and Abraham 2021)

Note: This figure presents event study coefficients for the same three outcomes as Figure 5, estimated using the methodology of Sun and Abraham (2021), which accounts for staggered treatment timing. Regressions include time and active substance-by-age-group fixed effects. Standard errors are clustered at the active substance-by-age-group level. For terminology, see the Data section.

Table 3: Poland: GDP and demographics (source: Eurostat)

	Poland		EU27
Indicator	2012	2023	2023
Population (millions)	38.06	36.62	441.26 (total)
% share of elderly (65+)	14	19.9	21.3 (mean)
Total fertility rate	1.33	1.29	1.43 (mean)
GDP per capita (€)	10 000	19 920	37 930 (mean)
Life expectancy at birth (total)	76.9	78.6	81.1 (mean)
male:	72.6	74.8	78.9 (mean)
female:	81.1	82.4	84.2 (mean)

A.2 Exclusion of the Drug

Figure 15 shows that including and later excluding a medication from the reimbursement list causes an initial sharp increase in consumption, followed by a relatively slow decline back to baseline levels. The only products treated in this manner were included in the first wave of the policy (September 2016) and excluded four months later. The event study coefficients capture the relative changes in consumption for individuals aged 75-79 and compared to those between 70 and 74.

Before the inclusion of the product, the coefficients are close to zero, consistent with parallel trends between the two age groups. Following the product's inclusion, there is a sharp and immediate increase in consumption, reflecting the policy's impact on access and affordability. The increase is very large, approximately 40%. However, after the product is removed from the reimbursement list (indicated by the second dashed line), consumption returns to pre-policy levels. Initially, purchases drop dramatically in the first month, likely reflecting the cessation of consumption by price-sensitive individuals and the effects of anticipatory stockpiling during the subsidy period. Patients who stockpiled subsidized medications may not need to repurchase immediately, compounding the sharp decline. Over subsequent months, the decline becomes more gradual, as longer-term users adjust their behavior and seek alternatives.

This pattern reflects the behavioral asymmetry between starting and discontinuing a medication. It may be easier to initiate treatment when costs are subsidized, but harder to give up a medication once started, especially for chronic conditions, due to habit formation, physician advice, or perceived health benefits.

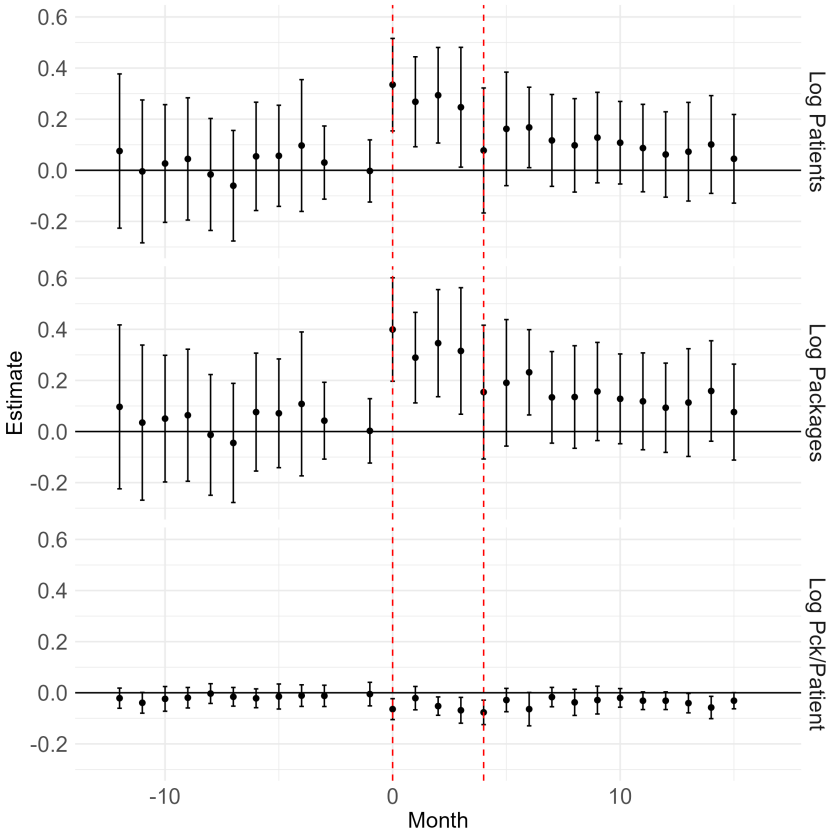

Figure 15: Event Study: Exclusion of a Product

Note: This figure displays event study coefficients estimated with method by Sun and Abraham (2021). The treated group is 75-79 and control is 70-74. All drugs were dropped before the expansion to younger cohorts. The outcome variable is the logarithm of the number of packages purchased for a given product. The first dashed line marks the time when products were included, while the second indicates when they were excluded. Standard errors are clustered at the product-by-age-group level.

A.3 Spillovers to Untreated Medication

We next examine whether the policy had spillover effects on the consumption of medications that were not made free at the time of the initial reform. Since nearly all drugs were eventually included by September 2023, we focus on the period from September 2015 to September 2017 and restrict the analysis to products that only became eligible after October 2017. These medications remained under standard co-sharing for all patients during the period of interest.

To assess spillovers, we compare the consumption of these untreated drugs between the eligible group (ages 75–79) and the non-eligible group (ages 70–74) before and after the September 2016 policy implementation. A potential mechanism for spillovers is that the policy increased visits to physicians, which could lead to more diagnoses and prescriptions, including for drugs not yet covered. Other possible channels include income effects or complementarity between medications.

We aggregate the data to the active substance level and estimate an event study

comparing the evolution of consumption in the eligible and non-eligible age-groups. The results are presented in Figure 16.

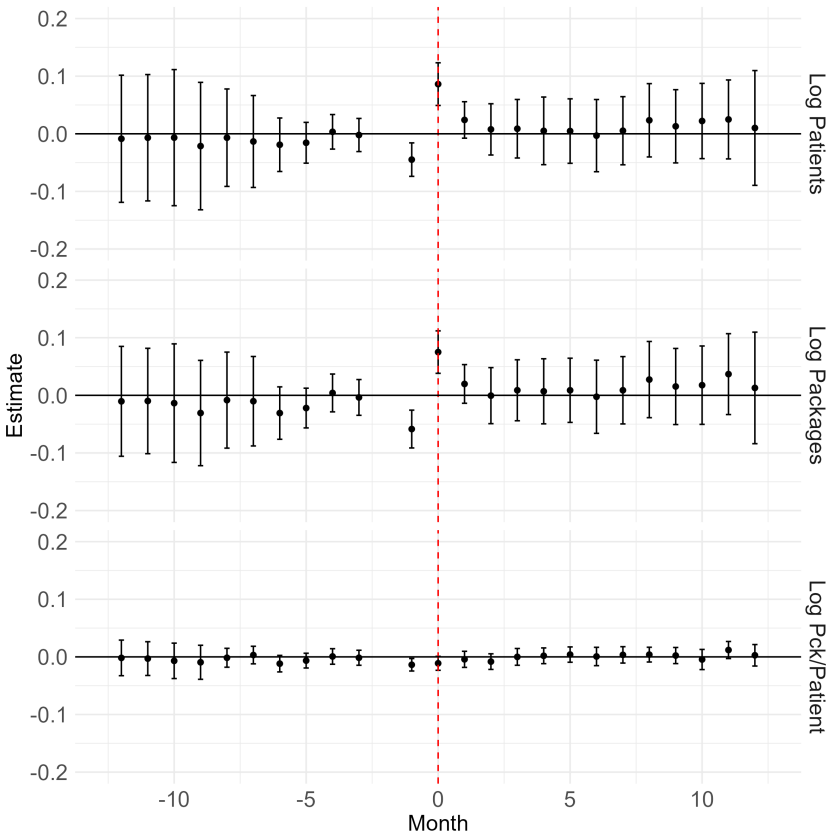

Figure 16: Event Study: Spillovers to Untreated Medication

Note: This figure presents event study coefficients estimated at the active substance le level using the methodology of Sun and Abraham (2021). Outcomes are the logarithms of (1) unique patients accessing the active substance, (2) number of packages sold, and (3) the ratio of packages to patients. Month 0 is September 2016. The sample includes only medications that became free after October 2017. The treated group is individuals aged 75 and over; the control group is those aged 70–74.

The results indicate parallel trends in consumption between the treatment and control groups prior to September 2016. Around the time of policy implementation, there is a modest decline in consumption immediately before the reform, followed by a temporary, statistically significant increase of approximately 9% in patients accessing the active substance in the first month after implementation. Subsequent post-policy coefficients are positive but not statistically significant. This pattern closely mirrors the timing of increased visits to physicians, suggesting that the observed spillovers are primarily driven by greater healthcare utilization at the point of eligibility. The temporary nature of the effect is less consistent with mechanisms such as complementarity or income effects, which would be expected to generate more persistent changes in consumption.

A.4 Consumption Heterogeneity by Therapeutic Use

Chronic-use medications are more price-sensitive than acute-use drugs, with affordability improvements leading to greater increases in demand for chronic treatments.

Figure 17 examines heterogeneity in the policy's average impact across different therapeutic classes (ATC 1st level) of medications using a difference-in-differences framework comparing eligible individuals to those ineligible in a year before and after the policy. The largest increases are observed for dermatological, metabolism, blood, and cardiovascular medications. These groups include drugs for managing diabetes or blood pressure. Their stronger effect likely reflecting their chronic nature and high baseline costs, which make them particularly responsive to the policy's subsidies.

In contrast, smaller effects are observed for drugs treating acute conditions such as antibiotics (anti infectives), which are often used for shorter durations and are difficult to avoid or delay. These findings align with prior studies, such as Einav et al. (2018), which identify greater price elasticities for drugs treating chronic conditions compared to acute, and Alpert (2016), which highlight higher sensitivity to future prices for chronic medications than for acute ones. In figure 18 we provide breakdown by more detailed categories (ATC 2nd level).

These insights are valuable for policymakers designing subsidy schemes, as they suggest that making a drug free is likely to have the greatest impact on demand for chronic-use medications, with smaller effects for acute-use drugs.

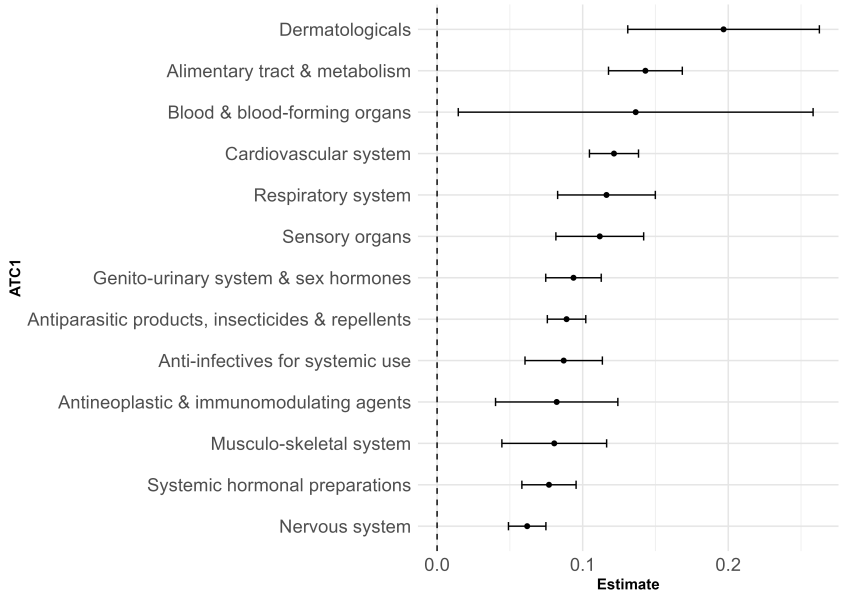

Figure 17: Heterogeneity in Consumption effect by Type

Note: This figure displays difference-in-difference coefficients for consumption within specific medication groups. Categories come from ATC 1st level codes The sample includes products available within a 12-month window before and after inclusion. The outcome variable is the natural logarithm of the number of packages purchased per capita for a given product. Regressions are weighted by consumption during the pre-inclusion period, and standard errors are clustered at the product-by-age-group level. For terminology, see the Data section.

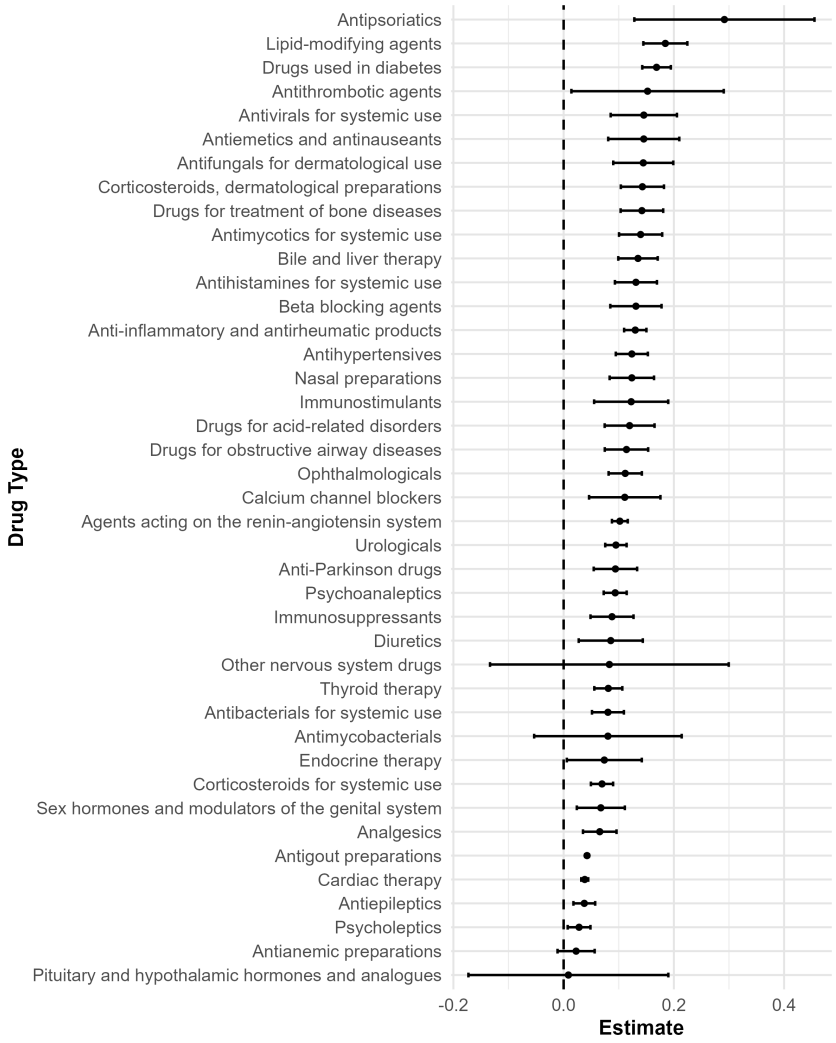

Figure 18: Heterogeneity in Consumption effect by Detailed Type

Note: This figure displays difference-in-difference coefficients for consumption within specific medication groups. Categories come from ATC 2nd level codes. The sample includes products available within a 12-month window before and after inclusion. The outcome variable is the natural logarithm of the number of packages purchased per capita for a given product. Regressions are weighted by consumption during the pre-inclusion period, and standard errors are clustered at the product-by-age-group level. For terminology, see the Data section.

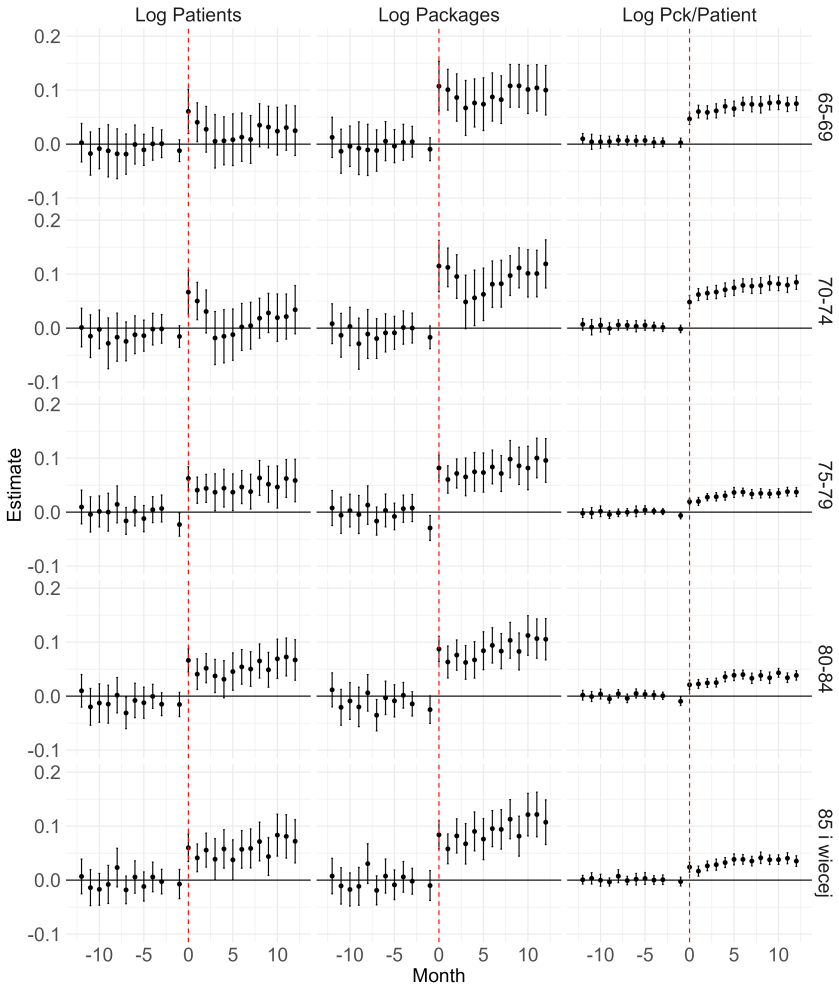

Figure 19: Heterogeneity in Consumption effect by Age

Note: This figure displays difference-in-difference coefficients for consumption for specific age groups. The control group is always 60-64. Estimation has been done using Sun and Abraham (2021). Standard errors are clustered at the substance-by-age-group level. For terminology, see the Data section.

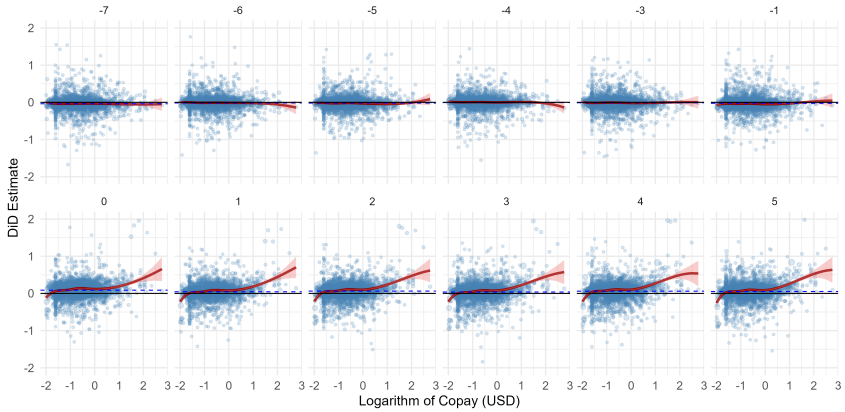

Figure 20: Continuous Event Study in Copay: Double Difference

Note: This figure presents an adaptation of the continuous event study method by (Callaway et al., 2024), which allows treatment effects to vary with a continuous variable. Each facet displays the DiD effect for a given month relative to inclusion, compared to the period 2 months before inclusion. The dots represent product-level difference-in-differences estimates for the logarithm of packages purchased per capita, with the size of each dot corresponding to the number of packages purchased by seniors pre-reform. The X-axis represents the logarithm of the average pre-inclusion copay (in USD). The dashed line indicates the average DiD estimate, while the solid line represents zero. The red curve represents a cubic B-spline with 7 degrees of freedom, fitted to the product-level DiD estimates using pre-inclusion copay as the predictor. The spline is estimated with weighted least squares, where weights are determined by the number of packages purchased for each product pre-reform. A 95% confidence interval is shown around the spline.

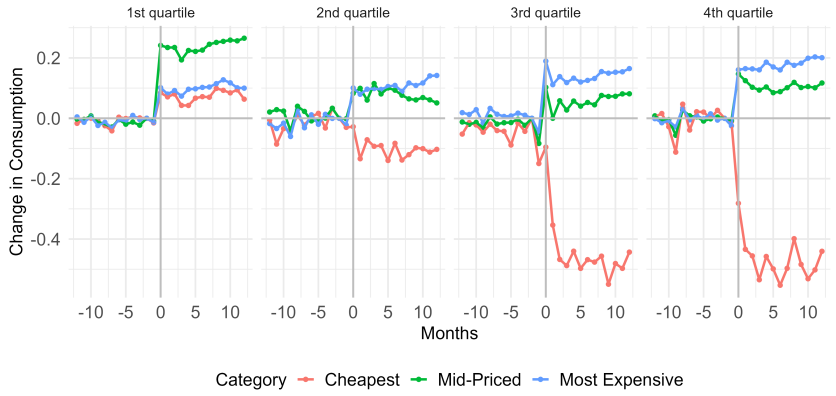

Figure 21: Consumption Changes by the Price per Dose of Treatment by Price Spread

Note: This figure presents changes in package consumption among eligible individuals over time around inclusion, compared to 2 months before inclusion, and relative to the oldest ineligible age group. Medications are categorized based on their relative price within the same active substance - package size - dosage combination. These combinations are divided into 4 quartiles depending on the ratio of the highest to lowest price. For terminology, see the Data section.

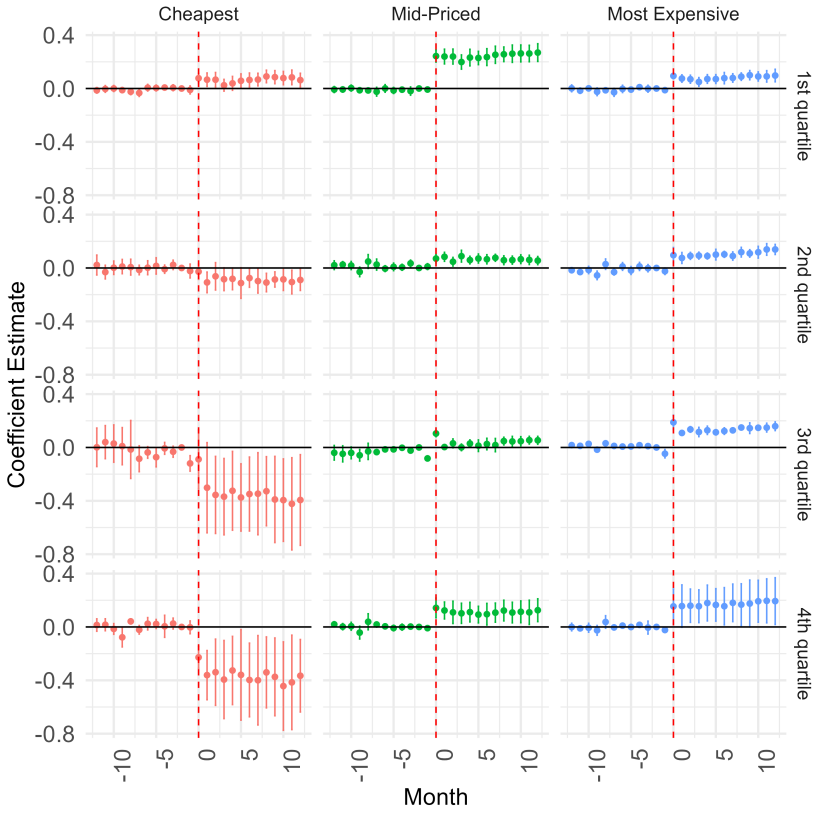

Figure 22: Consumption Changes by the Price per Dose of Treatment by Price Spread - Event Study

Note: This figure presents estimates in package consumption among eligible individuals over time around inclusion, compared to 2 months before inclusion, and relative to the oldest ineligible age group, using Sun and Abraham (2021). Medications are categorized based on their relative price within the same active substance - package size - dosage combination. These combinations are divided into 4 quartiles depending on the ratio of the highest to lowest price. For terminology, see the Data section.

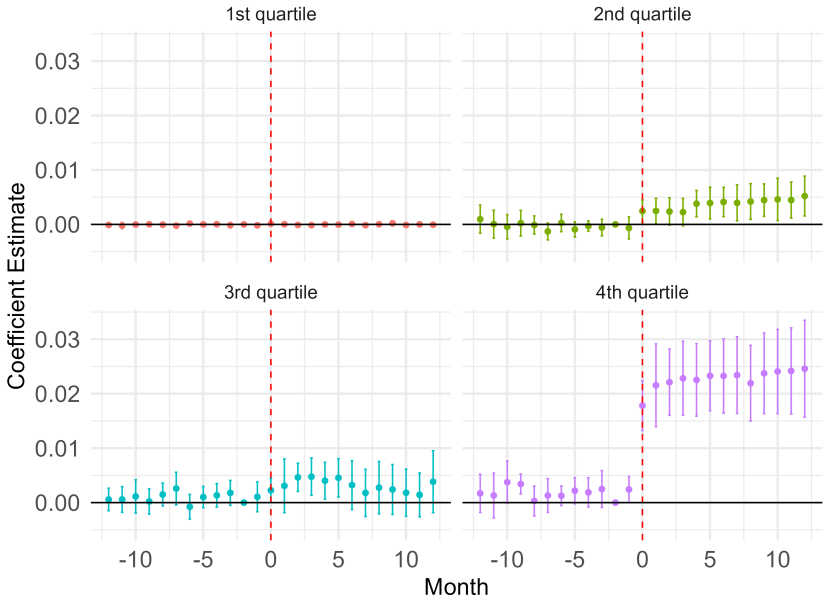

Figure 23: Cost of Treatment, by Price Spread

*Note:*This figure presents estimates in average price paid by the government for a subtance-packaging-dosage combination among eligible individual relative to the oldest ineligible age group, using Sun and Abraham (2021). These combinations are divided into 4 quartiles depending on the ratio of the highest to lowest price. For terminology, see the Data section.