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 Drugs 75+ program, which provides free prescription medications to individuals aged 75 and older, as a natural experiment. Using a difference-in-discontinuities approach, event studies, and detailed administrative and survey data, we draw three main conclusions. First, the program reduced out-of-pocket medication expenditures for seniors, substantially alleviating the risk of catastrophic health costs. Second, it improved access: medication consumption increased, particularly for higher-cost products, to some extent displacing cheaper alternatives. Third, 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

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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 for seniors in the context of Poland's Drugs 75+ program. Introduced in 2016, this policy provides free access to a subset of prescription medications for individuals aged 75 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 Drugs 75+ program on pharmaceutical expenditures and demand allocation, focusing on two key questions. First, how does providing free medications influence overall expenditures, both for households and the public payer? Second, does removing out-of-pocket costs alter demand allocation, such as shifting consumption toward higher-cost medications or increasing overall utilization?

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 aged 75 and older, creating a sharp age-based discontinuity. 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.

Our analysis of household spending uses data from detailed budget surveys to quantify the program's financial impacts on seniors. We employ a difference-in-discontinuities design, combining regression discontinuity and difference-in-differences approaches. This method exploits the age eligibility threshold to capture the local treatment effect at the discontinuity, while the temporal dimension allows us to disentangle pre-existing trends from the effects of the policy. This framework enables us to measure changes in

seniors' out-of-pocket expenditures on medications and their financial protection against catastrophic health-related costs.

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 2015 and 2022. 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.

Our findings reveal three key results. First, the introduction of the subsidy led to a reduction in household spending on medications. Monthly expenditures on medications decreased by $8 on average. Moreover, the program achieved a substantial 62% decline in the incidence of catastrophic health expenditures While the program's impact on average out-of-pocket spending was modest in absolute terms, it significantly decreased financial risks for seniors who face high probability of adverse health shocks.

Second, the program significantly increased consumption of reimbursed drugs, with an immediate rise of 8% that grew to 15% within 18 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 smaller decline in the use of cheaper alternatives, indicating a substitution toward pricier options. The effect was especially notable in markets with many producers, where the removal of price signals weakened competitive pressure, reducing its ability to lower government expenditure.

Third, 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 5 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 Drugs 75+ 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.

[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)

2.1.2 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).

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 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.

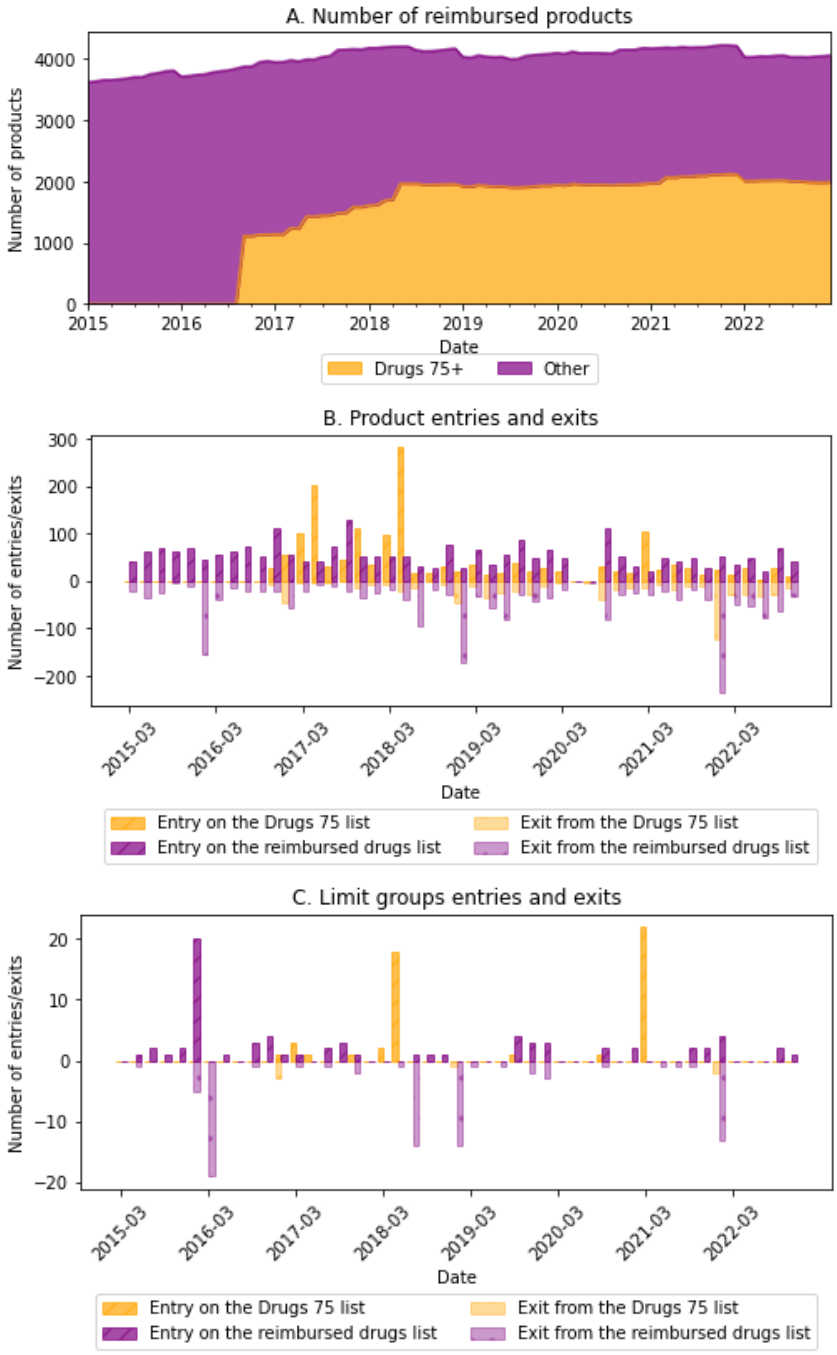
Figure 1 illustrates the evolution of the set covered by Drugs 75+ as well as the overall list of reimbursed drugs over the years 2015-2022. While, at the product level, there appears to be a lot of entries as well as exists, the situation is much less dynamic at the level of limit groups. Outside of 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 2015 to 2022 provided by the E-Health Center, 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 age groups: patients younger than 75 and those 75 and older.

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.

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



Note: Figures B and C present the changes to the the reimbursed drugs list and Drugs 75+ list, and do not show the creation of the Drugs 75+ in September 2016 with 1120 products and 39 limit groups

The product names allow us to identify the strength of the dose in each product. Combined with the DDD definition for each product and packaging size, we can obtain a standardised measure of consumption (standard units). Whenever the DDD is not

Table 1: Descriptive statistics of the reimbursed drugs sales dataset

	Mean	SD	Min	Max
Number of unique products	4364.62	198.78	3995.0	4542.0
Number of active substances	1379.62	70.02	1259.0	1470.0
Number of limit groups	339.12	14.34	323.0	363.0
Government Price ($)	18.05	62.95	0.22	1909.09
Sales Value (mil. $)	0.54	1.58	0.0	33.49
Total OOP (mil. $)	0.19	0.56	0.0	12.86
75+ OOP (mil. $)	0.03	0.11	0.0	4.29
Total Reimbursement (mil. $)	0.48	1.52	0.0	35.95
75+ Reimbursement (mil. $)	0.13	0.47	0.0	11.19
Consumption (mil. su)	2.76	12.21	0.0	621.19

Sales Value, OOP, Reimbursement and Consumption are totals per year per product

available for an active substance, we homogenize strength and doses across different products with the same active substance and form (mode of administration) to calculate standard units.

Table 1 presents an overview of the sales dataset. On average, the dataset contains sales data for 4365 products, organized into 339 limit group. There are on average 3.16 products per active substance. The government-fixed manufacturer prices vary a lot, with the mean at $18 per product. The average product brings more than $500 000 per year and almost $200 000 are paid out of pocket by the patients. The products consumed by the seniors aged 75 and older are cheaper.

Focusing on the consumption of the seniors aged 75 and older in Table 2, we can observe that the products included on the Drugs 75+ list constitute on average 41% of the products consumed by this population from the reimbursed drugs list. While the products on the list constitute a smaller share of the limit groups for this population, they are drugs with higher consumption levels and much lower prices, supporting the claim that the Drugs 75+ list was established with relevance for the senior population in mind as well as the cost-effectiveness of the treatments.

In Table 3 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 2015 and 2022 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

Table 2: Reimbursed drugs sales data for the 75+ population only

	Drugs 75+		Other	
	Mean	SD	Mean	SD
Number of unique products	1883.43	378.34	2691.12	760.67
Number of active substances	604.57	150.32	880.25	238.93
Number of limit groups	62.29	17.79	272.88	41.49
Government Price ($)	8.91	15.36	16.88	61.75
Sales Value (mil. $)	0.18	0.54	0.09	0.35
OOP (mil. $)	0.01	0.02	0.04	0.14
Reimbursement (mil. $)	0.22	0.62	0.07	0.33
Consumption (mil. su)	1.13	4.23	0.49	3.36

Drugs 75+ columns refer to the subset of products ever included on on the Drugs 75+ list between 2016 and 2022. Other products are reimbursed drugs not on the Drugs 75+ list. Sales Value, OOP, Reimbursement and Consumption are totals per year per product

Table 3: 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: The denominator for the per capita measures is the total population in the given age group in 2015 in Poland

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.

2.3 Household Budgets Survey

To analyze the impact of the reform on the financial well-being of the targeted population, we obtained data from Statistics Poland's Household Budgets Survey for 2015 to 2018. In this survey, sampled households keep a diary where they note all their expenditures. Households participate in the survey for 2 years, with half of the surveyed households replaced with a new cohort every year. Each household is observed twice, with observations exactly one year apart. The anonymised data contain rich information on the household demographics, notably the birth date of each member, and information on income and wealth.

The expenditures are recorded at a very granular level (e.g. Household equipment and maintenance - appliances - irons). For our purposes, the most relevant category is that of health expenditures. The health category is composed of three subcategories: medical products, ambulatory services and hospital services. Pharmaceuticals are an item in the

Figure 2: Consumption of reimbursed drugs in Poland 2015-2202, by subset and age group

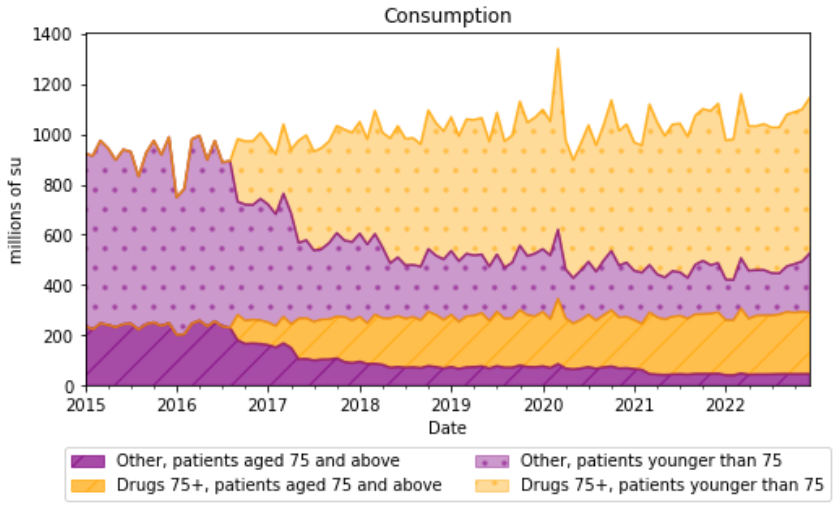
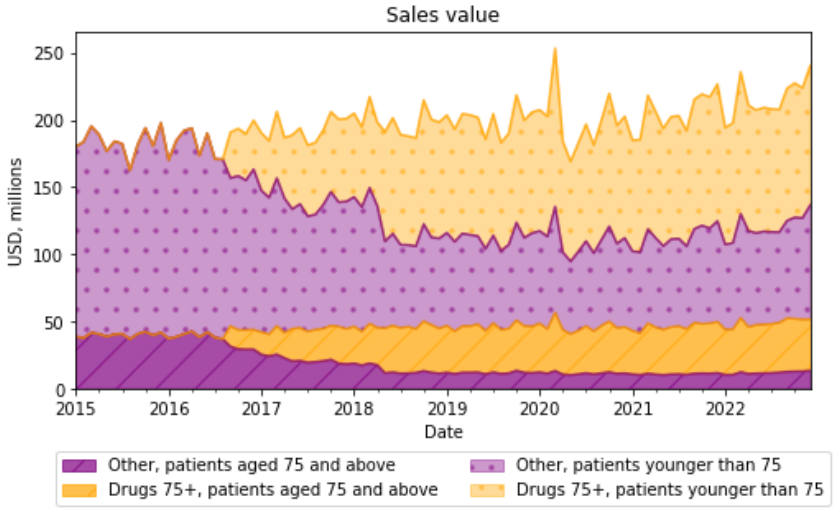


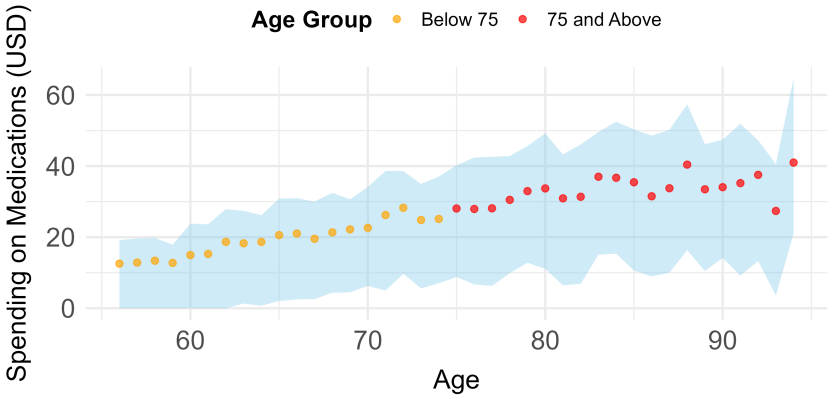
Figure 3: Sales of reimbursed drugs in Poland 2015-2202, by subset and age group



medical products subcategory, separate from, for example, medical appliances such as glasses or hearing aids.

In Figure 4 we show the average spending on pharmaceuticals by age of the oldest household member. The plot shows a clear upward trend - as the household ages, the medication spending increases. On average, 8% of disposable income of people over 75 is spent on medication.

Figure 4: Monthly household spending on medications by the age of the oldest member. Means from 2015 to 2018



3 Impact on Household Spending

3.1 Household Spending Empirical Approach

To analyze the impact on household financial situation, we employ a strategy that exploits the eligibility cutoff and the temporal dimension of the policy's introduction: Difference-in-Discontinuities.

3.1.1 Difference-in-Discontinuities

To evaluate the policy's impact, we employ a Difference-in-Discontinuities approach, leveraging the eligibility age cutoff for free drug access. This method builds on the framework introduced by Grembi et al. (2016), extending the traditional regression discontinuity design (RDD). In a standard RDD, the assumption is that counterfactual outcomes are continuous at the cutoff, ensuring that individuals just below and above the threshold are comparable except for their eligibility. Accordingly, any observed differences in outcomes near the cutoff can be attributed to the policy, providing a local treatment effect at the eligibility threshold. In our case, this effect pertains specifically to households whose oldest member has just crossed the eligibility cutoff at 75 years of age.

However, a traditional RDD is not applicable in this context due to the existence of a pre-existing program with the same age cutoff. Specifically, individuals aged 75 and older have been eligible for a pension supplement of approximately 40 USD per month for over two decades. This overlap creates ambiguity, as changes in outcomes at the discontinuity could be driven by either the pension supplement or the free drug policy introduced in 2016.

To disentangle these effects, we apply a Difference-in-Discontinuities approach, comparing changes in outcomes at the cutoff before and after the introduction of the free drug policy. Assuming additive effects between the policies, this method isolates the impact of the free drug policy

The difference-in-discontinuities estimate is calculated by first estimating RDD effects separately for the pre-policy and post-policy periods. In each RDD, the running variable

is the age of the oldest household member at the end of a given month. We leverage precise birth-date data to calculate exact ages, expressed in fractions of years. The focus on age at the end of the month is critical because eligibility depends on age at the time of purchase, allowing for potential delays in purchases until eligibility is attained. To ensure that our results are not driven by strategic adjustments in purchasing behavior, we conduct a robustness analysis using a donut RDD approach (Noack and Rothe, 2023), which excludes observations within three weeks of the 75th birthday.

We analyze three primary outcomes: (1) total spending on medication, (2) the share of disposable income allocated to medication, and (3) a binary indicator for high medication expenditure, defined as spending exceeding 10% of disposable income. This threshold corresponds to approximately the third quartile for households with an oldest member aged 74. These outcomes capture both direct financial impacts and the insurance value of the policy, potentially protecting against high expenditure stemming from negative health shocks.

For each RDD, we use a bias-corrected estimator with local polynomial regression and optimal bandwidth selection as proposed by Calonico et al. (2020). To ensure robustness, we supplement our analysis with parametric specifications that vary bandwidths and polynomial orders. All models are weighted by survey weights to ensure that the results are representative at the national level. Standard errors for the difference-in-discontinuity estimates are obtained using a nonparametric bootstrap procedure, drawing samples at the household level over 1,000 iterations.

We complement the difference-in-discontinuities approach by also employing a difference-in-differences framework to explore the policy's effects. Appendix A.2.1 provides a detailed description of this framework and presents the results, which are qualitatively similar but exhibit smaller magnitudes.

3.2 Household Spending Results

The difference-in-discontinuities analysis reveals a significant decline in medication spending following the introduction of the policy. Figure 5 visually illustrates this result by plotting the average medication spending at each completed year of age, both before and after the policy's implementation in September 2016. Before the policy, spending on medications increases steadily with age. After the policy, there is a pronounced downward shift in spending at age 75. Although spending continues to rise with age after the policy, it remains consistently lower than pre-policy levels.

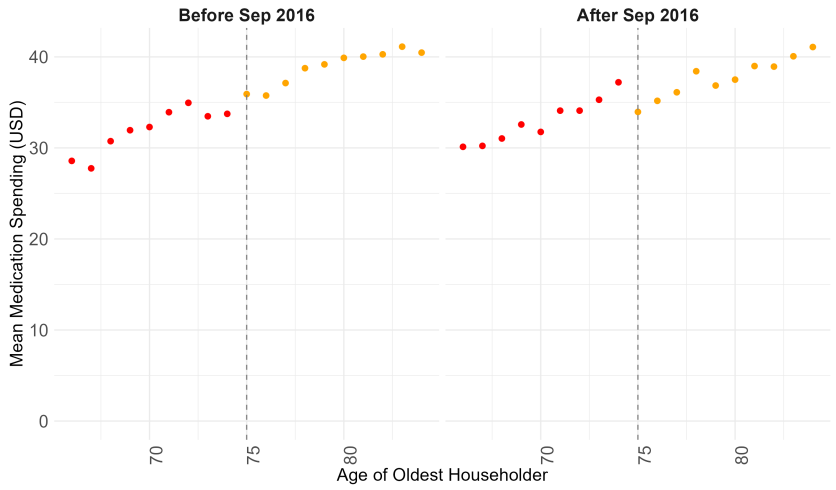


Figure 5: Households spending on Medications by Age of Oldest HH member and Time

Note: This figure presents mean medication spending in a households with the oldest household member of a given age. The averages are split by before and after entry of the policy.

The formal estimates of the difference-in-discontinuities analysis are reported in Table 4. Before the policy, there is a small and statistically insignificant upward jump in spending of \$2.63 at the eligibility threshold (p-value = 0.26, none of pre-policy jumps is significant). After the policy, spending exhibits a sharp and significant decline of \$5.72 at age 75. The difference-in-discontinuities estimate, which captures the net effect of the policy, indicates a reduction in spending of \$8.35 (significant at the 5% level). This reduction is substantial relative to the mean spending of \$35.70 at age 74, amounting to a 23% decline. While this result underscores the policy's effectiveness in reducing prescription drug spending, the remaining level of spending highlights its limitations. Many medications purchased by older adults might not be covered by the policy, as they fall outside the category of prescription drugs. Thus, although the policy achieves meaningful reductions in out-of-pocket expenses for prescription medications, its overall scope is constrained. Part of the effect may also be attenuated by reallocations to non-covered medications or higher spending for other household members.

Beyond reducing absolute spending, the policy also significantly impacts the share of disposable income allocated to medications. The difference-in-discontinuities estimate for the budget share of medication spending is -2 percentage points (p.p.), a sizable effect considering that households with a 74-year-old oldest member allocate 5.4% of their disposable income to medication.

Importantly, the policy demonstrates a strong insurance value by protecting households from high health-related expenditures. The probability of spending more than 10% of disposable income on medication decreases by 9.8 p.p., representing approximately a 62% reduction relative to the pre-policy mean. This suggests that the policy is highly effective in shielding households from severe financial shocks related to health expenditures. In Poland, this effectively eliminates financial risk associated with healthcare, as medication costs are the primary aspect of healthcare expenses borne by patients.

Table 4: Difference-in-Discontinuities

Outcome	Pre-Policy Est.	Post-Policy Est.	Diff-in-Disc	95% CI	Avg. Bandwidths	Mean at Age 74
Spending	2.633	-5.723	-8.356	[-16.9, -1.99]	Pre: 3.12, Post: 3.41	35.7
Budget Share	0.010	-0.009	-0.020	[-0.036, -0.005]	Pre: 2.30, Post: 3.98	0.054
Budget Share > 10%	0.057	-0.041	-0.098	[-0.194, -0.028]	Pre: 2.43, Post: 3.57	0.158

Note: This table reports the Difference-in-Discontinuities estimates from the main specification for three outcomes: Spending, Budget Share, and Budget Share exceeding 10% of income. The first two columns represent RDD estimates pre and post policy respectively, and the third one is the difference-in-discontinuities. Confidence intervals are calculated as percentiles of the distribution of differences from 1,000 bootstrap iterations. The average bandwidths applied in the pre- and post-policy periods are also derived from these bootstrap iterations.

Robustness checks confirm the stability of these findings. Estimates from the donut RDD specification, which excludes three weeks around the 75th birthday to address potential behavioral adjustments, remain consistent with the main results (Table 6). Similarly, parametric specifications (Table 7) yield slightly smaller estimates, with spending reductions ranging between \$9 and \$4, but all remain statistically significant.

3.2.1 Budget Reallocation

While the decline in spending on medications is relatively modest, it is statistically significant and raises questions about how households reallocate the freed-up resources. Figures 6 and 17 present estimates of the policy's impact on the share of disposable income allocated to other spending categories, using the Difference-in-Discontinuities (Diff-in-Disc) and Difference-in-Differences (DiD) frameworks, respectively.

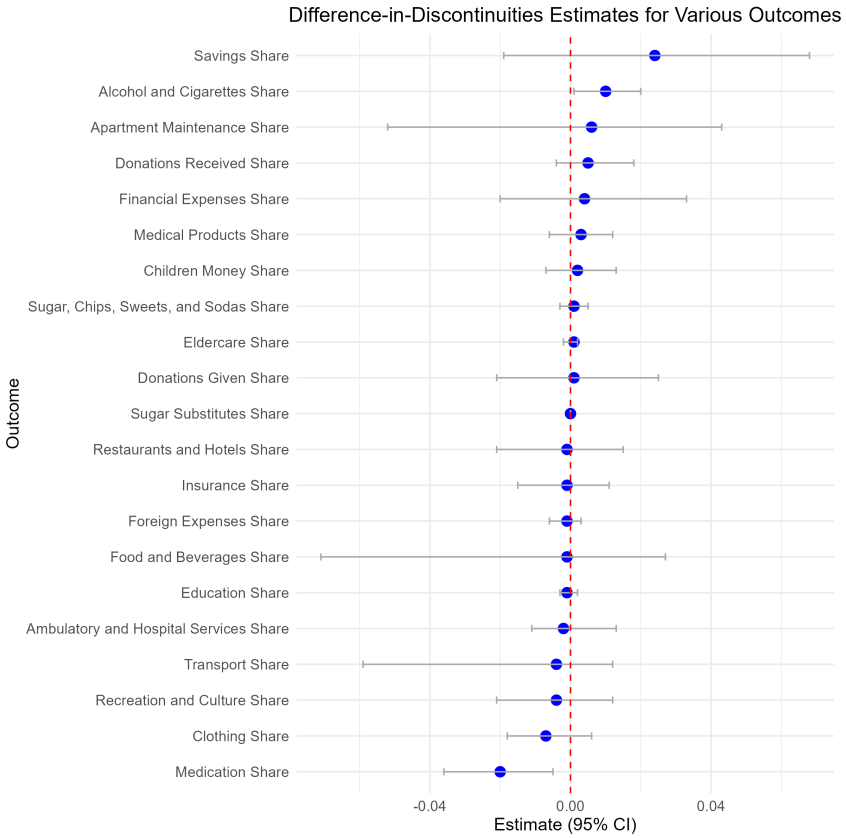


Figure 6: Diff-in-Disc Estimates for Alternative Outcomes

Note: This figure presents difference-in-disconituity estimates from the main specification for the alternative outcomes. Regressions are weighted by survey weights and the errors are clustered at the household level.

Figure 6 highlights the Diff-in-Disc estimates. The 2p.p. decrease in the share of income spent on medications is accompanied by a small, statistically insignificant increase in the savings share and a significant rise in the share of income allocated to alcohol and cigarettes. This shift may reflect a form of moral hazard, where the reduction in out-of-pocket costs for medications encourages spending on substances that could potentially increase future health risks and medication needs—now partially mitigated by the policy's coverage.

Overall, the policy yields mixed results. On one hand, there is a significant decline in spending upon reaching eligibility, highlighting its immediate financial relief. However, the smaller effects observed in the difference-in-differences framework suggest that the policy may have incentivized anticipatory spending among those nearing eligibility. Additionally, the policy appears to have temporarily encouraged risky behaviors, potentially reflecting moral hazard, as individuals reallocated resources to categories associated with heightened future health risks.

4 Impact on Consumption and Government Spending

4.1 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 aged 75 and older. 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. For certain outcomes, the key event is the policy's implementation in September 2016, which marked the largest inclusion of products. This approach analyzes the temporal evolution of outcomes for individuals aged 75 and older compared to those under 75, assuming that, in the absence of the policy, trends would have evolved in parallel across these groups. The estimation equation is as follows:

$$Y_{ita} = \sum_{k \neq -2, k=-18}^{18} \delta_k \cdot \mathbf{1}(t - T_i = k) \cdot 75\_\text{or}\_\text{over}_a + \gamma_{it} + \lambda_{ia} + \epsilon_{ita}, \tag{1}$$

where Y_{ita} represents the outcome for product 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 $75\_\text{or}\_\text{over}_a$, which equals one for individuals aged 75 and older. The coefficients δ_k capture the differential temporal impact of the policy on outcomes for individuals aged 75 and older relative to those under 75.

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, given that the list of free medications was announced in late August, less than one month before the policy's effective date.

We include product-by-age-group fixed effects (λ_{ia}) and product-by-time fixed effects (γ_{it}). 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 The primary outcome is the logarithm of the number of packages purchased,[2] weighted by the packages purchased in the reference period. For that outcome, we use a sample of products that were available for purchase with at least a partial subsidy in the entire period 2015-2022. Additional outcomes include the average price per dose paid by the government.

[2]To address cases with zero outcomes, we add 1 to the count before taking the logarithm.

4.1.1 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 change in consumption for each product before and after the policy, using a 12-month window on either side of its implementation (first difference). 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. As a robustness check, the appendix includes equivalent analysis where we calculate the Difference-in-Differences (DiD) estimates for each product—capturing the time difference and the difference across age groups—and model these estimates as a function of the copay.

4.2 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.

4.2.1 Increase in Purchases

The policy led to significant increases in the purchases of medications covered under the new reimbursement scheme. Figure 7 provides an intuitive visualization, depicting the raw per capita consumption of eligible medications for individuals aged 75 and older versus those under 75. Prior to the policy implementation, consumption trends between the two groups were similar, consistent with the parallel trends assumption. However, a noticeable upward shift is observed for the 75-and-older group immediately after the policy's introduction, providing preliminary evidence that the policy improved medication access for seniors.

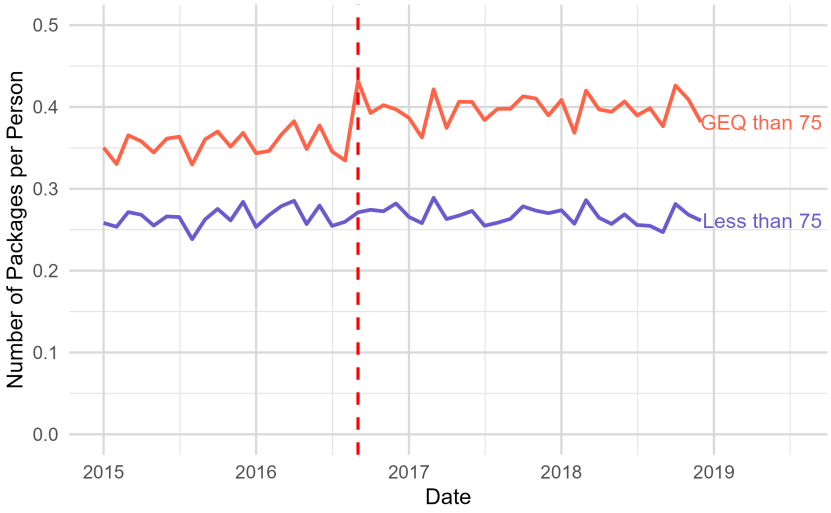


Figure 7: Medication Consumption per Person

Note: This figure illustrates the per capita (calculated with the overall population in that age group in the denominator) number of packages of eligible medication purchased by each age group. 'GEQ' denotes 'Greater or Equal. The dashed line marks the start of the policy.

To formalize this finding, Figure 8 presents the event study coefficients estimated from Equation 1, using the logarithm of eligible medication packages purchased as the outcome. The pre-treatment coefficients 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 consumption. This likely reflects anticipatory behavior, as individuals delayed purchases in expectation of obtaining free medication once the policy was enacted.

After the policy's implementation, consumption increased by 9% in the first month, likely driven by pent-up demand and stockpiling as individuals delayed purchases in anticipation of free medication. This was followed by a slight decline in the second month as stockpiles were consumed. Over time, consumption grew steadily, reaching a 15% increase one-and-a-half years later. This sustained growth reflects several factors: learning effects as seniors became more aware of the policy's benefits, adjustments to chronic treatment plans as doctors reevaluated regimens under the new affordability conditions, and gradual changes in prescription behavior by healthcare providers as they adapted to the policy. These findings demonstrate the policy's success in reducing financial barriers.

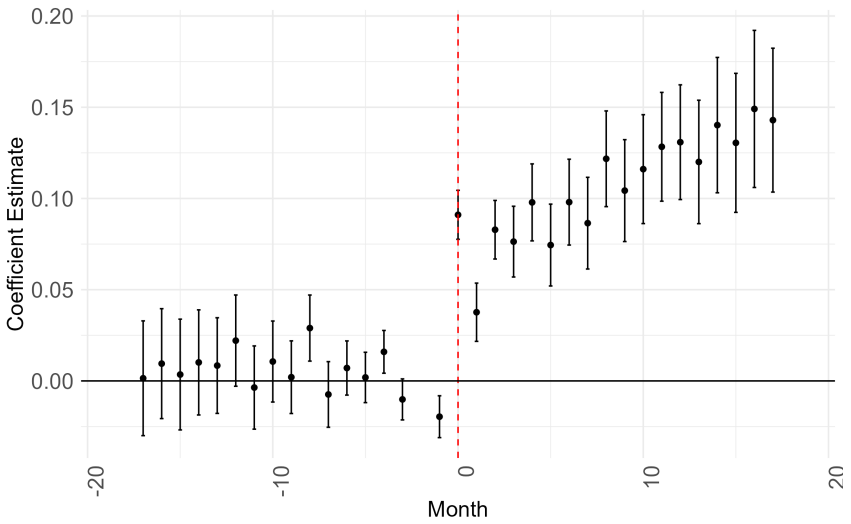


Figure 8: Event Study: Consumption

Note: This figure presents event study coefficients estimated from equation 1. The outcome variable is the logarithm of the number of packages purchased for a given product, plus one. Regressions are weighted by consumption in the reference period (-2) and include time fixed effects and product–by-age-group fixed effects. Standard errors are clustered at the product-by-age-group level.

To ensure robustness, Figure 16 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 18). This asymmetric response underscores our contribution, as it contrasts with most existing studies that primarily focus on responses to price increases. Additionally, heterogeneity analysis by therapeutic use (Figure 19) reveals that the policy's largest effects were concentrated among high-cost, chronic-use medications such as lipid-regulating and anticoagulant drugs, whose use may be easier to delay or avoid compared to acute medications like antibiotics, which are often required for immediate treatment.

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 [3]. 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. 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:

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

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

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 9 shows the results:

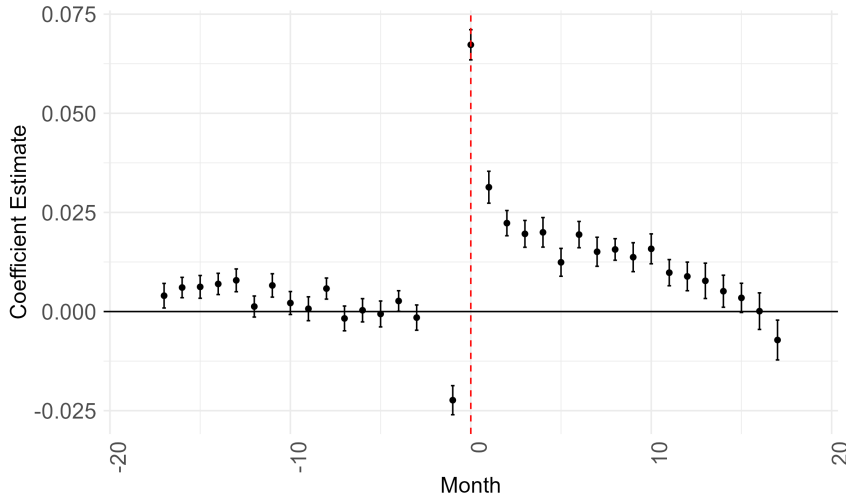


Figure 9: Event Study: Policy Impact on Visits to Primary Care Physicians

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.

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.

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

4.2.2 Continuous Treatment Approach

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

The binscatter analysis (Figure 10) 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 50% 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.

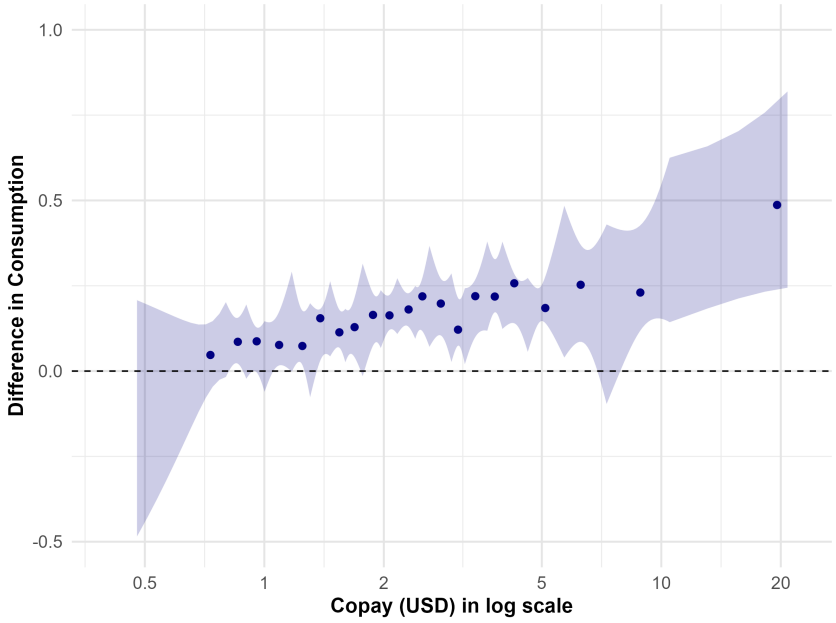


Figure 10: Consumption Change and Copay: Binscatter

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 (plus one) of packages purchased. The X-axis represents the average pre-inclusion copay (in USD) on a logarithmic scale.

Figure 11 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 time-difference, 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 13.6%. A linear fit suggests that a 1% increase in copay is associated with a 0.1% 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 6.8% increase at the 10th percentile copay ($0.82). In contrast, the highest effects are concentrated among previously cost-prohibitive medications, with a 25% increase at the 90th percentile ($6.60) and a 62% increase at the 99th percentile ($22).

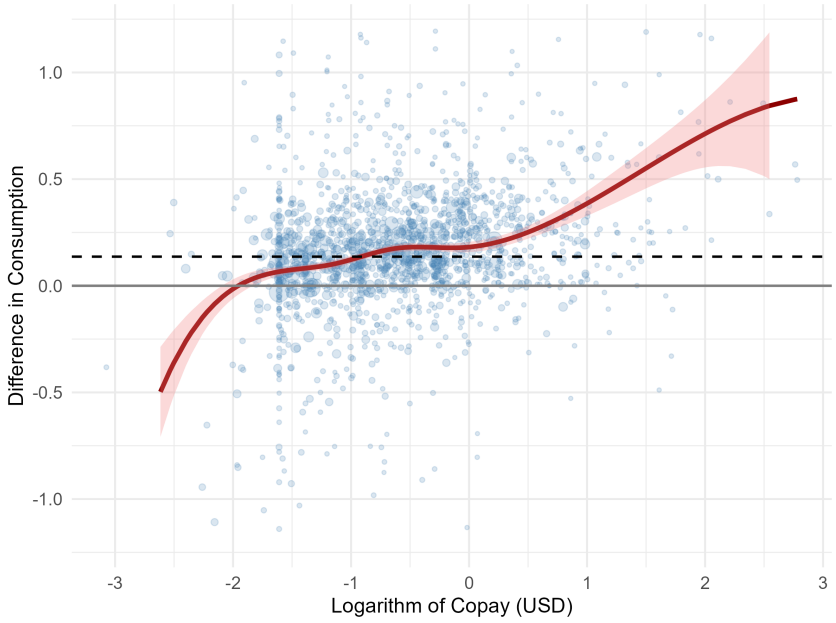


Figure 11: Continuous DiD in Copay

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. Figures 21 and 22 present analogous results in terms of Difference-in-Differences (DiD) estimates for each product, capturing both the pre-post differences and the differences across age groups. The observed patterns remain virtually unchanged.

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.

4.3 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. 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.

Within each group, we categorize products based on their pre-policy 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 active substances with at least five producers[4].

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.

[4]The magnitude of the substitution effect generally increases with the number of producers. The results for active substances with at least two producers are shown in Figure 23

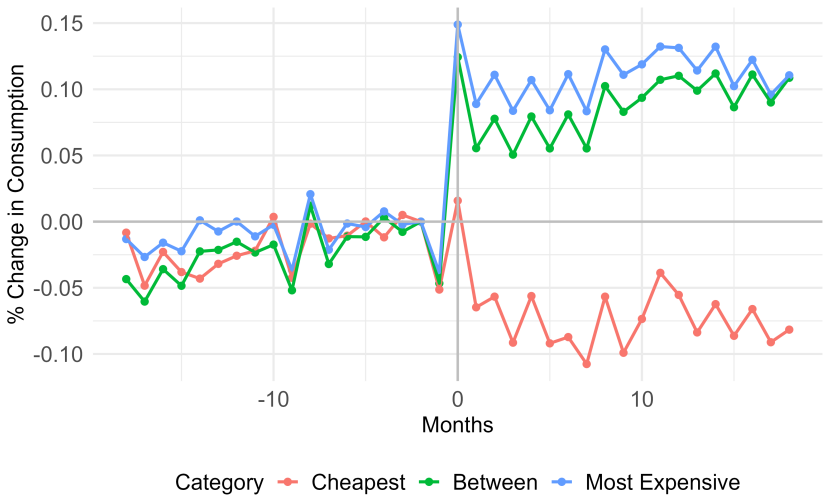


Figure 12: Consumption Changes by the Price per Dose of Treatment

Note: This figure presents changes in package consumption among individuals aged 75 and older over time around inclusion, compared to 2 months before inclusion, and relative to the age group below 75. Medications are categorized based on their relative price per dose within the same active substance. The sample includes only active substances with at least five producers.

The results confirm that the policy's impact is primarily driven by an increase in the consumption of more expensive substitutes. Figure 12 provides an intuitive visualization of these patterns, while Figure 13 formalizes them as an event study using Equation 1. The largest increase in consumption, between 15–20%, is observed for the most expensive medications. Mid-priced products experience a more moderate increase of around 10%. In contrast, the consumption of the cheapest products declines steadily over time, with the decrease exceeding 20% by 1.5 years after the policy's implementation. This shift may reflect behavioral preferences, such as a perceived quality advantage for branded medications over generics.

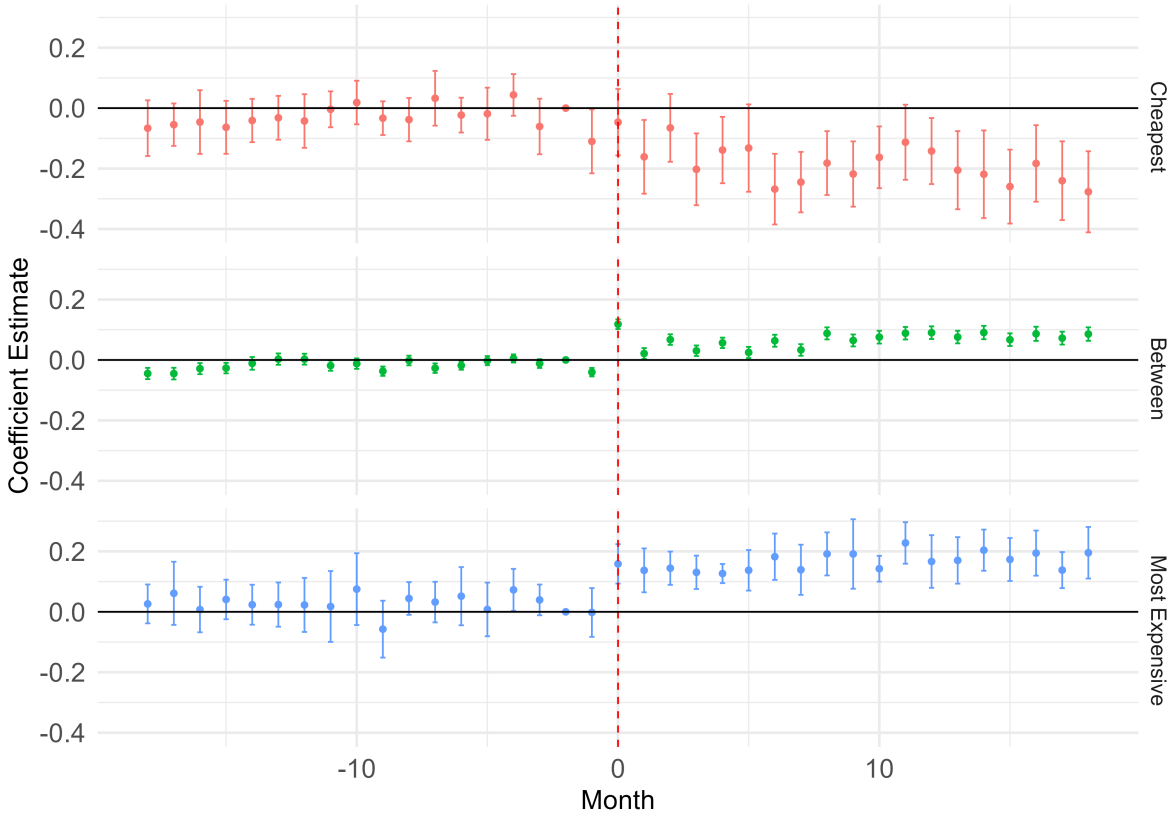


Figure 13: Event Study by the Price per Dose of Treatment

Note: This figure presents event study coefficients from Equation 1 with outcome being log +1 of packages purchased. 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.The sample includes only active substances with at least five producers.

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.

4.4 Cost of the treatment

The policy increased the average cost per dose of treatment for seniors by shifting consumption toward more expensive medications. Figure 14 illustrates the raw trends in the average price paid by the government per dose of active substance for eligible medications. It is calculated as the manufacturer's cost of packaging divided by the number of doses in the package, aggregated across all products. Before the policy, the two age groups had relatively similar costs per dose. After the policy, the under-75 age group (blue

line) shows stable trends, while the 75-and-older group (red line) exhibits a clear upward shift in average price, indicating that changes in consumption patterns have increased the government's cost per dose.

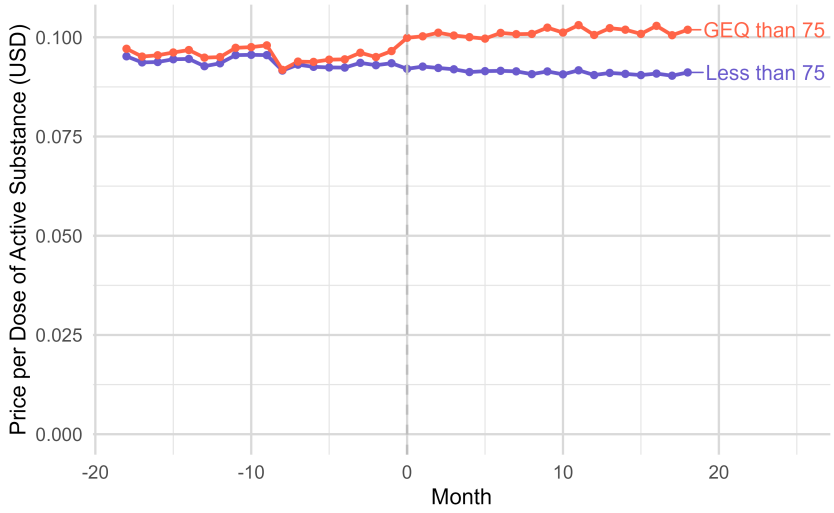


Figure 14: Cost of Treatment

Note: This figure displays the average price paid by the government per dose of active substance for insured products, separated by age group. The 75 and older age group (GEQ than 75) is shown in red, while the under-75 age group is shown in blue.

Figure 15 formalizes this result with an event study where the outcome is the logarithm of the average price per dose of active substance. The analysis uses Equation 1, but the unit of observation is the active substance rather than the product. The government's cost per dose of active substance is calculated as the total manufacturer cost of all packages purchased for a given group, divided by the number of doses in those packages.

This shift from the product level to the substance level is important because it affects the parallel trends. Selective changes in the prices of medications can differentially impact seniors' average cost per dose if they consume a different mix of products. Notably, a significant price change occurred in January 2016, well before the policy was discussed. To avoid confounding effects, the estimation is restricted to observations post-January 2016, limiting the pre-treatment period in a balanced event panel to 8 months[5].

The pre-treatment coefficients are small and close to zero, except for the final month, where anticipatory behavior likely influenced consumption. Post-policy, the average cost of treatment steadily increases, reaching approximately 1%. This reflects a shift toward greater consumption of expensive medications and reduced use of cheaper substitutes. In USD terms, this corresponds to the government paying an additional 0.1 cents per dose of active substance.

[5]Results using the full sample are presented in Figure 24.

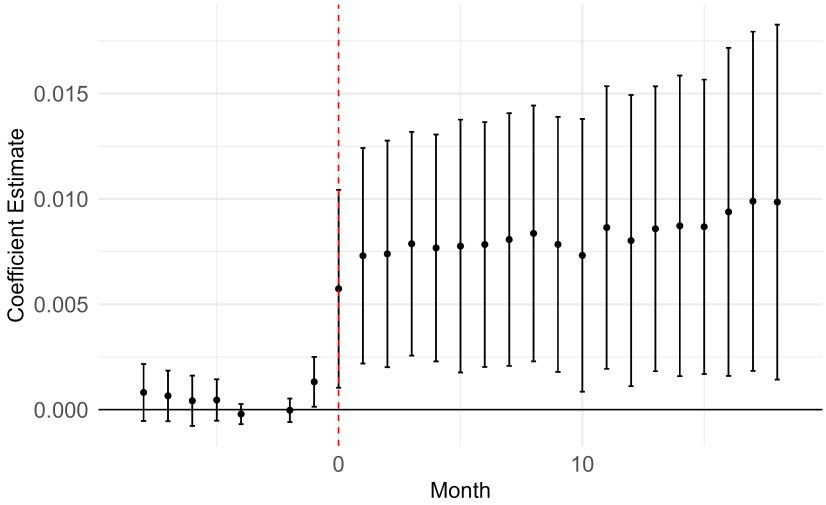


Figure 15: Event Study: Cost of Treatment

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 dose of active substance, plus one. The unit of observation is the active substance. Regressions are weighted by purchases and include time fixed effects as well as substance-by-age-group fixed effects. Standard errors are clustered at the substance-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.

5 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 Drugs 75+ program reveals three main findings. First, the program substantially reduced seniors' out-of-pocket medication expenditures, alleviating financial risks associated with catastrophic health costs. Second, the program increased overall medication consumption, particularly for higher-cost products, which displaced cheaper alternatives. Third, 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

Table 5: 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 Difference-in-Discontinuities

Table 6: Donut Difference-in-Discontinuities

Outcome	Pre-Policy Est.	Post-Policy Est.	Diff-in-Disc	95% CI	Avg. Bandwidths	Mean at Age 74
Spending	2.629	-7.955	-10.584	[-20.588, -3.357]	Pre: 3.28, Post: 2.73	35.903
Budget Share	0.010	-0.011	-0.022	[-0.042, -0.008]	Pre: 2.26, Post: 3.47	0.054
Budget Share > 10%	0.055	-0.052	-0.107	[-0.204, -0.039]	Pre: 2.49, Post: 3.26	0.157

Note: This table reports the Difference-in-Discontinuities estimates from the specification excluding 3 weeks around the 75th birthday for three outcomes: Spending, Budget Share, and Budget Share exceeding 10% of income. The first two columns represent RDD estimates pre and post policy respectively, and the third one is the difference-in-discontinuities. Confidence intervals are calculated as percentiles of the distribution of differences from 1,000 bootstrap iterations. The average bandwidths applied in the pre- and post-policy periods are also derived from these bootstrap iterations.

Table 7: Parametric Difference-in-Discontinuities

	Polynomial	Spending	Budget Share	Budget Share>10%	Obs
Bandwidth = 2 years					
2	1	-6.020** (2.980)	-0.013** (0.005)	-0.074** (0.030)	9877
2	2	-9.317** (4.553)	-0.017** (0.008)	-0.091* (0.047)	9877
2	3	-4.288 (6.019)	-0.014 (0.011)	-0.025 (0.066)	9877
Bandwidth = 3 years					
3	1	-6.715*** (2.496)	-0.011*** (0.004)	-0.057** (0.025)	13943
3	2	-6.434* (3.686)	-0.016** (0.006)	-0.092** (0.038)	13943
3	3	-8.880* (4.761)	-0.014 (0.009)	-0.073 (0.052)	13943
Bandwidth = 5 years					
5	1	-3.973** (1.974)	-0.007** (0.003)	-0.055*** (0.020)	22670
5	2	-6.879** (2.944)	-0.015*** (0.005)	-0.068** (0.030)	22670
5	3	-8.994** (3.939)	-0.017** (0.007)	-0.090** (0.041)	22670
Mean Outcome at Age 74					
2		35.747	0.054	0.158	

Note: Parametric estimates of the coefficient of interest. Bandwidth and polynomial order are as specified. Standard errors (in parentheses) are clustered at the household level. The outcomes are: (1) monthly spending on medication, (2) the share of total budget devoted to medications, and (3) an indicator for whether medication spending exceeds 10% of total disposable income.

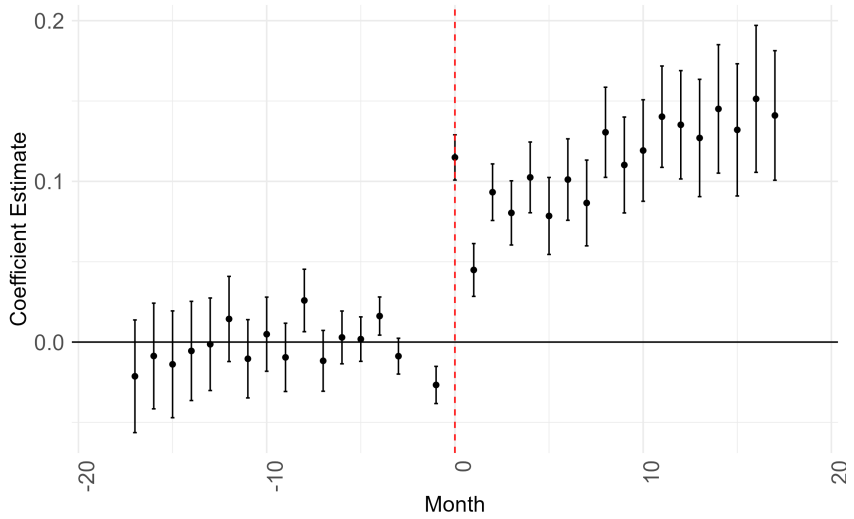

Figure 16: Robust Event Study: Consumption

Note: This figure presents event study coefficients from the approach of Sun and Abraham (2021). The outcome variable is the logarithm of the number of packages purchased for a given product, plus one. Regressions are weighted by consumption in the reference period (-2). Standard errors are clustered at the product-by-age-group level. Based on a sample of medication available during the entire period.

A.2.1 Difference-in-Differences Framework for Household Expenditures

To examine the effect of the policy on household spending and its heterogeneity by age, we employ a difference-in-differences (DiD) design. Unlike regression discontinuity design (RDD), which focuses on the immediate effect of an individual becoming eligible, this approach captures the average effect across all eligible households, including those with potentially longer exposure and differing needs. This approach contrasts the change in outcomes following the policy relative to the pre-policy period (first difference) for households with an oldest member aged 75 or older (treatment group) and those aged 65–74 (control group) (second difference). The identifying assumptions are that, absent the policy, the outcomes for these two groups would follow parallel trends and that the behavior of the control group (65–74) remains unaffected by anticipation effects.

Baseline Specification We define $\text{Post}_t = 1$ for months after the policy's introduction (September 2016–December 2018) and $\text{Post}_t = 0$ for the preceding period (January 2015–August 2016). Notably, the list of free drugs was further expanded during the post-policy period, though these subsequent expansions were modest. While studies such as Alpert (2016) highlight the potential for anticipation effects to influence behavior prior to policy implementation, the short notice of drugs covered under this policy—only a few days before its introduction in September 2016—likely minimized such effects. Moreover, any anticipation would likely lead to an underestimation of the policy's impact, as delayed spending before the policy would dampen observed differences in spending.

The following regression is estimated:

$$Y_{it} = \beta_0 + \beta_1 \,\text{HH Member } 75{+}_i + \beta_2\big(\text{Post}_t \times \text{HH Member } 75{+}_i\big) + \gamma_t + \lambda X_i + \epsilon_{it}, \quad (3)$$

where Y_{it} is the outcome of interest for household i at time t. We examine the same outcomes as in the case of the difference in discontinuities.

The variable HH Member $75{+}_i$ equals 1 if the oldest member of household i is 75 or older, and 0 otherwise. The interaction term $\text{Post}_t \times$ HH Member $75{+}_i$ isolates the DiD effect of the policy, with β_2 capturing the average treatment effect. Notably, more household members beyond the oldest may qualify for eligibility, potentially changing the observed effect.

We include time fixed effects, γ_t, to account for common shocks across all households in each time period. X_i represents a vector of covariates, which varies by specification: either geographic fixed effects or household fixed effects. Given the panel structure of the data, with each household observed twice over a 12-month interval, household fixed effects (λ_i) control for time-invariant unobserved characteristics such as household composition or baseline health conditions. Regressions are weighted by survey weights to ensure representativeness of the population, and standard errors are clustered at the household level.

Heterogeneous Effects by Age To explore heterogeneity in policy effects, we stratify the sample by the age of the oldest household member. This stratification is motivated by the potential for older households to have different medication needs, household compositions, and reliance on refundable prescriptions. The following regression is estimated:

$$Y_{it} = \beta_0 + \beta_1\big(\text{Post}_t \times 65\text{–}69\big) + \beta_2\big(\text{Post}_t \times 75\text{–}79\big) + \beta_3\big(\text{Post}_t \times 80{+}\big) + \gamma_t + \lambda_i + \epsilon_{it}. \quad (4)$$

Here, the omitted age category is 70–74, which serves as the baseline for comparison. The coefficients β_1, β_2, and β_3 capture the policy effects for the respective age groups relative to the 70–74 category. The coefficient β_1 for the 65–69 group functions as a placebo test, as this group is not eligible for the policy. The coefficients β_2 and β_3 measure policy effects for households with older members (75–79 and 80+, respectively). These regressions include time and hosehold fixed effects. The results are demonstrated in the tables 8 and 9

The results, presented in Table 8, show a significant reduction in medication spending, albeit of smaller magnitudes than RDD analysis. In the household fixed effect specification, monthly spending decreased by $2.35 on average for eligible households. This effect smaller effect likely reflects a differential response for households eligbile for some time. For instance, they might adjust by spending additional money on non-covered medication. Similarly, the share of disposable income allocated to medication drops by 0.48 percentage points (p.p.), and the likelihood of spending more than 10% of disposable income on medication decreases by 2.54 p.p. These results highlight the policy's sustained impact in alleviating financial burdens across eligible households.

Table 8: DiD Estimates

Dependent Variables:	Spending		Budget Share		Budget Share>10%	
Column:	(1)	(2)	(3)	(4)	(5)	(6)
Post Policy × Oldest HH member>75	-1.605**	-2.353**	-0.0041***	-0.0048***	-0.0153**	-0.0254**
	(0.6998)	(1.071)	(0.0011)	(0.0017)	(0.0068)	(0.0116)
Fixed-effects						
Region	Yes	Yes	Yes	Yes	Yes	Yes
Time	Yes	Yes	Yes	Yes	Yes	Yes
Household ID		Yes		Yes		Yes
R^2	0.02569	0.83148	0.01986	0.83124	0.01290	0.79221
Observations	51,705	51,705	51,429	51,429	51,429	51,429
Dependent variable mean	34.9	34.9	0.05	0.05	0.141	0.141

Note: This table presents difference-in-differences (DiD) estimates for three outcomes: (1,2) monthly spending on medications (in USD), (3,4) the share of total budget devoted to medications, and (5,6) an indicator for whether medication spending exceeds 10% of total disposable income. Standard errors (in parentheses) are clustered at the household level.

To investigate whether the differential effects are driven by age-specific impacts or anticipatory behavior, Table 9 reports the results of the difference-in-differences (DiD) analysis interacted with age groups.

Table 9: DiD Estimates by Age Groups

Dependent Variables:	Spending	Budget Share	Income Share > 10%
Column:	(1)	(2)	(3)
Post Policy × 65-69	-0.5433	-0.0006	-0.0083
	(1.384)	(0.0021)	(0.0146)
Post Policy × 75-79	-2.630*	-0.0039	-0.0301*
	(1.579)	(0.0025)	(0.0179)
Post Policy × 80+	-2.650*	-0.0063**	-0.0329*
	(1.602)	(0.0025)	(0.0170)
Fixed Effects			
Household ID	Yes	Yes	Yes
Time	Yes	Yes	Yes
Fit Statistics			
R^2	0.83142	0.83130	0.79239
Observations	51,669	51,393	51,393
Dependent variable mean	34.9	0.5	0.14

Note: This table presents difference-in-differences estimates split by three age groups for three outcomes: (1) monthly spending on medications (in USD), (2) the share of total budget devoted to medications, and (3) an indicator for whether medication spending exceeds 10% of total disposable income. Standard errors (in parentheses) are clustered at the household level.

First, the change for 65–69 age group is indistinguishable from the change in 70-74 group. This is a useful placebo check as households in this age group were not affected by the policy and their outcomes evolved in parallel. By contrast, households with members aged 75–79 and 80+ show significant reductions in spending and financial risk. While the magnitude of the decline in spending and in the probability of spending more than 10% of income is similar for both groups, the effect on the budget share is larger for the 80+ group, reflecting their higher baseline share dedicated to prescription medication. The overall lower estimates compared to Diff-in-Disc, may stem from behavioral readjustments just before and after the age-cutoff for eligibility, which are no longer apparent in the DiD framework.

Regarding budget reallocation, the DiD estimates in Figure 17 show a smaller decrease in the share of income dedicated to medications. While there is still a non-significant increase in savings, the observed rise in spending on alcohol and cigarettes is no longer evident. This discrepancy may reflect the DiD framework's inclusion of longer-term behavioral adjustments across all eligible households, where older age groups may exhibit declining propensities to consume such items.

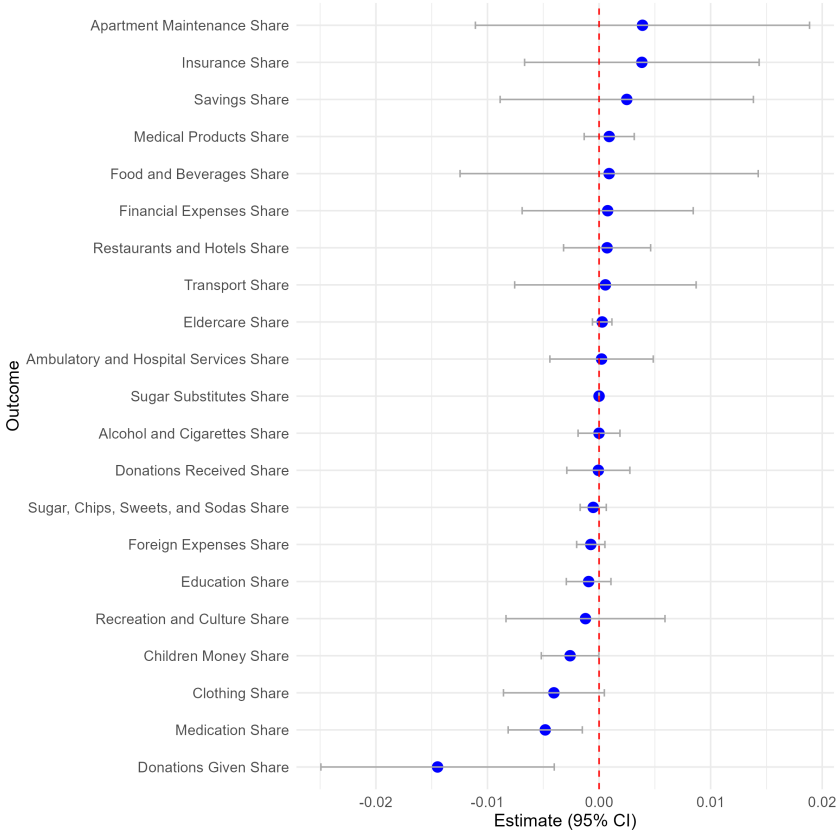

Figure 17: DiD Estimates for Alternative Outcomes

Note: This figure presents difference-in-differences estimates from the main specification for the alternative outcomes. Regressions are weighted by survey weights and include household and time fixed effects. The errors are clustered at the household level.

A.3 Exclusion of the Drug

Figure 18 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 and older compared to those under 75, adjusted for seasonal variation by subtracting the value from the same month in 2015.

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 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.

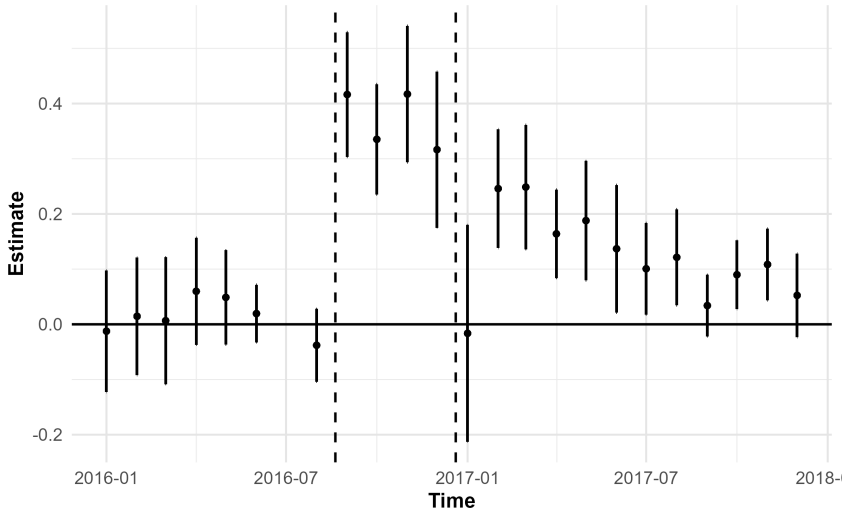

Figure 18: Event Study: Exclusion of a Product

Note: This figure displays event study coefficients estimated from a regression of the outcome on date dummies interacted with the age group dummy for 75+. The outcome variable is the logarithm of the number of packages purchased for a given product, plus one, adjusted by subtracting the value from the same month in 2015 to account for strong seasonal variation. The first dashed line marks the time when products were included, while the second indicates when they were excluded. Regressions are weighted by consumption in the reference period and include time fixed effects and product-by-age-group fixed effects. Standard errors are clustered at the product-by-age-group level.

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 19 examines heterogeneity in the policy's average impact across different therapeutic classes of medications using a difference-in-differences framework comparing individuals aged 75 and older to those under 75 in a year before and after the policy. The results reveal substantial variation in consumption changes. The largest increases are observed for lipid-regulating drugs and anticoagulants/antiplatelet medications, likely reflecting their chronic nature and high baseline costs, which make them particularly responsive to the policy's subsidies. Moderate increases are observed for drugs for bone diseases, antidepressants, and hormones/endocrine system drugs, including medication to manage diabetese, highlighting the role of affordability improvements in enhancing adherence to long-term treatment plans.

In contrast, smaller or insignificant effects are observed for drugs treating acute conditions such as antibiotics or antifungal drugs, 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.

These insights are valuable for policymakers designing subsidy schemes, as they sug-

gest 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.

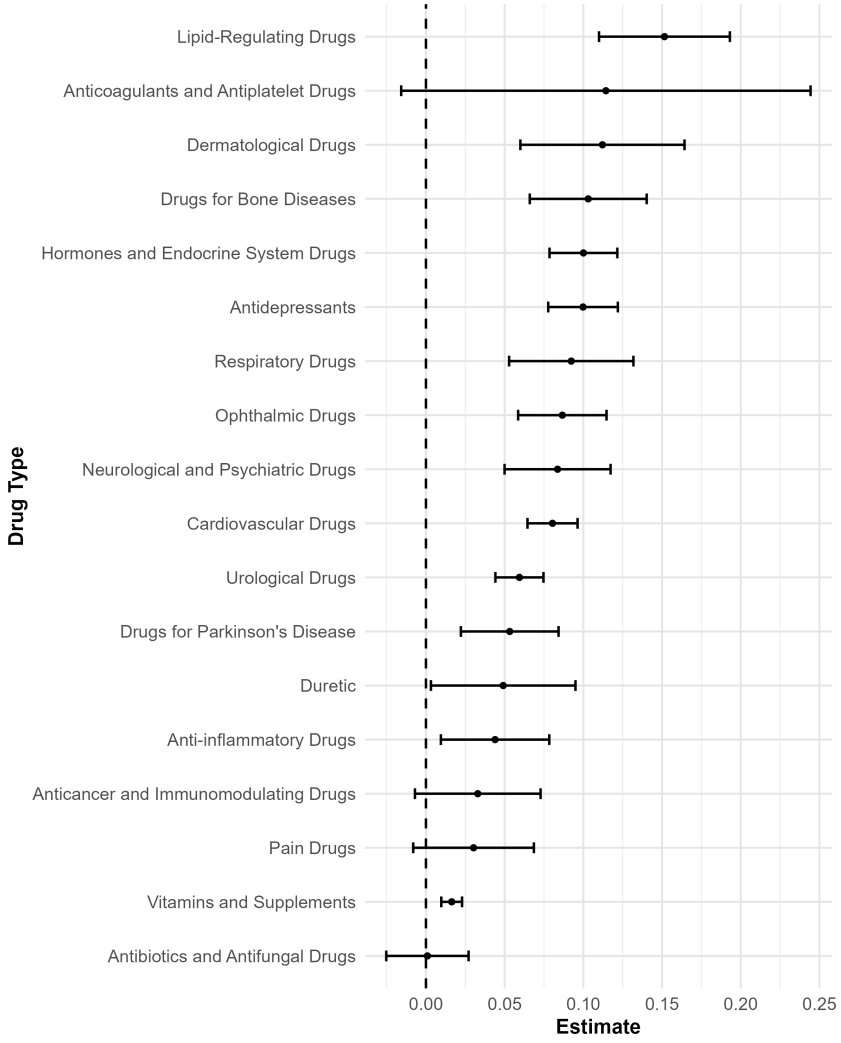

Figure 19: Heterogeneity in Consumption effect by Medication Type

Note: This figure displays difference-in-difference coefficients for consumption within specific medication groups. 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 for a given product, plus one. Regressions are weighted by consumption during the pre-inclusion period, and standard errors are clustered at the product-by-age-group level.

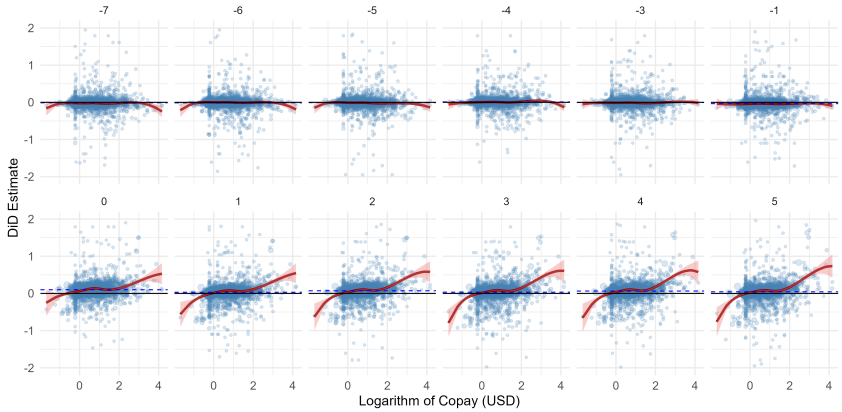

Figure 20: Continuous Event Study in Copay

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 change for a given month relative to inclusion, compared to the period 2 months before inclusion. The dots represent product-level pre-post changes for the logarithm (plus one) of packages purchased, 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 change, while the solid line represents zero. 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 are determined by the number of packages purchased for each product pre-reform. A 95% confidence interval is shown around the spline.

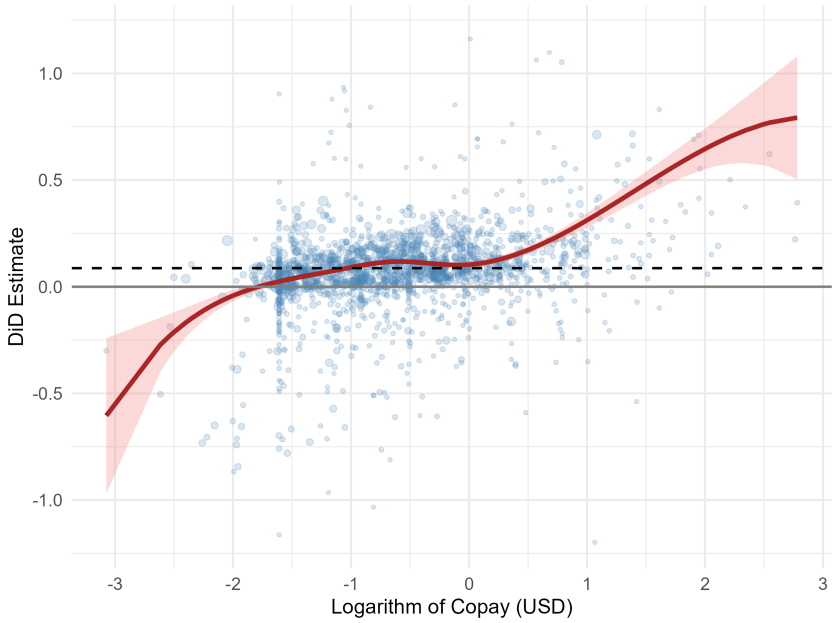

Figure 21: Continuous DiD in Copay: Double Difference

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 difference-in-differences estimates 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 DiD estimate, 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 DiD estimates, 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.

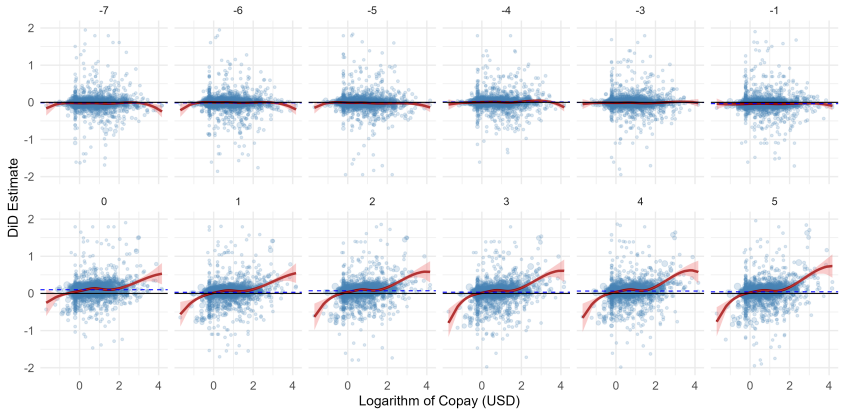

Figure 22: Continuous Event Study in Copay: Double Difference

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 (plus one) of packages purchased, 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.

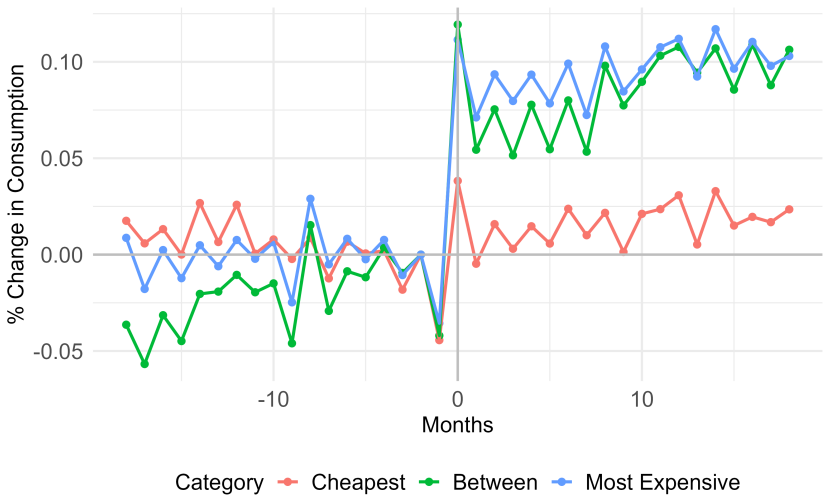

Figure 23: Consumption Changes by the Price per Dose of Treatment with at least 2 producers

Note: This figure presents changes in package consumption among individuals aged 75 and older over time around inclusion, compared to 2 months before inclusion, and relative to the age group below 75. Medications are categorized based on their relative price per dose within the same active substance. The sample includes only active substances with at least two producers.

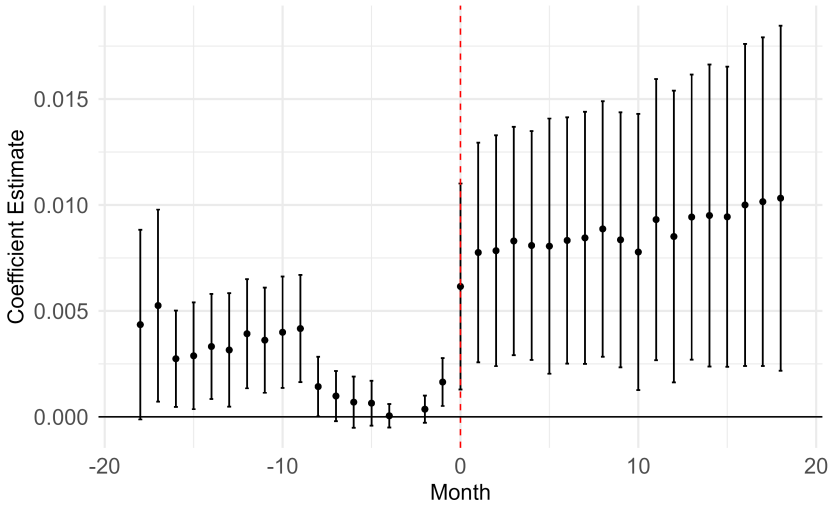

Figure 24: Larger Window Event Study: Cost of Treatment

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 dose of active substance, plus one. The unit of observation is the active substance. Regressions are weighted by purchases and include time fixed effects as well as substance-by-age-group fixed effects. Standard errors are clustered at the substance-by-age-group level.