The Financial and Behavioral Effects of Free Prescription Drugs: Evidence from a Policy Discontinuity in Poland

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Abstract

We provide causal evidence on the financial consequences and moral hazard effects of a universal prescription drug subsidy for seniors—a policy widely implemented in many countries. Our analysis leverages Poland's introduction of such a subsidy, which fully eliminated out-of-pocket costs for selected medications at age 75. Exploiting the sharp age eligibility threshold and policy timing, we apply a difference-in-discontinuities design to detailed household expenditure data. We find substantial reductions in medication spending and a 62% decrease in catastrophic drug expenditures, indicative of a strong insurance effect. However, these financial gains disproportionately accrued to wealthier households, raising distributional concerns. We also document increased household spending on alcohol and cigarettes, consistent with ex ante moral hazard. These findings demonstrate that while universal drug subsidies effectively reduce financial risk among older adults, they may also induce unintended behavioral responses and amplify existing inequities.

JEL Classification: I10, I13, I18

1 Introduction

In the context of aging populations, pharmaceutical subsidies for seniors have become an important policy tool. Older adults account for a disproportionate share of medication use, and out-of-pocket costs can pose serious barriers to treatment. These financial pressures threaten not only access to care but also the economic security of senior households. In response, many governments have introduced targeted drug subsidy programs to improve affordability and reduce financial risk. While most rely on partial subsidies or co-payment caps, some—including Italy, the United Kingdom, and Spain—provide certain medications free of charge to eligible groups. Despite their prevalence, there is limited causal evidence on the financial and behavioral effects of such policies for older adults.

This paper examines the financial and behavioral consequences of a universal, age-based prescription drug subsidy introduced in Poland. The Drugs 75+ policy eliminated out-of-pocket costs for a designated list of medications for individuals aged 75 and older, regardless of income or health status. Unlike tiered or means-tested programs, this reform offered full price elimination for eligible drugs. Poland provides an ideal setting for studying such a policy: the healthcare system is centrally administered through a single public insurer, inpatient and outpatient care is free at point of service, and pharmaceuticals represent the primary source of out-of-pocket medical expenses. Before the reform, many seniors faced high and unpredictable drug costs, exposing them to considerable financial risk.

By eliminating drug prices for seniors, the policy may relax current budget constraints and reduce exposure to future health-related shocks. Because of this insurance function, the policy may also displace precautionary behaviors—potentially altering consumption patterns more broadly rather than just spending on medication.The standard theoretical implications of insurance suggest that moral hazard may arise, with eligible individuals shifting their consumption toward goods that may be detrimental to health.

We use detailed expenditure micro-data from Poland's Household Budget Survey and implement a difference-in-discontinuities design (Grembi et al., 2016) that exploits the sharp eligibility threshold at age 75 and the timing of the policy's introduction. This approach isolates the causal effect of the policy. While the reform aimed to improve medication access—analyzed in related work (Majewska and Zaremba, 2025) our focus is on insurance value and consumption behavior.

First, we find that the policy significantly reduced out-of-pocket medication spending. Average monthly expenditures declined by \$8, representing a 23% reduction from a baseline of \$35. More substantially, the share of households experiencing catastrophic drug expenditures—defined as spending exceeding 10% of disposable income—fell by 62%. At the same time, we do not find evidence for reductions in a measure of poverty which considers income available after medication spending. Quantile treatment effects shows that the effects are concentrated in the upper tail of the distribution, consistent with strong insurance value.

The financial gains were most pronounced among households with high pre-policy drug spending, those living alone, and those composed entirely of older adults—groups most exposed to medication costs. However, higher-income and urban households also benefited disproportionately, likely because they had higher pre-policy spending and have better access to healthcare and pharmacy services, disproportionately benefit. This pattern raises concerns that the policy did not improve the financial situation of the most vulnerable seniors, and it may unintentionally reinforce existing financial disparities. It also explains the lack of effects on the poverty measure: only households far from the poverty line made savings thanks to the policy.

After noting a significant insurance function of the policy, we also find a shift in spending toward alcohol and cigarettes, particularly among households with the largest declines in medication costs. This behavioral response is consistent with ex-ante moral hazard: by reducing the perceived consequences of health shocks and improving the management of chronic conditions, the policy may have weakened incentives for alternative precautionary behavior. We find no evidence of meaningful changes in other consumption categories.

This paper contributes to the growing literature on the financial effects of public health coverage expansions, particularly pharmaceutical benefits. Most existing evidence comes from the United States, where insurance systems are fragmented and pricing is nonlinear. For instance, Finkelstein et al. (2012) show that gaining Medicaid reduces out-of-pocket spending and financial hardship. Related studies find Medicaid eligibility lowers medical expenses and poverty risk (Sommers and Oellerich, 2013; Dillender, 2017), while Medicare Part D has been widely studied for its effects on prescription drug use and costs (Einav et al., 2018; Park and Martin, 2017).

Our study departs from this literature in two key ways. First, we provide the first causal evidence on the financial effects of a universal, age-based drug subsidy that eliminates out-of-pocket medication costs without affecting other healthcare prices. In contrast to broader coverage expansions like Medicaid or Medicare Part D, Poland's Drugs 75+ policy removes only drug costs for seniors, within a single-payer system offering free inpatient and outpatient care. This offers a rare, clean setting to isolate the direct effects of pharmaceutical insurance, where medications are the main source of out-of-pocket health spending.

The Polish case also speaks to policy design in other countries with universal or near-universal healthcare and rising pharmaceutical burdens among the elderly. Similar non-means-tested pharmaceutical policies exist in Italy, Spain, and the UK. Poland is especially relevant because prescription drugs are the leading driver of catastrophic health expenditures, affecting up to 18% of households and pushing many into poverty (Łuczak and García-Gómez, 2012; Tambor and Pavlova, 2020). Moreover, prescription drug use rises with income (Moran and Simon, 2005), highlighting affordability as a barrier to access.

Second, we contribute to the literature on ex ante moral hazard—the idea that insurance may reduce incentives for healthy behavior. The evidence is mixed. Some studies find little responses in terms of unhealthy behaviors to coverage expansions (e.g. Newhouse and Insurance Experiment Group, 1993 Courbage and Coulon (2004); Card et al., 2008), or even improvements in behaviors in the long run (Soni, 2020), while others document increases in risky behaviors such as smoking or poor diet following insurance gains (Klick and Stratmann, 2007; Dave and Kaestner, 2009; Dave et al., 2019). Some evidence of ex-ante moral hazard has also been found in lower-income settings after coverage expansion (Yilma et al., 2012; Gitaharie et al., 2022).

We show that prescription drug coverage can produce immediate behavioral responses, with increased spending on alcohol and cigarettes. By isolating the final remaining out-of-pocket cost in an otherwise universal system, our setting offers a clean test of pharmaceutical insurance's behavioral impacts. These findings provide complementary evidence to existing studies that examine broader insurance expansions or long-run behavioral adjustments.

The rest of the paper proceeds as follows. Section 2.1 provides institutional context on the Drugs 75+ policy and related pharmaceutical reforms in Poland. Section 2.2 describes the data. Section 3.2.1 outlines the empirical strategy and presents the main findings on financial protection and reallocation. Section 4 concludes with policy implications and directions for future research.

2 Context and Data

Poland is the fifth biggest country in the European Union, after Germany, France, Italy, and Spain. Table 1 presents some basic statistics on the country's economy and demographics compared to the EU27 average. Even though the real GDP lags behind the EU average, the country has experienced rapid growth. 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 recent years, life expectancy at birth is below the EU average, and there is a large gap between men and women.

Table 1: 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)

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 seniors. 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 NFZ contracts through tenders to provide a set of predefined health services in predefined quantities, specified in 2009 by the Ministry of Health. 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. There is no cost-sharing for inpatient care, primary care, or outpatient specialist care.

The Polish public health insurance system is characterized by substantial patient cost-sharing for reimbursed outpatient medications, making pharmaceuticals the most significant component of out-of-pocket health expenditures. Before the Drugs 75+ policy, many prescription medications were eligible for partial reimbursement, but the level of support depended on the patient's diagnosed condition and the classification of the drug. Out-of-pocket costs did not depend on the patient's purchasing history. Reimbursement rates followed a tiered structure, with co-payment levels of 0%, 30%, 50%, 100%, or a fixed fee, applicable only to drugs listed on a formulary published by the Ministry of Health. This formulary contains the majority of the most commonly prescribed medications. In practice, patient co-payments were often higher than the formal rates because reimbursement was calculated based on the lowest-priced equivalent drug, and patients were responsible for paying any difference. Additionally, some medications were not reimbursed at all. This structure generated high out-of-pocket expenses, particularly among older adults and those with chronic conditions. Socioeconomic disparities in health outcomes remain one of the significant public health challenges in Poland (Sowada et al., 2019), and the Drugs 75+ policy represents a targeted intervention to mitigate these inequalities by removing cost barriers to essential medications for seniors.

The design of the Drugs 75+ policy is straightforward. As of September 1, 2016, individuals aged 75 or older became eligible for full reimbursement of prescription medications on a designated list published bi-monthly by the Ministry of Health. This list represents a subset of the broader set of partially reimbursed drugs under the existing system. For clarity, we refer to partially reimbursed drugs as those that received government co-pay support before the policy, and to fully reimbursed drugs as those covered under the Drugs 75+ program—a subset of the former.

To benefit from the program, patients must obtain a prescription from a primary care physician that includes a special annotation confirming eligibility. Reimbursement is also contingent on the drug being prescribed for approved medical indications. The selection of drugs included in the Drugs 75+ list was guided by three criteria: clinical relevance for the elderly population, safety and efficacy, and pre-policy accessibility.

The scope of the program has expanded over time. The initial 2016 list focused on medications for common chronic conditions among seniors, including hypertension, ischemic heart disease, thromboembolism, asthma, chronic obstructive pulmonary disease (COPD), diabetes, depression, and dementia. This initial set accounted for approximately 28.6% of the partially reimbursed drug list. Throughout 2017, and most notably in May 2018, the list was expanded to include specific cancer treatments, antibiotics, antiepileptics, opioids, and heparins. Following this extension, the Drugs 75+ list encompassed roughly 50% of the medications previously covered under partial reimbursement.

Table 2: Summary of Per-Person Monthly Prescription Medication Consumption Before and After Policy Change

	Policy	
Metric	Before	After
Panel A: Age < 75		
Out of Pocket per Person	1.603	1.685
Packages per Person	0.703	0.727
Total Cost per Person	4.965	5.283
Panel B: Age ≥ 75		
Out of Pocket per Person	6.533	2.680
Packages per Person	3.108	3.431
Total Cost per Person	18.465	21.237

Note: Based on administrative data on medication reimbursement obtained from the Polish government. The denominator for the per capita measures is the total population in the given age group in 2015 in Poland. Pre-policy corresponds to year 2015 and post-policy to year 2018

Table 2 summarizes per-person monthly prescription medication consumption and spending before and after the implementation of the Drugs 75+ policy, disaggregated by age group. Before the reform, individuals aged 75 and older consumed nearly 4.5 times more prescription medications than those under 75 and incurred proportionally higher out-of-pocket costs. In 2015, the average monthly cost of prescription medications among seniors was approximately $18.50 per person, of which $6.53 was paid out of pocket. Following the reform, out-of-pocket spending for this age group declined to $2.68, reflecting the impact of full reimbursement for a subset of medications. However, out-of-pocket costs did not fall to zero, as not all partially reimbursed drugs were included in the Drugs 75+ list.

2.2 Household Budgets Survey

We use microdata from the Polish Household Budget Survey (HBS) for the years 2015–2018.[1] Each month, a nationally representative sample of households is asked to complete a detailed expenditure diary for that month. Participating households keep a meticulous day-by-day record—verified during multiple enumerator visits—of all monetary outlays (cash, debit/credit card, or electronic transfer) as well as in-kind receipts, inter-household gifts, and other monetary transfers[2].

Expenditures then are categorized by the enumerators at a highly disaggregated level. Our analysis focuses on health-related spending, particularly the subcategory of medical products. This subcategory separately identifies pharmaceuticals, distinct from other items such as medical devices (e.g., eyeglasses or hearing aids), allowing us to isolate changes in drug consumption from other types of health spending.

[1] The data are collected by the national statistics office (GUS) and have been used in previous research, such as Gromadzki (2024).

[2] The monetary expenditures are originally in PLN which we express in USD using the average exchange rate in 2016.

Each household participates in the survey twice over a two-year period, and half of the sample is replaced annually. The dataset includes rich demographic information, including birthdates of all household members, which allows us to identify eligibility for the pharmaceutical subsidies at the time of the interview.

Our analysis focuses on people close to crossing the eligibility threshold, so we restrict the sample to households in which the oldest member is aged 65–85, yielding 46,976 observations. In Figure 1, we present average pre-policy pharmaceutical spending as a function of the age of the oldest household member in our sample. The data reveal a clear upward trend: medication expenditures rise with household age. Among households with members aged 75 and above, pharmaceutical spending accounts for approximately 8% of disposable income on average, with this share increasing with age. Nearly 20% of these households face catastrophic pharmaceutical expenditures, defined as spending exceeding 10% of disposable income. In addition, the poverty rate, measured using the European Union's relative poverty threshold[3], fluctuates between 15% and 20%. These patterns reveal the substantial financial burden that pharmaceuticals impose on elderly households and highlight their vulnerability to catastrophic health expenditures. These high expenditures are likely triggered by adverse health shocks—whether transitory (e.g., infections) or persistent (e.g., chronic diseases). Taken together, the evidence shows considerable scope for pharmaceutical policy intervention to alleviate financial hardship among seniors.

Table B1 in the Appendix provides additional summary statistics about demographic and spending characteristics of the households in the sample.

3 Estimation of the Policy Effects

3.1 Difference-in-Discontinuities

To evaluate the effects of the policy, we employ a difference-in-discontinuities approach, leveraging both the eligibility age cutoff for free drug access and the temporal dimension of the policy introduction in September 2016. 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[4].

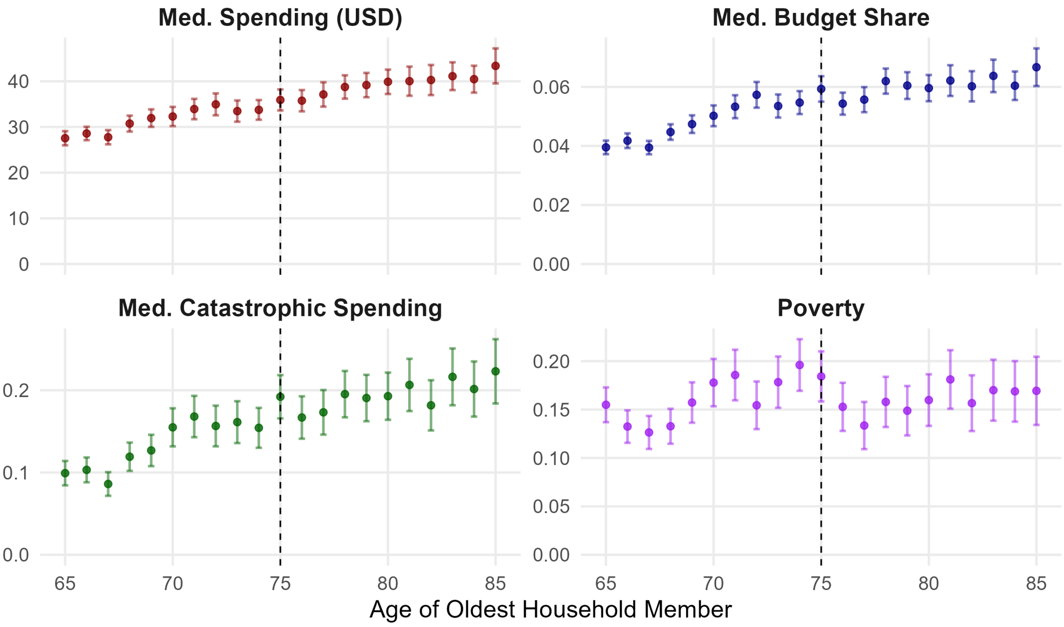
However, a traditional RDD is not applicable in this context due to a pre-existing program with the same age cutoff. Specifically, individuals aged 75 and older are eligible for a pension supplement of approximately 50 USD per month[5]. This overlap creates

[3]A household is considered poor if its equivalized disposable income—net of pharmaceutical expenditures—is below 60% of the national median.

[4]Because eligibility is based on individual age but the unit of observation is the household, this may attenuate treatment effects in multi-person households where only one member is eligible.

[5]The medical care supplement (*dodatek pielegnacyjny* in Polish), introduced in 1998, the amount is

Figure 1: Medication Expenditures by Age



Note: This figure shows pre-policy average expenditure on medication, budget share dedicated to medication, share of households with catastrophic spending on medication and households facing poverty. Catastrophic spending is defined as the share of disposable income spent on medication exceeding 10%. Poverty is measured using the European Union's relative poverty definition: weighted per capita household disposable income (net of medication expenditure) being below 60% of the national median. The vertical line marks 75 years. Error bars represent 95% confidence intervals.

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 Drugs 75+.

The difference-in-discontinuities estimate is calculated by first estimating RDD effects separately for the pre-policy and post-policy periods, and then taking the difference between them. 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 strategic adjustments in purchasing behavior do not drive our results, we conduct a robustness analysis using a donut RDD approach (Noack and Rothe, 2023), which excludes observations within three weeks of the 75th birthday. Our identification relies on the following assumptions: (1) outcomes would evolve smoothly across age in the absence of the drug policy; (2) the effect of the pre-existing pension supplement is stable over time and additive; (3) there is no manipulation of age reporting or birth timing.

updated every year and the cited figure refers to 2016.

We analyze four primary outcomes: (1) total spending on medication in (USD), (2) the share of disposable income allocated to medication, (3) a binary indicator for high (catastrophic) medication expenditure, defined as spending exceeding 10% of disposable income [6], (4) a binary indicator for whether the household is considered in poverty after the medication expenditures.

The poverty indicator is defined as having a per-capita disposable income, net of medication expenditures, that falls below 60% of the national median disposable income, following the European Union's definition of relative poverty[7]. Although the gross household income may remain unchanged, this poverty measure may react to the policy because it focuses on income available after medication expenditures. A reduction in out-of-pocket medication costs can directly shift households above or below this modified poverty threshold. Overall, these outcomes capture both direct financial impacts and the insurance value of the policy, potentially protecting against high expenditure stemming from negative health shocks.

We next examine whether the policy induces shifts in household spending across non-targeted categories. Two mechanisms may drive such reallocation: a direct liquidity effect stemming from a relaxed budget constraint, and an insurance effect that reduces the need for precautionary behaviors. The insurance channel, in particular, may lead households to reallocate spending toward goods that are riskier for health.

For each RDD, we use a bias-corrected estimator with local polynomial regression and optimal bandwidth selection as proposed by Calonico et al. (2020). We supplement our analysis with parametric specifications that vary bandwidths and polynomial orders to ensure robustness. 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.

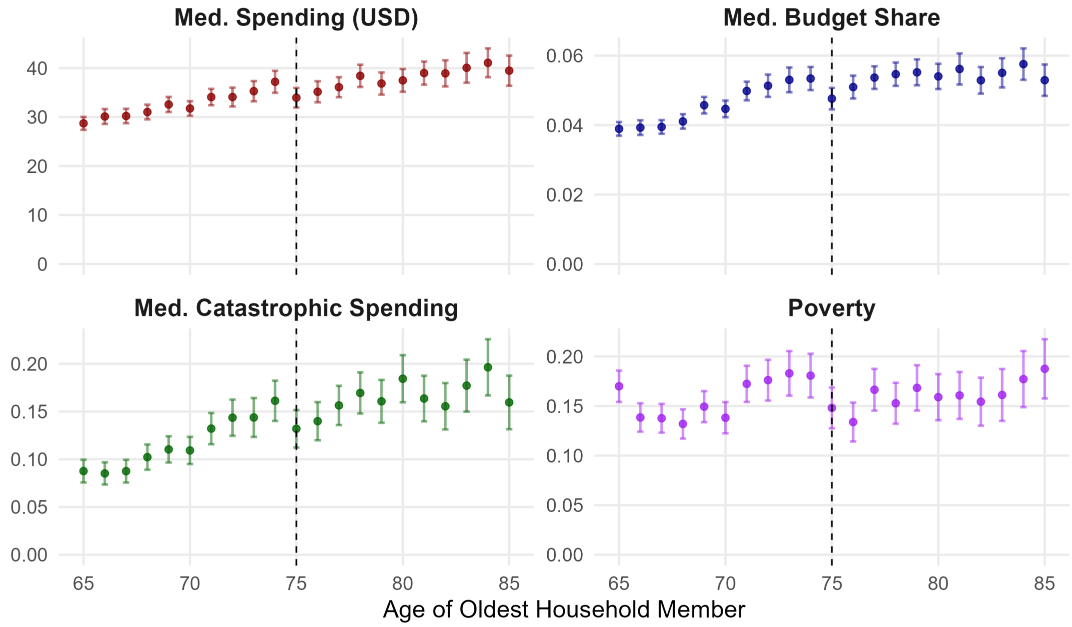
3.1.1 Results

We begin by visualizing average raw outcomes by age following the policy implementation in Figure 2. Across all outcomes, there is a distinct and sharp decline at age 75. While outcomes continue to rise gradually with age post-policy, they remain systematically lower than pre-policy levels. This contrasts sharply with the pre-policy trends in Figure 1, where no clear discontinuities are observed. While not apparent, given the potential confounding effect of a universal cash transfer occurring at age 75, we employ a difference-in-discontinuities design to isolate the policy's impact.

[6]This threshold corresponds to approximately the third quartile for households with an oldest member aged 74.

[7]We adjust household disposable income by an equivalence scale that accounts for household composition. Specifically, the household head is assigned a weight of 1.0, each additional member over 13 receives a weight of 0.7, and each child aged 13 or younger is assigned a weight of 0.5. Disposable income is then divided by the weighted household size to yield equivalized disposable income. We compute the median of this equivalized income distribution and define the relative poverty threshold as 60% of this median. A household is considered at risk of poverty after medical expenses if its equivalized disposable income, net of per-capita out-of-pocket medical expenditures, falls below this threshold.

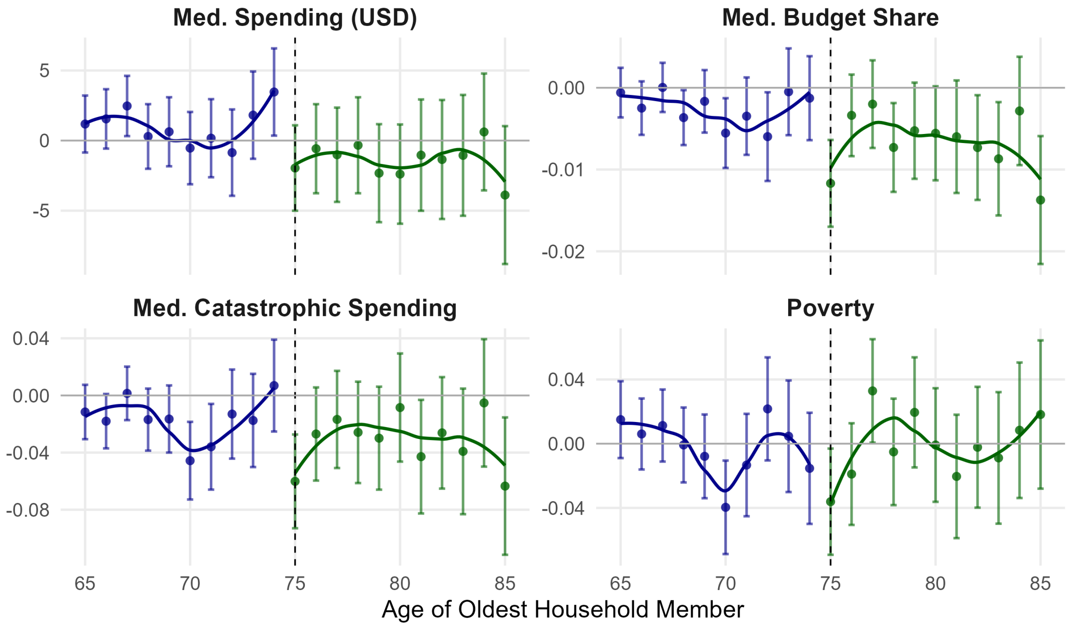
Figure 2: Post Policy Medication Expenditures by Age



Note: This figure shows post-policy average expenditure on medications, budget share dedicated to medications, share of households with catastrophic spending on medications and households facing poverty. Catastrophic spending is defined as the share of disposable income spent on medication exceeding 10%. Poverty is measured using the European Union relative poverty definition, weighted per capita household disposable income (net of medication expenditure) being below 60% of the national median. The vertical line marks 75 years. Error bars represent 95% confidence intervals.

To visualize this design, Figure 3 plots the difference in average outcomes between the post- and pre-policy periods for each age, overlaid with a smoothed loess curve. Since the confounding policy was present both before and after the introduction of free medication, its effect is differenced out. The graph confirms a pronounced break at the 75-year threshold for most outcomes, except poverty. We further quantify these effects in the formal analysis presented below.

Figure 3: Difference in Medication Expenditure by Age



Note: This figure shows post vs pre policy difference in outcomes by age of the oldest householders. The outcomes are average expenditure on medications, budget share dedicated to medications, share of households with catastrophic spending on medications, and households facing poverty. Catastrophic spending is defined as the share of disposable income spent on medication exceeding 10%. Poverty is measured using the European Union relative poverty definition, weighted per capita household disposable income (net of medication expenditure) being below 60% of the national median. The vertical line marks 75 years. Error bars represent 95% confidence intervals, and a smoothed curve is fitted using loess. n=.

Table 3 presents the formal estimates from the difference-in-discontinuities analysis. Before the policy, there is a slight, statistically insignificant increase in medication spending of $2.63 at the age 75 threshold (p-value = 0.26). In contrast, after the policy, we observe a significant decline of $5.72 in spending (significant at the 5% level). The estimated difference-in-discontinuities effect is a reduction of $8.36, with a 95% confidence interval ranging from $2.45 to $17.17. This represents a 23% decrease relative to the average spending of $35.75 at age 74. This substantial effect confirms that the policy significantly reduced out-of-pocket expenditures on prescription medications. However, the persistence of non-negligible spending levels indicates limitations in coverage — many drugs commonly used by older adults may not be included under the policy. Additionally, some of the attenuation may stem from greater consumption of complementary non-covered medications or shifting medication expenditures within the household to younger members.

The policy also significantly reduces the share of disposable income allocated to medications. The estimated decline in that share at age 75 is 2 percentage points, statistically significant at the 5% level. This is a very large effect, given that households with a 74-year-old oldest member spend approximately 5.4% of their disposable income on medications.

The most striking is the impact on financial risk protection. The share of households experiencing catastrophic medication expenditures falls by 9.8 percentage points, significant at the 5% level, corresponding to a 62% reduction relative to the pre-policy mean of 16%. This result shows the strong insurance value of the policy, which shields households from major health-related financial shocks. In the Polish context, where out-of-pocket medication spending is the main out-of-pocket healthcare expense, this represents a near elimination of exposure to catastrophic healthcare costs.

Finally, the estimated effect on poverty incidence is modest and statistically insignificant, corresponding to a reduction of 1.4 percentage points. One potential explanation is that the existing medical care supplement had already mitigated much of the poverty risk among senior households. Additionally, the absence of a significant poverty effect suggests that out-of-pocket expenditures on prescription medications, while burdensome for some, are not a principal determinant of poverty status in this context. This may reflect the nature of medication spending as a normal good that tends to increase with income (see Figure B1 in the Appendix for the observed positive correlation between income and pharmaceutical expenditure). Consequently, higher-income households, spending more on medications before the policy, now experience greater savings. However, since these households were not at risk of poverty, the resulting increases in their disposable income net of medication expenditures do not translate into measurable changes in poverty rates. This heterogeneity in the policy's financial impact is explored and empirically confirmed in the next section.

Table 3: Difference-in-Discontinuities

Outcome	Before	After	Diff-in-Disc	95% CI	Mean at 74
Spending	2.633	-5.723*	**-8.356**	[-17.171, -2.454]	35.747
Budget Share	0.010	-0.009**	**-0.020**	[-0.034, -0.007]	0.054
Catastrophic Spending	0.057	-0.041*	**-0.098**	[-0.189, -0.021]	0.16
Poverty	-0.029	-0.044*	-0.014	[-0.083, 0.100]	0.16

Note: This table reports the difference-in-discontinuities estimates from the main specification for four outcomes: Spending on Medication (in USD), Budget Share dedicated to Medications, Catastrophic Spending on Medication, and Poverty. Catastrophic spending is defined as the share of disposable income spent on medication exceeding 10%. Poverty is measured using the European Union relative poverty definition, weighted per capita household disposable income (net of medication expenditure) being below 60% of the national median. The first two columns represent RDD estimates pre- and post-policy, respectively, and the third is the difference-in-discontinuities. The stars are based on p-value for the before and after RDD estimates only (* being significant at 5% and ** at 1%). Sample size is 46,976. Errors are clustered at the household level. Confidence intervals are calculated as percentiles of the distribution of differences from 300 bootstrap iterations. These bootstrap iterations also derive the average bandwidths applied in the pre- and post-policy periods.

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 B2 in the Appendix). Similarly, parametric specifications (Table B3 in the Appendix) yield slightly smaller estimates, with spending reductions ranging between $9 and $4, but all remain statistically significant.

3.2 Heterogeneity in Policy Effects

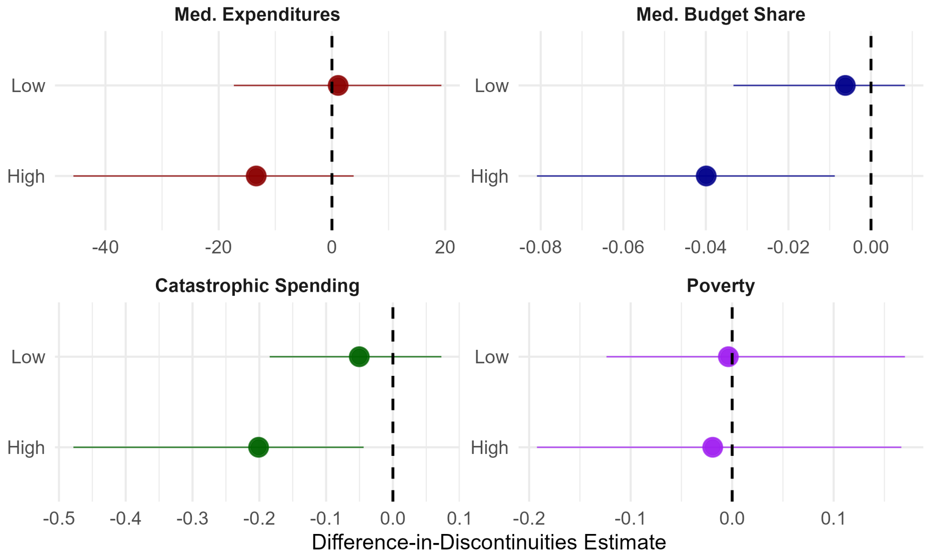
To better understand who experiences larger financial gains from the policy, we examine how its effects vary across key household characteristics. Figures 4 through 9 present estimates from the difference-in-discontinuities design, stratified by pre-policy medication burden, household size, age composition, income, and population density. Figure B2 in the Appendix confirms a low degree of correlation between these characteristics. Each subplot reports subgroup-specific effects on four outcomes: medication expenditures, the budget share allocated to medications, the incidence of catastrophic spending, and poverty. Error bars represent 95% confidence intervals based on bootstrap replications.

The largest effects are concentrated among households with the highest exposure and financial need: specifically, those with high pre-policy medication spending, single-person households, and households composed entirely of older adults. Interestingly, we also observe relatively strong effects among higher-income households and those residing in densely populated areas. These patterns may reflect higher pre-policy spending and better access to physician appointments or pharmacies among high-income households and in urban settings.

1. Policy Exposure

We begin by examining heterogeneity based on households' exposure to the policy. First, we consider the households' burden of medication expenditure. To do so, we restrict the sample to households observed at least once before the policy. We then divide them into high and low spenders based on their pre-policy medication budget share, using the sample median of 3.5% as the cutoff. We then estimate the difference-in-discontinuities separately for the high- and low-spending groups.

Figure 4: Effects by Pre-Policy Medication Budget Share

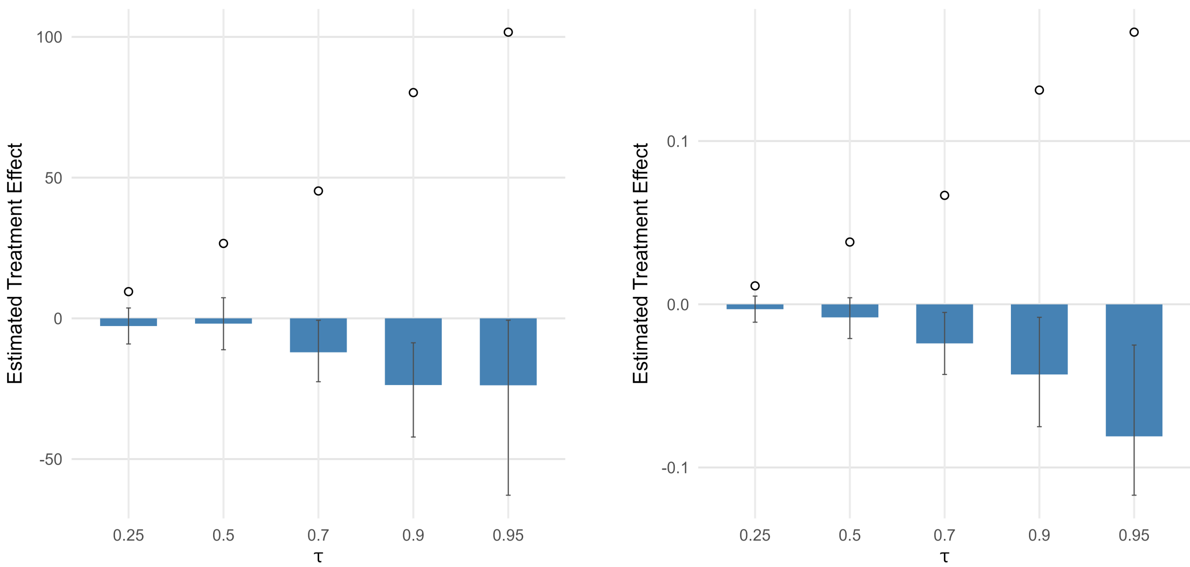


Note: This figure shows the heterogeneity of the effects of the policy by the pre-policy budget share of the household dedicated to medication. It is divided into two groups: low and high, with the median as the cutoff. The dot represents the difference-in-discontinuities estimate. Vertical line marks 0. Error bars represent 95% confidence intervals from bootstrap. Sample size is 23,445.

As shown in Figure 4, households with above-median pre-policy medication spending experienced substantially larger improvements across nearly all outcomes. While the decline in absolute medication expenditures is sizable, it is not statistically significant at the 5% level. However, the reduction in the budget share allocated to medications is both large and significant, amounting to approximately 4 percentage points. The most pronounced effect is observed in the incidence of catastrophic medication spending, which declines by 20 percentage points among high-exposure households—a substantial reduction in financial risk. In contrast, effects for the low-exposure group are small and statistically indistinguishable from zero across all outcomes. As in prior analyses, there is no meaningful impact on poverty in either subgroup, and the estimates remain imprecise with wide confidence intervals. These findings confirm that the policy delivers the greatest financial benefits to households most burdened by medication costs before its implementation.

To unpack further the distributional origins of the average treatment effects, we examine how the policy influenced different points in the outcome distribution. Specifically, we estimate quantile treatment effects (QTEs) using the methodology developed by Qu et al. (2024), which extends the regression discontinuity design (RDD) to quantile outcomes. We adapt this approach to our difference-in-discontinuities framework. We estimate treatment effects for the 0.25, 0.50, 0.70, 0.90, and 0.95 quantiles of both monthly medication spending and the budget share allocated to medications.

Figure 5: Quantile Treatment Effects on Medication Outcomes



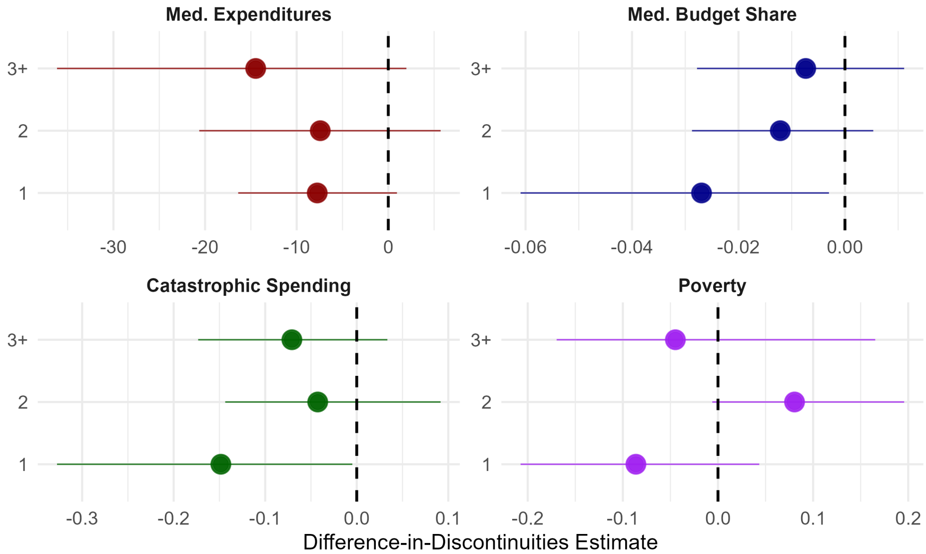
(a) Total Medication Spending (USD) (b) Budget Share of Medication

Note: These figures present estimated quantile treatment effects of the policy on the distribution of medication-related outcomes, using difference-in-discontinuities in quantiles. Blue bars represent the estimated difference at each quantile τ in (1) monthly medication spending in USD (left) and (2) the share of income spent on medications (right), comparing households just above and just below the age 75 threshold before and after the policy. Vertical lines denote 95% confidence intervals obtained from bootstrap. Hollow circles denote the corresponding quantiles at 74, allowing comparison to baseline values at each τ. Sample size is 46,976.

As illustrated in Figures 5a and 5b, the effects are highly concentrated in the upper tail of the distribution. We find no statistically significant changes at the 25th or 50th percentiles for either outcome, suggesting that lower and median spenders were largely unaffected. In contrast, substantial and statistically significant reductions are observed at the 70th, 90th, and 95th percentiles. This pattern indicates that the policy was particularly effective in mitigating extreme out-of-pocket medication costs, providing strong protection against financial risk for households facing the highest burdens. For the 90th and 95th percentiles of the budget share of medication, exceeding the 10% threshold for catastrophic spending, the policy succeeds at, on average, bringing these households below this threshold.

Next, we examine heterogeneity in policy effects by household size—another important exposure dimension. Since our running variable is the age of the oldest member, in single-person households, 100% of household members are potentially eligible for the policy once the age threshold is reached. In contrast, in larger households, only one individual is likely to qualify at the cutoff, meaning that a smaller share of the household benefits directly from the reform. While cases where spouses or cohabiting adults cross the eligibility threshold simultaneously are possible, such scenarios are less likely. We therefore stratify households into three groups: single-person, two-person, and households with three or more members.

Figure 6: Effects by Household Size



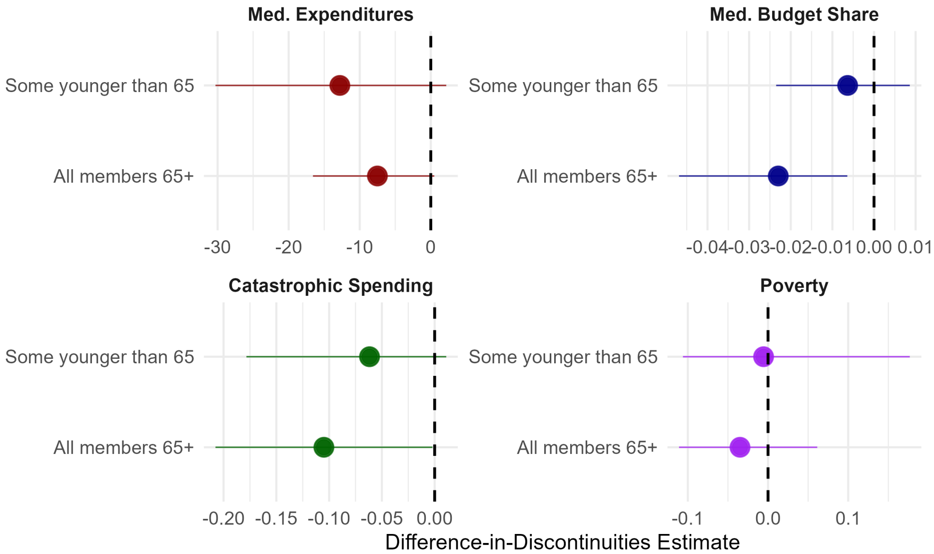
Note: This figure shows the heterogeneity of the effects of the policy by household size. The dot represents the difference-in-discontinuities estimate. Vertical line marks 0. Error bars represent 95% confidence intervals from bootstrap. Sample size is 46,976.

As shown in Figure 6, the results are somewhat noisy but broadly consistent with the hypothesis that smaller households, where a larger share of the household is affected, experience more substantial relative effects. While the point estimate for the decline in medication expenditures is slightly larger for larger households, it is not statistically significant and likely reflects higher baseline spending and incomes in those groups.

More tellingly, the most significant reductions in the medication budget share and the incidence of catastrophic spending are observed among single-person households. While the cross-group differences are not statistically significant—likely due to limited statistical power—they are directionally consistent and economically meaningful. Once again, we find no significant effect on poverty across any household size category. These patterns suggest that the policy offers powerful financial protection to single-person households, arguably among the most vulnerable to health-related financial shocks. With no capacity for intra-household risk pooling and only a single income to buffer medical expenses, such households would face heightened exposure to out-of-pocket health costs absent the policy.

As the final dimension of heterogeneity in exposure, we examine household age composition. Households composed entirely of older adults will likely be more exposed to the policy's benefits, as they allocate a larger share of their budget to medications. Even if only one member is formally eligible, there may be within-household sharing or cross-use of subsidized medications. To assess this, we divide the sample into households with all members aged 65 or older and at least one younger member.

Figure 7: Effects by Household Age Composition



Note: This figure shows the heterogeneity of the effects of the policy by household age composition. The dot represents the difference-in-discontinuities estimate. Vertical line marks 0. Error bars represent 95% confidence intervals from bootstrap. Sample size is 46,976.

As shown in Figure 7, the decline in the medication budget share is more pronounced in older-only households, consistent with their greater financial exposure to medical expenses. For the other outcomes, the differences between household types are relatively small and not statistically significant.

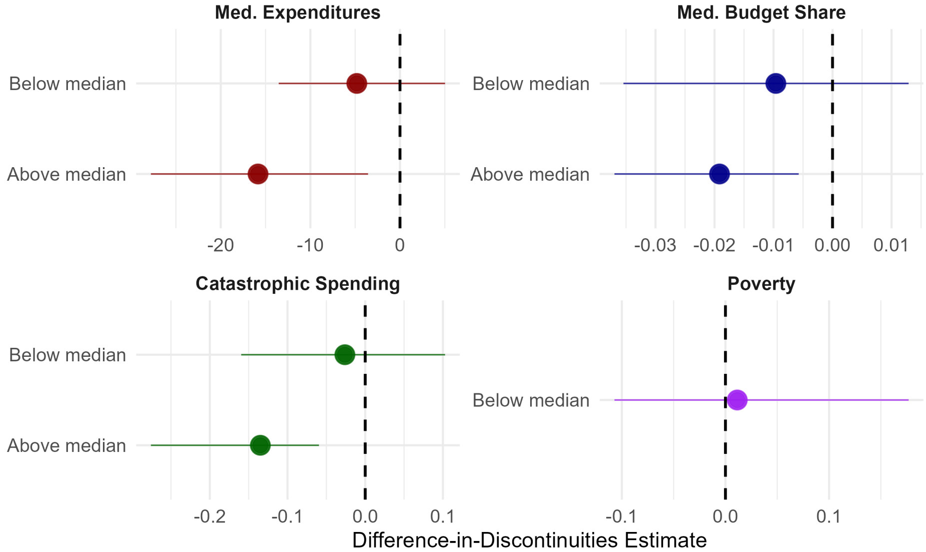
Overall, the heterogeneity analysis shows that the policy offers the most financial relief to households with the greatest need, particularly those that spent more on medication before the policy, live alone, or consist only of seniors. These results point to a degree of effective targeting. However, we now turn to distributional dimensions such as household income and geographic context to assess the broader equity implications.

2. Economic Vulnerability

We next examine whether the policy disproportionately affects economically disadvantaged groups, focusing on two dimensions: household income and the population density of the household's location.

We begin by analyzing heterogeneity by income, dividing households into two groups: those above and below the median level of per-capita disposable income. There are several reasons to expect differential effects by income. Higher-income households may spend more on medications at the baseline, given that prescription drugs are a normal good. They may also have better access to healthcare providers, which is a prerequisite for obtaining prescriptions and thus for benefiting from the policy. In contrast, lower-income households may have had limited medication consumption before the policy due to affordability constraints. While the policy may enable them to increase their medication use, this may not be reflected in observed expenditures, since covered medications are provided free of charge.

Figure 8: Effects by Household Income



Note: This figure shows the heterogeneity of the policy's effects by the household's per-capita disposable income. It is divided into two groups: below and above the median. The dot represents the difference-in-discontinuities estimate. Vertical line marks 0. Error bars represent 95% confidence intervals from bootstrap. Sample size is 46,976.

As shown in Figure 8, higher income households exhibit substantially larger reductions in absolute medication spending and the budget share devoted to medications. This does not necessarily mean that the policy does not provide relief to poor households. Instead, they might increase free consumption without a change in expenditures or reallocate the savings from the policy to a higher degree to other medications, not covered by Drugs 75+. Section A of the Appendix formalizes theoretically why poorer households experience lower financial effects. We show that the lack of effect on medication expenditures could stem from the poorest households struggling to afford the medication they needed before the reform. Underconsumption of prescription drugs (due to their affordability) decreases the financial gain from Drugs 75+. Rather than pointing to problems with the policy's targeting, the small effect on expenditures of the lower-income households can suggest that drug prices are an important barrier to access to treatment in Poland.

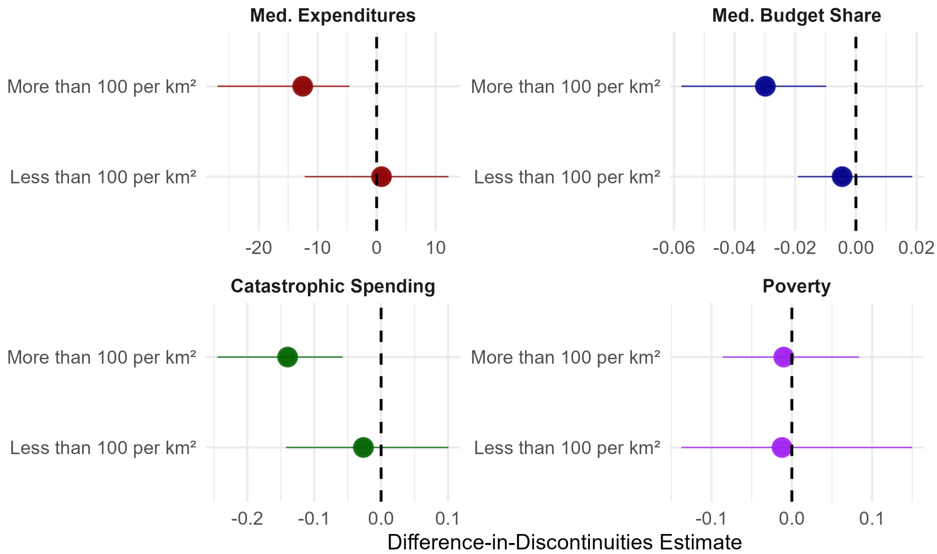
Higher-income households also experience a more substantial decline in the probability of catastrophic spending, indicating that the policy offered more effective financial protection to this group. On the other hand, the effect for the lower-income group could be attenuated by households whose income is too low to afford high medication spending. Last, the policy does not appear to significantly affect poverty rates[8]. This is unsurprising, given the lack of significant effects among poorer households.

Finally, we examine whether the policy's effects vary by household location, specifically population density. We divide households into two groups based on whether they reside in areas with more or fewer than 100 inhabitants per square kilometer. Residents in less densely populated areas often face a range of socioeconomic disadvantages. More

[8]By construction, households above the median income are not classified as poor, so no poverty effect is observed for them.

importantly, they may encounter greater barriers to healthcare access, including fewer providers authorized to prescribe medications and more limited proximity to pharmacies, which may hinder their ability to benefit from the policy. It needs to be noted, however, that the differences by income and location may also capture unobserved variation in health status or care-seeking behavior rather than just in healthcare access.

Figure 9: Effects by Location Density



Note: This figure shows the heterogeneity of the effects of the policy by population density. It is divided into two groups: below vs. above 100 inhabitants per km^2. The dot represents the difference-in-discontinuities estimate. Vertical line marks 0. Error bars represent 95% confidence intervals from bootstrap. Sample size is 46,976.

As shown in Figure 9, the entire effect of the policy is concentrated among households living in densely populated areas. These households experience substantial reductions in medication expenditures, budget share, and the incidence of catastrophic spending. In contrast, households in sparsely populated areas show no statistically or economically meaningful change across any outcome. As in previous analyses, we find no significant effect on poverty in either group.

The heterogeneity analysis confirms that the policy is most effective in financially protecting households with a high pre-policy medication burden and those most exposed due to household size and composition. However, the financial benefits appear to accrue disproportionately to households with greater socioeconomic advantage—those with higher incomes and those living in more urban areas. These groups are more likely to have access to the healthcare infrastructure necessary to utilize the policy fully. While the policy aims to alleviate financial risk among vulnerable senior households, these findings raise important concerns about distributional equity. The reform may inadvertently reinforce existing financial inequalities if more advantaged households are better positioned to capture its benefits.

3.2.1 Spending Reallocation

We find that the policy leads to a reduction of approximately $8 in monthly medication spending among seniors, along with a substantial decline in the probability of incurring high medication expenditures. These patterns suggest that the policy modestly relaxes the current-period budget constraint while also providing insurance against future health-related financial risks.

In light of these two effects, we may expect households to reallocate spending toward other categories.

To examine this possibility, Figure 10 reports difference in discontinuity estimates of the policy's impact on the spending allocated to other categories. We focus on consumption categories similar to those used by Gromadzki (2024), with greater emphasis on items particularly relevant to health and older populations. Specifically, following their approach, we classify food products based on their nutritional rating—from A (most healthful) to E (least healthful)—to assess potential shifts in dietary quality. In addition, we disaggregate health-related expenditures into more granular subcategories to explore whether the policy generates complementarities or substitution effects within different types of health spending.

Figure 10: Diff-in-Disc Estimates for Alternative Outcomes

Note: This figure presents difference-in-discontinuity estimates from the main specification for alternative spending categories. Regressions are weighted using survey weights. Confidence intervals are constructed using 500 bootstrap replications. Sample size is 46,976.

Figure 10 indicates that the observed \$8 reduction in medication spending is accompanied by a \$5 increase in expenditures on alcohol and cigarettes. This is the only statistically significant substitution effect ($p < 0.05$). The shift is also meaningful in magnitude: average monthly spending in this category at age 74 is \$13.1.

Changes in other expenditure categories are statistically insignificant and small when compared to their respective means. Interestingly, we do not observe any effects when it comes to spending in other health categories.

This increase in spending on categories potentially harmful to health—particularly alcohol and cigarettes—may reflect a form of moral hazard. A more relaxed budget constraint, combined with improved access to medication and a perceived insurance against future health shocks, can reduce the perceived costs of engaging in risky behaviors. For example, easier access to diabetes medication may lower the perceived health risks associated with alcohol consumption, thereby weakening incentives to abstain or moderate intake among individuals at metabolic risk.

This substitution effect is further supported by heterogeneity analyses, which show that groups experiencing larger declines in medication spending also exhibit greater increases in alcohol and cigarette consumption. Figures B4, B3, B5, B6, and B7 in the Appendix present results by pre-policy medication cost burden, household size, age composition, income level, and population density. Across most subgroups, we observe patterns consistent with substitution toward alcohol and cigarettes following the reduction in out-of-pocket medical costs.

These findings suggest that financial relief in one health domain may inadvertently lead to increased consumption of health-adverse goods, highlighting the importance of anticipating behavioral spillovers in the design of social policies.

4 Discussion and Conclusion

This paper evaluates the financial effects of Poland's Drugs 75+ policy, which introduced universal, age-based access to free prescription drugs for individuals aged 75 and older. Using a difference-in-discontinuities approach, we find modest reductions in average medication expenditures and a substantial decline in the incidence of catastrophic spending. Normatively, the policy offers strong insurance value by protecting seniors from large health-related financial shocks. While it may improve welfare by smoothing consumption in response to health shocks, a complete assessment would also require consideration of medication use, public costs, and health outcomes.

Heterogeneity analysis reveals that the largest financial gains accrued to households with high pre-policy medication spending, those living alone, and those composed entirely of older adults—groups most exposed to out-of-pocket medical expenses. However, we also find that higher-income and urban households benefited disproportionately, likely due to higher baseline spending and better access to healthcare providers and pharmacies. These results raise concerns about the distributional equity of universal subsidies: while the goal is to protect vulnerable seniors, better-off groups may be best positioned to take advantage of the policy—gaining both access and financial savings.

We also find evidence of reallocation toward alcohol and cigarette consumption, particularly among households experiencing the largest reductions in medication spending. This pattern is consistent with ex-ante moral hazard: insurance weakens incentives for precautionary health behavior

These findings have important implications for the design of pharmaceutical subsidy programs. While policies like Drugs 75+, Medicare Part D, and similar European exemptions are often presented as universal and equitable, our results suggest that financial benefits may concentrate among more advantaged groups with better access to healthcare infrastructure. Removing price barriers alone may be insufficient to ensure equitable outcomes; complementary efforts to expand provider and pharmacy access could be crucial. The observed reallocation toward alcohol and cigarettes also raises concern that intended health gains may be partially offset by behavioral responses. To counteract these spillovers, policymakers could consider introducing corrective taxes or targeted disincentives on health-adverse goods alongside subsidy expansions.

While our analysis provides robust evidence on financial protection, it does not capture the full scope of policy effects. Notably, we do not observe changes in medication adherence or health outcomes, which are partially addressed in Majewska and Zaremba (2025). Existing evidence (Chandra et al. (2024)) suggests drug affordability can influence health, indicating an important omitted margin. Our data also lack detail on prescription versus over-the-counter purchases, limiting analysis of within-category substitution. Finally, the increase in alcohol and cigarette spending should be interpreted cautiously; without direct behavioral data, we cannot rule out alternative explanations such as greater discretionary income.

Future research should examine the effects of such policies on health, provider behavior, and long-term healthcare expenditures to evaluate their full impact. Cross-country research could also examine whether similar age-based drug subsidies have differential impacts in more decentralized or privately financed systems.

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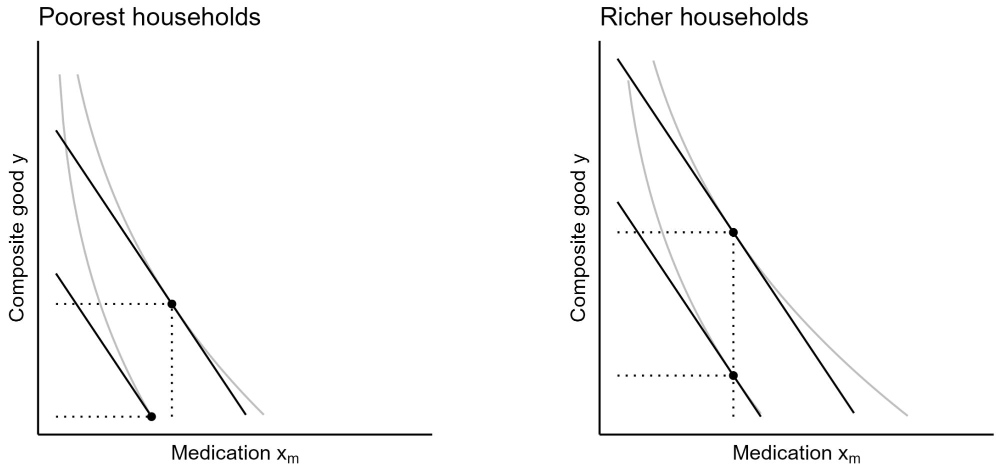
Appendix A Theoretical Predictions

The basic microeconomics concept of optimal choice under a changing budget constraint can provide intuitions and guide our interpretation of the empirical results. We can assume that households allocate their budgets to medication and a composite good, aggregating the consumption of everything else than medication. Within medication, we distinguish prescription drugs covered by Drugs 75+, for which the households spend e_m before the introduction of the policy and other drugs consumed, denoted by x_m acquired by the household at price p_x. The composite good is denoted by y and priced at p_y.

Drugs 75+ affects the optimal bundle consumed by a household and the budget at its disposal for x_m and y. Before the policy, the household's consumption is limited by the budget m: $p_x x_m + e_m + p_y y \leq m$. After the reform, households save e_m on prescription drugs and can allocate that amount to x_m and y, giving a budget constraint: $p_x x'_m + p_y y' \leq m$.

From the point of view of the optimal bundle in the (x_m, y) space, the policy results in a shift of the budget constraint to the right. The change in consumption depends on the shape of the household's preferences and its relative wealth. In Figure A1 we show the impact of the policy under quasi-linear utility, for relatively richer and poorer households (keeping the preferences and budget change constant).

Figure A1: Change in consumption due to the policy under quasi-linear utility $U(x_m, y) = bx_m^a + y$



Under quasi-linear utility, the optimal level of consumption of the good x_m depends on the prices and the shape parameters of the utility function. The savings from prescription drugs covered by the policy are fully allocated to the consumption of y unless the household was not able to purchase the optimal amount of medication before the policy and was in a corner solution as shown in the left-hand graph of Figure A1[9]. Assuming quasi-linear utility implies that the total budget affects the consumption of medication of the poorest households, but its optimal level - or the need - does not vary with income.

[9]The corner solution implies 0 consumption of other goods. We assume the household already satisfies some minimum basic needs before allocating the remaining budet m to x_m and y.

The poorest households will first allocate the savings from the policy to other medication, and only once their needs are satisfied in this area will they consume y. For households that are in the corner solution before and after Drugs 75+, we will not observe a change in total spending on medication: $p_x x'_m = p_x x_m + e_m$.

For households who were in a corner solution before the policy but after are not, the spending on medication will slightly decrease as part of the savings is allocated to y: $p_x x'_m < p_x x_m + e_m$. This decrease entails a small drop in the budget share of medication for these households. Finally, the richer households that were able to satisfy all their medication needs already before the policy do not change their consumption of x_m and allocate all their savings from free prescription drugs towards y. Only these households will see a decrease in overall medication spending equal to e_m.

Summarizing, we expect that the impact of the policy on household spending on medication and its budget share will depend on the income level of the household. For the poor, the policy does not affect spending at all or only to a small degree. The decrease in spending is the highest for households that are relatively richer and were able to buy all the needed medication already before the policy. Moreover, the impact of the policy will depend on the saving made, so the pre-policy spending on the covered prescription drugs. If poorer households were restricting their consumption of the covered drugs before the policy than equivalent (in terms of health status), richer households, their savings will also be smaller.

Appendix B Additional Results

Table B1: Summary Statistics by Age Category

Age of Oldest HH Member	55-65	65-75	75-85	Above 85
HH size	2.44	2.21	2.33	2.65
Mean HH Age	52.62	62.40	69.24	72.56
Share Female	0.54	0.60	0.63	0.64
Mean Disposable Income (USD)	845.07	770.00	781.45	887.93
Share Oldest Married	0.65	0.53	0.34	0.16
Share Oldest with Higher Education	0.14	0.15	0.12	0.08
Monthly Mean Spending (USD):				
Food	164.56	153.49	148.03	158.65
Health	38.14	47.35	54.17	57.76
Alcohol and Cigarettes	20.48	14.70	12.16	14.84
Housing and Utilities	142.25	138.20	136.38	143.32

Note: This table provides summary statistics on the households according to the age of the oldest household member. Based on pre-policy data.

Table B2: Donut Difference-in-Discontinuities

Outcome	Before	After	Diff-in-Disc	95% CI	Avg. Bandwidths	Mean at 74
Spending	2.629	-7.955	-10.584	[-20.297, -2.770]	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
Catastrophic Spending	0.055	-0.052	-0.107	[-0.199, -0.041]	Pre: 2.49, Post: 3.26	0.157
Poverty	-0.041	-0.039	0.002	[-0.081, 0.136]	Pre: 2.21, Post: 3.22	0.160

Note: This table reports the difference-in-discontinuities estimates from the specification excluding 3 weeks around the 75th birthday for four outcomes: Spending, Budget Share, Catastrophic Spending, and Poverty. 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. Sample size is 46,777.

Table B3: Parametric Difference-in-Discontinuities

Bandwidth	Polynomial	Spending	Budget Share	Budget Share>10%	Poverty	Obs
Bandwidth = 2						
2	1	-6.020** (2.980)	-0.013** (0.005)	-0.074** (0.030)	-0.041 (0.031)	9877
2	2	-9.317** (4.553)	-0.017** (0.008)	-0.091* (0.047)	-0.001 (0.047)	9877
2	3	-4.288 (6.019)	-0.014 (0.011)	-0.025 (0.066)	0.034 (0.063)	9877
Bandwidth = 3						
3	1	-6.715*** (2.496)	-0.011*** (0.004)	-0.057** (0.025)	-0.016 (0.026)	13943
3	2	-6.434* (3.686)	-0.016** (0.006)	-0.092** (0.038)	-0.036 (0.038)	13943
3	3	-8.880* (4.761)	-0.014 (0.009)	-0.073 (0.052)	0.010 (0.050)	13943
Bandwidth = 5						
5	1	-3.973** (1.974)	-0.007** (0.003)	-0.055*** (0.020)	-0.030 (0.021)	22670
5	2	-6.879** (2.944)	-0.015*** (0.005)	-0.068** (0.030)	-0.026 (0.031)	22670
5	3	-8.994** (3.939)	-0.017** (0.007)	-0.090** (0.041)	-0.016 (0.041)	22670
Mean Outcome at Age 74 for Bandwidth = 5						
		35.747	0.054	0.158	0.187	

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, (3) an indicator for whether medication spending exceeds 10% of total disposable income, and (4) relative poverty indicator. Sample size is 46,976.

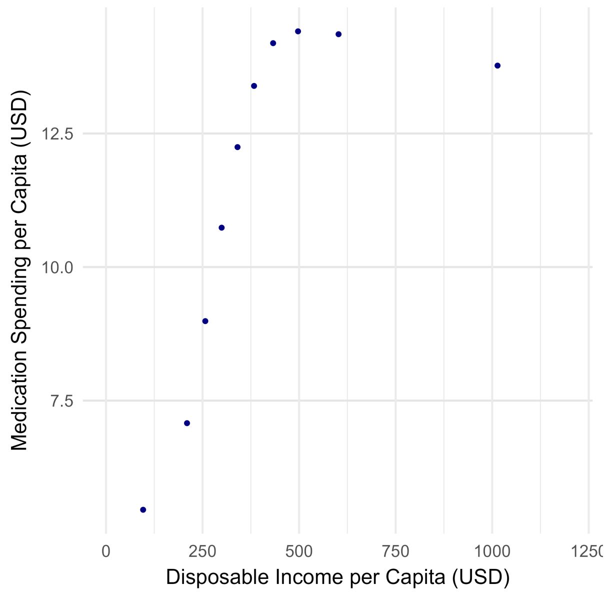


Figure B1: Binsreg of Medication Spending and Income

Note: This figure presents binscatter regression (with 10 bins representing deciles) of per capita spending on medication (USD) on per capita disposable income (USD) in the main estimation sample (n=46,976).

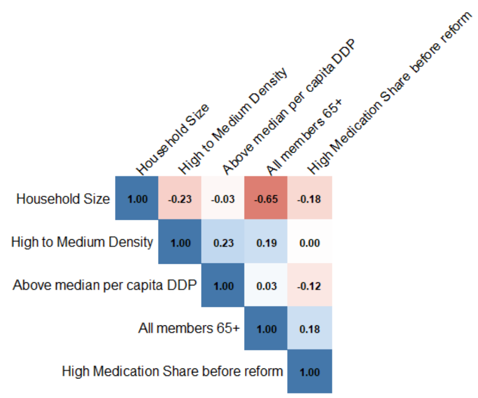


Figure B2: Correlation among Heterogeneity Variables

Note: This figure presents correlations between variables used for the heterogeneity analysis. Dark blue indicates strong positive correlation, dark red strong negative correlation and white zero correlation.

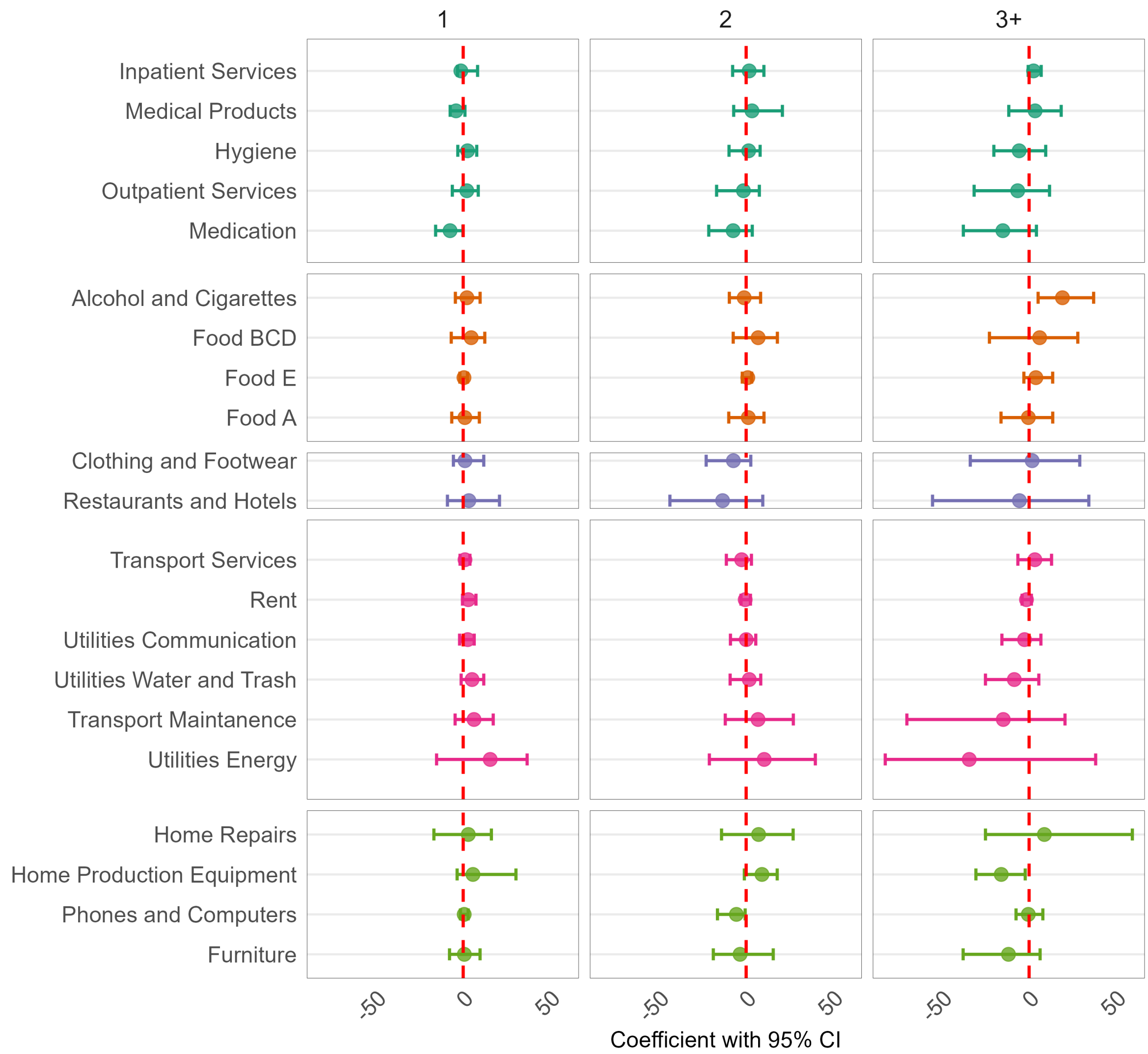


Figure B3: Diff-in-Disc Heterogeneity: Household Size

Note: This figure presents difference-in-disconituity estimates for the alternative outcomes split by household size. Regressions are weighted by survey weights. 95% confidence intervals are based on 500 bootstrap iterations. Sample size is 46,976.

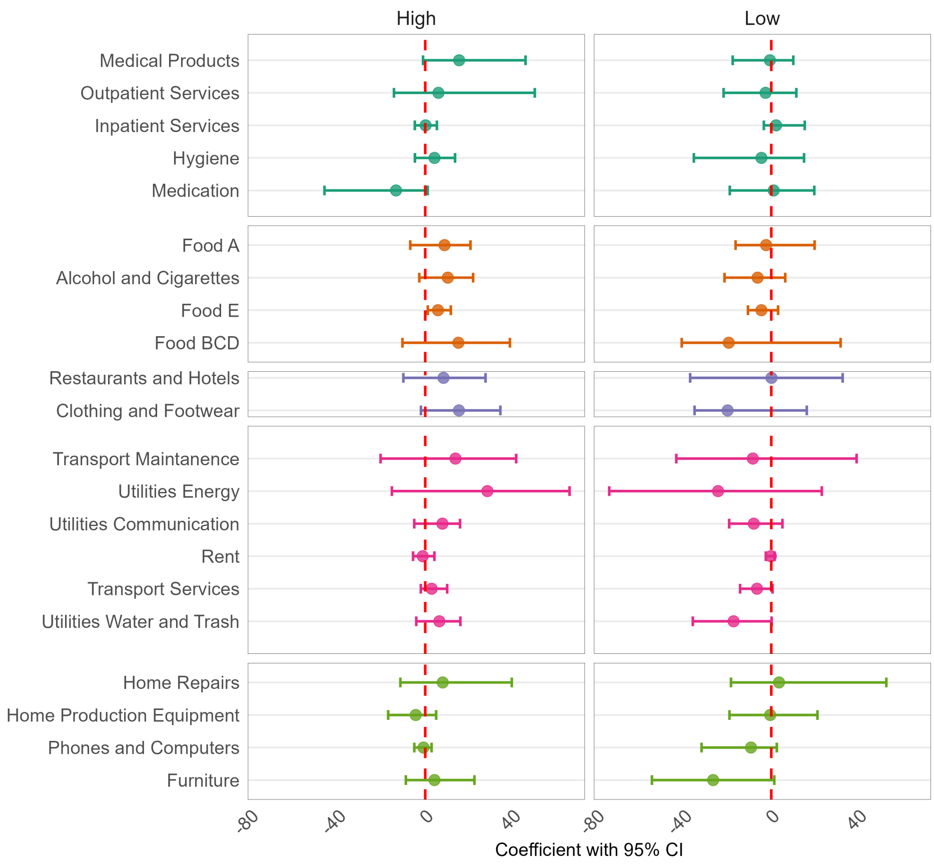


Figure B4: Diff-in-Disc Heterogeneity: Previous Medication Budget Share

Note: This figure presents difference-in-disconituity estimates for the alternative outcomes split (along median) by the pre-policy budget share of the household dedicated to medication . Regressions are weighted by survey weights. 95% confidence intervals are based on 500 bootstrap iterations. Sample size is 23,445.

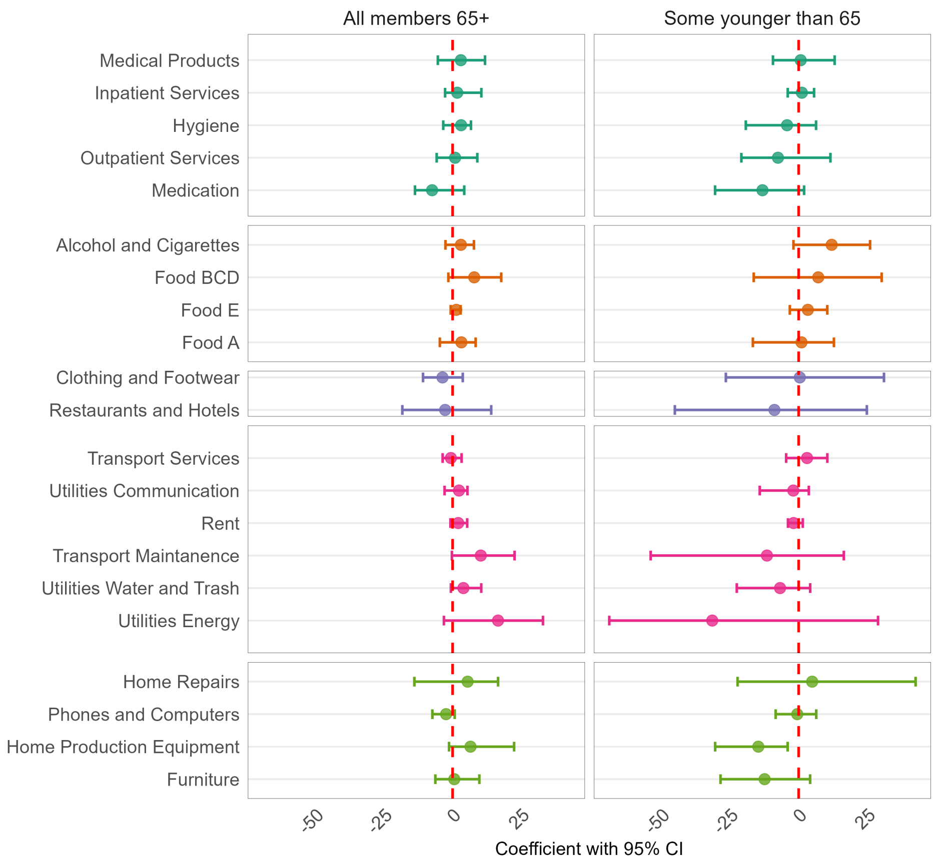


Figure B5: Diff-in-Disc Heterogeneity: Household Composition

Note: This figure presents difference-in-disconituity estimates from the main specification for the alternative outcomes. Regressions are weighted by survey weights. 95% confidence intervals are based on 500 bootstrap iterations. Sample size is 46,976.

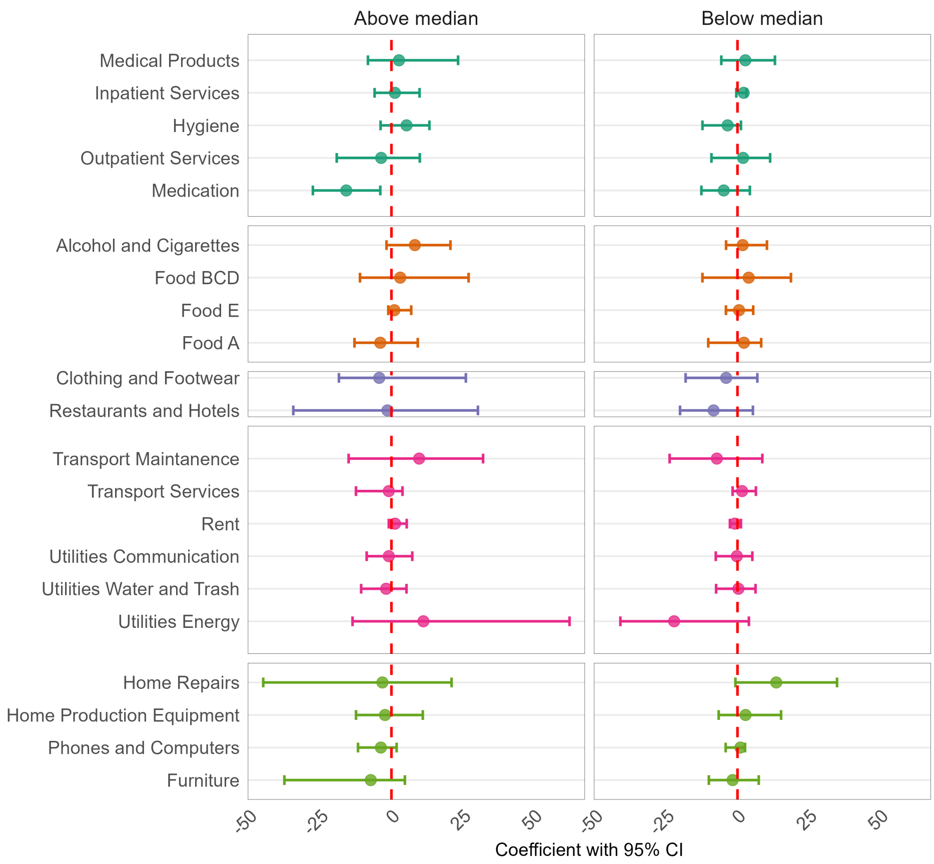


Figure B6: Diff-in-Disc Heterogeneity: Income

Note: This figure presents difference-in-disconituity estimates for the alternative outcomes split by per capita disposable income. Regressions are weighted by survey weights. 95% confidence intervals are based on 500 bootstrap iterations. Sample size is 46,976.

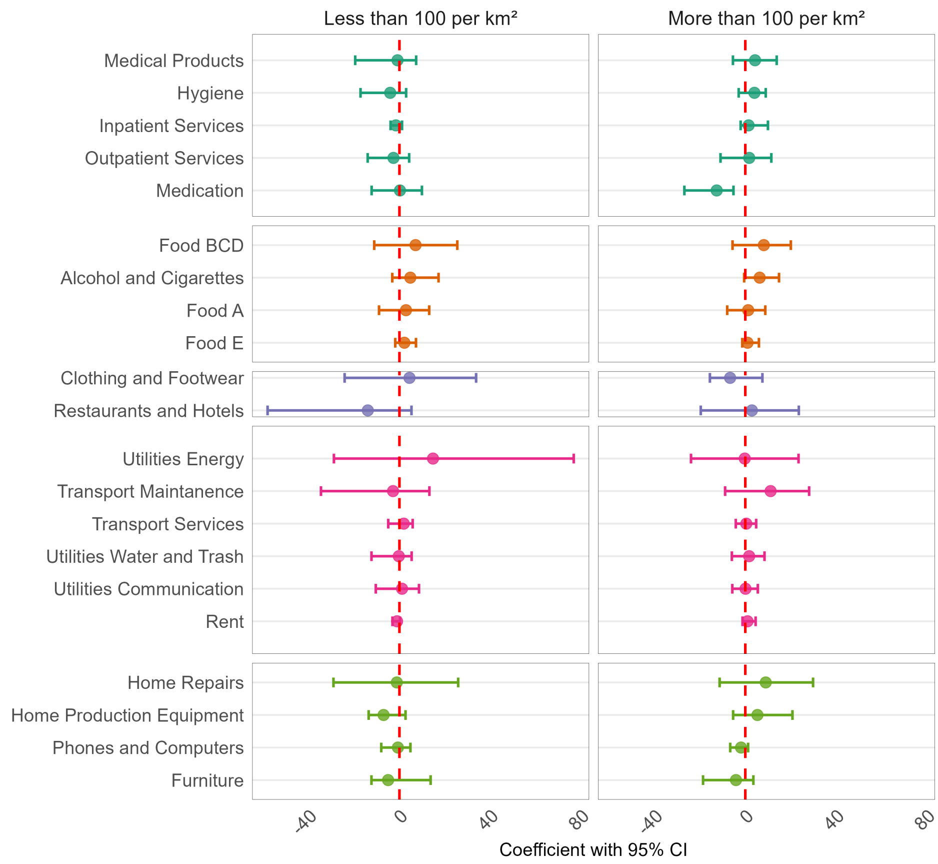


Figure B7: Diff-in-Disc Heterogeneity: Population Density

Note: This figure presents difference-in-disconituity estimates for the alternative outcomes by the population density of the location. It is divided into two groups: below vs above 100 inhabitants per km squared. Regressions are weighted by survey weights. 95% confidence intervals are based on 500 bootstrap iterations. Sample size is 46,976.