CESifo WORKING PAPERS

10480
2023

June 2023

Moral Hazard in Drug Purchases

Jouko Verho, Jarkko Harju

CESifo

Impressum:

CESifo Working Papers
ISSN 2364-1428 (electronic version)
Publisher and distributor: Munich Society for the Promotion of Economic Research - CESifo GmbH
The international platform of Ludwigs-Maximilians University's Center for Economic Studies and the ifo Institute
Poschingerstr. 5, 81679 Munich, Germany
Telephone +49 (0)89 2180-2740, Telefax +49 (0)89 2180-17845, email office@cesifo.de
Editor: Clemens Fuest
https://www.cesifo.org/en/wp
An electronic version of the paper may be downloaded
· from the SSRN website: www.SSRN.com
· from the RePEc website: www.RePEc.org
· from the CESifo website: https://www.cesifo.org/en/wp

CESifo *Working Paper No. 10480*

Moral Hazard in Drug Purchases

Abstract

We study the moral hazard effects of the drug copayment threshold in Finland using detailed prescription drug purchase data. The analysis reveals that the average drug costs increase discontinuously by 17% at the threshold above which out-of-pocket drug costs decrease substantially. Our results suggest an average price elasticity of -0.17, which indicates evident moral hazard costs. Approximately 80% of the overall effect is due to individuals buying drugs in larger quantities rather than purchasing higher-priced drugs. The heterogeneity analysis suggests that the responses are largest for drug categories taken on an as-needed rather than a regular basis.

JEL-Codes: I100, H510, D120.

Keywords: prescription drugs, moral hazard, health insurance.

Jouko Verho
VATT Institute for Economic Research
Helsinki / Finland
jouko.verho@vatt.fi

Jarkko Harju
Tampere University / Finland
jarkko.harju@vatt.fi

May 29, 2023
We are grateful to the Finnish Social Insurance Institution (Kela) for providing the data. We thank Katri Aaltonen, Kari Hämäläinen, Elina Jussila, Kaisa Kotakorpi, Tuomas Matikka, Pasi Pajula, Jukka Pirttilä, Leena Saastamoinen, Erkka Silvennoinen and Janne Tukiainen and conference participants in numerous conferences for insightful and helpful comments. We thank Aino Lintula for great research assistance. We are also grateful to the Academy of Finland (grant no. 346252 and 346253) for funding this project.

1 Introduction

Drug costs and retail pharmaceuticals form a large share of total health care expenditures in OECD countries, the latest estimate of this figure being more than 19% (OECD 2021). Most welfare systems around the world cover some share of an individual's drug costs. Typically, this coverage is effected through a copayment price schedule, whereby a share of the drug price or a fixed amount per prescription is funded by the government, creating a nonlinear pricing schedule for prescribed drugs. Although the objective is a noble one – reducing the cost of drugs so that people can afford them – it entails a potential for moral hazard behavior; that is, the demand for drugs increases as the out-of-pocket price decreases.

In this paper, we estimate the extent of moral hazard behavior in the Finnish institutional setting using a fixed copayment threshold. The sample analyzed comprises unique prescription- and transaction-level data of individuals, including all their prescription drug purchases in 2009. The data set includes individual-level characteristics as well as information on each transaction, such as the cost of the drug, the reimbursement details and the drug's Anatomical Therapeutic Chemical (ATC) classification. To estimate the extent of moral hazard behavior, we use the regression discontinuity design (RDD) at the annual copayment threshold (approximately €670), above which the out-of-pocket prices of prescribed drugs decrease substantially. While we focus on estimating the overall moral hazard behavior, we also aim to determine the type of behavior that dominates in the total effect. Here, we ask: Is the response driven by changes in quality (purchase of higher-priced drugs) or quantity (increased consumption)?

Despite the recent surge of quasi-experimental evidence focusing on the effects of copayment rules and government-subsidized drugs, some very important questions remain unanswered. Although some notable exceptions exist (see e.g. Einav et al. 2015 and Leibowitz et al. 1985), there is only limited evidence on the extent of moral hazard, an essential parameter in understanding the pharmaceutical market. While many earlier papers focus on drug copayment schedules, health insurances in these settings simultaneously cover other health care costs and services as well. The most notable papers in this vein are Finkelstein et al. (2012), which uses survey data on drug usage with experimental variation in the U.S.; Trottmann et al. (2012), which studies health insurance cost-sharing using Swiss data; and

Chandra et al. (2010), which examines the effects of the Medicaid program on drug usage. In this paper, we address the extent of moral hazard in a setting where the out-of-pocket price of drugs sharply decreases to almost zero without a direct link to other parts of the public health insurance system.

We find that average drug purchase costs increase sharply at the copayment threshold, when the out-of-pocket prices of the drugs decrease substantially from partly subsidized market prices to almost fully government-subsidized prices. This result suggests clear moral hazard behavior in response to drug price subsidies. The drug costs are approximately 17% larger than they would be were there no threshold. Our results are at odds with those of earlier papers finding that a large share of the overall effect is due to anticipation of the end of the year, when the copayment threshold is reset (see e.g. Simonsen et al. 2021 and Einav et al. 2015), for we do not observe large increases in drug purchases in the last weeks of the year.

We estimate the price elasticity of demand for prescribed drugs to be between -0.16 and -0.18. These values are well in line with those in the literature estimating price elasticities for drugs, examples being the papers by Einav et al. (2018), which found -0.24, and Abaluck et al. (2018), which derived an average elasticity for drug purchases of -0.13, both analyzing the U.S. institutional setting. Focusing on the reimbursement kink in Denmark, Simonsen et al. (2016) found price elasticities ranging from -0.2 to -0.7. Furthermore, our elasticity estimates are similar to those put forward in the classic study by Manning et al. (1987) for health care services demand (-0.2).

Previous studies have shown that moral hazard behavior does indeed occur in drug purchases (see e.g. Einav et al. 2015, Einav et al. 2017 and Kiil and Houlberg 2014, among others). However, the literature evaluating the exact extent of moral hazard costs and specifically distinguishing different sources of moral hazard behavior is limited. Our data and institutional setting allow us to improve the understanding of the mechanisms behind the overall behavioral responses observed. We assess to what extent the moral hazard behavior observed is due to consumption of higher-priced drugs, price reflecting the perceived quality of the drugs, or higher consumption of drugs. We further distinguish two quantity effects: 1) number of doses per purchase transaction and 2) number of purchase transactions. We find that the number of purchases drives the overall behavioral response, as approximately 80% of the total effect is due to an increase in prescription-level transactions. However, there is

also an evident increase above the threshold in the number of doses: there are approximately 4.5 more doses in a typical purchase, a 6.7% increase in relative terms. In contrast, we find an economically modest and statistically weak response where quality is concerned; that is, the average price of the drugs purchased is nearly unchanged at the threshold.

One additional important contribution of our study to the understanding of the relevant mechanisms is that we show a large heterogeneity in responses by type of drug. Our results indicate that the largest responses are in nervous system drugs, the relative effect being 27%, and the smallest responses in cardiovascular drugs, with a relative effect of 6%. A more detailed ATC-level heterogeneity analysis suggests that drugs taken on an as-needed basis rather than on a regular schedule, such as drugs to treat airway diseases or mental health conditions, have the largest responses. The variation in responses suggests large heterogeneity in price elasticity of demand across different types of drugs. On balance, our results have clear policy implications that, like the findings of Einav et al. (2018), cast doubt on the use of a uniform copayment threshold for all drugs such as that found in many countries. Furthermore, the largest relative response occurs when the physician prescribing the drugs works in psychiatry (33%) and when the physician is working in an institution other than a hospital or health care center. We also find that the most extensive moral hazard behavior occurs among relatively young individuals (15–54 years old), but there is no clear heterogeneity by gender or income groups.

This paper proceeds as follows. In Section 2, we describe the Finnish drug copayment rules, and in Section 3 we provide the details of the data and discuss our methods. Section 4 presents and discusses the results and Section 5 concludes.

2 Drug Co-Payment Rules in Finland

Finland applies a Nordic welfare model with an extensive social insurance system that, among other features, includes comprehensive public health care, sickness and disability benefits, and pensions. The Finnish social security system covers all those individuals who live in Finland on a permanent basis or those who work in Finland. The level of many social benefits is based on previous employment and earnings, with relatively high replacement rates. On the other hand, some benefits do not depend on previously earned income, examples being health

care, the national pension and social assistance, for which all permanent residents are eligible. The social security system is financed through taxes and social insurance contributions from employers and individuals.

Like many other developed countries, Finland also subsidizes purchases of prescribed drugs for individuals. The National Health Insurance in Finland covers most prescription drug purchases. In addition, if prescribed by a doctor, other types of pharmacy products are covered by the insurance, such as skin creams and clinical nutrients. The insurance does not cover over-the-counter medicines, and in some cases the coverage is limited to drugs prescribed for the treatment of specific diseases, but ultimately some 80% of all annual drug purchases are eligible for a subsidy. The Pharmaceutical Pricing Board confirms the reimbursement status for each drug separately and annually.

Reimbursements cover the drugs needed for a maximum of three months' use at a time. Pharmacies typically credit the reimbursement directly to individuals, but individuals can also claim the reimbursement from the Social Insurance Institution themselves within six months. Three different reimbursement rates apply. In 2009, our baseline year in the empirical analysis, the basic rate was 42% of the price, the higher special rate 72%, and the highest special rate 100%. Drugs with the highest rate each prescription carries a fixed three-euro fee, and they are used for the treatment of certain severe long-term diseases. Due to the extensive scope of the social security system in Finland, subsidies for drug purchases make up only a small fraction of total social security expenditures, the share being 2% in 2009.

Importantly, there is an annual copayment ceiling above which the out-of-pocket prescription drug prices sharply decrease. When the euro amount of an individual's annual out-of-pocket costs exceeds the copayment threshold, all drug prices drop to a fixed €1.5 copayment per transaction. In 2009, the copayment threshold was €672.70.[1] The Social Insurance Institution informs individuals by mail when the copayment ceiling is reached, making the copayment threshold salient for them. However, below the ceiling, it is not clear how well individuals are aware of their cumulative drug purchases during the year, as this depends on their efforts to keep track of the purchases.

To give a practical example, an individual who has spent a total of €1000 on prescription drugs covered by the basic rate of 42% will have accumulated copayments amounting

[1]The copayment threshold was €643.14 in 2008 and €672.70 in 2009 and 2010.

to €580. If the individual then makes an additional purchase of similar drugs for €500, the cumulative copayments will reach €870, exceeding the threshold, at which point the individual receives a letter from the Social Insurance Institution notifying them of their eligibility for additional reimbursements. In this case, the additional reimbursement would be €197.8 (870–672.2) minus the fixed fee. For subsequent drug purchases, the additional reimbursements can be granted directly. The individual need only present the letter at the pharmacy and pay €1.5 per purchase. Where individuals do not receive the reimbursement immediately, either because they did not present the letter at the pharmacy or their purchase exceeds the threshold for the first time, they are reimbursed after submitting an application to the Social Insurance Institution.[2]

This sharp decrease in out-of-pocket drug costs at the threshold can lead to two types of moral hazard responses: 1) substitution of suitable inexpensive drugs with more expensive branded counterparts and/or 2) consumption of larger quantities of drugs. The quantity effect in turn could result from two types of effects: a larger number of drug doses purchased per transaction and a larger number of drug items. The decrease in costs could also lead to individuals shopping more for prescriptions, that is, making more visits to doctors trying to convince them to prescribe more drugs. With our exceptional data, which we present next, we can not only investigate the overall moral hazard behavior but also examine all of these different margins separately.

Two additional institutional details are relevant for our study. First, those individuals who are unable to cover their purchases of prescription drugs out-of-pocket may receive social assistance for these expenses when below the threshold if they can demonstrate that their finances cannot cover the costs. This being the case, it is unlikely that individual financial constraints preventing access to medication would be a great concern in our study. Second, individuals cannot directly determine what type of drugs they buy from the pharmacy, as drug purchases are restricted by the prescription. However, generic substitution allows the pharmacy to replace the prescribed drug with an alternative drug containing the same active ingredient.

[2]In our data period, the Social Insurance Institution sent out letters when the threshold was exceeded, but at present a pharmacy can check the copayment status online.

3 Data and Methods

3.1 Data

Data description. We use data of all transactions of prescribed drugs in Finland in 2009. This data set is from the official prescription register operated by the Social Insurance Institution. The data cover all prescribed drug purchases of Finnish residents over 15 years of age whose annual drug costs exceeded €100. The data comprise, among other details, the date of purchase, the cost of the drug(s), the amount of reimbursement, the reimbursement category and the Anatomical Therapeutic Chemical (ATC) classification of the drug(s). Note, however, that the data do not cover drugs used in inpatient and institutional care or over-the-counter drugs. Using unique individual identifiers, we link customers' background characteristics to transaction-level data, the former including age, gender, region of residence and income at the end of previous year.

Definition of copayment measure. With the available data, we can construct a well-defined distribution representing the drug purchases below and above the annual copayment threshold. We calculate cumulative copayments over time but disregard the additional reimbursements that are granted above the threshold. Then we group transactions for each individual by the end of each calendar date because this captures accumulated copayments before the next purchase in a pharmacy. Using this definition, the same individual falls into as many different copayment bins as they have pharmacy visits in different dates.

Following the practical example in Section 2, we further clarify how we construct the copayment measure. Consider an individual with €1000 of total prescription costs on 30 June 2009 which are covered by the basic rate of 42%. In this case, the respective cumulative copayment measure would be €580 (1000·(1–0.42)) for the next visit. If the individual then purchases similar drugs for €500 on July 1st and August 1st, the cumulative copayments will reach €870 (1500·(1–0.42)) for the third purchase and the copayment threshold is exceeded. In this example, we would have generated three data points, at €0, €580 and €870, for this particular individual in our cumulative copayment distribution.

Sample restrictions. To exclude individuals using highly expensive medication, we restrict our data to those whose monthly drug costs are less than €10,000. In the main analysis,

we also categorically remove all drugs in the restricted reimbursement category ('U'), which includes very expensive drugs; in these cases, the copayment threshold is often exceeded with a single purchase, creating obvious lumpy behavior in drug purchases for this type of drugs, as can be seen in Appendix A, Figure 4. We also restrict our sample to transactions with cumulative copayments between €100 and €1500, as the number of transactions above €1500 is already quite low. As it is also unlikely that the threshold would have any effect on individuals whose annual drug costs total less than €100, we believe these data restrictions are negligible.

Descriptive statistics. Figure 1 illustrates the average value of purchase, in terms of our constructed measure, annual cumulative copayments in one-euro bins. We can further decompose this overall average effect and form measures for the price of a drug, number of doses purchased in a given transaction, and number of purchased items. On top of these, we observe the number of prescriptions used at the individual level, which enables us to investigate whether individuals try and succeed in shopping for prescriptions.

Table 1 shows the descriptive statistics for our baseline sample in the first column and average age, gender distribution and average income for the population in the second column. The latter column has been extracted from a data set called Income Distribution Statistics, which is a representative sample of the Finnish population produced annually by Statistics Finland. In our sample, the individuals are older on average than Finns at large, and the proportion of women is higher than that of men. Overall, the taxable income of individuals in our sample is clearly lower than the Finnish average.

The average purchase in our sample is €40, of which some €28 is reimbursement. On average, individuals purchase approximately 65 doses of drugs in a single transaction. However, we cannot calculate the doses for all drug purchases as the recommended doses are not defined for all drugs; for 7.7% of all drugs we cannot construct this measure, which is especially problematic for drug liquids. As the threshold in copayment is relatively high, only 4.6% of our observations are above the threshold, but the share of total drug expenditures above the threshold is much higher, 8.5%. Our sample comprises more than 2.5 million individuals and almost 35 million transactions.[3]

[3]Appendix B Table 3 shows the descriptive statistics by drug categories.

3.2 Methods

To quantify the effects of co-payment threshold on drug purchase costs, we use the discontinuity in out-of-pocket drug prices at €672. We estimate the effects using a regression discontinuity design (RDD) type of framework.

Formally, our regression model is:

$$y_{ipd} = \alpha + \beta_1 1[C_{id} \geq T] + \beta_2 (C_{id} - T) + \beta_3 1[C_{id} \geq T] \cdot (C_{id} - T) + e_{ipd}, \tag{1}$$

where y_{ipd} denotes the outcome of interest, that is, the average value of drugs purchased by individual i by purchase p on day d. The running variable C_{id} is the individual-level cumulative copayment measure at day d of the purchase p. T is the annual copayment threshold and e_{ipd} is the error term. The coefficient of interest is β_1, which captures the effect of the copayment threshold.

The average value of drug costs for individual y_{ipd} is the number of doses multiplied by the price of a dose for a given drug prescription aggregated over all purchased drug items. This measure captures the total effect at the threshold, but the data also enable us to distinguish two different effects that account for the total effect: 1) a quantity effect, that is, excess demand for doses, and 2) a quality effect, that is, the price of doses purchased, which reflects the quality of the drugs. The quantity effect can be further broken down into two components: number of doses per transaction and number of items purchased.

We acknowledge that in our empirical application individuals might be able to manipulate the running variable, C_{id}, to some degree. However, we have three important facts to rely on that alleviate doubts concerning the use of a regression discontinuity model in this setting. First, individuals cannot precisely control their decisions close to the threshold, as they are required to have a prescription written by a licensed physician. This is a minimum requirement to manipulate the running variable. While individuals can manipulate their behavior to some degree, many cannot cross the threshold unless they have a prescription enabling them to purchase drugs. It is also likely that at least some individuals below the threshold are not wholly aware of their accumulated annual drug purchases that are eligible for reimbursements; many people do not keep track of their drug purchase receipts, and reaching the threshold becomes salient only after receiving the notification letter from the Social Insur-

ance Institution. If many individuals whose purchases only marginally exceed the threshold are unaware of their cumulative copayments, our very local estimates at the threshold might be downward biased. These concerns are alleviated by the sharp increase in the take-up rates (share of individuals applying for drug expense reimbursements) at the threshold, evident in Appendix A, Figure 5. Moreover, we perform a large set of robustness checks for our local approach, the result of which are presented in subsection 4.4.

Second, our baseline results are not sensitive to a large set of robustness checks for different empirical choices. We perform an extensive set of robustness analyses for our empirical approach, including several donut hole choices in particular, which all lessen the concerns related to local manipulation of individuals close to the threshold. We present these tests in Appendix B and discuss them in subsection 4.4. Third, we examine the selection of individuals at the threshold and do not find any systematic, clear and sizable selection by individual-level characteristics, which we discuss in more detail below.

In our main analysis, for data access and computational reasons we use aggregated one-euro bin-level data on constructed copayment measure to estimate the baseline responses. In our main specification, we follow Calonico et al. (2014) and use the local-linear point estimator with an MSE-optimal bandwidth selector and symmetric bandwidths below and above the threshold. We use a triangular kernel function to weight the data points close to the threshold. To take into account smoothing bias, we use local-quadratic regression. In subsection 4.4, we show that our results are robust to all these choices and provide evidence that our main estimate remains very similar when using micro-level data.

Finally, we test whether or not there are any discontinuities in background characteristics at the threshold. Appendix B, Figure 12 applies the same baseline estimation technique as described above and shows the estimates on age, gender distribution and income below and above the threshold. For age, there seems to be a small, less than one-year, decrease above the threshold (upper left figure), but there is no discontinuity in the gender distribution (upper right figure). In income, there seems to be a slight discontinuity in that individuals above the threshold have higher income levels, on average, compared to those just below the threshold. However, the discontinuity estimate is relatively small in magnitude, €303 (SE 88), 1.6% in relative terms, which we do not see as dramatically hampering our identification strategy.

4 Results

4.1 Baseline Results

We start by visualizing the data with binned scatter plots in Figure 1, which also reports the RDD estimate and its standard error using our baseline choices described above in subsection 3.2. We observe that below the threshold drug purchase costs increase almost linearly with the annual cumulative copayment measure. At the threshold, there is a sharp increase in the level of average purchase costs. This provides compelling evidence that purchase costs are, on average, larger when the out-of-pocket costs of purchases dramatically decrease. The estimated local effect is approximately €8.6, implying an increase of over 17% in drug costs above the annual copayment threshold.

One explanation for this behavioral response in the drug purchase costs at the threshold could be that it is merely a very temporary end-of-the-year effect, such as that put forward as a prevalent explanation for moral hazard behavior in the literature; see e.g. Einav et al. (2015) and Simonsen et al. (2021). To examine this, the left-hand panel of Appendix A, Figure 6 shows the number of individuals purchasing prescription drugs and the right-hand side of the same figure plots their annual expenditure by the week (number) when the copayment ceiling is exceeded in 2009. This figure shows that there are indeed more purchases towards the end of the year, but this end-of-the-year effect does not seem to be as pronounced as in many previous papers. Appendix A, Figure 7 also shows the average expenditure for individuals by whether (right) or not (left) they reached the annual copayment ceiling in 2009. This descriptive evidence suggests some within-year behavioral responses as there are, on average, larger purchases just before the end of the year and also smaller average purchases in the beginning of the year. This pattern is likely explained by the fact that some two-thirds of individuals reach the copayment threshold in consecutive years, mainly because of their relatively advanced age or persistent illnesses. However, the magnitude of this response seems rather negligible. Similarly, if we remove drug purchases made in October, November and December, we clearly observe an increase at the threshold very similar to that seen in our baseline results, where we keep these months in the data (see Appendix A, Figure 8). On balance, as the response is quantitatively very similar after excluding the last three calendar

months from the data (or even slightly larger than the baseline estimate), our results suggest that the moral hazard behavior cannot be attributed exclusively to within-year anticipation.

Next, we repeat the same empirical approach as above for the different reimbursement rate categories, 42%, 72% and 100%. This analysis, the results of which are shown in Figure 2, tests whether the size of the incentive change at the threshold matters for the observed moral hazard behavior. The upper left panel shows the response for the most common drug category, 42% reimbursement, where the response is €7.3, reflecting a 14.6% relative change at the threshold. The upper right panel shows a somewhat larger response at the threshold in absolute terms, €8.5, and this is also similar in size in relative terms, 15.6%, for drugs in the 72% reimbursement category. Finally, the lower left panel shows no response to the 100% group, which entails only a minor incentive change at the threshold inasmuch as the fixed copayment decreases from €3 to €1.5. This last observation offers us a sanity check for our empirical approach as the reimbursement rate remains nearly unchanged below as well as above the threshold.

To illuminate the magnitudes of responses, we approximate the incentive change at the threshold using the average purchase costs by drug category. For the lowest reimbursement rate category, the average purchase costs are €27.4 just below the threshold, and with the 42% reimbursement rate the out-of-pocket cost for a typical customer is then approximately €15.9. Above the threshold, the out-of-pocket costs decrease to €1.5 for all drugs, which implies a 90.5% relative decrease at the threshold. For the 72% reimbursement category the average purchase cost is €45.1 – just below the threshold – and this gives an 88.1% decrease in the out-of-pocket drug costs. Using these relative changes in out-of-pocket costs, we can illustrate the drug price elasticities by drug type. As described above, the relative responses with respect to moral hazard behavior are very similar across two drug types, 14.6% and 15.6%, and likewise the relative out-of-pocket price changes are similar in size, 90.5% and 88.1%, respectively. In the light of these findings, the implied elasticities are -0.16 and -0.18, respectively. Using the drug cost shares of these drug categories and the implied elasticities, the weighted average elasticity is -0.17.

4.2 Distinguishing Responses

With our data, we can distinguish different sources of responses from the overall effect presented in Figure 1: 1) changes in the prices of purchased drugs (quality), and 2) changes in the number of drugs purchased (quantities). Furthermore, we can break this effect down into two component effects: a larger number of drug doses purchased per transaction, and a larger number of drug items. Figure 3 distinguishes these different response margins.

Quality effect

A potential explanation for the overall response is that individuals deviate from the default drug option. They either seek to buy higher-priced drugs when purchasing drugs from the pharmacy or collude with doctors when receiving a prescription, perhaps due to the drugs having fewer side effects or being perceived as higher in quality. As the upper right panel of Figure 3 shows, there is only a small discontinuity at the threshold in the average price of a dose purchased, 4.4% in relative terms. This result has two important implications: 1) individuals do not seem to be very actively changing drugs prescribed to them for more expensive alternatives when the out-of-pocket costs decrease sharply, and 2) there is no clear collusion between individuals and doctors leading to doctors writing prescriptions for more expensive drugs when the out-of-pocket costs for individuals decrease. In this empirical application, we cannot, however, distinguish these two mechanisms. However, Appendix A, Figure 9 shows that the number of doctor's appointments is rather continuous at the threshold, suggesting that above the threshold individuals do not seem to be very actively "shopping" for additional prescriptions from new doctors.

Quantity Effect

Next, we examine the quantity changes at the threshold. We start by examining the number of drug doses per transaction at the threshold. It seems that there is a clear increase in the number of doses per purchase above the threshold. Although an evident jump at the threshold can be seen in the upper left panel of Figure 3, with some 4.5 more doses purchased above the copayment threshold, in relative terms this is only 6.7% more doses compared to the level just below the threshold.

Finally, we examine the number of purchased items, that is, the number of prescriptions purchased, across the cumulative copayment distribution. As the number of purchased items decreases very quickly with copayment distribution, we restrict the analysis to the range €570 to €770 of cumulative copayment rather than the range €100 to €1500 used previously.[4] The lower left panel of Figure 3 shows an evident and large increase in the number of purchased items at the threshold, with almost 700 more items being purchased on average, indicating a 13.8% increase in relative terms. This evidence suggests that the main driver of the observed overall moral hazard behavior is an increase in the number of drug items. This in turn indicates that when out-of-pocket drug costs decrease sharply, many individuals start to use their previously prescribed and unused prescriptions.

One possible explanation for the observed results is that individuals increase the quantity of purchased drugs per visit but prolong purchase intervals, which might leave the total amount of purchased drugs unchanged. We can address this by examining the pharmacy visit intervals in days over the cumulative copayment measure. Appendix A, Figure 10 shows that there is no discontinuity in the average visit interval at the threshold, which suggests that the estimated increase in purchased quantity indeed leads to greater total amount of purchased drugs.

4.3 Heterogeneity of Responses

Table 2 brings together the RDD estimates for different subsamples. A first observation is that, unsurprisingly, the responses increase with larger overall annual drug costs. This is evident when we estimate the responses separately by annual drug expenditure percentiles (5, 20, 50, 80 and 95) in the first five columns of the upper panel of Table 2. The latter five columns of this panel show that there is no clear difference in response by individual income quintiles, with the exception that in the two lowest quintiles there seem to be somewhat smaller responses. The middle panel of Table 2 shows that women respond more than men and that the size of the response decreases with age, with individuals in the 15–54 age range having larger responses than those between 55 and 69 or over 70 years of age.

[4]Figure 13 in Appendix B shows the number of transactions with a wider range of cumulative copayment. The RDD estimate is very robust to the definition of how much data include to the estimation window.

The bottom panel of Table 2 shows the RDD estimates first by medical institution. The clear stand-out is the group "Other", especially in terms of relative responses. This group includes drugs prescribed by doctors who reported working in institutions other than public hospitals and health centers, for example, in private clinics. In terms of physician's field of specialization, the largest responses are found in the field of mental health. Note also that age has a clear correlation with type of illnesses in that, relatively speaking, mental illnesses are far more common among young individuals, whereas physical diseases are far more common among older persons.

The last four columns of the middle panel of Table 2 show that the largest heterogeneity in responses is by type of drug. Clearly, the largest response in euros and relative terms is in the category "nervous system", which includes drugs for mental health treatment. Drugs related to the respiratory system also have a rather large response at the threshold, especially compared to cardiovascular and gastroenteric drugs.

We further exploit our data to split the results by detailed ATC drug groups. The upper panel of Appendix A, Figure 11 shows first the relative RDD estimates (right axis) for the most frequently purchased one-letter ATC groups (covering 90.6% of all prescribed drugs purchased in Finland in 2009) in the order of share of drug costs (left axis). Similarly, the lower panel shows the relative effects by five-letter groups for the main levels of nervous system drugs (N) and drugs for airway diseases (R), which together account for 31.7% of all prescribed drug purchases. In some drug categories the point estimates are quite large but imprecise, examples being drugs for blood and blood-forming organs (B) and antineoplastic and immunomodulating agents (L). These results clearly show extensive heterogeneity across different main groups (upper panel) as well as within detailed ATC categories (lower panel). The largest consistent responses are among nervous system drugs (N) and drugs for airway diseases (R); here, Pregabalin, an antiepileptic (N03AX16), and inhalants (R03A) have the highest costs and very large relative effects. These can be described as medications taken on an as-needed basis.

4.4 Robustness checks

Our results are robust to several alternative definitions and choices. One potential challenge to our empirical approach is that individuals might have some leeway to manipulate the running variable. To evaluate the robustness of our local approach, we use what is known as the donut hole approach and exclude data symmetrically below and above the threshold in five-euro intervals up to €80. We also examine the robustness of our baseline result by varying the bandwidth selection.

Figures 14 and 15 in Appendix B show the estimates at 95% confidence intervals from these evaluations using these different donut holes and bandwidths. The figures also indicate the 95% confidence intervals for the baseline estimate (in gray) to offer a tractable comparison. This clearly suggests that our results are robust for moving away from the very local RDD approach in our baseline specification. The results are also robust for excluding data systematically with small intervals exclusively from the left of the threshold (lower left panel of Figure 14) or exclusively from the right (lower right panel of Figure 14).

Appendix B, Table 4 shows the estimates for using five placebo thresholds both below and above the actual threshold. Two of these are statistically significant with opposite signs and relatively small in absolute values, lending more credibility to our baseline results. In Appendix B, Table 5, we also show that the results are robust to varying the polynomial degree. We further find that our results are robust to the choice of kernel function, as is evident from Appendix B, Table 6. The results are also robust when not confining the analysis to euro-bin width averages, as is visible from column 1 in Appendix B Table 7, as well as for adding age, age squared, gender and disposable income as control variables (see column 2 in Appendix B, Table 7). Finally, we use data on prescription drug purchases in the years 2008 and 2010 to study the robustness of our baseline estimate in years close to our baseline sample. Appendix B, Table 8 shows that the RDD estimate is very similar in size in 2008 to our baseline estimate and a bit larger in 2010.

5 Conclusion

In this paper, we have demonstrated the moral hazard behavior in drug purchases. We have provided new insights into the current knowledge by estimating a -0.17 average price elasticity of demand for prescribed drugs and have shown that, contrary to a common finding in the literature (see e.g. Simonsen et al. 2021 and Einav et al. 2015), the behavior is not driven by anticipation of the end-of-year reset of the copayment threshold. Our results imply that the main driver of the overall response is individuals buying more drugs, in particular a larger number of drug items. Interestingly, our heterogeneity analysis reveals that the largest responses occur in the case of drugs taken on an as-needed basis rather than on a regular schedule.

Although we have reported clear responses on drug usage with respect to out-of-pocket prices, an obvious next step would be to study health outcomes, that is, ask whether larger drug purchases have any implications for people's health. At present, we do not have the data needed to carry out such an analysis and thus leave this question to be taken up in future research.

References

Abaluck, J., J. Gruber, and A. Swanson (2018). Prescription drug use under Medicare Part D: A linear model of nonlinear budget sets. *Journal of public economics 164*, 106–138.

Calonico, S., M. D. Cattaneo, and R. Titiunik (2014). Robust nonparametric confidence intervals for regression-discontinuity designs. *Econometrica 82*(6), 2295–2326.

Chandra, A., J. Gruber, and R. McKnight (2010). Patient cost-sharing and hospitalization offsets in the elderly. *American Economic Review 100*(1), 193–213.

Einav, L., A. Finkelstein, and M. Polyakova (2018). Private provision of social insurance: Drug-specific price elasticities and cost sharing in Medicare Part D. *American Economic Journal: Economic Policy 10*(3), 122–53.

Einav, L., A. Finkelstein, and P. Schrimpf (2015). The response of drug expenditure to nonlinear contract design: Evidence from Medicare Part D. *Quarterly Journal of Economics 130*(2), 841–899.

Einav, L., A. Finkelstein, and P. Schrimpf (2017). Bunching at the kink: Implications for spending responses to health insurance contracts. *Journal of Public Economics 146*, 27–40.

Finkelstein, A., S. Taubman, B. Wright, M. Bernstein, J. Gruber, J. P. Newhouse, H. Allen, K. Baicker, and O. H. S. Group (2012). The Oregon health insurance experiment: Evidence from the first year. *The Quarterly Journal of Economics 127*(3), 1057–1106.

Kiil, A. and K. Houlberg (2014). How does copayment for health care services affect demand, health and redistribution? A systematic review of the empirical evidence from 1990 to 2011. *The European Journal of Health Economics 15*(8), 813–828.

Leibowitz, A., W. Manning, and J. Newhouse (1985). The demand for prescription drugs as a function of cost-sharing. *Social Science & Medicine 21*(10), 1063–1069.

Manning, W., J. Newhouse, N. Duan, E. Keeler, and A. Leibowitz (1987). Health insurance and the demand for medical care: Evidence from a randomized experiment. *The American Economic Review 77*(3), 251–277.

OECD (2021). Health at a glance 2021 - OECD indicators. OECD Publishing.

Simonsen, M., L. Skipper, and N. Skipper (2016). Price sensitivity of demand for prescription drugs: Exploiting a regression kink design. *Journal of Applied Econometrics 31*(2), 320–337.

Simonsen, M., L. Skipper, N. Skipper, and A. I. Christensen (2021). Spot price biases in non-linear health insurance contracts. *Journal of Public Economics 203*, 104508.

Trottmann, M., P. Zweifel, and K. Beck (2012). Supply-side and demand-side cost sharing in deregulated social health insurance: Which is more effective? *Journal of Health Economics 31*(1), 231–242.

Tables and Figures

Table 1: Descriptive statistics

	Sample	Population
Demographics		
Age	61.09	47.8
	(17.05)	
Women (%)	60.06	51.28
Income (€)	20,830	24,481
	(18,580)	
Pharmaceutical drug use		
Cost (€)	40.38	
	(113.31)	
Reimbursement (€)	27.62	
	(110.20)	
DDD	65.48	
DDD missing (%)	7.67	
Purchases over ceiling (%)	4.60	
Costs over ceiling (%)	8.47	
N patients	2,546,000	
N observations	34,752,000	

Note: The table above reports sample averages and standard deviations (in parentheses) of individual-level characteristics and prescription drug costs in our data. DDD (Defined Daily Dose) is the average dose per day for a drug used for its main indication in adults. DDDs have not been established for all drug groups. The second column summarizes a data set called Income Distribution Statistics, which is a representative sample of the Finnish population, aiming to compare individuals with prescription drug purchases to average Finns.

Table 2: Heterogeneity Results: RDD estimates for different subsamples.

	Drug Cost Percentiles					**Income Quintiles**				
	p5	*p20*	*p50*	*p80*	*p95*	*q1*	*q2*	*q3*	*q4*	*q5*
RDD (€)	0.054	0.734	2.317	8.945	37.550	5.882	7.924	11.270	8.844	10.170
	(0.012)	(0.072)	(0.170)	(0.593)	(2.766)	(1.066)	(0.896)	(1.278)	(2.188)	(2.401)
Rel. effect (%)	1.04	7.41	11.61	15.96	21.48	12.11	16.73	22.72	14.66	15.80
Control mean	5.137	9.903	19.95	56.04	174.8	48.58	47.35	49.60	60.31	64.35
Bandwidth	157.6	106.3	143.4	141.5	123.4	128.7	169.5	163.0	123.5	153.7

	Gender		**Age**			**Type of Drugs**			
	Men	*Women*	*15-54*	*55-69*	*70-*	*Nervous System*	*Cardiovascular*	*Gastroentric*	*Respiratory System*
RDD (€)	8.139	9.093	14.230	9.892	4.576	13.060	1.997	4.895	12.13
	(1.031)	(0.728)	(1.459)	(1.214)	(0.499)	(0.838)	(0.356)	(0.989)	(1.121)
Rel. effect (%)	14.12	19.17	23.72	17.13	10.54	26.82	6.50	8.19	15.70
Control mean	57.65	47.44	60.00	57.73	43.41	48.69	30.74	59.76	77.27
Bandwidth	172.1	167.1	162.0	188.8	192.8	238.5	182.3	183.7	130.7

	Medical Institution				**Physician's Field of Specialization**				
	Health Center	*Hospital*	*NA*	*Other*	*General*	*Internal*	*None*	*Other*	*Psychiatry*
RDD (€)	5.878	9.973	7.270	13.74	6.680	8.212	6.552	16.31	16.26
	(0.485)	(2.554)	(0.905)	(1.133)	(0.763)	(4.490)	(0.603)	(2.279)	(2.350)
Rel. effect (%)	13.08	13.08	16.62	26.66	14.85	9.82	14.46	24.52	32.58
Control mean	44.93	76.26	43.75	51.53	44.98	83.65	45.31	66.52	49.91
Bandwidth	136.5	115.6	196.9	227.6	169.2	134.6	147.7	166.9	119.5

Note: This table reports the RDD estimates for different subsamples. The upper panel shows the estimates by annual drug expenditure percentiles (5, 20, 50, 80 and 95) and individual income quintiles. The middle panel depicts the estimates by gender, age groups and type of drugs, where type of drugs subsamples are defined by the four largest main ATC categories (N, C, A, R). The lower panel shows the estimates by medical institution and physician's field which is the registered specialization of the prescribing doctor.

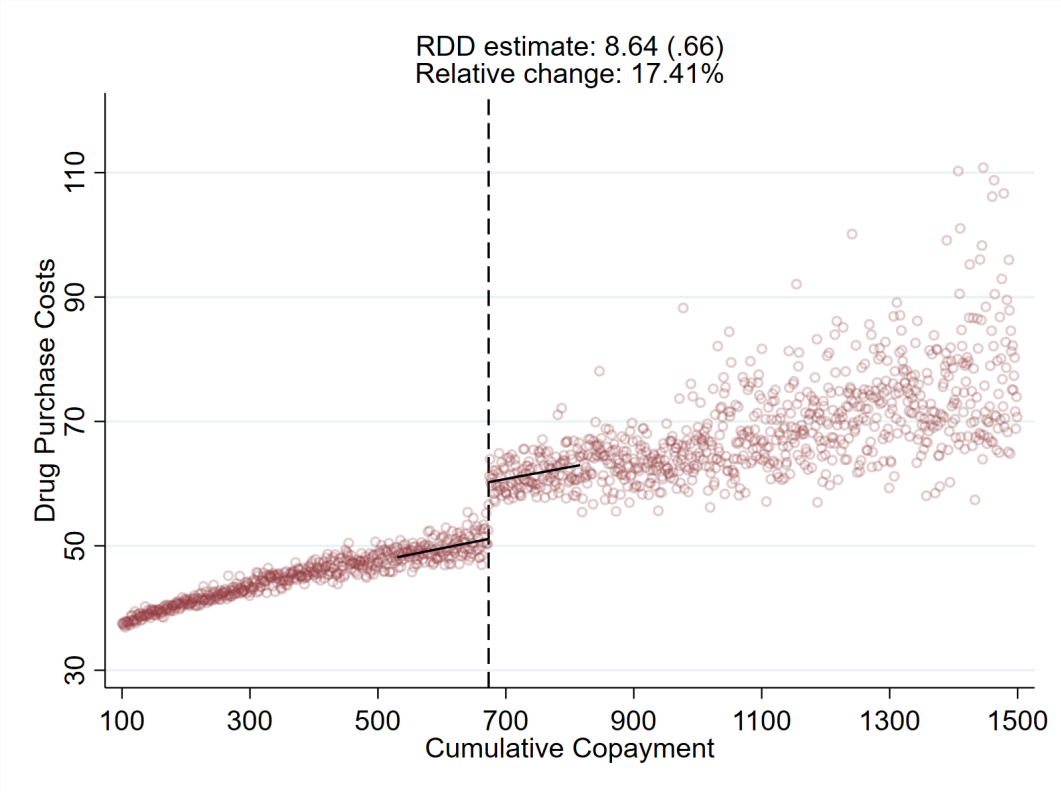

Figure 1: Drug purchase costs by cumulative copayment.

Note: The figure shows the average costs for one-euro bins of individuals' accumulated copayments. The RDD estimate in the subtitle shows the RDD estimates at the copayment threshold (€672) and the relative change is relative to the average level just below the threshold.

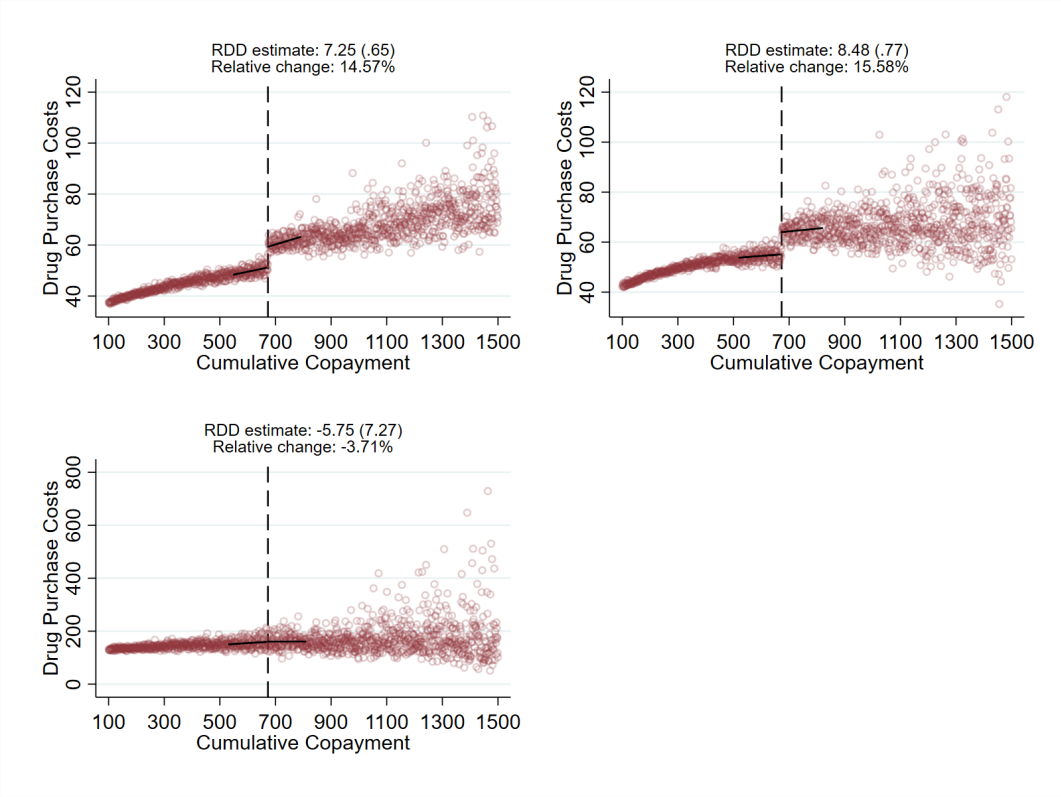

Figure 2: Drug purchase costs by reimbursement rate 42% (upper left), 72% (upper right) and 100% (lower left).

Note: The figure shows the average costs for one-euro bins of individuals' accumulated copayments by different copayment rate categories (42%, 72% and 100%). The RDD estimate in the subtitle shows the RDD estimates at the copayment threshold (€672) and the relative change is relative to the average level just below the threshold for different copayment rate categories, respectively.

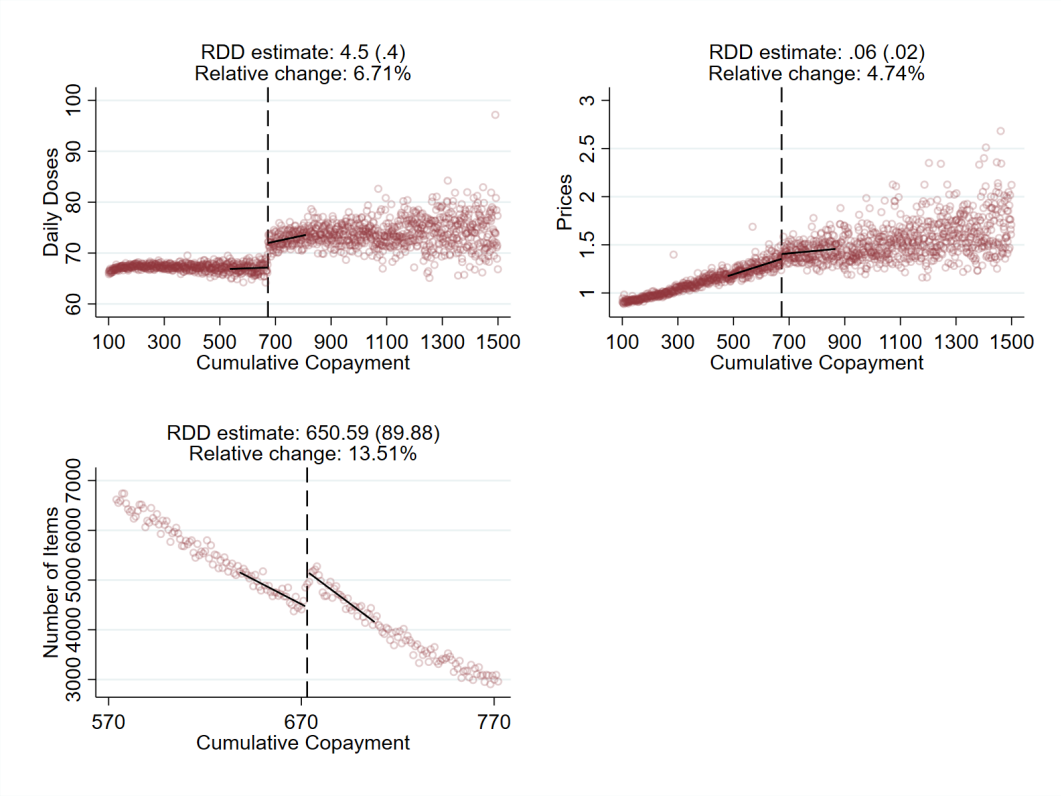

Figure 3: Distinguishing effects: Daily drug dose (upper left), price of prescription (upper right) and number of items (lower left).

Note: The figure shows the average costs for one-euro bins of individuals' accumulated copayments for daily dosage, price of drugs and number of drug items. The RDD estimate in the subtitle shows the RDD estimates at the copayment threshold (€672) and the relative change is relative to the average level just below the threshold for different outcomes, respectively.

A Online Appendix: Additional Figures and Tables

Table 3: Descriptive statistics by drug category

	O (42%)	Y (72%)	K (100 %)	U (42%)
Age	59.50	66.97	61.20	69.61
Women (%)	62.40	54.14	53.77	58.15
Income (1000 €)	21.56	19.45	17.82	20.66
Cost (€)	27.44	45.11	137.05	380.05
Reimbursement (€)	13.35	32.92	134.08	304.52
Purchases after threshold (%)	4.88	4.09	3.35	20.70
DDD	54.82	92.90	87.74	77.43
DDD not available (%)	9.27	3.44	3.76	43.71
N patients (1000)	2,460	800	485	140
N obs. (1000)	25,037	6,692	3,023	484

Note: The table reports the mean values of sample by drug category (O with reimbursement percent of 42%, Y with 72%, K with 100%, and U with 42%). The table contains average age, share of women, average income in thousands of euros, average cost and reimbursement in euros, percentage of purchases made after reaching the threshold, defined daily dose, percentage of observations where defined daily dose was not available, number of patients in thousands and number of observations in thousands.

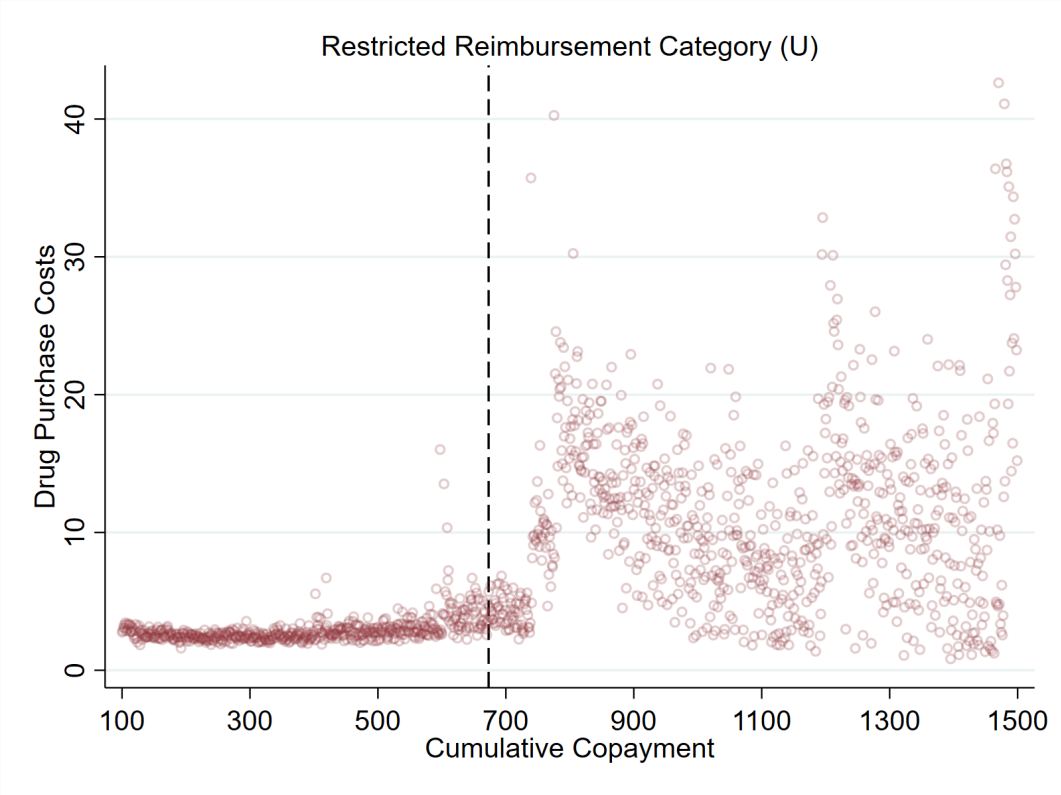

Figure 4: Drug purchase costs by cumulative copayment in Restricted Reimbursement Category (U).

Note: The figure shows the average costs for one-euro bins of individual's accumulated copayments of drug purchase costs in restricted reimbursement category (U): Drugs for severe and rare illnesses. Dashed vertical line marks the cumulative co-payment threshold (€672).

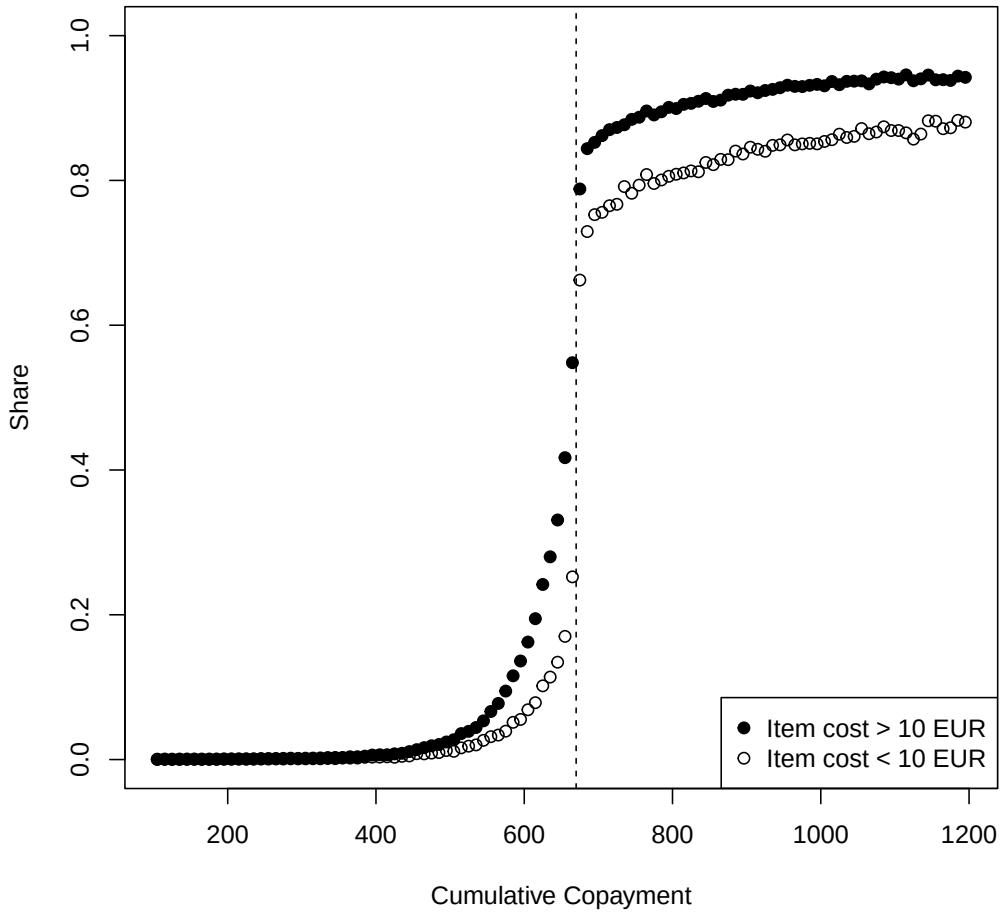

Figure 5: Take-up of additional reimbursements for drug items below and above €10 in cost.
Note: The figure shows the average share of purchases for ten-euro bins of individuals' accumulated copayments. Below the €672 threshold, individuals are eligible for additional reimbursements if the cumulative copayment exceeds the threshold in that purchase. After the threshold has been reached, all purchases are eligible for the additional reimbursement.

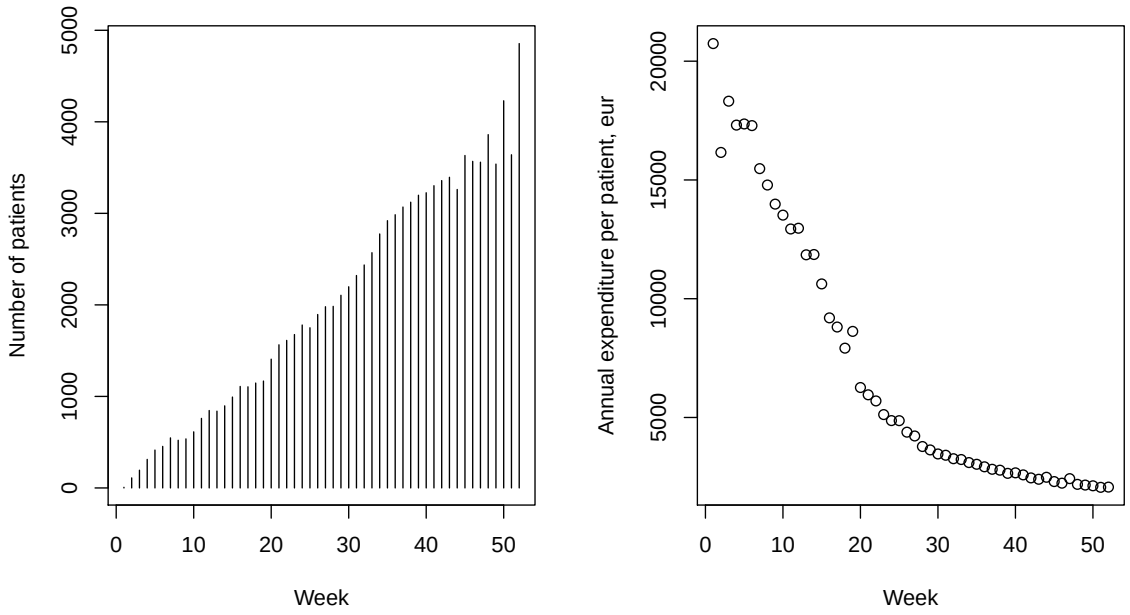

Figure 6: Number of individuals purchasing drugs (left) and their annual expenditure (right) by week.

Note: The figure shows the number of patients and annual expenditure per patient in euros by the week when the copayment threshold is exceeded in 2009.

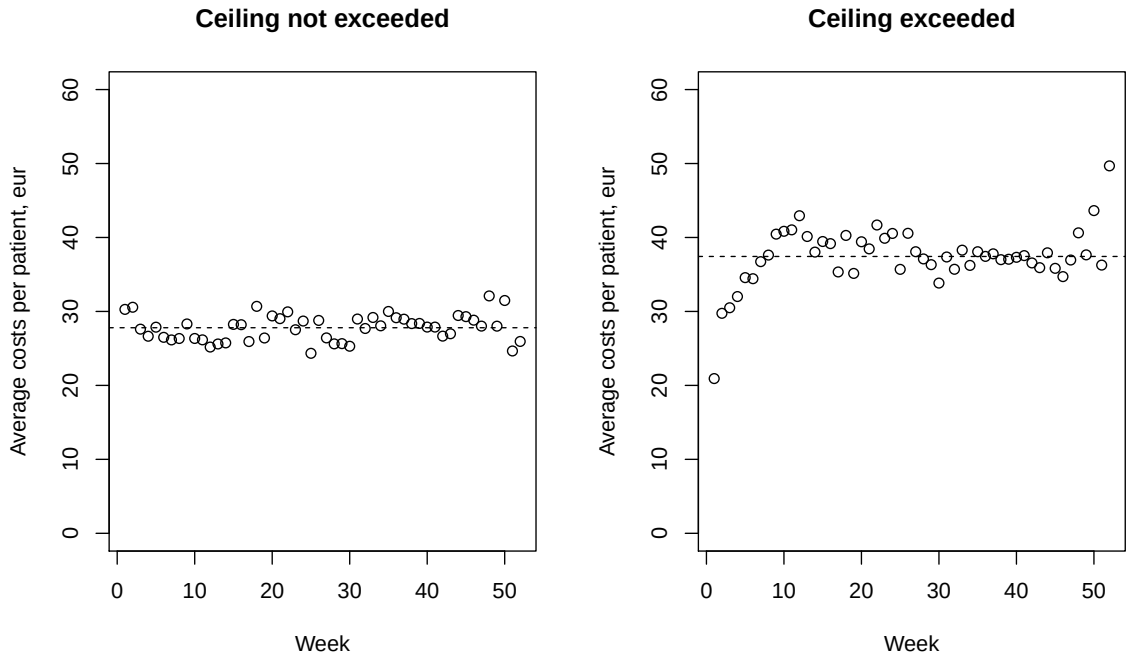

Figure 7: Average cost per patient by week: Individuals who did not reach the threshold (left) and individuals who exceeded the threshold (right).

Note: The figure shows average expenditure by week for individuals who did not reach the annual copayment threshold and for individuals who exceeded the threshold in 2009. In both panels, the dashed horizontal line reports the average of weekly costs.

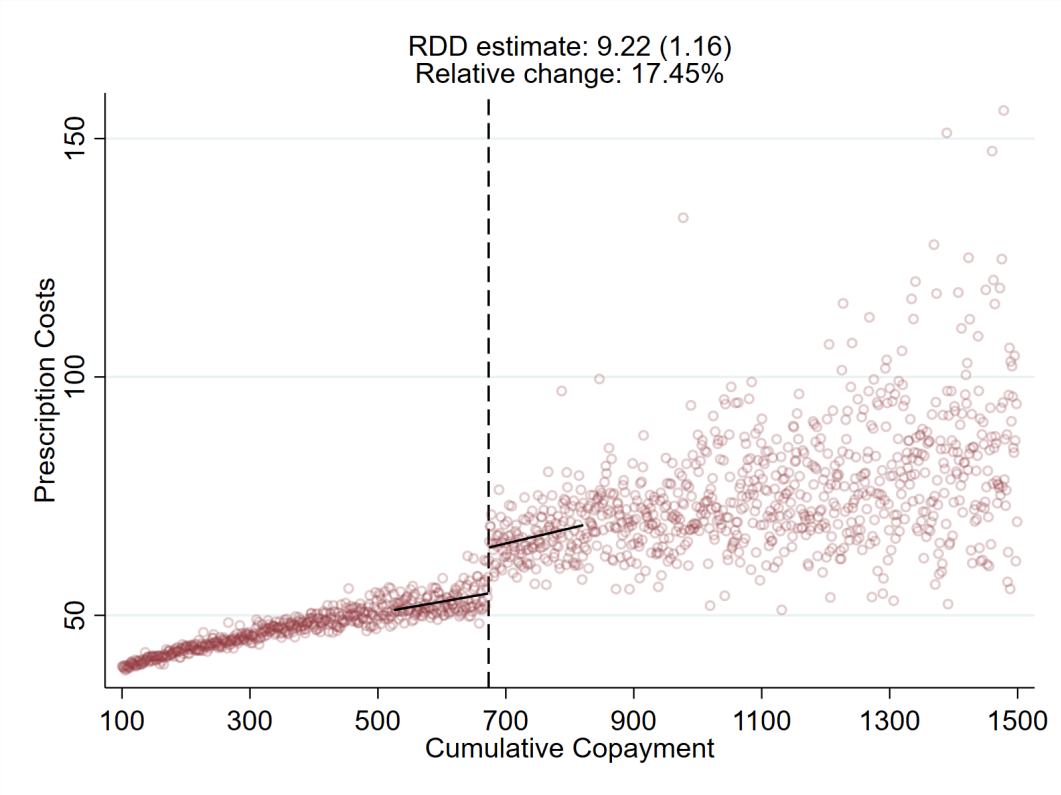

Figure 8: Prescription costs by cumulative copayment: Purchases from January to September only.

Note: The figure shows the average costs for one-euro bins of individuals' accumulated copayments for the prescription costs including only the purchases from January to September. The RDD estimate in the subtitle shows the RDD estimate at the copayment threshold (€672) and the relative change is relative to the average level just below the threshold.

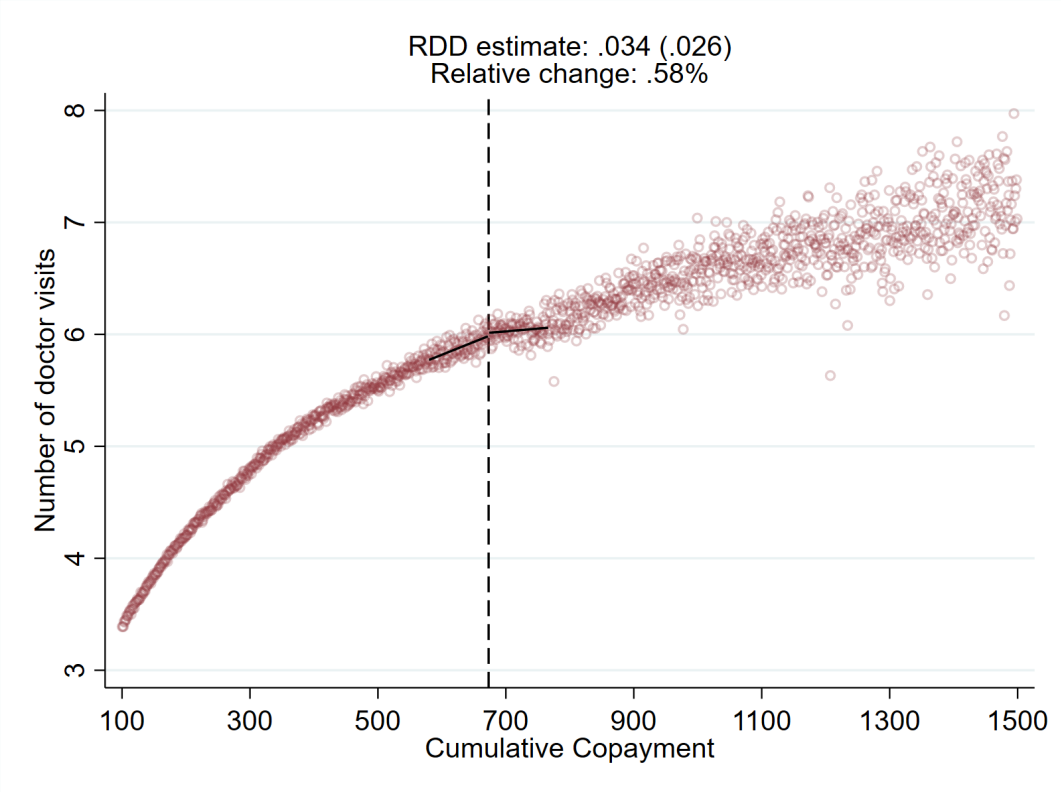

Figure 9: Number of doctor's appointments by cumulative copayment.

Note: The figure shows the average number of doctors prescribing drugs for one-euro bins of individuals' accumulated copayments. The RDD estimate in the subtitle shows the RDD estimate at the copayment threshold (€672) and the relative change is relative to the average level just below the threshold.

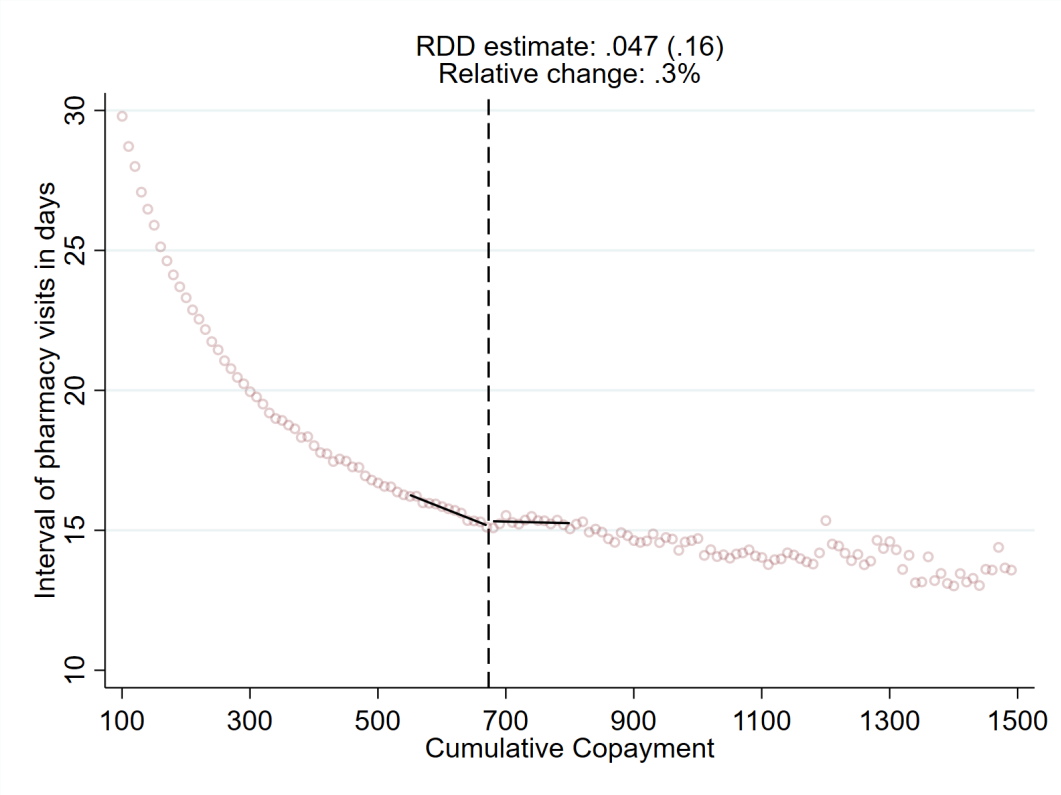

Figure 10: Interval of pharmacy visits in days by cumulative copayment.

Note: The figure shows the interval of pharmacy visits in days for ten-euro bins of individual's accumulated copayments of drug purchase costs. Dashed vertical line marks the cumulative co-payment threshold (€672).

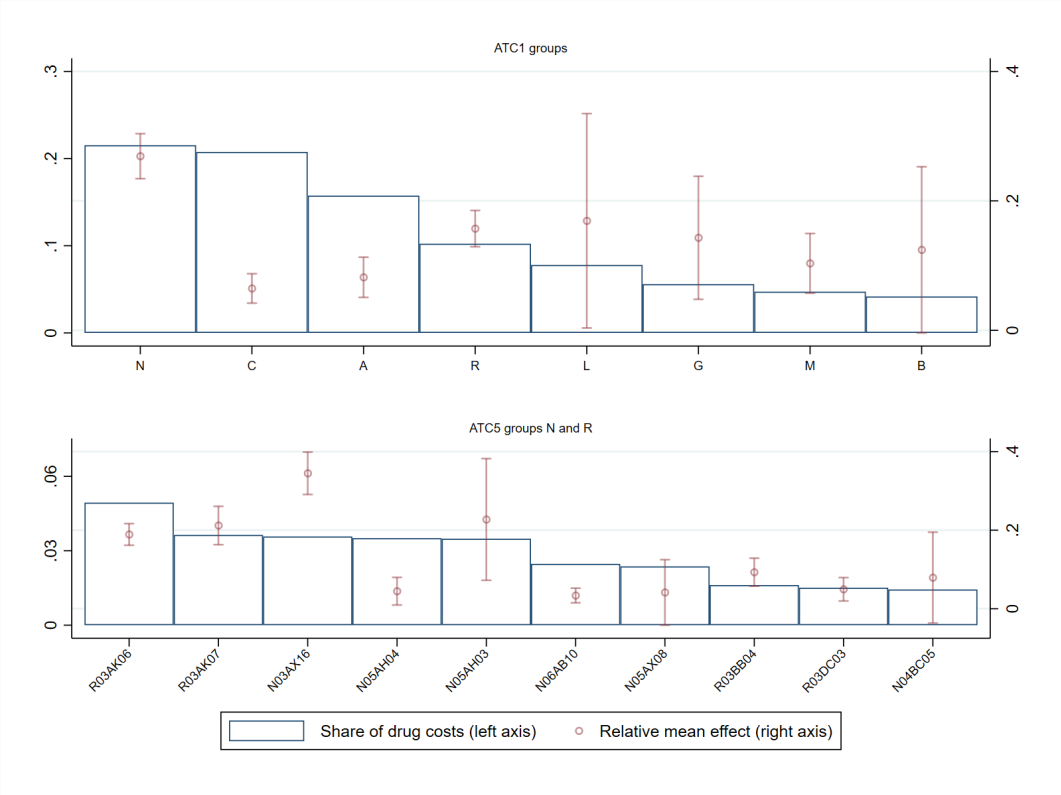

Figure 11: Relative RDD effects for different ATC drug groups: ATC1 groups (upper) and ATC5 groups N and R (lower).

Note: The figure shows the relative RDD effects and the share of drug costs for different ATC groups. The upper panel shows the relative RDD effects for ATC1 groups (N, C, A, R, L, G, M, and B). ATC1 groups are the main ATC categories with the highest shares of the total drug costs. The lower panel shows the relative RDD effects for ATC5 groups N and R (R03AK06, R03AK07, N03AX16, N05AH04, N05AH03, N06AB10, N05AX08, R03BB04, R03DC03, and N04BC05). ATC5 groups appear in the top 10 groups of the costs in drugs for the nervous system (N) and airway diseases (R).

B Online Appendix: Robustness Checks

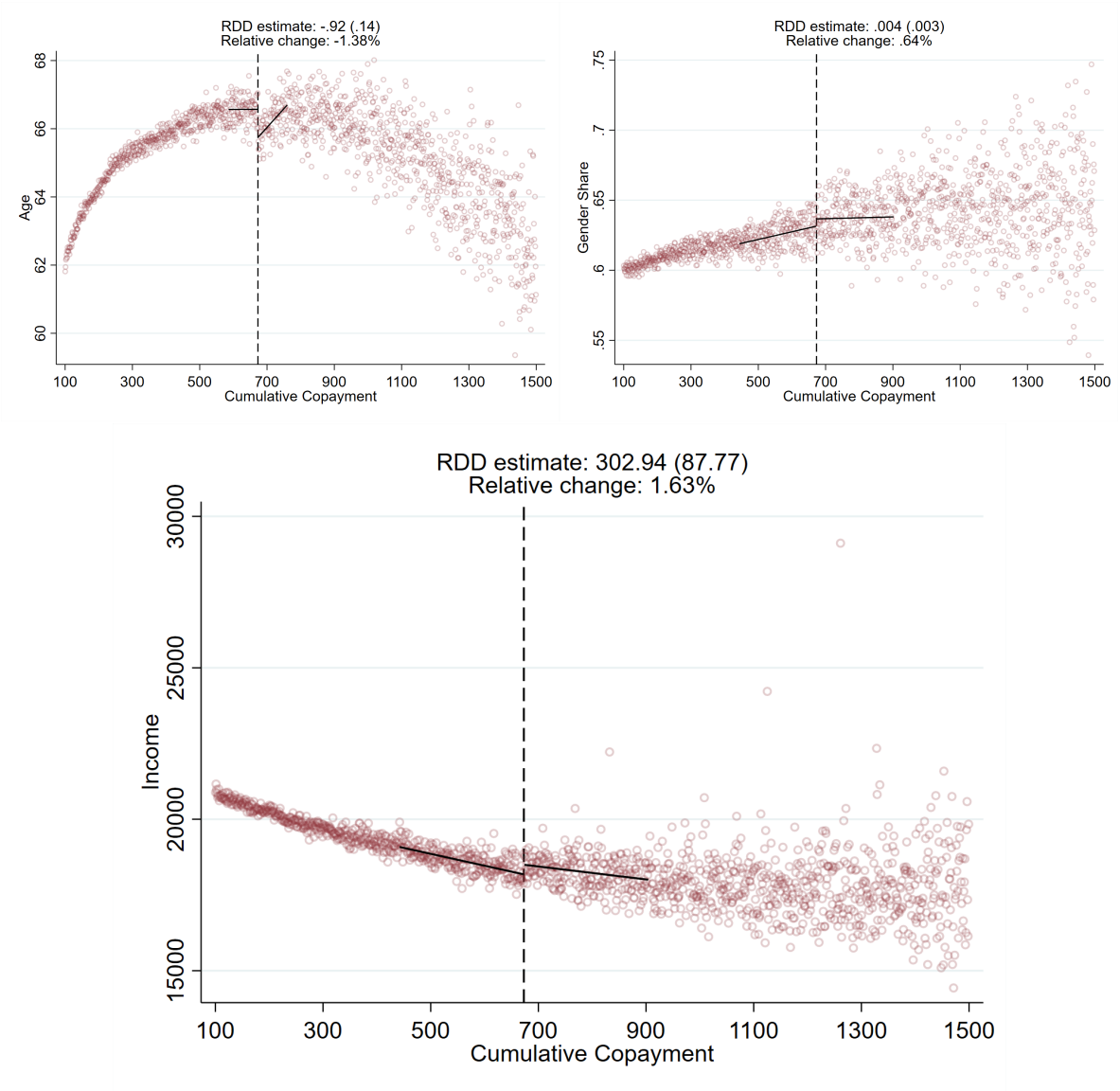

Figure 12: Individual characteristics at the threshold: Age (upper-left), gender share (upper-right) and income (lower panel).

Note: The figure shows the average costs for one-euro bins of individuals' accumulated copayments for age, gender share, and income. The RDD estimate in the subtitle shows the RDD estimate at the copayment threshold (€672) and the relative change is relative to the average level just below the threshold for different outcomes, respectively.

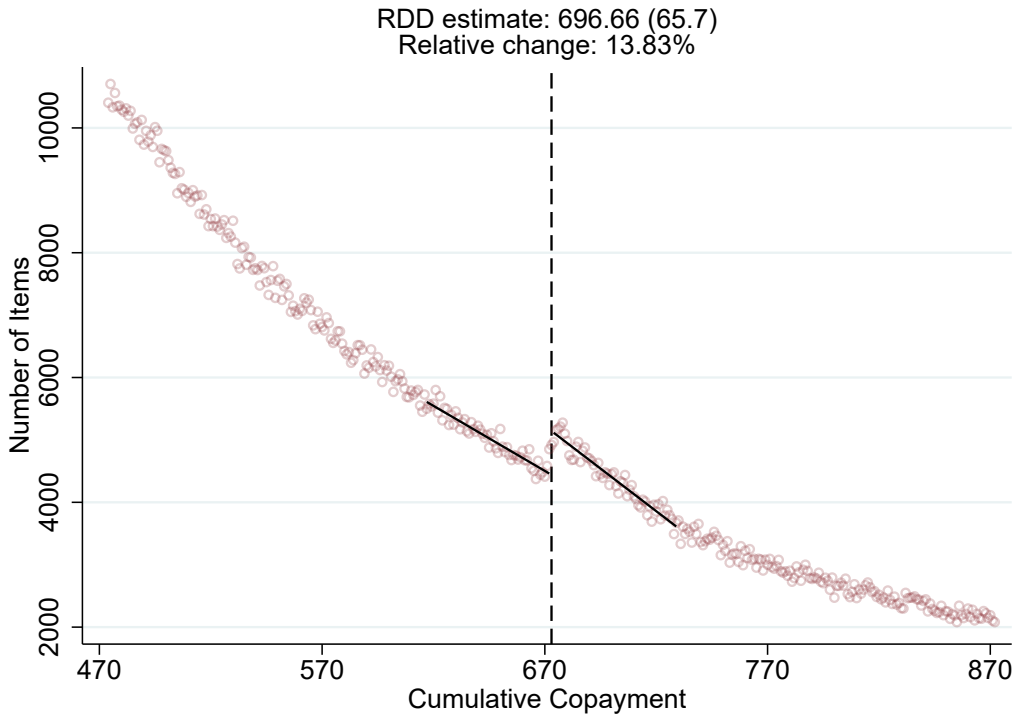

Figure 13: Number of transactions: Wider running variable.

Note: The figure shows the average costs for one-euro bins of individuals' accumulated copayments for the number of transactions, with a wider range of cumulative copayment (€470-870). The RDD estimate in the subtitle shows the RDD estimate at the copayment threshold (€672) and the relative change is relative to the average level just below the threshold.

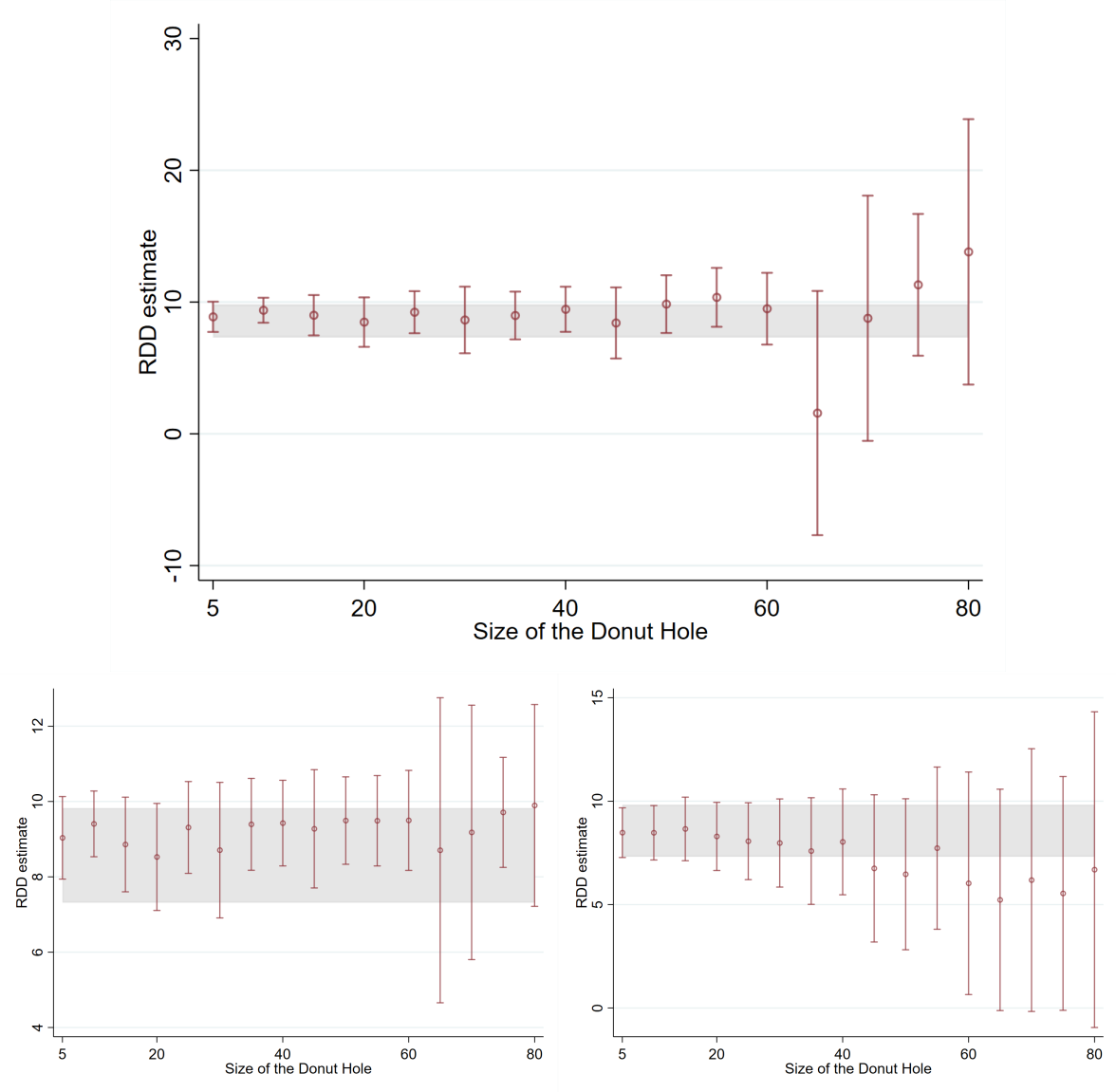

Figure 14: RDD estimates using different donut holes: Symmetric (upper panel), left (lower-left) and right (lower-right).

Note: The figure shows the RDD estimates at 95% confidence intervals using different donut holes and indicates the 95% confidence intervals for the baseline estimate.

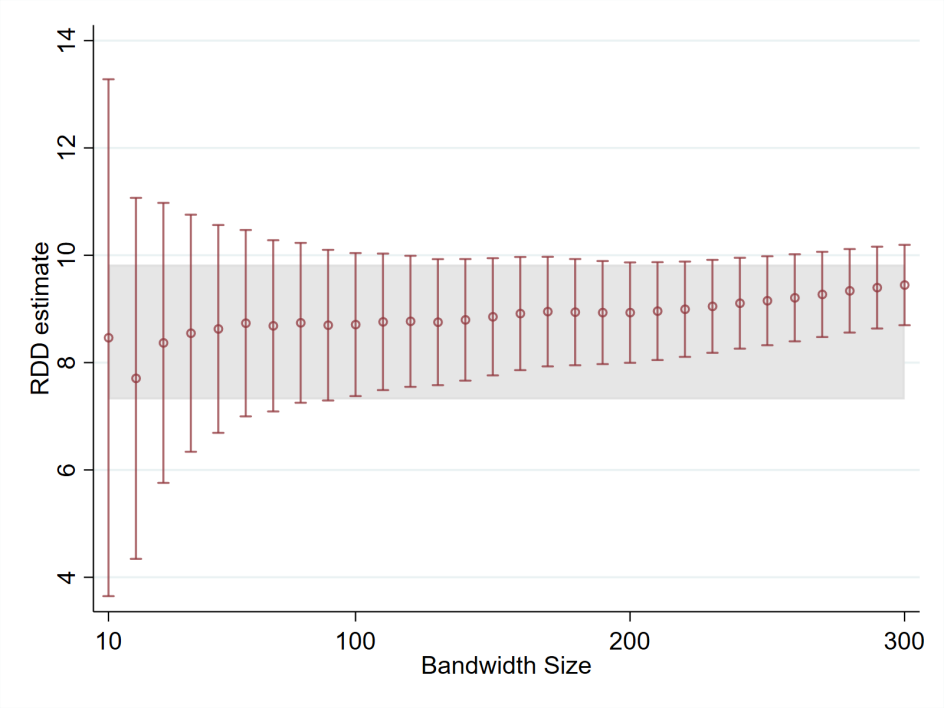

Figure 15: RDD estimates by different bandwidth choices.

Note: The figure shows the RDD estimates at 95% confidence intervals by different band width choices and indicates the 95% confidence intervals for the baseline estimate.

	Varying placebo thresholds									
Placebo threshold	323	373	423	473	523	823	873	923	973	1023
RD estimate	-0.476	-0.580	-0.371	2.434**	0.265	-2.397**	0.069	1.954	-0.056	1.370
SE	0.508	1.243	0.383	1.193	0.585	1.040	0.337	1.408	0.405	1.700

Table 4: Robustness Checks: RDD estimates using placebo thresholds.

Note: The table shows the RDD estimates and their standard errors for using five placebo thresholds both below (323, 373, 423, 473, and 523) and above (823, 873, 923, 973, and 1023) the actual threshold of €672.

	Number of polynomials							
	1 (Baseline)	2	3	4	5	6	7	8
RD estimate	8.644	8.659	8.505	8.749	8.214	8.212	8.157	8.857
SE	0.665	0.754	0.809	1.026	1.163	1.206	1.365	1.554

Table 5: Robustness Checks: RDD estimates with alternative polynomials.

Note: The table shows the RDD estimates and their standard errors with alternative polynomial degrees from the baseline of one polynomial to up to eight polynomials.

	Baseline		
	Triangular	Uniform	Epanechikov kernel
RD estimate	8.644	8.638	8.494
SE	0.665	0.675	0.643
Bandwidth	143.9	133.9	119.2

Table 6: Robustness checks: RDD estimates varying weighting.

Note: The table shows the RDD estimates, their standard errors, and bandwidths with different choices of kernel function (triangular, uniform, and Epanechikov kernel).

	RDD estimates using micro data	
	w/o controls	with controls
RD estimate	8.107	7.477
SE	0.600	0.598
Bandwidth	144	144

Table 7: Robustness checks: RDD estimates using micro data.

Note: The table shows the RDD estimates, their standard errors, and bandwidths estimated with micro data not confined to euro-bin width averages, without (left) and with (right) controls.

	RDD estimates by year		
	2008	Baseline	2010
RD estimate	8.080	8.644	9.943
	0.658	0.665	0.637
Bandwidth	129.1	143.9	162.2

Table 8: Robustness checks: RDD estimates by year.

Note: The table shows the RDD estimates and their standard errors, and bandwidths for years 2008, 2009 (baseline), and 2010.