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For instance, one may expect low income groups to react more strongly to cost-sharing than high incomes.
Using our structural microsimulation model, we estimate the expected response to changes in cost-sharing across gender, age and income groups.

We find an average elasticity of −0.11, with significant variation across age groups but minimal differences by income or gender.
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Responses to cost-sharing: Do socio-demographic characteristics matter?*

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Abstract

Patient cost-sharing in health insurance tends to reduce moral hazard, but the effect may differ between subgroups. For instance, one may expect low-income groups to react more strongly to cost-sharing than high incomes. With the help of a structural microsimulation model, we estimate the expected response to changes in cost-sharing across gender, age and income groups, also considering the interactions among these characteristics. We estimate the parameters of our model using Dutch individual-level healthcare data for the years 2011 to 2019. We find an overall average elasticity of approximately 0.11, with considerable variation in elasticities across age groups and but only minimal variation across income quintiles or between genders. An increase in cost-sharing causes the largest increase in out-of-pocket expenditure for the elderly.

JEL Codes: I11, I13, I14

Keywords: deductible, cost-sharing, healthcare consumption, microsimulation, Bayesian mixture model, moral hazard, out-of-pocket, risk, equity

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1 Introduction

Cost-sharing in health insurance involves shifting a share of healthcare costs to the patient in order to curb moral hazard and limit healthcare waste. In past decades, many countries have increased demand-side cost-sharing in an attempt to contain healthcare expenditures with the hope that this might also increase efficiency (Brot-Goldberg et al., 2017). Cost-sharing schemes vary by country and by type of care. The Netherlands, for example, uses a deductible, which is payable for all care that is covered by basic health insurance. Patients pay for the received care out-of-pocket until they reach the deductible amount[1]. The RAND Health Insurance Experiment (HIE) confirmed that individuals' healthcare demand is indeed influenced by changes in cost-sharing (Manning et al., 1987). The original price elasticity range of -0.1 to -0.2 identified by the RAND HIE has been re-examined and revised extensively in a variety of settings (Einav & Finkelstein, 2018; Kiil & Houlberg, 2014). In the Dutch context, estimates of price elasticity range from -0.09 to -0.14. Specifically, van Vliet (2004) estimated an overall elasticity of -0.14 for healthcare[2], while, more recently, Remmerswaal et al. (2023) found an overall elasticity of -0.09. Hence, it is well established that cost-sharing reduces overall healthcare demand.

But while reductions in spending may be reached using cost-sharing schemes, they may also exacerbate inequalities. High out-of-pocket (OOP) expenditures may be a disproportionate financial burden for certain subgroups. Further, there is a widespread concern that low-income individuals are more likely to forego care due to cost-sharing than high-income individuals as they may be unable to afford the costs. Especially, if this concerns necessary care, this could further widen (health) inequalities between income groups.

A more nuanced understanding of how various groups react to cost-sharing could provide valuable insights for policy decisions. Our findings may help to identify the groups most impacted by changes in the deductible. For example, if evidence suggests that low-income groups are more sensitive to cost-sharing compared to high incomes, this could indicate that they are foregoing valuable care. In such a case, policymakers could consider lowering the deductible or introducing income-based cost-sharing.

Several theories suggest heterogeneity in responses to cost-sharing by age and income. For example, having lower financial means may hinder the affordability of care (Chandra et al., 2014; Gross et al., 2022). In addition, liquidity constraints may cause individuals to concentrate on their immediate financial concerns and evoke myopic behavior (Mani et al., 2013; Mullainathan & Shafir, 2013; Shah et al., 2012). As a result, low-income individuals

[1]Other European countries have different cost-sharing arrangements in place, such as co-payments, where patients pay a fixed fee for each service, or co-insurance, where patients pay a percentage of the costs (Tambor et al., 2010).

[2]It's noteworthy that Van Vliet's study precedes the introduction of the Health Insurance Act in 2006. Before the implementation of this act, obtaining health insurance from a private insurer was voluntary and primarily undertaken by individuals with higher income (van Vliet, 2004). After the introduction of the Health Insurance Act, purchasing health insurance from a private insurer became mandatory (See Section 2.1).

might forego more (necessary) care and be more sensitive to changes in cost-sharing than those with higher incomes. However, the response to cost-sharing also depends on the level of healthcare expenditure. Low-income individuals, who are more likely to have chronic illnesses and higher healthcare expenditure (CBS, 2022; de Boer et al., 2019; Marmot, 2002; OECD, 2021), may be less sensitive to cost-sharing because they are more likely to exceed the deductible. The model that we use, estimates these two channels separately. Further, there is a strong correlation between health needs and age (Lowsky et al., 2013). Consequently, one can expect that the elderly require treatments almost irrespective of their associated costs and are likely to have lower response rates to changes in cost-sharing. Unlike for age and income, there is no obvious theoretical basis suggesting that men and women respond differently to cost-sharing. However, as discussed in the following paragraphs, some quantitative studies do find differences in response by sex.

While theories suggest that responses to cost-sharing differ among socio-demographic groups, quantitative research on this topic is limited and with varying conclusions. For example, the original RAND HIE found no clear differences in expenditures between high and low incomes in response to different co-insurance levels. Similarly, Cherkin et al. (1989) found no significant differences between different income groups in the frequency of primary care visits following the introduction of a $5 co-payment. More recently, Chandra et al. (2021) also found no significant differences in the responses to the introduction of high-deductible pharmaceutical plans by income. However, when analyzing the effect of liquidity constraints on healthcare demand, Gross et al. (2022) found a gradient based on income. They found that Medicare recipients living in the lowest income areas were five times more likely to refill their prescriptions directly following their social security payments than Medicare recipients living in the highest income areas, particularly when co-payments were required[3]. In contrast, Kato et al. (2022) found that higher income groups were more responsive to changes in the level of the co-insurance rate, most likely due to their higher share of elective care. Kato and colleagues found that the elasticity of demand for outpatient care ranged from 0 for low-income groups to -0.11 for high-income groups among a patient population aged 68-72 years.

As for differences in responses by gender, most studies find a stronger response for women than for men. For example, Cherkin et al. (1989) found that the drop in the frequency of primary care visits resulting from the introduction of a co-payment was twice as high for women than for men. Lambregts and Van Vliet (2018) also found a significantly stronger response by women when copayment was introduced in mental healthcare in the Netherlands. Skipper (2013) found that an exogenous shift in co-payment on pharmaceuticals in Denmark led to heterogeneous demand elasticities in the range of –0.36 to –0.5, with women, the elderly, and immigrants being affected the most[4]. Heterogeneity in

[3]The sample includes individuals enrolled in Medicare part D, a program for elderly receiving social security benefits (Evans & Moore, 2011).

[4]These elasticities refer to pharmaceutical care, which has been shown to elicit a higher response

demand elasticities across age groups has only been analyzed in a few papers. Conversely, most papers, such as those conducted by Chandra et al. (2021), Cherkin et al. (1989), Gross et al. (2022), and Kato et al. (2022), restrict their analysis to a specific age group. However, as previously mentioned, it is expected that elderly are less sensitive to changes in cost-sharing as they may require treatments almost irrespective of their costs.

The empirical research outlined in the previous two paragraphs mainly relies on unique changes in out-of-pocket payment for a narrowly defined group of individuals. For example, Chandra et al. (2021) investigated a quirk in the U.S. drug reimbursement policy for Medicare recipients as they reach the maximum drug reimbursement threshold, Cherkin et al. (1989) analyzed the number of primary care visits as a response to the introduction of a $5 co-payment for a working age group of employees, and Gross et al. (2022) analyzed the timing of prescription refills in relation to social security checks for the elderly. This focus on specific groups is primarily due to the heterogeneity in health coverage in the United States, where various socio-demographic groups typically have significantly different health insurance arrangements. This complicates the measurement of responses and its generalizability for the entire population. However, in the Netherlands, basic health insurance is mandatory and universal across insured individuals. This universal coverage along with a strictly defined basic package allows for the measurement of response heterogeneity across different socio-economic groups. Consequently, in the present paper, we aim to provide estimates that apply to large parts of the Dutch population and are differentiated by age, gender and income categories[5]. Additionally, we also consider the interaction between age, gender and income, as these may confound the direction and the magnitude of the response.

In the present paper, we analyze the response to cost-sharing by age, gender and income using a structural microsimulation model introduced by Boone and Remmerswaal (2024). We extend their previous analysis by exploring responses to cost-sharing by income. While Boone and Remmerswaal (2024) compared different cost-sharing schemes (deductible, co-insurance, shifted deductible[6]), our focus is specifically on deductibles.

First, we estimate the parameters used to model the distribution of expenditures based on age, gender, and income. Next, we use these parameters to simulate expenditures for two assumed deductibles: a low deductible of €300 and a high deductible of €600. With these two expenditure distributions we calculate the response to changes in the deductible which we summarize with a deductible elasticity[7]. We calculate the deductible

than overall healthcare expenditure.

[5]While our analysis focuses solely on income, we acknowledge that wealth could also influence how individuals respond to cost-sharing. For example, low-income individuals, such as retired elderly, may have significant wealth and therefore face fewer liquidity constraints. We leave the inclusion of a combined income-wealth measure for future research.

[6]With a shifted deductible, the deductible does not start at zero but instead starts after a specified level of expenditure has been reached

[7]Deductible elasticity resembles price elasticity of demand. A price elasticity of demand measures the change in demand for a product in response to a change in the price of the product. In

elasticities seperately for age groups, income groups and gender. Additionally, we explore their interactions, recognizing that income is influenced by both age and gender. Finally, we calculate the change in out-of-pocket expenditure across age-gender and income-gender groups. Examining these changes are insightful, as they are not only influenced by the deductible elasticities, but also by healthcare expenditures. This means that even with the same deductible elasticities, a group with higher mean healthcare expenses could experience a greater change in out-of-pocket payments.

We find an overall average elasticity of -0.11 which is in the same range as the elasticities found by Boone and Remmerswaal (2024), Manning et al. (1987), and van Vliet (2004). The variation in elasticity is substantial along the age dimension. For individuals aged 19-25, the elasticity is -0.18, whereas the elasticity decreases with age and is only -0.09 for individuals above 65 years. There is less variation along the gender and income dimensions. When it comes to changes in out-of-pocket expenditures, the elderly experience a more significant increase.

Our paper is structured as follows. Section 2 describes the institutional setting of our study and introduces the data. The model is presented in Section 3. Section 4 presents our findings, beginning with an analysis of differences across age groups, income groups, and gender individually, followed by an exploration of their interactions. Finally, Section 5 discusses our findings.

2 Setting and Data

2.1 Setting

We study the effects of changes in demand-side cost-sharing for curative care in the Netherlands[8]. The Dutch healthcare system is built on the principles of managed competition and mandatory basic health insurance (Enthoven & Van De Ven, 2007). Managed competition was introduced by the Health Insurance Act in 2006 to enhance affordability and quality of healthcare allowing Dutch insurers and providers to compete on quality and price. Health insurers negotiate and contract care with providers on behalf of their clients. They may selectively contract with certain providers considered to provide higher-quality and more efficient care while excluding other providers (Schäfer et al., 2010).

The government safeguards access to healthcare by defining a basic health insurance scheme, which is provided through private insurance companies. The basic health insurance scheme covers all essential healthcare services, such as hospital care, general practitioner care, prescription drugs and the majority of mental healthcare services, and is

the context of health insurance, this definition is often adapted to a change in the deductible (See Section 4.3 for the formula of the deductible elasticity).

[8]The organization of social care and long-term care differs from curative care and is therefore beyond the scope of this paper. When referring to healthcare, we refer to curative care.

compulsory for all Dutch residents. Insurers are obliged to accept all new applicants and refrain from price discrimination[9]. Each insured individual aged 18 and above pays a nominal premium for basic health insurance that was around €1500 a year in 2019 (Romp et al., 2019)[10]. Children under the age of 18 years are exempt from the nominal premium.

In addition to the nominal premium, residents aged 18 and above are subject to a mandatory deductible for healthcare covered by basic health insurance. The government sets this deductible level annually. Since 2016, the deductible has been set at €385, meaning individuals must pay the first €385 of their healthcare expenses out-of-pocket, while costs exceeding €385 are fully covered by health insurance. The deductible applies to most care, except for general practitioner, maternal, obstetric and home care. These exempt services account for approximately 10% of overall healthcare expenditures (Statistics Netherlands, 2022). In addition to the mandatory deductible, individuals may opt for voluntary deductibles ranging between €100 to €500, which will increase the (total) deductible but lower their nominal premium.

Table 1: Deductibles in the Netherlands, 18 years and above from 2011 to 2019.

Year	2011	2012	2013	2014	2015	2016	2017–2019
Mandatory deductible	€170	€220	€350	€360	€375	€385	€385
Change in mandatory deductible		€50	€130	€10	€15	€10	€0

Note: Individuals under 18 years of age are exempt from the mandatory deductible.

Individuals can also purchase supplementary insurance for services beyond the basic health benefits package, such as physiotherapy and dental care. In this paper, we concentrate on basic health insurance rather than the supplementary insurance market. These two markets are distinct, allowing individuals to purchase basic insurance from one provider and supplementary insurance from another.

2.2 Data

This paper uses rich, individual-level administrative data from the The Netherlands. The data is provided by Statistics Netherlands and contains detailed information on healthcare expenditures, income and individual background characteristics for all Dutch policyholders for the years 2011 to 2019.

2.2.1 Healthcare data

We use healthcare records for all Dutch policyholders ($\sim$ 17 mn.) aggregated to the level of the individual by type of care for the years 2011 - 2019. Our data is sourced from Vektis, an

[9] A risk adjustment system is used to compensate private insurers for the additional healthcare expenses of high-risk individuals.

[10] In addition to the nominal premium, total healthcare costs are financed using an income-dependent contribution and general taxes.

organization responsible for collecting and processing data from all Dutch health insurers. It includes care covered by basic health insurance according to the Health Insurance Act and several personal characteristics such as gender, age and the individual's annual choice of a voluntary deductible[11].

We follow the data cleaning steps outlined in Boone and Remmerswaal (2024). As the topic of interest is the impact of the deductible on expenditure, we limit our dataset to care categories that are subject to the deductible. That is, we exclude costs associated with the general practitioner, maternal care, obstetric care and home care. Although some of dental care falls under the deductible, this is limited to specific treatments and varies between children and adults. Consequently, we opted to exclude dental care from our variable healthcare expenditures.

In addition, we also exclude certain groups of individuals who may be extreme in their response to cost-sharing compared to the general population. This includes individuals who received mental healthcare, who opted for a voluntary deductible or were among the highest spenders during our study period[12]. Individuals who received mental healthcare are excluded due to an additional co-payment introduced in 2012, as these extra payments could influence an individual's sensitivity to the mandatory deductible.

We exclude individuals who opted for a voluntary deductible within our research period. Remmerswaal et al. (2019) show that these individuals do not adjust their healthcare consumption in response to a €100 increase of the mandatory deductible and including them would skew the results as they tend to be price-inelastic. Further, given that previous research suggests that individuals who choose a voluntary deductible are typically younger, male, live in a high-income area and have lower healthcare consumption, their inclusion could blunt the differences between various income-gender-age groups (Remmerswaal et al., 2019).

Lastly, we exclude individuals with the top 5% highest healthcare expenditures[13]. One goal of our analysis is to test whether there are differences in elasticity between income groups. These top spenders spend more than manifolds the mandatory deductible level; hence they are unlikely to react to a €300 change in the deductible. Including them would bias the overall elasticities towards zero, and hence we would not be able to detect any variation between different subgroups. Even after excluding the highest spenders, we

[11]We group individuals older than 90 years in one age category in order to ensure sufficient observations per income-gender-age category.

[12]See Table 8 and Table 9 in the Appendix for a detailed description of all dropped observations by income and age groups.

[13]Our dataset does not include the indicator for chronic illness and extended use of medication (labelled with DCG or PCG), which was present in the dataset utilized by Boone and Remmerswaal (2024). However, using the dataset of Boone and Remmerswaal (2024), we were able to reconstruct the healthcare expenditures of these chronically ill group and calculate where they lie in the distribution of total healthcare expenditures. This number was estimated to be approximately the top 5% spenders.

observe minimal differences between income groups.[14].

2.2.2 Income data

Income data is obtained from administrative records of the Tax and Customs Administration. We assume that healthcare expenditures are often financed on a household level, therefore we use standardized disposable household income to calculate income quintiles[15]. This involves aggregating the income of the household in which an individual resides and adjusting it for household size and composition. Consequently, children living with their parents have their parents' income attributed to them. Individuals with negative household incomes and household incomes below a certain percentage of the net minimum wage are excluded from our analysis, as it is unlikely that the household income will remain on a very low or negative income for an extended period without support, which may not be reflected in the income statistics (e.g. financial support from parents to students)[16]. We re-calculate the income quintiles for each year of our study period. Throughout this paper, we denote the first income quintile as Q1 or lowest income quintile, and the fifth income quintile as Q5 or highest income quintile. Our findings primarily focus on the lowest and highest income quintiles.

2.2.3 Machine learning

After combining healthcare and income data, we split our data into three sets: a train set, a validation set, and a test set (McElreath, 2020). We utilize stratified sampling to ensure that each independent set is representative across years, age, gender and income groups. The train dataset contains 60% of the total data and is used to estimate the parameters of the model. The validation set comprises 20% of the total data and is used to validate the predicted outcomes of the model. The remaining 20% of the total data is test data. After our paper is finalized for publication, the final fit of the model is assessed by comparing our predictions to the test data. We further elaborate on the estimation of parameters and the validation of the predicted outcomes in Section 3.

[14] As a robustness analysis, we also ran our model without dropping these top 5% percent spenders. As expected, our elasticities were drawn towards zero, but the ranking of elasticities across income, age and gender groups remained the same.

[15] The reference date for household data is January 1. Consequently, household income data for individuals aged 0 is often missing. We impute the missing data with household income data from age 1.

[16] In line with earlier research and policy work, we chose a cut-off of 63% of the net minimum wage (Koot et al., 2016). It is often argued that these very low-income households do not represent individuals with limited resources, but people with independent wealth, students or individuals taking a sabbatical.

2.2.4 Descriptive Statistics

In Table 2 and 3, we summarize the descriptive statistics for the five income groups by gender using the train dataset[17]. The percentage of individuals with positive healthcare expenditures is higher for women than for men (83% and 75%, respectively). Similarly, average healthcare expenditure is higher for women than for men: €923 vs. €786[18]. Income and expenditure on healthcare appears to be negatively correlated for both genders: for women mean expenditure ranges between €1077 for the lowest income quintile and €789 for the highest income quintile (and similarly €894 for the lowest income quintile and €688 for the highest income quintile for men). Additionally, the percentage of individuals with positive healthcare expenditures is highest in the lowest income group for both genders. See Table 10 and Table 11 in the Appendix for a summary of the descriptive statistics per age group.

Table 2: Summary of the train data by income quintiles for women, 2011–2019

	Lowest income quintile	Q2	Q3	Q4	Highest income quintile	Total
Number of observations (mln)	6.1	6.1	5.6	5.4	5.1	28.2
Age (yrs., mean)	44.19	45.54	40.34	40.43	41.20	42.46
Age (yrs., std. dev.)	28.01	27.20	25.08	23.62	22.54	25.61
Household income* (€, mean)	15,013	21,159	26,714	33,137	54,967	29,270
Household income* (€, std. dev.)	2,533	2,069	2,432	3,149	81,217	36,978
Fraction of positive expenditures	0.84	0.84	0.82	0.82	0.82	0.83
Expenditure (€, mean)	1,077	1,026	856	825	789	923
Expenditure (€, std. dev.)	1,607	1,566	1,427	1,397	1,354	1,485
Log expenditure (mean)	5.13	5.08	4.79	4.75	4.70	4.90
Log expenditure (std. dev.)	2.73	2.70	2.71	2.70	2.69	2.71

*Annual standardized disposable household income

As illustrated in Figure 1, income-related differences in healthcare expenditures begin in early childhood with noticeable variations for children between the ages of 0-18 years[19]. Between 19 to 25 years healthcare-related spending is similar for all income groups. For women, trends begin to diverge again during the reproductive years (25-44 years). Healthcare expenditures for women in the highest income quintile surge during this period[20]. After the reproductive years, the healthcare expenditure of women in the

[17]The number of observations represents the number of observations remaining after data cleaning. We use data from the Dutch population for the years 2011-2019. Consequently, multiple observations per person exist in our dataset. The unequal number of observations per income quintile is a result of our exclusion criteria

[18]Note that our analyses exclude general practitioner care, maternal care, obstetric care, home care, dental and mental health care (See Section 2.2.1). Consequently, the percentage of individuals with positive healthcare expenditures and the average healthcare expenditure is lower compared to figures reported by Statistics Netherlands (CBS, 2022).

[19]Note that our analysis utilizes standardized disposable household income data. Hence, children and students living with their parents have their parents' income attributed to them.

[20]The surge for the highest income quintile during the reproductive age is partly explained by the

Table 3: Summary of the train data by income quintiles for men, 2011–2019

	Lowest income quintile	Q2	Q3	Q4	Highest income quintile	Total
Number of observations (mln)	5.0	5.5	5.7	5.6	5.5	27.3
Age (yrs., mean)	38.94	42.34	39.42	40.01	41.46	40.45
Age (yrs., std. dev.)	26.79	26.42	24.30	23.03	22.34	24.62
Household income* (€, mean)	14,884	21,254	26,746	33,169	55,103	30,463
Household income* (€, std. dev)	2,604	2,072	2,434	3,157	85,972	40,866
Fraction of positive expenditures	0.76	0.77	0.75	0.74	0.74	0.75
Expenditure (€, mean)	894	898	752	710	688	786
Expenditure (€, std. dev.)	1,500	1,500	1,358	1,311	1,273	1,392
Log expenditure (mean)	4.53	4.56	4.28	4.21	4.23	4.36
Log expenditure (std. dev.)	2.95	2.94	2.92	2.91	2.88	2.92

*Annual standardized disposable household income

high-income quintile falls below that of women in the low-income quintile. (See Figure 11 in the Appendix for all income quintiles). Spending differences between income quintiles are smaller for men. In general, men with lower incomes tend to have higher healthcare expenditure compared to those with higher incomes. The model takes into account that differences in healthcare spending can influence how groups react to changes in deductibles.

3 Model

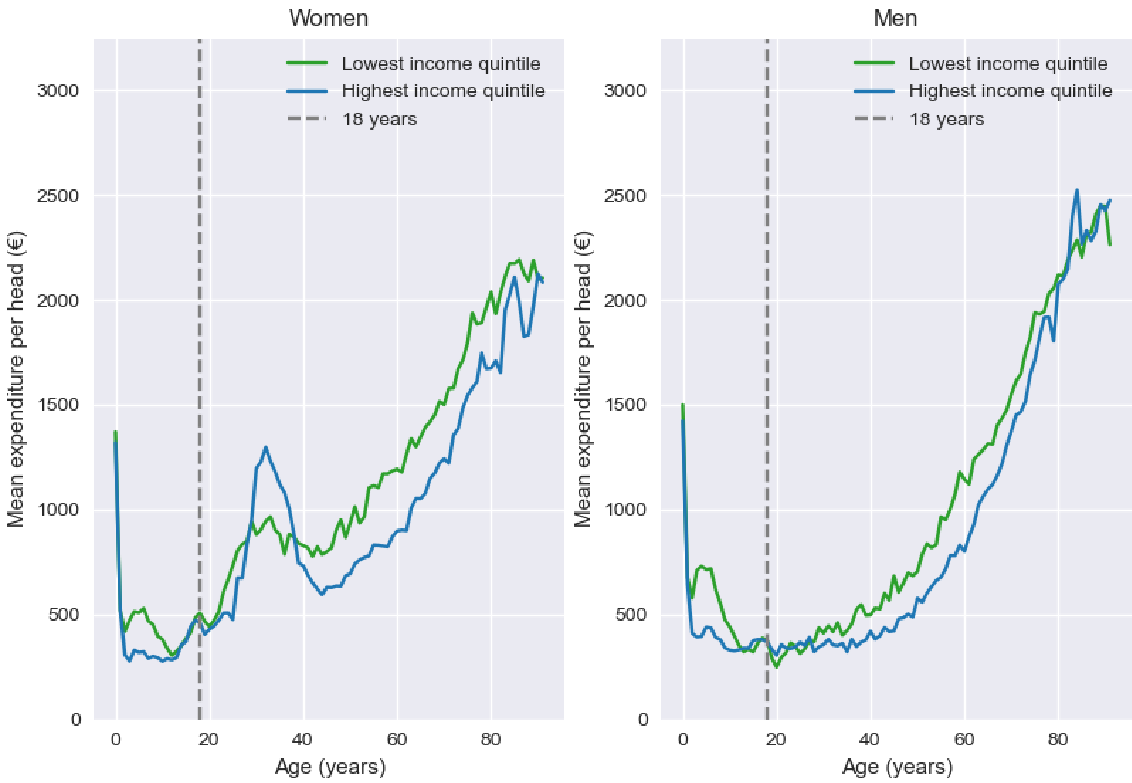
Our method builds on the model of Boone and Remmerswaal (2024) which is a Bayesian mixture model of healthcare expenditure with four underlying distributions. This mixture model can be interpreted in terms of individual optimization behavior if we assume that individuals face two types of healthcare expenditures: exogenous and endogenous expenditures. Exogenous expenditures represent high valuecare[21] *to the patient*, where the decision to accept care is unaffected by the (modest) deductible levels in our data (think of plasters on a broken leg, care following a heart attack). Endogenous care, on the other hand, represents low value care in the sense that a patient's decision to accept treatment depends on the effective price she is expected to pay under the deductible. Furthermore, the model assumes that individuals are able to predict their health status based on age, gender and income[22] and are rational in the sense that they can predict the *distribution*

data. In our analysis, we consider household income. Although household income is standardized for the composition of the household, couples still have higher income compared to singles. The high-income quintile therefore contains more women who are in a relationship. Women who are in a relationship are more likely to become pregnant and incur higher healthcare costs. In Section 5, we also argue that women with higher household incomes tend to spend more on healthcare when necessary as health is considered a normal good

[21]The value represents individuals' valuation of care and not the true medical value of a treatment. Further discussion on this topic can be found in Section 5.

[22]Thus, in our empirical approach health status is approximated by age, gender and income. To enhance this approximation we could include additional indicators, such as subjective health

Figure 1: Conditional mean expenditure for the highest and the lowest income quintiles in 2019



of care offered to them each year. In addition, the model assumes that individuals know their own valuation/utility of a treatment which they compare to the increase in OOP expenditure in case they accept the treatment.

Consequently, the model separates two margins that determine the extent to which expenditures react to a change in the deductible: (1) whether people are at the margin (expect expenditures around the deductible level) which affects their expected out-of-pocket (EOOP) price and (2) whether a change in EOOP lies around the utility of the treatment which affects individuals' treatment decisions.

The first margin determines whether a change in the deductible affects the price of a treatment paid by the patient. Instead of using the deductible as the treatment price in our model, we use a variation of the end-of-year-price which we denote as the EOOP price. The EOOP is the expected increase in an individuals' OOP expenditure if a treatment is accepted, taking into account other treatments that are accepted by the individual in the same period. Hence, it is possible that EOOP remains unchanged after an increase in the deductible because other (exogenous) treatments purchased by the individual have already depleted her deductible for the period. Technically speaking, EOOP is calculated

scores or healthcare expenditure from previous years. However, this would add complexity to the model, and the current model fit is already adequate (See Section 3.3.1).

by first taking the expectation (integral) over other expenditures during the period. Then we take the difference between expected OOP payments with and without the treatment.

The second margin determines whether the patient will accept the treatment based on her own expected utility derived from the treatment. If a patient attaches a high (expected) value to a treatment, a small change in EOOP will not affect her decision to accept. Hence, if we find that a certain income-gender-age group hardly reacts to a change in the deductible we can separate the two underlying causes: this group's expenditure is not at the *margin* and/or the treatment *value* for this group tends to exceed the higher expected OOP expenditure.

In the present paper, we use the model to estimate deductible elasticities by age, gender and income. Our analysis consists of four parts: (1) we estimate the parameters of our model using healthcare expenditures data for the years 2011 to 2019, (2) we use these parameters to simulate healthcare expenditures for different deductible levels, and we use the simulated expenditures to calculate (3) elasticities and (4) changes in out-of-pocket expenditures. Using the train dataset, we perform the estimation in part (1) for each income-gender-age group separately. Outcomes, such as healthcare expenditures, are predicted using the estimated parameters and compared to the validation data.

For each income-gender-age combination, we approximate the expenditure distribution with a mixture model consisting of four components, that is four underlying distributions (See Section 3.1). The component of this mixture model that remains constant across time regardless of the deductible level is considered exogenous with respect to the deductible. The other components do vary with the deductible level and are called endogenous care.

We denote exogenous and endogenous expenditures in euros by X and Y, resp. Further, we denote our observed healthcare expenditures by Z which consists of X and Y expenditures. Similarly to previous papers, we assume that Z is log-normally distributed conditional on being positive (Boone & Remmerswaal, 2024; Einav et al., 2013)[23]. Hence, we transform it into logs: z=log(1+Z)[24]. As a result, Z=0 if and only if z=0; otherwise $z > 0$. Assuming that Z|Z>0, conditional on being positive, has a log-normal distribution, z|z>0 is normally distributed.

In addition, we model the probability that an individual is offered exogenous treatment, denoted by ψ_x, and the probability that an individual is offered endogenous treatment, ψ_y. An exogenous treatment (x) is always accepted independently of the deductible, as exogenous treatments are of high value to the patient by assumption. An endogenous treatment (y) may be rejected depending on the deductible level and an individual's (expected) healthcare spending. The probability that an endogenous treatment is rejected is denoted by F.

[23]Boone and Remmerswaal (2024) show that this assumption is a reasonable representation of the data and discuss its computational advantages.

[24]We add 1 euro to z in order to avoid taking the logarithm of zero. This is a very small amount compared to expected healthcare expenditures (in the order of 100 euros or higher), which is unlikely to lead to any distortions.

3.1 Mixture model

Total (log) healthcare expenditure in our model consists of four possible outcome scenarios: positive x, y, z=x+y or no expenditure: (1) if z=0, then the values of both x and y are also equal to zero (x=0 and y=0). The probability of this happening is the multiplication of $(1-\psi_x)$ and $(1-\psi_y)$, when no treatments are offered or when y is offered but rejected: $(\psi_y F)$. Similarly, we have 3 additional scenarios where either (2) x > 0 and y = 0, (3) x = 0 and y > 0 or (4) both x, y > 0. The corresponding probabilities are presented in Table 4.

Table 4: The distribution of total log expenditure

component	probability
$x = y = 0$	$(1-\psi_x)(1-\psi_y+\psi_y F)$
$x > 0 = y$	$\psi_x(1-\psi_y+\psi_y F)$
$y > 0 = x$	$(1-\psi_x)\psi_y(1-F)$
$x, y > 0$	$\psi_x\psi_y(1-F)$

In line with the normality assumption on $z|z > 0$, we assume that x | x>0 and y | y>0 are also normally distributed. Hence, with the exception of x=y=0 all other components in Table 4 are also normally distributed with parameters μ_x, μ_y, and σ_x and σ_y, $\mu_x+\mu_y$and $\sqrt{{\sigma_x}^2+{\sigma_y}^2}$ respectively.

3.1.1 Expected out-of-pocket expenditure

As previously stated, the EOOP is the expected increase in an individual's OOP expenditure if a treatment is accepted, taking into account all other treatments that are accepted by the individual in the same period. Our assumption is that, at the beginning of each year, individuals know their *distribution* of endogenous and exogenous expenditures for the coming year. In other words: individuals are able to determine their health status, and thus expected healthcare expenditure, based on age, gender and income. Hence, when they are offered an endogenous treatment, they are able to calculate their expected out-of-pocket (EOOP) price for this treatment. We model the EOOP as an integral over x[25] for each income-gender-age category. This definition of EOOP captures the idea that, for example, a woman in her 30s, on average, has higher expected healthcare expenditures than a man of the same age due to expected healthcare costs associated with maternity. As these costs will likely be higher than the deductible, EOOP is lower and women's willingness to accept an endogenous treatment is, on average, higher than for men at the same age.

[25] See Boone and Remmerswaal (2024) for the mathematical details.

3.1.2 Accepting a treatment

We assume that cost-sharing affects healthcare expenditures through one channel: changes in price (EOOP) of a treatment for the patient. Thus, the probability that an endogenous treatment is accepted is a function of EOOP. We use the following cumulative distribution function to estimate the probability that an endogenous treatment is rejected:

$$F(EOOP) = 1 - \zeta e^{-\nu EOOP} \tag{1}$$

where $\nu > 0$ reflects the hazard rate $f(x)/(1 - F(x))$ and $\zeta \in \langle 0, 1]$ is the probability that a free treatment ($EOOP = 0$) is accepted[26]. We assume that the hazard rate is constant: $f(x)/0 - F(x) = \nu$. The higher EOOP, the higher the probability that the treatment is rejected. As EOOP goes to plus infinity, the treatment is rejected with probability 1. Furthermore, we think of F as the cumulative distribution function of treatment utility or treatment value (U). A treatment is rejected if the price exceeds value: $U < EOOP$. These parameters, ν, ζ, U and EOOP, are estimated per income-gender-age group, and jointly capture the price responsiveness of healthcare to changes in cost-sharing per group.

To illustrate, if liquidity constraints are an important hurdle for low incomes, we expect to see that the estimated ν for low incomes is far higher than ν for high incomes. The same increase in EOOP then leads to a larger increase in the probability of rejecting treatment for low incomes because they hit a liquidity constraint and cannot afford the treatment.

The caveat in terms of rationality is the following. If a patient rejects a treatment because her own valuation of the treatment U is lower than EOOP, it can be the case that the medical value of the treatment (say, in terms of qaly's) exceeds EOOP. If this medical value actually exceeds the (social) cost of the treatment, accepting the treatment would have been the efficient (welfare enhancing) outcome. But the estimated model just picks up the treatment choice of the patient; not whether this choice itself is a rational decision or efficient outcome.

Finding a large difference in ν and estimated elasticities for high and low incomes would be a signal/indication that people on low income are foregoing necessary care due to demand-side cost-sharing. But it would not be proof: it can be the case that low incomes are cutting back on low value care (moral hazard). As mentioned before, we actually do not find a clear difference in elasticities between income groups.

3.1.3 Age threshold for deductibles

In the Netherlands, the mandatory deductible kicks in when a person reaches the age of 18. In our model, we do not identify for what fraction of the year the individual faces the deductible in the year s/he turns 18. Instead, we include a parameter $\alpha \in \langle 0, 1]$ which

[26] A free treatment may be rejected due to e.g. travel costs, waiting lists or risks associated with the treatment.

weighs the effect of the deductible for the 18-year-olds. We consider α as the probability that an individual faces a deductible. If the value of α is around 0.5, birthdays are uniformly distributed throughout the year in our dataset.

3.2 Identification

We use data on Dutch healthcare expenditures for the years 2011-2019 to identify the parameters of the model. The Dutch setting, detailed in Section 2.1, offers three sources of variation that allow us to estimate these parameters.

First, we use the annual increase in mandatory deductibles (See Table 1) to identify changes in EOOP for income-gender-age groups. The EOOP is the expected increase in an individual's out-of-pocket expenditure if a treatment is accepted. The annual change in the deductible affects the individual's EOOP and this affects F or the probability of rejecting care. This allows us to identify ν and ζ in the function F.

Second, we use cross-sectional variation in healthcare expenditures among different income-gender-age groups to capture changes in healthcare use. The variation in expenditure between groups affects the probability of accepting an endogenous treatment. For example, the healthcare needs of a 30-year-old man are different from those of an 80-year-old man, with the younger individual typically demanding less (exogenous) care compared to the older individual. When being offered a treatment, the 80-year-old knows that he is likely to exceed his deductible anyway and hence the EOOP for an endogenous treatment is basically zero. For the 30-year-old man, this is not the case and accepting the endogenous treatment will, at the end of the year, cost him money. Hence, the EOOP of the younger man is higher and he is more likely to reject an endogenous treatment than an 80-year-old man.

Finally, we have a case of a clear-cut cross-sectional variation: healthcare is free for people till age 18, while individuals aged 18 or above face a mandatory deductible. This age threshold allows us to separate the effect of the introduction of the deductible on demand from other annual changes affecting healthcare expenditure, such as changes in the basic health insurance scheme. Besides, it introduces greater variability in deductible size, including a zero deductible.

The combination of these three sources of variation allows us to estimate the parameters of the model. For details of this identification see Boone and Remmerswaal (2024).

3.3 Estimation

The model is estimated using Bayesian methods with PyMC3 in Python (Salvatier et al., 2016). Bayesian estimation begins with prior distributions for the model parameters. These priors are updated using the data leading to posterior distributions. We assume that the number of observations in our train data is sufficient enough to allow for a relatively robust estimation of posterior distributions. Our priors are defined as in Boone and Remmerswaal (2024); see that paper for details on the specification of the priors and robustness checks.

3.3.1 Model fit

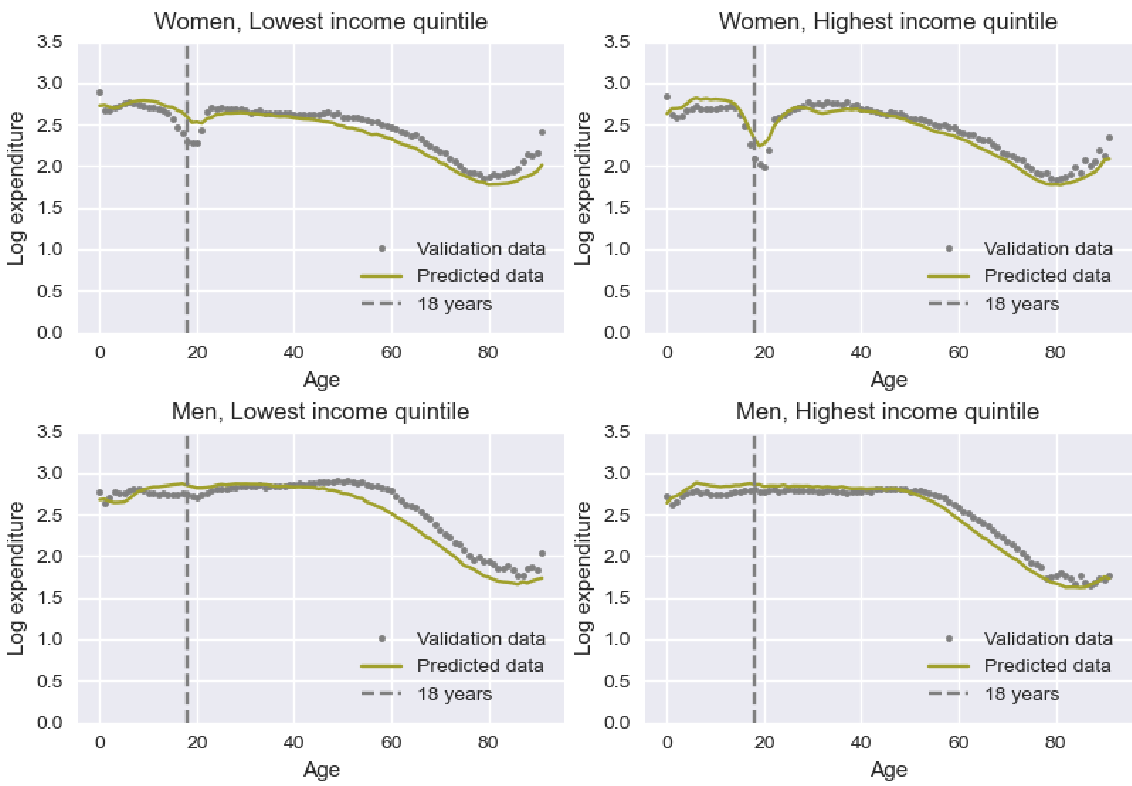
This subsection illustrates the fit of our model. We draw 10,000 samples of each parameter from our posterior distribution for each income-gender-age and year combination. In practice, this means drawing samples for each parameter, calculating the EOOP for each income-gender-age group and then determining which individuals get offered exogenous and endogenous treatments and which endogenous treatments are rejected because EOOP is too high relative to the treatment's utility (U). Using this procedure we obtain 10,000 predicted healthcare expenditures for each subgroup of men and women: 5 income groups, 92 age years[27] and 9 calendar years. Below we demonstrate goodness of fit using selected figures.

Figure 2 presents a comparison of predicted and observed values of mean healthcare expenditures by age and gender for the low and high-income groups. The blue dots denote the mean log healthcare expenditures of the validation dataset, while the solid green line denotes the same values predicted by our model. Figure 3 presents the standard deviation for the same groups. Both figures demonstrate an appropriate fit for our models in terms of first and second moments.

[27]Note that we group individuals older than 90 years in one age category to guarantee a sufficient number of observations within each income-gender-age group (See Section 2.2.1).

Figure 2: Mean of predicted vs validation results for log healthcare expenditures

Figure 3: Standard deviation of predicted vs validation results for log healthcare expenditures



3.4 Bootstrapping

Since our model relies on Bayesian statistics, we do not need to worry about traditional significance testing methods. To visualize the uncertainty surrounding our estimated elasticities, we bootstrap parameters from their posterior distributions and calculate the elasticity implied by these estimates. The histograms of the elasticity distributions presented below are based on 750 draws of elasticities.

4 Results

In the following section, we present the parameter estimates of our model and the predicted healthcare expenditures for two deductible levels (a high deductible of €600 and a low deductible of €300) for the highest and lowest income quintile across ages. Finally, we present elasticities and out-of-pocket expenditures by age- and income group and by gender individually, as well as by different combinations of age, income and gender.

4.1 Parameter estimates

In Tables 5 and 6, we describe the posterior distribution of the most important parameters by gender and income. Note that this is only a broad presentation of the parameters as they are aggregated across samples, ages and years. Table 12 and Table 13 in the Appendix present a summary of posterior distributions by age groups and gender.

Table 5: Summary of posterior distributions for women

	Lowest income quintile		Highest income quintile	
Variable	Mean	Std. dev.	Mean	Std. dev.
μ_x	4.803	0.125	4.751	0.147
μ_y	2.657	0.146	2.653	0.176
σ_x	0.944	0.169	0.995	0.180
σ_y	0.384	0.072	0.367	0.080
ψ_y	0.715	0.153	0.675	0.163
ψ_x	0.793	0.104	0.781	0.117
α	0.501	0.156	0.501	0.158
ν	0.001	0.001	0.001	0.001
ζ	0.716	0.156	0.701	0.180

Table 6: Summary of posterior distributions for men

	Lowest income quintile		Highest income quintile	
Variable	Mean	Std. dev.	Mean	Std. dev.
μ_x	4.889	0.137	4.868	0.128
μ_y	2.738	0.166	2.733	0.184
σ_x	1.035	0.225	1.103	0.234
σ_y	0.380	0.069	0.358	0.075
ψ_y	0.624	0.198	0.583	0.223
ψ_x	0.720	0.155	0.712	0.166
α	0.499	0.158	0.501	0.155
ν	0.001	0.001	0.001	0.001
ζ	0.676	0.185	0.654	0.196

Tables 5 and 6 show that parameters are similar across gender and income categories. The small differences that do exist point in the direction of lower health status for low-income men and women. For example, the mean of the normal distribution of the log healthcare expenditure is higher for the lowest income quintile for both exogenous (μ_x) and endogenous care (μ_y). This suggests that when individuals with low income get offered a treatment, it tends to be more expensive. Additionally, the probability of being offered a treatment (ψ_x, ψ_y) is higher for the lowest income quintile. Although the hazard rate, ν, is the same across the groups, the probability that someone accepts a free treatment, ζ, is higher for people in the lowest income quintile. This is in line with existing literature suggesting that low-income individuals tend to have lower health statuses and thus have a greater need for treatment compared to high-income individuals (See Section 1). Finally, as in Boone and Remmerswaal, 2024, the value of α around 0.5 is consistent with a uniform distribution of birthdays across the year.

Note that similar values for ν across income quintiles suggests that low incomes do not face strict liquidity constraints across the range of deductibles in our data. Liquidity constraints would imply a high value for ν for low incomes compared to high incomes (who are less likely to hit a liquidity constraint): an increase in EOOP would lead to a sharp increase in the probability F that a treatment is rejected. We do not find this in our data.

If we assume that agents are rational, meaning their valuation U of a treatment corresponds to its social or medical value, we can draw the following normative conclusion. An agent rejects a treatment if $U <$ EOOP. Due to health insurance, EOOP is typically lower than the treatment's full cost as society (through premiums and taxes) pays for the remainder. Thus, if an increase in the deductible leads an agent to reject a treatment and the agent is fully rational, this is welfare enhancing[28]. This efficiency gain should then be

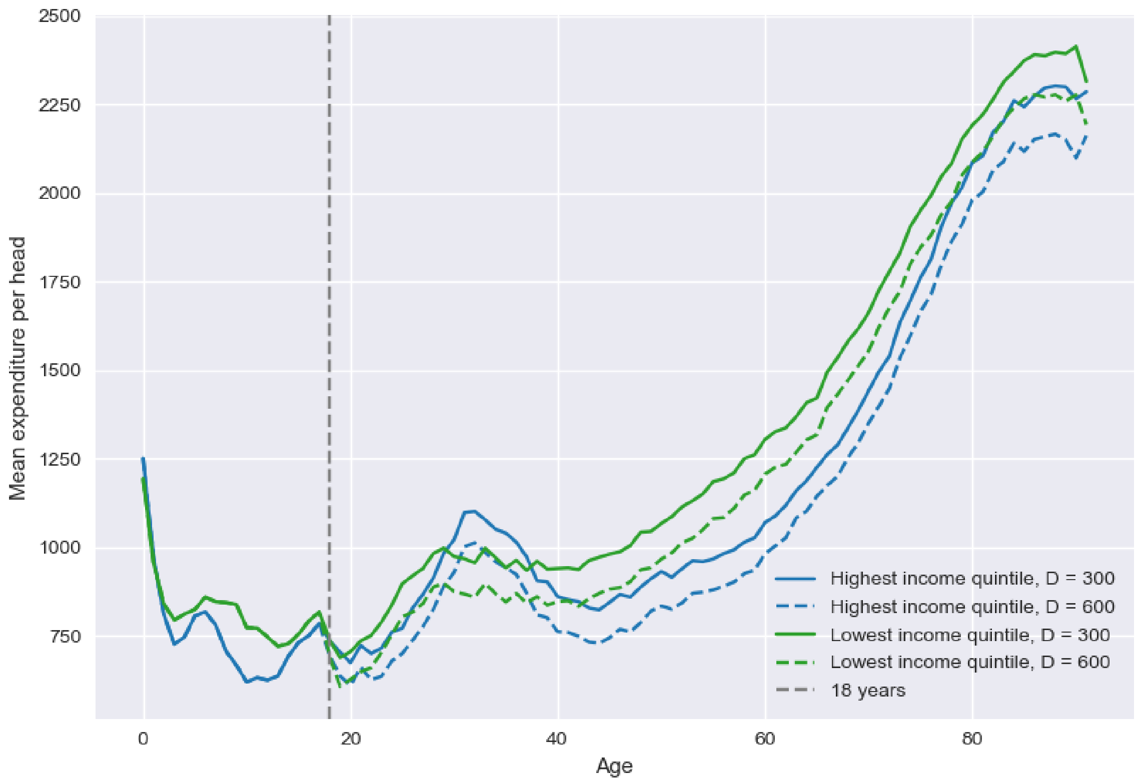
[28] An exception would be external effects of a treatment, say a vaccine. Then the social utility of treatment would exceed the private utility U.

weighed against the higher OOP risk for a risk averse agent. However, our analysis refrains from making this normative claim, because the rationality assumption does not hold for all agents[29]. Instead, the main purpose of our study is to show how agents respond to a change in EOOP in terms of magnitude. Thus, our parameter estimates show whether low-income individuals forego more care than high-income individuals in response to an increase in EOOP. This positive analysis does not rely on the rationality assumption.

4.2 Predicted healthcare expenditures

In the following section, we use the above described parameters to predict expenditure for a *hypothetical* high (€600) and a low deductible (€300). This helps us to illustrate how expenditure changes as the deductible changes. In Figure 4, we present the predicted expenditures for the hypothetical deductibles for both the highest and the lowest income quintiles across all ages. Expenditure is equivalent for high and low deductibles below the age of 18, as they are exempt from paying the deductible. As expected, expenditure is, on average, higher when the lower (€300) deductible is in place. In addition, lower income individuals spend significantly more than individuals from the highest income quintile.

Figure 4: Expenditure per head by income and deductible level



[29]This is further discussed in Section 5

4.3 Deductible elasticities

We use the predicted expenditures for a high (€600) and a low (€300) deductible to calculate deductible elasticities. Price elasticities of demand measure the change in demand for a product in response to a change in the price of that product. In the context of health insurance, this definition is often adapted to calculate a 'deductible elasticity' in the following way:

$$D = \frac{\Delta y}{\Delta D}\frac{\bar{D}}{\bar{y}} = \frac{\left(\overline{Y}_{600} - \overline{Y}_{300}\right)}{(600-300)} \cdot \frac{450}{\overline{Y}_{450}}$$

where $\overline{Y}_{300}$ and $\overline{Y}_{600}$ represent mean healthcare expenditures per head predicted by our model at €300 and at €600 deductible and an average deductible of €450 is used to normalize the elasticity: $\overline{Y}_{450}$ represents the amount of healthcare expenditure at this deductible level.

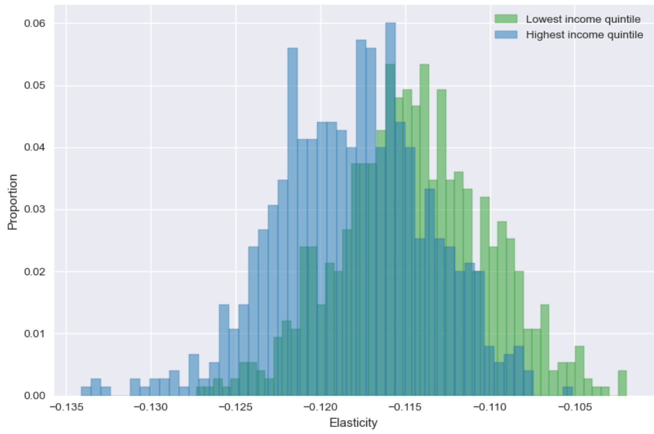
4.3.1 Elasticities by income, gender and age

We find that the overall average elasticity for all groups over 18 equals -0.11. In this section we examine age, income and gender as separate dimensions, as well as their interactions.

As shown in Figures 5 and 6, the variation in elasticity for income and sex is moderate: ranging from -0.11 to -0.12 between the lowest and highest income quintiles, and similarly between men and women. The elasticity distributions for these groups overlap to a considerable degree. Hence the data do not show that low incomes are clearly more elastic than high incomes or that women react obviously more strongly than men.

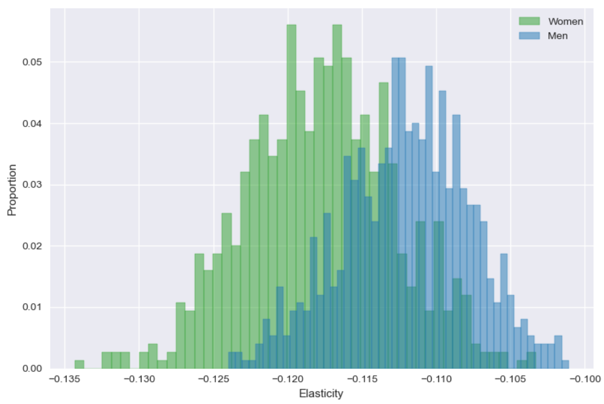
The lack of clear distinctions across income and gender dimensions is not due to the methodology we us, as we do observe very clear differences between age groups ranging from an elasticity of -0.18 for the 19-24 age group to -0.09 for 65 years and above (See Figure 7). These distributions do not overlap at all. Elasticities decline as people age. We attribute this decline to the demand for more high-value treatments that are inelastic with respect to the deductible. For example, we find that elderly have a higher probability of being offered an exogenous treatment (See ψ_x in Table 12 and Table 13 in the Appendix). In addition, we find that expenditure on exogenous treatments tend to be higher for elderly compared to younger individuals (See μ_x in Table 12 and Table 13 in the Appendix). As a result, elderly exhaust their deductible more frequently which lowers their EOOP. In Section 5 we explain how this influences the elasticity.

Figure 5: Bootstrapped distribution of elasticities by income quintile



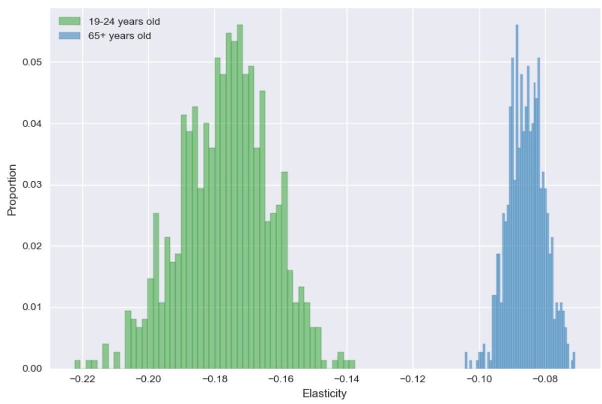
*The mean bootstrapped elasticity is -0.12 for the highest income quintile and -0.11 for the lowest income quintile.

Figure 6: Bootstrapped distribution of elasticities by gender



*The mean bootstrapped elasticity is -0.12 for women and -0.11 men.

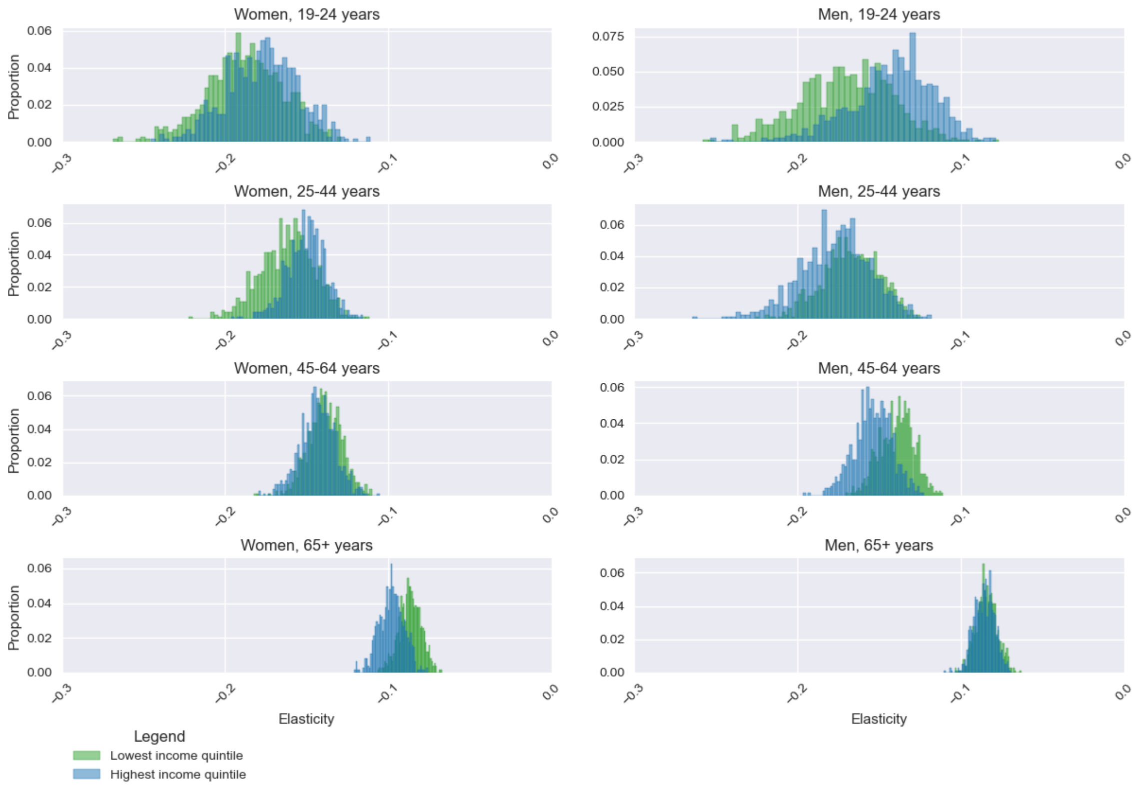
Figure 7: Bootstrapped distribution of elasticities by age



*The mean bootstrapped elasticity is -0.18 for the 19-24 age group and -0.09 for the age group 65 and above.

When considering the interaction between dimensions, our findings continue to show that elasticities vary considerably more by age than by income or gender (See Figure 8 and Table 7[30]). As illustrated in Figure 8, bootstrapped elasticities for the highest and the lowest income-groups often overlap, suggesting that the variation in response by income is only moderate.

Figure 8: Bootstrapped distribution of elasticities by age groups



[30]See Table 14 in the Appendix for the full version of this table, including all income quintiles.

Table 7: Deductible elasticities by income quintiles, all individuals $\geq$ 19 years

Age	**Income**	**Female**	**Male**
19-24	Q1	-0.188	-0.170
19-24	Q5	-0.177	-0.142
19-24	**Overall***	**-0.183**	**-0.172**
25-44	Q1	-0.162	-0.167
25-44	Q5	-0.150	-0.177
25-44	**Overall***	**-0.158**	**-0.170**
45-64	Q1	-0.139	-0.139
45-64	Q5	-0.143	-0.154
45-64	**Overall***	**-0.144**	**-0.146**
$\geq$65	Q1	-0.087	-0.085
$\geq$65	Q5	-0.098	-0.086
$\geq$65	**Overall***	**-0.089**	**-0.084**

*The overall elasticity is the mean elasticity of all quintiles per age group

4.4 Changes in out-of-pocket expenditure

Finally, we present the expected changes in out-of-pocket (OOP) expenditure as a response to an increase in the deductible. We focus on the interaction between two dimensions: age-gender groups and income-gender groups. The €300 (€300 to €600) increase in deductible imposes different levels of financial burden on subgroups. Figure 9 shows that the change in OOP expenditure increases with age as the elderly (i) are more likely to have positive health expenditures and (ii) are less likely to or less able to forego care in response to an increase in deductible (See Figure 8: elasticity is lower in absolute value).

Figure 10 demonstrates that the increase in OOP expenditure is slightly more pronounced for lower income groups compared to higher income groups. In the previous section we show that the elasticity for the lowest and the highest income quintile are similar. Therefore, the difference observed here can be explained by the higher level of expenditure for lower income individuals. On average, individuals with low income have poorer health and have higher healthcare expenses (also See Figure 1). An increase in deductible then translates into a larger increase in OOP expenditure.

In general, we find that the OOP expenditure increase resulting from a higher deductible level is more pronounced for the elderly, and, to a much lesser extent, for individuals with low income.

Figure 9: Change in OOP expenditure by age and gender

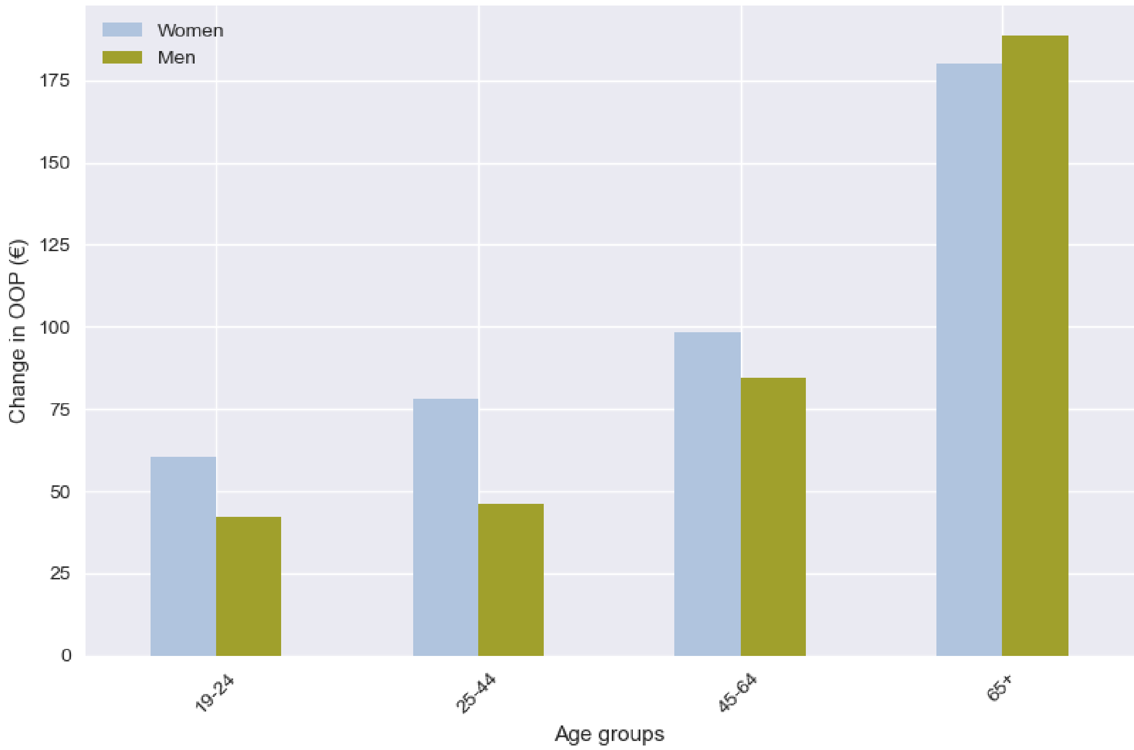
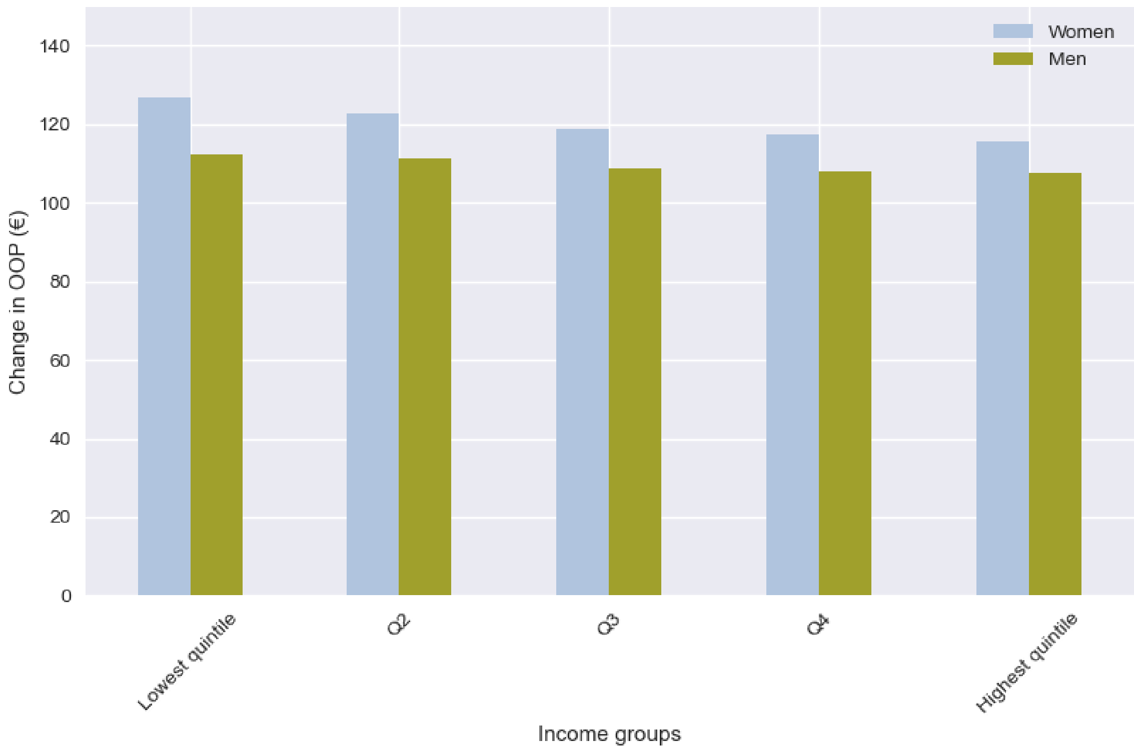


Figure 10: Change in OOP expenditure by income and gender



5 Discussion and policy implications

In the present paper, we use a structural microsimulation model to predict the response to a change in deductible for different income-gender-age categories. We estimate the parameters of our model by age, gender and income quintiles using observed healthcare spending for the years 2011 to 2019. Using the estimated parameters, we simulate counterfactual healthcare spending for two deductible levels: a low deductible of €300 and a high deductible of €600. We use these results to demonstrate the change in healthcare spending for the different subsegments of our data. We then calculate deductible elasticities and out-of-pocket expenditures.

Our results indicate an overall average deductible elasticity of approximately -0.11. This is within the range of elasticities found by Boone and Remmerswaal (2024), Manning et al. (1987), and van Vliet (2004). We find considerable variation in the overall average deductible elasticity per age group: varying from -0.18 for the age group 19-24 years to -0.09 for 66 years and above. There is less variation across gender and income.

Overall, in terms of the magnitudes of elasticities, the pattern is similar across age, gender and income. Groups with lower health status, and therefore higher expenditure, tend to be less elastic with respect to a deductible change for two reasons. First, lower health status involves high-value treatments to the patient for, say, a chronic illness. In the present paper, we call these exogenous expenditures (i.e. treatment decisions that are not affected by mandatory deductible levels in the relevant Dutch policy range, approx. up to €600). Second, people with low health status and high expenditure are no longer at the margin of the deductible increase as they have likely depleted their deductibles for exogenous treatments.

Consequently, this group hardly reduces expenditure in response to the deductible increase and carries a larger burden of the increase in terms of out-of-pocket expenditure. Groups with the largest increase in out-of-pocket expenditure are the elderly and, to a lesser extent, people on low income. In this sense, the rise in cost-sharing may reduce moral hazard, but it will do so at the expense of equity or solidarity.

There is widespread concern that low-income individuals are more likely than high-income individuals to forego treatment due to cost-sharing, as they may struggle to afford the associated costs. If this were the case, we would expect to observe higher values of ν and higher elasticities among low-income individuals, which our findings do not support. The results of our model indicate that low-income individuals do not forego care at a higher rate than high incomes. A few points merit consideration regarding the interpretation of this outcome.

Firstly, while income is commonly used as an indicator of financial limitations, it may not be the most accurate measure of liquidity constraints. Future research could benefit from indicators that include both wealth and income, or even more subjective measures, such as individuals' self-assessed ability to make ends meet.

Secondly, two opposing factors complicate the interpretation of responses to a change in the deductible by different income groups. On the one hand, we know that low income correlates with low health status requiring treatments that (i) are necessary almost irrespective of costs (think of insulin) and (ii) deplete the deductible anyway making the patient less responsive to a change in the deductible. On the other hand, we expect people on low income to be more sensitive to price, because (i) health is usually seen as a normal good and (ii) poverty can cause liquidity constraints that restrict healthcare expenditures.

The model distinguishes these two channels as follows: EOOP and the parameter ν measuring the degree to which EOOP affects the probability of rejecting treatment. We find that spending on exogenous care is higher (see μ_x in Tables 5 and 6) and therefore EOOP is indeed lower for low incomes. Consequently a change in the deductible has a smaller effect on low income EOOP than on high income EOOP. And we do not find a clear difference in ν between the income classes. This suggests that low incomes do not forego treatment due to OOP at a faster rate than high incomes. In this sense, there is no clear indication of unmet needs due to cost-sharing in the current Dutch environment.

A final consideration is that our model does not account for potential differences in rational decision-making across socio-economic groups. Research by Brot-Goldberg et al. (2017) shows that consumers do not always make rational choices in response to cost-sharing and may reduce high-value care that could prevent future costs. Additionally, Handel et al. (2024) found that, in the context of Dutch Health Insurance, choice quality relates to socioeconomic factors. Our model only identifies the "positive" effect of OOP on treatment choice. It does not directly speak to the normative question whether rejecting a treatment because it is expensive is an efficient choice or not. As our data does not include medical or survey measures of health status we cannot address this question in this paper.

If we would have found a stronger reaction to EOOP for low than for high incomes, this could have been a signal that low incomes reject also necessary care due to cost considerations. But we do not find this. Yet, we cannot exclude the possibility that low-income individuals make less rational decisions and as a result, are more likely to forego necessary care.

Our model has some limitations that originate from the data. For example, in our observed data, the deductible ranges from €170 to €385, which is relatively low from an international perspective[31]. It is likely that as deductibles increase, liquidity constraints start to play a larger role. In this sense, our results may not apply to significantly higher levels of cost-sharing. We show that over the Dutch relevant range of deductibles there are no clear differences between high and low incomes.

We exclude users of mental healthcare from our analysis due to additional co-payments in 2012. This can have implications for the estimated deductible elasticities and the

[31] As a comparison, the average deductible in the U.S. healthcare system was $1945 (€1788) per individual in 2020 according to the Commonwealth Fund (Collins et al., 2022).

observed differences between socio-economic groups. Previous research indicates mental health care has a different price-elasticity than other types of care and that low-income individuals tend to use more mental health care then high-income individuals (Amaddeo & Jones, 2007; Ellis et al., 2017; Lambregts & Van Vliet, 2018). As a result, it is plausible that including mental healthcare users in our analysis would slightly change our overall deductible elasticities. Future research could document the variation in demand responses for mental healthcare and further clarify the differences between socio-economic groups.

In conclusion, while our model has certain limitations, it performs well in predicting health care expenditures. This allows us to predict the reduction in healthcare expenditure in response to an increase in the deductible per age, gender and income. While theory suggests that individuals of different ages, genders, and income groups would respond to changes in healthcare deductibles to varying degrees, our study demonstrates that response only differs substantially between age groups. In contrast, the variations in response by gender and income are less pronounced than may be expected.

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6 Appendix

Table 8: Summary of the train dataset after dropping unused observations, by income quintile

	Q1	Q2	Q3	Q4	Q5
Complete train dataset					
Number of observations	17,164,952	17,321,958	17,375,327	17,377,915	17,316,982
Expenditure (€, mean)	2,598	2,235	1,740	1,569	1,432
Expenditure (€, std. dev.)	8,652	7,527	6,659	6,279	6,047
without the top 5% spenders					
Number of observations	15,941,146	16,262,099	16,599,716	16,702,507	16,723,806
Expenditure (€, mean)	1,090	988	831	781	738
Expenditure (€, std. dev.)	1,663	1,575	1,439	1,389	1,335
without mental health patients					
Number of observations	12,203,253	13,159,026	13,528,214	13,702,545	13,940,338
Expenditure (€, mean)	937	894	735	691	656
Expenditure (€, std. dev.)	1,527	1,489	1,340	1,293	1,246
without individuals who have ever chosen a voluntary deductible					
Number of observations	11,093,140	11,566,488	11,368,451	10,983,315	10,512,562
Expenditure (€, mean)	995	965	803	766	737
Expenditure (€, std. dev.)	1,563	1,536	1,394	1,355	1,314

Note: Our data contains all residents of the Netherlands for the years 2011-2019. Consequently, multiple observations per person exist in our dataset.

Table 9: Summary of the train dataset after dropping unused observations, by age group

	0-18	19-24	25-44	45-64	≥65
Complete train dataset					
Number of observations	18,676,465	5,458,190	21,300,574	24,797,276	16,324,629
Expenditure (€, mean)	872	961	1,320	2,017	4,041
Expenditure (€, std. dev.)	5,904	5,546	5,620	7,305	9,424
Train dataset without the top 5% spenders					
Number of observations	18,397,732	5,354,790	20,651,445	23,479,123	14,346,184
Expenditure (€, mean)	498	530	725	917	1,681
Expenditure (€, std. dev.)	1,055	1,160	1,400	1,485	1,853
without mental health patients					
Number of observations	15,538,826	3,878,124	15,189,378	19,001,812	12,925,236
Expenditure (€, mean)	431	374	532	775	1,610
Expenditure (€, std. dev.)	953	927	1,176	1,340	1,810
without individuals who have ever chosen a voluntary deductible					
Number of observations	14,454,489	2,673,619	10,870,803	15,394,376	12,130,669
Expenditure (€, mean)	443	425	604	859	1,661
Expenditure (€, std. dev.)	968	998	1,249	1,403	1,825

Table 10: Summary of the train data by age group for women, 2011–2019

	0-18	19-24	25-44	45-64	≥65	Total
Number of observations (mln)	7.2	1.2	5.4	7.7	6.7	28.2
Age (yrs., mean)	8.36	21.42	35.29	54.60	75.12	42.46
Age (yrs., std. dev.)	5.25	1.74	5.78	5.73	7.70	25.61
Household income* (€, mean)	28,952	29,651	28,785	32,786	25,851	29,270
Household income* (€, std. dev.)	35,498	33,397	25,878	44,535	36,750	36,979
Fraction of positive expenditures	0.70	0.84	0.82	0.86	0.94	0.83
Expenditure (€, mean)	409	524	810	917	1,654	923
Expenditure (€, std. dev.)	918	1,089	1,446	1,431	1,813	1,485
Log expenditure (mean)	3.62	4.34	4.62	5.12	6.38	4.90
Log expenditure (std. dev.)	2.74	2.43	2.70	2.56	2.10	2.71

*Annual standardized disposable household income

Table 11: Summary of the train data by age groups for men, 2011–2019

	0-18	19-24	25-44	45-64	≥65	Total
Number of observations (mln)	7.2	1.4	5.5	7.7	5.5	27.3
Age (yrs., mean)	8.28	21.42	35.12	54.50	73.56	40.45
Age (yrs., std. dev.)	5.31	1.73	5.83	5.73	6.72	24.62
Household income* (€, mean)	29,011	31,390	29,535	33,911	28,241	30,463
Household income* (€, std. dev.)	40,879	39,011	25,906	46,717	44,393	40,866
Fraction of positive expenditures	0.69	0.59	0.64	0.79	0.93	0.75
Expenditure (€, mean)	476	340	405	801	1,671	786
Expenditure (€, std. dev.)	1,014	905	982	1,372	1,839	1,392
Log expenditure (mean)	3.70	2.98	3.28	4.59	6.34	4.36
Log expenditure (std. dev.)	2.84	2.79	2.82	2.81	2.17	2.92

*Annual standardized disposable household income

Figure 11: Conditional mean expenditure per income quintile in 2019

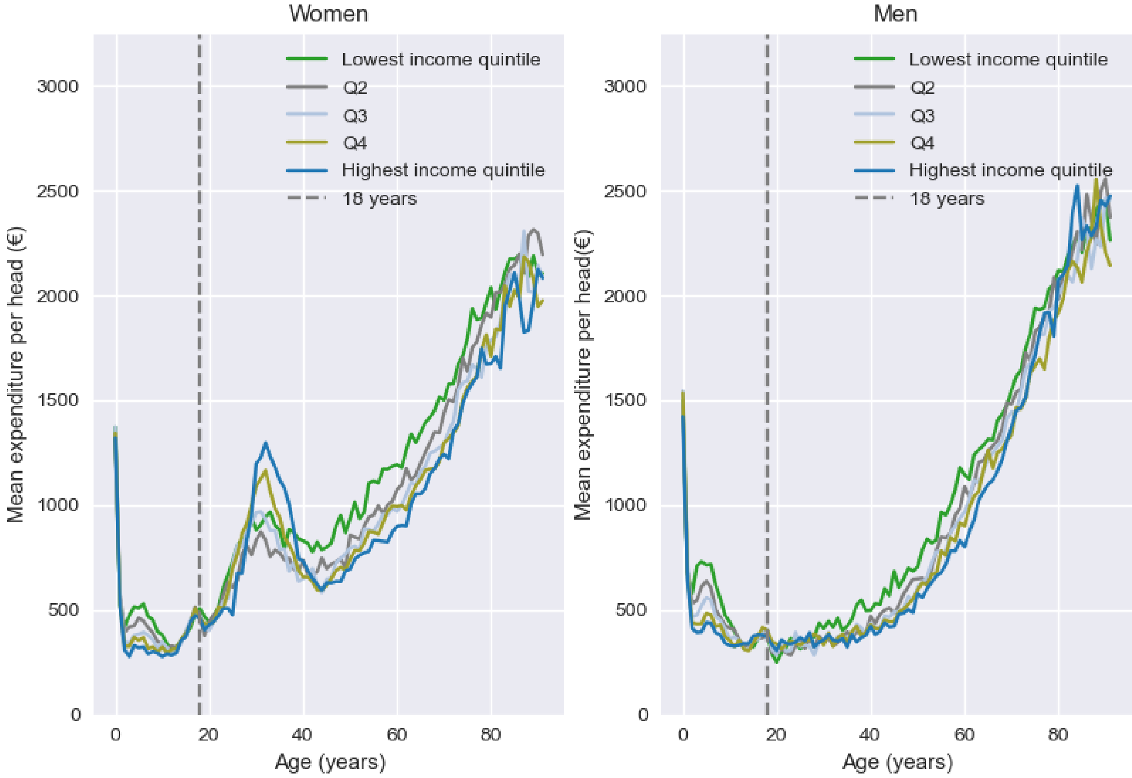

Table 12: Summary of posterior distributions for women by age

	19-24 yrs		≥65 yrs	
Variable	Mean	Std. dev.	Mean	Std. dev.
μ_x	4.585	0.129	4.809	0.093
μ_y	2.690	0.121	2.604	0.110
σ_x	1.065	0.059	0.816	0.049
σ_y	0.355	0.045	0.392	0.038
ψ_y	0.545	0.047	0.895	0.031
ψ_x	0.762	0.031	0.923	0.018
α	0.501	0.157	0.501	0.157
ν	0.001	0.000	0.000	0.000
ζ	0.661	0.024	0.887	0.006

Table 13: Summary of posterior distributions for men by age

	19-24 yrs		≥65 yrs	
Variable	Mean	Std. dev.	Mean	Std. dev.
μ_x	4.881	0.110	4.847	0.098
μ_y	2.886	0.116	2.638	0.113
σ_x	1.310	0.077	0.825	0.055
σ_y	0.366	0.043	0.371	0.036
ψ_y	0.372	0.044	0.890	0.022
ψ_x	0.518	0.027	0.936	0.011
α	0.499	0.156	0.499	0.156
ν	0.001	0.000	0.000	0.000
ζ	0.506	0.036	0.903	0.006

Table 14: Deductible elasticities by income quintiles, all individuals $\geq$ 18 years

Age	**Income**	**Women**	**Men**
19-24	Q1	-0.188	-0.170
19-24	Q2	-0.190	-0.192
19-24	Q3	-0.187	-0.177
19-24	Q4	-0.172	-0.177
19-24	Q5	-0.177	-0.142
19-24	**All**	**-0.183**	**-0.172**
25-44	Q1	-0.162	-0.167
25-44	Q2	-0.168	-0.169
25-44	Q3	-0.157	-0.164
25-44	Q4	-0.154	-0.171
25-44	Q5	-0.150	-0.177
25-44	**All**	**-0.158**	**-0.170**
45-64	Q1	-0.139	-0.139
45-64	Q2	-0.153	-0.150
45-64	Q3	-0.142	-0.142
45-64	Q4	-0.142	-0.146
45-64	Q5	-0.143	-0.154
45-64	**All**	**-0.144**	**-0.146**
$\geq$65	Q1	-0.087	-0.085
$\geq$65	Q2	-0.080	-0.079
$\geq$65	Q3	-0.087	-0.082
$\geq$65	Q4	-0.093	-0.087
$\geq$65	Q5	-0.098	-0.086
$\geq$65	**All**	**-0.089**	**-0.084**