The Socio-Economic Distribution of Choice Quality: Evidence from Health Insurance in the Netherlands*

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Abstract

Policy makers increasingly offer choice or rely on markets in the provision of public services (e.g., health insurance, retirement savings). Choice frictions can unwind the potential benefits of these policies from matching individuals to appropriate products. We use population-wide data on health insurance choices and health care utilization in the Netherlands to study how the quality of deductible choices relates to socio-economic factors. We document a striking choice quality gradient with respect to socio-economic status and show the importance of distributional considerations for policies that embed consumer choice. We also find that individuals with higher education levels and more analytic degrees or professions make markedly better decisions. The association with these educational variables strongly dominates the direct association with income, liquidity and wealth, when jointly controlling for key socio-economic factors.

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I Introduction

Consumer choice is a central aspect of market function and an important rationale for policymakers who increasingly rely on market solutions that provide choice in the provision of products viewed as public goods, such as retirement investments (see, e.g., Hastings et al. (2013) and Chetty et al. (2014)), schooling (see, e.g., Neilsen (2017)), electricity (see, e.g., Ito (2015)), and health insurance (see, e.g., Enthoven, Garber and Singer (2001)). One important argument for facilitating choice in such markets — rather than a uniform product, whether offered directly by the government or a regulated private firm — is the opportunity to match heterogeneous consumers with products that provide them with greater surplus.

In practice, if consumers make choice errors, as much prior work documents, the welfare gains from greater choice and competition are diminished, or even eliminated. Furthermore, to evaluate the welfare implications of choice-based policies, we are concerned not only with the average consumer-product match but with the distribution of choice quality and surplus (e.g., Mullainathan and Shafir (2013), Campbell (2016)). Of particular concern is the potential for choice-based policy to exacerbate inequality if consumers with lower socio-economic status are less able to make complex decisions or have less opportunity to engage with those decisions.

In this paper, we investigate consumer choices and their socio-economic determinants, with an emphasis on how inequality in choice quality can affect welfare. We study this in the context of health insurance provision in the Netherlands. The dimension we focus on is the choice of deductible — the amount in each year a consumer must pay out-of-pocket before insurance payments kick in. The Dutch setting is particularly well suited because we focuse solely on the financial aspects of insurance contracts that are orthogonal to other plan differences, making it more straightforward to assess choice quality. Moreover, we can leverage rich administrative data on the universe of the population of the Netherlands (approximately 17 million people) linked to individual insurance choices. Our data includes detailed information on demographics, health status, employment, income, net worth, liquidity, education level, fields of study and occupations.

We assess choice quality using a simple choice model together with precise health risk predictions generated with tools from machine learning (Einav et al. (2018)). Overall, we find that more than 50% of consumers would be better off choosing a higher deductible based on predicted health risk, but less than 10% actually do so. We show that the large gap between the model's predicted choices and observed choices (i) cannot be rationalized by reasonable risk preference estimates or standard models of moral hazard and (ii) is not explained by low financial liquidity in our data (see, e.g., Ericson and Sydnor (2018) and Finkelstein, Hendren and Luttmer (2019)).

We then study the socio-economic determinants of deductible choice and how it relates to predicted health risk. We document a striking socio-economic gradient in choice quality overall and find that education is particularly important. When predictably healthy, the take-up rate of a high deductible is more than 3 times as high - a difference of 18 percentage points - for individuals with an education level higher than college compared those with less than high school education. The difference is 13 percentage points for those with a college degree and 5 percentage points for those finishing high school. These associations hold demographics and income fixed. We also find a positive association between income and choice quality, but this association is no longer economically meaningful when holding demographics and education fixed.

Leveraging the granularity of the data, we further document a strong positive relationship between being trained or employed in an analytic field and deductible choice quality, all else equal. For example, statistics majors are 21 percentage points more likely to choose a high deductible when predictably healthy, relative to the collection of other fields. Conversely, those with training in security are 6 percentage points less likely to choose the high deductible when predictably healthy. We illustrate this relationship between the analytic nature of education fields and profession comprehensively across 90 education fields and 68 professions documented in our data. In comparison, all else equal, we find small associations between individuals' choice quality and their household finances including liquid savings, indebtedness and net worth.

We weave together our findings on heterogeneous choice quality in a welfare framework that classifies decision-making quality as a function of all these socio-economic characteristics jointly, conditional on health. We find, e.g., that the 5% best decision-makers not only are much more educated and predominantly trained in analytic fields, they also have an average gross income of 105,000 EUR, and net worth of about 250,000 EUR. Conversely, the 5% worst decision makers have average income of 40,000 EUR and net worth of 5,000 EUR. Distributional considerations are thus crucial when evaluating policies that embed consumer choice.

This paper relates to several distinct literatures, but is closest to prior work on insurance choice including papers without choice frictions (see Einav, Finkelstein and Mahoney (2021)) and many with choice frictions (see Handel and Schwartzstein (2019)). Relative to this prior work, the choice we study is simpler and the data we have are much deeper and more comprehensive in terms of socio-economic factors, allowing us to contribute in several key ways. We are able to study choice heterogeneity on many potentially important dimensions simultaneously for the same population. Prior work on Medicare Part D choices typically have the largest / most representative samples, but those are also the studies that have more limited measures of socio-economic heterogeneity. Conversely, studies with richer heterogeneity (see, e.g., Bhargava, Loewenstein and Sydnor (2017)), Fang, Keane and Silverman (2008)) occur either in specific contexts such as a large employer, or have limited sample size due to the nature of data used. We are not aware of other prior studies in this space that have the depth of data we use for underlying socio-economic factors, especially at the scale of an entire country. Our analysis also relates to papers that study choice quality and the incidence of consumer frictions in other domains (e.g., Allcott, Lockwood and Taubinsky (2019), Dubois, Griffith and O'Connell (2020)). Most notably, a number of papers leverage registry data to study choice quality and default effects at scale (e.g., Chetty et al. (2014), Andersen et al. (2020)).

II Institutional Context and Data

All individuals in the Netherlands are obligated to directly buy health insurance from a private health insurance market. The Health Insurance Act of 2006 introduced a managed competition model in which the government strictly regulates the contents of the basic health insurance package (see Kroneman et al. (2016) for a comprehensive overview of the Netherlands health system). The regulation also (i) prohibits price discrimination, (ii) prohibits the rejection of individuals from purchasing insurance and (iii) mandates that all individuals purchase basic coverage. Insurers compete for consumers on premiums, provider networks, and supplementary insurance offerings, which covers dental care and extra physical therapy. In 2015, there were 25 health insurers that together offered 53 separate insurance contracts. Yearly premiums for the mandatory health insurance with the smallest possible deductible have a mean of 1195 EUR and a fairly compact distribution around this mean (see Online Appendix Figure A.2). Consumers enroll between mid-November and the end of December for the following year. During that period, health insurers advertise their insurance packages through various media. If no action is taken by the consumer, she automatically extends her current contract. Relatively few consumers switch insurers each year (6.8% of individuals in 2015).

Regulation of deductible options for the basic coverage has been a central topic of the policy debate in the Dutch Parliment. Each individual faces a compulsory deductible (375 EUR in 2015), but can opt for an extra voluntary deductible of 100, 200, 300, 400 or 500 EUR on top of this compulsory deductible (maximum total deductible of 875 EUR in 2015). The compulsory deductible, introduced in 2008, has gradually increased from

150 EUR in 2008 to 385 EUR in 2017, while the options for the extra voluntary deductible have remained the same. By opting for a higher deductible, consumers receive a premium reduction. The right part of Figure A.2 in the Online Appendix shows the (unweighted) histogram of premium reductions consumers can get by electing the additional 500 EUR deductible across health plans in 2015. The distribution has a mean of 233 EUR and most of the mass lies between 200 and 300 EUR, making the deductible election a quite standardized decision across all insurance contracts.

II.A Data and Sample

We use data on health insurance choices and health expenditures for all individuals in the Netherlands. The data is linked at Statistics Netherlands to other administrative registers, which provide detailed information on individuals' income, wealth, education, employment and other demographic variables.

We restrict attention to all individuals who are at least 18 years old in January of the year in which they decide on their health insurance contract and deductible. We exclude from the sample adults who have incomplete health data records in the two previous years. The remaining sample consists of about 13.25 million adults in each year. As explained in Section III.A, we use a random sample of 1.25 million of these individuals to estimate and calibrate a cost prediction model, leaving approximately 12 million adults each year for the analyses, which we call our baseline sample. The Online Appendix provides sample summary statistics and distributions of health care expenditures for the year 2015.

Health Insurance Deductible Choices Data on health insurance contract choices in the years between 2013 and 2017 are obtained from Vektis, an organization that is responsible for the collection of data from all health insurers. Our data include only information on an insurer and deductible choice. We do not observe whether individuals purchase supplementary insurance, but these choice dimensions are orthogonal to the deductible choice except for minor price differences. Table A.3 in the Online Appendix shows the take-up of different deductible amounts in 2015. The voluntary deductible take-up in our sample is 9.06% in 2015. More than 2 out of 3 individuals opting for an extra deductible take the maximum extra deductible of 500 EUR.

Health Care Costs Data on health care costs contain annual health care expenditures by category. The categories included in spending covered by the deductible are medicines, hospital care, geriatric care, paramedical care and physiotherapy, mental health care, aids and tools for health, health care in foreign countries, health care transport, multidisciplinary care, sensory handicap care, and other care. The aggregate distribution is skewed with about 19 percent of individuals making zero expenditures and more than 10 percent of individuals spending more than 5000 EUR (see Online Appendix Figure A.1). Note that we also have data on preventive, maternal and GP care, but these are covered at zero cost by all insurers by law.

Education, Financial, and Demographic Data We obtain information on other variables from a number of administrative registers and link these to the health and insurance data. Our data includes standard demographics like age, gender and household status. We use third-party reported information from tax registers on household income and household wealth. The former includes pre-tax income from labor, self-employment and capital and government transfers. The latter includes information on net worth, liquid and other financial assets, mortgage and other debt. We also observe data on the highest formal education level attained for more than half of the sample. These data also include information on the specific field of study for individuals who proceed past high school as well as each individual's employment sector. We provide more detail about the different registers and variables in Online Appendix A.2.

III Deductible Choice and Health Risk

We consider a stylized model to assess choice quality, simplifying the decision to a binary choice between the baseline deductible of 375 EUR and adopting the full 875 EUR deductible while gaining the associated premium savings of 250 EUR. We approximate expected utility by:

$$U_{i,d} \approx \pi_i u_i(W_i - p_d) + (1 - \pi_i)\, u_i(W_i - p_d - d), \tag{1}$$

where π_i denotes the chance that expenditures stay below 375 EUR. In theory, the optimal decision depends on the probability distribution of expenditures between 375 EUR and 875 EUR too, but the share of expenditures that fall in this range is small and interior choices between the two levels are not easily rationalized under standard preferences (see Online Appendix Figure A.1). Empirically, most individuals who elect a deductible higher than the compulsory deductible choose the maximum possible deductible (see Online Appendix Table A.3). We develop a full model in the Online Appendix and study its sensitivity to our simplifying assumptions, showing they have minimal impact.

In expected payoff terms, $\bar{\pi} = 0.5$ is the (approximate) threshold leaving individuals indifferent between the two deductible options. There are various ways that 'frictionless' choices could differ from those in the simple model specified here. First, consumers could have classical risk aversion that pushes them towards choosing the low deductible option. For a standard but lower value of absolute risk aversion of 10^{-5} (e.g., Cohen and Einav (2007)), this threshold increases very slightly to 0.5006. For a very high level of absolute risk aversion of 10^{-3}, this threshold is still only 0.56 (see discussion in Barseghyan et al. (2018) for typical risk preference estimates in different contexts.) A model with constant relative risk aversion parameters typical of past work yields similarly small threshold changes. Figure 1 shows that variation in the choice threshold as a result of risk aversion is small relative to the dispersion in predicted cost distributions.[1]

Consumers could also have liquidity constraints that lead them to act in a risk averse manner when choosing a deductible (see Ericson and Sydnor (2018)). Note that in theory, liquidity and debt constraints could either increase the demand for insurance (to avoid large expenditures) or reduce the demand for insurance (to avoid paying the premium). As shown in Chetty and Szeidl (2007), under some assumptions one can characterize liquidity constraints as increased risk aversion, causing only small changes in the threshold as discussed. In our empirical analysis, we will show that the lack of liquid savings can explain only a very small portion of why consumers under-adopt the high deductible when healthy.

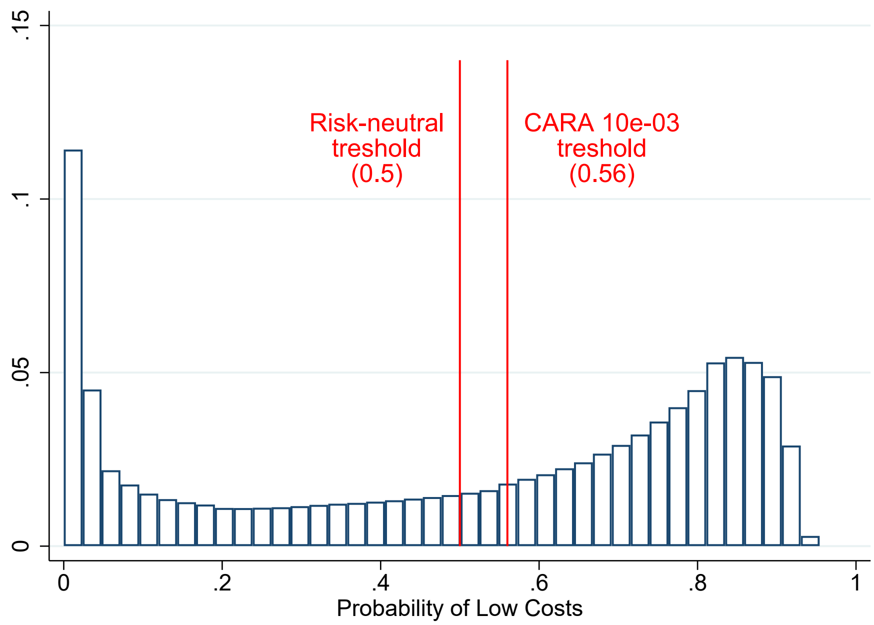
Moral hazard could cause consumers to reduce care consumption in response to greater cost sharing (e.g., Newhouse (1993), Einav, Finkelstein and Schrimpf (2015), Brot-Goldberg et al. (2017)). Under a classical model of moral hazard, our framework under-predicts value from the high deductible plan since it rules out reductions in care that are lower in value than the associated cost savings. Since our empirical results focus on significant under-adoption of higher deductibles, having the lower bound interpretation does not impact the main import of our results. In addition, our empirical analysis in Online Appendix A.5 suggests a limited role for moral hazard, corroborating earlier evidence in the Dutch context (Remmerswaal, Boone and Douven (2019)).

[1] In the Online Appendix we also analyze a related model of background risk where there is a correlation between health spending risk and other financial risk (see e.g. Campbell and Viceira (2002). For this to matter for our analysis, one has to assume a level of risk aversion that is implausibly high when integrating large scale background risk, due to the Rabin critique (Koszegi and Rabin (2006)).

III.A Cost Prediction Model

Given this framework, to assess deductible choice requires an estimate of individuals' risk of spending more than 375 EUR (π). We set up our prediction model as a binary classification algorithm. The yearly predictions of π_i are made using an ensemble learning model consisting of a random forest model, a boosted regression trees model and a LASSO model (see e.g. Einav et al. (2018)). We only include predictors that are known at the time of choice including gender, age, income ($t-2$, $t-1$), work status, education level, education field, and past health spending per category ($t-2, t-1$). In each year, there are approximately 20 variables for per-category health spending.

Figure 1: Distribution of Cost Probability Predictions



Notes: This figure shows the distribution of the predicted probabilities of having health costs below 375 EUR. These probabilities are obtained when predicting the binary variable (having insurable health costs below 375) with the ensemble machine learner described in Section III.A, and further in Online Appendix A.3. The figure presents the risk-neutral threshold for someone to choose the 500 EUR incremental deductible if the incremental premium reduction is the modal incremental premium reduction of 250 EUR. It then presents the same threshold for extreme risk-aversion (CARA coefficient $1 * 10^{-3}$).

We use a training sample of 1.25 million individuals, while all the results shown for the remainder of this paper use a hold-out sample of approximately 12 million observations each year. Online Appendix Figure A.3 describes the precision, fit, and outcomes of this model. The binned relationship between *ex ante* probabilities and *ex post* cost realizations is very strong almost directly tracking the 45-degree line and illustrating the very strong fit of our cost prediction model. Online Appendix Figure A.5 shows that the prediction model is similarly well-calibrated for subgroups of individuals with different ages, education levels and income quartiles, showing that any results finding different deductible take-up as a function of these variables (holding all else equal), is not due to cost mis-prediction. The cost model prediction accuracy is also plotted for individuals who take the 500 EUR deductible, and individuals who do not. While individuals who take up an extra 500 EUR deductible do have an *ex post* higher chance to be low cost relative to our model predictions, the figure illustrates how this gap is small, suggesting a minor role for the combined effects of private information about health risk or moral hazard conditional on the predictors, not big enough to have a meaningful impact on our main results.

Figure 1 presents the histogram of the predictions for the *ex ante* probability of being in the low spending group. There is substantial dispersion in predicted risks over the full range of potential probabilities. The distribution is bi-modal, with a substantial share of individuals having either a very low probability or a very high probability of being low spenders. We include threshold measures for choosing the 500 EUR deductible to demonstrate that the distribution of risk places a significant share of the population well above and below the cutoffs respectively.

III.B Deductible Choice

We next turn to studying how deductible choices relate to predicted health risk, the primary component of deductible choice in a frictionless, rational model. Panel A in Figure 2 plots the empirical relationship between predicted health risk and deductible choice and shows the optimal choice in the frictionless, rational model for comparison. Two key facts emerge. First, as expected, people who are healthier are more likely to elect the higher incremental 500 EUR deductible. Second, the relationship between risk and deductible choice is substantially weaker than one would expect if consumers were making utility-maximizing choices in the frictionless model. For example, the share of consumers in the healthiest predicted health bin electing the high deductible is only 17%. These individuals face a 90% chance of having costs below the lowest deductible, exposing themselves to an expected cost of only about 50 EUR when taking the highest deductible. Still, more than 80% of them forego on the 250 EUR savings in premium.

The same two key facts are confirmed when using only within-individual variation in predicted health risk (Online Appendix Table A.5). We recall that risk aversion, liquidity effects and moral hazard have little impact on optimal choices in our setting, as discussed in Section III. However, there are a plethora of models with choice barriers one could write down that could help rationalize the data (e.g., inertia, limited attention, misperceptions).[2] Regardless of the nature of the choice barriers, the evidence shows that these barriers need to be large.

This section has highlighted that the gap between the baseline 'frictionless' choice model and observed behavior is large and cannot be credibly explained with standard consumer preferences or constraints. The next section will show that the gap differs substantially across individuals with different demographic, educational, and financial characteristics, indicating an important socio-economic gradient in choice quality.

IV Socio-Economic Determinants of Deductible Choice

This section examines how different individual socio-economic factors change deductible choice with respect to health risk. We do so by (i) presenting non-parametric graphical evidence examining specific characteristics and (ii) with a regression framework that examines the impact of those characteristics conditional on many other characteristics. We rely on a simple OLS regression in a linear probability model:[3]

$$Y = \alpha + \gamma X + [\beta + \nu X]P(costs < 375) + \epsilon \tag{2}$$

where Y is an indicator variable taking the value of 1 when an individual takes the 500 voluntary deductible and 0 otherwise, $P(costs < 375)$ is the predicted probability of having costs lower than 375 EUR (π_i in our theoretical model), and X includes all variables of interest. The primary coefficients of interest are γ and ν. The former

[2] Online Appendix A.6 simulates the choices for a set of alternative models of decision-making that are proposed in the literature. A model with imperfect information and switching costs comes close to replicating the choice patterns we observe.

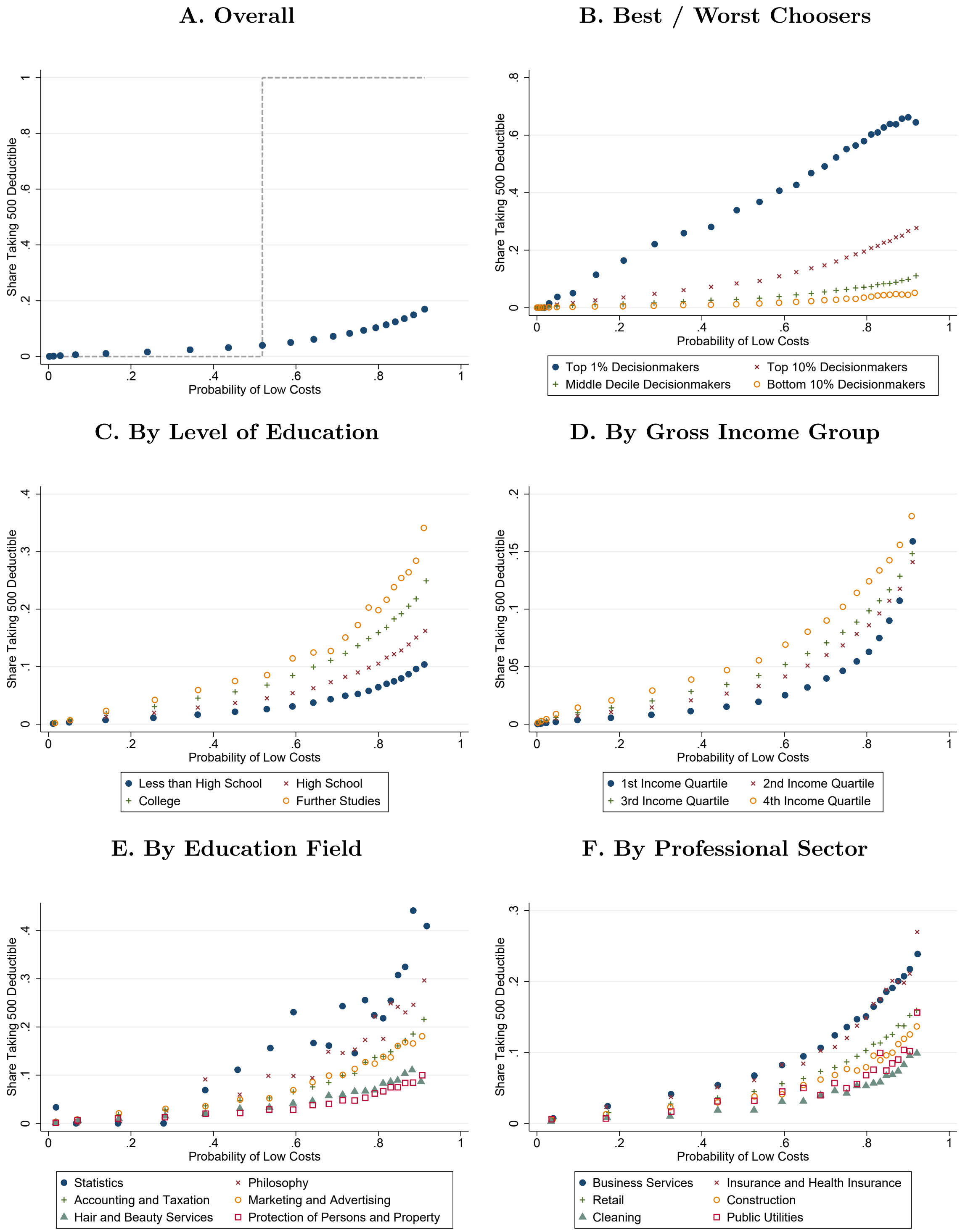
[3] We present alternative specifications, e.g., a probit model, in the Online Appendix, with little difference in findings.

captures how different observables affect the intercept, i.e., the average take-up of the 500EUR deductible by individuals who are the sickest (with $\pi_i = 0$). The latter measures how different factors affect the relationship between risk and deductible choice. $\gamma + \nu$ captures the impact on average take-up by individuals who are the healthiest (with $\pi_i = 1$). Each regression also includes year and insurer fixed effects. The insurer fixed effects control for potential differences in insurer marketing / steering, provider network, and/or differences in insurer incremental deductible premium, though as we showed earlier there is limited dispersion in the latter.

IV.A Socio-Economic Factors

Figure 2 plots the relationship between health and deductible take up by income and education side by side in Panels C and D. Both panels show an important gradient in the deductible take-up when people are predicted to be healthy. For example, those in the healthiest predicted risk vigintile with a college degree (i.e., bachelor or master) elect the higher deductible about 25% of the time and those with an advanced degree choose the highest deductible 35% of the time. In contrast, those with less than high school education in the healthiest predicted decile elect the higher deductible only 10% of the time and those with high school education only approximately 15% of the time. For all of these education levels, when people are predicted to be sick they almost never elect the higher deductible. The relations are qualitatively similar when comparing groups with different gross household income (including capital income and government transfers). Higher levels of income are associated with higher take-up of high deductible among the healthiest, though the differences are less pronounced. For example, the average take-up rate of the highest income quartile remains below 20%.

Figure 2: Deductible Take-up by Health Risk and Socio-economic Determinants



Notes: This figure show binned scatter plots of the relationship between the predicted probability of having costs below 375 EUR (staying under the voluntary deductible range) and the take-up of the voluntary 500 EUR extra deductible. Panel A presents this relationship for the entire population, alongside the optimal choice in the frictionless, rational model for comparison. Panel B presents this relationship for the best and worst cohorts of decisionmakers, conditional on predicted health risk, as estimated in our regressions and defined in Section IV.C. The bottom four panels show deductible choices as a function of predicted health (i) education level in Panel C (ii) household gross income quartile in Panel D (iii) 6 fields of study in Panel E and (iv) 6 professional sectors in Panel F. Panel D excludes individuals with gross income below minimum social assistance, which mostly consists of students, self-employed and households with negative capital income. For Panels E and F, refer to Tables A.9 and A.10 for an overview of the deductible take-up in all fields and sectors, respectively.

Table 1 presents results from the regression model in equation 2, including baseline demographics, but focusing on income and education. The estimated intercept and slope coefficients for the different characteristics correspond to γ and ν respectively in equation (2).

There is significant and economically meaningful variation in slopes, as expected based on the graphical evidence. The effects, however, are predominantly driven by differences in education. The interaction with the predicted health risk is indeed substantially larger for those with higher education reflecting the fact that individuals are more responsive to their health status in selecting the higher deductible with higher education levels. An individual in good health — *ex ante* very high probability of being low cost — who has completed graduate studies beyond college is 23% more likely to take up the high deductible than an equivalent person with less than a high school education.

Controlling for other factors, the interaction of income and the gradient of take-up is small in magnitude. The highest income quartile is only about 4% more likely to take up the high deductible if they are in good health compared to the lowest income quartile, all else equal. The three bottom income quartiles have basically the same take-up rates. Thus, though both income and education have similar and substantive relationships with choice quality independently, when considered together the results show a much stronger impact of education than of income.

In comparison to the variation in slopes, there is generally little variation in the intercepts. There are statistically significant differences in responsiveness to underlying health risks, though the magnitude of the effects are relatively small. As can be expected from the graphical evidence, some of these differences change when relaxing the linearity assumption on the relation between take-up and risk, but they are consistently small. The regressions in Table 1 also include controls for age, gender and household composition on deductible choice, controlling for health risk, income and education level. Despite the relative simplicity of the models we estimate, the overall patterns are very robust to alternative specifications. For brevity, we present those results in Online Appendix Table A.6.

IV.B Human vs. Financial Capital

Table 1 demonstrates that the strongest relationship between deductible take-up and observable characteristics is for education level. This is indicative of the potential role of expertise, cognitive ability or information frictions in insurance choices. To shed more light on the role these effects may play we perform the same analysis as above but use richer data on the specific field of education and professional sector of employment.

We first explore this graphically, plotting the relationship between deductible choice and predicted health risk by education field and professional sector in the bottom panels in Figure 2. Since there are many education fields and professional sectors, in the figures we present only 6 specific fields and sectors that are indicative of the broader patterns. Statistics majors are the most responsive to predicted health risk: they choose the additional deductible approximately 43% of the time when they are in the healthiest predicted health bin and choose the additional deductible almost never when they are in the sickest predicted bin. The effect stands in stark contrast to those with training in "Protection of Persons and Property" or "Hair and Beauty Services." Even for the healthiest group in those fields, take-up of the higher deductible is only approximately 10%. Similarly, for professions that are more analytical in nature, deductible choice is also higher for those with low risk.

Columns (2) and (3) in 1 present the corresponding regression analysis, including baseline controls for predicted health risk, income, education level, age, gender and household structure. Even controlling for these other factors, more quantitative / analytic fields of study or profession are more responsive to predicted health when making deductible choices. For example, among the predictably healthy, someone with statistics training is 28.2% more

Table 1: Deductible Take-Up: Baseline Regression Estimates

	(1)		(2)		(3)		(4)	
	Baseline		Education Field		Professional Sector		Liquidity and Financials	
	intercept	*slope*	*intercept*	*slope*	*intercept*	*slope*	*intercept*	*slope*
2nd Income Quartile	0.004***	-0.007***	0.005***	-0.016***	0.009***	-0.032***	0.005***	-0.022***
3rd Income Quartile	0.004***	0.007***	0.005***	-0.003***	0.010***	-0.018***	0.006***	-0.021***
4th Income Quartile	0.002***	0.039***	0.005***	0.025***	0.011***	0.012***	0.007***	-0.000
High School	-0.011***	0.057***	-0.012***	0.059***	-0.014***	0.055***	-0.010***	0.048***
College Degree	-0.034***	0.165***	-0.033***	0.165***	-0.039***	0.165***	-0.031***	0.152***
Further Studies	-0.047***	0.226***	-0.046***	0.227***	-0.054***	0.236***	-0.045***	0.217***
Statistics			-0.042**	0.247***				
Philosophy			-0.003	0.046***				
Accounting and Taxation			-0.003***	0.024***				
Marketing and Advertising			-0.000	-0.004				
Hair and Beauty			0.007***	-0.035***				
Protection of Persons			0.008***	-0.068***				
Business Services					-0.012***	0.045***		
Insurance					-0.025***	0.078***		
Retail					-0.002***	-0.002*		
Construction					-0.001	-0.018***		
Cleaning					0.003***	-0.033***		
Public Utilities					0.006***	-0.008*		
2nd Net Worth Quartile							0.003***	-0.004***
3rd Net Worth Quartile							0.000*	0.021***
4th Net Worth Quartile							-0.002***	0.061***
Has Savings > 2000EUR							-0.006***	0.028***
Has Mortgage Debt							-0.000	0.005***
Has Other Debt							0.005***	-0.023***
Constant	-0.041***		-0.043***		-0.050***		-0.042***	
Prob. Low Costs		0.098***		0.101***		0.117***		0.094***
Baseline Controls	YES		YES		YES		YES	
Year and Insurer FE	YES		YES		YES		YES	
Observations	57,100,388		30,799,129		32,299,835		57,013,765	

Notes: This table plots coefficients from our regressions studying deductible choice, as explained in Section IV. Each variable is interacted with the probability of having low health expenses; the impact on the intercept is reported in the first column, and the impact on the slope in the second column. The dependent variable in all specifications is a dummy that takes value of 1 when the individual takes up the voluntary 500 EUR extra deductible. The prob. costs < 375 EUR variable is obtained from our prediction algorithm. All regressions include baseline demographic controls, income quartiles and education dummies. The reference groups are the 1st income quartile and those with education lower than high school respectively. Columns (2)-(4) include additional controls: in Column (2), dummies for six selected educational fields of study, as well as their interactions with health risk. The reference category for field of study is all other fields of study; in Column (3) dummies for six selected professional sectors, as well as their interactions with health risk. The reference category is all other sectors; in Column (4), a dummy for liquidity (household savings>2000EUR), a dummy for having household mortgage debt and other household debt, household net worth quartiles, as well as their interactions with predicted health risk. *** p<0.01, ** p<0.05, * p<0.1 with robust standard errors.

likely to choose a higher deductible than someone with hair and beauty training, controlling for age, income, gender, and education level.

Table 2: Deductible Take-up and Field of Study

	Education Field	(1) Take-up of 500 Deductible	(2) Probability Low Costs	(3) Take-up of 500 Ded. | Being Predictably Healthy
1	**Statistics**	29%	87%	34%
2	Mathematics	21%	85%	27%
3	Physics	21%	91%	26%
4	Architecture and town planning	18%	88%	21%
5	Physical science	18%	82%	22%
6	Earth science	18%	88%	21%
7	**Philosophy and ethics**	17%	82%	21%
8	Medicine	17%	83%	20%
16	Sociology and cultural studies	14%	82%	18%
17	Mining and extraction	14%	91%	17%
18	Economics	14%	84%	17%
19	Humanities and Arts	14%	84%	18%
41	**Accounting and taxation**	11%	78%	14%
42	Agriculture, forestry and fishery	10%	81%	13%
43	**Marketing and advertising**	10%	80%	13%
83	Secretarial and office work	5%	65%	7%
84	**Protection of persons and property**	4%	78%	6%
85	Child care and youth services	4%	66%	6%
86	Computer use	4%	65%	6%
87	**Hair and beauty services**	4%	65%	5%
90	Literacy and numeracy	2%	62%	4%

Notes: For a selection of fields of study, this table shows: in Column (1), the fraction of individuals who take-up the 500 EUR extra deductible, in Column (2), the fraction of individuals with a probability of low costs < 375 EUR, and in Column (3), the fraction of individuals who take-up the 500 EUR extra deductible, conditional on having predicted health costs < 375 EUR. The full list of fields is provided in Online Appendix Table A.9.

Table 2 presents the relationship between the specific field of study and deductible choice for a broad selection of fields. Columns 1 and 2 show the share taking up the high deductible and the predicted low-cost probability respectively. The primary results of interest are presented in column 3, which shows the rate of take-up of the high deductible among those with a high probability of having low cost — the group for which we expect high adoption under the standard model. The table shows that quantitative fields are grouped at the top of the table, exhibiting greater responsiveness to predicted health risk when making deductible choices, while those in less quantitative fields are grouped at the bottom of the table, exhibiting lower responsiveness.[4] Online Appendix Table A.10 shows a very similar gradient by professional sector.

Moving from human to financial capital, we can leverage the availability of a range of financial variables in addition to income to confirm the limited importance of household finances. Column (4) in Table 1 shows that - while controlling for demographics, education and income - household liquid savings are positively correlated with deductible take up: having liquid savings of greater than 2000 EUR is associated with a 2.2 percentage point

[4]An exhaustive list of education fields is presented in Online Appendix Table A.9.

increase in deductible take up for those who are predictably healthy. As noted, liquidity and debt constraints could either increase the demand for insurance (to avoid large expenditures) or reduce the demand for insurance (to avoid paying the premium) (see Ericson and Sydnor (2018)). The sign of the effect we find is consistent with the former explanation. In line with this, we also find that households who are in debt (excluding mortgage debt) are also less likely to take-up the deductible. The effects, however, are small in both cases and only hold for those in good health. Finally, we find that take-up rate for wealthier individuals is higher on average. The differences become meaningful (about 6% percentage points) for the highest wealth quartile. Note that these effects are again fully driven by individuals with better health. That is, wealthier individuals are more responsive to taking the incremental deductible as they become healthier. Hence, rather than capturing wealth effects on insurance choices, this results could be simply indicative of choice barriers for people with fewer financial resources.

IV.C Heterogeneity in Choice Quality

We can use our earlier model of frictionless decision-making and define the welfare loss due to barriers to choice (expressed as a money-metric) as:

$$\Delta w_i^* = CE_i^* - CE_i, \tag{3}$$

denoting the certainty equivalent for individual i's observed choice by CE_i and for the utility-maximizing choice by CE_i^*. Under risk-neutrality ($\sigma = 0$), this welfare loss equals the expected cost savings from choosing the deductible that minimize one's expected out-of-pocket expenditures. As discussed before, allowing for plausible risk aversion makes only small differences to the value of choices in our setting.

Using the expected cost savings as a measure of consumer welfare, we find that approximately 52% of consumers would have been ex ante better off with the 500 EUR voluntary deductible in 2015, but less than 7% of consumers chose it. Only 54.4% of individuals chose the cost-minimizing deductible. The average amount of money left on the table per individual is 66.2 EUR. While small in absolute value, these savings are roughly half of the total surplus at stake in the decision, which defined as $|250 - (1 - \pi_i)500|$ comes down to 145 EUR on average.

In addition, we use this welfare metric together with our regression estimates to rank individuals based on choice quality conditional on health and examine the socio-economic factors that predict the best and worst choosers. To that purpose we use our main regression analysis with health risk interacted with all socio-economic determinants to predict deductible choice probabilities $d(X_{it}, \pi_{it})$, which we then translate into consumer welfare $\Delta w^{*,\sigma=0}(X_{it}, \pi_{it})$ based on equation IV.C. We then average the cost savings over the different health risks using the population distribution of predicted health risks to obtain $\Delta w^{*,\sigma=0}_{\pi_{pop}}(X_{it})$. We finally rank individuals from worst to best decision makers based on how much value they are predicted to leave on the table on average across a representative distribution of population health. We provide more detail on this procedure in Online Appendix A.7.1.

Figure 2 (panel B) illustrates the overall heterogeneity in choice quality in the population using this procedure, plotting the responsiveness of deductible choices to health risk for different quantiles of choice quality. The performance of the very best decision makers is striking relative to the others. The take-up rate of the top 1% of decision makers is much steeper, coming close to the 45-degree line, with high and appropriate take-up of the extra deductible when healthy. The median quality decision-maker, on the other hand, comes close to sticking to the compulsory deductible regardless of the underlying health risk, bearing significant expected losses due to

Table 3: Best and Worst Decision Makers

	Top 5% decisionmakers	*Bottom 5% decisionmakers*		*Top 5% decisionmakers*	*Bottom 5% decisionmakers*
	Mean			Over/underrepresentation	
Demographics			**Education level**		
Gender (male)	62%	28%	Less than high school	0.30	2.99
Age	36	63	High school	0.82	0.33
Has children	59%	34%	College	3.48	0.00
Has a partner	46%	90%	Further Studies	15.57	0.00
			Unknown	0.08	1.05
Financials					
Gross income	105,801	39,347	**Education field**		
Net worth	250,632	4,969	Statistics	19.66	0.00
Has Mortgage Debt	64%	19%	Philosophy	13.14	0.00
Has Other Debt	27%	53%	Economics	6.95	0.01
Has Savings >2000EUR	91%	38%	Tax and administration	3.30	0.01
			Marketing and advertising	1.91	0.06
	Over/underrepresentation		Hair and beauty services	0.64	1.79
Work Status			Protection of persons	0.38	2.24
Student	2.80	0.16			
Retired	0.07	2.47	**Professional sector**		
Self-employed	2.07	0.05	Business services	2.77	0.09
Employee	1.16	0.31	Insurance	2.13	0.07
On Benefits	0.32	1.94	Retail	1.10	0.34
			Construction	0.75	0.24
			Cleaning	0.26	1.40
			Public utilities	1.51	0.11
Observations					11,369,800

Notes: This table presents observable characteristics for the groups that our model considers to be the top 5% and the bottom 5% decision makers. The entries give either the average value of the variable in each group or the ratio of the proportion of consumers with that characteristic in each group relative to the proportion of consumers with that characteristic in the population overall. For example, the group of best decision makers has 6.95 time more economics majors, proportionally, than the population overall.

over-insurance and doing only slightly better than the bottom 10% of decisionmakers.

Table 3 compares the observable characteristics for the best and worst decision makers and paints a telling picture of who is making the best choices in our context. Not surprisingly, we find substantial differences in education, both in terms of the overall level and educational field. For example, those with college education are 3.48 times more likely to be in the best decision-making group and with further education are 15.57 times more likely. Individuals with quantitative degrees or occupations are similarly over-represented in this top group. For example, statisticians are 19.66 times and economists 6.95 times more likely to be present in the group of top decision-makers, while those in cleaning are 0.26 times as likely to be in this group.

While we have found that demographic and financial variables provide relatively limited explanatory power in addition to education, the differences between the best and worst decision-makers are striking. The best decision-makers have an average gross income of 105K EUR and net worth of about 250K EUR. The worst decision makers, though, only have an average income of 40k EUR and net worth of 5K EUR. Better decision makers are much more likely to have liquid savings, a mortgage, and much less like to be indebted otherwise. We also find that better decision-makers are significantly younger, more likely to be male and more likely to have children.

V Discussion

Using granular data from the Netherlands, we characterized nationwide quality in deductible choices and found that (i) these choices were poor on average, in line with prior work on default options, and (ii) higher SES consumers make better choices than lower SES consumers, with a meaningful impact on realized surplus. Most notably, highly educated individuals who have more quantitative training make better choices than their counterparts, holding constant other key factors like income, net worth, and health risk. A variety of other socio-economic factors have more limited impacts on choice quality, including household income, net worth and liquidity.

Given the importance of our results for policy, both for choice quality overall and for the choice quality - SES gradient, we believe that there are several fruitful directions for future research. At a micro level, it will be valuable to assess how different policy and technology solutions can improve choices in different market and regulatory environments, both overall and for lower SES consumers specifically. For example, a field experiment at scale (e.g., Banerjee et al. (2021)) distinguishing between distinct behavioral foundations and/or distinct behaviorally-motivated policies (e.g., Bhargava, Loewenstein and Sydnor (2017)) could provide valuable additional insights, especially if linked to data similar to what we use in this study. While Brot-Goldberg et al. (2021) show that default effects for Medicare Part D low-income enrollees are primarily due to inattention rather than switching costs, it is unclear whether the better choices we document for higher-SES consumers are due to increased attention, relative to lower-SES consumers, or due to better active decisions once paying attention. If higher SES consumers are more attentive but not much more sophisticated otherwise, this has important implications for the welfare impacts of policies and on our understanding of the potential for insurance markets to deliver value.[5].

In addition to understanding these underlying mechanisms, it is also important to study the distributional consequences of policies allowing for choice and explore policy options that try to mitigate these. For example, one could consider eliminating choice or, when allowing for choice, designing the choice menu to combat the regressive nature of choice quality by matching the default option closer to the typical low SES consumer than to the typical high SES consumer. Targeted defaults as a function of key consumer characteristics, as discussed in Handel and Kolstad (2015*a*) and Abaluck and Gruber (2016), are another interesting path forward. Our analysis provides a useful starting point to quantify the consumer welfare implications of such counterfactual policies, which we briefly explore in Online Appendix A.7.2. This counterfactual analysis confirms that the option to select a higher deductible in the Dutch context increases welfare most for the high-income individuals, who are healthier and make better choices. The value of this option is very limited for low-income individuals and may well become negative when factoring in equilibrium price changes.

[5] We are assessing the implications of peer effects, at work and at home, on choice quality in ongoing work (Handel et al. (2023))

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A Online Appendix

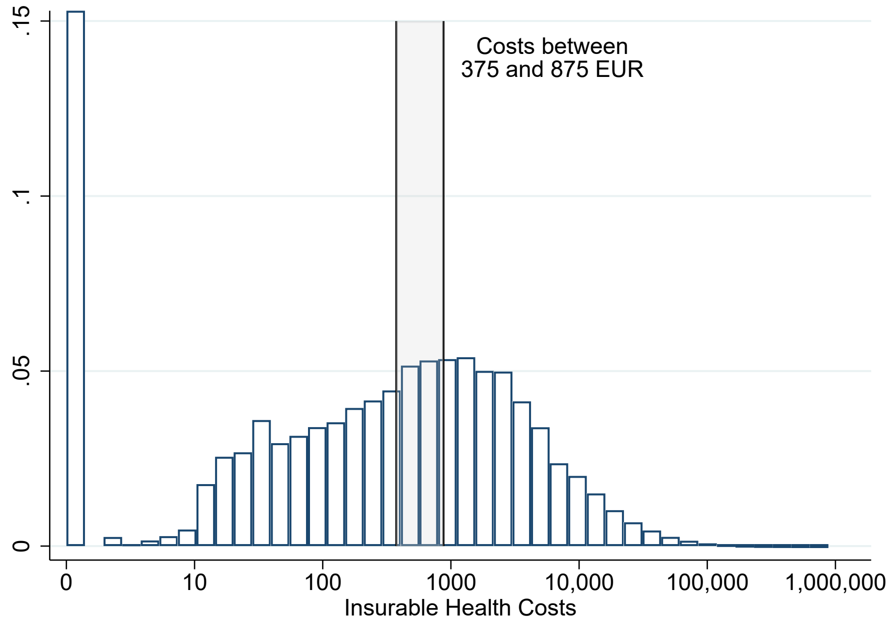
A.1 Summary Statistics

Table A.1: Summary Statistics

	Mean		Mean
Demographics		**Household Financial Status**	
Male	48.8%	Gross Household Income	73,289
Age	50.3	*10th Percentile*	*20,077*
Has Children	69.2%	*Median*	*60,358*
Has a Partner	62.9%	*90th Percentile*	*135,981*
Education Level		Household Net Worth	166,890
Less than High School	13.2%	*10th Percentile*	*-28,918*
High School	24.1%	*Median*	*32,694*
College	16.8%	*90th Percentile*	*403,923*
Further Studies	0.6%	Mortgage Debt	54.1%
Unknown	45.4%	Other Debt	34.2%
Employment Status		Savings > 2000 EUR	80.4%
Employee	44.3%		
Self-Employed	9.9%		
Retired	24.2%		
Student	6.3%		
Other Not Working	15.3%		
Observations			11,991,628

Notes: This table shows summary statistics for our full data sample in 2015, combining the prediction sample used for our cost model and the hold out sample used for our main analysis.

Figure A.1: Distribution of Insurable Health Care Costs



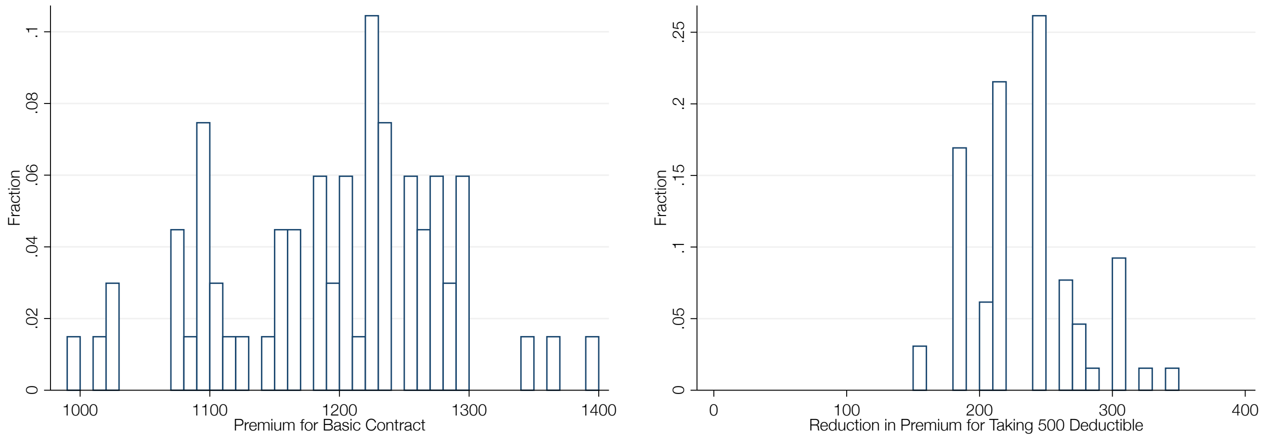
Notes: This figure shows the distribution of the $\log_{10}$ of total yearly insurable health care costs in 2015, for all individuals in our baseline sample. 13.1% of individuals have health costs falling in the 375 to 875 EUR interval.

Table A.2: Distribution of Annual Health Care Costs

	Mean	p10	p50	p90	p99
All Care	2,695	86	495	6,032	35,974
Insurable Care	2,272	0	332	5,043	31,133
Hospital Care	1,388	0	85	2,829	21,575
Medicines	320	0	53	758	3,253
Mental Care	243	0	0	0	4,801
Tools and Medical Aid	107	0	0	145	2,284
Geriatric Care	53	0	0	0	0
Transport	45	0	0	0	1,081
Multidisciplinary Care	33	0	0	124	397
Physiotherapic Care	32	0	0	0	1,095
Dental Care	26	0	0	0	825
Other Care	7	0	0	0	151
Sensory Handicap Care	3	0	0	0	0
Always Insured Care	423	75	121	327	8,042
Nursing Care	228	0	0	0	7,587
GP Care	157	75	119	272	659
Maternal Care	37	0	0	0	1,796
Observations					11,991,629

Notes: This table shows the distribution of health expenditures by subcategory, for the full sample in 2015. Expenditures are divided into insurable expenditures, that are subject to cost sharing (and to which the deductible applies) versus always insured expenditures, that are not subject to cost sharing. All values are in EUR.

Figure A.2: Distribution of Premia and Premium Reductions



Notes: This figure presents histograms of yearly premiums in 2015 for basic coverage (left-hand side) and premium reductions for those contracts when electing a maximal voluntary deductible of 500 for a total deductible of 875 EUR (right-hand side). Data on prices are obtained from homefinance.nl.

Table A.3: Distribution of Deductible Choices

Default Deductible	90.94%
Extra Deductible (+100 to +500EUR)	9.06%
Breakdown of Extra Deductible Choices	
+100EUR	10.64%
+200EUR	10.41%
+300EUR	6.02%
+400EUR	1.72%
+500EUR	71.21%

Notes: This table shows the breakdown of deductible choices in 2015. A large majority (90.94%) sticks to the default 375 EUR deductible. Of the 9.06% individuals that take an extra deductible, most individuals take the 500 EUR extra deductible.

A.2 Data Appendix

This Data Appendix provides information on the additional datasets we linked to our health cost and insurance data at Statistics Netherlands. Datasets are linked at the individual level based on anonymized individual identifiers. Please contact the authors for additional information on accessing these data.

Age and gender Dataset *Gbapersoontab* provides an overview of all people registered living in the Netherlands at any point since 1995. These registers form a basis for the administrative records of all individuals in the Netherlands. For our purposes, *Gbapersoontab* is used to obtain age and gender, and we use this person registry as the primary dataset to match all other datasets with.

Family and household links Family links come from the dataset *Kindoudertab*, which contains all known legal child-parent links. Household identifiers as well as family status variables in *Ipi* and *Inpatab* allow us to identify partners and other household links. Partnerships consist of all partners who are living in the same household.[6]

[6]This includes married partners, registered partners, but also partners who have not registered their partnership but are living in the same household.

Education *Hoogsteopltab* is a dataset that includes the highest attained educational course for each individual, and originates from several educational registers and survey data. We link each educational course to its relevant International Standard Classification of Education (ISCED) level and field of education. There is almost universal coverage for the youngest cohorts, but educational information is missing for many individuals aged over 40. Overall, we observe highest education obtained for 54.6% of our full sample.

Income and Employment Status Datasets *Ihi* and *Inhatab* contain information on households' income, and originates from tax authorities. Our main definition of income used in the analysis is household gross income (called *bruto inkomen* by Statistics Netherlands). Gross income includes all labor income and capital income, as well as government transfers (e.g., UI, DI, pensions), and other transfers and income. We also use a socio-economic classification variable *seccoal1*, which classifies each individual based on where the majority of his or her personal income comes from. This variable is obtained from datasets *Ipi* and *Inpatab*.

Wealth Dataset *Vehtab* contains information from tax authorities on households' assets and debts. This information is partly self-reported (on tax forms) and third-party reported. Assets include financial assets (savings, stocks, bonds, and other participations), real estate and other assets (such as cash and movable assets). Debts include mortgages, study debt and other debt. The net wealth variable in the main text equals household assets minus household debts.

Employee-Employer links We use the dataset *Spolisbus* to link individuals to their firms, colleagues and sector. *Spolisbus* is a highly detailed dataset with monthly information on all employment contracts in the Netherlands, collected by the tax authorities based on third-party reported data. We adopt the same definition of a firm as in the firm registry (*Algemeen Bedrijfsregister*) of Statistics Netherlands. We sum each individual's total hours worked by year by firm. For each individual, we then select the firm at which that individual has worked the most hours in each year. The colleagues that we identify are thus all individuals who work the majority of their hours at the same firm. The sector categorization that we adopt is made by the authorities based on the collective labor agreements.

Location We match every individual with their yearly 6-digit postcode based on their registered residence. For this, we use datasets *Gbaadresobjectbus* and *Vslgwbtab*. Postcodes are obtained for each year on 1 October, as this is close to the period of deciding on their health insurance contract. 6-digit postcode information is at a neighbourhood level, and there are 12'116 distinct postcodes in 2015.

A.3 Health Cost Predictions

In this Appendix, we describe the binary prediction algorithm that we use to obtain risk probabilities, and discuss its accuracy across different subgroups, and the most important predictors. We also discuss an alternative non-binary prediction algorithm and argue why the binary predictions are preferable for the analysis in this paper.

A.4 Prediction Algorithm

We use an ensemble machine learning algorithm to predict the probability that an individual's health costs will not exceed the mandatory deductible of 375 EUR in any given year. The prediction algorithm we use is a standard machine learning method for binary classification, an ensemble learner that consists in our case of a random forest model, gradient boosted regression trees and LASSO model. To avoid overfitting, we train and calibrate the prediction algorithm on a training sample of 1.25 million individuals. We then use this trained prediction algorithm to obtain predictions for a hold-out sample of about 12 million individuals. All the analyses and statistics in the paper are developed use only this hold-out sample.

The prediction method we use follows four steps, which closely resemble the steps used in Einav et al. (2018). First, we follow standard practice in machine learning by tuning key parameters that govern the prediction models by 3-fold cross-validation. Second, we train the three resulting prediction models separately. Third, we combine the three obtained predictions into one using a linear combination that we calibrate in the data. Finally, we calibrate the resulting final ensemble predictions using a linear spline. As there is some variation in the number and definition of predictors that we have across time, we repeat these four steps for all years of study (2013-2017). We describe each of the four steps in more detail here.

Parameter Tuning As the three machine learning models that we use have parameters that are choosable by the researcher, we follow standard practice and tune these parameters using 3-fold cross validation. More specifically, we tune the following parameters using 100,000 observations: minimal node size (mid.node.size), number of variables used at each node (mtry) for the random forest model, learning rate (eta) for the boosted regression trees, and the shrinkage parameter (lambda) for the LASSO.[7] For each of these parameters, we optimize among 5 alternatives. We tune these parameters using 3-fold cross validation, where we are optimizing the area under the receiver operating characteristic curve (AUC).[8] Thus, for each of the parameter values we want to test, the model is trained on 2 folds (subsets of the training sample), and then the performance is measured in the 3rd fold. The parameter values for which the AUC in the hold-out sample is highest for each prediction algorithm are: mtry = 10, min.node.size = 10, eta = 0.2, lambda = 0.0001.

Estimating the Models Using these tuned parameter values, all models are estimated using a training sample of 800,000 individuals.

Obtaining Ensemble Predictor We combine the predictions from the random forest, gradient boosting regression trees, and LASSO into one ensemble prediction. Following Einav et al. (2018), we construct the ensemble prediction to be the linear combination $p_{ensemble} = \hat{\beta}_{rf}\hat{p}_{rf} + \hat{\beta}_{gb}\hat{p}_{gb} + \hat{\beta}_{lasso}\hat{p}_{lasso}$, where $\hat{p}_x$ is the prediction from algorithm x and $\hat{\beta}_x$ is the associated weight.

We obtain estimates for the weights from a constrained linear regression (with no constant and the weights summing to one) of the dummy for having costs below 375 EUR on the three individual predicted probabilities. For this step, we use 100,000 observations that we did not use in either step of parameter tuning nor the estimation of the models. We find associated weights in 2015 that are $\hat{\beta}_{rf} = 0.67$, $\hat{\beta}_{gb} = 0.08$ and $\hat{\beta}_{lasso} = 0.25$.

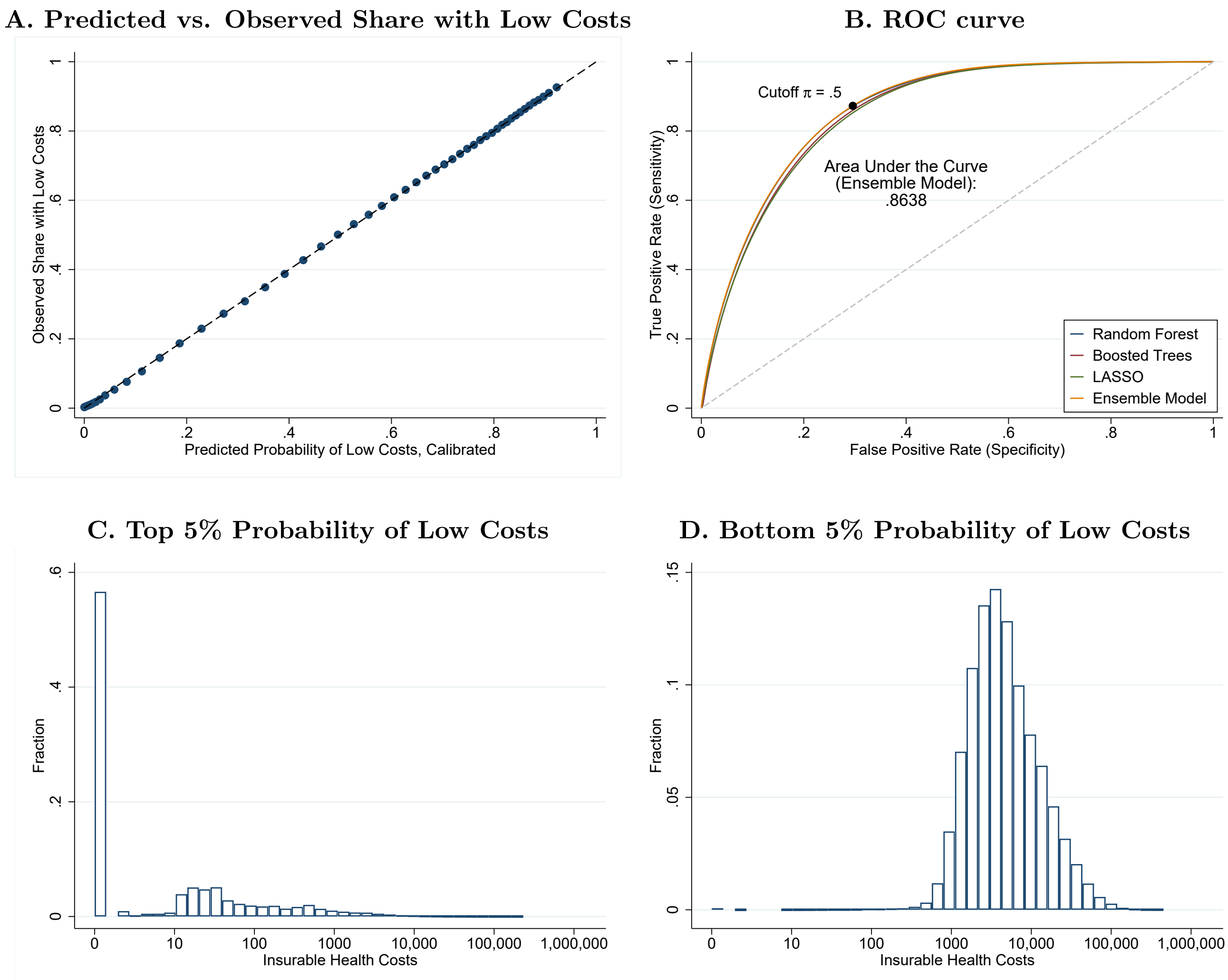
Calibrating Probabilities Finally, the raw probability predictions we get from the ensemble step are calibrated to the actual observed probabilities by estimating a linear spline. This calibration is done using 350,000 observations that are used in none of the previous steps. 10 equal sized bins are created based on the ranked predicted probability. In every bin the mean probability is calibrated to the observed mean probability for these observations. The piece-wise linear spline that follows from linearly interpolating all intermediary points serves as the last step in the prediction mechanism.

Prediction Fit Figure A.3 below presents key results illustrating the strong fit of our cost prediction model, for the year of 2015. Figure Panel A presents a binned scatter plot of our predicted probability of having low costs against the realized share of individuals with low costs. The predictions track the realized shares almost

[7] We use the package CARET in R that provides a standardized way to tune parameters. The prediction models we use are RANGER (random forest), XGBLINEAR (boosted regression trees), and GLMNET (LASSO).

[8] This is a common metric used in the machine learning literature to measure the performance of a prediction model.

Figure A.3: Predicted vs. Realized Costs

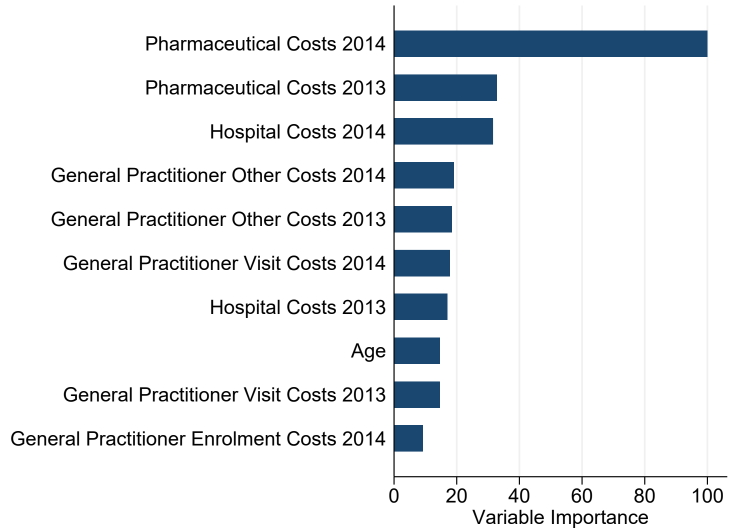


Notes: Panel A presents a binned scatter plot of our predicted probability of having low costs against the realized share of individuals with low costs. Panel B plots the ROC curve of the different prediction methods used. The bottom figures present ex-post cost realizations of individuals with predicted low (Panel C) and predicted high (Panel D) costs. The year is 2015 for all Figures.

exactly. Panel B plots the ROC curve of the different prediction methods used, showing a strong prediction of true positives relative to false positives. The bottom figures present ex-post cost realizations of individuals with predicted low (Panel C) and predicted high (Panel D) costs. These figures illustrate that our model fit is strong even at the tails and carefully distinguishes predictably healthy from predictably sick individuals.

Figure A.4 presents the importance of different predictors in the random forest model, which is the model with the highest weight in our ensemble prediction. Not surprisingly, the most important predictors are different categories of past pharmaceutical spending, with $t-1$ values being more important than $t-2$ values. Hospital costs, costs to primary care visits and age are other important variables in the random forest prediction.

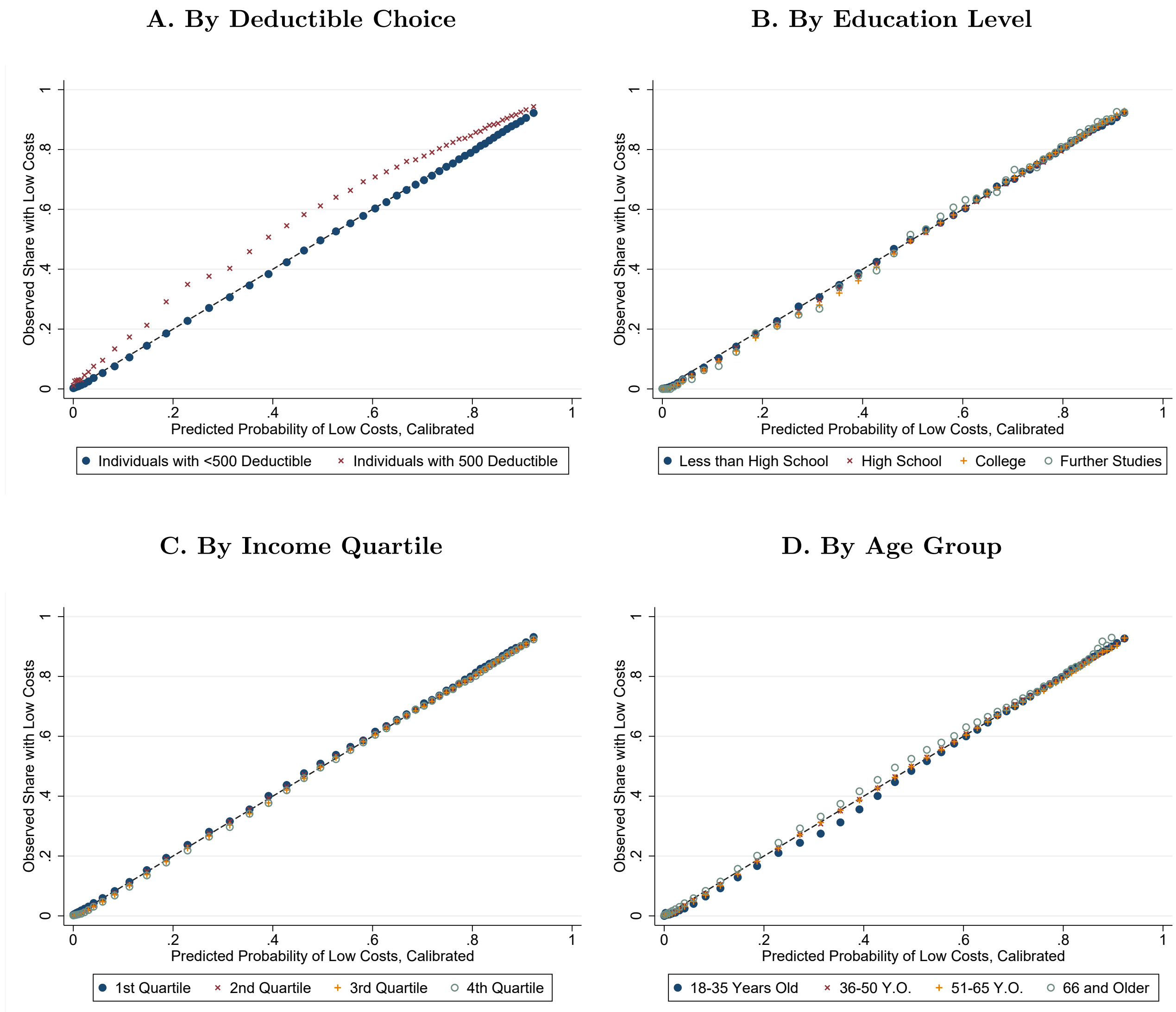
Figure A.4: Variable Importance in Prediction with Random Forest



Notes: This figure shows the importance of selected variables in the prediction of health cost risk using only a random forest model. Variable importance is measured by the mean decrease in gini, ie. the average of a variable's total decrease in node impurity, weighted by the proportion of samples reaching that node in each individual decision tree in the random forest.

Subgroup Fit While Figure A.3 shows a calibration plot for the entire sample, Figure A.5 shows a calibration plot for certain subgroups of the sample. As noted in the text, this is valuable to ensure that the heterogeneous choice quality we estimate is not in part related to differences in the cost prediction model by subgroup. We see from Panel B, C and D that probabilities are very precisely calibrated for distinct groups of education level, income quartile and age. This makes us comfortable that the observed differences in choice quality across these different groups are not due to differential prediction accuracy of our ensemble predictor.

Figure A.5: Predicted vs. Observed Share of Low Costs, by Subgroups



Notes: This figure shows the calibration plot of the predicted probability of low costs for various subgroups of the sample. Panel A plots our prediction against the observed share of people with health costs below 375 EUR, separately for people having chosen the 500 deductible and people who have not. Panel B does the same exercise splitting the sample by education level. In Panel C, the sample in split by income quartile, and in Panel D, by age group.

Asymmetric Information and Moral Hazard Panel A of Figure A.5 addresses a different issue: does enrolling in a higher deductible impact ex post cost realization relative to our prediction model? This takes on the classic issues of selection on private information (not included in our prediction model) and moral hazard (ex post utilization changes due to different prices). See Chiappori and Salanie (2000) for prior research describing a correlation test to jointly detect the presence of adverse selection on private information and moral hazard. Panel A shows that individuals who choose a 500 EUR deductible are more likely to have low costs than individuals who choose no extra deductible, conditional on the prediction of our model. This is consistent with some combination of additional selection on private information and moral hazard. However, the difference in the *ex post* realized low cost fraction relative to the predicted fraction is quite small, leading us to conclude that the private information and moral hazard, conditional on our predictors, is small. More specifically, the average gap across probability bins between individuals who choose and who do not choose an extra deductible is 6.667%. Taking into account that across probability bins, the average share with low costs among people without an extra deductible is 51.215%, we find that individuals who take a deductible are on average are 13.017% more likely to have low costs than our model predicts. Importantly, as discussed in Section III in the main text, to the extent that consumers spend less under a high deductible plan because of classical moral hazard, our model threshold for choosing the high deductible ($\pi = 0.5$ for risk neutral, $\pi = 0.56$ for very risk averse) is slightly high (i.e. more people should choose the high deductible) and the normative benefits from doing so in Section IV.C are too low, working against our main results.

Relatedly, Table A.4 below supports the discussion of behavioral hazard in Section III, suggesting that up front rational avoidance of ex post behavioral hazard is not a major concern. Specifically, conditional on one's predicted low cost bin, there are minimal impacts on key high-value care categories like preventive care, maternity care and drugs. There is a more significant impact on mental health spending, indicating some potential for moral hazard and or selection on private information in that domain.

Table A.4: Ex Post Health Expenses, by Subgroups

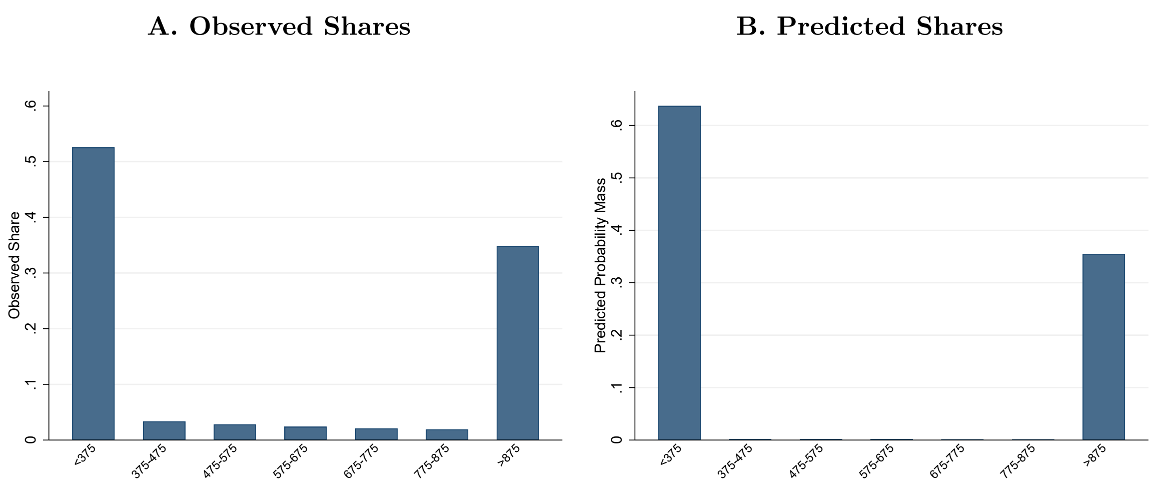
P(Low Costs)	Low Deductible	Any Incremental Deductible
N (Sample Size)		
0.6-0.7	1,156,446	91,263
0.7-0.8	1,514,402	171,016
0.8-0.9	1,850,417	298,369
0.9-1	471,746	96,877
Preventative Care (Always Insured)		
0.6-0.7	184.6	171.7
0.7-0.8	154.3	142.3
0.8-0.9	122.9	113.5
0.9-1	97.3	90.7
Drugs		
0.6-0.7	68.7	55.5
0.7-0.8	45.6	35.7
0.8-0.9	25.6	19.1
0.9-1	13.0	9.6
Maternity Care		
0.6-0.7	41.8	42.1
0.7-0.8	27.8	26.0
0.8-0.9	14.4	11.2
0.9-1	4.6	2.7
Mental Health		
0.6-0.7	234.3	173.2
0.7-0.8	155.5	117.0
0.8-0.9	98.0	66.1
0.9-1	64.9	38.0

Notes: This table presents statistics related to actual ex post spending on certain types of health care as a function of our ex ante prediction of the probability an individual has low costs. The top section gives the sample size for each group and subsequent sections give the mean EUR spent on each kind of care by individuals in each group. This table supports the discussion of behavioral hazard in Section III, suggesting that up front rational avoidance of ex post behavioral hazard is not a major concern.

Non-Binary Prediction. In Section III.A, we simplified the deductible choice problem in the Netherlands into a binary choice between selecting a 875 EUR deductible, or the mandatory 375 EUR deductible. This is a simplification, as in fact there are 6 different deductible choices possible, which apply to different brackets with cutoffs at 375, 475, 575, 675, 775 and 875 EUR. However, two pieces of evidence show that reducing the problem to a binary one is appropriate for our context.

First, Panel A of Figure A.6 shows that the ex-post observed shares within each intermediary deductible bracket are small. This means that only a small fraction of individuals fall into the intermediary deductible ranges, which decreases the likelihood that the intermediary deductibles are optimal choices. Second, we find that when using a machine learning classifier to predict which individuals are going to fall into the intermediary brackets, the predicted mass in these intermediary brackets is small. Panel B of Figure A.6 shows that ex-ante, a random forest model trained on an unbalanced sample will give less than 1% probability mass to the intermediate categories. This is largely due to the unbalanced classes, where the majority of individuals fall into the lowest or highest bracket. However, insofar as we cannot expect individuals to predict their future costs more accurately, the low probability with which most individuals are predicted to be in the intermediary deductible brackets further strengthens the case for a binary decision rule.

Figure A.6: Cost Predictions with Multiple Deductible Categories



Notes: Panel A plots the observed share of individuals with health costs in all the deductible health cost brackets in 2015. Panel B plots the predicted shares of individuals in all deductible health cost brackets, where the prediction is from a random forest with the same predictors as described in Section III.A.

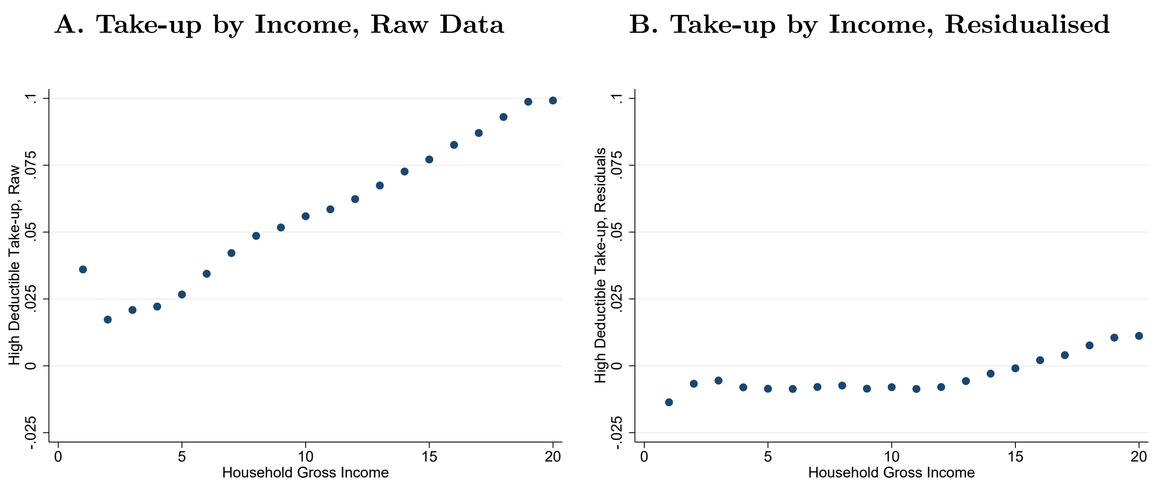
A.5 Deductible Choice: Appendix Figures and Tables

Table A.5: Deductible Take-up: Impact of Health and Income Changes

	(1)	(2)	(3)	(4)	(5)
	No FE	Individual FE	First difference	First difference	First difference
Probability of Low Costs	0.115***	0.0570***	0.0422***		
Prob. Low Costs, Positive Δ				0.00691***	
Prob. Low Costs, Negative Δ				-0.0670***	
Δ Prob. Low Costs > +2 Deciles					0.0102***
Δ Prob. Low Costs = +2 Deciles					0.00685***
Δ Prob. Low Costs = +1 Decile					0.00342***
Δ Prob. Low Costs = -1 Decile					-0.00277***
Δ Prob. Low Costs = -2 Deciles					-0.00636***
Δ Prob. Low Costs < -2 Deciles					-0.0202***
Income ('000 EUR)	6.06e-05***	1.57e-05***	6.63e-06***	6.65e-06***	6.85e-06***
Number of Individuals	12,317,248	12,317,248	12,074,444	12,058,624	12,074,444
Observations	47,685,794	47,685,794	35,368,540	35,216,196	35,368,540

Notes: This table presents the result of an OLS regression of take-up of the 500 EUR extra deductible on probability of low costs, changes in probability of low costs, income, and changes in income. In column (1), take-up of the high deductible is regressed on the probability to have health costs lower than 375 EUR, and on income in thousands of EUR. Column (2) adds individual fixed effects. Column (3) regresses the first difference of deductible take-up on the first difference of the probability of low costs and the first difference of income. Column (4) splits the first difference in two distinct variables, one containing only positive shocks, the other only negative shocks. Column (5) creates six dummies capturing shocks of various magnitudes: positive and negative shocks of one, two, and strictly more than two deciles. In Columns (4) and (5), income first difference remains unchanged compared to Column (3). All regressions include year fixed effects. *** p<0.01, ** p<0.05, * p<0.1 with robust standard errors.

Figure A.7: Deductible Take-up as a Function of Income



Notes: These figures plot the relationship between household gross income and the take-up of the 500 EUR extra deductible. Panel A plots take-up of 500 deductible by household income percentile. Panel B plots the residuals of an OLS regression of take-up of 500 EUR extra deductible on risk probability, four levels of education dummies, four age dummies, and indicators for gender, having a partner, and having children.

Table A.6: Robustness Check

	Baseline			500 vs. 0 Deductible			0 vs. >0 Deductible		
	Without	With Interaction		Without	With Interaction		Without	With Interaction	
	Interaction	*intercept*	*slope*	Interaction	*intercept*	*slope*	Interaction	*intercept*	*slope*
High School	0.017***	-0.011***	0.057***	0.018***	-0.012***	0.061***	0.025***	-0.014***	0.077***
College Degree	0.065***	-0.034***	0.165***	0.071***	-0.038***	0.181***	0.089***	-0.037***	0.210***
Further Studies	0.091***	-0.047***	0.226***	0.099***	-0.052***	0.250***	0.123***	-0.044***	0.275***
2nd Income Quartile	-0.003***	0.004***	-0.007***	-0.003***	0.004***	-0.007***	0.002***	0.009***	-0.005***
3rd Income Quartile	0.004***	0.004***	0.007***	0.005***	0.003***	0.009***	0.014***	0.011***	0.013***
4th Income Quartile	0.024***	0.002***	0.039***	0.026***	0.001***	0.045***	0.041***	0.015***	0.048***
36 to 50 years old	-0.011***	0.020***	-0.045***	-0.010***	0.022***	-0.046***	-0.006***	0.024***	-0.042***
51 to 65 years old	-0.004***	0.029***	-0.047***	-0.004***	0.030***	-0.048***	0.003***	0.036***	-0.045***
65+ years old	-0.001***	0.034***	-0.082***	0.000**	0.036***	-0.085***	0.007***	0.043***	-0.092***
Male	0.011***	-0.004***	0.025***	0.012***	-0.004***	0.028***	0.017***	-0.001***	0.030***
Has Partner	0.003***	-0.002***	0.013***	0.003***	-0.002***	0.014***	0.002***	-0.005***	0.018***
Has Children	-0.010***	0.004***	-0.028***	-0.011***	0.004***	-0.031***	-0.014***	0.004***	-0.035***
Self-employed	0.009***	-0.006***	0.026***	0.009***	-0.007***	0.028***	0.013***	0.000	0.023***
Constant	-0.042***	-0.041***		-0.045***	-0.043***		-0.055***	-0.044***	
Prob. Low Costs	0.122***		0.098***	0.129***		0.100***	0.169***		0.124***
Year and Insurer FE	YES	YES		YES	YES		YES	YES	
Observations	57,100,388	57,100,388		55,335,880	55,335,880		57,100,388	57,100,388	

	Baseline			Probit			Binary Pred. Low Costs		
	Without	With Interaction		Without	With Interaction		Without	With Interaction	
	Interaction	*intercept*	*slope*	Interaction	*intercept*	*slope*	Interaction	*intercept*	*slope*
High School	0.017***	-0.011***	0.057***	0.022***	0.006***	0.023***	0.019***	0.002***	0.032***
College Degree	0.065***	-0.034***	0.165***	0.051***	0.014***	0.051***	0.068***	0.013***	0.081***
Further Studies	0.091***	-0.047***	0.226***	0.063***	0.005**	0.081***	0.093***	0.019***	0.105***
2nd Income Quartile	-0.003***	0.004***	-0.007***	0.003***	0.030***	-0.040***	-0.001***	0.003***	-0.005***
3rd Income Quartile	0.004***	0.004***	0.007***	0.010***	0.041***	-0.044***	0.007***	0.008***	0.002***
4th Income Quartile	0.024***	0.002***	0.039***	0.024***	0.057***	-0.048***	0.027***	0.017***	0.016***
36 to 50 years old	-0.011***	0.020***	-0.045***	-0.008***	-0.007***	-0.001	-0.013***	-0.005***	-0.009***
51 to 65 years old	-0.004***	0.029***	-0.047***	0.000	0.001**	-0.002**	-0.012***	-0.005***	-0.006***
65+ years old	-0.001***	0.034***	-0.082***	-0.011***	-0.008***	-0.004***	-0.017***	-0.008***	-0.025***
Male	0.011***	-0.004***	0.025***	0.006***	0.007***	-0.002***	0.015***	0.001***	0.023***
Has Partner	0.003***	-0.002***	0.013***	0.005***	0.007***	-0.003***	0.003***	0.000***	0.008***
Has Children	-0.010***	0.004***	-0.028***	-0.009***	-0.000	-0.011***	-0.011***	-0.000	-0.020***
Self-employed	0.009***	-0.006***	0.026***	0.008***	0.018***	-0.013***	0.011***	0.005***	0.009***
Constant	-0.042***	-0.041***					-0.014***	-0.003***	
Prob. Low Costs	0.122***		0.098***	0.169***		0.191***			
Pred. Costs <375							0.062***		0.034***
Year and Insurer FE	YES	YES		YES	YES		YES	YES	
Observations	57,100,388	57,100,388		57,100,388	57,100,388		57,100,388	57,100,388	

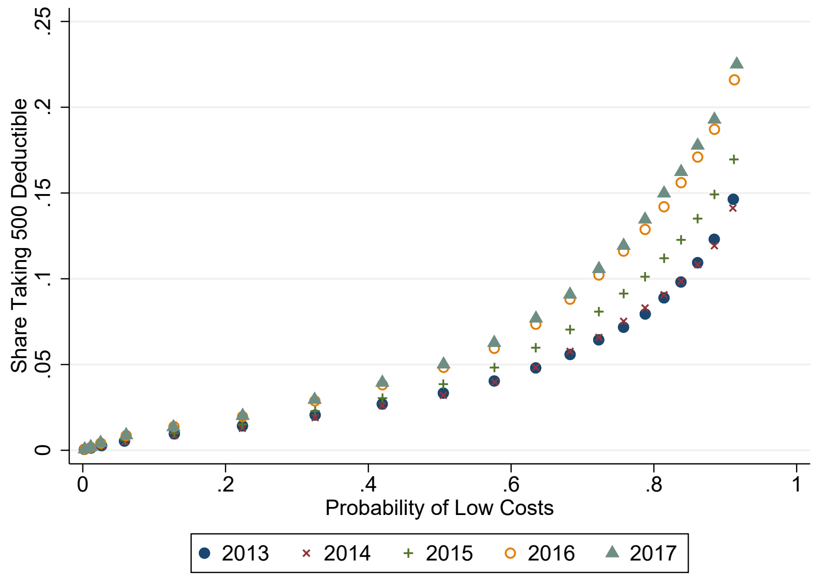
Notes: This table performs a range of robustness checks on our baseline results. In the top panel, we compare our baseline regression with alternative definition of take-up of the high deductible. In the baseline, we define take-up as choosing the 500 deductible, as opposed to choosing any other deductible. In the second top panel, we keep only choices that are the 500 or the 0 deductible, and drop intermediate choices. In the third top panel, we instead define take-up as choosing any deductible strictly greater than 0. In the second bottom panel, we compare our baseline OLS regression with a probit specification. Finally, in the third bottom panel, we replace our linear probability of low costs with a binary indicator taking value one if the individual is predicted to have health costs lower than 375 EUR. In each panel, we present a regression with and without interacting our regressors with the probability of low costs.

Table A.7: Deductible Take-up Regression, Non Interacted

	(1) Baseline	(2) Education Field	(3) Professional Sector	(4) Liquidity and Financials	(5) Environment
High School	0.017***	0.016***	0.017***	0.015***	0.014***
College Degree	0.065***	0.062***	0.066***	0.062***	0.056***
Further Studies	0.091***	0.089***	0.097***	0.089***	0.088***
2nd Income Quartile	-0.003***	-0.008***	-0.011***	-0.009***	-0.006***
3rd Income Quartile	0.004***	0.000	-0.002***	-0.004***	-0.000
4th Income Quartile	0.024***	0.019***	0.017***	0.011***	0.014***
36 to 50 years old	-0.011***	-0.008***	-0.010***	-0.012***	0.007***
51 to 65 years old	-0.004***	-0.001***	-0.002***	-0.012***	0.027***
65+ years old	-0.001***	0.005***	0.003***	-0.016***	0.020***
Male	0.011***	0.015***	0.014***	0.012***	0.017***
Has Partner	0.003***	0.006***	0.004***	0.003***	0.008***
Has Children	-0.010***	-0.013***	-0.012***	-0.007***	-0.006***
Self-employed	0.009***	0.007***	0.008***	0.005***	0.007***
Statistics		0.139***			
Philosophy		0.024***			
Accounting and Taxation		0.012***			
Marketing and Advertising		-0.004***			
Hair and Beauty		-0.012***			
Protection of Persons		-0.033***			
Business Services			0.022***		
Insurance			0.027***		
Retail			-0.003***		
Construction			-0.013***		
Cleaning			-0.012***		
Public Utilities			0.001		
2nd Net Worth Quartile				0.004***	
3rd Net Worth Quartile				0.012***	
4th Net Worth Quartile				0.029***	
Has Savings > 2000EUR				0.008***	
Has Mortgage Debt				0.002***	
Has Other Debt				-0.009***	
Share of Colleagues with 500 Ded.					0.226***
Share in Postcode with 500 Ded.					0.404***
Father With 500 Deductible					0.181***
Mother With 500 Deductible					0.237***
Constant	-0.042***	-0.056***	-0.063***	-0.043***	-0.135***
Prob. Low Costs	0.122***	0.145***	0.148***	0.119***	0.160***
Year and Insurer FE	YES	YES	YES	YES	YES
Observations	57,100,388	30,799,129	32,299,835	57,013,765	16,938,401

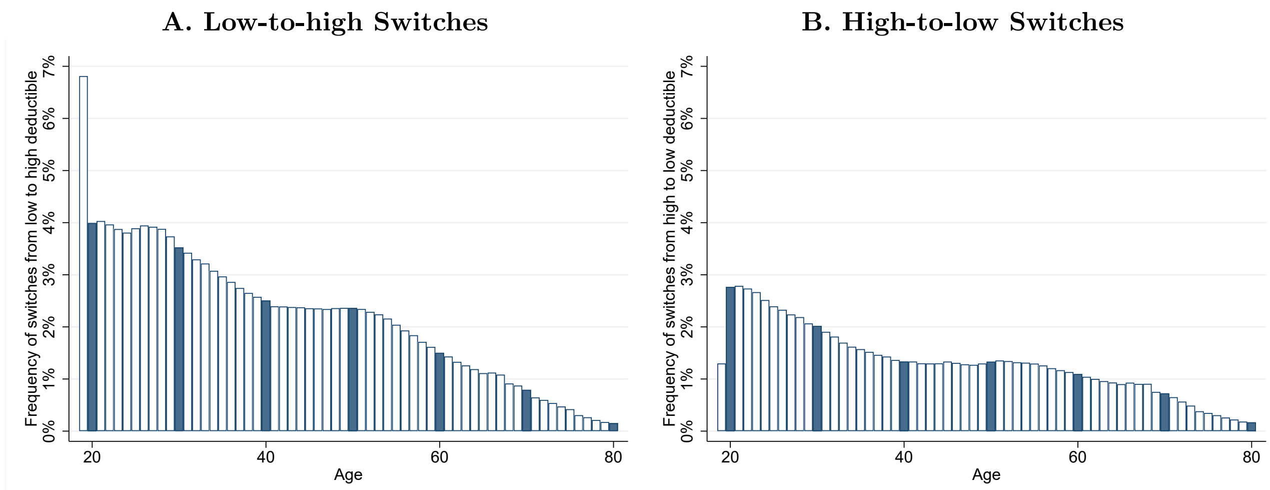
Notes: Notes from Table 1 apply; this table displays the same regressions without interacting the regressors with the probability of low costs.

Figure A.8: Deductible Choice Gradient by Year



Notes: This figure displays the relationship between take-up of the 500 deductible and the predicted probability of low costs, separately for the five years included in our final sample.

Figure A.9: Frequency of deductible switches by age



Notes: This figure displays the frequency of deductible switches by age, in years 2014 to 2017. Panel A displays only switches to a higher deductible, and Panel B to a lower deductible.

Table A.8: Predicted Health Risk by Observed and Optimal Deductible Choice

	2013	2014	2015	2016	2017
Probability of Low Costs	0.512	0.516	0.516	0.504	0.496
Healthy Individuals	0.752	0.758	0.760	0.759	0.762
Unhealthy Individuals	0.176	0.169	0.169	0.160	0.159
Individuals with 500 Deductible	0.748	0.760	0.763	0.762	0.763
Individuals with <500 Deductible	0.499	0.502	0.499	0.482	0.472
Share of Healthy Individuals	58.2%	58.9%	58.7%	57.4%	56.0%
Share of Individuals with the 500 Deductible	5.1%	5.3%	6.5%	8.0%	8.2%

Notes: This table displays, for the five years in our sample, the share of predictably healthy individuals and the share of individuals who took up the high deductible. It then shows the average probability of low costs for predictably healthy people (i.e., with a probability of low costs greater than .5), predictably unhealthy people, people who have taken up the 500 deductible and those who have not.

Table A.9: Deductible Take-up and Predicted Health by Field

	Education Field	(1) Take-up of 500 Deductible	(2) Probability Low Costs	(3) Take-up of 500 Ded. | Being Predictably Healthy
1	**Statistics**	29%	87%	34%
2	Mathematics	21%	85%	27%
3	Physics	21%	91%	26%
4	Architecture and town planning	18%	88%	21%
5	Physical science	18%	82%	22%
6	Earth science	18%	88%	21%
7	**Philosophy and ethics**	17%	82%	21%
8	Medicine	17%	83%	20%
9	Chemistry	16%	87%	20%
10	Biology and biochemistry	16%	83%	20%
11	Science, Mathematics and Computing	16%	85%	19%
12	Computer science	15%	87%	18%
13	Environmental protection	15%	86%	18%
14	Political science and civics	15%	85%	18%
15	Design	15%	85%	18%
16	Sociology and cultural studies	14%	82%	18%
17	Mining and extraction	14%	91%	17%
18	Economics	14%	84%	17%
19	Humanities and Arts	14%	84%	18%
20	Dental studies	14%	76%	18%
21	History and archaeology	13%	82%	16%
22	Business and administration	13%	82%	16%
23	Pharmacy	13%	73%	17%
24	Health	13%	79%	16%
25	Environmental protection technology	13%	84%	15%
26	Medical diagnostic and treatment technology	13%	81%	16%
27	Religion	13%	80%	17%
28	Law	13%	80%	16%
29	Psychology	12%	77%	16%
30	Management and administration	12%	81%	16%
31	Engineering and engineering trades	12%	87%	15%
32	Forestry	12%	86%	14%
33	Therapy and rehabilitation	12%	78%	15%
34	Finance, banking, insurance	12%	80%	15%
35	Social and behavioural science	12%	79%	15%
36	Health and Welfare	12%	80%	15%
37	Fisheries	12%	94%	15%
38	Journalism and reporting	12%	80%	14%
39	Training for teachers w. subject specialisation	11%	79%	14%
40	Education science	11%	75%	14%
41	**Accounting and taxation**	11%	78%	14%
42	Agriculture, forestry and fishery	10%	81%	13%
43	**Marketing and advertising**	10%	80%	13%
44	Chemical and process	10%	85%	12%
45	Arts	10%	80%	13%
46	Electronics and automation	10%	86%	12%

Table A.9: Deductible Take-up and Predicted Health by Field (cont'd)

47	Music and performing arts	10%	81%	12%
48	Training for teachers of vocational subjects	10%	81%	12%
49	Fine arts	10%	82%	12%
50	Humanities	10%	76%	12%
51	Library, information, archive	9%	78%	12%
52	Travel, tourism and leisure	9%	77%	12%
53	Electricity and energy	9%	88%	11%
54	Veterinary	9%	75%	12%
55	Mother tongue	9%	74%	12%
56	Audio-visual techniques and media production	9%	83%	10%
57	Building and civil engineering	9%	86%	10%
58	Life science	9%	79%	11%
59	Crop and livestock production	9%	79%	11%
60	Mechanics and metal work	9%	85%	10%
61	Wholesale and retail sales	8%	79%	11%
62	Foreign languages	8%	74%	11%
63	Motor vehicles, ships and aircraft	8%	87%	10%
64	Training for teachers at basic levels	8%	75%	10%
65	Materials (wood, paper, plastic, glass)	8%	86%	9%
66	Sports	8%	83%	10%
67	Teacher training and education science	8%	74%	10%
68	Military and defence	7%	81%	9%
69	Transport services	7%	83%	9%
70	Food processing	7%	78%	9%
72	Natural environments and wildlife	6%	86%	7%
73	Hotel, restaurant and catering	6%	77%	8%
74	Basic / broad, general programmes	6%	72%	9%
75	Social work and counselling	6%	70%	8%
77	Personal skills	6%	68%	8%
78	Textiles, clothes, footwear, leather	5%	70%	7%
79	Horticulture	5%	80%	6%
80	General Programmes	5%	71%	7%
81	Nursing and caring	5%	66%	7%
82	Domestic services	5%	66%	7%
83	Secretarial and office work	5%	65%	7%
84	**Protection of persons and property**	4%	78%	6%
85	Child care and youth services	4%	66%	6%
86	Computer use	4%	65%	6%
87	**Hair and beauty services**	4%	65%	5%
88	Occupational health and safety	4%	75%	5%
89	Training for pre-school teachers	3%	62%	0%
90	Literacy and numeracy	2%	62%	4%

Notes: For each field of study, this table shows: in Column (1), the fraction of individuals who take-up the 500 EUR extra deductible, in Column (2), the fraction of individuals with a probability of low costs < 375 EUR, and in Column (3), the fraction of individuals who take-up the 500 EUR extra deductible, conditional on having predicted health costs < 375 EUR.

Table A.10: Deductible Take-up and Predicted Health by Professional Sector

	Professional Sector	(1) Take-up of 500 Deductible	(2) Probability Low Costs	(3) Take-up of 500 Ded. | Being Predictably Healthy
1	**Business Services II**	13%	84%	16%
2	**Insurance and Health Insurance Firms**	12%	79%	15%
3	Business Services I	12%	82%	15%
4	Dairy Industry	12%	82%	14%
5	Banks	10%	81%	12%
6	Other Passenger Transport Land and Air	10%	79%	13%
7	Business Services III	10%	79%	13%
8	Agriculture	10%	85%	11%
9	Stoneware	9%	83%	11%
10	Publishers	9%	79%	11%
11	Cultural Institutions	9%	80%	11%
12	Telecommunications	9%	81%	12%
13	Government, Education and Science	9%	75%	12%
14	Food Industry	9%	80%	11%
15	Catering Industry I	9%	84%	10%
16	Tobacco Processing Industry	9%	76%	11%
17	Wholesale I	8%	82%	11%
18	Wholesale II	8%	81%	10%
20	Government, Police and Judiciary	8%	74%	11%
21	Wholesale of Wood	8%	82%	10%
22	Electronic Industry	8%	81%	13%
23	Carpentry	8%	83%	9%
24	Furniture and Organ Building	8%	83%	9%
25	Rail Construction	8%	78%	11%
26	NS Transport	8%	74%	10%
27	Sugar Processing Industry	7%	78%	10%
28	Chain Stores	7%	80%	9%
29	**Retail**	7%	79%	9%
30	Lending Industry	7%	81%	9%
31	Other Branches of Business	7%	79%	9%
32	Postal Transport	7%	72%	10%
33	Metal Industry	7%	80%	10%
34	**Construction**	7%	83%	9%
35	Merchant	7%	89%	8%
36	Mortar	7%	72%	9%
37	KLM Transport	7%	77%	9%
38	Bakeries	7%	79%	9%
39	Metal and Technical Industry	7%	82%	8%
40	Port Companies	7%	82%	9%
41	Chemical Industry	7%	79%	9%
42	General Industry	7%	81%	9%
43	Stone, Cement, Glass and Ceramic Industry	7%	77%	9%
44	Butchers Other	7%	80%	8%
45	Health, Mental and Social Industry	7%	71%	9%
46	Printing Industry	7%	80%	8%
47	Textiles Industry	7%	77%	9%
48	Inland Shipping	7%	83%	8%
49	Private Bus Transport	6%	70%	9%

Table A.10: Deductible Take-up and Predicted Health by Professional Sector (cont'd)

50 Government, Local Government	6%	70%	9%
51 Butchers	6%	79%	8%
52 Wood, Brush and Packaging Industry	6%	82%	8%
53 Other Goods Transport Land and Air	6%	80%	8%
54 Government, Defense	6%	82%	11%
55 **Government, Public Utilities**	6%	77%	7%
56 Public Transport	5%	65%	8%
57 Security	5%	75%	7%
58 Plastering	5%	85%	6%
59 Taxi and Ambulance	5%	65%	8%
60 Catering Industry II	5%	70%	7%
61 Painting Industry	5%	81%	6%
62 Port Classifiers	5%	79%	6%
63 Fishing	4%	81%	6%
64 Work and Integration	4%	64%	6%
65 Dredging Industry	4%	85%	9%
66 Government, Other Institutions	4%	60%	7%
67 Roofing	4%	82%	5%
68 **Cleaning**	3%	70%	5%

Notes: For each professional sector, this table shows: in Column (1), the fraction of individuals who take-up the 500 EUR extra deductible, in Column (2), the fraction of individuals with a probability of low costs < 375 EUR, and in Column (3), the fraction of individuals who take-up the 500 EUR extra deductible, conditional on having predicted health costs < 375 EUR.

A.6 Structural Choice Foundations

While it is not the focus of this paper to test different decision-making models, it is still useful to assess what kinds of micro-foundations can in principle rationalize the decision-making patterns that we document. This could also allow for a further refinement of the welfare analysis and policy recommendations. To shed some light on this, we simulate choice patterns under a range of distinct micro-foundations and compare the predictions of those simulations to our observed data. We consider a number of potential models of decision making that are proposed in the literature, including switching costs, loss aversion, imperfect information, rational inattention and mistakes.

A.6.1 Models of Choice Barriers

We first consider a model with default effects. Switching costs occur when consumers with a default plan option must pay some cost c_s to switch plans. This could be, e.g., a paperwork / transaction cost or reflect some reduced form of a multi-stage model with search and search costs. See a discussion of potential inputs into switching costs in Handel (2013). Specifically, setting the low deductible as the default plan option, a consumer chooses the high deductible if:

$$250 - (1 - \pi)500 - c_s > 0 \tag{4}$$

This assumes the model premium reduction of 250 EUR when taking the 500 EUR deductible. We consider heterogeneous population switching costs $c_s \sim U(0, 2 \times \bar{c}_s)$ for different average switching costs $\bar{c}_s$. As discussed, Brot-Goldberg et al. (2021) find strong default effects in Medicare Part D and show this is primarily due to inattention rather than switching costs. Note that we could alternatively model the default effects by for example allowing for a heterogeneous probability μ with which an individual is attentive and optimizes her deductible choice. Otherwise, she sticks to the default low deductible. The predicted choice patterns would be very similar.

Loss aversion occurs when losses loom larger than gains. In contrast with standard risk aversion, loss aversion can reduce the take-up of a deductible even when financial stakes are small. See Sydnor (2010)) for a discussion of loss aversion as a potential driver of the over-insurance of modest risks. Following Kőszegi and Rabin (2007), we assume that realized payoffs are evaluated relative to expected payoffs, conditional on the deductible choice made, and losses receive a relative weight λ. In our setup, agents will then choose the high deductible if:

$$250 - (1 - \pi)500 - (\lambda - 1)\pi(1 - \pi)500 > 0. \tag{5}$$

Decisions could be made based on imperfect information. In our context, imperfect information enters by allowing consumers to receive a noisy signal $\hat{\pi}$ about their health, where $\hat{\pi} = \pi + \epsilon$ and $\epsilon \sim N(0, \sigma_\epsilon)$. They make a decision based on that noisy signal and choose the high deductible (for the model premium reduction of 250) if and only if

$$250 - (1 - \hat{\pi})500 > 0. \tag{6}$$

where the signal-to-noise ratio equals $\sigma_\pi/\sigma_\epsilon$.

Alternatively, individuals may decide rationally whether to pay attention and acquire information. In our context, rational inattention means that consumers, again, receive a noisy signal about their health, but then decide whether or not to pay a cost c_r to learn the true value of his/her health risk. Upon receiving the signal, agents face an expected choice value that integrates over the probability distribution of their potential true health statuses.[9] The value of acquiring the accurate information depends on whether the information would change her deductible choice and thus on the condition density $f(\pi|\hat{\pi})$ for $\pi > .5$ and $\hat{\pi} < .5$ and vice versa.[10] The result of our rational inattention setup is that, if a consumer starts with the low deductible, they will choose the high deductible if and only if one of the following conditions holds:

$$\hat{\pi} > 0.5 \text{ and } \int_0^{0.5} [-250 + (1-\pi)500] f(\pi|\hat{\pi}) \, \mathrm{d}\pi < c_r \tag{7}$$

$$\hat{\pi} > 0.5 \text{ and } \int_0^{0.5} [-250 + (1-\pi)500] f(\pi|\hat{\pi}) \, \mathrm{d}\pi > c_r \text{ and } \pi > 0.5 \tag{8}$$

$$\hat{\pi} \leq 0.5 \text{ and } \int_{0.5}^{z} 1[250 - (1-\pi)500] f(\pi|\hat{\pi}) \, \mathrm{d}\pi > c_r \text{ and } \pi > 0.5 \tag{9}$$

The first condition results when consumers are so confident they are low that they don't find it worthwhile to pay the cost of precisely determining their health status, instead just electing to choose the high deductible right away. The second and third conditions occur when consumers decide to pay the cost to obtain a more precise signal, and are differentiated only by whether the initial signal value is bigger or smaller than the risk-neutral threshold of $\pi = 0.5$ for high deductible choice under the modal premium reduction.

Finally, consumers may simply make mistakes. In our model, we assume a share $1-\alpha$ of agents make rational, frictionless choices, while share α of agents make random choices.

A.6.2 Simulations

Figure A.1 presents simulations of the deductible take-up rate as a function of health risk for the alternative decision models. For comparison, each panel plots the observed take-up rates and the deductible choice for the case where consumers are rational, frictionless, and risk-neutral, as in Figure 2. As discussed before, in a frictionless world, all consumers below a 50% probability of clearing the low deductible will elect the high-deductible, which looks starkly different from the observed low take-up rates. Risk-aversion only slightly alters this threshold, moving it to a marginally higher probability of low spending for the case where consumers are risk-averse with CARA coefficient of $1 * 10^{-4}$ (Panel A).

We then turn to the simulations for a decision models with switching costs. Note that with a homogeneous switching cost of 119 EUR, about 10 percent of the population would take up the high deductible, which corresponds to the observed take up rate. However, with heterogeneous switching costs uniformly distributed around the same mean of 119 EUR, we still predict meaningfully more high deductible purchases than we observe in the data, especially as consumers become predictably healthier and healthier. Heterogeneous switching costs with a higher mean of 650 EUR (panel B) look much more similar to observed purchases as a function of health status. But this specification still predicts no purchasing of a high deductible for consumers with higher predicted probabilities of higher health spending. However, when we combine our model of high switching costs with our

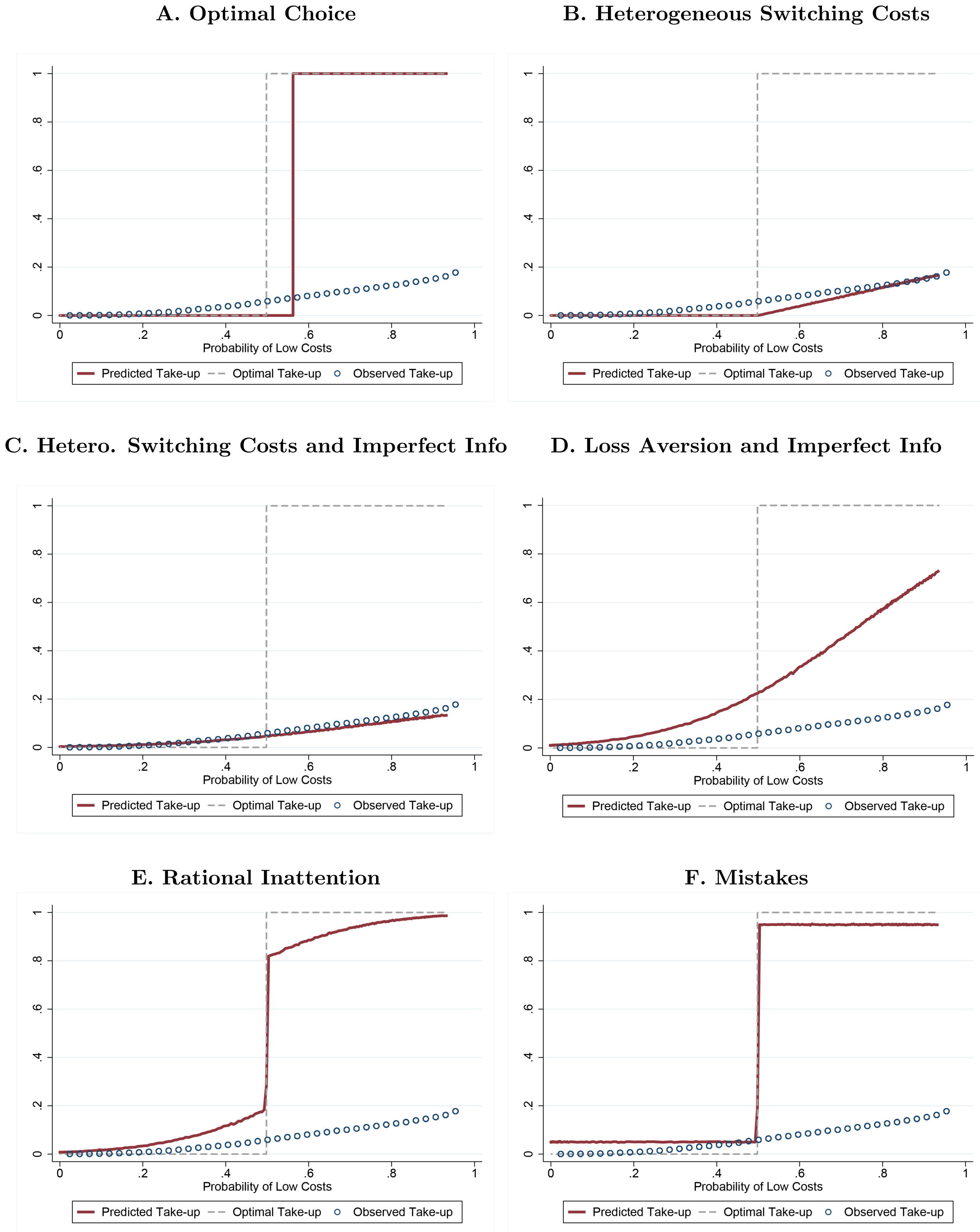
[9] Our model is similar in spirit to that laid out in Ho, Hogan and Scott Morton (2017), though there consumers obtain signals about plan characteristics while here they about signals about their own health status. We could recast our model as related to uncertainty about plan characteristics, likely with similar results.

[10] We simulate the conditional density by taking random draws from the empirical distribution of π and the normal distribution of ϵ. We then group the resulting π and $\hat{\pi}$ in ten bins of length 0.1, indexing them from 1 to 10. Then for each bin j of $\hat{\pi}$, we approximate the conditional density using:

$$p(\pi \in \pi_k | \hat{\pi} \in \hat{\pi}_j) = \frac{\#\text{individuals} \in \{\hat{\pi}_j \cap \pi_k\}}{\#\text{individuals} \in \hat{\pi}_j}$$

where π_k is bin k of π, and $\hat{\pi}_j$ is bin j of $\hat{\pi}$. To calculate the expected payoff, we use the middle value of each bin k of π.

Figure A.1: Deductible Take-up for Different Behavioral Models



Notes: This figure presents the results from decision-making simulations for the various models discussed in detail in the text. For each model, we contrast the predicted take-up rate with both the observed take-up rate and the take-up rate by a rational consumer in a frictionless world.

model of imperfect information about health status (with an assumed signal-to-noise ratio of 1), the simulated choices as a function of health status map very closely to observed choices (panel C).

Like switching costs for taking up the high deductible, loss-aversion helps to reduce the take-up rate of individuals around the 50% threshold. But similarly as for the case of risk aversion, the simulated take-up rates remain too high for reasonable loss-aversion parameters. Panel D simulates the deductible choices for a loss-aversion parameter of $\lambda = 2.25$ (i.e., when choosing the high deductible the payoff is reduced by $(2.25 - 1)\pi(1 - \pi)500$). Even with such strong loss aversion, individuals in very good health are predicted to always take up the deductible as the variance in financial payoffs they would get exposed to converges to zero.

Figure A.1 also presents results for the rational inattention model (panel E) and the random mistakes model (panel F). The simulations for the rational inattention model use an information acquisition cost of $c_r = 25$ (for much higher values, no one pays this cost to learn about their true health status, making the model's predictions the same as the imperfect information model). We see that the take-up rate becomes more responsive to health risk around the threshold value, since individuals have to have probabilistic signals close to the marginal thresholds to acquire information, even with a reasonably small cost of 25 EUR. Furthermore, consumers with larger probabilities of being healthy are predicted to purchase the higher deductible much more than they actually do in practice. So we would need to combine the model of rational inattention with high switching costs to obtain predictions that are closer to observed choices. The simulations for the random mistakes model assume that a random 10% of consumers make mistakes. Clearly, the overall take-up rate is too high, so we again need an extra force to lower the take-up rate. Moreover, in the random mistakes model, the take-up rate is now also too high for individuals who are predicted to have high costs. This would not be resolved by combining the mistakes model with the imperfect information model.

This section illustrates how simulations based on different choice models compare with our data. Though there are a plethora of models one could write down that could help rationalizing the data (e.g., inertia, limited attention), a model of high switching costs combined with imperfect information fits the data very well. Importantly, high switching costs would further decrease the welfare gains from offering deductible choice. While we don't structurally estimate these models in our current context, these simulations give a sense of what models might make sense to estimate, and potentially test formally vs. one another, to implement a more detailed investigation of the mechanisms underlying the choice patterns we have documented.

A.7 Consumer Welfare Analysis

This Appendix Section provides further details underlying our analysis of choice quality, the counterfactual analysis and the micro-foundations of choice frictions.

A.7.1 Predicted Choice Model

For our analysis of choice quality in Section IV.C, we start by predicting the deductible take-up rate $d(X_{it}, \pi_{it})$ as a function of their predicted health π_{it}, observables X_{it} and their interaction by running the regression:

$$Y = \alpha + \sum \beta_\delta 1[\pi = \delta] + \gamma X + \sum \nu_\delta 1[\pi = \delta] X + \epsilon$$

Here, Y is a binary variable that is 1 when an individual takes the 500 voluntary deductible and X is a rich set of controls, including demographics (gender, age, having children, living with a partner), financial variables (household gross income in deciles, net worth in quartiles, a dummy for having savings > 2000 EUR, for having a mortgage debt, for having another type of debt), education level and field and professional sector.

We then define

$$d_{\pi_{pop}}(X_{it}) = \sum_\delta d(X_{it}, \delta) \, dF_\delta,$$

which gives us the predicted deductible take-up rate for each observed X_{it} combination but as if there were a population of individuals with that X_{it} with the same health distribution as the overall population. In the same way, we predict the choice quality for individuals with demographic vector X_{it}, as captured by the probability to choose the contract that minimizes expected expenditures, $d^*_{\pi_{pop}}(X_{it})$, and the corresponding average financial loss $\Delta w^{*,\sigma}_{\pi_{pop}}(X_{it})$. That is,[11]

$$\begin{aligned}
d^{*,\sigma}_{\pi_{pop}}(X_i) &= \sum_\delta \{1[\pi_\delta \leq .5][1 - d(X_{it}, \delta)] + 1[\pi_\delta > .5] \, d(X_{it}, \delta)\} dF_\delta, \\
\Delta w^{*}_{\pi_{pop}}(X_{it}) &= \sum \{1[\pi_\delta \leq .5] \, d(X_{it}, \delta) \left[CE^\sigma_{\pi_\delta,0} - CE^\sigma_{\pi_\delta,500}\right] + 1[\pi_\delta > .5][1 - d(X_{it}, \delta)] \left[CE^\sigma_{\pi_\delta,500} - CE^\sigma_{\pi_\delta,0}\right]\} dF_\delta.
\end{aligned}$$

The choice quality varies through the deductible choice predicted by the set of demographics X_i for different health risks, but again reflects the population distribution of health risks.

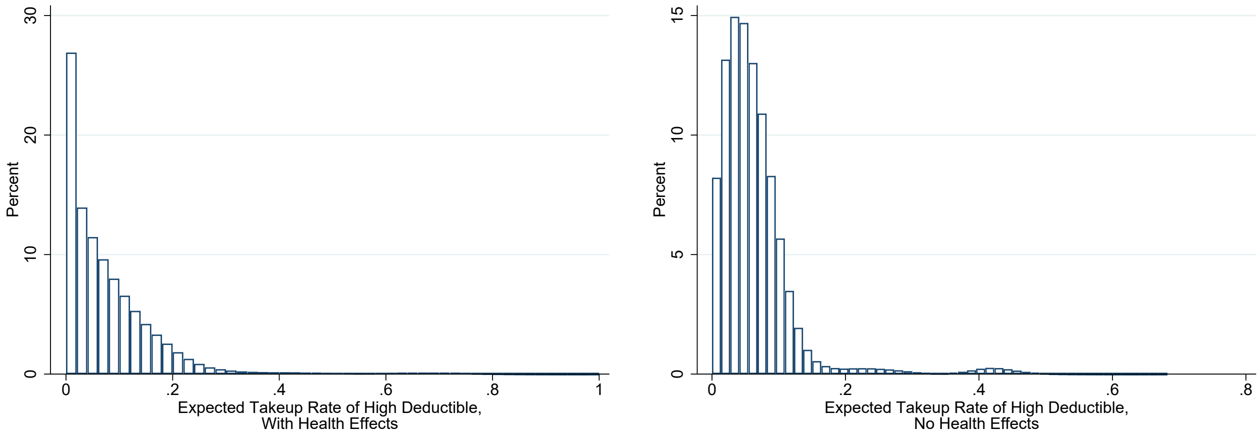
Figure A.2 compares the distribution of predicted deductible choice, with and without the effect of healthcare cost risk. These are denoted in previous equations as $d(X_{it}, \pi_{it})$ and $d_{\pi_{pop}}(X_{it})$ respectively. As shown before, health has a meaningful impact on deductible choice, but there is substantial heterogeneity in likelihood of choosing a deductible just as a function of X_{it}, netting out health effects. While losses range up to 200 EUR when factoring health risk into choices, when assuming the population distribution of health for a given X_i the expected loss ranges between 50 and 80 as a function of X_i. Panel A of Figure A.3 ranks individuals according to the quality of their choice first, as discussed in the text, and then shows the distribution of the probability to make the right decision for the different groups of quality choice. Panel B of Figure A.3 shows the probability of making the right decisions for different income groups.

A.7.2 Counterfactual Policies

This appendix studies the welfare impacts of counterfactual choice policies and aims to gauge the potential to improve consumer welfare in our specific context. First, we consider how much better off consumers would be if

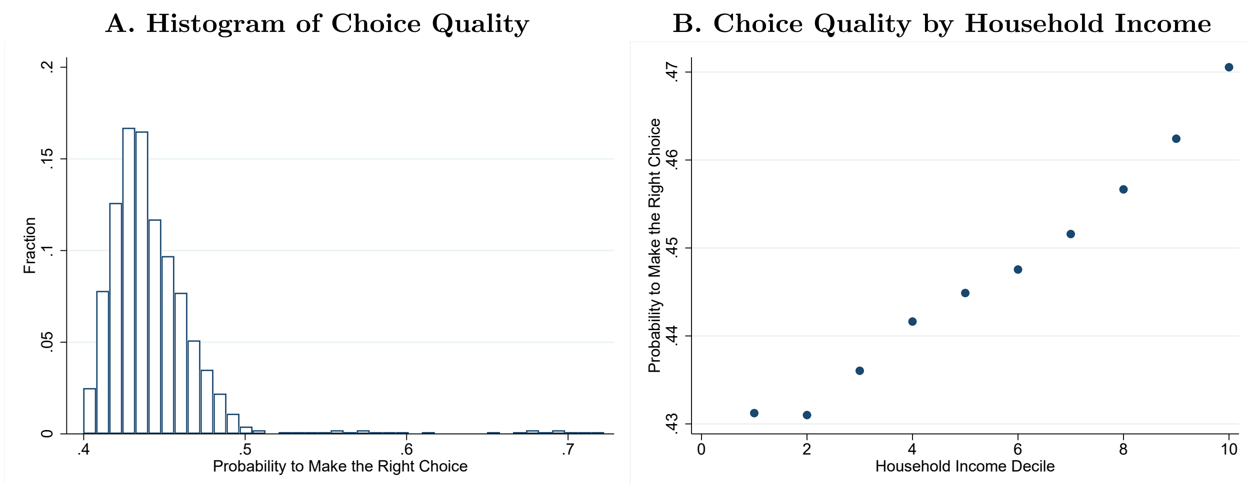
[11] Note that we use the average predicted risk for the different health deciles to calculate the certainty equivalents and to determine whether one should take up the deductible or not.

Figure A.2: Predicted Deductible Choice



Notes: This figure shows the distribution of predicted 500 EUR extra deductible take-up rate. Panel A shows the predicted 500 EUR deductible take-up with health effects, while Panel B shows the take-up without the health effects.

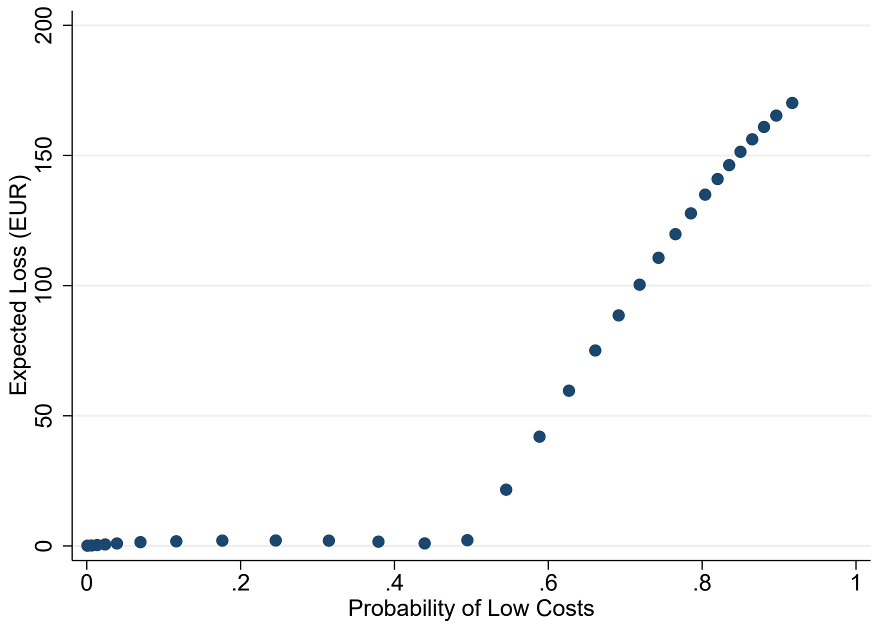
Figure A.3: Heterogeneity in Choice Quality



Notes: Panel A shows the distribution of probabilities that consumers make the right deductible choice for a given set of socio-economic characteristics $X_{i,t}$. The right choice is defined as the choice a rational consumer would make, as explained in Section III: to take the 500 EUR extra deductible if she expects her costs to be below 375 EUR with a probability larger than 0.5; to choose the low deductible otherwise. Individuals are binned in 1000 quantiles of choice quality; the variable displayed in this histogram is the binned average of the individual probability to make the right choice. Panel B shows the probability to make the right choice by income decile.

everyone were allocated to the best option for them *ex ante* (according to our estimates and welfare model). This is useful as a first-best benchmark given the current choice architecture. It is also a measure of the impact of policy interventions that improve consumer decision-making or use predictive models to establish "smart defaults" (Handel and Kolstad (2015*a*), Gruber et al. (2020)). Next, we consider the impact of two alternative policies that limit choice; one that offers only the high deductible option and one where only the low deductible option is offered. These policies are clearly feasible and also reflect the underlying trade-off between offering greater choice and exacerbating choice errors. By accounting for how the incidence of choice frictions falls on individuals with different observable characteristics, we explore not only the efficiency, but also the equity implications of

Figure A.4: Expected Loss and Health Cost Probability



Notes: This figure is a binned scatterplot of the relationship between the predicted probability of health costs below 375 EUR and the expected loss due to over- or under-insurance. For individuals with a predicted probability of low costs below 0.5, the expected losses due to under-insurance are very small (on average close to zero), as a very low fraction of people under-insures by taking the 500 EUR extra deductible. For individuals with a predicted probability of low costs above 0.5, expected losses due to over-insurance increase with this probability, and reach almost 170 EUR for people with a very high chance (0.9+) of low costs, as most people leave money on the table by over-insuring for costs that happen with a very low probability.

the different policy options.

In assessing the efficiency implications for each policy — the surplus generated by the plans chosen — we allow for four different values of risk aversion (assumed to be homogeneous in each implementation) including (i) risk neutral (ii) CARA $= 10^{-5}$ (iii) CARA $= 10^{-4}$ and (iv) CARA $= 10^{-3}$. To assess the equity implications we rely on income as the measure of inequality and consider alternative welfare weights for deciles of the income distribution. Following Atkinson (1970), the welfare of an individual in income decile y_δ is weighted by $y_\delta^{-\epsilon}/\left(\Sigma y_\delta^{-\epsilon}/10\right)$ for $\epsilon = .5$ and $\epsilon = 1.5$.[12] In our primary analysis, we rely on the observed correlations between health and socio-demographic status in the data. Later in the appendix, we also perform an analysis that assumes identical health distributions conditional on non-health X_{it}, using the predicted choice probabilities $d(X_{it}, \pi_{it})$.

Table A.1 presents the average welfare impact per person (in EUR) for the three different policies we consider. Column 1 presents the results for the scenario where individuals are allocated to their *ex ante* optimal deductible choice in the current environment. The average consumer welfare gain, when not weighted for inequality, is 68.8 EUR for risk neutral individuals. This gain decreases only slightly when introducing reasonable levels of risk aversion and is still 58 EUR for individuals assuming our highest level of risk aversion. When we weight for equity as a function of income the gain of the *ex ante* optimal allocation is reduced. With high inequality aversion the average benefit of this policy is 37.4 EUR for a risk neutral consumer. The decline results from the

[12] The Atkinson index of inequality uses a social welfare function of the form $y_i^{1-\epsilon}$ with $\epsilon \geq 0$ a measure of inequality aversion. Here, we weigh the welfare gain for each individual depending on income decile they are in by $y_\delta^{-\epsilon}/\left(\Sigma y_\delta^{-\epsilon})/10\right)$, which ensures comparability with the unweighted case. We could model equity concerns more broadly by differentially weighting outcomes for individuals as a function of their predicted health π_i and characteristics X_i.

Table A.1: Welfare Impact of Alternative Policies

	Optimal Deductible	High Deductible Only (875 EUR)	Low Deductible Only (375 EUR)
Risk Neutral			
Unweighted	68.8	-26.2	-8.3
Low Inequality Aversion	56.9	-64.4	-6.3
High Inequality Aversion	37.4	-133.6	-3.4
σ=.0001			
Unweighted	67.8	-28.1	-8.2
Low Inequality Aversion	56.0	-66.1	-6.2
High Inequality Aversion	36.8	-135.1	-3.3
σ=.001			
Unweighted	58.0	-44.6	-7.0
Low Inequality Aversion	47.7	-81.6	-5.3
High Inequality Aversion	30.9	-148.7	-2.7

Notes: This table shows the average welfare impact (in EUR per person) of three alternative policies concerning the extra deductible: optimal deductible (all individuals taking the optimal deductible given their health risk), high deductible only (only the 500 EUR extra deductible is available), and low deductible only (the low deductible is the only option). The welfare impact is calculated with equal weights for all income deciles, low inequality aversion or high inequality aversion. Weights y_δ are computed as $y_\delta^{-\epsilon}/\left(\Sigma y_\delta^{-\epsilon}/10\right)$ for $\epsilon = .5$ and $\epsilon = 1.5$. The welfare impact is calculated not controlling for health. The corresponding welfare impact when assigning each individual the population health distribution is in Appendix Table A.2. Our sample contains the choices of $9,415,666$ individuals in 2015 (out of $11,991,629$ individuals for which the probability of low costs and the deductible choice are both non missing), excluding students, self-employed people, individuals with a gross income below the social assistance level and individuals with missing observables.

fact that lower income individuals are less likely to be healthy and, thus, more likely to have the default option of a low deductible be the correct choice for them. Because most choice errors result from not actively choosing the higher deductible, there is less to be gained if many low income enrollees are better off in the low deductible plan. Appendix Table A.2 shows how this relationship is reversed when controlling for differences in health, reflecting the higher incidence of choice frictions among low-income individuals.

Columns 2 and 3 show the consumer welfare impacts when consumers are offered only the high deductible (with the corresponding premium reduction) or the low deductible, respectively. Neither policy that limits the choice offerings is welfare-increasing, even relative to the status quo where consumers are making poor choices in general. Mandating the extra 500 EUR deductible leads to a welfare losses with no inequality aversion of 22.6 EUR when risk neutral and 44.6 EUR with high risk aversion. With high inequality aversion, however, this policy is much worse, with welfare losses of 133.6 EUR when risk neutral and 148.7 EUR with high risk aversion. This policy is especially bad because it is forcing sick, lower income consumers into what would have been the wrong choice for them. Mandating a low deductible, on the other hand, has a much smaller impact due to the fact that, in practice, most people already choose that deductible. The small impact ranges between 0 and 10 EUR on average across the range of risk aversion and inequality aversion parameters we investigate.

Discussion Our counterfactual analysis allows to draw some important conclusions for choice-based policies more generally and for the specific implementation in the Netherlands, using a low baseline deductible with the option to take a higher deductible. While a policy that is able to move people to plans based on *ex ante* risk could substantially increase welfare, the welfare gain from the offered deductible choice is small. Moreover, due to both the correlation between income and health and the correlation between income and choice quality, accounting for higher inequality aversion actually reduces the welfare loss of this policy. The option to select a higher deductible increases welfare mostly for the high-income individuals, who are healthier and make better choices. The value of this option is very limited for low-income individuals and may well become negative when factoring in equilibrium price changes.

Importantly, our analysis has ignored any direct welfare effects of choice frictions beyond the misallocation to plans. In our setting we do not have good measures of potential costs associated with decision making. If making a decision imposes a cost on enrollees — as has been shown in a number of other settings (see e.g. Handel and Kolstad (2015*b*) in health insurance) — these costs may exceed the relatively small gains we find from offering the option to take a higher deductible. Our analysis has also been limited to consumer welfare without accounting for the potential implications of moral hazard and adverse selection. In the presence of moral hazard, the reduction in health expenditures in response to an extra deductible could benefit the insurer as discussed in Section III, but we also presented evidence of limited moral hazard with respect to the deductible policy. In the presence of adverse selection, we also expect equilibrium prices to respond to the regulation of choice, which would further affect sorting and consumer welfare. In particular, the option to buy less comprehensive coverage allows individuals with good health to contribute less to the health insurance system. We have ignored the pricing repercussions this may have.[13]

TABLE A.2: Counterfactual Policies, Controlling for Health Effects

	Optimal Deductible	High Deductible Only (875 EUR)	Low Deductible Only (375 EUR)
Risk Neutral			
Unweighted	63.7	-11.1	-5.3
Low Inequality Aversion	64.2	-10.6	-4.8
High Inequality Aversion	65.0	-9.8	-4.0
σ=.0001			
Unweighted	62.8	-12.8	-5.2
Low Inequality Aversion	63.2	-12.3	-4.7
High Inequality Aversion	64.0	-11.6	-3.9
σ=.001			
Unweighted	53.6	-28.6	-4.3
Low Inequality Aversion	53.9	-28.2	-3.9
High Inequality Aversion	54.5	-27.7	-3.3

Notes: Notes from Table A.1 apply. This table performs the same exercise, except that each individual is attributed the population's health distribution, such that the correlation between income and health is controlled for.

[13] By removing choice frictions, we may expect adverse selection to become worse (e.g., Handel, Kolstad and Spinnewijn (2019)). Interestingly, comparing the average predicted low-cost probability for workers taking the extra deductible (.763) and for those who should take the extra deductible (.760) suggests that in this context the pricing repercussions from reducing choice frictions may be limited.