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

Benjamin Handel, UC Berkeley
Jonathan Kolstad, UC Berkeley
Thomas Minten, London School of Economics
Johannes Spinnewijn, London School of Economics

June 22, 2023

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.

*We thank the Central Bureau of Statistics of the Netherlands and especially Annemieke Redeman for help with the data. Chloé de Meulenaer, Miguel Fajardo Steinhäuser and William Parker provided excellent research assistance. We thank Jason Abaluck, Anna Aizer, Saurabh Bhargava, Zarek Brot-Goldberg, John Campbell, Raj Chetty, Rebecca Diamond, Keith Ericson, Amy Finkelstein, Sebastian Fleitas, Jihye Jeon, Tim Layton, George Loewenstein, Neale Mahoney, Sarah Miller, Martin Salm, Josh Schwartzstein, Mark Shepard, Jon Skinner, Justin Sydnor and Richard Thaler for their discussions and comments. We thank seminar participants at Amazon, Delaware, Edinburgh University, IO^2 Stanford seminar series, Erasmus University Rotterdam, KULeuven, LSE, Monash University, UPF Barcelona, University of Virginia, University of Wisconsin, BU-Harvard-MIT health seminar, Statistics Netherlands, the 2021 AEA, 2021 ASHE, Essen Health Conference, KVS, the NBER Health Care, the NBER Public Economics, the Paris-London Public Economics, the CEPR Public Economics, the Sloan Economics of Inattention and the UPENN Behavioral Health meetings for excellent comments. We gratefully acknowledge funding by ERC (grant #716485), ESRC and STICERD. Some of the material in this paper was previously part of the manuscript titled "The Social Determinants of Choice Quality: Evidence from Health Insurance in the Netherlands," (Handel et al. (2020)).

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.

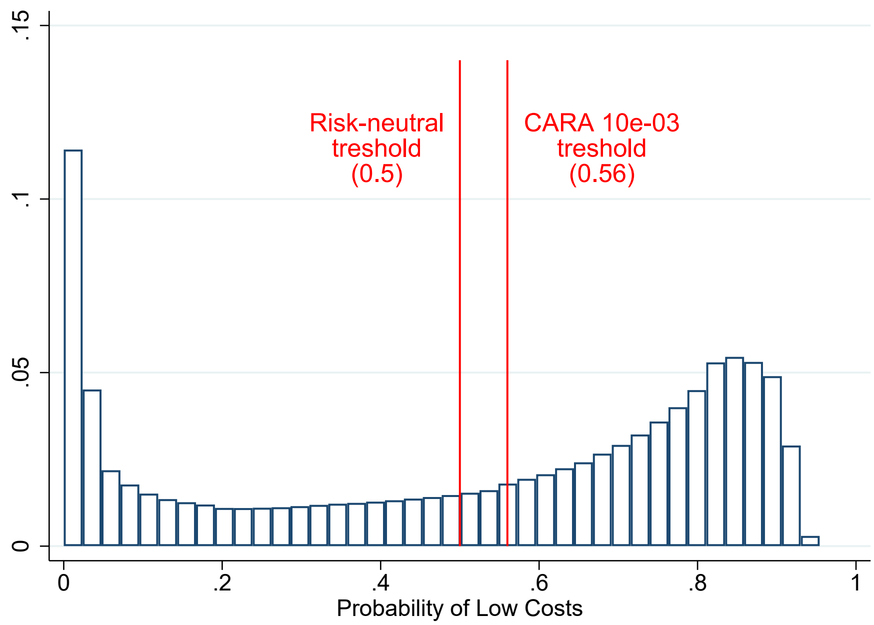
Moral hazard could cause consumers to reduce care consumption in response to greater cost sharing (e.g., Newhouse (1993), Einav, Finkelstein and Schrimpf (2015), Brot-Goldberg et al. (2017)). Under a classical model of moral hazard, our framework under-predicts value from the high deductible plan since 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.

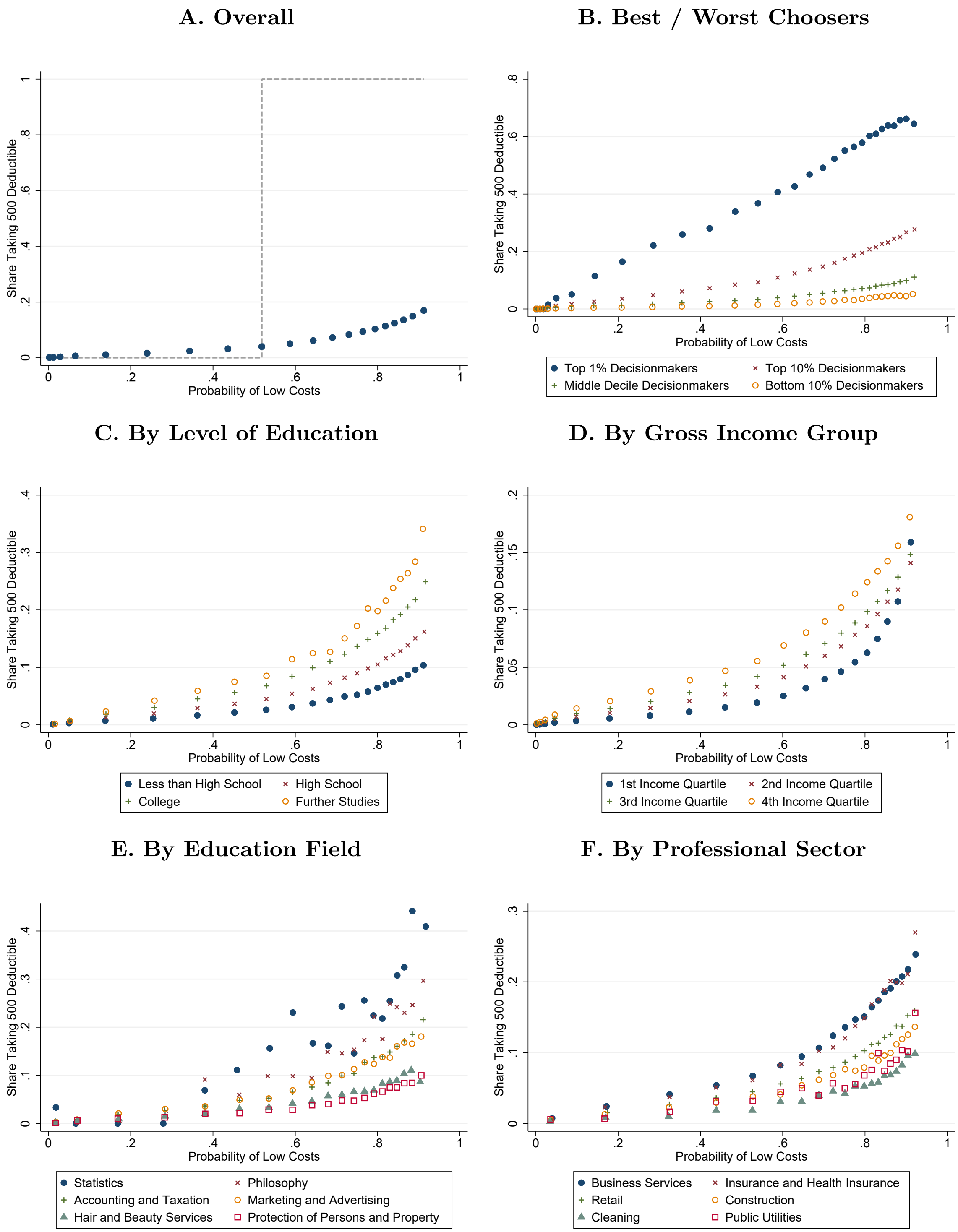
[3] We present alternative specifications, e.g., a probit model, in the Online Appendix, with little difference in findings.

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) Baseline		(2) Education Field		(3) Professional Sector		(4) 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))

References

Abaluck, Jason, and Jonathan Gruber. 2016. "Evolving Choice Inconsistencies in Choice of Prescription Drug Insurance." *American Economic Review*, 106(8): 2145–84. 14

Allcott, Hunt, Benjamin B Lockwood, and Dmitry Taubinsky. 2019. "Regressive sin taxes, with an application to the optimal soda tax." *The Quarterly Journal of Economics*, 134(3): 1557–1626. 2

Andersen, Steffen, John Y. Campbell, Kasper Meisner Nielsen, and Tarun Ramadorai. 2020. "Sources of Inaction in Household Finance: Evidence from the Danish Mortgage Market." *American Economic Review*, 110(October): 3184–3230. 2

Atkinson, Anthony. 1970. "On the Measurement of Inequality." *Journal of Economic Theory*, 2: 244–263. 26

Banerjee, Abhijit, Amy Finkelstein, Rema Hanna, Benjamin A Olken, Arianna Ornaghi, and Sudarno Sumarto. 2021. "The Challenges of Universal Health Insurance in Developing Countries: Experimental Evidence from Indonesia's National Health Insurance." *American Economic Review*, 111(9): 3035–63. 14

Barseghyan, Levon, Francesca Molinari, Ted O'Donoghue, and Joshua C. Teitelbaum. 2018. "Estimating Risk Preferences in the Field." *Journal of Economic Literature*, 56(2): 501–64. 4

Bhargava, Saurabh, George Loewenstein, and Justin Sydnor. 2017. "Choose to Lose: Health Plan Choices from a Menu with Dominated Option." *The Quarterly Journal of Economics*, 132(3): 1319–1372. 2, 14

Brot-Goldberg, Zarek C, Amitabh Chandra, Benjamin R Handel, and Jonathan T Kolstad. 2017. "What Does a Deductible Do? The Impact of Cost-Sharing on Health Care Prices, Quantities, and Spending Dynamics." *The Quarterly Journal of Economics*, 132(3): 1261–1318. 4

Brot-Goldberg, Zarek, Timothy Layton, Boris Vabson, and Adelina Wang. 2021. "The Behavioral Foundations of Default Effects: Theory and Evidence from Medicare Part D." University of Chicago Working Paper. 14, 20

Campbell, John, and Luis Viceira. 2002. *Strategic Asset Allocation: Portfolio Choice for Long-Term Investors.* Oxford University Press. 4

Campbell, John Y. 2016. "Restoring Rational Choice: The Challenge of Consumer Financial Regulation." *American Economic Review*, 106(5): 1–30. 1

Chetty, Raj, and Adam Szeidl. 2007. "Consumption Commitments and Risk Preferences." *The Quarterly Journal of Economics*, 122(2): 831–877. 4

Chetty, Raj, John N. Friedman, Søren Leth-Petersen, Torben Heien Nielsen, and Tore Olsen. 2014. "Active vs. Passive Decisions and Crowd-Out in Retirement Savings Accounts: Evidence from Denmark." *The Quarterly Journal of Economics*, 129(3): 1141–1219. 1, 2

Chiappori, Pierre-Andre, and Bernard Salanie. 2000. "Testing for Asymmetric Information in Insurance Markets." *Journal of Political Economy*, 108: 56–78. 8

Cohen, Alma, and Liran Einav. 2007. "Estimating Risk Preferences from Deductible Choice." *The American Economic Review*, 97(3): 745–788. 4

Dubois, Pierre, Rachel Griffith, and Martin O'Connell. 2020. "How Well Targeted Are Soda Taxes?" *American Economic Review*, 110(11): 3661–3704. 2

Einav, Liran, Amy Finkelstein, and Neale Mahoney. 2021. "The IO of Selection Markets." *Handbook of Industrial Organization*, 5(1): 389–426. 2

Einav, Liran, Amy Finkelstein, and Paul Schrimpf. 2015. "The Response of Drug Expenditure to Nonlinear Contract Design: Evidence from Medicare Part D." *Quarterly Journal of Economics*, 130(2): 841–899. 4

Einav, Liran, Amy Finkelstein, Sendhil Mullainathan, and Ziad Obermeyer. 2018. "Predictive Modeling of U.S. Health Spending in Late Life." *Science*, 360(6396): 1462–1465. 1, 5

Enthoven, Alain, Alan Garber, and Sara Singer. 2001. "Near-Universal Coverage Through Health Plan Competition: An Insurance Exchange Approach." *Covering America: Real Remedies for the Uninsured, Editors J. Meyer and E. Wicks*, Washington DC: 155–172. 1

Ericson, Keith Marzilli, and Justin R Sydnor. 2018. "Liquidity Constraints and the Value of Insurance." Working Paper. 1, 4, 12

Fang, Hanming, Michael Keane, and Daniel Silverman. 2008. "Sources of Advantageous Selection: Evidence from the Medigap Insurance Market." *Journal of Political Economy*, 116(2): 303–350. 2

Finkelstein, Amy, Nathan Hendren, and Erzo Luttmer. 2019. "The Value of Medicaid: Interpreting Results from the Oregon Health Insurance Experiment." *Journal of Political Economy*, 127(6): 2836–2874. 1

Gruber, Jonathan, Benjamin R Handel, Samuel H Kina, and Jonathan T Kolstad. 2020. "Managing Intelligence: Skilled Experts and AI in Markets for Complex Products." National Bureau of Economic Research. 25

Handel, Benjamin. 2013. "Adverse Selection and Inertia in Health Insurance Markets: When Nudging Hurts." *American Economic Review*, 103(7): 2643–2682. 20

Handel, Benjamin, and Jonathan Kolstad. 2015*a*. "Getting the Most From Marketplaces: Smart Policies on Health Insurance Choice." *Brookings Hamilton Project Discussion Paper 2015-08*. 14, 25

Handel, Benjamin, and Jonathan Kolstad. 2015*b*. "Health Insurance For Humans: Information Frictions, Plan Choice, and Consumer Welfare." *American Economic Review*, 105(8): 2449–2500. 28

Handel, Benjamin, and Joshua Schwartzstein. 2019. "Behavioral Economics and Health Care Markets." *Handbook of Behavioral Economics*. 2

Handel, Benjamin, Jonathan Kolstad, Thomas Minten, and Johannes Spinnewijn. 2020. "The Social Determinants of Choice Quality: Evidence from Health Insurance in the Netherlands." Working Paper No. 27785. 1

Handel, Benjamin, Jonathan Kolstad, Thomas Minten, and Johannes Spinnewijn. 2023. "Liquidity Constraints and the Value of Insurance." Working Paper. 14

Handel, Benjamin R, Jonathan T Kolstad, and Johannes Spinnewijn. 2019. "Information frictions and adverse selection: Policy interventions in health insurance markets." *Review of Economics and Statistics*, 101(2): 326–340. 28

Hastings, Justine, Chris Neilson, Anely Ramirez, Unika Shrestha, and Seth Zimmerman. 2013. "(Un)informed College Choice: Evidence From Chile." Brown University, Working Paper. 1

Ho, Kate, Joseph Hogan, and Fiona Scott Morton. 2017. "The Impact of Consumer Inattention on Insurer Pricing in the Medicare Part D Program." *The RAND Journal of Economics*, 48(4): 877–905. 21

Ito, Koichiro. 2015. "Do Consumers Respond to Marginal or Average Price? Evidence from Nonlinear Electricity Pricing." *American Economic Review*, 104(2): 537–563. 1

Koszegi, Botond, and Matthew Rabin. 2006. "A Model of Reference-Dependent Preferences." *Quarterly Journal of Economics*, 121(4): 1133–1165. 4

Kőszegi, Botond, and Matthew Rabin. 2007. "Reference-dependent risk attitudes." *American Economic Review*, 97(4): 1047–1073. 20

Kroneman, Madelon, Wienke Boerma, M van den Berg, P Groenewegen, J de Jong, and E. van Ginneken. 2016. "Netherlands: Health System Review." *Health Systems in Transition*, 18(2): 1–240. 2

Mullainathan, Sendhil, and Eldar Shafir. 2013. *Scarcity: Why having too little means so much.* Macmillan. 1

Neilsen, Christopher. 2017. "Targeted Vouchers, Competition Among Schools, and the Academic Achievements of Poor Students." Princeton Working Paper. 1

Newhouse, Joseph P. 1993. *Free for All? Lessons From the RAND Health Insurance Experiment.* Harvard University Press. 4

Remmerswaal, Minke, Jan Boone, and Rudy Douven. 2019. "Selection and Moral Hazard Effects in Healthcare." CPB Netherlands Bureau for Economic Policy Analysis Working Paper. 4

Sydnor, Justin. 2010. "Over(insuring) Modest Risks." *American Economic Journal: Applied Economics*, 2(4): 177–199. 20