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Information on cancer prevalence and oncologic insurance take-up: Evidence from a developing country

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Abstract

We study whether oncological insurance demand can be boosted by providing consumers with information on the likelihood of developing cancer at some point over their lifetime. We conducted a lab-in-the-field hypothetical choice experiment on oncological insurance with adults aged 40-68 of middle to high socioeconomic status in Lima, Peru. A random subset of participants received information on the likelihood of developing cancer before the age of 75. Participants were offered partial and full insurance options. Information increased take-up for full insurance by 18 percentage points (33% of the control group rate) but did not affect demand for partial insurance. Treatment effect arose mostly from participants who did not live with an oncology patient at home, suggesting information led participants to update their beliefs, and are similar by level of education, sex, and age. Our stylized model suggests that this effect is driven by consumers with low present bias (β>0.90). Our findings suggest that in developing countries, where information about the probability of developing cancer during one's lifetime is not widely known, providing this information can boost demand for insurance, but that present-bias can hinder this effect.

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1. INTRODUCTION

Demand for oncological insurance is low worldwide, despite high treatment costs and high probability of occurrence. For instance, Ferlay et al. (2020) estimate that 34% of people in developed countries will develop cancer at some point in their lifetime, and cancer treatment costs amount to an average of US$150,000 (AARP 2018), but only 55% of the US population is adequately insured (Collins et al. 2019). Reliable figures for developing countries are unavailable, but the situation is likely at least as grim.

In this paper, we report the results of a lab-in-the-field experiment where we study whether demand for oncological insurance can be boosted by providing information on the likelihood of developing cancer at some point over the consumer's lifetime. Information may increase willingness to pay (WTP) for health insurance if consumers underestimate the likelihood of developing cancer, but also by reducing ambiguity (Bryan 2019, Belissa et al. 2020). Providing information as stark, clear facts may also help overcome normalcy bias, a cognitive bias that leads us to underestimate the probability of an event that will disrupt our livelihoods significantly.

We conducted a hypothetical choice experiment on oncological insurance. Our study sample was comprised by adults aged 40-68 of middle to high socioeconomic status, who are the target market for oncological insurance providers. In the spirit of Kling et al. (2012), we provided information on the likelihood of developing cancer before the age of 75 to a random subset of participants. In addition, all participants received treatment cost information. Information on the likelihood of developing cancer increased full insurance take-up by 18 percentage points (33% of the control group rate) but did not affect partial insurance uptake.

The effects arise mostly from participants who do not live with an oncology patient at home. This suggests that information worked by leading participants to update their probabilities of developing cancer throughout their lifetimes, as participants who live with an oncology patient may already have formed such probabilities and are less susceptible to this type of information. On the other hand, there is no evidence of effect heterogeneity by age, sex, or education in our sample.

Given the intertemporal nature of this choice, we developed a stylized model that allows for quasi-hyperbolic discounting. Coupling the model with the findings from the experiment suggests that the effect on insurance demand arises from consumers with low degree of present bias ($\beta > 0.90$), who represent 53% of the study sample.

Our paper contributes to the literature on health insurance uptake, which has focused on the role of simplifying procedures (Kenney et al. 2009). We show that a light-touch intervention like providing information on the likelihood of developing cancer can boost demand for full insurance. More broadly, most of the literature on health insurance demand has studied suboptimal plan choice, which may arise from information frictions (Handel and Kolstad 2015) or behavioral biases like inattention and inertia. When choosing health insurance plans, consumers tend to focus too much on deductibles and are largely inattentive to monthly premiums and other plan characteristics (Shapira and Venezia 2008, Sydnor 2010, Bhargava et al. 2017, Abaluck and Gruber 2011, Barseghyan et al. 2013, Heiss et al. 2013). In addition, consumers exhibit inertia, as they rarely switch to better plans when conditions change (Bhargava et al 2017, Handel 2013, Kling et al 2012, Polyakova 2016, Handel et al 2019). Our findings contribute to this literature by showing that in a developing country setting, information also increases WTP for full insurance but not for partial insurance.

Our paper also contributes to the more specific literature on health insurance demand in developing countries. Most of the evidence in this field is from the USA, largely from Medicare Part D and large US firms. We provide evidence on health insurance demand in a developing country. We can expect insurance demand in developing countries to be starkly different, due to institutional and regulatory differences in insurance markets, besides the availability of information, income levels, risk attitudes, health preferences, among other factors.

In developing countries, the insurance literature has largely focused on agricultural insurance (see Carter et al. 2017). The literature shows that low demand is partly driven by farmers' lack of understanding of insurance contracts (see Giné and Yang, 2009; Cole et al., 2013; Hill and Robles, 2011). A recent stream of studies has started exploring the role of behavioral biases. For instance, Serfilippi et al. (2019) show that framing can increase insurance take-up. In turn, in a review of the literature, Carter et al. (2017) argue that present bias can play a role in insurance demand. Our findings suggest this to be the case even among high-income individuals.

This study shares all the limitations of hypothetical choice experiments. However, this type of experiments has been used in the literature to shed light on the drivers of health insurance demand (e.g., Bhargava et al. 2017). Moreover, the age range of our subject pool and its high level of schooling makes the study sample superior to the conventional choice of undergraduate students, for whom this type of choices is less palpable.

Taken together, our findings suggest that a light-touch intervention can boost demand for oncologic insurance in a developing country setting among well-educated adults, although present bias can moderate this effect.

2. A STYLIZED MODEL

We develop a stylized model to guide our analysis. Consider a two-period model. In period 1 the consumer is healthy and decides to purchase or not insurance for an illness that may appear in period 2. Income is denoted by x_t, the insurance premium is p, the discount factor is δ, and the present bias parameter is β. In period 2 the consumer develops the illness with probability π^n, in which case he or she faces monetary costs C_M and nonmonetary costs C_F. Insurance covers a fraction α of monetary costs.

Expected utility with insurance is given by:

$$EU_I^T = (x_1 - p) + \beta\delta[\, x_2 - p - \pi^n\, C_F - \pi^n \alpha C_M] \qquad (1)$$

Expected utility without insurance is, in turn:

TABLE I. Descriptive Statistics and Balance

Variable	Control Group	Treatment Group	Difference
Male	0.48	0.45	-0.03
	(0.50)	(0.50)	(0.06)
Age	51.05	51.30	0.25
	(6.00)	(5.35)	(0.67)
Completed tertiary education	0.77	0.71	-0.06
	(0.42)	(0.45)	(0.05)
Consumed tobacco in last week	0.23	0.29	0.07
	(0.42)	(0.46)	(0.05)
Consumed alcohol in last week	0.35	0.41	0.06
	(0.48)	(0.49)	(0.06)
Physical activity in last week	0.52	0.56	0.04
	(0.50)	(0.50)	(0.06)
Has health insurance	0.91	0.95	0.04
	(0.28)	(0.22)	(0.03)
Has oncologic insurance	0.30	0.37	0.07
	(0.46)	(0.48)	(0.06)
Household member has cancer	0.17	0.19	0.02
	(0.38)	(0.40)	(0.05)

The first two columns report mean (standard deviations in parentheses) for each treatment arm. The third column reports the difference in means (standard error in parentheses). Differences are statistically significant at the 0.10(*), 0.05(**) and 0.01(***) of confidence.

$$EU_U^T = x_1 + \beta\delta[(x_2 - \pi^n C_F - \pi^n C_M)] \tag{2}$$

The consumer chooses to buy insurance if (1)≥(2). From this, we can solve for the present bias parameter and show that the consumer purchases insurance if

$$\beta \geq \frac{p}{\delta(\pi^n C_M(1-\alpha)-p)} \tag{3}$$

Importantly, note that this inequality is binding for the marginal consumer. Ceteris paribus, a person with WTP above the market price must have a higher β (i.e. lower degree of present bias). Conversely, a person with WTP below market price must have a lower β. Thus, we propose that, in a neighborhood of the marginal consumer, one can approximate the present bias parameter by

$$\beta \approx \frac{p}{\delta(\pi^n C_M(1-\alpha)-p)} \times \frac{WTP}{p} \tag{4}$$

The adjustment is minimal, as in the neighborhood of the marginal consumer the ratio of WTP/p is close to 1.

3. STUDY SETTING, EXPERIMENTAL SETUP AND DATA

3.1 Health Insurance in Peru

In Peru, health insurance is offered by public and private providers. There are two types of public insurance providers: Seguro Social del Peru (EsSalud) and Seguro Integral de Salud (SIS), which cover 25 and 44% of the population, respectively (INEI 2018)[1]. EsSalud covers formal workers, while SIS covers households living below the poverty line. At least on paper, SIS also works as a safety net for the uninsured. Both EsSalud and SIS cover cancer treatment but, being severely underfinanced, waiting times are long and treatment quality is poor.

On the other hand, private insurance can be hired through an employer (EPS) or individually. Only 5% of the population has private health insurance (10% in Lima), and most privately insured workers are insured through their employers, as individually hired insurance is significantly more expensive and offers worse conditions (e.g. smaller caregiver networks and higher copays). Private insurance covers oncologic treatment, but due to a combination of lobbying and failures in the legal system, coverage lasts only while the patient holds the same type of insurance (either EPS or individual). So, if an EPS-insured worker develops cancer, she is covered only as long as she keeps her job. Once she stops working, EPS coverage stops and she would have to switch to individual insurance or public insurance. However, if she switched to individual insurance her cancer would be classified as a "non-coverable pre-existing condition" so she would have to pay out-of-pocket or seek treatment in the overcrowded public system. This is where oncologic insurance plays a role, as it covers individuals even if they switch across insurance systems. Oncologic insurance works as health insurance but only covers cancer treatment and can be full or partial. Partial insurance covers expenses up to a limit. Once the limit is reached the patient must transfer to SIS or pay out-of-pocket.

3.2 Experimental Setup and Data

We recruited study subjects using social media, targeting university students' parents. This choice was made to get a subject pool of age and socioeconomic status in line with private oncological insurance providers. Participants were invited to fill a short online survey on insurance after signing the informed consent forms. We recruited 314 participants, who were randomly assigned to treatment (N=153) or control (N=161) conditions. Of them, 288 responded our question on WTP for partial insurance and 289 responded our question on WTP for full insurance. The survey includes questions on sex, age, schooling, and risky health behaviors. Participants answered our survey privately, mostly at home, and without means of communicating with other participants, therefore we do not expect our results to be affected by information spillovers across treatment arms.

Table 1 presents descriptive statistics and shows that treatment arms were well balanced across observables. Almost half the participants were male, and their average age was 51 (age range 40-

[1] The figures for Lima are 32.1% and 28.8%, respectively (INEI 2018).

68). This is a highly educated sample: around three-quarters had completed tertiary education. This is higher than the overall share for Lima, where only 18% of adults in this age-range had reached that level. The age range and socioeconomic status of our subject pool makes them an ideal target market for oncological insurance providers. Regarding risky behaviors, roughly one-fourth of participants had consumed tobacco in the week leading to the experiment and 38% consumed alcohol. On the other hand, 54% conducted some sort of physical activity the week prior to the experiment. More than 90% of participants had health insurance and around one-third had oncologic insurance. Finally, 18% of participants had a household member with cancer. This high figure may partly reflect self-selection into the study sample, as people with an oncological patient at home may have been more prone to participate in a survey on oncological insurance. In section 4.1 we show that our results hold when we remove them from the sample.

After answering a short questionnaire, all participants received information on costs of cancer treatment in Peru, estimated by the Peruvian Association of Insurance Companies (APESEG) at S/.850,000-1'750,000 (US$260,000-530,000). The treatment group also received the following message "Official statistics show that the probability of developing cancer at some point in their life for a Peruvian citizen under 75 is 19%. The rate for females is 19% and for males is 18%." The control group did not receive this information.

We next presented two types of insurance: partial and full insurance. Partial insurance had a monthly cost of S/. 108 and offered coverage of up to S/. 750,000. Full insurance had a monthly cost of S/. 209. These figures correspond to actual insurance contracts offered by the largest provider in the country.

To estimate the present bias parameter using equation (4) one needs to identify individuals with WTP close to the market price. In the experiment, we elicited participants' willingness to pay for each insurance contract by asking them to report the highest price they would pay for each insurance contract. Eliciting WTP this way can introduce measurement error, so results must be interpreted with caution.

3.3 Empirical Strategy

Our estimating equations are of the form:

$$y_i = \gamma_0 + \gamma_1 T_i + \lambda' X_{0i} + \varepsilon_i \qquad (5)$$

Where y_i is individual i's outcome, T_i is an indicator that the participant received information on the probability of developing cancer over his or her lifetime, and X_{0i} are all the pre-treatment characteristics reported in Table 1. Given random assignment, OLS estimation of γ_1 renders an unbiased and consistent estimate of the average change in y_i caused by the information treatment.

We analyze treatment effect heterogeneity with the following specification

$$y_i = \delta_0 + \delta_1 T_i + \delta_2 Z_i + \delta_3 T_i Z_i + \omega' X_{0i} + \varepsilon_i \qquad (6)$$

TABLE II. Dependent variable: Willingness to pay is above market price

	Partial Insurance		Full Insurance	
	(1)	(2)	(3)	(4)
Received information treatment	0.000	-0.016	0.187***	0.178***
	(0.059)	(0.061)	(0.056)	(0.058)
Baseline Covariates	No	Yes	No	Yes
Observations	288	288	289	289
Mean Control	0.50	0.50	0.54	0.54

Dependent variable is an indicator that willingness to pay is greater than the monthly premium, for the insurance indicated in the column. Baseline covariates include: gender, age, level of education, indicators for tobacco consumption, alcohol consumption, physical activity, participation in health insurance, participation in oncology insurance and for a cancer patient in the household. Huber-White standard errors in parentheses. Statistically significant at the 0.10(*), 0.05(**) and 0.01(***) of confidence.

Where Z_i is the source of heterogeneity for subject i (presence of an oncology patient at home, education, sex, age, and present-bias parameter), and the other variables are as in equation (5). We use heteroskedasticity-robust Huber-White standard errors in all our analysis.

4. RESULTS

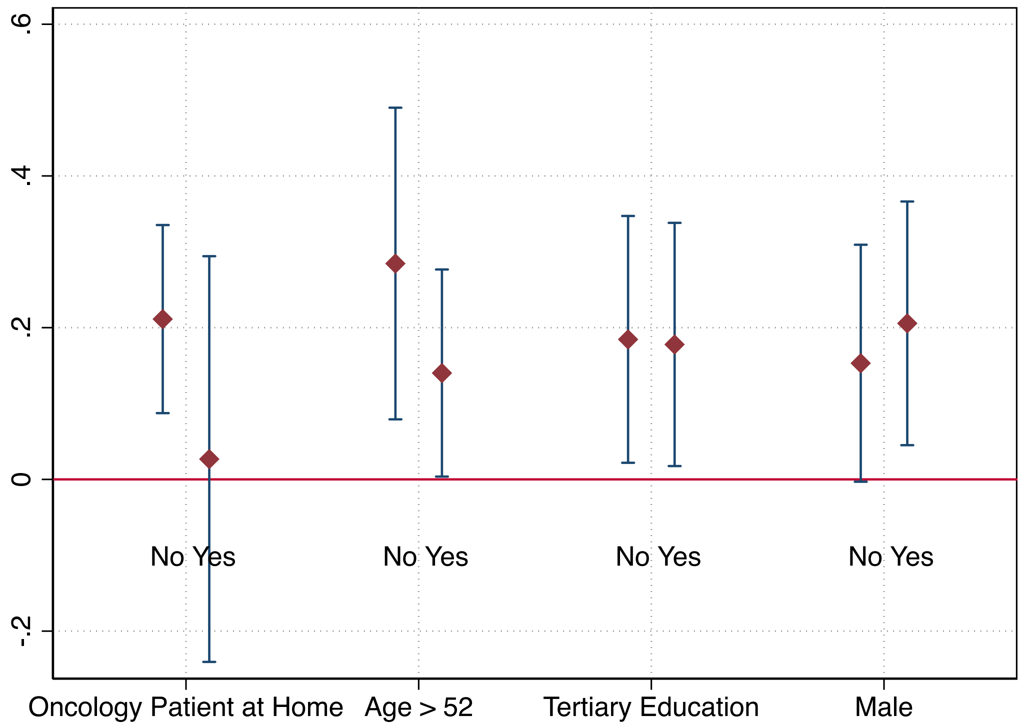
4.1 Main Results

Table 2 presents average treatment effects on insurance choice. Columns 1 and 2 report the effects on partial insurance, while columns 3 and 4 report the effects on full insurance. Information on the actual probability of developing cancer did not affect demand for partial insurance, while it increased uptake of full insurance by 18 percentage points (33% of the rate in the control group). The point estimates remain essentially unchanged when controlling for pre-treatment characteristics, which further supports the internal validity of our results, as it shows that, in line with the findings in Table 1, treatment was not related to individual determinants of demand for insurance.

The lack of effect on demand for partial coverage may owe to combined effects of high SES of our sample pool, loss aversion, and framing, since it was directly compared with full insurance, and the difference in monthly premium may have seem little compared with the difference in coverage.

We next turn to study treatment effect heterogeneity. Results are reported in Figure 1. We first split the sample between participants with an oncology patient at home and those without one. If treatment really worked by leading participants to update their probability of developing cancer, the information treatment should have a smaller effect among participants who live with a cancer patient because they may have formed some expectation of this probability well before the study.

Figure 1: Treatment Effect Heterogeneity



The vertical axis measures the estimated treatment effect on the probability that the participant takes-up full insurance. The figure shows that treatment had statistically significant effects irrespective of education, age, and sex. However, information affected demand for oncology insurance only among participants with no oncology patients living at home. 95% confidence intervals calculated with Huber-White standard errors.

In effect, the point estimate for this group is 0.03 and is not statistically significant, while average treatment effect for participants without an oncology patient at home is 0.21. The confidence interval for the group with an oncology patient at home is wider mainly due to sample size, as only 18% of study participants fall in this category (N = 53).

We next analyze effect heterogeneity by socioeconomic status. Average treatment effect is 0.28 for participants below the median age (52) and 0.14 for respondents above it, but the difference across groups is not statistically significant. Effects are practically identical between participants with or without tertiary education, at 0.18 in both cases. The point estimate for females is slightly smaller than males, at 0.15 and 0.21, respectively, but the difference across groups is not statistically significant.

TABLE III. Balance in the neighborhood of market price

	(1) WTP for partial insurance > market price
Received information treatment	-0.034
	(0.098)
Male	0.157
	(0.097)
Age	0.005
	(0.008)
Technical, incomplete	-0.072
	(0.425)
Technical degree	0.238
	(0.411)
College, incomplete	0.011
	(0.404)
College degree	-0.057
	(0.397)
Graduate studies, incomplete	0.064
	(0.416)
Graduate degree	-0.093
	(0.408)
Consumed tobacco in last week	0.044
	(0.132)
Consumed alcohol in last week	-0.034
	(0.095)
Physical activity in last week	-0.001
	(0.093)
Has health insurance	0.308
	(0.213)
Has oncologic insurance	-0.026
	(0.108)
Household member has cancer	0.048
	(0.118)
Observations	128
F-stat	0.84
p-value (F-stat)	0.64

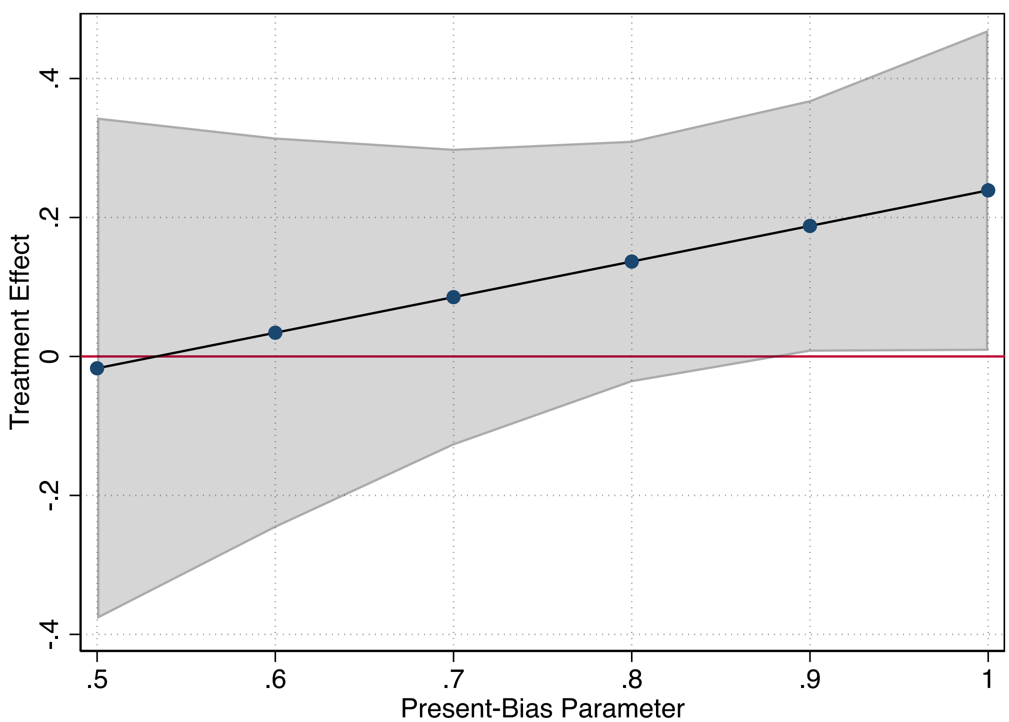
The outcome variable is an indicator that reported WTP for partial insurance is above market price. Sample is restricted to observations within S/.20 of the market price. Huber-White standard errors in parentheses. Statistically significant at the 0.10(*), 0.05(**) and 0.01(***) of confidence. This table shows that there are no differences in observables between individuals with reported WTP marginally above market price and those with WTP marginally below market price.

4.2 Present Bias

Our stylized model suggests that present bias could hinder the effects of information. To explore this issue, we estimate the present bias parameter using equation (4). We consider as "marginal consumers" all our study subjects who reported a WTP for partial insurance within a S/.20 window ($5.40) of the market price (S/.108, or $29.20). There are 128 observations in this window, 58 below market price, 20 exactly at market price, and 50 above it. We use WTP for partial insurance as this was not affected by the information treatment.

To offer support for the comparability of observations at both sides of the market price, we estimate a regression of having WTP above market price for insurance on all treatment and all the covariates in our main regression. Table 3 reports the results. Most coefficients are fairly small and none of them is statistically significant, implying that these covariates are well balanced across groups. Furthermore, the F-statistic for joint significance is 0.84 (p-value = 0.64). While we cannot rule out differences in unobservable variables, this is suggestive of no systematic differences across groups.

Figure 2: Treatment Effect on Full Insurance and Present Bias



The vertical axis measures the estimated treatment effect on the probability that the participant takes-up full insurance. The horizontal axis measures present bias (a higher present-bias parameter indicates less present bias). The figure shows that treatment had statistically significant effects only on individuals with present bias parameter above 0.9. Shaded are is the 95% confidence region with Huber-White standard errors.

We impose the following assumptions: Life expectancy of 80 years, probability of developing cancer is 19%, and treatment cost is S/.1’250,000 (so out of pocket expenditures are S/. 500,000). Under these assumptions, the resulting present bias parameter is 0.84 on average, with a standard deviation of 0.18. This is in line with the literature reviewed by Kremer et al. (2019), but slightly higher than in other settings in developing countries likely due in part to the high SES status and age of our study pool. When interacting present bias with treatment, we find that the effect on the take-up of full insurance is statistically significant only for individuals with present bias parameter above 0.90, who account for 53% of the sample.

5. CONCLUDING REMARKS

We show that informing the likelihood of developing cancer at some point over the course of life, can raise uptake of oncology insurance, particularly full insurance. Our participant pool resembles the target market for this type of insurance: highly educated, middle aged, from mid-to-high socioeconomic status. Among them, the effect does not differ by age, education, or gender. This suggests that information campaigns can increase insurance demand substantially in middle-income countries. Importantly, present bias may hinder the effects of information, as information has statistically significant effects only on individuals with a low degree of present bias.

Our study’s main caveat is its reliance on a hypothetical choice experiment, which may not necessarily translate into actual purchasing decisions. However, if actual purchasing decisions are proportional to behavior in the lab, one could expect our intervention to have an effect in the same direction on actual purchases.

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